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Lasso Quintile Regression Model to Identify the Variables Influencing the Phenomenon of Divorce in Iraqi Population Commutes

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Abstract

Identifying the important variables in building regression models is considered one of the fundamental challenges in constructing a good model. Therefore, selecting potential independent variables that have a direct impact on the dependent variable provides us with accurate explanations of the capabilities of our study model. Additionally, the chosen model should be capable of generalizing the phenomenon under study. And with a high predictive capability. There are classic methods used in selecting optimal variables, but these methods have drawbacks, including the need for a significant amount of time and the lack of accuracy in results due to dealing with a large number of regression models. However, recently, a set of variable selection methods has been proposed that focus on estimating model characteristics and selecting variables simultaneously, within a very short period of time. One of these methods is the Lasso method. To obtain a regression model characterized by a set of features compared to the traditional regression model, ridge regression can be used. To achieve variable selection in the ridge regression model, the Lasso method can be integrated to obtain a Lasso quantile regression model. In estimating and selecting the factors associated with a phenomenon that threatens Iraqi population communities, namely the phenomenon of divorce. The phenomenon of divorce is the process of separation between spouses and the final termination of the legal marriage contract. Divorce is a common social phenomenon in many cultures and societies around the world, posing challenges to individuals, families, and society as a whole.The causes of divorce can be diverse and complex. These reasons may include marital incompatibility, ongoing family conflicts, communication difficulties, marital infidelity, domestic violence, cultural and religious differences, financial problems, lack of social support, and other factors. The phenomenon of divorce affects all parties involved in the marital relationship. It can have psychological and emotional effects on spouses and children, if they have any, including anxiety, depression, sadness, anger, and feelings of disappointment. Children may struggle to adapt to family changes and may experience division and feelings of guilt or rejection. In current paper. We identify the important variables that effecting on phenomenon of divorce by using one of important variable selection approach

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1. Introduction

The variables selection are important for model fitting in various ways. Where, This process is frequently carried out to improve models' interpretability and usability. In addition, a number of the regression coefficients will be inadequately defined and too variable to be useful for making predictions due to the large number of independent variables. The identification and selection of important variables in a regression model lead to significant benefits in interpreting those variables and make the model more generalizable. Since the seminal work of (Tibshirani (1996)) variable selection has become a highly popular topic. Tibshirani (1996) presents a wonderful approach that is focus on variables selection and estimating model parameters in a very brief amount of time. This method is called Least Absolute Shrinkage and Selection Operator(Lasso). The quantile regression model is incredibly insightful, Despite not adhering to normal assumptions, It is resilient against of outlier values(Cade, B. S., & Noon, B. R. (2003). When the extremely skewed and non-central placement of the response distribution ,the quantile regression model appropriate (Levin, J. (2002). The quantile regression model has elasticity to study the phenomena at many segments, via different quantile regression lines. So, the quantile regression model gives us a full picture about the complete relationship between a dependent variable and independent variables via more than one quantile regression line. When the Lasso technique is combined with the quantile regression model, the result is a highly interpretable and informative model. (Li and Zhu, (2008) were proposed regularization quantile regression model via using lasso method. In this paper ,we using this method for analyzing of phenomenon of divorce in Iraqi population commutes via five quantile level.

2. Lasso quantile regression model

2.1. Lasso regression

Lasso Regression is a technique for simultaneously estimating coefficients and variables selection. Tibshirani (1996) introduces this technique. The following provides the Lasso regression coefficients:

$$\hat{\beta}^{lasso} = minimize \sum_{i=1}^{n} \left(y - X\hat{\beta}\right)^2 \quad s.t \sum_{j=1}^{k} |\beta_j| \leq t \tag{1}$$

where y is dependent variable , X is matrix of independent variable and $\sum_{j=1}^{p} |\beta_j| \leq t$ $L_{1-} norm\ for\ regreesion\ coefficents.\ t$ is the tuning parameter that determines how much shrinkage occurs , Penalized matters are provided by:

$$\widehat{\beta}^{lasso} = minimize\left\|y - X\hat{\beta}\right\|_2^2 + \lambda\|\beta\|_1 \tag{2}$$

It is possible to rewrite equation (2) as follows:

$$\hat{\beta}^{lasso} = minimize \sum_{i=1}^{n} \left(y - X\hat{\beta}\right)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \tag{3}$$

The following equation was rewritten using the matrices formula:

$$\hat{\beta}^{lasso} = minimize(y - X\beta)^t(y - X\beta) + \lambda|\beta_j|I_n \tag{4}$$

where I_n is an $(p \times p)$ identity matrix and $|\beta_j|$ is a diagonal matrix of coefficients. We can rewrite equation (4) as following :

$$\hat{\beta}^{lasso} = minimize(y^t y - y^t X\beta - \beta^t X^t y + \beta^t X^t X\beta) + \lambda|\beta_j|$$

The partial derivative to β,

$$\frac{\hat{\beta}^{lasso}}{\partial\beta} = -2y^t X + 2X^t X\beta + \lambda sign(\beta) \tag{5}$$

Where Sign (β) is defined as follow :

$$\text{Sign}(\beta) = \begin{bmatrix} sign(\beta_1) \\ sign(\beta_2) \\ \vdots \\ sign(\beta_p) \end{bmatrix}$$

$$-2y^tX + 2X^tX\beta + \lambda sign(\beta) = 0$$

$$-y^tX + X^tX\beta + \frac{1}{2}\lambda sign(\beta) = 0$$

After going through a series of derivations, we obtain Lasso regression estimators using specialized Lasso regression algorithms.

$$\hat{\beta}^{lasso} = \left(X^tX - \frac{\lambda}{2}\left|\hat{\beta}^{ols}\right|^{-1}\right)^{-1} X^ty \tag{6}$$

However, $if \lambda = 0$ $then \left(\hat{\beta}^{lasso}\right) = \left(\hat{\beta}^{ols}\right)$*(more detail see Wessel van Wieringen 2009)*

Features of the estimation of lasso regression coefficients, it is a biased estimator and reducing the variance of coefficients as follows:

$$var\left(\hat{\beta}^{lasso}\right) = \sigma^2 \left(X^tX - \frac{\lambda}{2}\left|\hat{\beta}^{ols}\right|^{-1}\right)^{-1} X^tX \left(X^tX - \frac{\lambda}{2}\left|\hat{\beta}^{ols}\right|^{-1}\right)^{-1} \tag{7}$$

where $var(y) = \sigma^2$.

However, i$f\lambda = 0$ $then\, var\left(\hat{\beta}^{lasso}\right) = var\left(\hat{\beta}^{ols}\right)$

2.2. Lasso Quantile Regression Model

The quantile regression model assumes that the dependent variable (y) can be written as

$$y_i = x_i^t\beta_\tau + \varepsilon_i, \qquad \tau \in (0,1), \qquad [i = 1,2, \dots . n] \tag{8}$$

where x_i^t is a $1 \times k$ of vector of independent variables, β_τ is a $k \times 1$ of parameters of quantile regression ., ε_i is the random error unknown distribution. (Koenker and Bassett, (1978)) clear up the parameters estimation of quantile regression by:

$$\min_{\beta_\tau} \sum_{\boldsymbol{i=1}}^{\boldsymbol{n}} \rho_\tau(y_i - x_i^t\beta_\theta) \tag{9}$$

where $\rho_\tau(\varepsilon_i)$ is the loss function $(\rho_\tau(\varepsilon_i) = \varepsilon_i\{\tau - I(\varepsilon_i \leq 0)\}$. Also, we can rewrite the loss function as following:

$$\rho_\tau(\varepsilon) = \begin{cases} \tau\varepsilon & if\ \varepsilon \geq 0 \\ -(1-\tau)\varepsilon & if \varepsilon < 0 \end{cases} \tag{10}$$

Since there is no differentiated of equation (10) at the origin point (0), to derive the equation (10) via using the linear programming procedure (Koenker and D'Orey, (1987)). When performing important variable selection in a quantile regression model (lasso quantile regression), it can be accomplished using the following equation:.

$$\min_{\beta_\tau} \sum_{\boldsymbol{i=1}}^{\boldsymbol{n}} \rho_\tau(y_i - x_i^t\beta_\tau) + \lambda \parallel \beta_\tau \parallel, \quad \tau \in (0,1), \qquad [i = 1,2, \dots n] \tag{11}$$

where , $\lambda \parallel \beta_\tau \parallel$ is penalty lasso , λ ($(\lambda \geq 0)$ is the shrinkage parameter. Unfortunately, the equation (11) is no differentiated at zero(Fadel 2017). Therefore, there are many methods for estimation of parameters for lasso quantile regression (He et al, (2019). The best package for coefficients estimation and variable selection in quantile regression model is (glmnet). It is proposed and developed by Trevor Hastie, Jerome Friedman, Rob Tibshirani, Noah Simon, and others.

3. Phenomenon of divorce in Iraqi population commutes

There are numerous variables that influence the phenomenon of divorce in Iraqi communities. Some of these variables have a direct impact, while others have an indirect impact. There may be variables that contribute to modeling this phenomenon, but their effect is ambiguous and unclear. Therefore, excluding these variables can have positive implications for the model's performance. However, the exclusion process should be carried out using specialized statistical methods designed for this purpose to ensure the removal of unnecessary variables and rely on the important variables in model construction. This is necessary to ensure the interpretive power of the studied model in explaining the phenomenon of divorce. In this paper we focus one dependent variable and some independent variables as the following:

Variables name	Symbol of variables	Type of variables
y	The number of divorces within a family.	Dependent variable
x_1	Living together with parents	Dependent variable
x_2	Financial difficulties	Dependent variable
x_3	The number of visits to parents per month	Dependent variable
x_4	Marital infidelity	Dependent variable
x_5	The age of the wife at the time of marriage	Dependent variable
x_6	The number of hours spent on the internet	Dependent variable
x_7	Persistent threat of divorce by the husband to his wife	Dependent variable
x_8	Excessive jealousy leading to mutual distrust	Dependent variable
x_9	Neglecting marital duties	Dependent variable
x_{10}	Difficulties in understanding and communicating with family members	Dependent variable
x_{11}	The number of children	Dependent variable

The data for this study was collected through a questionnaire survey distributed to 130 divorced women. After data collection, the questionnaire data was transcribed and digitally processed. Following data cleansing, the data was prepared and analyzed using the designated method.

Table 1 :Estimates and confidence intervals for the quantile level (0.16) of Q Reg coefficients of the real data.

Variables	Coefficients	Lower confidence intervals	upper confidence intervals
Intercept	1.005	0.562	1.217
x_1	0.462	0.293	0.634
x_2	0.000	-0.004	0.075
x_3	0.951	1.103	0.634
x_4	0.434	0.141	0.671
x_5	0.245	0.058	0.482
x_6	0.000	-0.122	0.261
x_7	0.803	0.081	1.031
x_8	-0.351	-0.018	-0.662
x_9	0.183	0.081	0.332
x_{10}	-0.212	-0.011	-0.441
x_{11}	0.452	0.241	0.401

Based on the data displayed in the above table, we can see that some independent variables positively impact the number of divorces that occur in one family . On the other hand, there are independent variables that have a negative (inverse) effect on the number of divorces within a single family. Additionally, there are two variables that do not have any effect, as their coefficients are equal to zero. Where, the variable x_2 and x_6 are not effecting on response variable. However, the response variable (the frequency of divorces within a family) is affected differently by the remaining independent variables. at quantile level (0.16). The following figure provides more precise details.

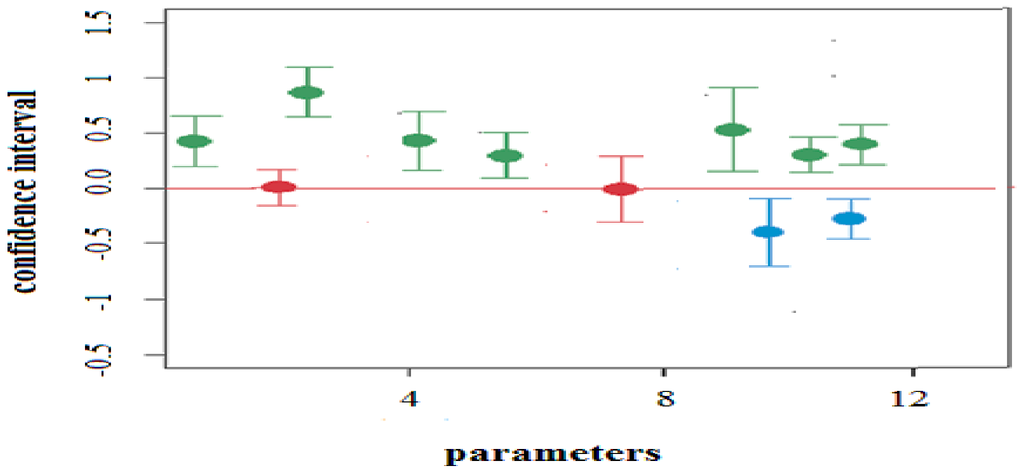

Figure (1): shown the confidence interval for coefficients estimation at quantile level (0.16) .

We can see from the above graphic that the shapes colored green are independent variables that positively affect the response variable. However, the blue-colored shapes denote independent variables that negatively impact the response variable. Conversely, the red-colored shapes stand for independent variables that don't affect the response variable, at quantile level (0.16)

Table 2: Estimates and confidence intervals for the quantile level (0.33) of Q Reg coefficients of the real data.

Variables	Coefficient		
Intercept	1.360	0.711	1.974
x_1	0.487	0.110	0.705
x_2	0.000	-0.118	0.126
x_3	0.000	-0.220	0.291
x_4	0.402	0.113	0.611
x_5	0.239	0.142	0.420
x_6	0.000	-0.101	-0.923
x_7	0.542	0.123	0.824
x_8	0.389	0.083	0.405
x_9	-0.416	-0.132	0.501
x_{10}	-0.210	-0.086	-0.434
x_{11}	0.360	0.211	0.474

Based on the data displayed in the above table, we can see that some independent variables positively impact the number of divorces that occur in one family . On the other hand, there are independent variables that have a negative (inverse) effect on the number of divorces within a single family. Additionally, there are three variables that do not have any effect, as their coefficients are equal to zero. Where, the variables x_2 , x_3 ,and x_6 are not effecting on response variable. However, the response variable (the frequency of divorces within a family) is affected differently by the remaining independent variables. at quantile level (0.33). The following figure provides more precise details.

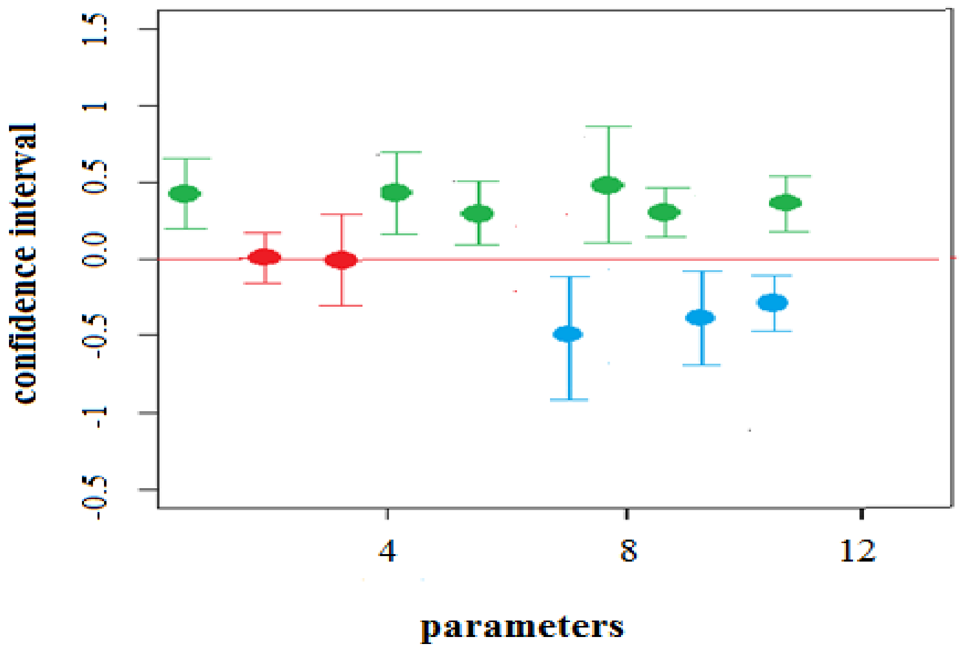

Figure (2): shown the confidence interval for coefficients estimation at quantile level (0.33) .

We can see from the above graphic that the shapes coloured green are independent variables that positively affect the response variable. However, the blue-colored shapes denote independent variables that negatively impact the response variable. Conversely, the red-colored shapes stand for independent variables that don't affect the response variable, at quantile level (0.33)

Table 3: Estimates and confidence intervals for the quantile level (0.50) of Q Reg coefficients of the real data.

Variables	Coefficient		
Intercept	0.306	0.222	0.390
x_1	0.412	0.210	0.616
x_2	0.000	-0.341	0.301
x_3	0.000	-0.208	0.115
x_4	0.411	0.159	0.608
x_5	-0.259	-0.117	-0.843
x_6	0.283	0.102	0.401
x_7	-0.384	-0.188	-0.675
x_8	0.000	-0.113	0.330
x_9	-0.321	-0.118	-0.401
x_{10}	0.410	0.157	0.768
x_{11}	0.326	0.122	0.390

Based on the data displayed in the above table, we can see that some independent variables positively impact the number of divorces that occur in one family . On the other hand, there are independent variables that have a negative (inverse) effect on the number of divorces within a single family. Additionally, there are three variables that do not have any effect, as their coefficients are equal to zero. Where, the variables x_2, x_3 , and x_8 are not effecting on response variable. However, the response variable (the frequency of divorces within a family) is affected differently by the remaining independent variables. at quantile level (0.50). The following figure provides more precise details.

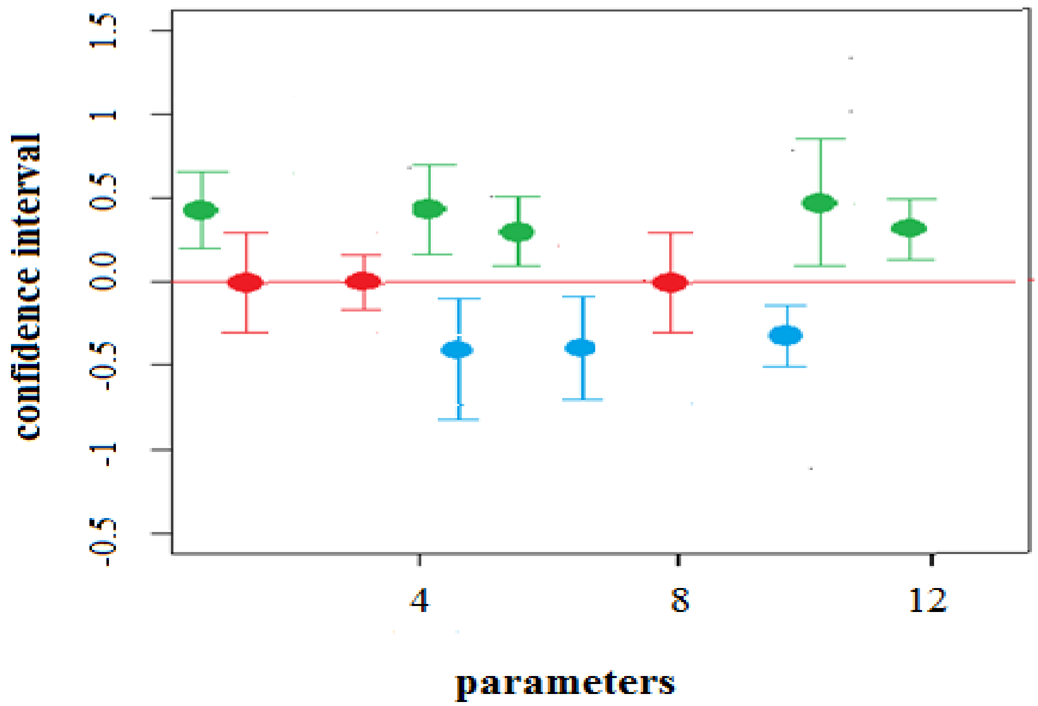

Figure (3): shown the confidence interval for coefficients estimation at quantile level (0.50) .

We can see from the above graphic that the shapes coloured green are independent variables that positively affect the response variable. However, the blue-colored shapes denote independent variables that negatively impact the response variable. Conversely, the red-colored shapes stand for independent variables that don't affect the response variable, at quantile level (0.50)

Table 4: Estimates and confidence intervals for the quantile level (0.66) of Q Reg coefficients of the real data.

Variables	Coefficient		
Intercept	0.001	-0.011	0.012
x_1	0.000	-0.001	0.001
x_2	0.000	-0.000	0.001
x_3	0.118	-0.151	-0.075
x_4	0.047	-0.034	0.125
x_5	-0.003	-0.410	0.115
x_6	0.000	-0.002	0.002
x_7	0.049	-0.059	0.120
x_8	0.011	-0.002	0.022
x_9	-0.106	-0.148	-0.062
x_{10}	0.003	-0.399	0.120
x_{11}	0.010	-0.016	0.034

Based on the data displayed in the above table, we can see that some independent variables positively impact the number of divorces that occur in one family . On the other hand, there are independent variables that have a negative (inverse) effect on the number of divorces within a single family. Additionally, there are three variables that do not have any effect, as their coefficients are equal to zero. Where, the variables x_2, x_3 and x_6 are not effecting on response variable. However, the response variable (the frequency of divorces within a family) is affected differently by the remaining independent variables. at quantile level (0.66). The following figure provides more precise details.

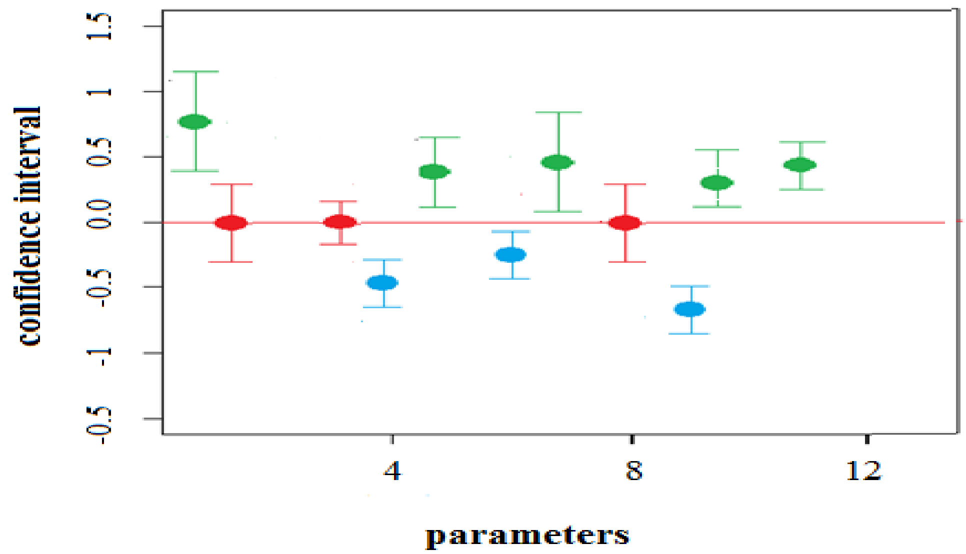

Figure (4) shown the confidence interval for coefficients estimation at quantile level (0.66) .

We can see from the above graphic that the shapes coloured green are independent variables that positively affect the response variable. However, the blue-colored shapes denote independent variables that negatively impact the response variable. Conversely, the red-colored shapes stand for independent variables that don't affect the response variable, at quantile level (0.66)

Table 5: Estimates and confidence intervals for the quantile level (0.83) of Q Reg coefficients of the real data.

Variables	Coefficient		
Intercept	-0.106	-0.144	-0.067
x_1	0.110	-0.157	-0.071
x_2	0.000	-0.123	0.183
x_3	0.000	-0.020	0.034
x_4	0.004	-0.010	0.018
x_5	0.127	-1.915	0.394
x_6	0.000	-0.192	0.021
x_7	0.263	0.156,	0.372
x_8	0.046	-0.036,	0.122
x_9	0.049	-0.059,	0.120
x_{10}	0.008	-0.010	0.045
x_{11}	-0.106	-0.144	-0.067

Based on the data displayed in the above table, we can see that some independent variables positively impact the number of divorces that occur in one family . On the other hand, there are independent variables that have a negative (inverse) effect on the number of divorces within a single family. Additionally, there are three variables that do not have any effect, as their coefficients are equal to zero. Where, the variables x_2, x_3 and x_6 are not effecting on response variable. However, the response variable (the frequency of divorces within a family) is affected differently by the remaining independent variables. at quantile level (0.83). The following figure provides more precise details.

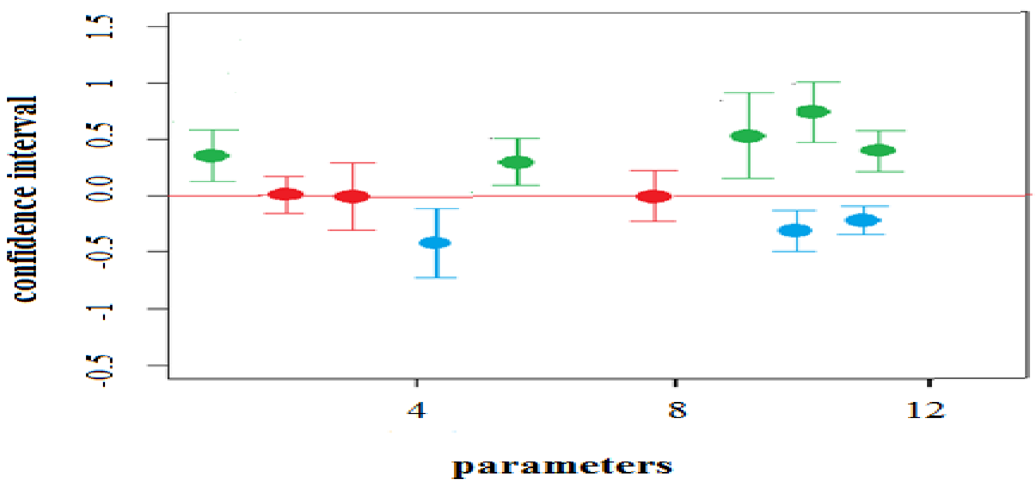

Figure (5): shown the confidence interval for coefficients estimation at quantile level (0.83) .

We can see from the above graphic that the shapes coloured green are independent variables that positively affect the response variable. However, the blue-colored shapes denote independent variables that negatively impact the response variable. Conversely, the red-colored shapes stand for independent variables that don't affect the response variable, at quantile level (0.83)

4. Conclusions and Recommendations

4.1. Conclusions

It is clear from the data that are provided and condensed in the analysis tables that independent variables (Living together with parents) and (Financial difficulties) have no discernible effect on the response variable (The number of divorces within a family.) at any of the five quantile levels. This implies that the model under examination in our study can be mathematically modeling without using these two variables. The variables (The number of visits to parents per month)(Marital infidelity)(Persistent threat of divorce by the husband to his wife)(Excessive jealousy leading to mutual distrust)(Difficulties in understanding and communicating with family members)(have a positive influence on the response variable (The number of divorces within a family), whereas the variables (The age of the wife at the time of marriage)(Neglecting marital duties) (The number of children) have a negative effect on the response variable (The number of divorces within a family), according to all of the results shown throughout the five quantile levels .

4.2. Recommendations

We recommend considering alternative variable selection methods that possess good characteristics and fulfill the requirements (orcal). These methods should be effective even in cases where Multicollinearity arises among the variables. Examples of such methods include (additive lasso) or (elastic-net) techniques, which can provide us with reliable estimates and variable selection even when the sample size is smaller than the number of independent variables$(p > n)$. When using the quantile regression model, especially in social phenomena, it is advisable to increase the quantile levels to provide comprehensive coverage of all data points related to the studied phenomenon. By using a larger number of quantile regression lines, we can achieve more robust estimates in interpreting the variables of the studied phenomenon.

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نموذج انحدار لاسو القسيمي للتعرف على المتغيرات المؤثرة في ظاهرة الطلاق لدى سكان العراق

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وزارة التربية، تربية الديوانية، الديوانية، العراق	

المستخلص

تحديد المتغيرات المهمة في بناء نماذج الانحدار يُعتبر أحد التحديات الأساسية في إنشاء نموذج جيد. لذلك، يوفر اختيار المتغيرات المستقلة المحتملة التي لها تأثير مباشر على المتغير المعتمد تفسيرات دقيقة لقدرات نموذج الدراسة الخاص بنا. بالإضافة إلى ذلك، يجب أن يكون النموذج المختار قادرًا على تعميم الظاهرة المدروسة وأن يتمتع بقدرة تنبؤية عالية. هناك طرق كلاسيكية تُستخدم في اختيار المتغيرات المثلى، ولكن هذه الطرق لها عيوب، بما في ذلك الحاجة إلى كمية كبيرة من الوقت وعدم الدقة في النتائج بسبب التعامل مع عدد كبير من نماذج الانحدار. ومع ذلك، تم اقتراح مجموعة من طرق اختيار المتغيرات مؤخرًا تركز على تقدير خصائص النموذج واختيار المتغيرات في نفس الوقت، وذلك في فترة زمنية قصيرة جدًا. واحدة من هذه الطرق هي طريقة لاسو (Lasso).يمكن استخدام الانحدار lasso للحصول على نموذج انحدار يتميز بمجموعة من الميزات مقارنة بالنموذج الانحدار التقليدي. ولتحقيق اختيار المتغيرات في نموذج الانحدار القسيمي ، يمكن دمج طريقة لاسو للحصول على نموذج انحدار لاسو القسيمي .في تقدير واختيار العوامل المرتبطة بظاهرة تهدد مجتمعات السكان العراقية، وهي ظاهرة الطلاق، يمكن استخدام نموذج الانحدار لاسو القسيمي. ظاهرة الطلاق هي عملية الانفصال بين الأزواج وإنهاء العقد الزوجي القانوني. الطلاق هو ظاهرة اجتماعية شائعة في العديد من الثقافات والمجتمعات حول العالم، وتشكل تحديات للأفراد والأسر والمجتمع ككل. أسباب الطلاق يمكن أن تكون متنوعة ومعقدة. يمكن أن تشمل هذه الأسباب عدم التوافق الزوجي، والصراعات الأسرية المستمرة، وصعوبات التواصل، والخيانة الزوجية، والعنف الأسري، والاختلافات الثقافية والدينية، والمشاكل المالية، وعدم وجود الدعم الاجتماعي، وعوامل أخرى. تؤثر ظاهرة الطلاق على جميع الأطراف المشاركة في العلاقة الزوجية. يمكن أن تكون لها تأثيرات نفسية وعاطفية على الأزواج والأطفال، إن وجدوا، بما في ذلك القلق والاكتئاب والحزن والغضب والشعور بخيبة الأمل. قد يواجه الأطفال صعوبة في التكيف مع التغيرات العائلية وقد يعانون من الانقسام والشعور بالذنب أو الرفض. في الورقة الحالية، نهدف إلى تحديد المتغيرات المهمة التي تؤثر في ظاهرة الطلاق باستخدام أحد أساليب اختيار المتغيرات المهمة، وهو نموذج الانحدار لاسو القسيمي.

معلومات البحث

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تاريخ تقديم البحث:20/2/2024
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الكلمات المفتاحية:
اختيار متغير، لاسو، الانحدار القسيمي، حزمة العنصر.

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