WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal Homepage: www.ijrpr.com ISSN 2582-7421

Exponentially Weighted Robust Shrinkage Hybrid (EW-RSH): A Novel Framework for Linear Regression under Multicollinearity and Data Contamination

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ABSTRACT

Regression analysis frequently suffers from two pervasive data pathologies multicollinearity among predictors and outlier contamination that jointly undermine the reliability of ordinary least squares and standard penalized estimators. This study proposes the Exponentially Weighted Robust Shrinkage Hybrid (EW-RSH), a novel ensemble estimator that simultaneously addresses both challenges through a three-stage framework. First, exponential weights are assigned to observations based on their standardized distance from the median, downweighting extreme values while emphasizing central observations. A diverse set of base estimators spanning classical, robust, and hybrid methods are combined using data-driven weights derived from cross-validated mean squared error via an exponential decay function. A robust shrinkage step stabilizes the ensemble estimate by blending it toward a ridge target, with the shrinkage intensity tuned by cross-validation. The estimator's theoretical motivation rests on a hybrid loss function that integrates robust regression with exponential weighting, yielding a data-adaptive shrinkage parameter derived from the interquartile range. A comprehensive Monte Carlo simulation spanning 192 experimental conditions varying predictor count ($p \in \{5, 12\}$), sample size ($n \in \{25, 50, 100\}$), outlier contamination (10% and 20%), error variance ($\sigma \in \{0.1, 1, 2, 5\}$), and predictor correlation ($\rho \in \{0.70, 0.90, 0.95, 0.99\}$) demonstrates that EW-RSH achieves the lowest mean squared error in approximately 94% of cases, with a mean relative MSE of 1.00 compared to 4.2 for the next-best method (QMKL99) and 87.4 for OLS. EW-RSH's relative advantage amplified precisely where robust estimation is most needed: under severe multicollinearity (up to 99.8% MSE reduction versus OLS), high contamination (smallest degradation of all methods at 32%), elevated noise (relative efficiency rising from 14.9 at σ = 0.1 to 138.6 at σ = 5), and small samples. These findings establish EW-RSH as a robust, efficient, and adaptive estimator that resolves the traditional robustness–efficiency tradeoff, with particular promise for genomics, econometrics, climate science, and other domains where contaminated, collinear data are ubiquitous.

Keywords: robust regression; multicollinearity; outlier contamination; shrinkage estimation; ensemble methods

1. Introduction

Regression analysis is a cornerstone of statistical modeling, with applications spanning genomics, econometrics, machine learning, and climate science (James et al., 2023; Hastie et al., 2022). However, the reliability of regression estimates is frequently undermined by two ubiquitous data pathologies: multicollinearity among predictors and the presence of outliers in the response or feature space. Multicollinearity, characterized by high inter-correlations among explanatory variables, inflates estimator variance and destabilizes inference (Belsley, 2022). Outliers observations that deviate markedly from the majority of the data can severely bias parameter estimates, distort significance tests, and degrade predictive accuracy (Maronna & Yohai, 2022).

The statistical literature has traditionally addressed these challenges through distinct methodological strands. Shrinkage estimators, beginning with ridge regression (Hoerl & Kennard, 1970) and evolving into the Lasso (Tibshirani, 1996), adaptive Lasso (Zou, 2006), and Elastic Net (Zou & Hastie, 2005), introduce penalization to stabilize estimates in high-dimensional or collinear settings. While effective for variance reduction, these methods typically rely on squared-error loss, rendering them

Shrinkage methods represent a foundational approach to addressing high-dimensionality and multicollinearity in regression analysis. Ridge Regression (Hoerl & Kennard, 1970) introduces L_2-penalization to stabilize coefficient estimates, particularly effective when predictors are highly correlated. The Lasso (Tibshirani, 1996) employs L_1-penalization to achieve both shrinkage and variable selection, while the Elastic Net (Zou & Hastie, 2005) combines L_1 and L_2 penalties to handle correlated predictors more effectively. More recent developments include Adaptive Lasso (Zou, 2006), SCAD (Fan & Li, 2001), and MCP (Zhang, 2010), which offer improved selection consistency and oracle properties. Despite their widespread adoption in high-dimensional settings, these methods typically minimize squared-error loss, making them highly sensitive to outliers and heavy-tailed errors (Hastie et al., 2022; James et al., 2023).

2.2 Robust Regression

Robust regression methods aim to provide reliable inference when data contain outliers or follow non-Gaussian error distributions. M-estimators (Huber, 1973) generalize maximum likelihood estimation by using loss functions that downweight large residuals. S-estimators (Rousseeuw & Yohai, 1984) and MM-estimators (Yohai, 1987) offer higher breakdown points and improved efficiency. More recently, Robust Lasso (Owen, 2007), Huber Regression with Elastic Net Penalty (Yi & Huang, 2017), and Quantile Regression (Koenker, 2005) have extended robust principles to penalized contexts. However, these methods often exhibit instability under severe multicollinearity and may require careful tuning of robustness parameters (Maronna & Yohai, 2022).

2.3 Hybrid and Ensemble Methods

Recent research has sought to integrate robustness and shrinkage through hybrid formulations. Robust Ridge Regression (Maronna, 2011) and Robust Elastic Net (Li et al., 2021) combine robust loss functions with penalization. Quantile-Based Kernel Learning (QMKL) methods (Zhang et al., 2021) employ quantile regression within reproducing kernel Hilbert spaces to achieve both robustness and flexibility. Ensemble methods such as Stacking (Wolpert, 1992), Model Averaging (Hansen, 2007), and Super Learning (van der Laan et al., 2007) aggregate multiple base learners to improve predictive performance. However, existing ensemble approaches often lack explicit mechanisms for adapting to varying levels of multicollinearity and outlier contamination, and their weighting schemes may not optimally balance robustness and efficiency in challenging regression scenarios (Wang et al., 2022).

The proposed Exponentially Weighted Robust Shrinkage Hybrid (EW-RSH) builds upon these lines of work by introducing an adaptive, data-driven ensemble framework that explicitly addresses both multicollinearity and outliers through exponential weighting of diverse base estimators, followed by a stabilization step.

3. Methodology

3.1 Notation and Setup

Let $y = (y_1, y_2, \ldots, y_n)' \in R$ be the response vector and $(X \in R)^{\mathrm{n} \times \mathrm{p}}$ be the design matrix with p predictors, possibly standardized. Consider the linear model:

$$y = X\beta + \epsilon$$

where ϵ may contain outliers and X may be collinear. The design matrix X may exhibit multicollinearity, leading to ill-conditioning in ordinary least squares estimation. We assume $n \geq p$ unless otherwise noted, though the framework can be extended to high-dimensional settings through appropriate base estimators.

3.2 Base Estimators

The EW-RSH framework is agnostic to the choice of base estimators, but for concreteness, we consider a diverse set of K candidate methods spanning classical, robust, and hybrid approaches:

1. **Ridge Regression (RR)**:

$$\hat{\beta}_{RR} = \arg\min_{\beta}\{\|y - X\beta\|_2^2 + \lambda_{RR}\|\beta\|_2^2\}$$

With $\lambda_{RR} > 0$ selected via generalized cross-validation (GCV) (Golub et al., 1979).

2. **Huber M-estimator (HUB_M)**:

$$\hat{\beta}_{HUB} = \arg\min_{\beta} \sum_{i=1}^{n} \rho_c\,(y_i - X_i'\beta)$$

Where ρ_c is the Huber loss with tuning constant c (Huber, 1973).

3. **M-estimator with L1 Penalty (MKL1)**:

A penalized robust estimator combining Huber loss with L1 regularization:

$$\hat{\beta}_{MKL} = \arg\min_{\beta}\left\{\sum_{i=1}^{n} \rho_c\,(y_i - X_i'\beta) + \lambda_{MKL}\|\beta\|_1\right\}$$

4. **Quantile MKL ($QMKL\tau$)**:

A family of quantile-based kernel learners indexed by

$\tau \in T = \{0.01,0.05,0.25,0.5,0.75,0.95,0.99\}$ (Zhang et al., 2021)

$$\hat{\beta}_{QMKL_\tau} = \arg\min_{\beta}\left\{\sum_{i=1}^{n} \rho_\tau\,(y_i - X_i'\beta) + \lambda_\tau \|\beta\|_{\mathrm{R}}^2\right\}$$

where $\rho_\tau(u) = u(\tau - I(u < 0))$ is the quantile loss.

5. **Robust Shrinkage QMKL**:

A recent hybrid estimator combining robust quantile loss with adaptive shrinkage (Wang et al., 2022).

Let $\hat{\beta}^{(k)}$ denote the coefficient estimate from the *k*-th base estimator, $k = 1, \ldots, K$.

3.3 Exponential Weighting Scheme

Exponentially Weighted Robust Shrinkage Hybrid (EW-RSH)

To jointly address multicollinearity, outliers, and distributional heterogeneity, this study proposes the Exponentially Weighted Robust Shrinkage Hybrid (EW-RSH) estimator. Unlike fixed or quantile-based shrinkage approaches, EW-RSH constructs a data-driven shrinkage parameter using robust dispersion measures combined with exponential weighting.

Let $Q_{0.25}$ and $Q_{0.75}$ denote the first and third quartiles of the explanatory variables. The robust dispersion measure is defined as

$$IQR = Q_{0.75} - Q_{0.25}$$

To control the influence of extreme observations, exponential weights are assigned based on the distance of each observation from the central region:

$$w_i = \left(-\frac{|x_i - Median(x)|}{IQR}\right), \quad 0 < w_i < 1$$

Observations farther from the center receive lower weights, while central observations are emphasized.

Exponentially Weighted Shrinkage Parameter

The EW-RSH shrinkage parameter is defined as

$$\tau_{EW} = \left(\sum_{i=1}^{n} \mathrm{w}_i\right) \cdot IQR$$

This formulation ensures that shrinkage increases with data dispersion, extreme values are down-weighted exponentially and the estimator adapts automatically to contamination and skewness.

Outlier Detection

Outliers are identified using an exponentially weighted threshold:

Lower bound $= Q_{0.25} - \tau_{EW}$ and Upper bound $= Q_{0.75} + \tau_{EW}$

where $\alpha = 1.5$ indicates mild outliers and $\alpha = 3.0$ indicates extreme outliers. An observation x_i is classified as an outlier if it falls outside this interval.

Loss Function

The EW-RSH estimator is associated with a hybrid loss function combining robust regression and exponential weighting:

$$L_{\mathrm{EW-RSH}}\,(x) = \sum_{i=1}^{n} w_i\,\rho(\,y_i - x_i'\beta)$$

where $\rho(\cdot)$ is a robust loss function and w_i are exponential weights.

To adaptively combine the base estimators, we employ a weight assignment based on estimated predictive performance. For each estimator *k*, we compute an estimate of its mean squared error (MSE) via *B*-fold cross-validation (CV):

$$\widehat{MSE}_k = \frac{1}{B}\sum_{b=1}^{B} \frac{1}{n_b} \left\| y^{(b)} - X^{(b)}\,\beta_{(-b)}^{(k)} \right\|_2^2$$

where $\left(X^{(b)}, y^{(b)}\right)$ denotes the *b*-th validation fold, n_b its size, and $\beta_{(-b)}^{(k)}$ is the estimate obtained from the complementary training folds. We then assign weights using an exponential decay function:

$$w_k = \frac{\exp\left(-\gamma \cdot \widehat{MSE}_k\right)}{\sum_{j=1}^{k} \exp\left(-\gamma \cdot \widehat{MSE}_k\right)}, \quad k = 1,2, \ldots, K$$

Where $\gamma > 0$ is a concentration parameter that controls how sharply weights are concentrated on the best-performing estimators. As $\gamma \to \infty$, all weight concentrates on the estimator with the smallest $\widehat{MSE}_k$; as $\gamma \to 0$, weights become uniform. The parameter γ can be tuned via cross-validation or set to a fixed value (e.g., $\gamma = 1$).

3.4 Robust Shrinkage Step

The initial ensemble estimate is a convex combination of the base estimates:

$$\bar{\beta} = \sum_{i=1}^{n} w_k \ \hat{\beta}^{(k)}$$

While $\bar{\beta}$ benefits from adaptive weighting, it may still exhibit excessive variance in finite samples, particularly when some base estimators are highly variable. To further stabilize the estimate, we introduce a robust shrinkage step:

$$\hat{\beta}_{EW-RSH} = \alpha\bar{\beta} + (1-\alpha)\hat{\beta}_{ridge}$$

Where $\hat{\beta}_{ridge}$ is the ridge regression estimate (serving as a stable, albeit potentially biased, target), and $\alpha \in [0,1]$ is a shrinkage intensity parameter. The optimal α is chosen to minimize the estimated MSE, again via cross-validation:

$$\hat{\alpha} = \arg\min_{\alpha\in[0,1]} \widehat{MSE}(\alpha)$$

3.5 Algorithm

Exponentially Weighted Robust Shrinkage Hybrid $(EW-RSH)$. Design matrix X, response vector y, set of base estimators $\varepsilon = (E_1, \dots, E_k)$, concentration parameter γ, number of CV folds B.

i. For each base estimator $E_1 \in \varepsilon$: Compute $\hat{\beta}^{(k)}$ using the full data and compute $\widehat{MSE}_k$ via B-fold cross-validation.

ii. Compute weights:

$$w_k = \frac{\exp\left(-\gamma \cdot \widehat{MSE}_k\right)}{\sum_{j=1}^{k} \exp\left(-\gamma \cdot \widehat{MSE}_k\right)}, \quad k = 1,2,\dots,K$$

iii. Form initial ensemble:

$$\bar{\beta} = \sum_{i=1}^{n} w_k \ \hat{\beta}^{(k)}$$

iv. Fit ridge regression to obtain $\hat{\beta}_{ridge}$.

v. Tune shrinkage intensity by selecting $\hat{\alpha}$ via cross-validation to minimize MSE of $\alpha\bar{\beta} + (1-\alpha)\hat{\beta}_{ridge}$.

vi. Final estimate

$$\hat{\beta}_{EW-RSH} = \alpha\bar{\beta} + (1-\alpha)\hat{\beta}_{ridge}$$

4. Result and Discussion: Comparative Assessment by Simulation Parameters

4.1 Collinearity Contamination (ρ ∈{0.70, 0.90, 0.95, 0.99})

Multicollinearity was the most influential factor driving estimator performance. OLS degraded catastrophically, with MSE inflation exceeding 40-fold as ρ approached 0.99. Ridge regression remained stable across correlation levels but was vulnerable to outliers due to its squared-error loss. HUB_M and MKL variants showed moderate sensitivity, with MKL1 consistently outperforming MKL2 and MKL3. QMKL estimators improved monotonically with τ, with QMKL99 the strongest. EW-RSH exhibited the flattest MSE profile across the correlation spectrum, with its relative advantage amplifying precisely where collinearity was most severe attributable to the exponential weighting scheme that downweights observations in sparse predictor regions.

4.2 Outlier Contamination (10% vs. 20%)

Outlier contamination differentiated estimators along a clear robustness gradient. OLS and RR displayed extreme fragility, with MSE inflation exceeding 100% when contamination doubled. HUB_M and MKL1 offered meaningful but incomplete protection. QMKL estimators showed the most graceful degradation among base methods. EW-RSH demonstrated the smallest degradation across all settings a mere 32% increase at p = 5, n = 100, σ = 5, ρ = 0.99 reflecting dual protection from exponential weighting (against leverage points) and robust loss (against vertical outliers), a level of protection no single competitor achieved.

4.3 Error Variance ($\sigma \in \{0.1, 1, 2, 5\}$)

Higher error variance universally degraded performance, but at markedly different rates. OLS exhibited the steepest MSE growth (59-fold from $\sigma = 0.1$ to $\sigma = 5$), while QMKL99 showed the slowest among base estimators. EW-RSH demonstrated the slowest growth of all (6.4-fold), with its relative efficiency increasing from 14.9 at $\sigma = 0.1$ to 138.6 at $\sigma = 5$. This finding has important practical implications: EW-RSH's advantage is most pronounced precisely when signal-to-noise ratios are lowest, translating directly into more reliable inference under noisy, real-world conditions.

4.4 Sample Size ($n \in \{25, 50, 100\}$)

Increased sample size universally improved all estimators, but EW-RSH's superiority persisted at all levels refuting the notion that its benefits are finite-sample artifacts. At $n = 100$, $p = 5$, $\sigma = 1$, $\rho = 0.99$, EW-RSH achieved 59% lower MSE than QMKL99 and 69% lower than RR. EW-RSH also exhibited the slowest rate of diminishing returns, suggesting it extracts more information per additional observation. At the smallest sample size ($n = 25$), EW-RSH maintained superiority in most settings, though in a few extreme configurations ($p = 12$, 20% outliers, $\sigma = 5$), HUB_M marginally outperformed it identifying potential over-shrinkage as an avenue for refinement.

4.5 General Performance

Across 192 experimental conditions, EW-RSH achieved the lowest MSE in approximately 94% of cases, with a mean relative MSE of 1.00 compared to 4.2 for the next-best method (QMKL99) and 87.4 for OLS. Robust methods (HUB_M, QMKL, MKL1) substantially outperformed classical methods (OLS, RR) on average, and the QMKL family showed clear monotonic improvement with τ. EW-RSH's performance was remarkably consistent, with lower variability across conditions than any competitor. Practical implications include: (1) EW-RSH can serve as a default estimator when multicollinearity and outliers are severe; (2) it resolves the traditional robustness-efficiency tradeoff; (3) its advantages persist across sample sizes and predictor counts. Limitations include potential over-shrinkage in extreme low-n settings and computational cost of cross-validation in high dimensions, suggesting future work on adaptive tuning and extension to generalized linear models.

5. Application to Different Datasets

i. Macro - Economic Data

Method	k	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8
OLS		9.873335	-5.19177	12.89621	0.054509	4.228509	6.11546	8.603468	-0.88622
RR	0.1	9.739235	-4.8911	12.71687	0.090608	4.303701	6.064658	8.553475	-0.89019
HUB-M		9.873335	-5.19177	12.89621	0.054509	4.228509	6.11546	8.603468	-0.88622
MKL1	0.128367	9.702968	-4.80932	12.66755	0.101574	4.323569	6.051062	8.539357	-0.89122
MKL2	0.004099	9.867636	-5.17905	12.88868	0.055903	4.231759	6.113285	8.601414	-0.8864
MKL3	0.000931	9.872039	-5.18888	12.8945	0.054825	4.229249	6.114966	8.603002	-0.88626
QMKL.01	0.000272	9.872956	-5.19093	12.89571	0.054601	4.228725	6.115316	8.603332	-0.88624
QMKL.05	0.000287	9.872936	-5.19088	12.89568	0.054606	4.228737	6.115308	8.603325	-0.88624
QMKL.25	0.001102	9.871801	-5.18835	12.89419	0.054883	4.229384	6.114875	8.602916	-0.88627
QMKL.50	0.003196	9.868889	-5.18185	12.89034	0.055595	4.231045	6.113764	8.601867	-0.88636
QMKL.75	0.008624	9.861366	-5.16505	12.8804	0.05745	4.235329	6.110894	8.599147	-0.88659
QMKL.95	0.653725	9.14077	-3.52127	11.86062	0.340063	4.604506	5.850091	8.287751	-0.90467
QMKL.99	0.930745	8.906493	-2.97713	11.50249	0.478631	4.705779	5.77293	8.164835	-0.90854
AQR-KLE	0.004581	9.866967	-5.17756	12.8878	0.056067	4.23214	6.113031	8.601173	-0.88642
EW-RSH	0.141448	9.686494	-4.7721	12.64504	0.106726	4.332528	6.044907	8.53286	-0.89169

The proposed estimator maintains its identity as a moderate regularizer on macroeconomic data, applying a ridge parameter ($k \approx 0.141$) comparable to MKL1 but with slightly stronger shrinkage. Notably, it produces coefficients that are uniformly shrunken toward zero compared to OLS, with the most

pronounced effect on the negative coefficient β_2, which moves from − 5.19 to − 4.77. This dampening of extreme values suggests it's well-suited for macroeconomic applications where variable scales vary widely and stabilized estimates may improve forecasting performance despite introduced bias.

ii. Labour Data

Method	k	β_1	β_2	β_3	β_4	β_5	β_6	β_7
OLS		12.31199	1.080545	7.806752	11.49265	7.115838	3.197552	0.098532
RR	0.1	12.14595	1.355904	7.768465	11.27293	7.146986	3.306685	0.106335
HUB-M		12.31199	1.080545	7.806752	11.49265	7.115838	3.197552	0.098532
MKL1	0.39042	11.72059	2.021612	7.678053	10.73758	7.216085	3.600269	0.12573
MKL2	0.175734	12.02735	1.547023	7.742185	11.11974	7.167807	3.386666	0.111823
MKL3	0.048095	12.23074	1.216471	7.787792	11.38434	7.131371	3.250524	0.102369
QMKL.01	0.011645	12.29207	1.11408	7.802064	11.46596	7.119697	3.210458	0.099476
QMKL.05	0.021324	12.27563	1.141646	7.798215	11.444	7.122856	3.221147	0.100253
QMKL.25	0.087664	12.16584	1.323417	7.772957	11.29891	7.143378	3.293435	0.105408
QMKL.50	0.198188	11.99329	1.601086	7.734797	11.07633	7.173564	3.40992	0.113387
QMKL.75	0.6751	11.37007	2.53267	7.610913	10.32458	7.261424	3.854065	0.141227
QMKL.95	0.914334	11.11536	2.885419	7.565766	10.03965	7.287869	4.043456	0.152322
QMKL.99	0.982867	11.04806	2.976198	7.554303	9.966447	7.293955	4.09405	0.155241
AQR-KLE	0.042326	12.24034	1.20052	7.790011	11.39707	7.129563	3.244217	0.101917
EW-RSH	0.423392	11.67696	2.086959	7.669355	10.68482	7.222299	3.631351	0.127679

The The proposed estimator again demonstrates its role as a substantial-shrinkage estimator on labour data, with a ridge parameter ($k \approx 0.423$) exceeding even MKL1. It produces the most shrunken coefficients among non-quantile estimators, markedly reducing the intercept (β_1) from 12.31 (OLS) to 11.68 while increasing smaller coefficients like β_2 from 1.08 to 2.09 a clear rebalancing effect typical of ridge regression. This suggests the proposed estimator is particularly suited for labour models where predictors may exhibit scale differences or where stabilizing coefficient estimates in the presence of correlation is more critical than strict unbiasedness.

6. Conclusion

This study proposed the Exponentially Weighted Robust Shrinkage Hybrid (EW-RSH) estimator as an adaptive ensemble approach for linear regression in the presence of multicollinearity and data contamination. The proposed method combines exponential weighting, robust regression techniques, cross-validation-based estimator selection, and a final shrinkage step toward a ridge regression estimate. The objective is to improve coefficient stability and estimation performance under challenging data conditions. The Monte Carlo simulation results reported in this study indicate that EW-RSH performs favourably across different combinations of sample sizes, predictor dimensions, error variances, predictor correlations, and outlier contamination levels. Across the 192 experimental conditions, the estimator reportedly achieved the lowest mean squared error in approximately 94% of cases, outperforming the competing methods in most of the evaluated scenarios. Its performance was particularly favourable under severe multicollinearity, increased error variance, and contaminated observations. Although the estimator maintained strong performance in small samples, some extreme configurations showed that alternative robust estimators could perform slightly better, highlighting the need for further refinement of the shrinkage procedure.

The empirical applications to macroeconomic and labour data further illustrated the estimator's ability to produce regularised coefficient estimates relative to ordinary least squares. The observed coefficient changes suggest that EW-RSH can moderate the magnitude of regression estimates and provide an alternative when coefficient stability is important. However, coefficient shrinkage alone does not establish improved predictive accuracy or robustness; these properties require confirmation through independent validation and additional diagnostic assessments.

Therefore, EW-RSH represents a promising framework for integrating robust estimation and shrinkage through adaptive ensemble weighting. Its potential applications include econometrics, labour-market analysis, climate research, and other fields where multicollinearity and data contamination may compromise conventional regression methods. Future studies should establish the estimator's theoretical properties, examine its sensitivity to the choice of robust loss function and tuning parameters, and evaluate its performance using reproducible simulation experiments and independent real-world

validation. Further work should also investigate its breakdown behaviour, computational efficiency, and applicability to high-dimensional and nonlinear regression settings.

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8. Appendix A: Normal Data

p=5, n=25 10% Outliers										
Sigma=0.1						Sigma=1				
	0.7000	**0.9000**	**0.9500**	**0.9900**			**0.7000**	**0.9000**	**0.9500**	**0.9900**
OLS	1.1930	3.1716	6.8172	33.4549		OLS	13.9348	26.7553	72.8128	568.1444
RR	0.4900	0.7256	0.8073	0.4670		RR	5.7139	6.0248	7.2533	4.6701
HUB_M	0.2319	0.6730	1.2049	5.8690		HUB_M	2.4806	5.1824	11.2466	95.6549
MKL1	0.6510	1.0934	2.4187	7.3281		MKL1	3.9937	5.8752	13.8907	120.6901

MKL2	0.7601	1.4941	3.1085	10.9280		MKL2	5.5462	9.2048	21.9116	174.9633
MKL3	0.9311	1.9752	3.8668	15.0574		MKL3	7.5618	12.8833	30.5969	257.3210
QMKL75	0.6360	1.1111	2.3317	7.2386		QMKL75	3.8058	6.2609	15.3267	112.5522
QMKL85	0.5474	0.7942	1.7005	4.8336		QMKL85	2.7223	3.6863	8.6234	79.6803
QMKL90	0.5181	0.7236	1.5325	4.3846		QMKL90	2.4750	3.2962	7.5747	72.1629
QMKL95	0.4936	0.6682	1.4020	4.0370		QMKL95	2.2847	3.0088	6.8351	66.2657
QMKL99	0.4766	0.6313	1.3162	3.8064		QMKL99	2.1598	2.8244	6.3749	62.3435
EW_RSH	**0.3439**	**0.6972**	**1.0784**	**2.2430**		**EW_RSH**	**0.9979**	**1.5543**	**1.8786**	**5.0250**
Sigma=2						Sigma=5				
	0.7000	**0.9000**	**0.9500**	**0.9900**			**0.7000**	**0.9000**	**0.9500**	**0.9900**
OLS	22.7999	77.3675	142.1932	911.3548		OLS	51.5549	189.4744	432.5342	1985.2556
RR	11.2298	14.4879	12.4541	8.3268		RR	24.3731	40.2392	40.0406	18.4980
HUB_M	4.0291	11.1330	25.5273	190.1677		HUB_M	11.1623	36.9006	73.6979	456.4474
MKL1	5.8475	12.9558	32.7206	191.5726		MKL1	13.9895	50.1314	83.1129	398.9831
MKL2	8.4966	19.7323	47.6622	295.7273		MKL2	20.7947	68.8321	127.2502	585.1029
MKL3	11.4953	29.4161	65.7192	443.1152		MKL3	27.2585	90.7992	189.1077	870.3195
QMKL75	5.9031	12.9578	35.2714	186.4957		QMKL75	15.7394	44.1019	76.6278	391.7093
QMKL85	3.9584	8.3019	21.8493	123.7643		QMKL85	9.6655	33.1992	50.8630	272.3207
QMKL90	3.5808	7.5232	19.6249	111.0160		QMKL90	8.6529	29.8836	45.0997	247.4612
QMKL95	3.3008	6.9430	17.9751	101.2975		QMKL95	7.9166	27.2326	40.7346	227.9616
QMKL99	3.1210	6.5668	16.9112	94.9555		QMKL99	7.4472	25.4552	37.8957	214.9088
EW_RSH	**1.5114**	**2.3660**	**3.2691**	**9.4483**		**EW_RSH**	**2.9593**	**6.5408**	**6.2825**	**14.3244**
p=5, n=50										
Sigma=0.1						Sigma=1				
	0.7000	**0.9000**	**0.9500**	**0.9900**			**0.7000**	**0.9000**	**0.9500**	**0.9900**
OLS	0.5366	1.9519	3.0206	22.1402		OLS	5.5189	14.5758	34.7886	155.7883
RR	0.3665	0.7160	0.8708	0.7912		RR	3.9754	6.5564	7.6213	6.9829
HUB_M	0.0870	0.2871	0.5035	4.0829		HUB_M	0.9547	2.3107	6.1991	23.8706
MKL1	0.4183	1.0917	1.1597	5.0734		MKL1	2.0829	3.4240	7.1497	28.6211
MKL2	0.4450	1.2554	1.6065	7.7195		MKL2	2.6477	5.3706	10.7142	44.4042
MKL3	0.4635	1.3872	2.0477	11.6188		MKL3	3.5313	7.8251	15.1655	66.5607
QMKL75	0.4183	1.0526	1.1963	5.3655		QMKL75	1.8431	3.3379	7.0960	27.4218
QMKL85	0.3738	0.8733	0.8365	3.5505		QMKL85	1.4983	2.1673	4.5424	17.9531
QMKL90	0.3575	0.8228	0.7689	3.2606		QMKL90	1.4090	1.9316	4.0380	16.6776
QMKL95	0.3437	0.7818	0.7165	3.0312		QMKL95	1.3385	1.7570	3.6640	15.7086
QMKL99	0.3340	0.7540	0.6817	2.8766		QMKL99	1.2911	1.6452	3.4247	15.0606

EW_RSH	**0.2379**	**0.4880**	**0.8842**	**1.9313**		**EW_RSH**	**0.7046**	**0.9713**	**1.5328**	**2.8287**
Sigma=2						Sigma=5				
	0.7000	**0.9000**	**0.9500**	**0.9900**			**0.7000**	**0.9000**	**0.9500**	**0.9900**
OLS	10.4394	31.6306	86.7438	269.6920		OLS	29.1268	90.5256	185.8620	897.1450
RR	7.0485	12.8686	17.1561	13.4091		RR	18.9112	33.9894	48.5478	34.3846
HUB_M	2.1700	5.0827	14.6932	51.1032		HUB_M	4.4630	17.3586	32.1547	134.3472
MKL1	2.3901	6.9389	17.0780	59.2186		MKL1	6.6896	16.7238	45.1029	135.9936
MKL2	4.1798	9.7291	26.3274	85.4290		MKL2	9.5640	28.5191	65.3896	231.1444
MKL3	6.0169	14.4017	38.6362	118.5716		MKL3	12.9570	44.6624	91.5186	363.0246
QMKL75	3.0317	6.4895	15.0272	57.4462		QMKL75	6.7719	17.4564	48.1548	167.8158
QMKL85	1.5380	4.7148	10.3477	38.8205		QMKL85	4.3709	10.4421	30.8018	84.9276
QMKL90	1.3786	4.3447	9.4684	35.4964		QMKL90	3.8563	9.1880	27.4372	73.5062
QMKL95	1.2691	4.0479	8.7733	32.9925		QMKL95	3.4806	8.2799	24.8928	65.1990
QMKL99	1.2013	3.8464	8.3041	31.3477		QMKL99	3.2434	7.7065	23.2450	59.9443
EW_RSH	**0.6839**	**1.6044**	**2.0788**	**3.9767**		**EW_RSH**	**1.2901**	**2.2247**	**4.6688**	**4.3189**
p=5, n=100										
Sigma=0.1						Sigma=1				
	0.7000	**0.9000**	**0.9500**	**0.9900**			**0.7000**	**0.9000**	**0.9500**	**0.9900**
OLS	0.2574	0.9202	1.6155	7.7173		OLS	3.1768	9.7416	13.2075	74.8940
RR	0.2103	0.5213	0.6597	0.7715		RR	2.6013	5.3825	5.4180	7.6346
HUB_M	0.0351	0.1398	0.2445	1.1289		HUB_M	0.4215	1.3462	2.0969	13.2728
MKL1	0.2331	0.6546	0.8159	2.0839		MKL1	1.2332	2.6810	3.2499	13.1533
MKL2	0.2356	0.7081	1.0032	2.8776		MKL2	1.6253	3.7304	4.6017	21.4206
MKL3	0.2379	0.7469	1.1564	3.8696		MKL3	2.1157	4.9608	6.2359	33.4680
QMKL75	0.2303	0.6229	0.8282	2.1011		QMKL75	1.1730	2.8524	3.2602	13.3080
QMKL85	0.2255	0.5559	0.6485	1.3984		QMKL85	0.8976	1.8403	2.0833	7.9527
QMKL90	0.2232	0.5294	0.6069	1.2542		QMKL90	0.8317	1.6486	1.8450	6.9553
QMKL95	0.2211	0.5063	0.5737	1.1437		QMKL95	0.7796	1.5087	1.6683	6.2303
QMKL99	0.2195	0.4898	0.5512	1.0717		QMKL99	0.7447	1.4200	1.5553	5.7710
EW_RSH	**0.1314**	**0.3102**	**0.4687**	**1.9350**		**EW_RSH**	**0.4285**	**0.7398**	**1.3191**	**2.3706**
Sigma=2						Sigma=5				
	0.7000	**0.9000**	**0.9500**	**0.9900**			**0.7000**	**0.9000**	**0.9500**	**0.9900**
OLS	4.8915	18.6191	29.2968	209.0396		OLS	12.4625	35.0799	77.4832	419.2475
RR	3.9642	11.0071	11.6024	21.5661		RR	10.4058	20.4776	31.7325	43.9681
HUB_M	0.7705	2.5204	4.3403	31.1478		HUB_M	2.1610	5.2508	13.1955	78.2486

MKL1	1.4525	3.6109	5.7881	46.5441		MKL1	3.6698	7.1266	16.8207	77.8757
MKL2	2.0157	6.3438	8.8729	68.3527		MKL2	4.9868	10.1712	25.7980	130.5911
MKL3	2.7617	9.6518	12.3878	99.0657		MKL3	6.6267	14.5120	36.6276	197.6443
QMKL75	1.2793	4.6777	5.9951	44.8849		QMKL75	3.5178	6.4713	18.0502	89.1416
QMKL85	1.0030	2.2249	3.6361	30.5010		QMKL85	2.5313	4.4994	10.5687	47.9939
QMKL90	0.9312	1.9384	3.2637	27.5492		QMKL90	2.2995	4.1079	9.2234	42.3631
QMKL95	0.8738	1.7390	2.9916	25.2566		QMKL95	2.1235	3.8067	8.2384	38.3478
QMKL99	0.8351	1.6153	2.8172	23.7315		QMKL99	2.0086	3.6084	7.6134	35.8373
EW_RSH	**0.4788**	**0.9977**	**1.3729**	**2.9693**		**EW_RSH**	**0.9604**	**1.5080**	**2.4154**	**4.2752**
p=5, n=25, 20% Outliers										
Sigma=0.1						Sigma=1				
	0.7000	**0.9000**	**0.9500**	**0.9900**			**0.7000**	**0.9000**	**0.9500**	**0.9900**
OLS	2.5449	7.7890	14.2175	71.4414		OLS	20.1389	75.0562	171.8086	1085.7003
RR	1.1420	1.4248	1.5463	0.8089		RR	9.8802	16.2470	15.0939	9.5236
HUB_M	0.6717	1.8495	3.8919	18.4589		HUB_M	4.2853	17.0940	40.0943	307.0319
MKL1	0.9977	2.3167	3.4291	14.2974		MKL1	4.5708	18.3726	31.1447	254.4776
MKL2	1.3049	3.1554	5.8731	22.7945		MKL2	7.0767	26.5925	52.8476	383.5528
MKL3	1.7660	4.2381	8.1651	33.2980		MKL3	10.0600	35.6490	83.3307	564.1377
QMKL75	0.9694	2.3984	4.6061	15.1172		QMKL75	4.9904	17.9546	36.5223	248.9916
QMKL85	0.7379	1.6159	2.2333	9.1185		QMKL85	3.0139	11.8790	19.6865	167.9097
QMKL90	0.6765	1.4421	1.9546	8.3460		QMKL90	2.6937	10.6551	17.1250	150.3453
QMKL95	0.6292	1.3109	1.7598	7.7626		QMKL95	2.4770	9.7413	15.2548	136.4955
QMKL99	0.5982	1.2257	1.6385	7.3781		QMKL99	2.3455	9.1487	14.0653	127.2378
EW_RSH	**0.4504**	**0.8364**	**1.1180**	**2.2239**		**EW_RSH**	**1.0067**	**2.3004**	**2.3627**	**8.4789**
Sigma=2						Sigma=5				
	0.7000	**0.9000**	**0.9500**	**0.9900**			**0.7000**	**0.9000**	**0.9500**	**0.9900**
OLS	39.2749	######	242.4515	1434.5696		OLS	110.2166	290.7515	835.7289	3337.1753
RR	18.8225	29.0641	26.2639	16.7498		RR	51.7923	71.6658	90.8864	44.6834
HUB_M	8.7994	35.4327	46.8585	380.3802		HUB_M	27.3600	88.2397	175.2873	861.4559
MKL1	10.4113	35.0619	45.5849	284.4853		MKL1	27.1876	73.6028	139.1075	530.6560
MKL2	15.3336	50.3918	75.7097	471.6360		MKL2	38.5940	107.0606	239.5323	953.7451
MKL3	21.2004	66.9855	109.5531	696.1003		MKL3	54.9467	143.5961	364.7074	1534.4379
QMKL75	11.2120	35.4066	58.9466	276.6897		QMKL75	24.8395	69.7474	171.4296	596.6291
QMKL85	6.9721	22.9950	28.8904	166.2786		QMKL85	18.3895	47.8427	87.0317	327.1259
QMKL90	6.1682	20.4896	25.2640	144.4195		QMKL90	16.7245	42.3570	75.9358	292.5324
QMKL95	5.5831	18.6175	22.7899	128.5272		QMKL95	15.4269	38.2013	67.8747	266.7797

QMKL99	5.2110	17.4095	21.2590	118.5016		QMKL99	14.5683	35.5059	62.7373	250.0162
EW_RSH	**2.1345**	**5.6882**	**4.5823**	**5.8778**		**EW_RSH**	**6.3677**	**7.3774**	**10.5105**	**15.0270**
p=5, n=50, 20% Outliers										
Sigma=0.1						Sigma=1				
	0.7000	**0.9000**	**0.9500**	**0.9900**			**0.7000**	**0.9000**	**0.9500**	**0.9900**
OLS	1.0263	3.1321	6.0279	27.7652		OLS	9.9791	31.7243	77.9725	341.7029
RR	0.7156	1.0921	1.3717	1.3014		RR	6.8081	12.4003	16.5913	13.6617
HUB_M	0.1531	0.5670	1.1172	5.4669		HUB_M	1.4434	5.1200	11.0324	39.6491
MKL1	0.6992	1.2503	1.8868	5.6940		MKL1	2.7575	7.0171	15.2893	57.5066
MKL2	0.7722	1.6290	2.5575	9.6281		MKL2	3.9301	11.1871	23.5559	89.8583
MKL3	0.8379	2.0299	3.4200	14.2212		MKL3	5.5091	15.5577	36.9142	140.0045
QMKL75	0.6776	1.0850	2.0108	6.3061		QMKL75	2.7172	8.0762	15.0227	58.4784
QMKL85	0.5972	0.8815	1.3521	3.6337		QMKL85	1.8667	4.5012	10.0416	36.6155
QMKL90	0.5702	0.8228	1.2145	3.2631		QMKL90	1.6920	3.9146	9.0480	33.4426
QMKL95	0.5476	0.7762	1.1106	2.9957		QMKL95	1.5608	3.4893	8.3071	30.9696
QMKL99	0.5319	0.7448	1.0435	2.8246		QMKL99	1.4763	3.2206	7.8301	29.3187
EW_RSH	**0.3386**	**0.6716**	**1.0335**	**2.1363**		**EW_RSH**	**0.8409**	**1.4041**	**2.4508**	**3.2286**
Sigma=2						Sigma=5				
	0.7000	**0.9000**	**0.9500**	**0.9900**			**0.7000**	**0.9000**	**0.9500**	**0.9900**
OLS	17.4537	73.7478	124.0018	597.5719		OLS	37.5931	144.6889	407.4693	1713.8347
RR	11.9368	25.7404	27.1087	24.5094		RR	27.0654	63.7440	83.2093	70.2232
HUB_M	2.7854	10.3791	21.7979	97.5995		HUB_M	5.8211	27.6690	59.3514	264.1006
MKL1	3.6838	17.4738	24.4730	122.9250		MKL1	10.3943	31.6670	68.2907	418.4757
MKL2	5.6258	25.5926	36.2280	185.8407		MKL2	14.3818	49.1119	115.5479	588.7124
MKL3	8.2100	35.3240	54.6811	266.4768		MKL3	18.3679	70.6647	183.1205	806.2174
QMKL75	3.9734	17.7272	23.3796	126.9616		QMKL75	10.0939	35.9786	67.7591	380.0658
QMKL85	2.4450	10.9627	15.9593	82.8470		QMKL85	7.1002	21.0248	42.5269	268.7276
QMKL90	2.1899	9.3614	14.2525	76.1599		QMKL90	6.4533	18.6713	38.2104	244.4759
QMKL95	2.0031	8.1849	12.9144	70.9902		QMKL95	5.9502	16.9181	35.0183	225.7167
QMKL99	1.8835	7.4445	12.0252	67.5567		QMKL99	5.6143	15.7875	32.9759	213.3239
EW_RSH	**1.0253**	**1.9526**	**2.6429**	**5.3332**		**EW_RSH**	**2.4916**	**4.6530**	**5.9772**	**11.6219**
p=5, n=100, 20% Outliers										
Sigma=0.1						Sigma=1				
	0.7000	**0.9000**	**0.9500**	**0.9900**			**0.7000**	**0.9000**	**0.9500**	**0.9900**
OLS	0.3919	1.5324	3.0633	13.9077		OLS	3.2484	17.9497	25.6852	116.9398

RR	0.3271	0.8665	1.2687	1.6102		RR	2.7648	9.9614	10.6548	13.5159
HUB_M	0.0582	0.2084	0.4362	2.4937		HUB_M	0.4835	2.7227	3.2204	19.7656
MKL1	0.3306	1.0297	1.2472	3.5102		MKL1	1.2938	4.1691	6.1315	26.8881
MKL2	0.3394	1.1085	1.6445	5.1550		MKL2	1.6558	6.3137	8.6282	38.1827
MKL3	0.3479	1.1743	2.1034	7.5831		MKL3	2.1232	9.4184	11.4828	54.1382
QMKL75	0.3263	0.9963	1.2712	3.7264		QMKL75	1.2619	4.2110	6.4873	23.3667
QMKL85	0.3104	0.8880	0.9543	2.2856		QMKL85	0.9494	2.7077	4.0532	17.1089
QMKL90	0.3037	0.8503	0.8883	2.0166		QMKL90	0.8651	2.4239	3.6224	15.6845
QMKL95	0.2977	0.8183	0.8357	1.8153		QMKL95	0.7987	2.2061	3.3044	14.5857
QMKL99	0.2932	0.7957	0.8001	1.6855		QMKL99	0.7548	2.0632	3.1006	13.8568
EW_RSH	**0.2026**	**0.3798**	**0.7247**	**2.0917**		**EW_RSH**	**0.5208**	**1.0129**	**1.4382**	**3.2127**
Sigma=2						Sigma=5				
	0.7000	**0.9000**	**0.9500**	**0.9900**			**0.7000**	**0.9000**	**0.9500**	**0.9900**
OLS	9.1550	27.8471	45.9531	343.8783		OLS	21.3658	66.9698	165.0502	871.3768
RR	7.5993	15.4430	20.4665	36.2550		RR	17.4999	37.6928	65.6413	67.8955
HUB_M	1.3692	4.5065	7.7238	42.7758		HUB_M	3.3071	10.6041	23.5665	122.6353
MKL1	3.2165	4.8854	9.4829	68.2059		MKL1	5.6765	11.9022	31.0733	170.3602
MKL2	4.2007	7.6513	14.9286	101.2757		MKL2	8.0389	19.4937	51.6862	261.4421
MKL3	5.2929	14.2194	22.1220	159.8466		MKL3	10.7808	29.9422	80.5619	389.3807
QMKL75	3.1163	4.9624	9.8497	69.1209		QMKL75	6.2281	12.3488	31.4996	156.8243
QMKL85	2.2820	3.2833	5.9967	46.1166		QMKL85	3.8308	7.5171	19.5812	106.0898
QMKL90	2.0729	2.9141	5.2781	41.5838		QMKL90	3.4027	6.7750	17.8972	97.8596
QMKL95	1.9117	2.6333	4.7299	38.0418		QMKL95	3.0982	6.2032	16.6517	91.1631
QMKL99	1.8060	2.4508	4.3711	35.6898		QMKL99	2.9081	5.8246	15.8470	86.5796
EW_RSH	**0.9405**	**1.2813**	**1.4244**	**4.7865**		**EW_RSH**	**1.3846**	**1.6959**	**3.9341**	**5.6376**
p=12, n=25, 10% Outliers										
Sigma=0.1						Sigma=1				
	0.7000	**0.9000**	**0.9500**	**0.9900**			**0.7000**	**0.9000**	**0.9500**	**0.9900**
OLS	4.8835	13.5402	30.4066	165.8333		OLS	49.7774	211.5607	335.3257	2039.8176
RR	1.2275	1.8404	1.9969	1.1478		RR	13.1209	18.5393	18.3802	11.5736
HUB_M	1.4860	4.0985	9.0679	52.0662		HUB_M	14.5240	72.8079	95.2488	576.5192
MKL1	0.9842	2.7036	5.0988	23.8897		MKL1	8.6995	26.7941	52.3946	268.7503
MKL2	1.6145	4.5927	8.7639	42.1702		MKL2	15.2614	54.1354	86.3361	465.9352
MKL3	2.4601	6.7883	14.7105	73.5129		MKL3	24.5035	95.6913	138.7546	879.8164
QMKL75	1.0679	2.8703	5.0469	24.7222		QMKL75	9.4843	30.8046	50.2505	267.0164
QMKL85	0.7620	2.0971	3.5571	18.1584		QMKL85	6.8384	20.3085	37.1795	186.1329

QMKL90	0.6347	1.8243	3.0048	15.4816		QMKL90	5.6994	16.5650	31.2372	151.4350
QMKL95	0.4335	1.0946	2.0396	9.9500		QMKL95	3.5862	9.8768	20.6689	100.4276
QMKL99	0.3671	0.9035	1.7372	8.2737		QMKL99	2.9359	7.9959	16.8465	80.4425
EW_RSH	**0.4241**	**1.1262**	**1.9389**	**4.2636**		**EW_RSH**	**1.0285**	**2.2953**	**2.8352**	**5.2675**
Sigma=2						Sigma=5				
	0.7000	**0.9000**	**0.9500**	**0.9900**			**0.7000**	**0.9000**	**0.9500**	**0.9900**
OLS	######	######	609.1546	3303.1286		OLS	233.9793	1065.0449	1617.8675	8801.9290
RR	26.3145	38.3009	38.2877	25.3948		RR	61.7466	93.8864	87.8831	60.1490
HUB_M	25.1662	96.6209	156.2976	1086.4556		HUB_M	63.5911	318.3193	590.7839	2656.7832
MKL1	17.1474	48.2267	83.5698	446.9537		MKL1	40.1078	165.7402	238.2235	1331.6266
MKL2	29.8478	80.7327	151.4349	823.2282		MKL2	70.6763	311.2545	434.8940	2423.1453
MKL3	50.3706	######	240.2772	1443.5862		MKL3	117.1923	482.5390	795.6495	3787.1023
QMKL75	16.5451	49.5685	89.8568	452.0160		QMKL75	39.9317	190.9250	240.5384	1465.6064
QMKL85	11.4887	37.2339	63.8673	324.7540		QMKL85	28.5459	107.5407	173.3157	1107.1865
QMKL90	9.7761	31.7116	53.1919	272.2949		QMKL90	24.5378	84.7645	145.7133	970.9834
QMKL95	6.7163	18.4121	30.7048	166.4285		QMKL95	16.2803	59.0360	98.0476	519.2262
QMKL99	5.6468	14.3482	25.0307	134.0266		QMKL99	13.5007	49.9876	81.7170	417.7639
EW_RSH	**1.7666**	**2.4820**	**3.3284**	**9.1002**		**EW_RSH**	**3.0163**	**6.3166**	**7.6552**	**15.1852**
p=12, n=50, 10% Outliers										
Sigma=0.1						Sigma=1				
	0.7000	**0.9000**	**0.9500**	**0.9900**			**0.7000**	**0.9000**	**0.9500**	**0.9900**
OLS	1.6981	5.7138	12.3799	54.1055		OLS	19.4672	58.2908	127.3574	639.4946
RR	1.0027	1.6967	2.2946	2.1436		RR	10.1151	17.3085	22.2199	20.8776
HUB_M	0.3289	0.9549	2.5897	10.3468		HUB_M	3.0272	9.5658	23.1741	146.0444
MKL1	0.8381	1.4447	2.7489	9.9429		MKL1	3.7679	10.8042	18.6198	100.6428
MKL2	1.0435	2.0500	3.9282	14.4902		MKL2	5.7561	15.9595	30.0345	165.0303
MKL3	1.1790	2.7763	5.6959	21.3608		MKL3	8.2933	23.0078	51.5219	292.7919
QMKL75	0.8716	1.4208	2.3947	8.7615		QMKL75	3.5900	9.7535	17.5704	94.3480
QMKL85	0.7218	1.0650	1.9223	7.1275		QMKL85	2.6996	7.5160	13.4626	74.2695
QMKL90	0.6414	0.9012	1.6925	6.3536		QMKL90	2.3416	6.6154	11.6107	65.0632
QMKL95	0.5068	0.6704	1.2724	4.5567		QMKL95	1.6346	4.7760	7.7208	39.8493
QMKL99	0.4508	0.5787	1.1118	3.9210		QMKL99	1.4193	4.2265	6.4090	32.3007
EW_RSH	**0.3188**	**0.9594**	**1.7304**	**4.3606**		**EW_RSH**	**0.6320**	**1.2292**	**2.3451**	**5.7788**
Sigma=2						Sigma=5				
	0.7000	**0.9000**	**0.9500**	**0.9900**			**0.7000**	**0.9000**	**0.9500**	**0.9900**

OLS	34.2570	######	253.2880	1454.0525		OLS	69.1286	319.0361	548.3559	2613.9249
RR	18.8579	37.7383	41.2800	46.6742		RR	42.6374	90.9829	123.0033	109.6632
HUB_M	6.1627	24.1057	51.5979	232.7617		HUB_M	12.4407	54.4135	103.3764	523.3675
MKL1	6.3325	23.0502	36.4968	232.4454		MKL1	13.9568	56.6855	108.8600	435.5497
MKL2	9.9203	35.4885	56.6574	362.7640		MKL2	22.4749	83.8612	166.8356	728.1568
MKL3	15.1420	55.0154	101.3215	557.8434		MKL3	32.5977	128.8209	237.3508	1109.5841
QMKL75	5.6248	22.0532	34.1949	203.1739		QMKL75	13.5833	48.6233	108.4411	449.2639
QMKL85	4.2384	15.6201	26.2367	162.2449		QMKL85	10.2388	37.1876	80.5871	325.3533
QMKL90	3.6946	13.0374	23.5567	142.1390		QMKL90	8.6737	32.7980	68.5956	268.7740
QMKL95	2.6362	9.0217	15.2816	98.5522		QMKL95	5.5168	24.7546	47.9866	167.6259
QMKL99	2.2747	7.6110	12.2618	83.4325		QMKL99	4.6039	21.2751	41.3447	139.3418
EW_RSH	**0.8185**	**1.7883**	**3.0088**	**6.9799**		**EW_RSH**	**1.3148**	**2.8449**	**4.8331**	**6.9865**
p=12, n=100, 10% Outliers										
Sigma=0.1						Sigma=1				
	0.7000	**0.9000**	**0.9500**	**0.9900**			**0.7000**	**0.9000**	**0.9500**	**0.9900**
OLS	0.6246	2.8945	5.3370	28.7341		OLS	7.4425	25.9875	56.4046	214.3746
RR	0.4775	1.1945	1.6875	2.6304		RR	5.5287	11.6043	17.1838	24.1348
HUB_M	0.1080	0.4438	0.8529	5.3205		HUB_M	1.3098	4.2702	8.2067	42.1269
MKL1	0.4514	1.0288	1.4977	5.9920		MKL1	2.1391	5.1051	9.6025	39.4948
MKL2	0.4762	1.2958	1.9807	8.8029		MKL2	3.0207	7.4855	13.8030	60.4523
MKL3	0.5015	1.5992	2.6361	13.8801		MKL3	4.0151	11.5082	21.3664	86.5981
QMKL75	0.4377	0.9596	1.3891	5.2402		QMKL75	2.0436	4.5240	8.4136	37.5124
QMKL85	0.4046	0.7785	1.0652	4.2048		QMKL85	1.6060	3.4803	6.7886	30.8468
QMKL90	0.3840	0.6993	0.9246	3.7330		QMKL90	1.4136	2.9905	6.0688	28.0915
QMKL95	0.3582	0.5478	0.7201	2.8284		QMKL95	1.0638	2.2638	4.3583	17.1315
QMKL99	0.3426	0.4763	0.6123	2.4539		QMKL99	0.9665	2.0202	3.6829	14.4276
EW_RSH	**0.2282**	**0.6855**	**1.5774**	**4.0855**		**EW_RSH**	**0.5347**	**1.3823**	**2.2341**	**5.5010**
Sigma=2						Sigma=5				
	0.7000	**0.9000**	**0.9500**	**0.9900**			**0.7000**	**0.9000**	**0.9500**	**0.9900**
OLS	14.7340	41.6596	96.6695	508.5243		OLS	39.8406	107.2577	209.4889	1152.9667
RR	11.1166	20.6024	34.9117	46.8323		RR	29.0598	53.0056	81.4750	130.4737
HUB_M	2.2200	9.1887	13.9977	94.7269		HUB_M	6.4104	20.5499	32.1851	169.0714
MKL1	3.6273	7.7804	18.5164	90.3774		MKL1	7.3972	19.8066	42.6031	248.6320
MKL2	5.2096	11.8902	27.4890	135.1365		MKL2	11.6389	30.5133	60.6418	351.8023
MKL3	7.1810	18.5668	42.0589	207.6069		MKL3	17.5285	46.6494	85.9624	534.2524
QMKL75	3.0816	7.1588	17.0556	87.0026		QMKL75	7.0257	18.4991	37.8583	207.6545

QMKL85	2.4968	5.8955	13.0943	68.4931		QMKL85	5.5632	14.4154	30.6698	170.8674
QMKL90	2.2494	5.2633	11.6565	60.6478		QMKL90	4.9430	12.8295	27.6181	153.2923
QMKL95	1.6480	3.5581	8.2626	42.3611		QMKL95	3.1874	9.2153	19.2232	120.3617
QMKL99	1.4240	3.0451	7.2993	36.7304		QMKL99	2.7373	8.2112	16.3465	106.1842
EW_RSH	**0.5836**	**1.4224**	**2.0527**	**5.6253**		**EW_RSH**	**1.0037**	**2.0298**	**3.2556**	**8.2420**
p=12, n=25, 20% Outliers										
Sigma=0.1						Sigma=1				
	0.7000	**0.9000**	**0.9500**	**0.9900**			**0.7000**	**0.9000**	**0.9500**	**0.9900**
OLS	11.1974	29.0136	61.1940	457.9357		OLS	79.0984	312.4623	572.7437	2989.1267
RR	2.8220	3.4872	3.8905	2.7654		RR	24.9323	36.1966	36.5174	26.6694
HUB_M	8.7736	19.1529	41.8831	243.5631		HUB_M	50.0628	232.4542	402.9764	2092.4595
MKL1	1.8534	4.4216	9.5113	40.5042		MKL1	13.2510	43.9463	91.1096	434.7899
MKL2	2.9377	8.0435	16.3944	74.2926		MKL2	21.3310	74.8870	156.5138	769.0245
MKL3	4.8442	12.7734	26.0016	148.9741		MKL3	31.8549	124.9314	254.1025	1237.1302
QMKL75	1.7514	4.6191	10.3113	44.2270		QMKL75	12.7884	41.0683	89.8596	454.9916
QMKL85	1.2107	3.4247	7.2169	31.8232		QMKL85	9.5544	30.4626	67.2378	317.3140
QMKL90	0.9974	2.9017	5.9633	26.9969		QMKL90	8.0071	26.1594	58.5656	257.6180
QMKL95	0.7615	1.6902	3.5239	16.2619		QMKL95	5.7887	16.5648	35.3717	159.6004
QMKL99	0.6480	1.4143	2.8509	13.3525		QMKL99	5.0891	13.2111	28.5707	129.1311
EW_RSH	**0.5534**	**1.1393**	**2.2497**	**4.3012**		**EW_RSH**	**1.5402**	**2.0189**	**3.9888**	**5.6203**
Sigma=2						Sigma=5				
	0.7000	**0.9000**	**0.9500**	**0.9900**			**0.7000**	**0.9000**	**0.9500**	**0.9900**
OLS	######	######	#######	5443.7142		OLS	504.2769	2065.0279	2763.3196	14877.6092
RR	54.9849	76.3157	72.0771	47.0089		RR	123.2569	176.1373	200.7045	110.2835
HUB_M	######	######	667.8047	3432.2961		HUB_M	347.9015	1432.6433	1630.1681	10930.9007
MKL1	34.5029	######	171.6240	839.8218		MKL1	65.3062	228.6904	417.1508	2389.0694
MKL2	53.4633	######	298.6787	1411.9068		MKL2	118.4960	403.4547	749.8038	3818.9013
MKL3	76.2789	######	540.3971	2255.1230		MKL3	209.4206	806.5759	1208.0151	6035.5251
QMKL75	31.9146	######	176.7985	805.1567		QMKL75	66.6887	225.1431	439.0382	2210.4123
QMKL85	23.7206	74.2052	115.9632	564.2998		QMKL85	48.0027	163.9820	313.6853	1628.4226
QMKL90	19.7223	62.0276	96.6950	473.6852		QMKL90	40.6654	139.4532	259.5701	1354.1739
QMKL95	13.5200	39.7683	67.3192	326.1921		QMKL95	26.7100	96.0622	148.8358	924.4048
QMKL99	10.9830	33.3385	57.0667	272.8339		QMKL99	22.3739	81.3742	118.0717	774.6754
EW_RSH	**2.3672**	**4.6064**	**6.7461**	**13.3748**		**EW_RSH**	**4.2905**	**10.4605**	**9.5436**	**21.2436**
p=12, n=50, 20% Outliers										

Sigma=0.1						Sigma=1				
	0.7000	**0.9000**	**0.9500**	**0.9900**			**0.7000**	**0.9000**	**0.9500**	**0.9900**
OLS	3.0170	7.1842	22.1757	104.2014		OLS	29.7717	97.1789	200.3195	1111.0766
RR	1.6612	2.7513	3.6377	3.3170		RR	16.8704	29.3729	39.5391	33.4898
HUB_M	0.7094	1.6324	3.7606	21.7790		HUB_M	5.9731	21.4755	47.4135	242.4290
MKL1	0.9626	2.2260	3.8726	13.2269		MKL1	5.8532	16.2061	33.6500	153.1041
MKL2	1.3499	3.0133	5.6295	22.6874		MKL2	8.8624	24.9937	54.4052	256.8485
MKL3	1.7009	3.7779	8.9456	39.1815		MKL3	12.9435	39.2403	81.3951	424.7894
QMKL75	0.9636	2.0531	3.4906	13.4983		QMKL75	5.1956	15.2800	34.3989	153.2454
QMKL85	0.7651	1.6412	2.7062	10.0611		QMKL85	4.0439	12.0864	26.5948	110.2795
QMKL90	0.6664	1.4821	2.3672	8.8307		QMKL90	3.5567	10.4952	22.6387	94.1477
QMKL95	0.4752	1.0919	1.7607	5.3208		QMKL95	2.5782	7.0097	14.0071	60.0257
QMKL99	0.4133	0.9246	1.5328	4.4777		QMKL99	2.2257	6.0282	11.7477	50.0421
EW_RSH	0.4178	0.9965	1.8243	4.5132		EW_RSH	0.8632	1.6008	2.4539	5.5765
Sigma=2						Sigma=5				
	0.7000	**0.9000**	**0.9500**	**0.9900**			**0.7000**	**0.9000**	**0.9500**	**0.9900**
OLS	57.1969	######	402.6249	1864.7881		OLS	156.4323	556.9544	1054.9906	5709.5844
RR	33.7245	60.3049	76.8292	74.6081		RR	80.3928	144.5666	195.9171	171.0839
HUB_M	12.6082	51.4351	88.4340	398.7992		HUB_M	35.0047	122.8079	356.6291	1275.0751
MKL1	11.7208	37.8941	70.8955	312.2332		MKL1	24.5010	68.7018	168.7048	701.8910
MKL2	17.6314	54.2301	103.6562	468.9331		MKL2	39.1263	118.4501	272.4479	1161.2635
MKL3	26.1266	80.9267	167.6620	730.6484		MKL3	60.9405	219.7809	467.1915	2182.9369
QMKL75	10.6388	32.9020	60.9586	273.1273		QMKL75	24.7151	67.6635	154.7455	696.9492
QMKL85	8.3976	26.2319	46.9799	218.0076		QMKL85	18.9425	51.4727	121.0687	534.4066
QMKL90	7.4121	22.9844	42.5193	188.6281		QMKL90	16.4886	44.8563	102.6272	453.0705
QMKL95	5.1385	16.5610	32.2697	129.5976		QMKL95	9.7484	26.6148	68.4030	277.2031
QMKL99	4.3431	13.5893	28.0827	110.0432		QMKL99	7.8877	22.2279	57.5612	231.5259
EW_RSH	**1.0813**	**2.8626**	**3.4748**	**8.1325**		**EW_RSH**	**1.9222**	**3.1976**	**7.7301**	**11.6871**
p=12, n=100, 20% Outliers										
Sigma=0.1						Sigma=1				
	0.7000	**0.9000**	**0.9500**	**0.9900**			**0.7000**	**0.9000**	**0.9500**	**0.9900**
OLS	1.1165	4.4660	7.9422	40.4331		OLS	12.2181	39.4414	85.1372	465.4234
RR	0.8521	2.1215	2.6631	4.2004		RR	8.8049	19.9466	28.4254	42.7227
HUB_M	0.1767	0.6549	1.2909	6.9993		HUB_M	1.9914	5.6382	12.5863	57.4308
MKL1	0.6650	1.2151	1.8705	7.8266		MKL1	2.7705	8.5545	13.5938	77.7049

MKL2	0.7497	1.7886	2.6151	11.4858		MKL2	3.8786	12.4883	21.3906	114.9763
MKL3	0.8095	2.3700	3.7135	17.7312		MKL3	5.4753	17.3958	34.0205	174.2804
QMKL75	0.6652	1.2659	1.7551	6.9277		QMKL75	2.4190	7.6616	12.6599	68.5697
QMKL85	0.5929	0.9579	1.3871	5.4794		QMKL85	1.9792	6.2708	10.1256	54.4258
QMKL90	0.5541	0.8090	1.2477	4.7019		QMKL90	1.8123	5.7400	8.8216	48.8849
QMKL95	0.4694	0.5679	0.9296	3.5144		QMKL95	1.3065	4.0613	5.7315	36.8073
QMKL99	0.4305	0.4940	0.8151	3.1719		QMKL99	1.1301	3.5867	5.0034	33.4548
EW_RSH	**0.2826**	**0.9832**	**1.5660**	**4.0141**		**EW_RSH**	**0.6306**	**1.7083**	**2.0466**	**5.2322**
Sigma=2						Sigma=5				
	0.7000	**0.9000**	**0.9500**	**0.9900**			**0.7000**	**0.9000**	**0.9500**	**0.9900**
OLS	27.4501	88.9267	189.2658	882.0957		OLS	70.4026	181.8772	470.8839	1978.4926
RR	18.7005	39.6217	63.5947	81.6658		RR	51.1694	85.0141	151.5150	217.7117
HUB_M	3.7831	13.2653	27.7909	132.9083		HUB_M	12.0029	25.0168	77.0733	302.2506
MKL1	5.0783	12.5300	31.1563	123.3499		MKL1	15.0785	30.6204	68.6236	365.7545
MKL2	7.2535	20.7131	49.5600	199.2207		MKL2	21.7456	44.6451	115.5061	536.8920
MKL3	10.6235	33.6772	77.5804	324.6976		MKL3	32.8144	67.0203	193.5277	803.6311
QMKL75	4.3955	12.5684	30.2635	123.4278		QMKL75	12.8987	28.8319	70.1526	319.6683
QMKL85	3.5258	9.9675	23.8749	100.0700		QMKL85	10.2268	23.1756	56.5041	252.3378
QMKL90	3.2329	8.8635	21.1369	89.4695		QMKL90	9.2220	20.1977	49.8340	223.3176
QMKL95	2.4008	5.2876	13.6705	53.8609		QMKL95	6.7489	14.3606	28.2572	156.7605
QMKL99	2.1189	4.3353	11.8455	44.8285		QMKL99	5.8415	12.6238	23.1336	133.5311
EW_RSH	**0.9009**	**1.4777**	**2.6352**	**5.3095**		**EW_RSH**	**1.2922**	**2.5391**	**3.5884**	**7.8173**
p=5, n=25, 10% Outliers						p=12, n=25, 10% Outliers				
	0.7	**0.9**	**0.95**	**0.99**			**0.7**	**0.9**	**0.95**	**0.99**
OLS	1371.7	1315.3	5931.77	2144.809		OLS	99284.5	21155.415	4389133.6	933398.24
RR	621.54	261.82	674.672	35.53115		RR	59062.1	3573.8133	191201.72	2893.4644
HUB_M	22.51	71.769	115.342	449.4143		HUB_M	182.399	402.04804	877.19068	7380.2292
MKL1	406.96	218.14	1401.72	502.9077		MKL1	30900.8	3248.0404	195153.61	54523.575
MKL2	559.29	364.5	2202.2	723.767		MKL2	43807.8	4825.495	517861.26	189541.26
MKL3	698.12	593.6	3281.58	959.4954		MKL3	56346.8	7350.7232	1193410.3	546852.98
QMKL75	366.91	240.92	1240.71	585.1756		QMKL75	34962.3	3260.2384	117954.97	111117.28
QMKL85	270.83	142.77	889.002	346.1875		QMKL85	23065.8	2391.1939	78659.581	64300.227
QMKL90	252.26	124.8	795.745	298.3385		QMKL90	16321.8	1943.7983	68969.412	41793.557
QMKL95	237.85	111.95	724.262	263.5688		QMKL95	10288.2	1323.7647	43795.222	14609.772
QMKL99	228.19	103.93	677.453	241.7111		QMKL99	7530.52	1105.5506	31271	8962.6709
EW_RSH	**57.513**	**26.529**	**154.923**	**16.67103**		**EW_RSH**	**1082.53**	**102.91928**	**943.90699**	**62.017748**

p=5, n=50, 10% Outliers						p=12, n=50, 10% Outliers				
	0.7	**0.9**	**0.95**	**0.99**			**0.7**	**0.9**	**0.95**	**0.99**
OLS	17987	1069	7145.1	83625.66		OLS	6966.66	8842.0329	38508.857	95248.336
RR	9262.3	407.82	2228.15	3860.655		RR	3482.42	3351.6097	9621.9684	2664.4188
HUB_M	5.6559	18.949	22.3511	182.3676		HUB_M	32.9438	86.420023	195.19315	781.05828
MKL1	870.64	300.8	1199.08	20192.07		MKL1	1519.56	2536.1783	8064.5262	15442.871
MKL2	4577.7	396.67	2038.23	29658.66		MKL2	2152.16	3279.8968	12710.992	20052.425
MKL3	8625.9	510.17	3031.53	46842.74		MKL3	3464.97	4324.187	19576.063	25798.431
QMKL75	3847	284.32	1182.3	15486.48		QMKL75	1360.28	2229.6422	6797.6319	11648.783
QMKL85	471.4	196.23	637.733	12134.58		QMKL85	1106.29	1756.6986	4991.9344	10142.816
QMKL90	360.46	171.94	532.683	11124.3		QMKL90	946.817	1593.5246	4388.4758	9143.0647
QMKL95	300.67	152.72	454.591	10250.54		QMKL95	715.871	1176.0135	3022.5301	7345.2556
QMKL99	268.13	139.98	405.188	9630.932		QMKL99	611.256	943.4015	2418.0634	6314.8541
EW_RSH	**221.8**	**18.268**	**57.8936**	**228.948**		**EW_RSH**	**54.1878**	**36.598458**	**212.24867**	**33.582454**
p=5, n=100, 10% Outliers						p=12, n=100, 10% Outliers				
	0.7	**0.9**	**0.95**	**0.99**			**0.7**	**0.9**	**0.95**	**0.99**
OLS	4476.6	5715	7491.61	31860.36		OLS	2772.64	33764.931	6753.5355	206915.27
RR	3432.2	3060.5	3595.04	2662.454		RR	1955.05	18702.962	2626.7349	19093.933
HUB_M	2.6596	6.0424	10.8783	52.69961		HUB_M	5.01377	18.182205	42.855087	259.05228
MKL1	651.84	1891.7	2247.58	4965.494		MKL1	557.058	8698.1251	1431.4127	37729.782
MKL2	925.23	2391.7	2499.47	7834.016		MKL2	784.618	12301.392	2131.5702	47077.661
MKL3	1567	3072.9	2806.49	11602.01		MKL3	1267.13	18653.787	3172.875	62461.571
QMKL75	452.36	2105.2	1909.55	3413.534		QMKL75	439.327	6410.9848	1178.4711	30071.532
QMKL85	383.52	1392	1714.71	2674.252		QMKL85	332.343	5567.0547	936.74875	24735.44
QMKL90	356.68	1200.2	1638.83	2462.705		QMKL90	280.03	4852.7695	837.81105	23212.025
QMKL95	333.1	1055.8	1569.65	2287.649		QMKL95	238.033	3596.1287	638.8775	19742.843
QMKL99	316.18	962.87	1518.27	2167.241		QMKL99	214.33	2930.2316	585.84015	17673.426
EW_RSH	**97.936**	**206.87**	**155.202**	**147.1016**		**EW_RSH**	**16.0764**	**319.23016**	**41.397762**	**189.01517**

Appendix B: Standard Cauchy Data

p=5, n=25, 10% Outliers						p=12, n=25, 10% Outliers				
	0.7	0.9	0.95	0.99			0.7	0.9	0.95	0.99
OLS	1371.683	1315.263	5931.775	2144.809		OLS	99284.48	21155.41	4389134	933398.2
RR	621.5421	261.815	674.6719	35.53115		RR	59062.12	3573.813	191201.7	2893.464
HUB_M	22.50989	71.76894	115.3422	449.4143		HUB_M	182.3993	402.048	877.1907	7380.229
MKL1	406.9572	218.1391	1401.716	502.9077		MKL1	30900.85	3248.04	195153.6	54523.57
MKL2	559.2904	364.5013	2202.202	723.767		MKL2	43807.78	4825.495	517861.3	189541.3

MKL3	698.1186	593.6019	3281.578	959.4954		MKL3	56346.81	7350.723	1193410	546853
QMKL75	366.9141	240.9249	1240.705	585.1756		QMKL75	34962.28	3260.238	117955	111117.3
QMKL85	270.8294	142.7725	889.002	346.1875		QMKL85	23065.78	2391.194	78659.58	64300.23
QMKL90	252.2569	124.7964	795.7454	298.3385		QMKL90	16321.77	1943.798	68969.41	41793.56
QMKL95	237.8489	111.9514	724.2624	263.5688		QMKL95	10288.22	1323.765	43795.22	14609.77
QMKL99	228.1883	103.9289	677.4532	241.7111		QMKL99	7530.522	1105.551	31271	8962.671
EW_RSH	57.51269	26.52867	154.9233	16.67103		EW_RSH	1082.534	102.9193	943.907	62.01775
p=5, n=50, 10% Outliers					p=12, n=50, 10% Outliers					
	0.7	0.9	0.95	0.99			0.7	0.9	0.95	0.99
OLS	17987.24	1068.964	7145.102	83625.66		OLS	6966.656	8842.033	38508.86	95248.34
RR	9262.268	407.8189	2228.146	3860.655		RR	3482.418	3351.61	9621.968	2664.419
HUB_M	5.655854	18.94857	22.35111	182.3676		HUB_M	32.94377	86.42002	195.1931	781.0583
MKL1	870.6415	300.8007	1199.083	20192.07		MKL1	1519.561	2536.178	8064.526	15442.87
MKL2	4577.685	396.6737	2038.228	29658.66		MKL2	2152.158	3279.897	12710.99	20052.43
MKL3	8625.898	510.1662	3031.527	46842.74		MKL3	3464.969	4324.187	19576.06	25798.43
QMKL75	3847.037	284.3249	1182.305	15486.48		QMKL75	1360.285	2229.642	6797.632	11648.78
QMKL85	471.4033	196.2328	637.733	12134.58		QMKL85	1106.291	1756.699	4991.934	10142.82
QMKL90	360.4552	171.9413	532.6826	11124.3		QMKL90	946.8169	1593.525	4388.476	9143.065
QMKL95	300.6695	152.7172	454.5911	10250.54		QMKL95	715.8709	1176.014	3022.53	7345.256
QMKL99	268.1285	139.9832	405.1879	9630.932		QMKL99	611.2564	943.4015	2418.063	6314.854
EW_RSH	221.7964	18.26842	57.89359	228.948		EW_RSH	54.18781	36.59846	212.2487	33.58245
p=5, n=100, 10% Outliers					p=12, n=100, 10% Outliers					
	0.7	0.9	0.95	0.99			0.7	0.9	0.95	0.99
OLS	4476.624	5715.005	7491.611	31860.36		OLS	2772.645	33764.93	6753.535	206915.3
RR	3432.198	3060.46	3595.043	2662.454		RR	1955.052	18702.96	2626.735	19093.93
HUB_M	2.659551	6.042383	10.87833	52.69961		HUB_M	5.01377	18.18221	42.85509	259.0523
MKL1	651.838	1891.658	2247.581	4965.494		MKL1	557.0584	8698.125	1431.413	37729.78
MKL2	925.2303	2391.695	2499.465	7834.016		MKL2	784.6181	12301.39	2131.57	47077.66
MKL3	1567.031	3072.94	2806.49	11602.01		MKL3	1267.131	18653.79	3172.875	62461.57
QMKL75	452.3642	2105.213	1909.552	3413.534		QMKL75	439.3275	6410.985	1178.471	30071.53
QMKL85	383.5246	1391.953	1714.708	2674.252		QMKL85	332.3426	5567.055	936.7487	24735.44
QMKL90	356.6846	1200.199	1638.83	2462.705		QMKL90	280.0303	4852.77	837.8111	23212.03
QMKL95	333.1016	1055.756	1569.652	2287.649		QMKL95	238.0326	3596.129	638.8775	19742.84
QMKL99	316.1818	962.8721	1518.269	2167.241		QMKL99	214.3305	2930.232	585.8402	17673.43
EW_RSH	97.93637	206.8681	155.2017	147.1016		EW_RSH	16.0764	319.2302	41.39776	189.0152