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Fateh Belaïd, Christophe Rault

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Energy Expenditure in Egypt: Empirical Evidence Based on a Quantile Regression Approach

Abstract

This paper investigates the key factors affecting household energy expenditure in Egypt. Based upon the latest 2015 Egyptian HIECS Survey, we develop a quantile regression model with an innovative variable selection approach via Adaptive Lasso Regularization technique to untangle the spectrum of household energy expenditure. Unsurprisingly, income, age, household size, housing size, and employment status are salient predictors for energy expenditure. Housing characteristics have a moderate impact, while socio-economic attributes have a much larger one. The largest variations in household energy expenditures in Egypt are mainly due to variations in income, household size, and housing type. Our findings document substantial differences in household energy expenditure, originating from the asymmetric tails of the energy expenditure distribution. This outcome highlights the added value of implementing quantile regression methods. Our empirical results have various interesting policy implications regarding residential energy efficiency and carbon emissions reduction in Egypt.

JEL-Codes: C110, C210, D120, Q400.

Keywords: residential energy expenditure, energy efficiency, quantile regression, Adaptive Lasso, Egypt.

Fateh Belaïd
Faculty of Management, Economics & Sciences
Lille Catholic University
France – 59000 Lille
fateh.belaid@univ-catholille.fr

*Christophe Rault**
University of Orléans, LEO
Orléans / France
christophe.rault@univ-orleans.fr
http://chrault3.free.fr/

*corresponding author

1. Introduction

The building sector is one of the largest energy-consuming sector in most countries. For instance, 40 to 45% of Europe's energy consumption comes from buildings with a further 5-10% required for the manufacturing and transport of construction products and components. Besides, the building sector accounts for 20.1% of the total delivered energy consumed worldwide (International Energy Outlook, 2016). It would contribute up to one-third of global annual greenhouse gas emissions. In the last decade, the International Energy Agency highlighted that building design and the renovation of existing and aging dwellings would have the highest untapped energy savings potential achievable: about 80% of the economic potential of energy efficiency in buildings would remain untapped.

Energy consumption in the housing sector accounts for about 30% of worldwide energy consumption (IEO, 2016). The urgent issues of fighting climate change, enhancing energy transition and improving energy security have put the residential sector of most countries at the center of attention because of its large energy-savings potential, achievable through implementing energy efficiency investments. Thus, for several decades, improving energy efficiency in the residential sector has been of concern for public policy. Despite its importance, existing studies supporting these informed energy policies are sparse in developing countries (Adusah-Poku, and Takeuchi, 2019). This observation constitutes the foundation of this research, which aims at addressing the critical question of the various dimensions of energy expenditure. Specifically, it investigates the role of socio-economic and housing characteristics in shaping domestic energy expenditure in Egypt. The empirical analysis is based upon the latest 2015 Egyptian Household Income, Expenditure, and Consumption Survey (HIECS). The main purpose of this research is to illustrate the extent of the energy expenditure process, and to investigate reasons why households use less or more energy.

The motivation for this research is grounded in literature on the driver of energy consumption/expenditure in the residential sector, which has been the subject of a debate for many years (Bélaïd, 2016, 2017; Adusah-Poku, and Takeuchi, 2019). Growing attention in energy economics literature has been directed to the drivers of energy consumption/expenditure and efficient policy interventions to alleviate their negative impacts. Given the lack of micro individual data on energy expenditures and consumption, studies on household energy spending in developing countries are limited (Adusah-Poku and Takeuchi, 2019). In addition, despite the growing emphasis on reducing household energy demand to promote energy efficiency and environmental quality, our understanding of its main determinants in Egypt remains thin. Up to now, empirical research on developing countries has mainly focused on household access to modern cooking fuels and factors influencing their choice of fuel (Akpalu, Dasmani, & Aglobitse, 2011; Adusah-Poku & Takeuchi, 2019).

The existing research studies can be grouped into two main research fields. The first research strand focuses on investigating the drivers of household energy demand and energy choices (Barnes *et al.*, 2005; Ouedraogo, 2006; Chambwera and Folmer, 2007; Akpalu *et al.*, 2011; Adusah-Poku & Takeuchi, 2019). The second strand relates to the studies focusing specifically on investigating the validity of the energy ladder hypothesis (Hosier and Dowd, 1987; Farsi *et al.*, 2007; Bello, 2011). Most of this research argues that energy price, income, household size, access to modern infrastructure and education are the key determinants of household choice in cooking fuel.

As stated above, given the importance of residential energy consumption/expenditure on driving carbon emissions, surprisingly, little attention has been paid to understand the dynamic patterns of energy consumption and expenditure in developing countries. As far as we know, the determinants of household energy expenditure in Egypt has never been studied using micro level data. Furthermore, up to now, existing research on energy consumption with individual data factors concentrates largely on the Energy Access and fuel choices.

In Egypt, the related stakes are particularly important. It is worth noting that the building sector represents about 42% of global energy consumption (Fahmy *et al.*; 2014). Activities related to residential energy consumption (space cooling, heating, cooking, lighting, water heating, and refrigeration) together represent one of the largest sources of carbon emissions in Egypt. In addition, in the recent year due to shortages in natural gas supply and inadequate transmission and generation capacity Egypt undergoes frequent electricity blackouts.

Focusing on the Egyptian case, this paper examines the role of various factors in shaping household energy expenditure. Such a study should allow for a better understanding of household energy expenditure and also to model and predict energy consumption according to relevant household and housing characteristics.

Energy policymakers are increasingly concerned about understanding the main drivers of household energy expenditure/use, which is seen as a key strategy for reducing energy demand in the residential sector. The reduction of energy consumption and greenhouse gases have been put on the agenda of most sectors. Among them, the building sector, and more specifically, the residential sector, has been designated by the Intergovernmental Panel on Climate Change (IPCC) as having the biggest untapped energy-saving potential[1].

Starting with this conjecture, this research contributes to the literature on residential energy consumption in several ways. First, it introduces several dimensions of exploring the spectrum of energy expenditure through which the energy debate connects to household environment. Second, we address the gap in the empirical econometric methods used to explain the effects of its predominant drivers in other studies. The proposed quantile model helps

[1] International Panel for Climate Change: https://www.ipcc.ch/pdf/presentations/poznan-COP-14/diane-urge-vorsatz.pdf

to differentiate the effects of several variables on the entire consumption distribution. Third, we provide research on an issue that has been rather limited in Egypt due to the lack of information and availability of disaggregated data on household energy expenditure. Finally, the proposed innovative variables selection technique based on the Adaptive Lasso Regularization technique (hereafter Alasso), not only selects the relevant factors to make the model easy to interpret, but it also enhances the accuracy and stability of the predictors, avoiding the so-called curse of dimensionality. The main objective of using Alasso is to improve selection accuracy and computational efficiency of our econometric model.

From a policy-making perspective, our empirical findings have various policy implications regarding future energy policy in Egypt. First, it highlights the need to consider their differential impact on domestic energy expenditure /consumption. Second, the results could be helpful for recognizing the most efficient interventions for fuel poverty reduction schemes. In addition to enrich the energy policy debate, this study aims at contributing to the ongoing research on residential energy consumption by providing a more elaborate overview on its various facets.

The remainder of this article is built-up as follows: Section 2 describes the data used, the variables definition, as well as the empirical specification. Section 3 summarizes and discusses the main empirical results. Section 4 briefly presents a robustness analysis. Finally, section 5 provides conclusions and related policy implications.

2. Data and empirical methodology

2.1 Data

Based upon the latest 2015 Egyptian HIECS Survey provided by the Economic Research Forum (ERF), we develop an empirical model exploring the main determinants of energy expenditure in Egypt, including housing attributes, household socio-demographic factors and appliances. The survey combines valuable information on household income and housing expenditure, including electricity, gas and other fuel expenditures. In addition, to valuable information on household socio-economic attributes (*e.g.*, age of the head, marital status, gender, ethnicity, etc.), the survey contains rich data on housing characteristics and conditions, including housing size, type of structure, source of energy, health facility, etc.

The 2015 HIECS and 2013 HEIS are rich data sets containing over 240 variables. These surveys provide detailed information on household income and housing expenditure, including electricity, gas and other fuel expenditures. In addition to valuable information on household socio-economic attributes (*e.g.*, age of the head, marital status, gender, ethnicity, etc.), the survey contains rich data on housing characteristics and conditions, including housing size, type of structure, source of energy, health facility, etc. The explanatory factors have been selected based on the existing literature and availability in our dataset. Descriptions and descriptive statistics for the factors used in the econometric analysis are displayed in Table 1 and Table 2.

Table 1
List and description of the qualitative modeling variables

Variable	**Categories**	Freq.
Gender of the head (SEXHD)	1 Male	82.45
	2 Female	17.55
Education level of the head (EDUHD)	1. None	41.71
	2. Primary/Lower secondary	14.16
	3. Secondary	31.95
	5. University	12.18
Source of income (INCSM)	1. Salary	59.98
	2. Household business	27.01
	3. Remittances from country or abroad	22.01
Household composition (HCOMP)	1. 1-2 adults, no children	17.23
	2. 1-2 adults, 1-2 children	18.28
	3. 1-2 adult, 3 or more children	23.53
	4. 3 or more adults, 0-1children	23.92
	5. 3 or more adults, 2-3 children	13.17
	6. 3 or more adults, 4 or more children	3.88
Main activity status of the head (MASHD)	1. Employed	72.95
	3. Homemaker (Housewife)	8.70
	5. Pensioners/retired/disabled	1.25
	6. Others	17.10

Head living in couple (MARRIEDC)	0 No couple present in household 1 Married couple head and spouse	21.47 78.52
Age of the head (AGEHD)	Less than 39 From 40 to 48 From 49 to 59 More than 60	23.63 24.82 26.06 25.49
Number of rooms (ROOM)	1 to 2 Rooms 3 Rooms 4 Rooms More than 4 Rooms	9.54 39.86 36.91 13.69
Type of dwelling (DWLTYP)	1 House 3 Apartment 4 Others	17.58 77.66 4.76
Type of tenure (DWLTEN)	1 Rented 2 Owned 3 Provide free	14.37 72.09 13.54
Urban structure (RURURB)	0 Rural 1 Urban	56.45 43.55
Has Internet (INTERNET	0 No 1 Yes	82.79 17.21
Has a computer or laptop (COMPUTER)	0 No 1 Yes	68.65 31.35
Has a Vacuum (VACUUM)	0 No 1 Yes	78.41 21.59
Has an air conditioner (COND)	0 No 1 Yes	87.12 12.88

Table 2
List and description of the quantitative modeling variables.

Variable	Label	N	Mean	Std. Dev.	Minimum	Maximum
Energy expenditure	EDWE	11729	1033	420	228	2990
Household income	TOTDINC	11729	41903	27160	2745	526000
Age of the head	AGEHD	11729	50	14	18	99

Fig.1 displays the distribution of domestic energy expenditure in Egypt, which ranges from 228 to 2990 with an average bill of 1033, and a standard deviation of 420.

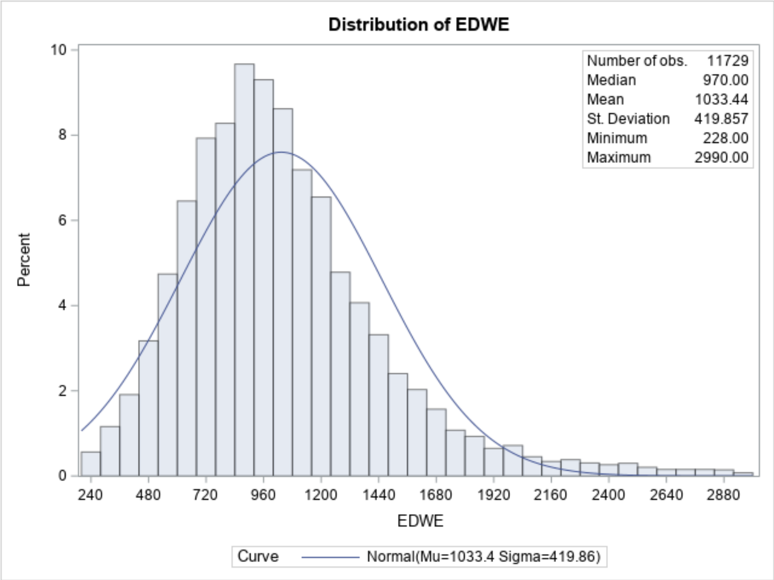

Fig.1. Distribution of energy expenditure in Egypt

Distribution of energy expenditure regarding houehold income is displayed in Fig. 2. It can be noticed that energy expenditure is positively correlated with household income, *i.e.* it increases along with income.

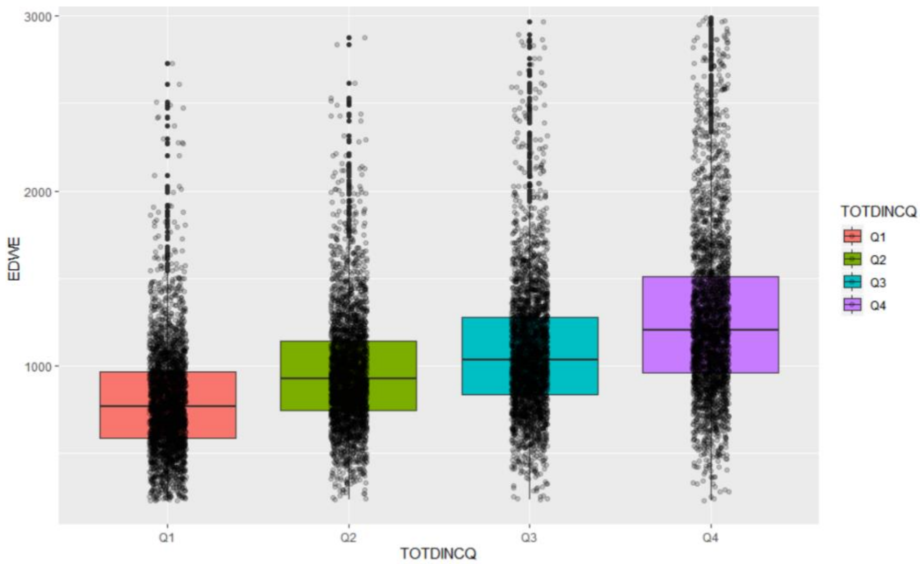

Fig.2. Energy expenditure and income distribution in Egypt.

2.2. Empirical methodology

In the previous literature, household energy demand is commonly examined within the household production theory, assuming that individuals get satisfaction from energy through the services integrated in it (Lancaster, 1966). The consumer demand theory developed by Lancaster (1996) documents that consumer drive utility from certain specific attributes of the goods, but not from the goods themselves *per se* and is the object of consumer utility or preference. For example, in the case of energy, consumers do not require electricity for itself, but rather for the warmth, electricity ability to power appliances, and potential to provide lighting.

Most research on household energy expenditure/consumption using micro level implement OLS regression, from which estimates are the conditional means of the parameters of the model. This approach may capture how households adjust their energy expenditure with respect to variations in their contextual and socio-economic factors. Nonetheless, it has limited information to consider the expenditure of households who spend less or more in energy than the average. Accordingly, interpretation of the drivers of energy expenditure based on the conditional mean cannot consider the differences among heterogeneous households in Egypt. For policy purposes, it will be enlightening to untangle the spectrum of energy demand of those household at the tail of the energy expenditure distribution.

In order to explore distributional effects, rather than average, of household energy expenditure, we develop a bottom-up statistical approach based on a quantile regression model and an innovative variable selection approach via Adaptive Lasso Regularization technique (Alasso). In most studies of household energy use/expenditure and its various determinant factors, the approach used to examine socio-economic and housing influences has essentially been limited to multiple linear regressions (Tso and Guan, 2014). The proposed Alasso variables selection method not only allows for the selection of relevant factors to get a parsimonious model easy to interpret, but it also provides enhanced prediction accuracy, stability, and it avoids dimensionality. The main objective of using Alasso is to improve selection accuracy and computational efficiency of our model and provide a comprehensive picture of the key determinants of energy expenditure.

To select appropriate control variables from our selected factors, we use adaptive Lasso selection technique, which is a regularized linear regression approach outperforming OLS regression in terms of out-of-sample prediction performance through reducing model complexity and inducing shrinkage bias (Ahrens *et al.*, 2019). The first advantage of Alasso as a selection technique relies on its bias variance trade-off. A second advantage stems from its concave optimization property, which helps to solve the absolute maximizer efficiently suffering from the multiple local issue. In addition, Zou (2006) documented that Alasso approach is selection consistent and enjoy the oracle properties. Alasso compared to the other oracle procedures, *e.g.* Smoothly Clipped Absolute Deviation penalty, is computationally more appealing, since we can get effectively its entire solution path. Further Alssao, may serve as a selection model technique, particularly when faced with a large number of putative predictors, as it is able to provide sparse solutions (Ahrens *et al.*, 2019). Alasso regularized approach relies on tuning parameters that control the type and degree of penalization. In this paper we used various approach to properly select our tuning parameters, including cross validation, Akaike information criterion, rigorous penalization and square-root Lasso approach.

The penalized log-likelihood for the Alasso is defined by the following equation:

$$l_p(\beta) = l(y|\beta) - \lambda \sum_{j=1}^{p} \widetilde{\omega}_j \left|\beta_j\right| \dots eq. 1$$

, where $l(y|\beta) = \sum_{i=1}^{n} \log f(y_i|x_i, \beta, \varphi)$, and $\widetilde{\omega}_j = 1/\left|\tilde{\beta}_j\right|^{\gamma}$ is the weight vector with $\gamma > 0$ the power parameter. The penalized estimates of Alasso are obtained by maximizing Eq. 1.

Therefore, the ALSSO estimates are given by:

$$\hat{\beta}_{ALASSO} = \underset{\beta}{\operatorname{argmax}}\left\{l(\beta) - \lambda \sum_{j=1}^{p} \tilde{\omega}_j |\beta_j|\right\} \ldots eq.2$$

Quantile regression is considered as an extension of the standard least squares estimation of conditional mean models to the estimation of a set of models for several conditional quantile functions. Quantile regression first developed by Koenker and Bassett (1978) and developed further by (Koenker and Hallock, 2001), seeks to generalize the idea of univariate quantile estimation to the estimation of conditional quantile functions, *i.e.* the quantiles of the conditional distribution of the dependent variable are formulated as functions of the observed covariates.

As stated above, energy expenditure is not homogeneous across households. Therefore, OLS based on the conditional mean is not appropriate to differentiate the impact of the various predictors with respect to energy expenditure distribution across households. However, quantile regression estimates the impact of the individual explanatory variables on a specified quantile of the dependent variable (*e.g.*, 5^{th}, 15^{th}, 50^{th} and 95^{th} quantiles).

Using quantile instead of OLS regression has two major advantages. First, since household are heterogeneous, quantile approach allows inferences with respect the effect of explanatory factors conditional on the amount spent on energy. When degree of data variations is important, it is clear that quantile regression is a better strategy. The quantile regression parameters assess the variation in a specified quantile of household energy expenditure as a response to a one-unit variation in the explanatory variable. Second, rather than assuming the normality of the error terms conditional on the repressors, no assumption is made on the error term distribution. Thus, estimates from a quantile approach are more flexible and exhibit stronger robustness compared to those from OLS models.

Therefore, using quantile regression model allows for more flexibility in the estimation of the considered predictors effect on residential energy expenditure by enabling us to estimate a range of conditional quantile functions.

The quantile regression model can be considered as a location model (Koenker and Bassett, 1978). We assume that:

$$P(y_i \leq \tau | x_i) = F_{\mu_\theta}(\tau - x_i' \beta_\theta | x_i) \ldots eq. 3$$

, where $(y_i, x_i), i = 1, \ldots, n$ is a sample from some population, and x_i represents a $K * 1$ vector of regressors.

Eq.3 can be reformulated as follows:

$$y_i = x_i' \beta_\theta + u_{\theta_i} \text{ with } Q_\theta(y_i | x_i) = x_i' \beta_\theta, \qquad 0 < \theta < 1 \ \ldots eq. 4$$

$Q_\theta(y_i | x_i)$ depicts the conditional quantile of y_i on x_i. It is assumed that u_{θ_i} satisfies the quantile restriction $Q_\theta(u_{\theta_i} | x_i) = 0$.

The linear conditional quantile function can be estimated by solving the equation below:

$$\min_b \left\{ \sum_{i: y_i \geq b} \theta |y_i - b| + \sum_{i: y_i < b} (1 - \theta) |y_i - b| \right\} \ \ldots eq. 5$$

In our study, the standard log-linear demand equation used to investigate the drivers of energy expenditure can be written as:

$$y_i = x_i' \beta_\theta + u_{\theta_i} \text{ with } Q_\theta(y_i | x_i) = x_i' \beta_\theta \ \ldots eq. 6$$

In our model y_i is the vector of household energy expenditure (in logarithm), x is a vector of all the regressors, β is the vector coefficients to be estimated, and u_{θ_i} is a vector of the residuals. $\hat{\beta}_\theta$ the estimator of the θ^{th} quantile regression that minimizes over the objective function below (Cameron and Trivadi, 2013):

$$\min_{\beta}\frac{1}{n}\left\{\sum_{i:y_i\geq x_i'\beta}\theta|y_i-x_i'\beta_\theta|+\sum_{i:y_i<x_i'\beta}(1-\theta)|y_i-x_i'\beta_\theta|\right\}=\min_{\beta}\frac{1}{n}\sum_{1}^{n}\varphi_\theta(u_{\theta_i})\quad ...eq.7$$

, where $\varphi_\theta(\lambda)=\big(\theta-I(\lambda<0)\big),\ I(.)$ is the usual indicator and λ is the check function.

The standard errors and confidence limits for parameter estimates are obtained using asymptotic and bootstrapping methods. According to Koenker and Hallock (2001), the results originated from both approaches are robust. In this study we use bootstrap method following Hao and Naiman (2007).

As a robustness analysis, we employed deterministic multivariate and Bayesian linear regression model. The detailed modeling framework and implemented procedures of this study are displayed in Fig.3.

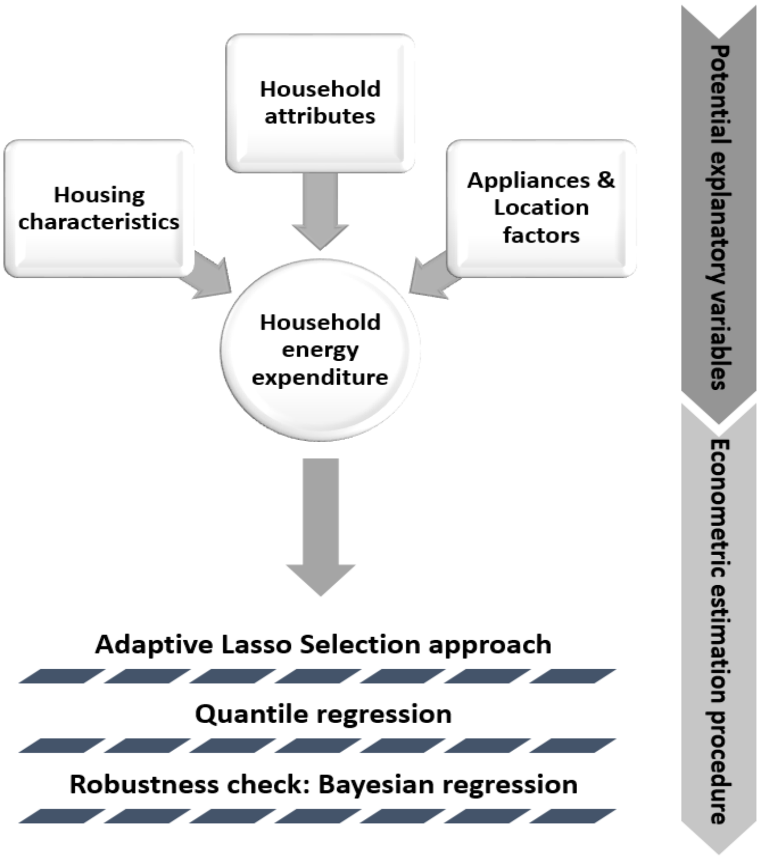

Fig.3. Empirical strategy and modeling framework

3. Empirical results and discussion

We develop an empirical bottom-up approach employing household socio-economics attributes, housing characteristics, location, and household appliance to estimate domestic energy expenditure in Egypt. First, we estimate a quantile regression model to investigate and identify the effect of the various explanatory factors on residential energy expenditure. Then, as a robustness analysis, we consider a multivariate linear regression model and a Bayesian linear regression model. The final models include all the factors selected using the Adaptive Lasso selection approach.

The adaptive Lasso shrinkage pattern is displayed in the Figs in Appendix A. The results of quantile and OLS models are displayed in Table 3. The Quantile regression estimates graphs are displayed in Appendix B. The results indicate that most of the explanatory variables used in the models are statistically significant, at 1% level at least, and have the expected signs.

The direction and magnitude of the energy household income are consistent with the findings in the literature. The models estimate show that household income has a significant positive impact on energy expenditure, *i.e.* an increase in the income implies a systematic increase in energy expenditure, suggesting that energy is a normal and necessity good. Income elasticity ranges from 0.25 to 0.27. The income elasticity from OLS is 0.25. We notice that income effects on energy expenditure are quite similar across the considered quantiles. The 50th quantile of energy expenditure distribution has the lowest income elasticity (0.25). The highest income elasticity is observed for those whose energy expenditure is at 25th quantile.

Households experiencing elevated income may well increase expenditure of energy through the purchasing of large and new appliances, increasing comfort, etc. These finding are in line we the existing literature. Previous studies argued that income level stimulates household energy demand, and thus should exert a substantial positive impact on energy expenditure. Petersen (2012), Salari and Javid (2017), and Taale and Kyeremeh (2019) found a significant positive relationship between household electricity expenditure and income level. Further, Khandker *et al.*, (2012) documented that income plays an important role in increasing energy expenditures among Indian households. Note that factors related to household attributes and income are reasonably self-explanatory. In fact, household income may partially proxy ownership of the not observed durable goods, durable quality, and housing energy performance (Baker, 1989).

Estimates displayed in Table 3 confirms that the age of the head has a positive effect on energy expenditure in Egypt. Estimates displayed in columns 2-5 reveal the different features of the coefficients of the age of the head changing from the bottom to top quantiles. The age of the head effects on energy expenditure increases from the 25th quantile to the 50th quantile, and decreases over the 0.75 quantile. The coefficients are 0.008, 0.016, 0.13, and 0.13. There is no consensus about the age effect on household energy expenditure in literature. Some empirical studies document a positive linear relationship, some highlight a nonlinear relationship, and others substantiate a non-causal effect between the age of the head and energy expenditure. Petersen (1982) argued that residential energy expenditure follows an inverted U-shape curve. This statement coincides with the results of Bélaïd (2016; 2017) in the case of France. One rational explanation of these results stems from the life cycle theory (Fritzsche, 1981), suggesting that residential energy consumption increases through child rearing years, and declines when children leave home. Krishnamurthy and Kriström (2015) document a significant and positive effect of the age of the head on energy expenditure. Further, Jones *et al.* (2015) argue that energy expenditure tends to be higher for household aged between 50 and 65 years. Adding to this literature, Huebner *et al.* (2015) suggest that household age has no significant impact on energy consumption/expenditure.

Table 3
Quantile and OLS model estimates

	Quantile 0.25	Quantile 0.5	Quantile 0.75	Quantile 0.90	OLS
Intercept	3.985***	4.401***	4.587***	4.719***	4.329***
Income	0.274***	0.251***	0.254***	0.263***	0.253***
Age of the head	0.008**	0.016***	0.013***	0.013**	0.013***
Business Vs. Salary	0.027**	0.025***	0.026**	0.036***	0.036***
Remittances vs. Salary	-0.014	-0.022	-0.005	0.030	-0.002
Mal vs. Female	0.051***	0.049***	0.031**	-0.006	0.044***
1-2 adults, no children vs. Adults >3, >4 children	-0.234***	-0.262***	-0.200***	-0.188***	-0.211***
1-2 adults, 1-2 children	-0.111***	-0.156***	-0.130***	-0.111***	-0.099***
1-2 adult, 3 or more children	-0.068***	-0.114***	-0.101***	-0.093***	-0.070***
3 or more adults, 0-1children	-0.074***	-0.119***	-0.096***	-0.106***	-0.082***
3 or more adults, 2-3 children	-0.015	-0.086***	-0.075***	-0.091***	-0.037**
Employed vs. Retired	-0.016	-0.014	-0.013	-0.027	-0.017
Homemaker vs. Retired	0.061***	0.049**	0.046**	-0.013	0.047***
Others vs. Retired	0.029	0.020	0.027	-0.001	0.032
Number of Rooms	0.018***	0.021***	0.017***	0.021***	0.028***
Apartment vs. House	-0.172***	-0.123***	-0.104***	-0.114***	-0.130***
Rented vs. Owner	-0.059***	-0.027***	-0.029***	-0.015	-0.039***
Urban vs. Rural	0.017**	-0.020**	-0.042***	-0.062***	-0.005
No conditioner	-0.142***	-0.149***	-0.156***	-0.150***	-0.162***

***, **, * denote significance at 1%, 5% and 10% level.

As expected, household size has a significant impact on energy in Egypt. However, this impact is nonlinear and varies across the energy expenditure distribution. For example, moving from 1-2 adults with children to more than three adults and four children increases energy expenditure by 23%, while moving from 1-2 adults and 1-2 children to more than three adults and four children increases energy expenditure by 11%. Any additional household member has a decreasing impact on energy consumption. Results also indicate that the impact of household size is larger on energy expenditure on the 50th quantile than on the 25th quantile. The finding that household size is a significant driver of energy expenditure/consumption is not new. This coincide with the results of Longhi (2015), Lévy *et al.* (2014), and Belaid *et al.* (2019). Zhou and Teng (2013) found that energy expenditure increases by 8% for every additional household member. Nevertheless, some studies argued that household size has a significant negative impact on energy expenditure (Druckman and Jackson, 2008; Taale and Kyeremeh, 2019). For example, Behera and Ali (2016) suggest that family size has a negative impact on electricity expenditure. This can be explained by a potential economy of scale attributed to a large family size.

Looking at the effect of gender, results show a positive and significant effect of gender on energy expenditure across all quantiles. Men-headed household energy expenditure is higher compared with women-headed households. The estimation ranges from 0.006 to 0.51, and the magnitude of the effect decreases at the upper tail of the energy expenditure. These results coincide with the proposition of Carlsson-Kanyama and Lindén (2007), who documented the positive role of gender in explaining energy expenditure. They suggest that household headed by men spend between 14 and 21% more energy than household headed by women. These results support the assertion that men-headed household tend to be wealthier, and use more appliance compared with women-headed household.

The house size variable, measured in terms of number of rooms has a very well determined positive effect on energy expenditure in Egypt, which is quite different across quantiles. The housing size role to explain household energy consumption/expenditure has been widely documented in the literature. Our estimates range from 0.017 to 0.28. These findings coincide with the results of Kaza (2010), Longhi (2015), and Bélaïd (2017). This explicitly advocates that households with a large number of rooms tend to have higher energy needs compared with households in smaller housing-units. Accordingly, McLoughlin *et al.* (2015) document that energy consumption in Ireland increases by 15.4% for every additional bedroom.

Considering the tenancy status, our results show that it has a significant impact on energy expenditure in Egypt across all quantiles. We found renters spend more on energy compared to homeowners. Our findings are not in line with Bélaïd (2016) results, claiming that tenants consume about 22% less energy than homeowners. Further, this result contradicts the occupancy hypothesis underlying a significant inverse relationship between home ownership and domestic energy expenditure. The argument advanced by this theory is that rented-occupied dwelling contain poor energy efficiency investment because renters are not motivated to invest in energy efficiency for a rented unit. The argument behind this theory underlines a principal agent issue. Economic literature has long recognized that market failures including, inefficient energy pricing, environmental externalities, lack of information, and principal-agent conflicts can lead to inefficiently low levels of investment in energy efficiency (Gillingham and Palmer, 2014; Gerarden et *al.*, 2015). Principal-agent conflicts - “split-incentives” are amongst the most mentioned market failure explanation for the energy efficiency gap.

This conflict arises when one agent makes decision relating energy consumption, but another agent benefits or pays from that decisions. Such a situation may lead to an increased energy demande or reduced energy efficiency of the dwelling (Gillingham and Palmer, 2014).

Concerning the housing type, our results show that this factor is statisticaly significant and confirm its relevance to explain the variation in energy expenditure. They sugget that houshold living in appartment spend 10 to 18% less in energy than housholds living in single housing unit. These results coincide with the proposition of Bélaïd *et al.* (2019), who documented the positive role of housing type in shaping energy consumption/expenditure in France. They suggest that households living in multi-unit housing consume 14%-25% less electricity than people living in individual housing-units, depending on the quantile.

The coefficients of location area are statistically significant at least at 5% for the quantiles, but not significant for OLS regression. The coefficient of location area declines consistently along the distribution of energy expenditure. At the 25th quantile, the coefficient is 0.017. It rises around 400% to be -0.062 at the 90th quantile. The results indicate that households living in urban areas at the 25th quantile spend higher amount compared to those living in rural area. However, household living in urban areas after the 25th quantile spend lower amount in energy compared to the base category. The significant positive impact of urban areas on energy expenditure at lower tail of energy expenditure distribution may be explained by the Urban Heat Island phenomenon effect, underlying that in dense built-up area temperatures tend to be higher compared with less dense area (Taale and Kyeremeh, 2019). Nevertheless, regarding the negative effect of urban areas on energy expenditure, various explanations can be given. First, in rural areas households tend to live in large detached houses. Second, housing units of those people have poor energy performance, which is reflecting a positive association with their energy expenditure (Lévy *et al.*., 2014; Belaïd, 2018).

The conditioner presence is used to capture the impact of household appliance on energy expenditure. The coefficient of this variable from OLS regressions is negative and statistically significant, the coefficient is of -0.16. Similarly, the quantile regression coefficients are all negative and statistically significant at least at 1%. The magnitude of the coefficient declines slightly from -0.14 at the 25th quantile to -0.15 at the 90th quantile. This finding suggests that conditioner has a positive impact on household energy expenditure. It indicates that households without conditioner spend lower amount in energy along the energy expenditure distribution compared to the base category, *i.e.* household with conditioner. These findings add to claims made in the literature about the positive effect of appliances stock on energy consumption/expenditure (Halvorsen and Larsen, 2001; Belaïd and Garcia, 2016).

Finally, among the variables that control for the household employment status of household head, the quantile regression results indicate that homemakers spend more in energy compared to retired ones. The effect is not statistically significant at 90th quantile, and the highest coefficient is obtained for those whose energy expenditure is at 25th quantile. One possible explanation is that unemployed persons and homemakers tend to spend more time at home, and consume higher amount of energy on their activities. This significant impact of household head employment status on energy expenditure is in line with the literature, confirming that unemployment contributes to higher energy expenditure by expanding the time spent at home (Taale and Kyeremeh, 2019).

4. Robustness check

We conduct here a robustness check to assess the sensitivity of our results to model specifications. In addition to replacing the continuous of age and income with qualitative factors, we also use a Bayesian linear regression model to explore the main factors shaping energy expenditure in Egypt. The major advantage of a Bayesian approach is its ability to take into account, and to represent the full uncertainties related to model and coefficient estimates. This flexibility makes estimates from Bayesian models to have a stronger robustness, mainly against outlying observations, compared to that of an OLS approach. Further, working with parameter posterior distributions allows abundant additional statistical inference (Permai *et al.*, 2018).

The results are displayed in Table 4. The Bayesian regression diagnostics graphs are displayed in Appendix C.

Table 4

Bayesian regression model estimates

Parameter	Mean	Standard Deviation	Percentiles 25%	50%	75%
Intercept	4.270	0.094	4.206	4.269	4.333
LTOTDINC	0.262	0.008	0.256	0.262	0.267
AGEHD	0.001	0.000	0.001	0.001	0.002
Business	0.027	0.008	0.022	0.027	0.032
Remittance	-0.006	0.011	-0.014	-0.006	0.001
SEXHD1	0.037	0.012	0.028	0.037	0.045
HCOMP1	-0.223	0.019	-0.236	-0.223	-0.210
HCOMP2	-0.113	0.019	-0.126	-0.113	-0.101
HCOMP3	-0.078	0.018	-0.090	-0.078	-0.066
HCOMP4	-0.087	0.018	-0.098	-0.087	-0.075
HCOMP5	-0.051	0.019	-0.063	-0.051	-0.038
Employed	-0.019	0.012	-0.027	-0.019	-0.010
Homemaker	0.043	0.017	0.031	0.042	0.054
Others	0.025	0.030	0.005	0.025	0.045
ROOM	0.023	0.003	0.021	0.023	0.026
APARTN	-0.132	0.016	-0.142	-0.132	-0.121
Tenant	-0.041	0.008	-0.046	-0.041	-0.035
RURURB0	-0.011	0.007	-0.016	-0.011	-0.006
COND0	-0.146	0.010	-0.153	-0.146	-0.139
Dispersion	0.120	0.002	0.119	0.120	0.121

In general, the results of our robustness approach are in agreement with the results of our previous, and support our previous assertions regarding the determinants of energy expenditure in Egypt. However, although the robustness procedure suggests that our findings are promising, there are some caveats that should be mentioned. First, since our dataset do not contain information on energy prices, our models may be subject to omitted variable bias. The second caveat may stem from the data quality. In fact, due to the behavioral nature and complexity, information gained from questionnaire may introduce observational errors. This bias may affect the robustness and model accuracy. This constitutes an area of further research. Accordingly, interpretation and generalization of the results ought to be treated with caution.

5. Conclusions and policy implications

This article has presented a new perspective on energy expenditure in Egypt. Its insights are driven by considering recent consumption survey and bottom-up empirical approach to explore the relationship between residential energy expenditure and various explanatory factors. The empirical analysis has been based on a bottom-up statistical approach along quantile regression and Adaptive Lasso Regularization technique.

Understanding the key drivers of energy consumption/expenditure has gained more attention in developed countries than in developing ones. One reason may be the economic conditions and the energy context. In addition, there is still a lack of knowledge on how energy expenditure connects to the socio-economic attributes of the household, on the relative prominence of these attributes, and whether variations in individual's socio-demographic conditions translate in variations in energy expenditure (Longhi, 2015). One rational explanation is the lack of suitable micro-level data incorporating information on various aspects of occupants' energy consumption and lives.

In this article we investigated some aspects of residential energy expenditure in Egypt. Specifically, we discussed the role of various predictors in shaping household energy expenditure, including differences between renters and owners, income, age of the head, household size. Using quantile regression, this study allowed the differentiation of the effects with respect to energy expenditure distribution. Our empirical analysis yielded various interesting findings. In particular, it documented that the factors influencing housing energy expenditure in Egypt vary with the distribution of energy expenditure. Housing characteristics have a moderate impact, while socio-economic attributes have a much larger impact. The largest variations in household energy expenditures in Egypt are mainly due to variations in income, household size, and housing type.

A large share of a country's energy use is, directly or indirectly, driven by household decision. Accordingly, energy consumption reduction at the household level in an effective and efficient way to reduce carbon emissions and enhance a country's environmental quality. The reduction of non-renewable energy consumption and greenhouse gases has been put on the agenda of most sectors worldwide. Among them, the building sector, and more specifically, the residential sector, has been designated by the Intergovernmental Panel on Climate Change (IPCC) as having the biggest untapped energy-saving potential[2]. However, energy transition in the residential sector is facing a major challenge. While binding commitments relative to the reduction of energy consumption and the increase of energy efficiency have been taken at the national and international scale[3], their success depends on the good-will and capacity to act of millions of the housing stock inhabitants, whether it concerns energy saving behaviors or energy efficiency investments. In recent years, because energy savings in the residential sector have

[2] International Panel for Climate Change: https://www.ipcc.ch/pdf/presentations/poznan-COP-14/diane-urge-vorsatz.pdf
[3] See Energy Efficiency Directive and Energy Performance Building Directive revised in 2018: https://euroace.org/euroace-positions/energy-performance-buildings-directive-epbd/

not reached the expected level and are behind on meeting the closest-in-time energy goals, designing efficient policies capable of fostering energy efficiency investments has become urgent in most countries.

From the policy perspective, our findings provide valuable insights for policymakers in quest of efficient policy interventions related to the role of residential energy consumption in reducing carbon emissions. In addition, the findings are helpful for countries in implementing policies to enhance environmental quality and step on the path of significant reduction in residential energy consumption. Roughly, our findings suggest that residential energy expenditure, at a household level, stems from a complex dynamic process, which is not only shaped by a wide range of energy use drivers, including individual attributes and contextual conditions, but also by the dynamic relationship between occupants and their environment. This conjecture constitutes a strategic information vector for policy makers in the implementation of future energy efficiency policies. It suggests that targeting policies toward specific households may improve energy efficiency policy effectiveness and provide a gateway to instigate low energy instruments tailored to high energy consumers. Regarding the policy-makers' perspective, focusing on this complex nexus of energy expenditure, housing, and contextual factors can be helpful in expanding more effective energy efficiency policies in the residential setting. Further, our findings, call to focus more efforts on: (i) behavioral change approaches to convenience occupants about the energy conservation benefits, and (ii) using gentle nudges to persuade individuals to desirable behavior and to promote more environmentally energy use behavior.

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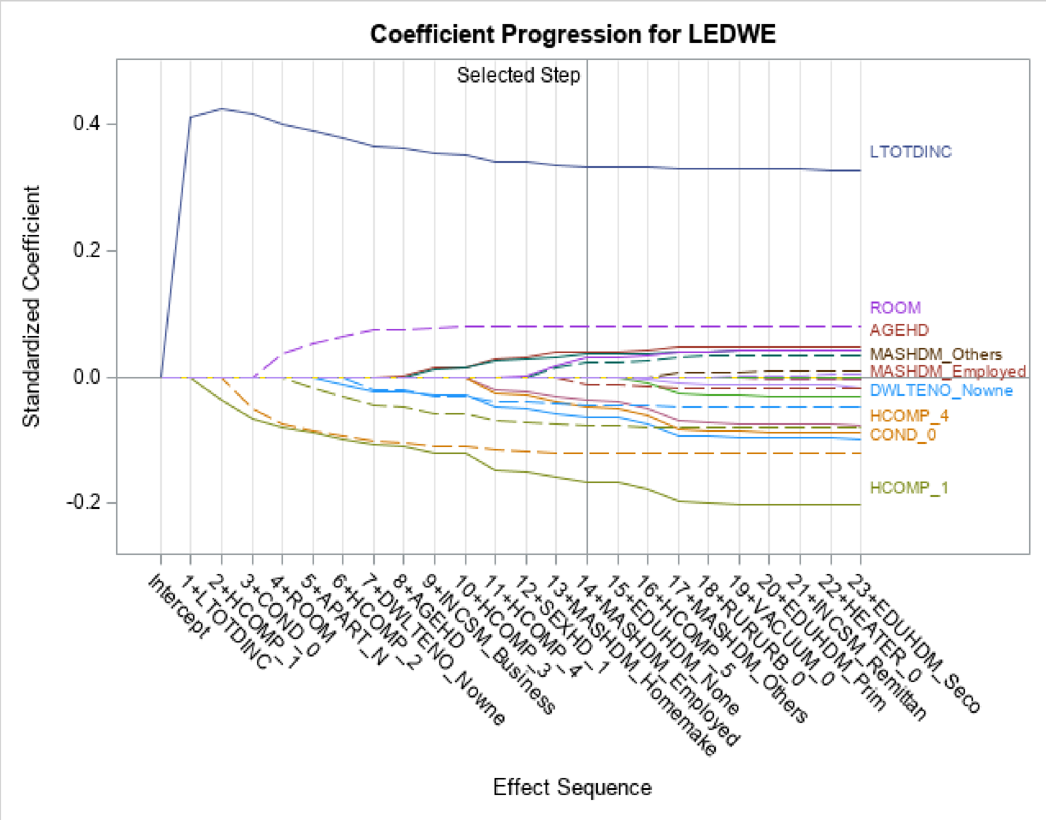
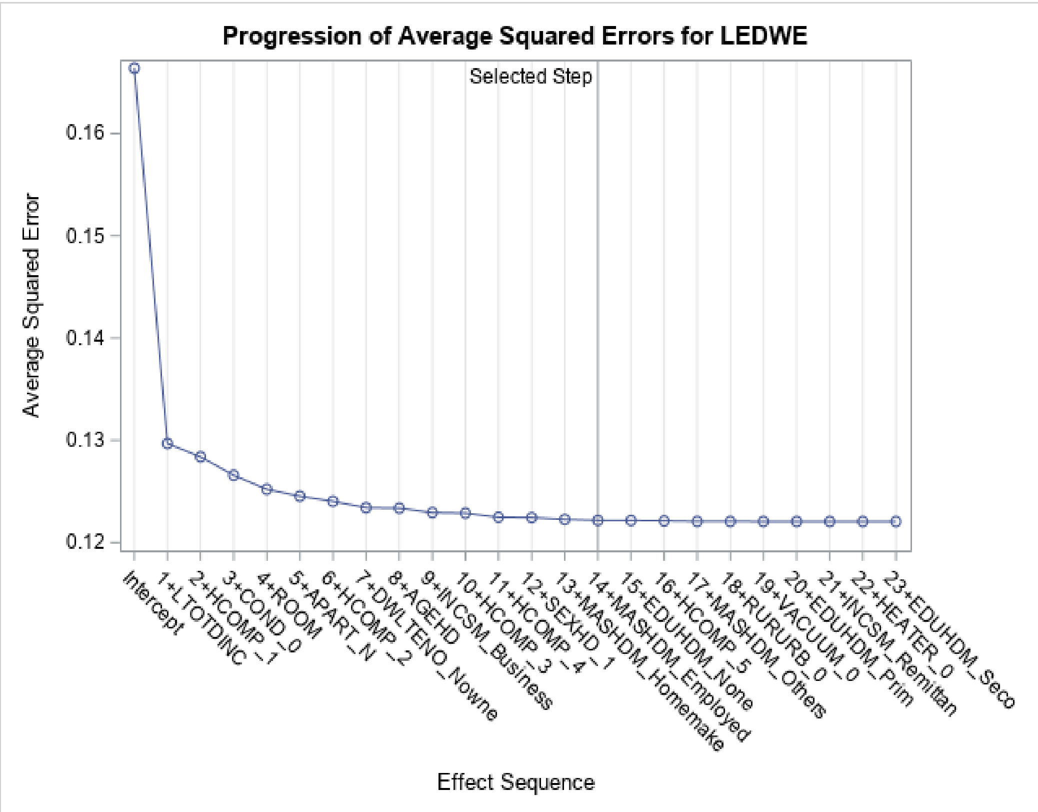
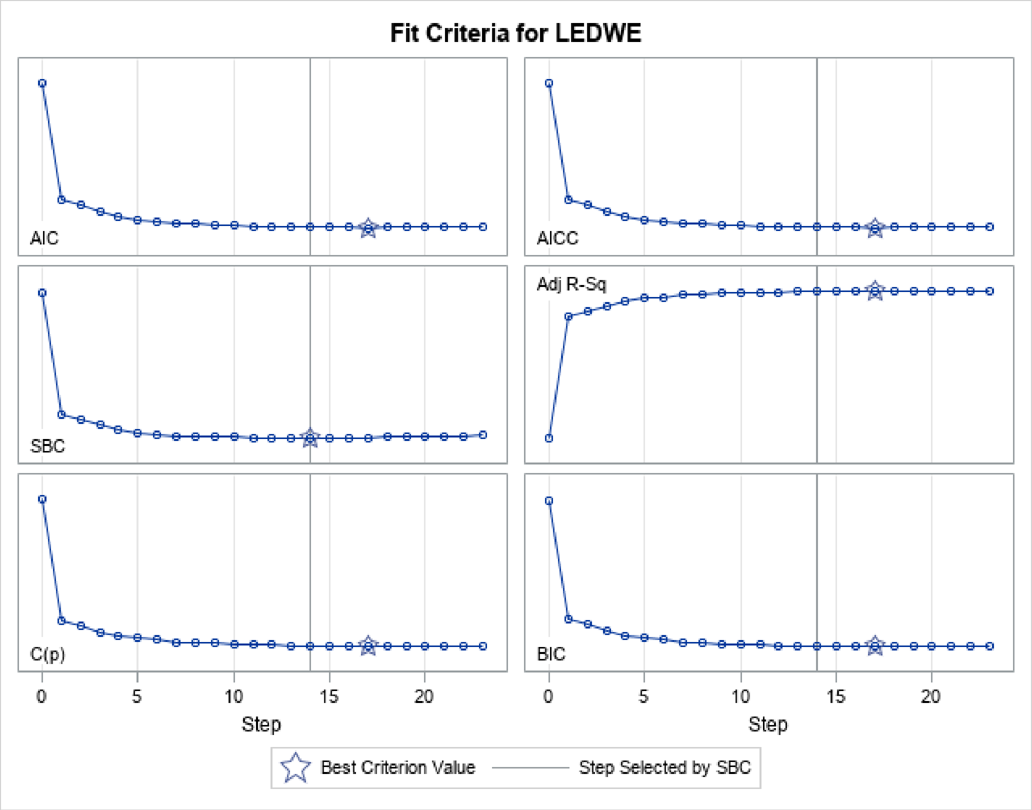
Appendix A. Adaptive Lasso shrinkage pattern

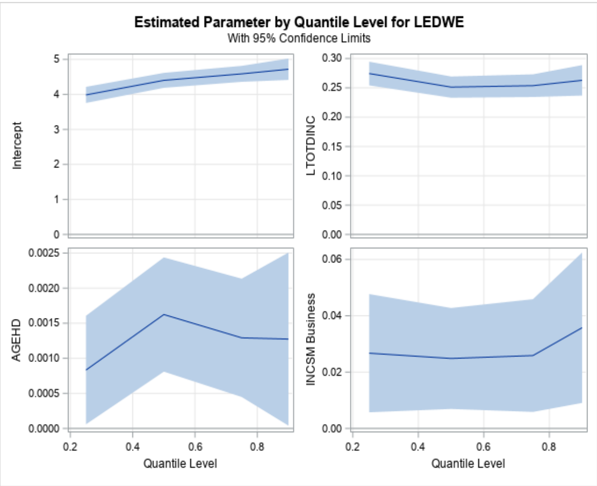


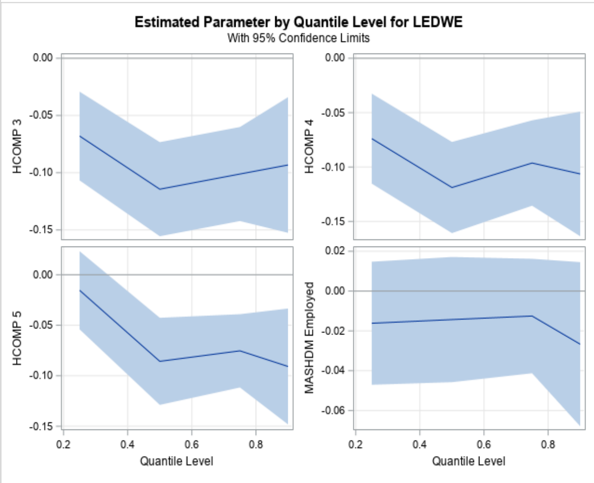


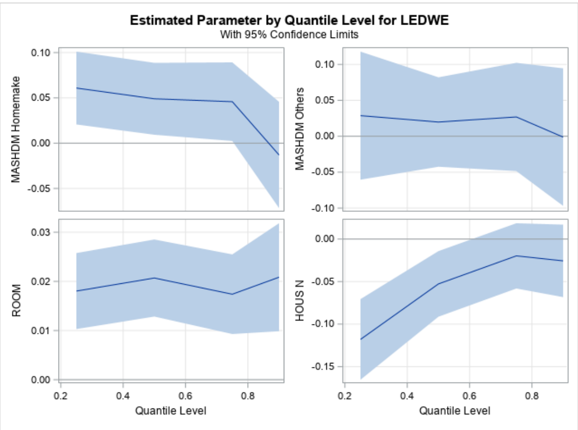


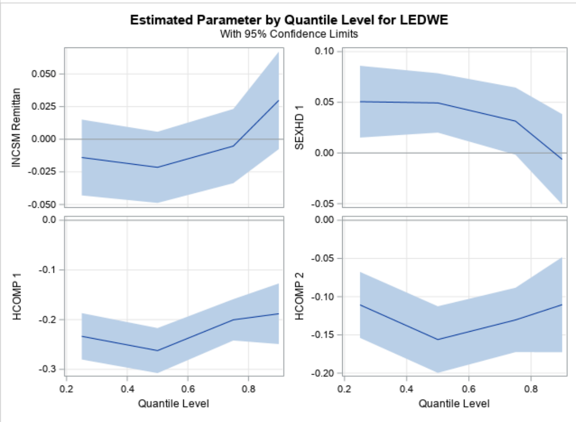
Fit Criteria for LEDWE
AIC
AICC
Adj R-Sq
SBC
C(p)
BIC
0
5
10
15
20
Step
Best Criterion Value
Step Selected by SBC

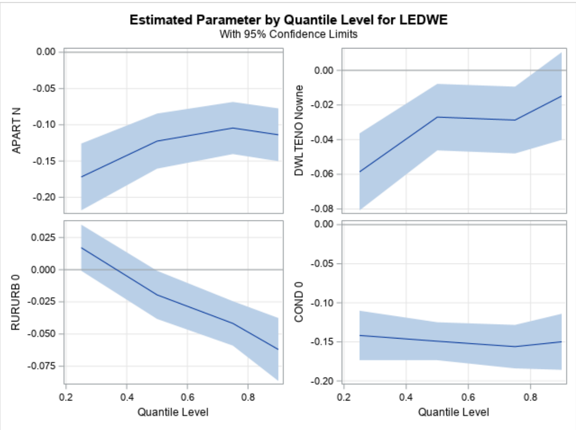
Appendix B. Quantiles regression graphs



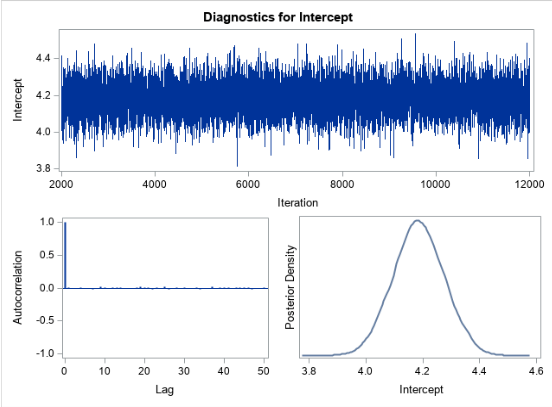


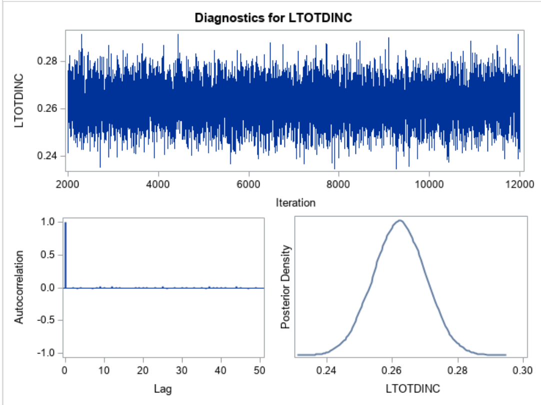


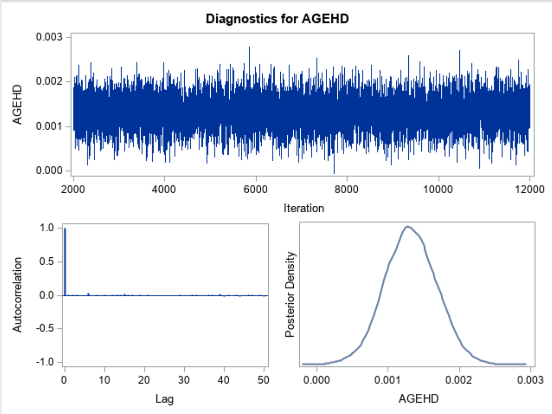


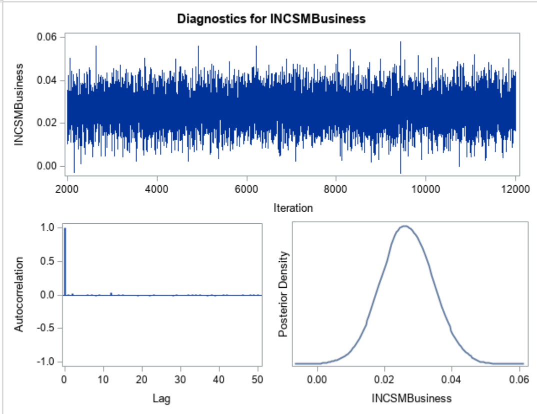


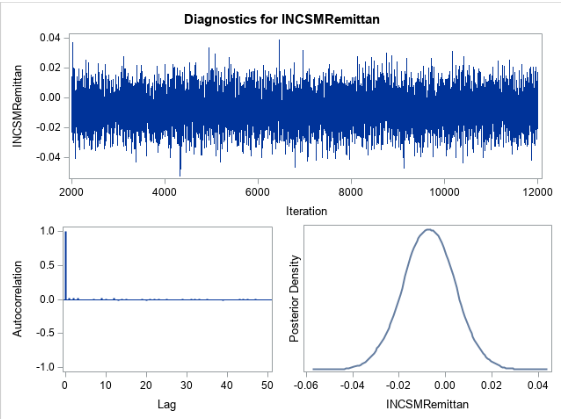
Appendix C. Bayesian regression diagnostics

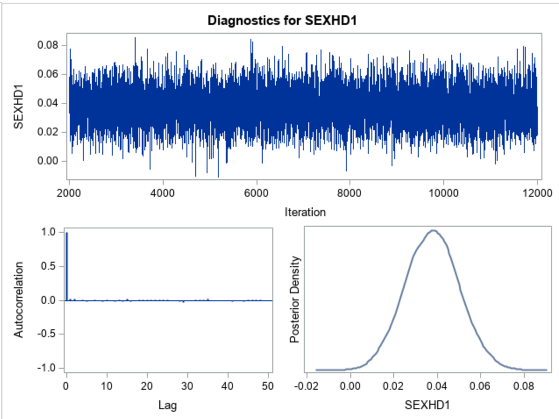


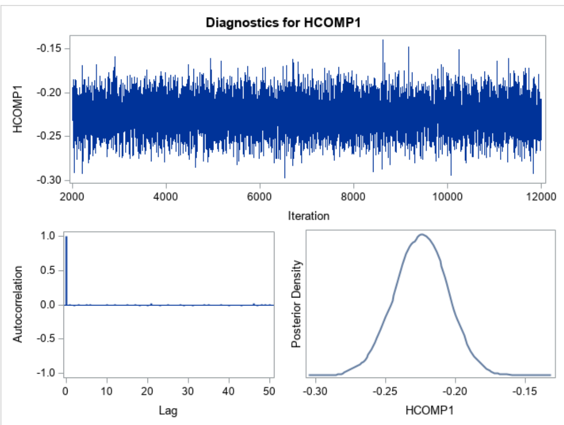


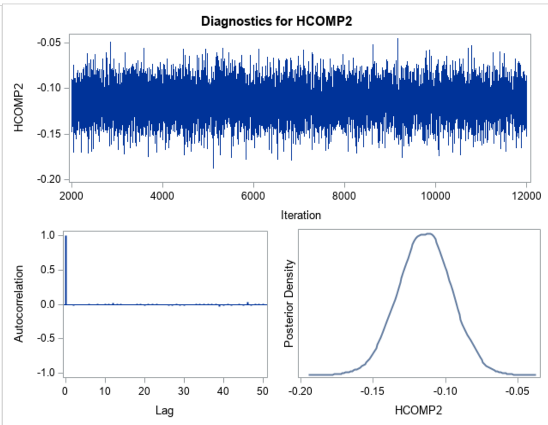


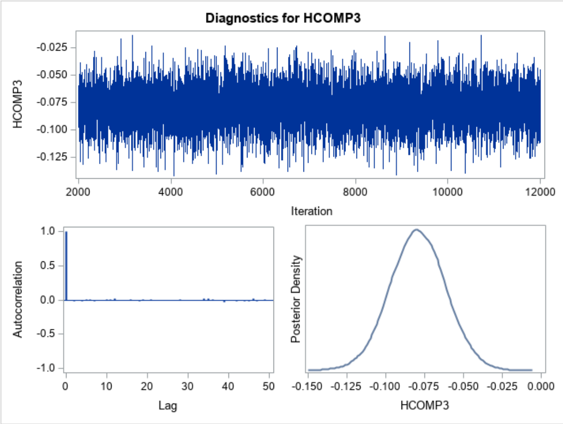








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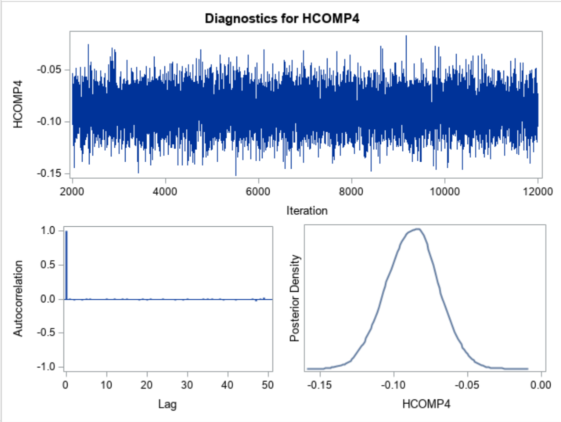
HCOMP3
Iteration
Autocorrelation
Lag
Posterior Density
HCOMP3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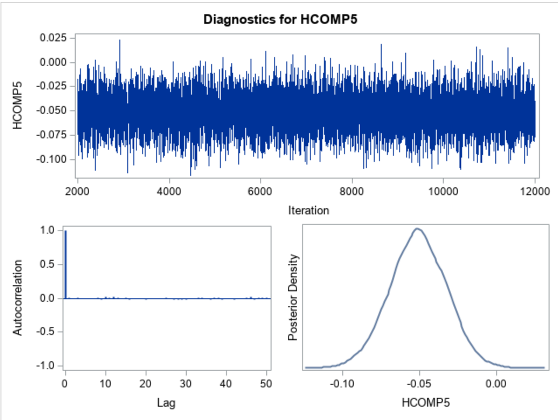
HCOMP4
Iteration
Autocorrelation
Lag
Posterior Density
HCOMP4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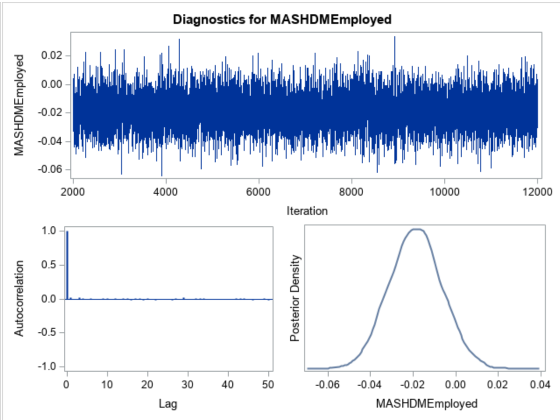
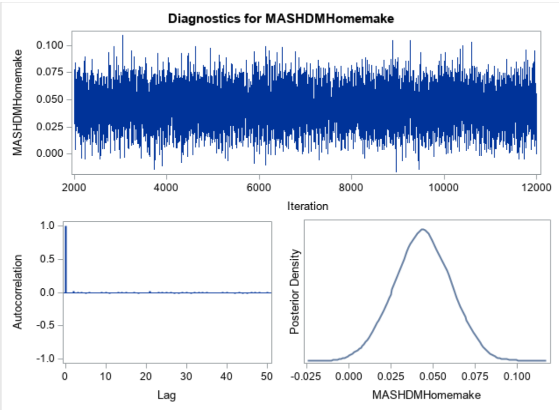
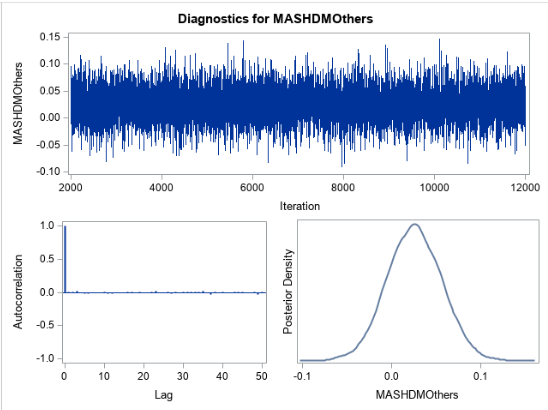
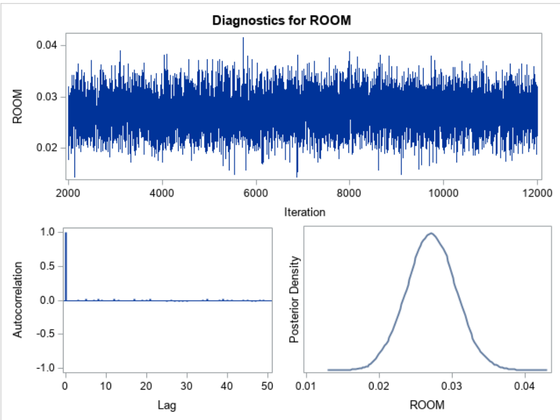
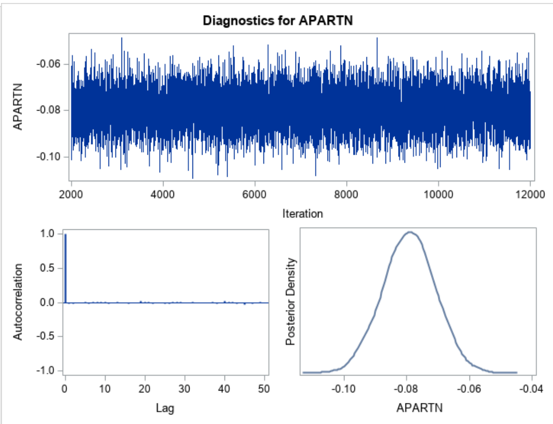
HCOMP5
Iteration
Autocorrelation
Lag
Posterior Density
HCOMP5


Diagnostics for MASHDMEmployed
MASHDMEmployed
Iteration
Autocorrelation
Lag
Posterior Density
MASHDMEmployed


Diagnostics for MASHDMHomemake
MASHDMHomemake
Iteration
Autocorrelation
Lag
Posterior Density
MASHDMHomemake


Diagnostics for MASHDMOthers
MASHDMOthers
Iteration
Autocorrelation
Lag
Posterior Density
MASHDMOthers


Diagnostics for ROOM
ROOM
Iteration
Autocorrelation
Lag
Posterior Density
ROOM


Diagnostics for APARTN
APARTN
Iteration
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Lag
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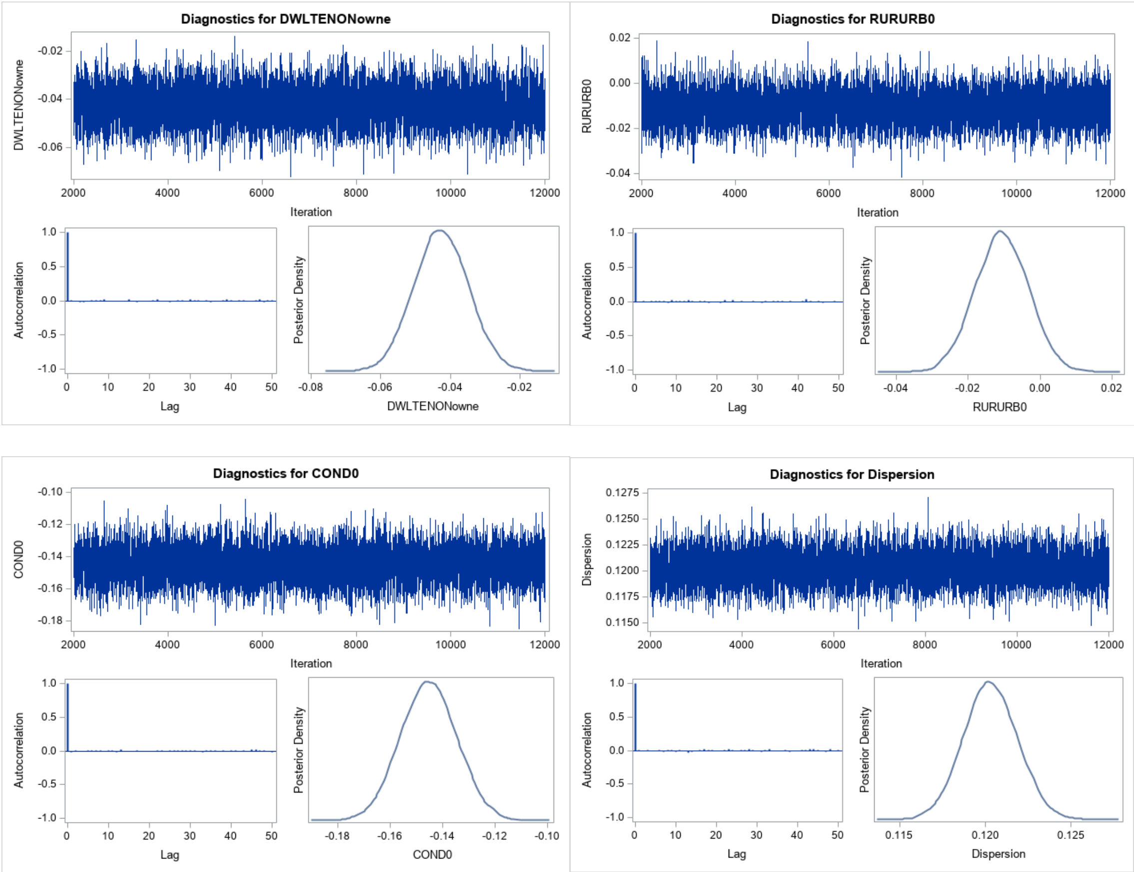

Diagnostics for DWLTENONowne
DWLTENONowne
Iteration
Autocorrelation
Lag
Posterior Density
Diagnostics for RURURB0
RURURB0
Iteration
Autocorrelation
Lag
Posterior Density
Diagnostics for COND0
COND0
Iteration
Autocorrelation
Lag
Posterior Density
Diagnostics for Dispersion
Dispersion
Iteration
Autocorrelation
Lag
Posterior Density