A Note on Power Differentials in Data Preparation between Trimming and Winsorizing
Edward J. Lusk, Michael Halperin and Frank Heilig

Abstract
It has been demonstrated that consideration must be given to the effect that outliers have on the parameters of the OLS regression used to generate the usual Risk and Return profile of firms in market studies, in particular: Total Firm Risk, the CAPM β, the usual surrogate for Systematic Risk, Idiosyncratic Risk, Jensen’s α, the SPI and the TPI. We address, for the first time, an important related question: As there are two ways to deal with outliers in the OLS-regression space: Trimming and Winsorizing each of which has a possible different effect on Power; are there practical Power differentials between Trimming an Winsorizing. Results: We find that there are no differences in bi-variate tests against the usual Null between Trimming and Winsorizing over the market performance profile; as this is the case one prefers Trimming as it avoids the possibility of agenda serving replacement.

Key words: OLS-Regression outliers, Moral Hazard Selection
Jel Classification: G11, G12, G32, G30

INTRODUCTION
Recent research on trimming for outliers has demonstrated that major inference problems can be caused by failing to adequately prepare data for input to statistical decision support systems. For example, Lusk, Halperin and Heilig (2010) detail major inference differences in the analysis of a data set of: Old Economy, Recently Opened IPO, and New Economy firms that were traded on major exchanges respecting their financial performance. They report:

“- - - we see in a meaningful way the importance of reporting the details of the trimming that is required in using the CAPM OLS-regression. While the signal to noise issues were not in play, - - -, inference profile changes not only in magnitude but in direction as a function of trimming. The non-screened profile suggests positive performance differences in favor of the IPO for Jα, the SPI and the TPI while the screened data from Table I show the opposite — i.e., Jα, the SPI and the TPI relationships favor the OE grouping. Also, interesting is that the IR and β profiles are consistently in the same direction which of course further would confound the analysis of the inference profiles as between the screened and the non-screened inference results.”

This result underscores the importance of preparing the data that is used to draw inferences from market studies where the inference machine is the OLS two-parameter one-stage linear regression. However, it also raises a critical question that has to do with the nature of screening itself. Screening for market studies can take the form of outlier identification and elimination — i.e., Trimming or replacement of the outliers called Winsorizing.¹

While Trimming and Winsorizing protocols achieve the same critical objective of eliminating the effect of outliers, there can be, in theory, power differences between the two protocols. Power, will be computed for our purposes, as: [1 - the False Negative Error for a parametric test controlling for a non-directional False Positive Error of 0.05]. The power trade-off between these two protocols is simple to demonstrate. Trimming eliminates data points, and therefore power falls as sample size is reduced. However, power is simultaneously increased because the points eliminated are “outliers”, which by

¹ An interesting alternative possibility is transforming the input dataset with the intention to create less extreme relative values using the following Box-Cox transformation set [BCT]:

\[ y = (x^\theta - 1)/\theta. \]

While this has found useful applications in many domains to address variance stabilization, it is not a viable method for studies of market trading returns as the BCT fails for many values of \( x \). For example as returns, the \( x \) variable, are sometimes zero, \( \theta = -1 \), the inverse transform will not work or as returns are often negative \( \theta = \sqrt{0.5} \), the root transform, will not work. Therefore the only practical possibility is to use techniques of outlier identification and then modification.

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definition, are responsible for more variance than “non-outliers”. Aside from unrealistic examples of repetitive trimming, it is a practical axiom that initial outlier screens increase overall power because the power increase from variance reduction outpaces the power loss due to sample size reduction. In Winsorizing, the points are replaced, and therefore the sample size remains the same and power is unaffected. However, because the points replaced are “outliers”, variance decreases and so power increases. However, compared to Trimming, where the points are eliminated, there can be a relative power decrease as such outliers must be replaced.

This raises the following question in selecting between the Trimming and Winsorizing: What is the expected power difference between Trimming and Winsorizing? In developing information that addresses this question the answer to which has not hereto for been reported in the literature, we wish to note that there is no practical way to develop expectations that are reasonable generalizations because (i) the number of Winsorizing protocols are very large, and (ii) there is a different power differential-possible for each of the various replacement protocols. This is to say that there is no practical way to generate theoretical results regarding power differentials. Moreover, in deciding between Trimming and Winsorizing, one must also consider the “judgmental” aspect of Winsorizing. That is, Winsorizing requires that a decision maker select how the outlier points are to be replaced. Experience suggests that this “judgmental” aspect of Winsorizing can be troublesome in the sense that judgmental replacement is often difficult to explain to individuals who must use these judgmentally modified data as input to their DSS. Decision makers are often concerned about agenda serving data manipulations that arise in the moral hazard context, in particular where there are information asymmetries. This is the point of departure of our study.

We wish to address that following question: Do we find evidence that data Trimming compared to Winsorizing protocols are associated with power differences in stock market studies where the inference model is OLS regression of firm returns with matched market returns? The inference consequence is that if we determine that Power for the Winsorizing protocol is not greater than for Trimming, then one would prefer Trimming to Winsorizing as there is not the same moral hazard risk with Trimming that exists, by definition, for Winsorizing. In the case where the power for Winsorizing were to be superior to Trimming at a level that one would consider meaningful then one must address the moral hazard issue.

**STUDY PARTICULARS**

In the following study we:

1. Detail the accrual of the firms used in testing the above research question of relative power differentials in a market context.
2. Select the set of Risk and Return firm performance measures that will be used to test for profile differences between Trimming and Winsorizing, and in so doing compute, the related power for the specific test realizations which is the focus of the study.
3. Detail the Trimming and Winsorizing protocols used that follow the studies of Lusk, Halperin & Heilig (2010) and Lusk, Halperin, & Petrov (2011).
4. Provide a validation test for generalizing the power results. The validations expectation is that there will be differences in the firm performance profile controlling on Trimming and Winsorizing as compared to Not Screening for outliers.
5. Present the various power test information over the profile measures and discussion of the results. As context for the power differential test information we will test the Trimming and Winsorizing effects on the Risk and Return measures. This is important related information because the power tests are conditional on the expectation that there will be no differential effect on the Risk and Return measures due to the outlier screening protocol. This simply means that the final performance profile as measured by the Risk and Return measures is expected to be similar for Trimming or Winsorizing. This in contrast to the validation test in 4. above where one does expect that outlier screening will create a different performance profile compared to the case where outliers are not screened.
6. Conclude with a summary of the paper and suggest future topics to be investigated.

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ACCRUAL OF THE STUDY FIRMS

We selected a random sample of 41 companies listed on the NYSE with daily data for returns for the period 2002 through 2007 using the CRSP™ on the WRDS™ platform. We will use this time period to develop profile expectations for Trimming and Winsorizing that will speak to the generalizability of the power results.

The Profiling Measures Used to Calibrate the Effect of Trimming for Outliers

We have selected the following measures of Risk and Return typically used market profile studies. Risk Measures Interestingly there are three exhaustive measures of Risk due to the definition of Markowitz (1952) that the standard deviation of the period returns surrogates for Risk. These are: Total Risk, Systematic Risk, and Residual or Idiosyncratic Risk. Total Risk is just the standard deviation of the period returns. Systematic Risk is the slope of the OLS regression of the matched returns of the Firm regressed with those of the Market usually surrogated by the S&P500. This is, of course, the CAPM-β due to the work of: Sharpe (1964), Lintner, (1965) and Mossin (1966). Finally, there are two measures of Idiosyncratic Risk; one offered by Sharpe (1970) and the other, a derivative measure, offered by Ben-Horim and Levy (1980). The Ben-Horim and Levy measure is preferred to the Sharpe measure as the Sharpe measure has been shown to be biased on the high side. See Ben-Horim and Levy (pp. 293-4).

Computationally the Ben-Horim and Levy measure is:

\[
\text{IR}_{BL/L} = \sigma_f - \beta \times \sigma_m
\]

Where:
\(\sigma_f\) and \(\sigma_m\) are the standard deviation of the firm and market respectively, and \(\beta\) is the slope of the OLS-filter for the firm and the market returns.

Return Measures Jensen’s \(\alpha\), the Sharpe Performance Index [SPI], and the Treynor Performance Index [TPI]. Jensen’s \(\alpha\) There are two ways to create Jensen’s \(\alpha\). When one has a time-matched measure of the risk free rate, such as the 30 day US Treasury Bill rate, one can adjust the two time series, the firm and the market, and run the usual OLS-filter. The intercept will be the measure of \(\alpha\). The method that we used was to employ the following formula of Nielsen and Vassalou (2004).

\[
\text{J} = \bar{r}_f - (\bar{r}_f + \hat{\beta}_f [\bar{r}_m - \bar{r}_f])
\]

Where:
\(\bar{r}_f\) is average return of the firm,
\(\bar{r}_f\) is the average risk free return,
\(\hat{\beta}_f\) is the estimated CAPM firm beta/slope,
\(\bar{r}_m\) is the average return of the market.

This form best indicates the nature of Jensen’s \(\alpha\) as the excess of the average return, \(\bar{r}_f\), over the projected average return, \(\bar{r}_f + \hat{\beta}_f [\bar{r}_m - \bar{r}_f]\). \(\alpha\) gives an indication of the return performance of the organization relative to the return of the market portfolio after considering the risk-free rate. A positive (negative) \(\alpha\) indicates that the company outperformed (was outperformed by) the market portfolio respecting excess return.

The Sharpe Performance Index (SPI) is measured as:

\[
\text{SPI} = \frac{\bar{r}_f - \bar{r}_f}{\sigma_f}
\]

and the Treynor Performance Index (TPI) is measured as:

\[
\text{TPI} = \frac{\bar{r}_f - \bar{r}_f}{\hat{\beta}_f}
\]

These indices give the organization’s average return over the average risk-free rate, noted as excess return, as a percentage of company risk. The SPI is the excess return of the organization relative to
its total risk, as measured by the standard deviation of the returns of the company. The standard deviation of returns is the standard definition of total risk due to Markowitz. Thus, the SPI is a measure of excess return as a percentage of total firm risk. The TPI uses the same numerator as does the SPI, but divides it by the firm’s period beta; which is, as discussed above, the index multiplier of the relative return of the organization compared to that of the market portfolio. In this sense, TPI is excess return as a percentage of non-diversifiable risk or systematic risk, whereas the SPI is indexed on total risk (excess return relative to total firm risk). These are the standard performance-index comparisons that have been used for more than 25 years to judge the relative performance of organizations, as calibrated on volatility or risk of the organization.

Trimming: Trimming and Winsorizing Protocols

Winsorizing was first introduced by W. J. Dixon (p. 385) who notes:

“Winsor [4] and perhaps others have suggested using for the magnitude of an extreme, poorly known, or unknown observation the magnitude of the next largest (or smallest) observation. We shall show that when symmetry is maintained (or proper adjustment is made) this practice results in estimators of the mean whose efficiencies are scarcely distinguishable from those of best linear estimators. For non-symmetrical censoring, it is demonstrated that optimum simple estimators of the mean result from these ‘Winsorized' estimators”.

One recognizes that Winsorizing is just the trimmed mean transformation introduced by Blackman and Tukey (1958) or the spectral windowing often used in frequency or periodogram studies (Jenkins and Watts (1968) and Bloomfield (1976)) except that in Winsorizing there is a data specific replacement required for the windowed data points. Winsorizing creates a slight problem if one is trying to be sensitive to the moral hazard issue of agenda-serving selective replacement. Winsorizing is often found as the screening technique in market studies as it helps with precision. See: Blackman and Tukey (1958), Cowan and Sergeant (2001), Dlugosz, Fahlenbrach, Gompers and Metrick (2006), Campbell, Hilscher, and Szilagyi, (2008), Cooper, Gulen, and Schill (2008), Fama and French (2008) and McInnis, (2010). An excellent summary rationalization for Winsorizing is offered by Cooper, Gulen, and Schill (2008, p. 1632):

“To examine the effects of outliers in the asset growth distribution, we winsorize the asset growth distribution at the 1% and 99% points of the distribution. Winsorizing the data has the effect of making the asset growth relationship stronger.”

We will now consider, in detail, the three outliers screens that are often used in practice: Winsorizing/Trimming, Outlier Trimming in non-relational Cartesian Coordinate space and Relational Outlier Trimming. For each of these screens, relative to the Trimming arm of the study, the identified outliers will be eliminated.

The Empirical Rule Window

The Empirical Rule [ER] introduced by Abraham De Moivre (1667-1754) [See Hald, (1998, p. 21), simply states that: very often the distribution of collected observations may be characterized using the Mean and the Standard Deviation [Sd] as follows:

68% of the observed data fall into the interval: [Mean ± 1Sd],
95% of the observed data fall into the interval: [Mean ± 2Sds], and
99% of the observed data fall into the interval: [Mean ± 3Sds].

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Using this remarkable empirical observation, an Empirical Rule Window [ERW] for our study was formed as follows: Assuming that a reasonable parameterization of the ERW is to conserve 95% of the data, DS(t), then a TW that screens for 2½% of the data on the high and the low side is a reasonable place to start as a first filter. The ERW-parameterization for all time points, t, is:

IF [DS(t)] > [Mean + 2 x Sd], then eliminate DS(t);
IF [DS(t)] < [Mean – 2 x Sd], then eliminate DS(t);
IF Not then use DS(t) in the modified DS.

Outliers in Cartesian Coordinate Space: The Box Plot

The Box-Plot [BP] was developed by John Tukey [1915-2000]; they are called Box-Plots because they are box shaped. The BP is a median centered measure that uses a fixed expansion of the Inter-Quartile Range [IQR] to construct an interval outside of which the points are identified as BP-outliers. We have selected this measure because the ER-Window is parametric as it uses the arithmetic mean and standard deviation to create the trimming interval whereas the BP uses the median and the IQR as the location and dispersion metric, and so gives a “Non-Parametric” perspective. This adds a robustness dimension to the data modification procedures.

The BP is in the SAS/JMP™ Data Description APP-Platform and also is easily programmed in Excel in the MS-Office™ suite. We will be using the SAS/JMP™-default parameterization that sets the outlier trimming interval at:

BP Window: [(25th Percentile Data Pt – 1.5 x IQR) to (75th Percentile Data Pt + 1.5 x IQR)]

Any D(t) value that falls outside of this interval is marked as a BP outlier. These limits are sometimes called “Whisker-Limits.”

The Correlation Screen due to Prasanta Chandra Mahalanobis (1932)

The third outlier filter is a relational filter to that screens for outliers in the Pearson product moment space—or what are called “correlation outliers”. To identify such relational outliers in the correlation space created by the Firm returns and the Market returns which are used to develop the above mentioned firm profiling measures, we recommend the Mahalanobis Screen [MS] as it is part of the SAS/JMP™ APPs. The programming for the MS may be found in Sall, J., Creighton, L. and Lehman (2005). As the MS is the third filter, it is not likely to be affected by extreme outliers. Our testing shows that the MS and the 95% Pearson Probability Ellipses are essentially the same in the percentage detection of outliers. Consider now the ways that these three screens are used in the two Winsorizing protocols.

Winsorizing: Adjacent Outlier Smoothing [AOS]

The AOS algorithm trimming was programmed in MS Excel using VBA [Visual Basic for Applications] and uses the following three step method:

1. If a company or market return outlier is detected by WW, then the value is replaced by the mean of the adjacent values.
2. In the second step the routine does this form of replacement again, but this time with the non-parametric BoxPlot.
3. In the last step, the MS, which is relational, looks for outliers by using the already WW and BP checked values of company and market return as an input. If a MS outlier is detected, the values for the company and market return are also replaced by the mean of their adjacent values.

This can result in multiple individual point replacements, where a value which was replaced during the WT and BP trimming stages, will be again identified and this new value will be replaced once again.
Winsorizing: MS-BlueLine Outlier Replacement [BLR]

The BLR screen uses the Mahalanobis Screen as programmed in SAS/JMP™ APPs to develop the actual replacement value for the identify outlier. The programming for the Mahalanobis Screen [MS] may be found in Sall, J., Creighton, L. and Lehman (2005). The first two steps are identical to the adjacent outlier smoothing as the outliers detected by WW and BP are simply replaced by the mean of their adjacent values as discussed above. However, for the outliers identified as lying outside the 95% Mahalanobis ellipse are “moved” to the border of the 95% Mahalanobis ellipse. Specifically, the BLR routine solves the following Mahalanobis distance measure equation:

\[
d_i = \left( \frac{R^C_i - \bar{R}^C_i}{R^M_i - \bar{R}^M_i} \right) \begin{pmatrix} \text{COV}(R^C_i; R^C_i) & \text{COV}(R^C_i; R^M_i) \\ \text{COV}(R^M_i; R^C_i) & \text{COV}(R^M_i; R^M_i) \end{pmatrix}^{-1} \begin{pmatrix} R^C_i - \bar{R}^C_i \\ R^M_i - \bar{R}^M_i \end{pmatrix}
\]

Fixing \(d\) as the critical distance (MD BlueLine) that is used to detect an outlier and solving for \(\bar{R}_C\) in the following equation:

\[
\bar{R}_C = \bar{R}_M \frac{\text{COV}[R_C; R_M]}{\text{COV}[R_M; R_M]} \left( \bar{R}_M \frac{\text{COV}[R_C; R_M]}{\text{COV}[R_M; R_M]} \right)^2 - \left( \bar{R}_M \frac{\text{COV}[R_C; R_M]}{\text{COV}[R_M; R_M]} \right) - \frac{\text{det}(\sum \text{COV}) \cdot d^2 \cdot \bar{R}_M}{\text{COV}[R_M; R_M]} \right) + \bar{R}_C.
\]

Where: \(R_C\) and \(R_M\) or the Returns for the Company and the Market respectively.

\(\bar{R}_C\) is therefore the value that lies on the upper- or lower side of the ellipse according to a given market return.

These two Winsorizing screens are programmed in Excel. The authors are happy to share the Paste&Compute APP for these computations. Consider now the validation of the representativeness of the accrued dataset.

Validation Hypothesis: Trimming compared to No-Data Modification

Here we are offering a validation of the generalizability of the study by testing the expectations for the accrual time period of the data. This is a reasonability check on validity in the sense that if the random accrual happened to create a set of test firms that were not representative of the accrual time period, then one might be misled by the power inferences drawn. See Lusk, Halperin and Heilig (2010) who use validation testing for a sample of firms from the Internet Bubble Time period. For our sample, firms were accrued as follows: the time period selected was 2002 to 2007, which is the year beginning with the enactment of Sarbanes-Oxley (2002) to the year before the beginning of the global financial crisis created by the sub-prime debacle most often identified with Lehman Bros, LLP in 2008. This created a six year window for measuring the market performance, which is a year more than the usual minimum accrual period used by many of the firms that report the results of the market performance, in particular \(\beta\). See Ibbotson (2010). For this time period, we expect to find the following results for the six market measures that we will be using for our power study:

For the SPI, \(i\text{Risk}\) and the Total Firm Risk, we expected that the Trimming would create lower values in the accrual time period compared to those using non-screened data. This is expected as Trimming will eliminate outliers around the OLS-regression line, and therefore directly reduce \(i\text{Risk}\) and Total Firm Risk, measured as the root of return variance—i.e., the range of variable residual distances will be lower with Trimming. This lower value will also have a direct effect on the SPI as excess return is not expected to be effected by Trimming. Therefore total risk will be lower due to Trimming and the SPI will be expected to be higher—i.e., it is divided by a smaller dominator.

For \(\beta\), the TPI and Jensen’s \(a\) we do not expect to find directional differences in the accrual time period because during 2002-2007, as there was controlled growth with many periods of downside
corrections, and then a slow V-bound recovery. For example, most Indices during this period showed modest gains compared to the Bubble Period. In this type of market we would expect Trimming to filter out about the same number of high and low return points thus leaving $\beta$, the slope of the OLS-Regression un-adjusted. Therefore the excess-OLS regression that produces the measure of Jensen’s $\alpha$ is also unmodified as the $\beta$-slope is linear, indicating that if there was a slope reorientation this ridged-motion re-orientation would affect an intercept [Jensen’s $\alpha$] re-positioning. Because $\beta$ is not expected to change, and the high and low returns are likely to be equally filtered, then Jensen’s $\alpha$ is likely to be unaffected by trimming for the selected time period. Finally, as the TPI is the ratio of excess return over systematic risk — i.e., $\beta$, then the TPI is expected to not be effected by trimming. In summary, if we do not find these six logical relationships in evidence for our sample of firms, this would call into question the generalizability of our power results, which of course is the focus of our study.

The results of the relationships for which we have developed the above logical directional effects are presented in Table I following.

**Insert table 1 here**

It is clear from Table I that all six validation expectations discussed above are well founded. In addition, all of the non-parametric p-values follow exactly the inference expectation provided and tested using the usual parametric methods. We offer this as a validation of the representativeness of the random sample of the 41 firms that we sampled from the time period 1 Jan 2002 to 31 Dec 2007.

**Power Test information**

To test the power relationships, we will compute the power using the SAS/JMP v.9 (2010) power software for the contrasts of the Non-Modified Data for the 41 accrued firms against Trimming, and then against AOB-Winsorizing, and BLR-Winsorizing for each of the six performance measures. This will generate six power measures for Trimming, and 12 for the Winsorizing protocols. The final inferential analysis will then be a contrast of the six measures for the Trimming against the 12 measures produced by Winsorizing. As power is a bounded variable, we will use the usual parametric mean displacement test assuming unequal variances. Because the research relationship of interest is whether Winsorizing tests have higher average power than does Trimming, one would use a directional p-value for FPE inference. However for conservatism and robustness reporting, we will report two tailed p-values and indicate the non-parametric results using the Wilcoxon Rank Sum test.

Given the above discussion, the power information for the Trimming and Winsorizing Contrast with the original non-modified data is presented in Table II:

**Insert table-2 here**

**DISCUSSION**

The results are clear; there is no practical difference between the Power attained in this Market study for Trimming compared to the Winsorizing filters. This result also invites the observation that the detectable difference between the Trimming and Winsorizing was, of course, largely due to the sample size for inference that was a part of the selected study design. However, even if one were to have managed to have sufficient points of testing to produce detection of small differences between the average power for Trimming [49.7%] and Winsorizing [47.7%] there would have been no practical differential effect. These results are simply summarized as follows. As there is no practical difference in Power between Trimming — i.e., with outlier elimination, and Winsorizing — i.e., with selective replacement, and that one prefers Trimming as it does not require decision maker intervention to select the replacement values as is the case where Winsorizing is the filtering protocol.

**Trimming is preferred as a general outlier filter for market return studies**

As related information there were no statistically significant differences between the individual six profiling statistics for the three outlier-test arms at p-values less than 0.05. This means that the values of the six performance measure taken individually were not different for: the Trimming, or AOS-Winsorizing, or BLR-Winsorizing contrasts which is one of the conditions rationalizing the above Power results.
SUMMARY AND CONCLUSION
We conclude that in market return studies using the OLS regression model associated with the CAPM to generate the usual market performance measures of Risk and Return, that, as there is no effective power difference between Trimming and Winsorizing and Trimming is both the simplest outlier trimming methodology and the one that avoids the possibility of selective data conditioning, Trimming is recommended over Winsorizing.

In future studies, power studies could of course be conducted for variants of the single $\beta$, studies such as those conducted by Fama and French (1993) where there are two factors in play for developing information for profiling the firm. Our study invites such continued power examinations.

REFERENCES
http://www.benthamscience.com/open/tobj/openaccess2.htm
Table I Validation Directional Information

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<thead>
<tr>
<th>Variables</th>
<th>Non-Mod Data Mean</th>
<th>Trimming Mean</th>
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Table-2

<table>
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<th>Param : Non-Param</th>
<th>Trimming Mean : Range</th>
<th>Winsorizing Mean : Range</th>
<th>p-values</th>
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<td>Power</td>
<td>0.497 : [0.05 to 0.997]</td>
<td>0.477 : [0.11 to 0.954]</td>
<td>0.87 : 1.0</td>
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</table>

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