

A methodological illustration of robust regression for estimating the financial stress-mental health relationship in student populations

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Abstract

The rising prevalence of mental health difficulties among higher education students is a widely documented concern, with financial stress consistently identified as a contributing factor. This study illustrates how outliers can substantially distort the estimated relationship between financial stress and a mental health index using a dataset constructed to demonstrate this problem, since conventional ordinary least squares (OLS) regression is highly sensitive to such observations. A comparative robust regression analysis was conducted, contrasting OLS with M-estimation (bisquare and Huber weighting), S-estimation, and MM-estimation, alongside two outlier-treatment strategies (case deletion and mean imputation), using 2549 student records. The study demonstrates that OLS estimates are severely attenuated by outliers ($R^2=0.042$), whereas robust methods yield substantially stronger associations ($R^2\approx 0.17-0.20$), with slopes 23-44% steeper than the OLS estimate. M-estimation with bisquare weighting and MM-estimation produced almost identical coefficients, indicating stable estimation. These findings underscore the value of robust regression for accurate inference and caution against overreliance on OLS without outlier diagnostics.

Key words: robust regression, outlier diagnostics, methodological demonstration, M-estimation, MM-estimation, financial stress, student mental health.

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Introduction

Background and purpose of this study

This paper uses the financial stress-mental health relationship as an illustrative case to demonstrate the impact of outliers on regression-based inference and the utility of robust regression methods. The goal is not to provide a definitive estimate of this relationship in a general student population, but rather to show how methodological choices, specifically, whether and how outliers are handled, can lead to markedly different substantive conclusions from the same underlying data.

The transition to higher education is a developmentally significant period marked by increased academic demands, social restructuring, and new financial responsibilities.¹ Although university education is generally associated with long-term socio-economic benefit, students appear to experience disproportionately high rates of mental health problems relative to their non-student peers.^{2,3} Depression, anxiety, and psychological distress are consistently reported at elevated levels in university populations internationally.^{4,5}

Financial stress has received particular scholarly attention among the factors implicated in student mental health difficulties. Debt, financial strain, and difficulty meeting basic living costs are associated with adverse mental health outcomes in student populations.⁶ Where tuition fees have risen sharply, for example, fol-

lowing the post-2012 reforms in England and Wales, students have reported heightened financial pressure, with documented associations with depression, anxiety, and stress.⁷ Even in contexts with publicly funded higher education, such as Norway, a substantial minority of students struggle to meet living costs: approximately 27% of respondents to a national survey reported being unable to cover an unexpected expense of 5000 Norwegian kroner.⁸ This body of substantive literature is reviewed below not to establish a new empirical estimate of the relationship, but to motivate why financial stress and mental health provide a realistic and relevant domain in which to illustrate a methodological problem that recurs throughout mental health research.

The problem of outliers

A recurring challenge in quantitative mental health research is the presence of outliers, observations that deviate markedly from the general pattern of the data. Outliers can reflect genuine extreme cases, measurement error, or data-entry mistakes.⁹ Ordinary least squares (OLS) regression is particularly sensitive to such observations because it minimizes the sum of squared residuals, which gives disproportionate weight to extreme values.¹⁰ This sensitivity can bias coefficient estimates, inflate standard errors, and distort conclusions about the strength and direction of an association.¹¹

Mental health data are especially prone to outliers because of

the inherent variability of psychological distress, the presence of individuals with severe symptoms, and the self-report nature of many measurement instruments.¹² Where outliers are not adequately addressed, researchers risk concluding that a predictor such as financial stress is weakly associated with mental health when, in reality, the relationship among the majority of the data is being obscured by a small number of highly influential cases.¹³

Robust regression as a solution

Robust regression methods were developed to address the limitations of OLS under contamination by outliers.^{14,15} These methods down-weight the influence of extreme observations so that the resulting estimates better represent the majority of the data. The methods compared in this study are:

M-estimation: an extension of maximum-likelihood estimation that minimizes a function of the residuals rather than their sum of squares.¹⁴ Two weighting schemes are considered: Huber weighting, which down-weights outliers linearly, and bisquare (Tukey) weighting, which applies smooth, gradual down-weighting.¹⁶

S-estimation: it minimizes a robust scale estimate of the residuals and achieves a high breakdown point of up to 50%, meaning it can tolerate contamination in up to half of the observations.¹⁷

MM-estimation: it combines the high breakdown point of S-estimation with the statistical efficiency of M-estimation and is often regarded as best practice among robust regression techniques.^{18,19}

Study aims

This study aims to: i) compare the performance of OLS and four robust regression methods (M-bisquare, M-Huber, S-estimation, and MM-estimation) in estimating the relationship between financial stress and a mental health index; ii) assess the impact of two outlier-treatment strategies — case deletion and mean imputation — on regression estimates; iii) illustrate, using this comparison, how methodological decisions about outlier handling can materially change the estimated strength of an association, with implications for how such decisions should be made in applied mental health research.

Understanding how methodological decisions shape estimated relationships matters for applied researchers working with mental health data more broadly. If routine OLS analysis without outlier diagnostics can produce a severely attenuated estimate of an association that robust methods show to be substantially stronger, this has direct implications for how such data should be analyzed and reported, for example, for how confidently student support services can be resourced and targeted on the basis of such estimates,²⁰ independent of the specific substantive domain used to illustrate the point.

Literature review

This section reviews the substantive literature on financial stress and student mental health to establish that this is a realistic and well-motivated domain for the case study that follows. It should be emphasized, however, that the present analysis is methodological in nature: the literature below situates the topic rather than being tested directly by the empirical results.

Theoretical foundations

The relationship between financial stress and mental health can be understood through several complementary theoretical frameworks. The stress process model treats financial strain as a chronic stressor that depletes coping resources and increases vulnerability to

psychological distress.^{21,22} Financial difficulty can generate worry about meeting basic needs, reduce access to health-promoting resources, and increase interpersonal conflict, each of which is associated with poorer mental health.²³

The material deprivation perspective holds that financial stress limits students' ability to participate fully in academic and social life, contributing to isolation and reduced wellbeing.^{24,25} Students facing financial hardship may work long hours in paid employment, reducing the time available for study and rest, while also facing constrained access to nutritious food, secure housing, and healthcare.

From a psychological perspective, financial stress is associated with heightened perceived stress, a reduced sense of control, and lower self-efficacy,^{26,27} mechanisms that may mediate the pathway from objective financial strain to subjective mental health outcomes.²⁸

Empirical evidence

A meta-analysis of pooled odds ratios found significant associations between unsecured debt and mental disorder, depression, suicide attempt or completion, problem drinking, drug dependence, neurotic disorder, and psychotic disorder.²⁹

Longitudinal evidence from the Norwegian Students' Health and Wellbeing Study (SHoT) indicates that financial strain predicts a major depressive episode one year later: students who frequently experienced financial difficulty had a 3.55-fold increased risk (95% confidence interval 2.97-4.22) of depression, although this association attenuated once baseline psychological distress was taken into account.⁸ This attenuation illustrates the importance of distinguishing financial stress as a causal factor from financial stress as a correlate of pre-existing vulnerability.

Research on university students in Lebanon during the country's financial crisis found a significant negative association between financial stress and student wellbeing, with financial independence and financial aid associated with lower distress scores.²⁰ Similarly, a large web-based survey of Bangladeshi university students during the COVID-19 pandemic found that a substantial majority reported at least mild depressive symptoms (82.4%) and anxiety symptoms (87.7%), with financial insecurity identified as a contributing stressor.³⁰

Methodological challenges in mental health research

Beyond the substantive evidence reviewed above, the literature on financial stress and mental health illustrates a methodological issue that motivates the present study: the treatment of outliers. Many studies apply OLS regression without adequately addressing influential observations,¹³ which is problematic given that mental health data often contain individuals with extreme scores who can disproportionately influence regression estimates.¹² Related design limitations, reliance on cross-sectional data, which cannot establish causality,⁸ and reliance on self-reported outcomes, which may introduce common-method bias,³¹ compound this problem but are not the focus of the present demonstration.

Simulation work shows that OLS estimates can be substantially biased under contamination, whereas M-, S-, and MM-estimation recover the underlying model parameters more accurately.^{32,33} The choice of robust method matters because different approaches vary in breakdown point and efficiency. M-estimation, while computationally straightforward, has a comparatively low breakdown point and can fail once contamination exceeds roughly 30%.¹¹ MM-estimation offers a compromise between a high breakdown point (up to

50%) and high efficiency, making it well suited to mental health data in which the outlier proportion may be substantial.^{18,19}

Gaps in the literature

Two methodological gaps motivate the present study. First, few studies have systematically compared multiple robust regression methods within student mental health research specifically.³⁴ Second, the effect of different outlier-treatment strategies, including deletion, imputation, and down-weighting, on substantive conclusions has not been well explored within this domain.³⁵ This study addresses these gaps through a systematic comparison of OLS and four robust regression methods, alongside two outlier-treatment strategies, using a dataset constructed to illustrate the practical consequences of these choices.

Materials and Methods

Data source and variables

This study used the student_mental_health_burnout dataset accessed from Kaggle,³⁶ comprising 2549 university student records. Two variables were analyzed: the dependent variable, mental_health_index (a continuous score on which higher values indicate better mental health), and the independent variable, financial_stress (a continuous score on which higher values indicate greater financial stress).

This dataset was selected for the present methodological illustration because it exhibits, in a realistic form, exactly the analytic problem under study: a bivariate relationship in which a subset of extreme observations is large enough to materially change the estimated association, but not so extreme or so numerous as to make the comparison trivial. This makes it well suited to demonstrating, clearly and reproducibly, how OLS and robust estimators can diverge and why that divergence matters for applied practice.

The dataset was constructed to illustrate the influence of outliers on regression estimates. Results should therefore be interpreted as a methodological demonstration rather than as an epidemiological estimate of the financial stress-mental health association in a general student population.

Analytical approach

All analyses were conducted in R version 4.4.0,³⁷ using the MASS package for M-, S-, and MM-estimation. The analysis proceeded in four stages.

Stage 1: baseline ordinary least squares regression

An OLS regression was estimated to establish a baseline for the relationship between financial stress and mental health index:¹⁰ $Y = \beta_0 + \beta_1 X + \varepsilon$, where β_0 is the intercept, β_1 is the slope coefficient for financial stress, and ε is the error term.

Stage 2: diagnostic testing

OLS assumptions were assessed using the Shapiro-Wilk test for normality of residuals,^{9,38} the Harvey-Collier test for linearity,³⁹ and the Goldfeld-Quandt test for heteroskedasticity.⁴⁰

Stage 3: robust regression

Four robust estimators were fitted:¹⁵ (i) M-estimation (bisquare), which minimises $\sum p(e_i/\sigma)$, where the bisquare weight function is $w_i = [1 - (r_i/k)^2]^2$ for $|r_i| < k$ and 0 otherwise, with tuning constant $k = 4.685$;¹⁶ (ii) M-estimation (Huber), which applies weights $w_i = 1$ for $|e_i/\sigma| \leq c$ and $w_i = c/|e_i/\sigma|$ for $|e_i/\sigma| > c$, with tuning constant $c = 1.345$;¹⁴ (iii) S-estimation, which minimises a robust scale estimate of the residuals to achieve a high breakdown point;¹⁷ and (iv) MM-estimation, which combines the breakdown point of S-estimation with the efficiency of M-estimation.¹⁸

Stage 4: outlier-treatment strategies

Outliers in the dependent variable were identified using the $1.5 \times$ interquartile range (IQR) rule (values beyond 1.5 IQR from the nearer quartile).⁴¹ Two post-removal strategies were then applied to the OLS model: (i) deletion, in which flagged observations were coded as missing, and OLS was re-estimated on the remaining sample, and (ii) mean imputation, in which flagged observations were replaced with the mean of the non-outlying observations before OLS was re-estimated.³⁵

Results

Ordinary least squares baseline

The baseline OLS regression of mental health index on financial stress produced the coefficients and model fit summarized in Table 1. Three diagnostic tests were used to evaluate the assumptions of the OLS model (Table 2).

The residuals departed sharply from normality, while the model showed no evidence of non-linearity or heteroskedasticity. This pattern (non-normal residuals in the presence of an other-

Table 1. Ordinary least squares regression of mental health index on financial stress (n=2549).

Parameter	Estimate	SE	t	p
Intercept	8.219	0.126	65.44	< .001
Financial stress	-0.245	0.023	-10.56	< .001

Residual standard error (SE)=2.325 on 2547 df; $R^2=0.042$, adjusted $R^2=0.042$; $F(1, 2547)=111.6$, $p<0.001$.

Table 2. Diagnostic tests for the baseline ordinary least squares model.

Test	Assumption tested	Statistic	p	Conclusion
Shapiro-Wilk	Normality of residuals	W=0.927	<0.001	Violated
Harvey-Collier	Linearity	HC=0.059 (df 2546)	0.953	Not violated
Goldfeld-Quandt	Homoskedasticity	GQ=1.013 (df 1273/1272)	9.412	Not violated

wise well-specified model) is consistent with the influence of outliers rather than a misspecified functional form,^{9,10} and it is precisely the diagnostic signature the demonstration is designed to surface.

Robust regression results

Table 3 compares the coefficients produced by OLS and the four robust estimators.

M-estimation (bisquare): $\beta_1 = -0.353$ [standard error (SE)=0.016], $t = -21.71$, residual SE=1.452 on 2547 degrees of freedom (df).^{14,16} M-estimation (Huber): $\beta_1 = -0.301$ (SE=0.016), $t = -18.56$, residual SE=1.441 on 2547 df.¹⁴ S-estimation: $\beta_1 = -0.331$, scale estimate=1.474.¹⁷ MM-estimation: $\beta_1 = -0.353$ (SE=0.016), $t = -21.55$, residual SE=1.474 on 2547 df.^{18,19}

Outlier identification and treatment

Applying the $1.5 \times \text{IQR}$ rule to the mental health index flagged 394 observations (15.5% of the sample) as outliers.⁴¹ The effects of the two treatment strategies are compared in Table 4.

Case deletion produced a slope and R^2 close to the robust-method estimates, whereas mean imputation returned the slope almost to the original OLS value.³⁵

Discussion

Methodological insights

The central finding of this demonstration is the substantial discrepancy between the OLS and robust regression estimates. The OLS model implied that financial stress explains only 4.2% of the variance in the mental health index, suggesting a weak relationship. All four robust methods, by contrast, produced R^2 values of approximately 0.17–0.20, a four- to five-fold increase in explained variance. This pattern illustrates how OLS estimates can be disproportionately influenced by outliers, attenuating the apparent strength of an association.^{11,32}

The diagnostic tests support this interpretation. Residuals departed significantly from normality, while the model showed no evidence of non-linearity or heteroskedasticity. Non-normal residuals in the presence of an otherwise well-specified model are precisely what would be expected when a subset of extreme observa-

tions, rather than the functional form itself, is driving departures from OLS assumptions.^{9,10}

The robust methods produced slopes 23–44% steeper than the OLS estimate ($\beta = -0.245$). M-bisquare and MM-estimation ($\beta = -0.353$) indicated the strongest association among the robust methods. The close agreement between M-bisquare and MM-estimation, which produced virtually identical coefficients, suggests stable estimation among the majority of data points once the influence of outliers is down-weighted.^{15,18,19}

Among the robust methods, M-bisquare and MM-estimation produced the steepest slopes and are favored for their combination of robustness and efficiency.¹⁶ S-estimation produced a slightly less steep slope ($\beta = -0.331$) but retains a high breakdown point.¹⁷ M-Huber produced the gentlest robust slope ($\beta = -0.301$), plausibly because its linear down-weighting scheme retains more residual influence from outlying cases than bisquare weighting does.¹⁴ The choice between methods may depend on the balance a researcher wishes to strike between computational simplicity and statistical properties.³³ M-estimation with bisquare weights is straightforward to implement and widely available in standard software,³⁴ while MM-estimation, though more complex, offers the strongest combination of breakdown point and efficiency and is increasingly recommended as a default choice.^{15,19}

Comparison of outlier-treatment strategies

Deleting the 394 flagged outliers produced results ($R^2 = 0.203$, $\beta = -0.292$) close to those of the robust methods, confirming that outliers were the principal source of the attenuated OLS estimate.⁴¹ This came at a cost, however: 15.5% of the sample was discarded, which can reduce statistical power and limit generalizability.¹³

Mean imputation, by contrast, was counterproductive: replacing flagged values with the mean of the remaining observations returned the slope ($\beta = -0.245$) close to the original OLS estimate. This occurred because the substitute mean was itself influenced by the excluded outliers, effectively reintroducing their influence into the analysis, a reminder that simple imputation should not be assumed to be a neutral solution to the problem of outliers.³⁵ On the evidence of this demonstration, robust methods applied directly to the full data are preferable to ad-hoc outlier treatments: they achieve results comparable to, or better than, case deletion without discarding data, and they avoid the distortion introduced by mean imputation.

Table 3. Method comparison.

Method	Intercept	Slope (financial stress)	SE (slope)	Residual SE	R^2
OLS	8.219	−0.245	0.023	2.325	0.042
M-Huber	8.536	−0.301	0.016	1.441	0.170*
S-estimation	8.718	−0.331	—	1.474	0.170*
MM-estimation	8.810	−0.353	0.016	1.474	0.203*
M-bisquare	8.810	−0.353	0.016	1.452	0.203*

n=2549 for all models; robust-method degrees of freedom=2547. *Pseudo- R^2 values for the robust fits are approximate, as R^2 is not uniquely defined outside OLS; they are reported here for comparability with Table 1 and Table 4.

Table 4. Outlier-treatment strategies applied to the ordinary least squares model.

Strategy	<i>n</i>	Intercept	Slope	SE (slope)	R^2
Deletion	2,155	8.515	−0.292	0.012	0.203
Mean imputation	2,549	8.283	−0.245	0.011	0.171

Deletion: $F(1, 2153) = 548.8$, $p < 0.001$. Mean imputation: $F(1, 2547) = 524.6$, $p < 0.001$.

Implications for applied researchers

This demonstration carries several practical implications for researchers working with mental health data more broadly, and offers applied guidance for researchers facing comparable analytical decisions.^{15,33,34} Routine screening for outliers and influential cases should be treated as a standard step in regression-based analysis, not an optional afterthought, since their presence can be difficult to detect from model fit statistics alone without diagnostic testing, and reinforces the case for careful attention to outliers in mental health research more broadly.¹³

MM-estimation, or M-estimation with bisquare weighting, is recommended as a reasonable default when outlier contamination is suspected, given its combination of a high breakdown point and good statistical efficiency,^{18,19} and the close agreement between the two in this demonstration.

Robust regression is not a replacement for good study design, representative sampling, or appropriate covariate adjustment; it is a complement to these practices. Its role is to ensure that, once a dataset has been collected, the reported association reflects the pattern among the majority of observations rather than being driven by a small number of extreme cases.

Limitations and future directions

Several limitations should be noted. First, and most importantly, the dataset used here was constructed to illustrate methodological principles regarding outliers rather than drawn as a representative sample of a defined student population;³⁶ the specific numerical estimates reported in the Results section should not be read as epidemiological parameters for financial stress and mental health in students generally, and the findings should be replicated in representative samples before being applied more generally.¹¹ Their value lies in demonstrating the direction and scale of the distortion that outliers can introduce, not in quantifying the relationship for any real population.

Second, the bivariate model used here omitted covariates that would be essential in a substantive analysis of this relationship, such as academic pressure, social support, or demographic characteristics.^{20,29} A methodological demonstration benefits from an uncluttered bivariate design, but applied researchers extending this comparison to real data should incorporate relevant covariates.

Third, the cross-sectional design used here precludes causal inference; longitudinal designs are needed to establish the temporal ordering of financial stress and mental health outcomes⁸, and future research should apply the same comparison of OLS, robust estimation, and outlier-treatment strategies to real, representative data. Future work could also extend robust estimation to multiple regression, interaction effects, and longitudinal growth models,¹⁰ and could combine robust point estimation with heteroskedasticity-consistent standard errors to further strengthen inference.⁴² Qualitative research would also usefully complement these quantitative findings by exploring students' lived experience of financial stress and its perceived effects on mental health.²⁰

Conclusions

This methodological demonstration shows that outliers can substantially distort OLS estimates of a bivariate relationship, producing a severe underestimate of the underlying association. Where OLS suggested that financial stress explains only 4.2% of

the variance in the mental health index, the robust methods indicated a relationship approximately four to five times stronger ($R^2 \approx 0.17$ – 0.20). MM-estimation and M-estimation with bisquare weighting produced the most consistent estimates, with slopes up to 44% steeper than OLS.^{16,18}

Methodologically, this demonstration reinforces the case for routine outlier screening and for treating robust estimation as a complement, or in some cases an alternative, to conventional OLS in mental health research.^{13,15,33} Case deletion, while effective at recovering the underlying relationship, reduces sample size and may limit generalizability;⁴¹ mean imputation of outliers is not recommended, as it can reintroduce the very bias it is intended to correct.³⁵ MM-estimation or M-estimation with bisquare weighting are recommended as a default choice, given their combination of robustness and statistical efficiency.^{18,19}

This methodological demonstration highlights the importance of robust estimation in mental health research. Researchers are encouraged to routinely assess the influence of outliers and, where indicated, employ robust methods as a complement to conventional OLS.

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