A New Analysis Strategy for Designs with Complex Aliasing

Andrew Kane
Fuqua School of Business
Duke University
Durham, NC 27708

Abhyuday Mandal*
Department of Statistics
University of Georgia
Athens, GA 30602

Abstract

Non-regular designs are popular in planning industrial experiments for their run-size economy. These designs often produce partially aliased effects, where the effects of different factors cannot be completely separated from each other. In this paper, we propose applying an adaptive lasso regression as an analytical tool for designs with complex aliasing. Its utility compared to traditional methods is demonstrated by analyzing real-life experimental data and simulation studies.

Keywords: adaptive lasso, regression, variable selection, run-size economy

*This research is in part supported by the NSA Grant H98230-13-1-0251.

1 Introduction

Screening designs are widely used for identifying important factors in industrial experiments. In many practical situations, engineers prefer to identify only a few factors that can be adjusted to yield outcomes with desired characteristics. This approach is appropriate because the effect sparsity principle (Wu and Hamada, 2009, p. 173) suggests that only a handful of factors relative to the total number of factors needs to be considered. Regular designs can be used for such screening experiments, but a disadvantage of such designs is that the run sizes grow exponentially with the number of factors. For example, a full factorial design with k factors at 2 levels requires 2^k runs. Fractional factorial designs reduce the number of runs at the expense of making the estimates for the effects of certain factors indistinguishable from one another based on the observed data. This is especially the case for the conventional orthogonal components (OC) parameterization of factorial effects (Wu and Hamada, 2009, p. 274), which we consider throughout for analyzing an experiment. Specifically, under their run size reductions, these designs force sets of main effects and/or interactions to be completely correlated, or aliased, under the OC system, making it impossible to disentangle their effects without additional runs.

Non-regular designs avoid these pitfalls by forcing factors and interaction effects to be partially, but not completely, aliased. Popular examples of such designs include orthogonal arrays (Hedayat, Sloane, and Stufken, 1999) and Plackett-Burman designs (Plackett and Burman, 1946). Hamada and Wu (1992) recognized that one can take advantage of this partial correlation and, with additional assumptions, effectively use non-regular designs to identify significant interactions that would otherwise be missed.[1]

However, the existing methods available in the literature for analyzing data from such designs are not satisfactory. Some of these methods do not enforce effect heredity, which can lead to the identification of an uninterpretable model. Others rely on prior knowledge the researcher may not possess of the nature of the true model, such as assumptions on the maximum number of effects that are in the model. Some methods require supervision on

[1]The interested reader may refer to the review paper by Xu et al. (2009) for the development of research on non-regular designs.

the part of the researcher, or qualitative evaluations in certain steps of the method. This supervision can lead to the resulting model being somewhat subjective.

In this paper we propose a technique based on adaptive lasso regression (Zou, 2006) for variable selection in the presence of partially aliased factorial effects. Our algorithm identifies a set of significant factors while enforcing the effect heredity principle, without requiring the researcher to possess any special knowledge on the nature of the true model, or to supervise the algorithm and make subjective decisions. In this regard, our algorithm provides a user-friendly and accurate approach to identify significant effects. Its effectiveness and consistency are demonstrated by means of simulations for a wide variety of models and designs.

As a motivating example, consider the experiment conducted by Bringham Young University graduate students to improve the accuracy of an automated car-fueling system. The details of the experiment are described in Grimshaw et al. (2001). The students identifed 10 factors (ring type, ring thickness, lighting type, lighting angle, gas-cap angle (Z axis), gas-cap angle (Y axis skew), car-distance, threshold step-value, sharpening and smoothing, denoted by A to J in our paper) and employed a 20-run Plackett-Burman design to investigate how each factor affected the variance of the system's perception of distance. As we will see later, different algorithms identify different models, some of which are clearly better than others. For example, Method 1 (discussed in Section 3.1) identifies a model which does not obey the effect heredity principle, whereas the proposed method identifies a model that does.

The rest of the paper is organized as follows: in Section 2, we discuss complex aliasing and the unique challenges it poses to variable selection algorithms. In Section 3, we describe some existing methods used for variable selection in designs with complex aliasing. In Section 4, we introduce the adaptive lasso and our algorithm. We conduct extensive simulations in Section 5 to demonstrate the performance of the proposed algorithm. Concluding remarks are provided in Section 6. Some details are relegated to the appendix. We provide additional details of the simulation results in the supplementary materials.

2 What is a Complex Aliasing Pattern?

Any experiment with fewer runs than the corresponding full factorial design must partially compromise the ability to estimate all factorial effects. This is because in these experiments, some factorial effects are *aliased* with one another. As a result, a factor not under consideration can confound the effect of a factor of interest to the researcher. Suppose a response y is generated from the model $y = X_1\beta_1 + X_2\beta_2 + \epsilon$, whereas the assumed or working model is $y = X_1\beta_1 + \epsilon$. Here X_1 and X_2 are part of the model matrix whereas β_1 and β_2 represent the corresponding factorial effects, and ϵ is the random error. Under the working model, the ordinary least squares (OLS) estimate of the regression parameters are given by $\hat{\beta}_1 = (X_1^T X_1)^{-1} X_1^T y$. This estimate is not unbiased, and it is easy to show that the expectation of $\hat{\beta}_1$ is $E(\hat{\beta}_1) = \beta_1 + (X_1^T X_1)^{-1} X_1^T X_2 \beta_2$. Hence the bias of $\hat{\beta}_1$ is $L\beta_2$, where $L = (X_1^T X_1)^{-1} X_1^T X_2$. This L is called the alias matrix since it contains the aliasing coefficients for the estimate of β_1. Two effects are said to be "partially aliased" if the absolute value of their aliasing coefficient is strictly between 0 and 1. In case of "complete" aliasing, it becomes 1. For non-regular designs like orthogonal arrays or Plackett-Burman designs, an enormous number of two-factor interactions become partially aliased with the main effects. This justifies the use of the terminology "complex aliasing".

For illustration, consider the cast fatigue experiment discussed in Hunter et al. (1982). The experimenters used a Plackett-Burman design, shown in the appendix, with 12 runs to study the effects of seven factors (initial structure, bead size, pressure, heat, cooling rate, and polish final treatment, denoted by A to G) on the fatigue life of weld-repair castings. Each factor includes a high and a low level, which are denoted by $+1$ and -1, respectively. The lifetime was recorded and the log of the value was calculated as the response (Wu and Hamada, 2009). Note that the Plackett-Burman design used for this experiment ensures that main effects are not fully aliased with each other and, instead, are partially aliased with interaction effects. Employing the effect hierarchy principle to rule out significant effects involving more than two factors, the expectation of the OLS estimate for effect D, for example, is as follows [2]:

$$\begin{aligned}E(\hat{D}) &= D-\frac{1}{3}AB+\frac{1}{3}AC+\frac{1}{3}AE+\frac{1}{3}AF-\frac{1}{3}AG-\frac{1}{3}BC+\frac{1}{3}BE\\&\quad -\frac{1}{3}BF-\frac{1}{3}BG-\frac{1}{3}CE-\frac{1}{3}CF-\frac{1}{3}CG-\frac{1}{3}EF-\frac{1}{3}EG+\frac{1}{3}FG. \end{aligned} \quad (1)$$

Consequently, the OLS estimate for each main effect will be biased by the interaction effects. Even with the assumption that only main effects and two-factor interactions are nonzero, and all other factorial effects are ignorable, each of the main effects is partially aliased with 15 two-factor interactions. This is called complex aliasing.

3 Traditional Analysis Methods for Designs with Complex Aliasing

Three empirical principles, effect sparsity, effect hierarchy, and effect heredity, have often been used to analyze data from a screening experiment. Simply put, the effect sparsity principle suggests that the total number of important effects in a factorial experiment is small. The effect hierarchy principle (Chipman, 1996) states that main effects are more likely to be important than two-factor interactions, which in turn are more likely to be important than three-factor interactions, and so on. And according to the effect heredity principle, it is unlikely that a two-factor interaction is significant unless at least one of its parent main effects is also significant. Li et al. (2006) conduct a meta-analysis of two-level factorial experiments in the literature, and find that all three principles hold. In particular, they find strong evidence in support of the effect heredity principle.

The two most popular frequentist methods use these principles to eliminate the necessity of searching through all possible model combinations, greatly reducing computation time and coding complexity. They are credited to Hamada and Wu (1992) and are described next.

[2] Part of the interaction effects matrix X_2 and the complete alias matrix L are given in the Appendix.

3.1 Method 1

The first method, Method 1, utilizes a stepwise selection technique in determining the best model:

1. Let k be the total number of factors. For each factor A, consider a model with A and all possible two-factor interactions (AB, AC, AD, etc.) involving A. Apply a stepwise regression procedure to select a model and record its significant effects. Repeat this process for the rest of the $k-1$ factors. Out of the k selected models, choose the best one and proceed to Step 2.

2. Use the stepwise regression procedure to select significant effects from a model that consists of all the main effects and the two-factor interactions from the best model in the previous step.

3. Following the effect heredity principle, consider all the effects identified in the previous step, as well as the two-factor interactions that have at least one parent factor identified as significant in the previous step. At this stage, interaction effects suggested by the experimenter may also be included. Use the stepwise regression procedure to determine which effects are significant. Using this model, go to Step 2.

4. Repeat Steps 2 and 3 until there are no further changes in effects identified as significant.

Method 1 greatly simplifies variable selection since the method assumes that higher-order interactions are insignificant and includes, at most, two-factor interactions. The disadvantage of this method is that it is subjective since it incorporates expert opinion, and hence, effect heredity is not consistently enforced in all steps of the method. In some applications, this may give rise to an uninterpretable model.

3.2 Method 2

Relying on the effect sparsity principle, Method 2 assumes that the final model has no more than h effects. This method uses a sensible model selection criterion, e.g., the Mallows'

C_p, the Akaike Information Criterion (AIC), or the Bayesian Information Criterion (BIC), to select significant variables from an exhaustive set of possible models. The steps for Method 2 are as follows:

1. Let h be the maximum number of effects that may be contained in the final model.
2. Search through all possible models with no more than h effects that satisfy the effect heredity principle.
3. Determine which model is best according to some model selection criteria and declare it the final model using Method 2.

The drawbacks for Method 2 are clear. It assumes that one already knows the maximum number of truly significant effects. In practice, the true number of significant effects is seldom known and must be computed through statistical analysis. Moreover, as h becomes larger, the total number of evaluations multiplies, dramatically increasing the computation time of the method.

4 Proposed Method

The traditional methods, while not necessarily ineffective, rely on the experimenter having relatively detailed prior knowledge of the nature of the true model. As an alternative variable selection method more suited to experiments whose true model is unknown, we propose using a modification of lasso regression, adaptive lasso, for designs with complex aliasing.

Lasso regression solves a minimization problem similar to OLS regression, with the addition of an ℓ_1 penalty on the size of the $\hat{\beta}$ coefficients (Tibshirani, 1996). Adaptive lasso chooses each $\hat{\beta}_j$ by minimizing

$$\sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j x_{ij}\right)^2 + \lambda\sum_{j=1}^{p} w_j\,|\beta_j| = \text{Residual sum of squares} + \text{penalty} \qquad (2)$$

where p is the total number of factorial effects being entertained, n is the run size, i and j are indices used to represent an observation and a factorial effect, respectively, and $\lambda \sum_{j=1}^{p} w_j\,|\beta_j|$

is the penalty on the size of the vector of factorial effects. The smaller the weight on a specific coefficient, the less the size of that coefficient is penalized in the regression, and the less likely it is that the coefficient will fall to 0 as λ increases. Zou (2006) proposes assigning each $\hat{w}_j$ as a function of the OLS estimate of β_j and demonstrates that the adaptive lasso using this weighting system has the "oracle property": it consistently identifies variables with true non-zero coefficients.

We propose an algorithm that applies the adaptive lasso to a dataset several times and chooses the best resulting model that obeys effect heredity. Its ℓ_1 penalty will force certain regression coefficients to be 0, implying that these factors are not significant. The factors that the adaptive lasso regression assigns non-zero values to are deemed "significant effects." Once we have applied the adaptive lasso m times, we remove solutions that do not obey effect heredity, ensure the resulting solutions obey effect heredity, and rank them by some model selection criteria (in our case, BIC). The solution that ranks best according to the criteria is the adaptive lasso algorithm solution. The proposed algorithm is as follows:

1. Divide the observations into r folds. For each of the r folds,
   (a) Use the other $r - 1$ folds as a training set. Fold r will be the testing set.
   (b) In the training set, find the lasso solutions that correspond to a grid of potential penalty terms.
   (c) Record the difference between the predicted and actual values of the response in the testing set for each lasso solution.
2. From the errors found in Step 1, compute the mean squared error of the lasso prediction across all r test sets for each value of the penalty term. The penalty value λ^* that minimizes this MSE is the lasso penalty.
3. Compute the lasso solution $\hat{\beta}_1, \ldots, \hat{\beta}_p$ given λ^*. Assign the inverse of the absolute value of the coefficients, $1/|\hat{\beta}_1|, \ldots, 1/|\hat{\beta}_p|$, to be the weights for the adaptive lasso penalty $\hat{w}_1, \ldots, \hat{w}_p$, respectively.

4. Remove the effects whose lasso coefficients are 0 from consideration. Apply Steps 1 and 2 again using the weights found in Step 3 to minimize equation (2). The estimated coefficients are the adaptive lasso solution.

5. Repeat Steps 1 through 4 above, m times, recording the non-zero effects from each application of the adaptive lasso.

6. For each model $k < m$

   (a) If there is at least one main effect in model k, remove every interaction term that does not obey effect heredity within model k.

   (b) If there are no main effects in model k, examine the set of models that contain the interaction effects of model k and combinations of main effects such that every interaction effect obeys effect heredity within the model. For example, if model k consists of the interaction effect of A and B, the models entertained contain as factors (A, AB), (B, AB) and (A, B, AB). Apply some model selection criterion to this set of models and select the best model.

7. The significant effects of the solution $k^* \in 1, ..., m$ that ranks best according to the criteria are the variables the algorithm identifies as belonging to the true model.

To implement the adaptive lasso, we use the `R` package `parcor` developed by Kraemer and Schaefer (2015) to estimate partial correlation matrices for gene association networks (Kraemer et al., 2009). This method allows the adaptive lasso to perform variable selection even when the number of effects of interest exceeds the number of observations, as is often the case when studying interaction effects in designs with complex aliasing.

We apply this algorithm with $m = 5, 10, 20$, and 100. In our experience, the results of our simulations in Section 5 do not vary much, and we chose to report the results for $m = 5$. Finally, we set $r = 10$ for all designs, although this can be lowered for designs with fewer than 10 observations. Note that the algorithm can accommodate p which is larger than n. The `R` codes for applying this method can be obtained from `http://faculty.franklin.uga.edu/amandal`.

For illustration, consider the motivating cast fatigue example. Hunter et al. (1982) originally found that effects F and D were the most significant among all effects. However, Wu and Hamada (2009) concluded that F and FG were significant. The difference between these two conclusions is a result of the complex aliasing of the design. In equation (1), if we ignore all second order interactions except FG, we find that

$$E(\hat{D}) = D + \frac{1}{3}FG.$$

Therefore, the estimate for main effect D is biased by the FG interaction: D is partially aliased with FG. Since the design makes the main effects partially aliased with interaction effects, this ambiguity cannot be resolved. Wu and Hamada (2009) argued that a model with F and FG is better, with a significantly higher R^2. After applying the adaptive lasso algorithm on the data, we found that F and FG were significant in our results as well.

Now we analyze the data for the motivating nozzle experiment mentioned in the introduction. We apply each method to this example. Method 1 identifies the model with G and BJ as significant factors. This model, although sparse, is hard to interpret. On the other hand, the proposed adaptive lasso method identifies B and BJ as significant effects. This model obeys weak heredity principle and hence is more interpretable, even though it has a slightly lower R^2 value (0.46 as opposed to 0.56). Method 2 identifies the same model with $h = 2$, whereas a bigger value of h leads to more complicated models.

5 Simulations

To compare the effectiveness of the adaptive lasso algorithm to the traditional methods more generally, we used five different designs to simulate data for various models with different magnitudes of factorial effects and different model variances, and applied each method to each simulation setup. For each design, we simulated data from several models with normally distributed errors whose standard deviations σ equal 0.1, 0.25, 0.5, 0.75, or 1.0. Continuous, quadratic, and linear factors are considered. Coefficients were randomly generated from two uniform distributions: $U(0.5, 1.5)$ for "big" effects and $U(0.1, 0.3)$ for "small" effects. [3] We assume that interaction and quadratic effects[4] were big only if their parent main effects were big as well.

For each combination of design, model, effect sizes, and standard deviation of the error term, we simulated 100 datasets. In each simulation, once we had generated the data, we applied the adaptive lasso algorithm, Method 1, and Method 2 with $h = 2$, 3, and 4, as well as the Dantzig selector (Candes and Tao, 2007, Phoa et al., 2009), the LARS method used by Yuan et al. (2007), and the nonnegative garotte method proposed by Yuan et al. (2009). A brief discussion of these methods, along with a complete list of data generating processes, is provided in the supplementary materials.

The five different designs considered for simulation are as follows:

1. **Cast Fatigue Experiment:** The first simulation corresponds to the motivating cast fatigue experiment discussed in Hunter et al. (1982). The design used was a 12-run Plackett-Burman design with seven factors.

2. **Contaminant Experiment:** The second simulation corresponds to the contaminant experiment discussed in Miller and Sitter (2001). This industrial experiment was conducted to investigate ways of reducing the toxic contaminant from the waste stream of a chemical process. This is a 24-run design with nine two-level factors given by columns A to I of Table 1 in their paper.

3. **Antiviral Drug Experiment:** Xu et al. (2014) discussed an antiviral drug experiment where a 34-run design was used, with five factors each at three levels. In this simulation, we considered the design given by columns A to E of Table 1 in their paper.

[3]These specifications are similar to the motivating cast fatigue example, where the data can be thought of as being generated from the model $Y = A + AB + \epsilon$ with A and AB having coefficients with absolute value close to 0.5 and model standard deviation close to 0.25.

[4]Following Wu and Hamada (2009, p. 287), we define the quadratic effect of a three-level factor as being proportional to $(y_2 - y_1) - (y_1 - y_0)$ where y_0, y_1 and y_2 represent the observations at levels 0, 1 and 2, respectively.

4. **Wood Pulp Experiment:** Chipman et al. (1997) described a study involving some hard-to-control factors. We took the design for this wood pulp production process, given by the columns A to K of Table 4 in their paper. This is a 19-run design with 11 factors. Three of these factors, denoted by E, I and K, were continuous, and we simulated data involving continuous factors as well.

5. **Ceramics Experiment:** Finally we considered an 18-run design used to study Silicon nitrate ceramic discussed in the unpublished Ph.D. dissertation of Yuan (1998). This mixed-level design has one factor (A) at two levels and six factors (denoted by B to G) at three levels.

Figure 2 presents the percentage of simulations each algorithm correctly identified a model, separated by design and model size, and aggregated over smaller values of σ, 0.10 and 0.25. The results for the proposed adaptive lasso algorithm are in a shade of red behind the other methods. In Figure 3, the bars show the average number of effects identified by different methods. Here also the adaptive lasso algorithm corresponds to a shade of red behind the other methods. Note that the adaptive lasso algorithm is more conservative than the traditional methods, but less conservative than the Dantzig selector. This balance may suggest that the adaptive lasso algorithm is more likely to choose a model of the correct size.

The results from these simulations show that the adaptive lasso algorithm provides a versatile and effective variable selection procedure compared to the other methods. The adaptive lasso algorithm outperforms the others except in the case that the true model contains exactly one effect (in which case the Dantzig selector is more accurate) or when the maximum number of effects for Method 2, h, is set to the true number of significant effects. Phoa et al. (2009) use a conservative modification of the AIC to select the final model for the Dantzig selector; this criterion makes it more likely the Dantzig selector will choose a small model, which makes it more appropriate for sparse models than complex ones. While Method 2 performs well when h is set appropriately, the effective implementation of Method 2 may be difficult in practice because h is rarely known in advance. In contrast, the adaptive lasso algorithm performs relatively well for models of all sizes, and does not require knowledge of the size of the model as Method 2 does.

6 Conclusions

In this paper, we proposed using an adaptive lasso algorithm for analysing data from designs with complex aliasing − this algorithm is easy to use and does not require much user intervention or prior knowledge of the nature of the true model. For a variety of models, and especially for cases with errors with low standard deviations, the algorithm provides an effective model identification method that outperforms traditional methods dealing with complex aliasing in several different kinds of design. As demonstrated by our simulations, the algorithm identifies the exact model more frequently than either of the traditional frequentist methods. Furthermore, it outperforms more recently developed algorithms in identifying larger, more complicated models. While other analysis methods have been proposed such as Chipman et al. (1997)'s Bayesian variable selection strategy, those methods are computationally intensive and have not been considered here. We propose the usage of the algorithm because of its effectiveness and ease of implementation. The `R` codes are available from the author's website, and do not require any specialized knowledge or subjective judgement. Our results indicate that the adaptive lasso algorithm can be used to reliably identify models in the presence of complex aliasing. However, one should keep in mind that the final model obtained by any data analysis technique should always be assessed using residual diagnostics and other tools, before drawing inference on the significance of factorial effects.

7 Acknowledgement

The authors would like to thank the Editor, an associate editor and the reviewers for comments and suggestions that substantially improved the manuscript. They also thank Dr. C. F. Jeff Wu for his helpful suggestions. They are thankful to Ms. Samantha Cao as well for her comments.

Figure 1: *Correctly Identified Models for Different Experiments*

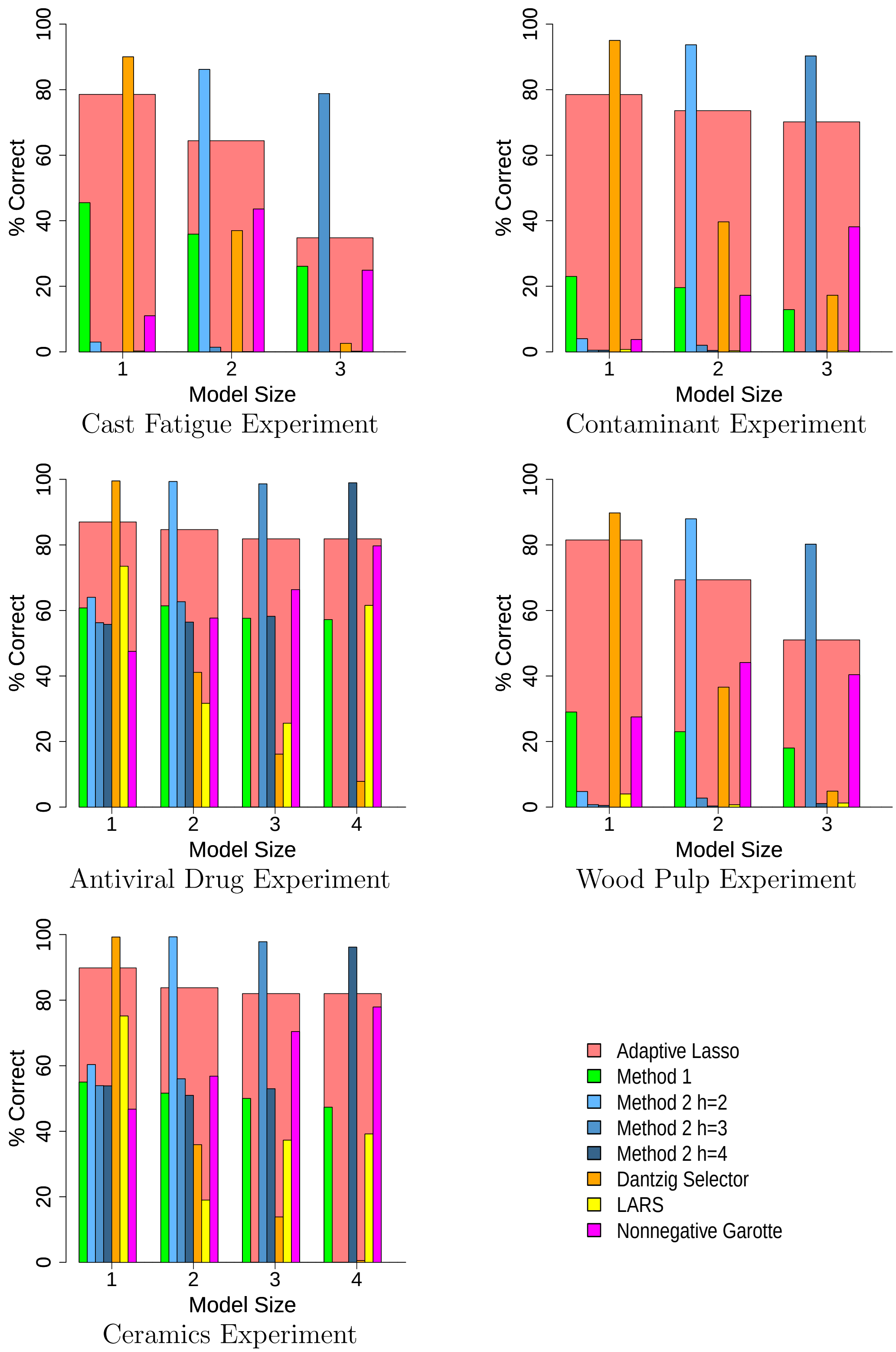
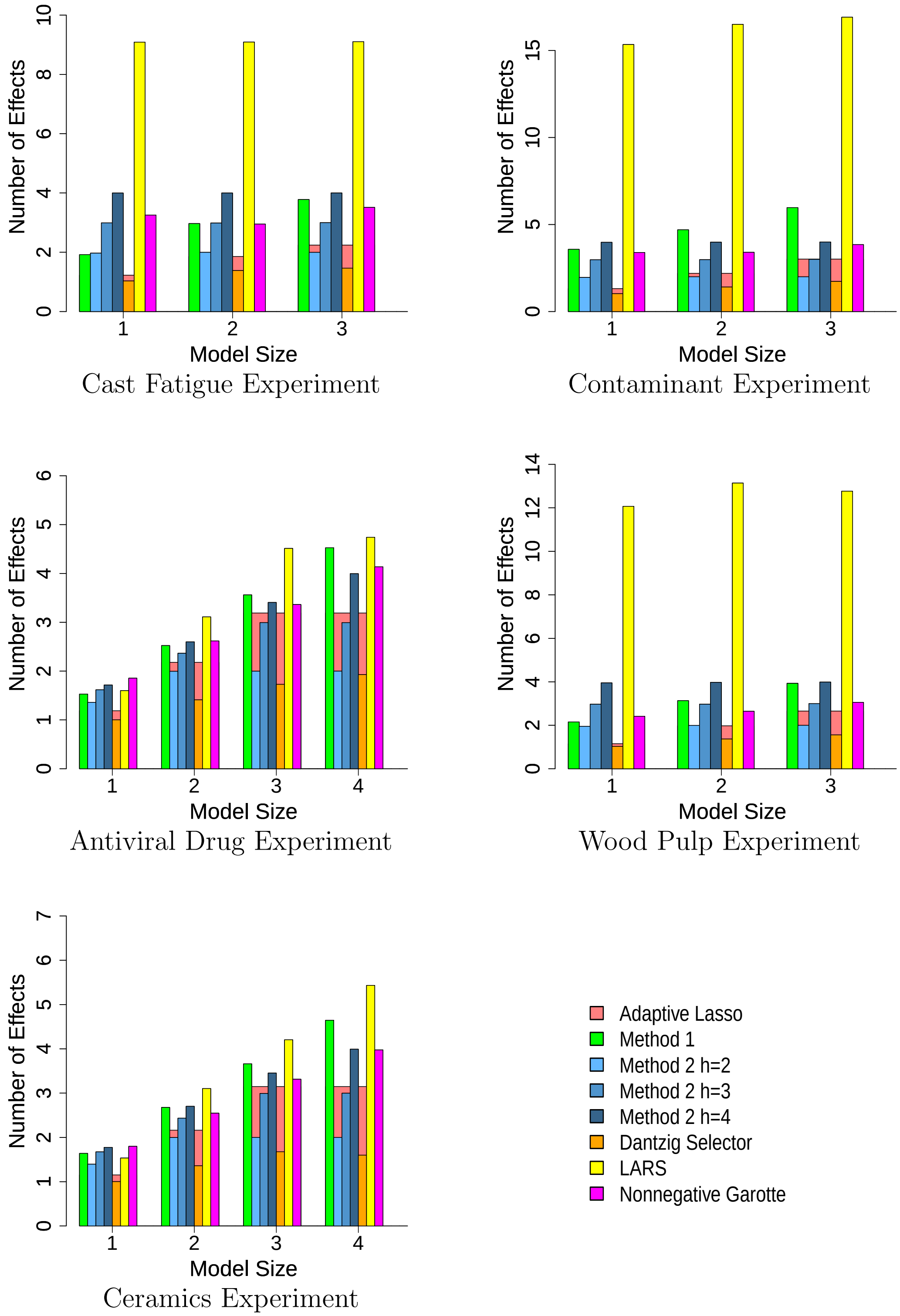


Figure 2: *Number of Significant Effects Identified for Different Experiments*



Appendix

Table A.1: Cast Fatigue Design and Data

A	B	C	D	E	F	G	Response
$+1$	$+1$	-1	$+1$	$+1$	$+1$	-1	6.058
$+1$	-1	$+1$	$+1$	$+1$	-1	-1	4.733
-1	$+1$	$+1$	$+1$	-1	-1	-1	4.625
$+1$	$+1$	$+1$	-1	-1	-1	$+1$	5.899
$+1$	$+1$	-1	-1	-1	$+1$	-1	7.000
$+1$	-1	-1	-1	$+1$	-1	$+1$	5.752
-1	-1	-1	$+1$	-1	$+1$	$+1$	5.682
-1	-1	$+1$	-1	$+1$	$+1$	-1	6.607
-1	$+1$	-1	$+1$	$+1$	-1	$+1$	5.818
$+1$	-1	$+1$	$+1$	-1	$+1$	$+1$	5.917
-1	$+1$	$+1$	-1	$+1$	$+1$	$+1$	5.863
-1	-1	-1	-1	-1	-1	-1	4.809

Table A.2: X_2 matrix for Cast Fatigue Design

AB	AC	AD	AE	AF	AG	BC	$\dots$
$+1$	-1	$+1$	$+1$	$+1$	-1	-1	$\dots$
-1	$+1$	$+1$	$+1$	-1	-1	-1	$\dots$
-1	-1	-1	$+1$	$+1$	$+1$	$+1$	$\dots$
$+1$	$+1$	-1	-1	-1	$+1$	$+1$	$\dots$
$+1$	-1	-1	-1	$+1$	-1	-1	$\dots$
-1	-1	-1	$+1$	-1	$+1$	$+1$	$\dots$
$+1$	$+1$	-1	$+1$	-1	-1	$+1$	$\dots$
$+1$	-1	$+1$	-1	-1	$+1$	-1	$\dots$
-1	$+1$	-1	-1	$+1$	-1	-1	$\dots$
-1	$+1$	$+1$	-1	$+1$	$+1$	-1	$\dots$
-1	-1	$+1$	-1	-1	-1	$+1$	$\dots$
$+1$	$+1$	$+1$	$+1$	$+1$	$+1$	$+1$	$\dots$

Table A.3: Alias Matrix L for the Cast Fatigue Experiment

	AB	AC	AD	AE	AF	AG	BC	BD	BE	BF	BG	CD	CE	CF	CG	DE	DF	DG	EF	EG	FG
A	0	0	0	0	0	0	$-\frac{1}{3}$	$-\frac{1}{3}$	$-\frac{1}{3}$	$\frac{1}{3}$	$-\frac{1}{3}$	$\frac{1}{3}$	$-\frac{1}{3}$	$-\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{3}$	$-\frac{1}{3}$	$-\frac{1}{3}$	$-\frac{1}{3}$	$-\frac{1}{3}$
B	0	$-\frac{1}{3}$	$-\frac{1}{3}$	$-\frac{1}{3}$	$\frac{1}{3}$	$-\frac{1}{3}$	0	0	0	0	0	$-\frac{1}{3}$	$-\frac{1}{3}$	$-\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{3}$	$-\frac{1}{3}$	$-\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{3}$	$-\frac{1}{3}$
C	$-\frac{1}{3}$	0	$\frac{1}{3}$	$-\frac{1}{3}$	$-\frac{1}{3}$	$\frac{1}{3}$	0	$-\frac{1}{3}$	$-\frac{1}{3}$	$-\frac{1}{3}$	$\frac{1}{3}$	0	0	0	0	$-\frac{1}{3}$	$-\frac{1}{3}$	$-\frac{1}{3}$	$\frac{1}{3}$	$-\frac{1}{3}$	$\frac{1}{3}$
D	$-\frac{1}{3}$	$\frac{1}{3}$	0	$\frac{1}{3}$	$\frac{1}{3}$	$-\frac{1}{3}$	$-\frac{1}{3}$	0	$\frac{1}{3}$	$-\frac{1}{3}$	$-\frac{1}{3}$	0	$-\frac{1}{3}$	$-\frac{1}{3}$	$-\frac{1}{3}$	0	0	0	$-\frac{1}{3}$	$-\frac{1}{3}$	$\frac{1}{3}$
E	$-\frac{1}{3}$	$-\frac{1}{3}$	$\frac{1}{3}$	0	$-\frac{1}{3}$	$-\frac{1}{3}$	$-\frac{1}{3}$	$\frac{1}{3}$	0	$\frac{1}{3}$	$\frac{1}{3}$	$-\frac{1}{3}$	0	$\frac{1}{3}$	$-\frac{1}{3}$	0	$-\frac{1}{3}$	$-\frac{1}{3}$	0	0	$-\frac{1}{3}$
F	$\frac{1}{3}$	$-\frac{1}{3}$	$\frac{1}{3}$	$-\frac{1}{3}$	0	$-\frac{1}{3}$	$-\frac{1}{3}$	$-\frac{1}{3}$	$\frac{1}{3}$	0	$-\frac{1}{3}$	$-\frac{1}{3}$	$\frac{1}{3}$	0	$\frac{1}{3}$	$-\frac{1}{3}$	0	$\frac{1}{3}$	0	$-\frac{1}{3}$	0
G	$-\frac{1}{3}$	$\frac{1}{3}$	$-\frac{1}{3}$	$-\frac{1}{3}$	$-\frac{1}{3}$	0	$\frac{1}{3}$	$-\frac{1}{3}$	$\frac{1}{3}$	$-\frac{1}{3}$	0	$-\frac{1}{3}$	$-\frac{1}{3}$	$\frac{1}{3}$	0	$-\frac{1}{3}$	$\frac{1}{3}$	0	$-\frac{1}{3}$	0	0

References

Candes, E. and Tao, T. (2007) The Dantzig selector: Statistical estimation when p is much larger than n. *The Annals of Statistics, 35*. pp 2313-2351.

Chipman, H. (1996) Bayesian Variable Selection With Related Predictors. *Canadian Journal of Statistics, 24*. pp 17-36.

Chipman, H.; Hamada, M. and Wu, C.F.J. (1997) A Bayesian Variable-Selection Approach for Analyzing Designed Experiments with Complex Aliasing *Technometrics, 39*. pp 372-381.

Grimshaw, S. D.; Collings, B. J.; Larsen, W. A. and Hurt, C. R. (2001) Eliciting Factor Importance in a Designed Experiment. *Technometrics, 43*. pp 133-146.

Hamada, M. and Wu, C.F.J. (1992) Analysis of Designed Experiments with Complex Aliasing. *Journal of Quality Technology, 24*. pp 130-137.

Hedayat, A.S.; Sloane, N.J.A. and Stufken, J. (1999) Orthogonal Arrays: Theory and Applications. *Springer Texts in Statistics*, New York.

Hunter, G.B.; Hodi, F.S. and Eager, T.W. (1982) High-Cycle Fatigue of Weld Repaired Cast Ti-6Al-4V. *Metallurgical Transactions, 13A*. pp 1589-1594.

James, G.; Hastie, T.; Tibshirani, R. and Witten, D. (2013) An Introduction to Statistical Learning with Applications in R. *Springer Texts in Statistics*, New York.

Kraemer, N.; Schaefer, J. and Boulesteix, A.-L. (2009) Regularized Estimation of Large-Scale Gene Regulatory Networks with Gaussian Graphical Models. *BMC Bioinformatics*, 10:384, `http://www.biomedcentral.com/1471-2105/10/384`.

Kraemer, N. and Schaefer, J. (2015) Regularized Estimation of Partial Correlation Matrices. `https://cran.r-project.org/web/packages/parcor/parcor.pdf`.

Li X.; Sudarsanam, N.; and Frey, D. D. (2006) Regularities in Data from Factorial Experiments. *Complexity, 11*. pp 32-45.

Miller, A. and Sitter, R.R. (2001) Using the Folded-Over 12-Run Plackett-Burman Design to Consider Interactions. *Technometrics, 43*. pp 44-55.

Phoa, F. K. H.; Pan, Y. and Xu, H. (2009) Analysis of Supersaturated Designs via the Dantzig Selector. *Journal of Statistical Planning and Inference, 139*. pp 2362-2372.

Plackett, R.L. and Burman, J.P. (1946) The Design of Optimum Multifactorial Experiments. *Biometrika, 33*. pp 305-325.

Tibshirani, R. (1996) Regression Shrinkage and Selection via the Lasso. *Journal of the Royal Statistical Society, Ser. B, 58*. pp 267-288.

Wu, C.F. and Hamada, M. (2009) Experiments: Planning, Analysis, and Optimization, 2nd Edition. *Wiley*, New York.

Xu, H.; Jaynes, J. and Ding, X (2014) Combining Two-Level and Three-Level Orthogonal Arrays for Factor Screening and Response Surface Exploration. *Statistica Sinica, 24*. pp 269-289.

Xu, H.; Phoa, F. K. H. and Wong, W. K (2009) Recent Developments in Nonregular Fractional Factorial Designs. *Statistics Surveys, 3*. pp 269-289.

Yuan, C. G. (1998) The Optimization of Mechanical Properties of Si_3N_4 Ceramics using Experimental Designs. *Unpublished PhD Dissertation; Department of Materials Science and Engineering, University of Michigan.*

Yuan, M.; Joseph, V. R. and Lin, Y. (2007) An Efficient Variable Selection Approach for Analyzing Designed Experiments. *Technometrics, 49*. pp 430-439.

Yuan, M.; Joseph, V. R. and Zou, H. (2009) Structured Variable Selection and Estimation *The Annals of Applied Statistics, 3*. pp 1738-1757.

Zou, H. (2006) The Adaptive Lasso and Its Oracle Properties. *Journal of the American Statistical Association, 101*. pp 1418-1429.

A New Analysis Strategy for Designs with Complex Aliasing

Supplementary Materials

First we give a very brief introduction to three different methods used to compare other techniques in Section 6 of the paper. Then we will produce the simulation results in different tables.

Dantzig selector

The Dantzig selector, originally developed by Candes and Tao (2007), minimizes the sum of the absolute value of the variable coefficients subject to a constraint on the correlation matrix of the explanatory variables and residuals. Precisely, the Dantzig selector coefficients $\hat{\beta}^{DS}$ solves the following problem:

$$\underset{\hat{\beta}}{\text{argmin}} ||\hat{\beta}||_1 \text{ such that } ||X'r||_\infty \leq \delta$$

for a fixed δ, where $r = Y - X\hat{\beta}$. We use the Dantzig selector implemented in the `R` package `flare` to find significant effects for each δ in a grid. The authors propose both a supervised and an automatic procedure for the appropriate δ. We follow the automatic procedure, where the models corresponding to each δ are ranked according to some model selection criterion. We use the author's proposed criterion, $mAIC$, to select the final model:

$$mAIC = \frac{n}{p}\log(RSS/n) + \frac{2p^2}{\sqrt{n}}$$

where p is the total number of regression coefficients, n is the total number of data points, and RSS is the residual sum of squares. In the interest of a fair numerical comparison in our simulations, we impose a further step in the algorithm to ensure the final model obeys effect heredity. We drop all interaction effects that do not have at least one of their parent main effects present in the final model. Because all of our simulated data are based on models with effect heredity, this simple additional step unambiguously improves the performance of the Dantzig selector. However, we show that even with this additional step, the adaptive lasso algorithm outperforms the Dantzig selector in all but the most sparse models.

LARS

Yuan, Joseph and Lin (2007) extend a least angle regression (LARS) algorithm for variable selection to incorporate effect heredity. In regular LARS, the algorithm starts by setting the coefficient of every factor to be zero. Then the algorithm identifies the individual regressor (x_i) with the highest correlation to the response and increases the estimate of its coefficient β_i in the direction of the sign of its correlation with the response, noting the corresponding residual (r). The coefficient stops increasing when another predictor (x_j) is at least as highly correlated with r as x_i is. Next it increases (β_i, β_j) in their joint least squares direction until another predictor is as correlated with the residual, and so on. Yuan et al. (2007) provide algorithms that incorporate both strong and weak heredity into the variable selection method. They suggest that the LARS algorithm yields the most accurate results when supervised, such as when the final model is selected by visually looking at solution paths. However, to compare this method against the others, we employ the BIC to select the final model. We show that, with this form of automatic selection, the LARS algorithm struggles to accurately identify the true model in our simulations.

Nonnegative Garotte

Yuan, Joseph, and Zou (2009) adapted the nonnegative garotte estimator (Breiman 1995) for variable selection under effect heredity. The nonnegative garrote estimate of variable j, $\hat{\beta}_j^{NG}$, is the product of shrinkage factor θ_j and the OLS estimate $\hat{\beta}$. The shrinkage factors are chosen to minimize residual errors subject to a budget constraint M:

$$\underset{\theta}{\operatorname{argmin}} ||Y - Z\theta||^2 \text{ such that } \sum \theta_j < M \text{ and } \theta_j \geq 0$$

where $Z_{ij} = x_{ij}\hat{\beta}_j$. Factors may disappear from the regression model if their shrinkage factor is 0. The authors impose further restrictions on θ to enforce effect heredity. In our simulations, we study the nonnegative garotte algorithm with weak effect heredity. This gives interpretable models, and also does not need the researcher to supervise the selection process as some other algorithms do. We show that it is a strong competitor to the adaptive lasso algorithm for models with several effects, but tends to overestimate the number of effects in models. Thus, it is not as effective for sparser models.

Simulation Results

Tables 1 through 10 describe the simulation results for the five different experiments discussed in Section 6 of the paper. Each table has a column named "Size" which refers to the size of the factorial effects of the corresponding model. For example, "B+S+S" corresponding to the model $A + B + AB$ would represent a situation where the coefficient for A is "big" and the coefficients of B and AB are "small". Recall that for a "big" effect, we drew the coefficient randomly from $U(0.5, 1.5)$, and for a "small" effect, it was drawn from $U(0.1, 0.3)$. As usual, for the two-level experiments, the factor levels were $+1$ and -1. For three-level factors, we used the linear-quadratic system of coding, and all two-factor interactions reported here are linear-by-linear interactions. For a three-level factor, this linear-quadratic system codes the linear effects of the three levels as $(-1, 0, 1)$ and the quadratic effects as $(1, -2, 1)$. Here for notational simplicity we suppress the subscript l and by A, we mean the linear effect of A, which could be denoted by A_l. For the quadratic effect, we explicitly use the subscript q and denote it by A_q. In that same spirit, A_lB_l interaction will simply be denoted by AB. Tables 1 through 5 record the percentage of times each method identifies the correct model for the five different experiments discussed in Section 6 of the paper. Similarly, Tables 6 through 10 record the average number of significant effects in the final models identified by each methods under consideration.

References

Breiman, Leo. (1995) Better Subset Regression Using the Nonnegative Garrote. *Technometrics, 37*. pp 373-384.

Candes, E. and Tao, T. (2007) The Dantzig selector: Statistical estimation when p is much larger than n. *The Annals of Statistics, 35*. pp 2313-2351.

Phoa, F. K. H.; Pan, Y. and Xu, H. (2009) Analysis of Supersaturated Designs via the Dantzig Selector. *Journal of Statistical Planning and Inference, 139*. pp 2362-2372.

Yuan, M.; Joseph, V. R. and Lin, Y. (2007) An Efficient Variable Selection Approach for Analyzing Designed Experiments. *Technometrics, 49*. pp 430-439.

Yuan, M.; Joseph, V. R. and Zou, H. (2009) Structured Variable Selection and Estimation *The Annals of Applied Statistics, 3*. pp 1738-1757.

Table 1: Correctly Identified Models for Cast Fatigue Experiment in Hunter et al. (1982)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
A	B	0.10	100	49	3	0	0	100	0	38
A	B	0.25	91	51	1	0	0	100	0	3
A	B	0.50	65	34	3	0	0	99	0	0
A	B	0.75	60	42	6	1	0	85	0	0
A	B	1	45	39	4	0	0	74	0	0
A	S	0.10	84	44	3	0	0	95	1	2
A	S	0.25	39	38	5	0	0	65	0	1
A	S	0.50	7	11	0	0	0	25	0	0
A	S	0.75	6	9	1	0	0	13	0	0
A	S	1	3	7	0	0	0	10	0	0
$A+B$	B + B	0.10	100	35	100	0	0	85	0	89
$A+B$	B + B	0.25	81	35	100	1	0	85	0	46
$A+B$	B + B	0.50	51	40	98	0	0	71	0	10
$A+B$	B + B	0.75	28	28	82	0	0	39	0	3
$A+B$	B + B	1	19	26	65	1	0	27	0	3
$A+B$	B + S	0.10	71	35	99	0	0	1	0	83
$A+B$	B + S	0.25	31	31	71	0	0	0	0	14
$A+B$	B + S	0.50	6	11	33	0	0	1	0	2
$A+B$	B + S	0.75	3	8	21	1	0	0	0	1
$A+B$	B + S	1	4	2	15	0	0	4	0	0
$A+B$	S + S	0.10	82	21	95	0	0	40	0	14
$A+B$	S + S	0.25	10	15	44	0	0	12	0	0
$A+B$	S + S	0.50	1	3	10	0	0	1	0	0
$A+B$	S + S	0.75	0	0	5	0	0	0	0	0
$A+B$	S + S	1	0	1	4	0	0	0	0	0
$A+AB$	B + B	0.10	100	55	100	4	0	94	0	96
$A+AB$	B + B	0.25	90	57	100	7	0	89	0	56
$A+AB$	B + B	0.50	68	55	98	1	0	70	0	19
$A+AB$	B + B	0.75	48	48	93	1	0	51	0	5
$A+AB$	B + B	1	20	26	75	1	0	34	0	0
$A+AB$	B + S	0.10	81	48	98	1	0	1	0	82
$A+AB$	B + S	0.25	33	30	71	1	0	1	0	19
$A+AB$	B + S	0.50	9	11	27	0	0	0	0	1
$A+AB$	B + S	0.75	4	10	18	0	0	0	0	1
$A+AB$	B + S	1	2	5	11	1	0	1	0	0
$A+AB$	S + S	0.10	74	52	96	2	0	27	1	21
$A+AB$	S + S	0.25	20	17	60	1	0	9	0	3
$A+AB$	S + S	0.50	4	2	15	0	0	1	0	0
$A+AB$	S + S	0.75	1	1	6	0	0	1	0	0
$A+AB$	S + S	1	1	1	7	0	0	0	0	0

Table 1: Correctly Identified Models for Cast Fatigue Experiment in Hunter et al. (1982)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$A+B+AB$	B + B + B	0.10	99	52	0	100	0	6	0	92
$A+B+AB$	B + B + B	0.25	82	28	0	100	0	0	0	64
$A+B+AB$	B + B + B	0.50	38	19	0	97	1	0	0	35
$A+B+AB$	B + B + B	0.75	23	25	0	77	0	0	1	17
$A+B+AB$	B + B + B	1	7	13	0	51	0	0	0	2
$A+B+AB$	B + B + S	0.10	68	32	0	99	0	0	0	13
$A+B+AB$	B + B + S	0.25	30	33	0	72	0	0	0	6
$A+B+AB$	B + B + S	0.50	10	10	0	37	0	0	0	3
$A+B+AB$	B + B + S	0.75	1	5	0	13	0	0	0	0
$A+B+AB$	B + B + S	1	2	5	0	10	0	0	0	1
$A+B+AB$	B + S + B	0.10	56	41	0	98	0	0	0	25
$A+B+AB$	B + S + B	0.25	21	25	0	71	0	0	0	17
$A+B+AB$	B + S + B	0.50	5	10	0	28	0	0	0	5
$A+B+AB$	B + S + B	0.75	3	2	0	19	0	0	0	3
$A+B+AB$	B + S + B	1	3	0	0	7	0	0	0	2
$A+B+AB$	B + S + S	0.10	45	43	0	96	0	0	0	4
$A+B+AB$	B + S + S	0.25	5	12	0	41	0	0	4	2
$A+B+AB$	B + S + S	0.50	0	6	0	14	0	0	0	0
$A+B+AB$	B + S + S	0.75	0	0	0	2	0	0	1	1
$A+B+AB$	B + S + S	1	0	0	0	2	0	0	0	0
$A+B+AB$	S + S + S	0.10	53	33	0	93	1	0	1	31
$A+B+AB$	S + S + S	0.25	5	7	0	32	0	0	1	4
$A+B+AB$	S + S + S	0.50	1	2	0	5	0	0	0	3
$A+B+AB$	S + S + S	0.75	0	0	0	1	0	0	0	1
$A+B+AB$	S + S + S	1	0	0	0	0	0	0	0	0
$A+B+C$	B + B + B	0.10	100	25	0	100	0	51	0	94
$A+B+C$	B + B + B	0.25	81	35	0	100	0	19	0	70
$A+B+C$	B + B + B	0.50	18	14	0	93	0	4	0	14
$A+B+C$	B + B + B	0.75	19	23	0	72	0	2	0	6
$A+B+C$	B + B + B	1	5	15	0	48	0	2	0	3
$A+B+C$	B + B + S	0.10	68	32	0	96	0	0	0	81
$A+B+C$	B + B + S	0.25	31	19	0	67	0	0	0	36
$A+B+C$	B + B + S	0.50	6	5	0	22	0	0	0	11
$A+B+C$	B + B + S	0.75	2	1	0	16	0	0	0	2
$A+B+C$	B + B + S	1	0	2	0	6	0	0	0	1
$A+B+C$	B + S + S	0.10	72	30	0	98	0	0	0	63
$A+B+C$	B + S + S	0.25	12	15	0	42	0	0	0	9
$A+B+C$	B + S + S	0.50	0	6	0	11	0	0	0	0
$A+B+C$	B + S + S	0.75	0	1	0	2	0	0	0	0
$A+B+C$	B + S + S	1	0	0	0	1	0	0	0	0

Table 1: Correctly Identified Models for Cast Fatigue Experiment in Hunter et al. (1982)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$A+B+C$	S + S + S	0.10	68	34	0	96	0	2	0	45
$A+B+C$	S + S + S	0.25	7	7	0	34	0	0	0	5
$A+B+C$	S + S + S	0.50	0	0	0	1	0	0	0	0
$A+B+C$	S + S + S	0.75	0	0	0	0	0	0	0	0
$A+B+C$	S + S + S	1	0	0	0	1	0	0	0	0
$A+B+AC$	B + B + B	0.10	43	28	0	100	0	0	0	42
$A+B+AC$	B + B + B	0.25	23	22	0	100	0	0	0	38
$A+B+AC$	B + B + B	0.50	7	27	0	95	0	0	0	13
$A+B+AC$	B + B + B	0.75	4	16	0	79	0	0	0	5
$A+B+AC$	B + B + B	1	0	7	0	44	0	0	0	0
$A+B+AC$	B + B + S	0.10	29	35	0	99	0	0	0	0
$A+B+AC$	B + B + S	0.25	3	15	0	55	0	0	0	0
$A+B+AC$	B + B + S	0.50	2	7	0	31	0	0	0	0
$A+B+AC$	B + B + S	0.75	1	2	0	11	0	0	0	0
$A+B+AC$	B + B + S	1	0	4	0	8	0	0	0	0
$A+B+AC$	B + S + B	0.10	24	41	0	100	0	0	0	1
$A+B+AC$	B + S + B	0.25	3	29	0	78	0	0	0	0
$A+B+AC$	B + S + B	0.50	2	8	0	28	0	0	0	0
$A+B+AC$	B + S + B	0.75	1	6	0	20	0	0	0	0
$A+B+AC$	B + S + B	1	1	1	0	13	0	0	0	0
$A+B+AC$	B + S + S	0.10	4	34	0	93	0	0	0	0
$A+B+AC$	B + S + S	0.25	0	7	0	35	0	0	0	0
$A+B+AC$	B + S + S	0.50	0	1	0	7	0	0	0	0
$A+B+AC$	B + S + S	0.75	0	0	0	1	0	0	0	0
$A+B+AC$	B + S + S	1	1	1	0	5	0	0	0	1
$A+B+AC$	S + B + S	0.10	4	29	0	97	0	0	0	0
$A+B+AC$	S + B + S	0.25	0	10	0	46	0	0	0	0
$A+B+AC$	S + B + S	0.50	0	1	0	10	0	0	0	0
$A+B+AC$	S + B + S	0.75	0	0	0	6	0	0	0	0
$A+B+AC$	S + B + S	1	0	1	0	4	0	0	0	0
$A+B+AC$	S + S + S	0.10	7	29	0	98	1	0	0	5
$A+B+AC$	S + S + S	0.25	1	1	0	28	0	0	0	0
$A+B+AC$	S + S + S	0.50	0	0	0	1	0	0	0	0
$A+B+AC$	S + S + S	0.75	0	0	0	0	0	0	0	0
$A+B+AC$	S + S + S	1	0	0	0	1	0	0	0	0

Table 2: Correctly Identified Models for Contaminant Experiment in Miller and Sitter (2001)

Model	Size	σ	Lasso	Method 1	Method 2 $h=2$	Method 2 $h=3$	Method 2 $h=4$	Dantzig selector	LARS	Nonneg-Garotte
A	B	0.10	100	24	1	0	0	100	1	6
A	B	0.25	89	22	5	1	1	100	1	3
A	B	0.50	68	22	1	0	0	100	2	0
A	B	0.75	49	20	5	0	0	94	0	1
A	B	1	52	23	4	0	0	89	1	3
A	S	0.10	82	27	6	0	0	100	0	4
A	S	0.25	43	19	4	1	1	80	1	2
A	S	0.50	18	17	5	0	0	31	0	0
A	S	0.75	2	6	1	0	0	12	2	0
A	S	1	4	5	0	0	0	12	0	0
$A+B$	B + B	0.10	100	15	100	1	1	87	0	19
$A+B$	B + B	0.25	87	11	100	1	1	84	0	19
$A+B$	B + B	0.50	60	14	100	1	0	84	0	7
$A+B$	B + B	0.75	56	17	97	0	0	84	0	6
$A+B$	B + B	1	34	19	86	0	0	76	0	6
$A+B$	B + S	0.10	85	19	100	3	1	0	0	21
$A+B$	B + S	0.25	57	11	84	0	0	2	0	8
$A+B$	B + S	0.50	20	8	45	0	0	2	0	1
$A+B$	B + S	0.75	10	2	33	0	0	1	0	0
$A+B$	B + S	1	3	0	16	0	0	5	0	0
$A+B$	S + S	0.10	91	17	100	0	0	38	0	11
$A+B$	S + S	0.25	29	9	71	0	0	22	0	0
$A+B$	S + S	0.50	5	4	17	1	0	6	0	0
$A+B$	S + S	0.75	0	2	7	0	0	4	0	0
$A+B$	S + S	1	0	0	1	0	0	0	0	0
$A+AB$	B + B	0.10	100	28	100	4	1	85	1	21
$A+AB$	B + B	0.25	86	32	100	3	1	86	1	22
$A+AB$	B + B	0.50	70	28	100	1	0	87	0	12
$A+AB$	B + B	0.75	47	26	97	3	0	78	0	8
$A+AB$	B + B	1	45	23	91	4	1	66	2	8
$A+AB$	B + S	0.10	86	24	100	5	0	0	0	39
$A+AB$	B + S	0.25	49	27	87	3	0	1	0	14
$A+AB$	B + S	0.50	10	10	51	0	0	0	0	4
$A+AB$	B + S	0.75	5	5	19	2	0	2	0	1
$A+AB$	B + S	1	1	4	13	0	0	1	0	0
$A+AB$	S + S	0.10	91	21	100	2	0	45	0	33
$A+AB$	S + S	0.25	22	21	82	2	0	26	2	0
$A+AB$	S + S	0.50	9	11	32	2	0	4	0	1
$A+AB$	S + S	0.75	3	1	13	0	0	2	0	0
$A+AB$	S + S	1	2	0	4	1	1	0	1	1

Table 2: Correctly Identified Models for Contaminant Experiment in Miller and Sitter (2001)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$A+B+AB$	B + B + B	0.10	100	14	0	100	0	75	1	22
$A+B+AB$	B + B + B	0.25	94	20	0	100	1	75	0	28
$A+B+AB$	B + B + B	0.50	61	11	0	100	0	68	1	17
$A+B+AB$	B + B + B	0.75	37	11	0	94	0	55	0	12
$A+B+AB$	B + B + B	1	25	13	0	80	0	40	0	15
$A+B+AB$	B + B + S	0.10	87	14	0	100	1	1	1	61
$A+B+AB$	B + B + S	0.25	51	19	0	80	0	0	1	49
$A+B+AB$	B + B + S	0.50	9	4	0	39	0	0	0	8
$A+B+AB$	B + B + S	0.75	2	4	0	13	0	0	0	2
$A+B+AB$	B + B + S	1	3	0	0	12	0	3	0	1
$A+B+AB$	B + S + B	0.10	86	17	0	100	0	0	1	26
$A+B+AB$	B + S + B	0.25	68	11	0	91	0	0	0	22
$A+B+AB$	B + S + B	0.50	17	9	0	48	0	1	3	11
$A+B+AB$	B + S + B	0.75	10	5	0	19	0	0	0	6
$A+B+AB$	B + S + B	1	4	1	0	14	0	2	2	4
$A+B+AB$	B + S + S	0.10	86	17	0	100	0	0	0	67
$A+B+AB$	B + S + S	0.25	37	9	0	72	0	0	3	33
$A+B+AB$	B + S + S	0.50	2	2	0	13	0	0	1	2
$A+B+AB$	B + S + S	0.75	0	2	0	9	0	0	2	1
$A+B+AB$	B + S + S	1	0	0	0	2	0	0	0	1
$A+B+AB$	S + S + S	0.10	90	14	0	100	1	20	0	66
$A+B+AB$	S + S + S	0.25	13	11	0	65	0	8	1	5
$A+B+AB$	S + S + S	0.50	4	0	0	11	0	1	1	1
$A+B+AB$	S + S + S	0.75	0	0	0	1	0	0	0	1
$A+B+AB$	S + S + S	1	0	0	0	1	0	0	0	0
$A+B+C$	B + B + B	0.10	100	10	0	100	0	81	0	37
$A+B+C$	B + B + B	0.25	84	7	0	100	0	65	0	66
$A+B+C$	B + B + B	0.50	47	6	0	100	0	56	0	29
$A+B+C$	B + B + B	0.75	39	15	0	99	1	61	0	15
$A+B+C$	B + B + B	1	24	6	0	79	0	43	0	6
$A+B+C$	B + B + S	0.10	88	8	0	100	0	0	0	48
$A+B+C$	B + B + S	0.25	57	11	0	85	1	0	0	47
$A+B+C$	B + B + S	0.50	14	6	0	38	0	0	0	9
$A+B+C$	B + B + S	0.75	8	3	0	21	0	1	0	5
$A+B+C$	B + B + S	1	4	2	0	12	0	2	0	3
$A+B+C$	B + S + S	0.10	88	12	0	100	0	1	0	52
$A+B+C$	B + S + S	0.25	41	4	0	69	1	0	0	30
$A+B+C$	B + S + S	0.50	3	2	0	14	0	0	0	3
$A+B+C$	B + S + S	0.75	0	1	0	7	0	0	0	0
$A+B+C$	B + S + S	1	0	0	0	3	0	0	0	1

Table 2: Correctly Identified Models for Contaminant Experiment in Miller and Sitter (2001)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$A+B+C$	S + S + S	0.10	84	12	0	100	0	21	0	28
$A+B+C$	S + S + S	0.25	24	7	0	58	0	2	0	8
$A+B+C$	S + S + S	0.50	2	1	0	8	0	2	0	0
$A+B+C$	S + S + S	0.75	0	0	0	3	0	2	0	0
$A+B+C$	S + S + S	1	0	0	0	1	0	0	0	0
$A+B+AC$	B + B + B	0.10	100	13	0	100	0	75	1	21
$A+B+AC$	B + B + B	0.25	92	15	0	100	0	64	1	30
$A+B+AC$	B + B + B	0.50	41	11	0	100	0	68	0	18
$A+B+AC$	B + B + B	0.75	34	19	0	96	0	54	0	16
$A+B+AC$	B + B + B	1	28	16	0	87	0	48	0	15
$A+B+AC$	B + B + S	0.10	79	14	0	100	1	0	0	67
$A+B+AC$	B + B + S	0.25	46	9	0	77	0	1	0	36
$A+B+AC$	B + B + S	0.50	12	5	0	45	0	1	0	9
$A+B+AC$	B + B + S	0.75	2	4	0	9	0	0	2	0
$A+B+AC$	B + B + S	1	2	5	0	8	0	0	0	0
$A+B+AC$	B + S + B	0.10	92	23	0	100	2	0	0	31
$A+B+AC$	B + S + B	0.25	67	15	0	90	0	2	0	28
$A+B+AC$	B + S + B	0.50	15	8	0	47	1	0	0	7
$A+B+AC$	B + S + B	0.75	9	6	0	26	0	2	0	8
$A+B+AC$	B + S + B	1	4	3	0	11	0	2	0	2
$A+B+AC$	B + S + S	0.10	82	15	0	99	0	0	0	60
$A+B+AC$	B + S + S	0.25	44	14	0	73	0	0	0	21
$A+B+AC$	B + S + S	0.50	4	3	0	15	0	0	0	4
$A+B+AC$	B + S + S	0.75	1	0	0	7	0	0	0	1
$A+B+AC$	B + S + S	1	0	0	0	1	0	0	1	0
$A+B+AC$	S + B + S	0.10	82	11	0	100	0	0	0	59
$A+B+AC$	S + B + S	0.25	35	8	0	76	1	0	1	28
$A+B+AC$	S + B + S	0.50	1	2	0	28	0	0	0	4
$A+B+AC$	S + B + S	0.75	0	0	0	8	0	0	0	0
$A+B+AC$	S + B + S	1	1	1	0	5	0	0	0	0
$A+B+AC$	S + S + S	0.10	92	18	0	100	2	18	0	59
$A+B+AC$	S + S + S	0.25	16	14	0	73	0	9	0	9
$A+B+AC$	S + S + S	0.50	0	1	0	13	0	1	0	1
$A+B+AC$	S + S + S	0.75	1	0	0	5	0	0	0	0
$A+B+AC$	S + S + S	1	0	0	0	2	0	0	0	0

Table 3: Correctly Identified Models for Antiviral Drug Experiment in Xu et al. (2014)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
A	B	0.10	100	65	67	64	64	100	78	61
A	B	0.25	91	52	56	45	45	100	69	39
A	B	0.50	81	59	62	54	52	100	72	37
A	B	0.75	78	59	61	51	51	100	69	26
A	B	1	82	68	75	67	67	94	76	17
A	S	0.10	86	65	68	56	54	100	73	44
A	S	0.25	71	61	65	60	60	98	74	46
A	S	0.50	47	50	55	50	48	71	60	34
A	S	0.75	25	35	46	43	43	45	44	6
A	S	1	19	29	40	39	38	31	42	0
$A+B$	B + B	0.10	100	52	100	53	51	89	0	67
$A+B$	B + B	0.25	95	58	100	61	58	91	0	58
$A+B$	B + B	0.50	77	64	100	66	64	84	0	60
$A+B$	B + B	0.75	69	53	100	54	51	83	0	43
$A+B$	B + B	1	55	46	99	47	42	82	0	39
$A+B$	B + S	0.10	97	59	100	62	59	2	0	56
$A+B$	B + S	0.25	67	53	98	56	52	1	0	57
$A+B$	B + S	0.50	45	45	80	46	42	1	0	43
$A+B$	B + S	0.75	20	26	42	25	23	2	0	24
$A+B$	B + S	1	12	17	30	17	17	5	0	12
$A+B$	S + S	0.10	80	59	100	60	58	42	0	52
$A+B$	S + S	0.25	61	59	97	59	57	31	0	53
$A+B$	S + S	0.50	34	37	63	37	35	21	0	31
$A+B$	S + S	0.75	5	9	19	10	10	8	0	7
$A+B$	S + S	1	5	5	8	6	6	8	0	9
$A+AB$	B + B	0.10	100	64	100	64	55	90	27	75
$A+AB$	B + B	0.25	89	61	100	61	52	81	22	62
$A+AB$	B + B	0.50	81	73	100	75	65	89	29	54
$A+AB$	B + B	0.75	78	61	100	63	52	83	31	39
$A+AB$	B + B	1	74	64	99	66	56	80	30	32
$A+AB$	B + S	0.10	94	65	100	66	57	2	0	57
$A+AB$	B + S	0.25	70	69	94	69	64	0	0	56
$A+AB$	B + S	0.50	42	51	65	48	45	0	0	37
$A+AB$	B + S	0.75	15	26	45	27	23	2	0	16
$A+AB$	B + S	1	10	18	20	18	16	3	1	11
$A+AB$	S + S	0.10	75	59	100	60	51	31	30	46
$A+AB$	S + S	0.25	68	60	100	60	53	31	31	38
$A+AB$	S + S	0.50	43	40	56	45	42	18	25	30
$A+AB$	S + S	0.75	8	8	24	15	14	8	17	11
$A+AB$	S + S	1	7	6	11	9	8	9	12	8

Table 3: Correctly Identified Models for Antiviral Drug Experiment in Xu et al. (2014)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h = 2$	$h = 3$	$h = 4$	selector		Garotte
$A + B + AB$	B + B + B	0.10	100	55	0	100	55	79	57	86
$A + B + AB$	B + B + B	0.25	91	54	0	100	54	67	62	75
$A + B + AB$	B + B + B	0.50	61	47	0	100	47	73	55	47
$A + B + AB$	B + B + B	0.75	63	54	0	100	53	62	61	50
$A + B + AB$	B + B + B	1	61	52	0	97	52	63	56	36
$A + B + AB$	B + B + S	0.10	96	52	0	100	53	0	70	73
$A + B + AB$	B + B + S	0.25	53	44	0	96	44	0	55	53
$A + B + AB$	B + B + S	0.50	33	37	0	73	38	0	55	31
$A + B + AB$	B + B + S	0.75	20	30	0	41	30	0	43	27
$A + B + AB$	B + B + S	1	13	19	0	27	19	1	40	14
$A + B + AB$	B + S + B	0.10	100	62	0	100	62	1	44	88
$A + B + AB$	B + S + B	0.25	68	56	0	99	58	0	50	73
$A + B + AB$	B + S + B	0.50	45	45	0	74	46	0	46	44
$A + B + AB$	B + S + B	0.75	21	25	0	39	25	0	35	17
$A + B + AB$	B + S + B	1	20	23	0	35	22	3	39	19
$A + B + AB$	B + S + S	0.10	100	56	0	100	57	0	75	67
$A + B + AB$	B + S + S	0.25	58	56	0	93	57	0	75	55
$A + B + AB$	B + S + S	0.50	20	24	0	49	24	0	63	26
$A + B + AB$	B + S + S	0.75	14	14	0	20	15	0	34	12
$A + B + AB$	B + S + S	1	0	2	0	5	2	0	13	2
$A + B + AB$	S + S + S	0.10	83	62	0	100	62	20	55	56
$A + B + AB$	S + S + S	0.25	64	61	0	94	62	4	65	48
$A + B + AB$	S + S + S	0.50	19	19	0	30	18	1	28	17
$A + B + AB$	S + S + S	0.75	3	7	0	9	5	2	11	6
$A + B + AB$	S + S + S	1	0	0	0	0	0	0	2	3
$A + B + C$	B + B + B	0.10	100	43	0	100	43	72	0	60
$A + B + C$	B + B + B	0.25	91	44	0	100	44	64	0	59
$A + B + C$	B + B + B	0.50	60	46	0	100	47	71	0	50
$A + B + C$	B + B + B	0.75	52	41	0	100	41	74	0	37
$A + B + C$	B + B + B	1	55	50	0	99	50	61	0	42
$A + B + C$	B + B + S	0.10	99	49	0	100	49	0	0	72
$A + B + C$	B + B + S	0.25	70	50	0	97	50	0	0	59
$A + B + C$	B + B + S	0.50	46	49	0	80	49	0	0	45
$A + B + C$	B + B + S	0.75	27	30	0	53	28	0	0	30
$A + B + C$	B + B + S	1	23	25	0	29	25	1	0	24
$A + B + C$	B + S + S	0.10	95	52	0	100	54	0	0	64
$A + B + C$	B + S + S	0.25	55	49	0	95	49	0	0	59
$A + B + C$	B + S + S	0.50	22	24	0	44	24	0	0	23
$A + B + C$	B + S + S	0.75	5	5	0	14	5	0	0	4
$A + B + C$	B + S + S	1	1	2	0	5	1	1	0	1

Table 3: Correctly Identified Models for Antiviral Drug Experiment in Xu et al. (2014)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$A+B+C$	S + S + S	0.10	78	53	0	100	53	21	0	60
$A+B+C$	S + S + S	0.25	49	47	0	93	47	7	0	42
$A+B+C$	S + S + S	0.50	22	22	0	39	22	6	0	20
$A+B+C$	S + S + S	0.75	4	5	0	5	5	2	0	4
$A+B+C$	S + S + S	1	1	2	0	2	2	2	0	2
$A+B+AC$	B + B + B	0.10	100	51	0	100	51	72	26	83
$A+B+AC$	B + B + B	0.25	89	59	0	100	60	64	29	75
$A+B+AC$	B + B + B	0.50	70	54	0	100	55	58	24	57
$A+B+AC$	B + B + B	0.75	63	59	0	100	59	66	28	48
$A+B+AC$	B + B + B	1	65	59	0	100	60	65	23	52
$A+B+AC$	B + B + S	0.10	97	54	0	100	54	0	24	76
$A+B+AC$	B + B + S	0.25	59	58	0	99	58	0	15	49
$A+B+AC$	B + B + S	0.50	41	40	0	72	41	0	21	32
$A+B+AC$	B + B + S	0.75	19	24	0	33	23	0	13	17
$A+B+AC$	B + B + S	1	14	18	0	27	18	0	15	13
$A+B+AC$	B + S + B	0.10	97	58	0	100	59	0	0	82
$A+B+AC$	B + S + B	0.25	62	52	0	99	53	0	0	54
$A+B+AC$	B + S + B	0.50	28	28	0	64	29	0	0	25
$A+B+AC$	B + S + B	0.75	25	26	0	48	23	0	0	17
$A+B+AC$	B + S + B	1	12	16	0	24	13	0	0	12
$A+B+AC$	B + S + S	0.10	96	56	0	100	57	0	0	66
$A+B+AC$	B + S + S	0.25	56	54	0	97	55	0	0	58
$A+B+AC$	B + S + S	0.50	31	36	0	50	36	0	0	31
$A+B+AC$	B + S + S	0.75	5	7	0	10	7	0	0	8
$A+B+AC$	B + S + S	1	4	6	0	7	5	0	0	4
$A+B+AC$	S + B + S	0.10	96	52	0	100	53	0	72	70
$A+B+AC$	S + B + S	0.25	60	53	0	94	56	0	73	56
$A+B+AC$	S + B + S	0.50	26	31	0	55	39	0	57	26
$A+B+AC$	S + B + S	0.75	8	9	0	23	12	0	20	8
$A+B+AC$	S + B + S	1	6	8	0	14	10	0	15	11
$A+B+AC$	S + S + S	0.10	86	59	0	100	60	16	30	67
$A+B+AC$	S + S + S	0.25	50	51	0	94	52	10	26	42
$A+B+AC$	S + S + S	0.50	18	19	0	45	30	2	18	20
$A+B+AC$	S + S + S	0.75	4	8	0	14	10	3	7	7
$A+B+AC$	S + S + S	1	0	1	0	2	1	0	3	2
$A+A_q$	B + B	0.10	100	57	100	59	50	85	73	60
$A+A_q$	B + B	0.25	93	58	100	61	53	83	78	55
$A+A_q$	B + B	0.50	79	70	100	71	63	86	77	52
$A+A_q$	B + B	0.75	77	67	100	68	61	78	81	47
$A+A_q$	B + B	1	68	62	100	63	51	78	72	38

Table 3: Correctly Identified Models for Antiviral Drug Experiment in Xu et al. (2014)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$A+A_q$	B + S	0.10	99	72	100	74	61	8	74	75
$A+A_q$	B + S	0.25	79	70	100	71	62	4	76	63
$A+A_q$	B + S	0.50	57	57	87	58	50	2	64	41
$A+A_q$	B + S	0.75	33	42	57	41	37	5	42	33
$A+A_q$	B + S	1	24	32	35	28	22	7	19	15
$A+A_q$	S + S	0.10	87	63	100	63	58	47	79	57
$A+A_q$	S + S	0.25	70	67	99	69	65	22	80	51
$A+A_q$	S + S	0.50	50	39	76	56	50	16	60	29
$A+A_q$	S + S	0.75	34	15	50	35	34	10	46	14
$A+A_q$	S + S	1	21	7	34	23	21	10	34	6
$A+A_q+B+B_q$	B + B + B + B	0.10	100	68	0	0	100	37	84	91
$A+A_q+B+B_q$	B + B + B + B	0.25	94	64	0	0	100	43	75	85
$A+A_q+B+B_q$	B + B + B + B	0.50	67	55	0	0	100	44	78	83
$A+A_q+B+B_q$	B + B + B + B	0.75	63	61	0	0	100	51	73	70
$A+A_q+B+B_q$	B + B + B + B	1	62	55	0	0	100	38	81	66
$A+A_q+B+B_q$	B + B + B + S	0.10	100	59	0	0	100	0	80	84
$A+A_q+B+B_q$	B + B + B + S	0.25	77	62	0	0	99	0	81	82
$A+A_q+B+B_q$	B + B + B + S	0.50	52	54	0	0	86	1	77	62
$A+A_q+B+B_q$	B + B + B + S	0.75	35	34	0	0	59	1	64	45
$A+A_q+B+B_q$	B + B + B + S	1	21	23	0	0	39	3	56	21
$A+A_q+B+B_q$	B + B + S + S	0.10	100	57	0	0	100	0	78	80
$A+A_q+B+B_q$	B + B + S + S	0.25	63	51	0	0	99	0	79	77
$A+A_q+B+B_q$	B + B + S + S	0.50	32	32	0	0	83	0	71	43
$A+A_q+B+B_q$	B + B + S + S	0.75	16	17	0	0	42	0	44	18
$A+A_q+B+B_q$	B + B + S + S	1	13	11	0	0	35	0	38	13
$A+A_q+B+B_q$	B + S + B + S	0.10	100	59	0	0	100	3	76	96
$A+A_q+B+B_q$	B + S + B + S	0.25	60	44	0	0	99	3	68	90
$A+A_q+B+B_q$	B + S + B + S	0.50	41	42	0	0	74	1	56	46
$A+A_q+B+B_q$	B + S + B + S	0.75	22	24	0	0	34	0	39	26
$A+A_q+B+B_q$	B + S + B + S	1	15	14	0	0	19	1	21	13
$A+A_q+B+B_q$	B + S + S + S	0.10	98	68	0	0	100	0	87	92
$A+A_q+B+B_q$	B + S + S + S	0.25	67	57	0	0	100	0	82	77
$A+A_q+B+B_q$	B + S + S + S	0.50	28	33	0	0	73	0	59	39
$A+A_q+B+B_q$	B + S + S + S	0.75	13	9	0	0	28	0	30	8
$A+A_q+B+B_q$	B + S + S + S	1	4	5	0	0	12	0	11	3
$A+A_q+B+B_q$	S + S + S + S	0.10	81	55	0	0	100	22	72	93
$A+A_q+B+B_q$	S + S + S + S	0.25	55	55	0	0	98	0	76	53
$A+A_q+B+B_q$	S + S + S + S	0.50	23	19	0	0	72	1	60	19
$A+A_q+B+B_q$	S + S + S + S	0.75	14	6	0	0	30	1	30	7
$A+A_q+B+B_q$	S + S + S + S	1	6	2	0	0	11	0	13	2

Table 3: Correctly Identified Models for Antiviral Drug Experiment in Xu et al. (2014)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$A+AB+A_q$	B + B + B	0.10	100	69	0	100	71	72	16	91
$A+AB+A_q$	B + B + B	0.25	99	77	0	100	77	57	11	84
$A+AB+A_q$	B + B + B	0.50	78	69	0	100	69	67	15	64
$A+AB+A_q$	B + B + B	0.75	81	71	0	100	72	66	13	59
$A+AB+A_q$	B + B + B	1	75	72	0	99	72	58	10	54
$A+AB+A_q$	B + B + S	0.10	100	67	0	100	67	1	36	90
$A+AB+A_q$	B + B + S	0.25	78	69	0	100	69	2	37	77
$A+AB+A_q$	B + B + S	0.50	58	62	0	88	61	1	27	47
$A+AB+A_q$	B + B + S	0.75	49	55	0	69	53	1	18	38
$A+AB+A_q$	B + B + S	1	28	41	0	54	37	8	14	23
$A+AB+A_q$	B + S + B	0.10	90	59	0	100	59	0	0	61
$A+AB+A_q$	B + S + B	0.25	74	70	0	99	71	0	0	68
$A+AB+A_q$	B + S + B	0.50	42	45	0	66	46	0	0	38
$A+AB+A_q$	B + S + B	0.75	18	26	0	39	25	0	0	20
$A+AB+A_q$	B + S + B	1	20	25	0	29	24	3	0	14
$A+AB+A_q$	B + S + S	0.10	99	77	0	100	77	0	0	79
$A+AB+A_q$	B + S + S	0.25	73	67	0	98	68	0	0	58
$A+AB+A_q$	B + S + S	0.50	39	42	0	59	41	0	0	32
$A+AB+A_q$	B + S + S	0.75	14	19	0	21	18	1	0	11
$A+AB+A_q$	B + S + S	1	6	9	0	10	8	1	0	7
$A+AB+A_q$	S + S + S	0.10	91	72	0	100	72	12	7	72
$A+AB+A_q$	S + S + S	0.25	72	76	0	98	76	5	14	47
$A+AB+A_q$	S + S + S	0.50	31	24	0	52	35	6	6	24
$A+AB+A_q$	S + S + S	0.75	14	12	0	21	15	1	3	8
$A+AB+A_q$	S + S + S	1	4	1	0	12	7	1	3	4
$A+AB+C+C_q$	B + B + B + B	0.10	100	64	0	0	100	62	62	93
$A+AB+C+C_q$	B + B + B + B	0.25	94	60	0	0	100	49	64	85
$A+AB+C+C_q$	B + B + B + B	0.50	71	56	0	0	100	46	59	66
$A+AB+C+C_q$	B + B + B + B	0.75	54	47	0	0	100	62	63	45
$A+AB+C+C_q$	B + B + B + B	1	63	64	0	0	100	62	58	56
$A+AB+C+C_q$	B + B + B + S	0.10	100	53	0	0	100	0	49	85
$A+AB+C+C_q$	B + B + B + S	0.25	76	61	0	0	100	1	54	75
$A+AB+C+C_q$	B + B + B + S	0.50	51	53	0	0	81	0	46	54
$A+AB+C+C_q$	B + B + B + S	0.75	49	54	0	0	66	0	39	43
$A+AB+C+C_q$	B + B + B + S	1	24	24	0	0	38	0	26	20

Table 3: Correctly Identified Models for Antiviral Drug Experiment in Xu et al. (2014)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h = 2$	$h = 3$	$h = 4$	selector		Garotte
$A + AB + C + C_q$	B + B + S + S	0.10	100	56	0	0	100	0	33	95
$A + AB + C + C_q$	B + B + S + S	0.25	63	52	0	0	100	0	36	71
$A + AB + C + C_q$	B + B + S + S	0.50	38	35	0	0	82	0	23	29
$A + AB + C + C_q$	B + B + S + S	0.75	24	28	0	0	54	0	24	25
$A + AB + C + C_q$	B + B + S + S	1	7	7	0	0	28	1	8	6
$A + AB + C + C_q$	B + S + B + B	0.10	95	67	0	0	100	0	63	80
$A + AB + C + C_q$	B + S + B + B	0.25	63	49	0	0	91	0	53	67
$A + AB + C + C_q$	B + S + B + B	0.50	37	45	0	0	67	0	50	37
$A + AB + C + C_q$	B + S + B + B	0.75	23	25	0	0	38	0	52	22
$A + AB + C + C_q$	B + S + B + B	1	13	15	0	0	23	0	35	14
$A + AB + C + C_q$	B + S + B + S	0.10	99	47	0	0	100	0	34	91
$A + AB + C + C_q$	B + S + B + S	0.25	67	62	0	0	98	0	43	75
$A + AB + C + C_q$	B + S + B + S	0.50	34	39	0	0	58	0	32	37
$A + AB + C + C_q$	B + S + B + S	0.75	11	12	0	0	22	0	20	11
$A + AB + C + C_q$	B + S + B + S	1	9	11	0	0	14	1	12	8
$A + AB + C + C_q$	B + S + S + S	0.10	100	51	0	0	100	1	0	87
$A + AB + C + C_q$	B + S + S + S	0.25	59	57	0	0	98	0	0	68
$A + AB + C + C_q$	B + S + S + S	0.50	20	17	0	0	54	0	0	18
$A + AB + C + C_q$	B + S + S + S	0.75	10	8	0	0	25	0	0	6
$A + AB + C + C_q$	B + S + S + S	1	4	2	0	0	10	0	1	4
$A + AB + C + C_q$	S + S + B + B	0.10	100	52	0	0	100	0	58	76
$A + AB + C + C_q$	S + S + B + B	0.25	68	58	0	0	94	0	80	59
$A + AB + C + C_q$	S + S + B + B	0.50	30	28	0	0	57	0	59	31
$A + AB + C + C_q$	S + S + B + B	0.75	11	14	0	0	29	0	37	16
$A + AB + C + C_q$	S + S + B + B	1	9	7	0	0	15	0	12	10
$A + AB + C + C_q$	S + S + B + S	0.10	100	56	0	0	100	0	80	90
$A + AB + C + C_q$	S + S + B + S	0.25	58	58	0	0	96	0	77	56
$A + AB + C + C_q$	S + S + B + S	0.50	24	25	0	0	46	0	49	24
$A + AB + C + C_q$	S + S + B + S	0.75	15	12	0	0	19	0	22	14
$A + AB + C + C_q$	S + S + B + S	1	1	0	0	0	2	0	4	2
$A + AB + C + C_q$	S + S + S + S	0.10	80	55	0	0	100	13	59	82
$A + AB + C + C_q$	S + S + S + S	0.25	56	59	0	0	96	1	63	56
$A + AB + C + C_q$	S + S + S + S	0.50	26	22	0	0	56	3	40	21
$A + AB + C + C_q$	S + S + S + S	0.75	4	3	0	0	15	0	12	7
$A + AB + C + C_q$	S + S + S + S	1	4	2	0	0	6	1	5	2

Table 4: Correctly Identified Models for Wood Pulp Experiment in Chipman et al. (1997)

Model	Size	σ	Lasso	Method 1	Method 2 $h=2$	Method 2 $h=3$	Method 2 $h=4$	Dantzig selector	LARS	Nonneg-Garotte
A	B	0.10	100	24	6	0	0	100	5	63
A	B	0.25	96	29	3	1	0	100	3	22
A	B	0.50	77	33	6	2	1	100	8	13
A	B	0.75	72	41	6	1	1	92	4	4
A	B	1	45	25	1	1	1	75	1	7
A	S	0.10	94	40	8	2	2	99	4	21
A	S	0.25	36	23	2	0	0	60	4	4
A	S	0.50	9	8	1	1	0	18	0	1
A	S	0.75	4	5	0	0	0	7	0	0
A	S	1	1	3	0	0	0	8	0	0
$A+B$	B + B	0.10	100	22	100	0	0	92	0	66
$A+B$	B + B	0.25	88	15	100	1	0	90	0	37
$A+B$	B + B	0.50	58	22	100	6	2	84	0	15
$A+B$	B + B	0.75	40	26	95	3	1	66	0	6
$A+B$	B + B	1	29	20	65	3	1	47	0	3
$A+B$	B + S	0.10	87	20	100	3	1	2	0	64
$A+B$	B + S	0.25	29	14	70	1	0	0	0	9
$A+B$	B + S	0.50	15	12	40	2	0	5	0	6
$A+B$	B + S	0.75	4	6	19	0	0	0	0	0
$A+B$	B + S	1	2	1	4	0	0	2	0	0
$A+B$	S + S	0.10	83	25	100	2	1	43	0	36
$A+B$	S + S	0.25	11	6	52	1	0	16	0	3
$A+B$	S + S	0.50	1	1	6	0	0	1	0	0
$A+B$	S + S	0.75	0	1	2	0	0	2	0	0
$A+B$	S + S	1	0	0	1	0	0	1	0	0
$A+AB$	B + B	0.10	100	30	100	4	1	91	3	87
$A+AB$	B + B	0.25	93	33	100	5	2	92	5	61
$A+AB$	B + B	0.50	70	34	99	5	0	76	2	30
$A+AB$	B + B	0.75	60	41	97	3	2	56	3	26
$A+AB$	B + B	1	36	25	84	3	1	56	3	16
$A+AB$	B + S	0.10	87	43	99	7	0	1	0	71
$A+AB$	B + S	0.25	44	24	66	2	1	0	0	38
$A+AB$	B + S	0.50	13	16	33	3	1	0	0	11
$A+AB$	B + S	0.75	10	4	13	0	0	4	0	5
$A+AB$	B + S	1	5	4	12	1	0	2	0	2
$A+AB$	S + S	0.10	85	31	100	8	0	38	4	48
$A+AB$	S + S	0.25	32	16	66	3	0	19	2	4
$A+AB$	S + S	0.50	6	8	24	0	0	3	1	1
$A+AB$	S + S	0.75	2	2	9	0	0	2	1	1
$A+AB$	S + S	1	0	0	2	1	0	1	0	0

Table 4: Correctly Identified Models for Wood Pulp Experiment in Chipman et al. (1997)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$A+B+AB$	B + B + B	0.10	100	24	0	100	1	21	3	90
$A+B+AB$	B + B + B	0.25	86	27	0	100	1	18	2	71
$A+B+AB$	B + B + B	0.50	52	22	0	100	1	12	4	40
$A+B+AB$	B + B + B	0.75	33	24	0	81	0	2	3	16
$A+B+AB$	B + B + B	1	15	19	0	63	0	2	3	9
$A+B+AB$	B + B + S	0.10	75	28	0	100	2	0	0	77
$A+B+AB$	B + B + S	0.25	35	27	0	73	5	0	0	37
$A+B+AB$	B + B + S	0.50	10	10	0	29	2	0	0	10
$A+B+AB$	B + B + S	0.75	6	5	0	16	0	0	0	6
$A+B+AB$	B + B + S	1	1	3	0	8	0	0	0	0
$A+B+AB$	B + S + B	0.10	67	25	0	100	1	0	5	71
$A+B+AB$	B + S + B	0.25	23	18	0	78	0	0	0	19
$A+B+AB$	B + S + B	0.50	11	6	0	29	0	0	1	3
$A+B+AB$	B + S + B	0.75	0	4	0	14	0	0	3	3
$A+B+AB$	B + S + B	1	4	0	0	7	0	0	2	0
$A+B+AB$	B + S + S	0.10	68	23	0	99	0	0	0	72
$A+B+AB$	B + S + S	0.25	16	16	0	47	1	0	4	23
$A+B+AB$	B + S + S	0.50	1	2	0	7	0	0	3	0
$A+B+AB$	B + S + S	0.75	0	0	0	2	0	0	1	0
$A+B+AB$	B + S + S	1	0	1	0	2	1	0	1	0
$A+B+AB$	S + S + S	0.10	76	28	0	97	0	1	2	56
$A+B+AB$	S + S + S	0.25	8	9	0	40	1	0	1	6
$A+B+AB$	S + S + S	0.50	1	0	0	6	0	0	0	1
$A+B+AB$	S + S + S	0.75	0	0	0	0	0	0	0	0
$A+B+AB$	S + S + S	1	0	1	0	1	0	0	0	0
$A+B+C$	B + B + B	0.10	44	13	0	100	0	0	0	9
$A+B+C$	B + B + B	0.25	25	16	0	100	2	0	0	8
$A+B+C$	B + B + B	0.50	11	8	0	91	0	0	0	0
$A+B+C$	B + B + B	0.75	11	5	0	61	1	0	0	0
$A+B+C$	B + B + B	1	3	9	0	39	0	0	0	0
$A+B+C$	B + B + S	0.10	31	17	0	97	0	0	0	2
$A+B+C$	B + B + S	0.25	15	8	0	55	1	0	0	0
$A+B+C$	B + B + S	0.50	6	4	0	18	0	0	0	0
$A+B+C$	B + B + S	0.75	1	3	0	5	0	0	0	0
$A+B+C$	B + B + S	1	0	0	0	1	0	0	0	0
$A+B+C$	B + S + S	0.10	7	9	0	91	0	0	0	5
$A+B+C$	B + S + S	0.25	1	5	0	20	0	0	0	0
$A+B+C$	B + S + S	0.50	0	1	0	6	0	0	0	0
$A+B+C$	B + S + S	0.75	0	0	0	0	0	0	0	0
$A+B+C$	B + S + S	1	0	0	0	0	0	0	0	0

Table 4: Correctly Identified Models for Wood Pulp Experiment in Chipman et al. (1997)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h = 2$	$h = 3$	$h = 4$	selector		Garotte
$A+B+C$	S + S + S	0.10	19	15	0	85	2	0	0	4
$A+B+C$	S + S + S	0.25	0	1	0	11	0	0	0	1
$A+B+C$	S + S + S	0.50	0	1	0	1	0	0	0	0
$A+B+C$	S + S + S	0.75	0	0	0	1	0	0	0	0
$A+B+C$	S + S + S	1	0	0	0	0	0	0	0	0
$A+B+AC$	B + B + B	0.10	100	20	0	100	1	0	0	83
$A+B+AC$	B + B + B	0.25	78	17	0	100	2	0	0	76
$A+B+AC$	B + B + B	0.50	33	16	0	94	2	0	0	22
$A+B+AC$	B + B + B	0.75	15	25	0	90	1	0	1	8
$A+B+AC$	B + B + B	1	7	20	0	55	0	0	1	2
$A+B+AC$	B + B + S	0.10	69	26	0	99	1	0	0	6
$A+B+AC$	B + B + S	0.25	23	16	0	68	0	0	0	3
$A+B+AC$	B + B + S	0.50	4	5	0	20	0	0	0	3
$A+B+AC$	B + B + S	0.75	1	2	0	11	0	0	0	1
$A+B+AC$	B + B + S	1	0	1	0	6	0	0	0	0
$A+B+AC$	B + S + B	0.10	61	28	0	100	1	0	0	58
$A+B+AC$	B + S + B	0.25	27	20	0	75	2	0	0	11
$A+B+AC$	B + S + B	0.50	4	9	0	28	1	0	0	1
$A+B+AC$	B + S + B	0.75	0	2	0	17	0	0	0	1
$A+B+AC$	B + S + B	1	1	1	0	9	0	0	0	0
$A+B+AC$	B + S + S	0.10	50	20	0	98	0	0	0	36
$A+B+AC$	B + S + S	0.25	11	12	0	48	1	0	0	8
$A+B+AC$	B + S + S	0.50	0	1	0	5	0	0	0	0
$A+B+AC$	B + S + S	0.75	0	0	0	2	0	0	0	0
$A+B+AC$	B + S + S	1	0	0	0	0	0	0	0	0
$A+B+AC$	S + B + S	0.10	67	23	0	97	3	0	2	7
$A+B+AC$	S + B + S	0.25	15	9	0	55	1	0	1	1
$A+B+AC$	S + B + S	0.50	0	3	0	11	2	0	1	0
$A+B+AC$	S + B + S	0.75	0	0	0	5	0	0	0	0
$A+B+AC$	S + B + S	1	0	0	0	1	0	0	0	0
$A+B+AC$	S + S + S	0.10	62	19	0	97	1	0	0	52
$A+B+AC$	S + S + S	0.25	5	9	0	46	2	0	1	7
$A+B+AC$	S + S + S	0.50	0	1	0	5	0	0	0	0
$A+B+AC$	S + S + S	0.75	0	0	0	1	0	0	0	0
$A+B+AC$	S + S + S	1	0	0	0	1	0	0	0	0
$A+E$	B + B	0.10	100	26	100	2	0	91	0	84
$A+E$	B + B	0.25	86	30	100	4	0	94	0	58
$A+E$	B + B	0.50	67	18	100	0	0	82	0	28
$A+E$	B + B	0.75	51	19	88	3	2	68	0	5
$A+E$	B + B	1	25	20	70	1	0	50	0	2

Table 4: Correctly Identified Models for Wood Pulp Experiment in Chipman et al. (1997)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$A+E$	B + S	0.10	85	28	100	1	0	3	0	59
$A+E$	B + S	0.25	44	25	79	3	1	3	0	9
$A+E$	B + S	0.50	8	7	31	0	0	2	0	3
$A+E$	B + S	0.75	3	2	16	0	0	1	0	0
$A+E$	B + S	1	3	4	13	1	1	3	0	0
$A+E$	S + B	0.10	86	19	99	1	0	3	0	74
$A+E$	S + B	0.25	38	16	71	3	0	2	0	25
$A+E$	S + B	0.50	9	8	33	1	0	1	0	1
$A+E$	S + B	0.75	2	3	17	0	0	0	0	0
$A+E$	S + B	1	0	1	8	0	0	2	0	0
$A+E$	S + S	0.10	87	21	99	2	0	38	0	43
$A+E$	S + S	0.25	22	16	58	2	0	14	0	6
$A+E$	S + S	0.50	2	2	12	0	0	4	0	2
$A+E$	S + S	0.75	1	0	5	0	0	4	0	0
$A+E$	S + S	1	1	0	0	0	0	1	0	0
$A+E+E^2$	B + B + B	0.10	100	24	0	100	0	60	1	96
$A+E+E^2$	B + B + B	0.25	98	24	0	100	0	35	0	77
$A+E+E^2$	B + B + B	0.50	58	24	0	91	2	40	0	29
$A+E+E^2$	B + B + B	0.75	39	16	0	68	0	34	0	8
$A+E+E^2$	B + B + B	1	30	5	0	57	1	18	0	2
$A+E+E^2$	B + B + S	0.10	59	34	0	95	1	1	2	91
$A+E+E^2$	B + B + S	0.25	40	13	0	41	0	0	2	52
$A+E+E^2$	B + B + S	0.50	17	5	0	9	0	2	0	8
$A+E+E^2$	B + B + S	0.75	8	0	0	11	0	7	0	4
$A+E+E^2$	B + B + S	1	6	0	0	3	0	5	0	0
$A+E+E^2$	B + S + S	0.10	64	16	0	94	0	6	6	76
$A+E+E^2$	B + S + S	0.25	24	4	0	48	0	1	5	6
$A+E+E^2$	B + S + S	0.50	4	0	0	13	0	1	4	0
$A+E+E^2$	B + S + S	0.75	1	0	0	5	0	2	1	0
$A+E+E^2$	B + S + S	1	3	0	0	4	0	0	0	0
$A+E+E^2$	S + B + B	0.10	51	25	0	100	3	0	0	83
$A+E+E^2$	S + B + B	0.25	49	19	0	77	1	0	0	43
$A+E+E^2$	S + B + B	0.50	13	6	0	28	1	0	0	6
$A+E+E^2$	S + B + B	0.75	3	2	0	10	0	0	0	2
$A+E+E^2$	S + B + B	1	4	1	0	8	0	0	0	0
$A+E+E^2$	S + B + S	0.10	53	19	0	92	0	0	0	82
$A+E+E^2$	S + B + S	0.25	25	7	0	27	0	0	0	20
$A+E+E^2$	S + B + S	0.50	3	1	0	3	0	0	0	3
$A+E+E^2$	S + B + S	0.75	0	0	0	1	0	0	0	0
$A+E+E^2$	S + B + S	1	1	0	0	1	0	0	0	0

Table 4: Correctly Identified Models for Wood Pulp Experiment in Chipman et al. (1997)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$A+E+E^2$	S + S + S	0.10	91	21	0	95	0	18	0	73
$A+E+E^2$	S + S + S	0.25	20	5	0	36	0	3	0	7
$A+E+E^2$	S + S + S	0.50	2	0	0	5	0	0	0	0
$A+E+E^2$	S + S + S	0.75	1	0	0	1	0	0	0	0
$A+E+E^2$	S + S + S	1	1	0	0	0	0	0	0	0
$A+E+EI$	B + B + B	0.10	100	23	0	100	2	0	1	92
$A+E+EI$	B + B + B	0.25	95	19	0	100	0	0	0	83
$A+E+EI$	B + B + B	0.50	59	26	0	99	1	0	0	45
$A+E+EI$	B + B + B	0.75	27	20	0	88	2	0	1	18
$A+E+EI$	B + B + B	1	8	12	0	67	1	0	0	3
$A+E+EI$	B + B + S	0.10	86	23	0	99	2	0	0	47
$A+E+EI$	B + B + S	0.25	32	23	0	87	3	0	0	13
$A+E+EI$	B + B + S	0.50	5	10	0	38	0	0	0	5
$A+E+EI$	B + B + S	0.75	0	7	0	16	2	0	0	0
$A+E+EI$	B + B + S	1	1	2	0	8	0	0	0	0
$A+E+EI$	B + S + S	0.10	62	17	0	100	1	0	1	74
$A+E+EI$	B + S + S	0.25	11	7	0	53	0	0	0	8
$A+E+EI$	B + S + S	0.50	1	0	0	8	0	0	0	0
$A+E+EI$	B + S + S	0.75	0	1	0	11	0	0	0	0
$A+E+EI$	B + S + S	1	0	0	0	4	0	0	0	0
$A+E+EI$	S + B + B	0.10	74	23	0	99	1	0	0	34
$A+E+EI$	S + B + B	0.25	44	16	0	71	1	0	0	13
$A+E+EI$	S + B + B	0.50	12	5	0	37	0	0	0	6
$A+E+EI$	S + B + B	0.75	3	3	0	20	0	0	0	0
$A+E+EI$	S + B + B	1	0	1	0	12	0	0	0	0
$A+E+EI$	S + B + S	0.10	77	21	0	100	0	0	0	31
$A+E+EI$	S + B + S	0.25	17	14	0	55	0	0	0	7
$A+E+EI$	S + B + S	0.50	2	2	0	9	0	0	0	2
$A+E+EI$	S + B + S	0.75	0	1	0	4	0	0	0	0
$A+E+EI$	S + B + S	1	0	0	0	1	0	0	0	0
$A+E+EI$	S + S + S	0.10	78	18	0	99	1	0	0	55
$A+E+EI$	S + S + S	0.25	4	7	0	45	2	0	0	7
$A+E+EI$	S + S + S	0.50	0	1	0	7	1	0	0	1
$A+E+EI$	S + S + S	0.75	0	0	0	0	0	0	0	0
$A+E+EI$	S + S + S	1	0	0	0	0	0	0	0	0

Table 4: Correctly Identified Models for Wood Pulp Experiment in Chipman et al. (1997)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$A+E+AE$	B + B + B	0.10	100	27	0	100	2	67	3	79
$A+E+AE$	B + B + B	0.25	93	20	0	100	3	66	1	67
$A+E+AE$	B + B + B	0.50	57	20	0	98	0	43	3	35
$A+E+AE$	B + B + B	0.75	28	17	0	81	1	34	2	13
$A+E+AE$	B + B + B	1	23	14	0	66	2	19	6	5
$A+E+AE$	B + B + S	0.10	75	26	0	100	2	1	4	74
$A+E+AE$	B + B + S	0.25	41	23	0	72	1	0	0	30
$A+E+AE$	B + B + S	0.50	18	11	0	29	0	1	1	11
$A+E+AE$	B + B + S	0.75	8	6	0	20	0	0	0	6
$A+E+AE$	B + B + S	1	2	1	0	2	0	0	0	0
$A+E+AE$	B + S + S	0.10	69	21	0	98	1	0	7	54
$A+E+AE$	B + S + S	0.25	21	10	0	52	2	0	4	6
$A+E+AE$	B + S + S	0.50	2	3	0	13	1	0	3	0
$A+E+AE$	B + S + S	0.75	0	2	0	9	0	0	0	1
$A+E+AE$	B + S + S	1	0	0	0	2	1	0	1	0
$A+E+AE$	B + S + B	0.10	68	24	0	99	1	0	5	79
$A+E+AE$	B + S + B	0.25	40	14	0	75	2	0	4	28
$A+E+AE$	B + S + B	0.50	7	2	0	26	0	0	6	2
$A+E+AE$	B + S + B	0.75	7	2	0	16	0	1	5	2
$A+E+AE$	B + S + B	1	4	2	0	6	0	0	5	1
$A+E+AE$	S + B + B	0.10	75	19	0	99	0	5	3	45
$A+E+AE$	S + B + B	0.25	52	19	0	73	1	1	1	18
$A+E+AE$	S + B + B	0.50	21	11	0	32	0	1	1	4
$A+E+AE$	S + B + B	0.75	14	5	0	14	0	3	2	1
$A+E+AE$	S + B + B	1	5	3	0	12	1	0	1	0
$A+E+AE$	S + B + S	0.10	76	26	0	99	5	4	6	87
$A+E+AE$	S + B + S	0.25	41	16	0	56	0	0	3	39
$A+E+AE$	S + B + S	0.50	4	3	0	9	0	0	3	2
$A+E+AE$	S + B + S	0.75	1	1	0	2	0	1	0	1
$A+E+AE$	S + B + S	1	0	0	0	1	0	0	0	0
$A+E+AE$	S + S + S	0.10	85	21	0	100	3	20	3	62
$A+E+AE$	S + S + S	0.25	15	9	0	42	0	3	2	10
$A+E+AE$	S + S + S	0.50	1	0	0	3	0	0	2	1
$A+E+AE$	S + S + S	0.75	0	0	0	0	0	0	0	0
$A+E+AE$	S + S + S	1	0	0	0	0	0	0	0	0

Table 5: Correctly Identified Models for Ceramics Experiment in Yuan (1998)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
A	B	0.10	100	58	62	57	57	100	85	58
A	B	0.25	96	51	60	51	51	100	74	51
A	B	0.50	81	53	57	44	43	100	66	19
A	B	0.75	81	53	60	55	54	100	84	17
A	B	1	77	49	59	53	50	97	75	16
A	S	0.10	86	59	62	52	52	100	68	38
A	S	0.25	80	53	60	53	53	98	75	39
A	S	0.50	49	46	49	44	43	74	63	15
A	S	0.75	34	36	46	41	41	48	53	8
A	S	1	13	19	33	32	31	27	32	10
B	B	0.10	100	47	52	47	47	100	73	44
B	B	0.25	97	65	67	60	60	100	78	55
B	B	0.50	82	59	63	60	59	100	82	27
B	B	0.75	76	58	62	55	55	100	77	8
B	B	1	70	45	50	43	42	96	71	6
B	S	0.10	85	49	51	49	49	100	79	42
B	S	0.25	66	54	60	54	54	94	72	28
B	S	0.50	38	35	44	42	42	60	56	5
B	S	0.75	17	24	35	33	33	33	41	4
B	S	1	10	10	20	17	16	16	22	3
$A+B$	B + B	0.10	100	48	100	58	51	90	0	73
$A+B$	B + B	0.25	93	47	100	50	48	81	0	52
$A+B$	B + B	0.50	81	45	100	47	44	82	0	45
$A+B$	B + B	0.75	80	59	100	65	55	82	0	36
$A+B$	B + B	1	63	41	98	45	41	72	0	24
$A+B$	B + S	0.10	88	44	100	51	46	0	0	62
$A+B$	B + S	0.25	56	42	98	47	46	0	0	45
$A+B$	B + S	0.50	36	31	73	35	34	0	0	27
$A+B$	B + S	0.75	20	19	38	27	22	0	0	12
$A+B$	B + S	1	8	5	18	7	7	2	0	5
$A+B$	S + S	0.10	82	45	100	53	51	33	0	56
$A+B$	S + S	0.25	59	45	98	48	44	26	0	37
$A+B$	S + S	0.50	18	19	50	18	18	12	0	10
$A+B$	S + S	0.75	11	18	25	15	14	11	0	6
$A+B$	S + S	1	4	8	14	7	7	10	0	3
$A+AB$	B + B	0.10	100	59	100	69	61	84	26	78
$A+AB$	B + B	0.25	96	64	100	66	59	83	24	55
$A+AB$	B + B	0.50	82	56	100	61	51	78	23	49
$A+AB$	B + B	0.75	72	65	100	68	58	83	24	46
$A+AB$	B + B	1	63	50	99	57	49	81	19	26

Table 5: Correctly Identified Models for Ceramics Experiment in Yuan (1998)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$A+AB$	B + S	0.10	91	53	100	58	49	0	0	57
$A+AB$	B + S	0.25	60	51	95	57	51	0	0	44
$A+AB$	B + S	0.50	41	42	71	45	38	0	0	32
$A+AB$	B + S	0.75	17	24	38	24	21	0	0	22
$A+AB$	B + S	1	6	17	23	16	14	3	0	11
$A+AB$	S + S	0.10	88	64	100	69	57	40	23	53
$A+AB$	S + S	0.25	64	54	99	59	53	31	20	46
$A+AB$	S + S	0.50	35	36	67	39	32	13	27	25
$A+AB$	S + S	0.75	14	12	25	14	14	4	13	6
$A+AB$	S + S	1	7	6	12	10	8	6	17	2
$B+AB$	B + B	0.10	100	48	100	56	51	86	0	67
$B+AB$	B + B	0.25	94	51	100	53	48	94	0	50
$B+AB$	B + B	0.50	80	54	100	57	48	90	1	42
$B+AB$	B + B	0.75	75	58	100	63	57	92	4	35
$B+AB$	B + B	1	75	58	100	64	61	78	4	24
$B+AB$	B + S	0.10	96	60	100	62	56	1	0	66
$B+AB$	B + S	0.25	66	55	97	58	51	0	0	54
$B+AB$	B + S	0.50	45	47	67	44	39	0	0	31
$B+AB$	B + S	0.75	25	29	38	26	23	2	0	20
$B+AB$	B + S	1	5	14	20	10	7	7	0	7
$B+AB$	S + S	0.10	83	58	100	61	59	35	1	55
$B+AB$	S + S	0.25	74	61	99	63	53	34	8	47
$B+AB$	S + S	0.50	33	26	55	39	34	17	8	22
$B+AB$	S + S	0.75	16	11	30	24	24	6	9	4
$B+AB$	S + S	1	12	7	22	15	13	6	5	1
$A+B+AB$	B + B + B	0.10	100	44	0	100	49	77	60	95
$A+B+AB$	B + B + B	0.25	98	58	0	100	60	65	67	71
$A+B+AB$	B + B + B	0.50	77	46	0	100	50	69	67	52
$A+B+AB$	B + B + B	0.75	75	53	0	100	58	54	64	49
$A+B+AB$	B + B + B	1	64	46	0	98	50	63	62	39
$A+B+AB$	B + B + S	0.10	98	54	0	100	57	0	87	83
$A+B+AB$	B + B + S	0.25	74	43	0	99	49	0	84	57
$A+B+AB$	B + B + S	0.50	35	27	0	67	32	0	71	35
$A+B+AB$	B + B + S	0.75	26	28	0	40	27	1	64	24
$A+B+AB$	B + B + S	1	21	14	0	27	15	2	46	13
$A+B+AB$	B + S + B	0.10	95	45	0	100	51	0	56	79
$A+B+AB$	B + S + B	0.25	77	57	0	100	57	0	53	70
$A+B+AB$	B + S + B	0.50	42	37	0	69	39	0	60	38
$A+B+AB$	B + S + B	0.75	23	25	0	41	21	0	53	19
$A+B+AB$	B + S + B	1	12	17	0	31	16	3	65	14

Table 5: Correctly Identified Models for Ceramics Experiment in Yuan (1998)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h = 2$	$h = 3$	$h = 4$	selector		Garotte
$A + B + AB$	B + S + S	0.10	100	52	0	100	54	0	78	79
$A + B + AB$	B + S + S	0.25	65	46	0	97	52	0	87	57
$A + B + AB$	B + S + S	0.50	26	21	0	44	22	0	64	17
$A + B + AB$	B + S + S	0.75	4	7	0	14	8	0	34	7
$A + B + AB$	B + S + S	1	8	8	0	8	6	0	22	7
$A + B + AB$	S + B + B	0.10	100	47	0	100	52	1	64	81
$A + B + AB$	S + B + B	0.25	74	52	0	99	58	1	60	65
$A + B + AB$	S + B + B	0.50	48	44	0	74	43	0	55	34
$A + B + AB$	S + B + B	0.75	34	26	0	54	29	1	61	25
$A + B + AB$	S + B + B	1	18	17	0	33	16	0	58	18
$A + B + AB$	S + B + S	0.10	100	51	0	100	53	1	88	72
$A + B + AB$	S + B + S	0.25	68	58	0	95	61	0	83	59
$A + B + AB$	S + B + S	0.50	27	25	0	52	24	0	59	23
$A + B + AB$	S + B + S	0.75	17	25	0	35	25	0	47	21
$A + B + AB$	S + B + S	1	5	6	0	10	6	1	17	5
$A + B + AB$	S + S + S	0.10	83	53	0	100	56	18	63	61
$A + B + AB$	S + S + S	0.25	64	56	0	92	57	5	62	55
$A + B + AB$	S + S + S	0.50	20	21	0	37	22	2	41	17
$A + B + AB$	S + S + S	0.75	9	8	0	13	9	3	16	9
$A + B + AB$	S + S + S	1	2	2	0	3	2	1	0	2
$A + B + C$	B + B + B	0.10	100	45	0	100	49	64	0	84
$A + B + C$	B + B + B	0.25	93	50	0	100	53	63	0	60
$A + B + C$	B + B + B	0.50	71	38	0	100	42	67	0	52
$A + B + C$	B + B + B	0.75	60	43	0	100	43	61	0	43
$A + B + C$	B + B + B	1	66	47	0	97	52	60	0	53
$A + B + C$	B + B + S	0.10	96	39	0	100	43	0	0	84
$A + B + C$	B + B + S	0.25	61	37	0	92	40	0	0	52
$A + B + C$	B + B + S	0.50	34	34	0	71	34	0	0	35
$A + B + C$	B + B + S	0.75	17	15	0	35	17	0	0	17
$A + B + C$	B + B + S	1	11	12	0	24	13	0	0	13
$A + B + C$	B + S + S	0.10	95	53	0	100	54	0	0	74
$A + B + C$	B + S + S	0.25	58	39	0	90	41	0	0	42
$A + B + C$	B + S + S	0.50	23	23	0	42	23	0	0	19
$A + B + C$	B + S + S	0.75	7	9	0	14	9	0	0	8
$A + B + C$	B + S + S	1	3	1	0	5	1	0	0	1
$A + B + C$	S + S + S	0.10	79	40	0	100	44	22	0	56
$A + B + C$	S + S + S	0.25	45	37	0	90	35	7	0	37
$A + B + C$	S + S + S	0.50	19	19	0	30	18	1	0	15
$A + B + C$	S + S + S	0.75	3	3	0	3	2	1	0	4
$A + B + C$	S + S + S	1	0	0	0	1	0	0	0	0

Table 5: Correctly Identified Models for Ceramics Experiment in Yuan (1998)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$A+B+AC$	B + B + B	0.10	100	52	0	100	55	70	16	78
$A+B+AC$	B + B + B	0.25	93	43	0	100	45	67	16	67
$A+B+AC$	B + B + B	0.50	76	51	0	100	52	62	17	60
$A+B+AC$	B + B + B	0.75	73	48	0	100	52	67	21	60
$A+B+AC$	B + B + B	1	71	54	0	97	58	49	19	51
$A+B+AC$	B + B + S	0.10	96	49	0	100	53	0	28	81
$A+B+AC$	B + B + S	0.25	56	31	0	92	35	0	21	57
$A+B+AC$	B + B + S	0.50	28	24	0	60	27	0	20	35
$A+B+AC$	B + B + S	0.75	16	21	0	32	15	1	15	19
$A+B+AC$	B + B + S	1	9	13	0	16	13	0	14	11
$A+B+AC$	B + S + B	0.10	93	34	0	100	40	0	0	83
$A+B+AC$	B + S + B	0.25	72	57	0	100	59	0	0	73
$A+B+AC$	B + S + B	0.50	38	39	0	70	39	0	0	43
$A+B+AC$	B + S + B	0.75	18	15	0	34	16	0	0	15
$A+B+AC$	B + S + B	1	16	14	0	27	13	2	0	12
$A+B+AC$	B + S + S	0.10	96	54	0	100	57	0	0	80
$A+B+AC$	B + S + S	0.25	69	45	0	96	49	0	0	60
$A+B+AC$	B + S + S	0.50	23	30	0	49	31	0	0	25
$A+B+AC$	B + S + S	0.75	6	7	0	11	5	0	0	6
$A+B+AC$	B + S + S	1	2	3	0	7	5	0	0	2
$A+B+AC$	S + B + S	0.10	98	38	0	100	43	0	81	79
$A+B+AC$	S + B + S	0.25	61	46	0	97	49	0	83	61
$A+B+AC$	S + B + S	0.50	32	32	0	62	35	0	64	35
$A+B+AC$	S + B + S	0.75	6	10	0	22	14	0	29	8
$A+B+AC$	S + B + S	1	3	5	0	16	8	1	15	5
$A+B+AC$	S + S + S	0.10	81	46	0	100	52	15	21	75
$A+B+AC$	S + S + S	0.25	56	46	0	94	48	7	27	44
$A+B+AC$	S + S + S	0.50	21	25	0	39	25	0	13	14
$A+B+AC$	S + S + S	0.75	9	11	0	10	10	0	4	8
$A+B+AC$	S + S + S	1	0	1	0	2	1	0	2	2
$B+B_q$	B + B	0.10	100	52	100	55	49	66	83	85
$B+B_q$	B + B	0.25	97	60	100	62	57	70	83	74
$B+B_q$	B + B	0.50	87	52	100	60	54	59	89	60
$B+B_q$	B + B	0.75	79	57	100	62	57	60	87	44
$B+B_q$	B + B	1	71	58	100	61	49	56	80	26

Table 5: Correctly Identified Models for Ceramics Experiment in Yuan (1998)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$B+B_q$	B + S	0.10	100	45	100	46	42	27	93	61
$B+B_q$	B + S	0.25	79	55	100	58	53	7	84	55
$B+B_q$	B + S	0.50	69	62	94	64	59	3	76	49
$B+B_q$	B + S	0.75	47	45	80	47	42	5	37	27
$B+B_q$	B + S	1	20	35	50	28	27	11	15	8
$B+B_q$	S + S	0.10	90	57	100	61	55	32	83	67
$B+B_q$	S + S	0.25	71	47	100	51	46	4	80	37
$B+B_q$	S + S	0.50	62	51	87	61	55	9	78	29
$B+B_q$	S + S	0.75	35	19	63	39	35	2	47	5
$B+B_q$	S + S	1	29	10	40	28	26	6	38	5
$B+B_q+C+C_q$	B + B + B + B	0.10	100	40	0	0	100	0	83	100
$B+B_q+C+C_q$	B + B + B + B	0.25	93	50	0	0	100	0	65	96
$B+B_q+C+C_q$	B + B + B + B	0.50	83	45	0	0	100	0	66	88
$B+B_q+C+C_q$	B + B + B + B	0.75	70	42	0	0	100	0	66	74
$B+B_q+C+C_q$	B + B + B + B	1	58	40	0	0	100	0	63	72
$B+B_q+C+C_q$	B + B + B + S	0.10	100	42	0	0	100	0	18	96
$B+B_q+C+C_q$	B + B + B + S	0.25	85	51	0	0	100	0	8	88
$B+B_q+C+C_q$	B + B + B + S	0.50	57	49	0	0	93	0	12	66
$B+B_q+C+C_q$	B + B + B + S	0.75	36	44	0	0	75	0	4	50
$B+B_q+C+C_q$	B + B + B + S	1	14	31	0	0	51	0	2	27
$B+B_q+C+C_q$	B + B + S + S	0.10	100	52	0	0	100	0	72	98
$B+B_q+C+C_q$	B + B + S + S	0.25	75	51	0	0	100	0	51	85
$B+B_q+C+C_q$	B + B + S + S	0.50	41	34	0	0	87	0	29	49
$B+B_q+C+C_q$	B + B + S + S	0.75	11	14	0	0	61	0	15	21
$B+B_q+C+C_q$	B + B + S + S	1	5	7	0	0	32	0	10	5
$B+B_q+C+C_q$	B + S + B + S	0.10	98	40	0	0	100	0	24	95
$B+B_q+C+C_q$	B + S + B + S	0.25	67	51	0	0	100	0	22	75
$B+B_q+C+C_q$	B + S + B + S	0.50	36	41	0	0	84	0	16	50
$B+B_q+C+C_q$	B + S + B + S	0.75	18	40	0	0	52	0	3	31
$B+B_q+C+C_q$	B + S + B + S	1	1	11	0	0	18	0	3	6
$B+B_q+C+C_q$	B + S + S + S	0.10	99	47	0	0	100	0	5	95
$B+B_q+C+C_q$	B + S + S + S	0.25	64	56	0	0	100	0	8	76
$B+B_q+C+C_q$	B + S + S + S	0.50	22	32	0	0	77	0	1	34
$B+B_q+C+C_q$	B + S + S + S	0.75	7	16	0	0	46	0	3	12
$B+B_q+C+C_q$	B + S + S + S	1	6	7	0	0	27	0	4	7
$B+B_q+C+C_q$	S + S + S + S	0.10	90	40	0	0	100	0	72	95
$B+B_q+C+C_q$	S + S + S + S	0.25	40	27	0	0	99	0	60	59
$B+B_q+C+C_q$	S + S + S + S	0.50	23	13	0	0	73	0	24	22
$B+B_q+C+C_q$	S + S + S + S	0.75	5	3	0	0	25	0	15	4
$B+B_q+C+C_q$	S + S + S + S	1	5	3	0	0	10	0	7	2

Table 5: Correctly Identified Models for Ceramics Experiment in Yuan (1998)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$B+BC+B_q$	B + B + B	0.10	100	59	0	100	62	37	6	96
$B+BC+B_q$	B + B + B	0.25	93	60	0	100	64	30	3	90
$B+BC+B_q$	B + B + B	0.50	82	62	0	100	65	35	4	75
$B+BC+B_q$	B + B + B	0.75	75	53	0	100	58	29	3	70
$B+BC+B_q$	B + B + B	1	59	57	0	94	64	29	0	53
$B+BC+B_q$	B + B + S	0.10	100	56	0	100	56	8	32	85
$B+BC+B_q$	B + B + S	0.25	87	63	0	100	69	9	22	84
$B+BC+B_q$	B + B + S	0.50	58	59	0	99	61	1	11	63
$B+BC+B_q$	B + B + S	0.75	34	43	0	75	41	6	5	44
$B+BC+B_q$	B + B + S	1	32	43	0	65	40	10	6	33
$B+BC+B_q$	B + S + B	0.10	75	64	0	100	66	0	0	82
$B+BC+B_q$	B + S + B	0.25	59	59	0	86	59	0	0	69
$B+BC+B_q$	B + S + B	0.50	30	33	0	46	35	0	0	38
$B+BC+B_q$	B + S + B	0.75	10	17	0	23	17	0	0	14
$B+BC+B_q$	B + S + B	1	5	16	0	18	10	0	0	13
$B+BC+B_q$	B + S + S	0.10	98	56	0	100	58	0	0	83
$B+BC+B_q$	B + S + S	0.25	58	52	0	89	52	0	0	58
$B+BC+B_q$	B + S + S	0.50	22	30	0	39	21	0	0	25
$B+BC+B_q$	B + S + S	0.75	7	12	0	14	9	0	0	8
$B+BC+B_q$	B + S + S	1	4	8	0	9	6	0	0	11
$B+BC+B_q$	S + S + S	0.10	82	58	0	100	62	7	0	86
$B+BC+B_q$	S + S + S	0.25	51	61	0	91	58	2	1	59
$B+BC+B_q$	S + S + S	0.50	27	30	0	53	35	1	2	29
$B+BC+B_q$	S + S + S	0.75	3	3	0	9	6	0	1	3
$B+BC+B_q$	S + S + S	1	3	1	0	7	5	1	1	2
$B+BC+D+D_q$	B + B + B + B	0.10	100	52	0	0	100	5	68	94
$B+BC+D+D_q$	B + B + B + B	0.25	97	55	0	0	100	3	62	95
$B+BC+D+D_q$	B + B + B + B	0.50	83	57	0	0	100	3	74	84
$B+BC+D+D_q$	B + B + B + B	0.75	63	45	0	0	98	3	66	71
$B+BC+D+D_q$	B + B + B + B	1	55	49	0	0	90	14	59	62
$B+BC+D+D_q$	B + B + B + S	0.10	100	53	0	0	100	7	48	95
$B+BC+D+D_q$	B + B + B + S	0.25	78	48	0	0	100	0	50	83
$B+BC+D+D_q$	B + B + B + S	0.50	55	47	0	0	83	3	45	57
$B+BC+D+D_q$	B + B + B + S	0.75	38	39	0	0	62	6	31	47
$B+BC+D+D_q$	B + B + B + S	1	29	28	0	0	47	5	25	25

Table 5: Correctly Identified Models for Ceramics Experiment in Yuan (1998)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h = 2$	$h = 3$	$h = 4$	selector		Garotte
$B + BC + D + D_q$	B + B + S + S	0.10	99	57	0	0	100	0	39	94
$B + BC + D + D_q$	B + B + S + S	0.25	71	54	0	0	100	0	40	89
$B + BC + D + D_q$	B + B + S + S	0.50	32	38	0	0	80	0	35	42
$B + BC + D + D_q$	B + B + S + S	0.75	15	12	0	0	52	0	23	15
$B + BC + D + D_q$	B + B + S + S	1	14	11	0	0	34	0	15	9
$B + BC + D + D_q$	B + S + B + B	0.10	75	47	0	0	100	0	0	20
$B + BC + D + D_q$	B + S + B + B	0.25	54	40	0	0	80	0	0	26
$B + BC + D + D_q$	B + S + B + B	0.50	23	20	0	0	32	0	2	13
$B + BC + D + D_q$	B + S + B + B	0.75	10	9	0	0	15	1	4	7
$B + BC + D + D_q$	B + S + B + B	1	8	6	0	0	9	0	4	6
$B + BC + D + D_q$	B + S + B + S	0.10	97	50	0	0	100	1	9	91
$B + BC + D + D_q$	B + S + B + S	0.25	61	52	0	0	82	0	7	73
$B + BC + D + D_q$	B + S + B + S	0.50	21	19	0	0	24	0	1	24
$B + BC + D + D_q$	B + S + B + S	0.75	12	11	0	0	14	0	5	13
$B + BC + D + D_q$	B + S + B + S	1	4	5	0	0	5	0	2	6
$B + BC + D + D_q$	B + S + S + S	0.10	99	46	0	0	100	0	0	91
$B + BC + D + D_q$	B + S + S + S	0.25	58	49	0	0	86	0	0	72
$B + BC + D + D_q$	B + S + S + S	0.50	19	21	0	0	34	0	0	16
$B + BC + D + D_q$	B + S + S + S	0.75	4	5	0	0	10	0	0	6
$B + BC + D + D_q$	B + S + S + S	1	2	1	0	0	2	0	0	1
$B + BC + D + D_q$	S + S + B + B	0.10	92	47	0	0	100	0	71	31
$B + BC + D + D_q$	S + S + B + B	0.25	52	34	0	0	79	0	58	17
$B + BC + D + D_q$	S + S + B + B	0.50	14	16	0	0	28	0	33	8
$B + BC + D + D_q$	S + S + B + B	0.75	3	4	0	0	8	0	20	3
$B + BC + D + D_q$	S + S + B + B	1	0	0	0	0	3	0	5	1
$B + BC + D + D_q$	S + S + B + S	0.10	96	54	0	0	100	0	65	94
$B + BC + D + D_q$	S + S + B + S	0.25	55	41	0	0	80	0	60	67
$B + BC + D + D_q$	S + S + B + S	0.50	13	14	0	0	23	0	26	15
$B + BC + D + D_q$	S + S + B + S	0.75	5	4	0	0	9	0	13	7
$B + BC + D + D_q$	S + S + B + S	1	4	0	0	0	4	0	4	2
$B + BC + D + D_q$	S + S + S + S	0.10	83	52	0	0	100	0	62	89
$B + BC + D + D_q$	S + S + S + S	0.25	49	42	0	0	79	0	48	58
$B + BC + D + D_q$	S + S + S + S	0.50	8	5	0	0	22	0	32	9
$B + BC + D + D_q$	S + S + S + S	0.75	2	1	0	0	2	0	7	3
$B + BC + D + D_q$	S + S + S + S	1	2	0	0	0	1	0	4	0

Table 6: Number of Significant Effects for Cast Fatigue Experiment in Hunter et al. (1982)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
A	B	0.10	1	2.02	1.97	2.99	4	1	9.15	1.99
A	B	0.25	1.10	2.01	1.99	2.99	4	1	8.99	3
A	B	0.50	1.53	2.46	1.97	3	4	1	9	4.06
A	B	0.75	1.53	2.03	1.94	2.98	4	1.06	9.21	4.45
A	B	1	1.66	2.11	1.96	2.99	4	1.14	9.16	4.84
A	S	0.10	1.10	1.86	1.97	3	4	1.03	9.04	3.59
A	S	0.25	1.71	1.79	1.95	2.99	3.99	1.10	9.17	4.44
A	S	0.50	1.68	1.65	2	3	4	1.14	9.30	4.70
A	S	0.75	1.62	1.53	1.98	2.99	4	1.12	9.20	4.79
A	S	1	1.45	1.77	1.98	2.99	4	1.18	9.18	5.08
$A+B$	B + B	0.10	2	3.42	2	3	4	1.85	9.03	2.16
$A+B$	B + B	0.25	2.21	3.43	2	2.99	4	1.85	8.79	2.69
$A+B$	B + B	0.50	2.57	3.19	2	3	4	1.71	9.20	3.74
$A+B$	B + B	0.75	2.29	3.07	2	3	4	1.40	9.11	4.41
$A+B$	B + B	1	2.11	2.40	2	2.99	4	1.39	8.95	4.53
$A+B$	B + S	0.10	1.71	3.63	2	3	4	1.01	9.07	2.07
$A+B$	B + S	0.25	1.64	2.59	1.98	3	4	1	8.98	3.34
$A+B$	B + S	0.50	1.43	2.16	1.96	3	4	1.02	9.08	4.06
$A+B$	B + S	0.75	1.49	2.14	1.98	2.98	4	1.04	9.08	4.39
$A+B$	B + S	1	1.76	2.05	2	3	4	1.11	9.34	4.80
$A+B$	S + S	0.10	2.04	3.72	2	3	4	1.41	9.10	3.52
$A+B$	S + S	0.25	1.50	2.62	2	3	4	1.20	9.20	4.49
$A+B$	S + S	0.50	1.50	1.77	2	3	4	1.18	9.23	4.91
$A+B$	S + S	0.75	1.63	1.66	1.98	2.98	4	1.11	9.29	4.94
$A+B$	S + S	1	1.80	1.56	1.98	3	4	1.09	9.21	4.92
$A+AB$	B + B	0.10	2	2.87	2	2.96	4	1.94	9.37	2.04
$A+AB$	B + B	0.25	2.12	2.79	2	2.93	4	1.89	9.08	2.61
$A+AB$	B + B	0.50	2.38	2.66	2	2.99	4	1.70	9.27	3.63
$A+AB$	B + B	0.75	2.47	2.41	2	2.99	3.99	1.52	9.13	4.43
$A+AB$	B + B	1	2.48	2.60	2	2.98	4	1.35	9.34	4.69
$A+AB$	B + S	0.10	1.81	3.02	2	2.99	4	1.01	9.01	2.06
$A+AB$	B + S	0.25	1.48	2.68	2	2.99	3.99	1.01	8.83	3.01
$A+AB$	B + S	0.50	1.47	2.29	1.98	3	4	1	9.10	4.03
$A+AB$	B + S	0.75	1.61	2.23	1.98	2.98	4	1.03	9.18	4.72
$A+AB$	B + S	1	1.89	1.94	1.97	2.99	4	1.07	9.07	4.75
$A+AB$	S + S	0.10	2.11	2.79	2	2.98	3.99	1.27	9.29	3.23
$A+AB$	S + S	0.25	1.66	2.05	1.99	2.99	4	1.16	9.33	4.19
$A+AB$	S + S	0.50	1.72	1.69	1.99	2.98	4	1.18	9.21	4.75
$A+AB$	S + S	0.75	1.70	1.69	1.99	2.99	4	1.13	9.35	4.98
$A+AB$	S + S	1	1.68	1.52	1.97	2.99	4	1.13	9.27	4.92

Table 6: Number of Significant Effects for Cast Fatigue Experiment in Hunter et al. (1982)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$A+B+AB$	B + B + B	0.10	2.98	3.89	2	3	4	1.82	9.18	3.12
$A+B+AB$	B + B + B	0.25	3.23	4.38	2	3	4	1.51	9.19	3.41
$A+B+AB$	B + B + B	0.50	3.21	3.66	2	3	3.99	1.35	9.28	4.14
$A+B+AB$	B + B + B	0.75	3.05	3.12	2	3	4	1.25	9.19	4.54
$A+B+AB$	B + B + B	1	2.44	2.40	2	3	4	1.14	9.34	4.96
$A+B+AB$	B + B + S	0.10	2.68	4.44	2	3	4	1.89	9.10	2.96
$A+B+AB$	B + B + S	0.25	2.47	4.06	2	3	4	1.84	9.34	3.09
$A+B+AB$	B + B + S	0.50	2.47	3.70	2	3	4	1.65	9.07	4.04
$A+B+AB$	B + B + S	0.75	2.46	3.60	2	3	4	1.41	9.07	4.54
$A+B+AB$	B + B + S	1	2.22	2.69	1.99	2.99	4	1.35	9.14	4.75
$A+B+AB$	B + S + B	0.10	2.56	4.07	2	3	4	1.85	9.38	2.77
$A+B+AB$	B + S + B	0.25	2.36	3.93	2	3	4	1.85	9.37	2.96
$A+B+AB$	B + S + B	0.50	2.45	3.07	2	2.98	4	1.60	9.11	3.89
$A+B+AB$	B + S + B	0.75	2.42	2.94	2	3	3.99	1.43	9.11	4.35
$A+B+AB$	B + S + B	1	2.37	2.26	2	3	4	1.28	9.23	4.73
$A+B+AB$	B + S + S	0.10	2.26	4.28	2	3	4	1	9	3.57
$A+B+AB$	B + S + S	0.25	1.66	3.41	2	3	4	1	8.72	3.45
$A+B+AB$	B + S + S	0.50	1.41	2.51	2	3	4	1.03	8.80	4.22
$A+B+AB$	B + S + S	0.75	1.59	2.30	1.98	3	4	1.05	8.89	4.53
$A+B+AB$	B + S + S	1	1.68	2	1.95	3	4	1.13	9.07	4.81
$A+B+AB$	S + S + S	0.10	2.57	3.54	2	3	3.99	1.32	9.20	3.77
$A+B+AB$	S + S + S	0.25	1.91	2.18	1.99	2.99	4	1.14	9.26	4.52
$A+B+AB$	S + S + S	0.50	1.68	1.78	1.99	2.99	4	1.16	9.19	4.82
$A+B+AB$	S + S + S	0.75	1.68	1.60	1.99	3	3.99	1.13	9.09	4.81
$A+B+AB$	S + S + S	1	1.89	1.83	2	3	4	1.07	9.29	5.03
$A+B+C$	B + B + B	0.10	3	5.24	2	3	4	2.39	9.15	3.07
$A+B+C$	B + B + B	0.25	3.17	4.57	2	3	4	2	9.01	3.31
$A+B+C$	B + B + B	0.50	4	4.71	2	3	4	1.67	9.07	4.35
$A+B+C$	B + B + B	0.75	3.42	3.73	2	3	4	1.62	9.20	4.70
$A+B+C$	B + B + B	1	2.73	2.98	2	3	4	1.53	9.22	5
$A+B+C$	B + B + S	0.10	2.68	5.03	2	3	4	1.85	9.13	2.90
$A+B+C$	B + B + S	0.25	2.63	4.23	2	3	4	1.82	9.09	3.24
$A+B+C$	B + B + S	0.50	2.81	3.65	2	3	4	1.66	9.15	3.95
$A+B+C$	B + B + S	0.75	2.31	3.35	2	3	4	1.52	9.05	4.66
$A+B+C$	B + B + S	1	2.14	3.04	2	3	4	1.42	9.06	4.96
$A+B+C$	B + S + S	0.10	2.65	4.47	2	3	4	1.01	9.03	2.89
$A+B+C$	B + S + S	0.25	1.93	3.68	1.99	3	4	1	9.12	3.77
$A+B+C$	B + S + S	0.50	1.62	2.52	2	3	4	1.01	9.08	4.34
$A+B+C$	B + S + S	0.75	1.83	2.31	1.99	2.99	4	1.07	9.12	4.62
$A+B+C$	B + S + S	1	1.88	2.44	2	3	4	1.15	8.84	4.89

Table 6: Number of Significant Effects for Cast Fatigue Experiment in Hunter et al. (1982)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$A+B+C$	S + S + S	0.10	2.80	4.51	2	3	4	1.47	9.09	3.70
$A+B+C$	S + S + S	0.25	1.75	2.85	1.99	2.99	4	1.23	9.12	4.53
$A+B+C$	S + S + S	0.50	1.57	1.84	2	3	4	1.16	9.15	4.84
$A+B+C$	S + S + S	0.75	1.42	1.66	2	3	3.99	1.15	9.17	5.05
$A+B+C$	S + S + S	1	1.65	1.67	2	3	4	1.17	9.34	4.89
$A+B+AC$	B + B + B	0.10	2.23	3.17	2	3	4	1.13	8.99	4.21
$A+B+AC$	B + B + B	0.25	1.90	3.09	2	3	4	1.21	9.14	4.27
$A+B+AC$	B + B + B	0.50	1.75	2.79	2	3	4	1.19	8.99	4.69
$A+B+AC$	B + B + B	0.75	1.86	2.76	1.99	3	4	1.33	9.17	4.73
$A+B+AC$	B + B + B	1	1.79	2.07	1.99	3	4	1.24	9.02	5.27
$A+B+AC$	B + B + S	0.10	2.30	4.41	2	3	4	1.80	8.96	3.13
$A+B+AC$	B + B + S	0.25	2.23	4	2	3	4	1.81	9.10	3.11
$A+B+AC$	B + B + S	0.50	2.39	3.55	2	3	4	1.67	9.14	3.75
$A+B+AC$	B + B + S	0.75	2.27	2.87	2	3	4	1.43	9.14	4.55
$A+B+AC$	B + B + S	1	2.17	2.84	2	3	4	1.28	9.13	4.84
$A+B+AC$	B + S + B	0.10	2.24	4.19	2	3	4	1.90	8.94	2.76
$A+B+AC$	B + S + B	0.25	2.13	3.55	2	2.98	4	1.81	9.11	3.18
$A+B+AC$	B + S + B	0.50	2.39	3.40	2	2.98	4	1.66	9.22	4.01
$A+B+AC$	B + S + B	0.75	2.28	2.45	2	2.99	4	1.46	9.21	4.56
$A+B+AC$	B + S + B	1	2.16	2.31	2	2.98	4	1.31	8.97	4.98
$A+B+AC$	B + S + S	0.10	1.50	4.01	2	2.99	4	1	8.86	3.65
$A+B+AC$	B + S + S	0.25	1.36	2.73	1.99	3	4	1	9	3.49
$A+B+AC$	B + S + S	0.50	1.41	2.17	1.99	2.99	4	1.01	9.05	4.03
$A+B+AC$	B + S + S	0.75	1.61	2.06	1.98	3	3.99	1.09	9.29	4.57
$A+B+AC$	B + S + S	1	1.72	1.89	1.99	3	4	1.11	9.19	4.80
$A+B+AC$	S + B + S	0.10	1.52	3.32	1.99	3	4	1	9.10	3.56
$A+B+AC$	S + B + S	0.25	1.38	2.80	1.98	3	4	1	9.09	3.79
$A+B+AC$	S + B + S	0.50	1.59	1.98	1.97	3	4	1.01	8.86	4.24
$A+B+AC$	S + B + S	0.75	1.81	1.74	1.98	2.98	4	1.02	9.27	4.90
$A+B+AC$	S + B + S	1	1.43	2.03	1.97	2.99	4	1.15	9.06	4.96
$A+B+AC$	S + S + S	0.10	1.66	3.10	2	3	3.99	1.13	9.03	4.58
$A+B+AC$	S + S + S	0.25	1.54	2.20	1.99	2.99	4	1.16	9.28	4.61
$A+B+AC$	S + S + S	0.50	1.62	1.71	1.99	2.99	4	1.12	9.20	4.95
$A+B+AC$	S + S + S	0.75	1.59	1.54	2	2.99	4	1.15	9.39	4.91
$A+B+AC$	S + S + S	1	1.51	1.74	2	3	4	1.11	9.28	4.98

Table 7: Number of Significant Effects for Contaminant Experiment in Miller and Sitter (2001)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
A	B	0.10	1	3.40	1.99	2.99	4	1	14.98	3.09
A	B	0.25	1.15	3.56	1.95	2.98	3.96	1	15.59	3.26
A	B	0.50	1.71	3.93	1.99	2.98	3.96	1	15.64	3.68
A	B	0.75	2.53	4.29	1.95	2.99	3.99	1.04	16.53	4.09
A	B	1	2.46	3.42	1.96	2.98	3.98	1.13	16.06	4.04
A	S	0.10	1.24	3.68	1.94	2.99	3.98	1	15.22	3.15
A	S	0.25	1.88	3.66	1.96	2.94	3.97	1.11	15.56	4.07
A	S	0.50	2.41	2.85	1.95	2.99	3.99	1.23	15.46	4.14
A	S	0.75	2.18	3.23	1.99	2.97	3.98	1.34	14.98	4.23
A	S	1	2.37	3.25	2	2.98	3.97	1.32	15.53	4.19
$A+B$	B + B	0.10	2	5.27	2	2.99	3.97	1.87	16.41	3.22
$A+B$	B + B	0.25	2.15	4.64	2	2.99	3.98	1.84	16.01	3.07
$A+B$	B + B	0.50	2.81	5.37	2	2.99	4	1.84	15.87	3.64
$A+B$	B + B	0.75	3.24	5.32	2	3	4	1.84	16.24	3.87
$A+B$	B + B	1	4.23	5.03	2	2.99	3.99	1.83	16.76	3.96
$A+B$	B + S	0.10	1.85	5.28	2	2.97	3.98	1	15.62	3.14
$A+B$	B + S	0.25	2.08	4.94	2	3	4	1.02	16.12	3.48
$A+B$	B + S	0.50	2.14	3.91	1.98	3	3.99	1.02	16.19	3.79
$A+B$	B + S	0.75	2.75	3.98	1.98	2.99	3.97	1.05	15.68	4.14
$A+B$	B + S	1	2.35	3.59	1.96	2.99	3.99	1.17	15.48	3.83
$A+B$	S + S	0.10	2.11	5.15	2	3	3.99	1.38	16.60	3.44
$A+B$	S + S	0.25	2.98	4.74	2	3	3.99	1.33	16.91	4.14
$A+B$	S + S	0.50	2.16	3.70	2	2.99	3.99	1.40	16.01	4.34
$A+B$	S + S	0.75	2.19	3.15	1.97	2.98	3.98	1.28	15.37	4.05
$A+B$	S + S	1	2.56	3.26	2	2.97	3.99	1.40	15.27	3.88
$A+AB$	B + B	0.10	2	4.51	2	2.96	3.97	1.85	16.09	3.66
$A+AB$	B + B	0.25	2.18	4.31	2	2.97	3.97	1.86	16.24	3.51
$A+AB$	B + B	0.50	2.65	4.50	2	2.99	4	1.87	16.59	3.64
$A+AB$	B + B	0.75	3.45	4.20	2	2.97	3.99	1.78	17.22	3.93
$A+AB$	B + B	1	3.41	3.86	2	2.96	3.98	1.70	16.06	3.79
$A+AB$	B + S	0.10	1.86	4.68	2	2.95	3.99	1	16.87	3
$A+AB$	B + S	0.25	1.78	3.77	1.99	2.97	4	1.01	16.86	3.25
$A+AB$	B + S	0.50	2.18	3.83	1.96	3	3.98	1	16.60	3.84
$A+AB$	B + S	0.75	2.04	3.40	1.98	2.95	3.95	1.08	14.86	4.10
$A+AB$	B + S	1	2.72	3.61	1.97	3	3.99	1.24	15.53	4.18
$A+AB$	S + S	0.10	2.07	4.64	2	2.98	4	1.45	16.90	2.96
$A+AB$	S + S	0.25	3.29	4.45	2	2.98	3.99	1.32	17.32	3.96
$A+AB$	S + S	0.50	2.78	3.21	1.99	2.97	4	1.19	15.59	4.18
$A+AB$	S + S	0.75	2.22	3.30	2	3	3.99	1.24	16.37	3.93
$A+AB$	S + S	1	2.12	3.60	1.98	2.97	3.96	1.28	15.97	3.99

Table 7: Number of Significant Effects for Contaminant Experiment in Miller and Sitter (2001)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$A+B+AB$	B + B + B	0.10	3	6.09	2	3	4	2.74	16.55	4.49
$A+B+AB$	B + B + B	0.25	3.08	5.57	2	3	3.99	2.71	16.84	4.19
$A+B+AB$	B + B + B	0.50	3.74	5.83	2	3	4	2.62	17.57	4.22
$A+B+AB$	B + B + B	0.75	4.51	6.47	2	3	4	2.50	17.18	4.31
$A+B+AB$	B + B + B	1	4.81	5.46	2	3	4	2.30	16.50	4.08
$A+B+AB$	B + B + S	0.10	2.87	6.34	2	3	3.99	1.95	17.43	3.65
$A+B+AB$	B + B + S	0.25	2.71	5.41	2	3	4	1.91	16.33	3.35
$A+B+AB$	B + B + S	0.50	3.21	5.58	2	3	4	1.82	17.64	3.93
$A+B+AB$	B + B + S	0.75	3.79	5.07	2	2.99	3.97	1.79	16.88	4.08
$A+B+AB$	B + B + S	1	3.68	4.72	2	3	4	1.84	16.93	4.15
$A+B+AB$	B + S + B	0.10	2.86	6.20	2	3	4	1.87	17.45	4.51
$A+B+AB$	B + S + B	0.25	2.94	5.97	2	3	4	1.78	16.99	4.23
$A+B+AB$	B + S + B	0.50	3.60	5.12	2	2.99	3.99	1.87	16.31	4.02
$A+B+AB$	B + S + B	0.75	3.55	4.50	1.99	2.95	3.98	1.80	16.55	3.75
$A+B+AB$	B + S + B	1	3.85	4.46	2	2.97	3.98	1.69	16.83	3.83
$A+B+AB$	B + S + S	0.10	2.84	6.14	2	3	4	1	17.17	3.53
$A+B+AB$	B + S + S	0.25	2.78	5.77	2	2.99	4	1	17.07	3.63
$A+B+AB$	B + S + S	0.50	2.38	4.62	1.99	2.98	3.97	1.03	17.59	3.80
$A+B+AB$	B + S + S	0.75	2.26	4.20	1.99	2.97	3.98	1.08	16.20	3.99
$A+B+AB$	B + S + S	1	2.45	3.62	1.96	2.97	3.98	1.17	15.89	3.96
$A+B+AB$	S + S + S	0.10	3.11	5.96	2	3	3.99	1.68	17.01	3.45
$A+B+AB$	S + S + S	0.25	4.22	5.60	2	2.99	4	1.49	16.81	4.25
$A+B+AB$	S + S + S	0.50	2.38	3.67	1.99	2.99	3.96	1.28	16.28	4.32
$A+B+AB$	S + S + S	0.75	2.12	3.10	1.99	2.97	3.97	1.26	15.31	4.24
$A+B+AB$	S + S + S	1	2.20	2.99	2	2.99	3.99	1.32	15.03	4.15
$A+B+C$	B + B + B	0.10	3	6.65	2	3	4	2.78	16.31	3.77
$A+B+C$	B + B + B	0.25	3.18	6.26	2	3	4	2.61	16.97	3.35
$A+B+C$	B + B + B	0.50	4.28	7.78	2	3	4	2.52	17.33	3.91
$A+B+C$	B + B + B	0.75	4.80	6.47	2	3	3.99	2.56	16.45	4.24
$A+B+C$	B + B + B	1	4.94	6.19	2	2.99	4	2.35	16.29	4.37
$A+B+C$	B + B + S	0.10	2.88	7.50	2	3	4	1.89	17.15	3.67
$A+B+C$	B + B + S	0.25	3.01	6.53	2	3	3.99	1.91	16.99	3.48
$A+B+C$	B + B + S	0.50	3.25	5.70	2	3	3.99	1.85	16.16	3.74
$A+B+C$	B + B + S	0.75	3.66	5.28	2	3	4	1.77	17.40	4.06
$A+B+C$	B + B + S	1	3.54	4.81	2	3	4	1.83	16.55	4.04
$A+B+C$	B + S + S	0.10	2.88	6.57	2	3	4	1.03	16.20	3.60
$A+B+C$	B + S + S	0.25	2.77	6.24	2	3	3.98	1.01	17.20	3.74
$A+B+C$	B + S + S	0.50	2.65	4.56	1.99	3	4	1.01	16.22	3.95
$A+B+C$	B + S + S	0.75	2.43	3.96	2	2.98	3.99	1.04	16.62	3.94
$A+B+C$	B + S + S	1	3.15	4.12	1.98	2.94	3.98	1.27	16.66	4.02

Table 7: Number of Significant Effects for Contaminant Experiment in Miller and Sitter (2001)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$A+B+C$	S + S + S	0.10	3.18	6.36	2	3	4	1.70	16.58	3.90
$A+B+C$	S + S + S	0.25	4.07	5.44	2	3	3.99	1.38	17.09	4.34
$A+B+C$	S + S + S	0.50	2.63	3.51	1.99	2.98	4	1.41	17	4.30
$A+B+C$	S + S + S	0.75	2.01	3.61	1.99	3	4	1.61	16.64	4.41
$A+B+C$	S + S + S	1	2.48	3.40	1.95	2.96	3.97	1.26	15.54	4.10
$A+B+AC$	B + B + B	0.10	3	6.41	2	3	4	2.62	17.56	4.37
$A+B+AC$	B + B + B	0.25	3.09	6.36	2	3	4	2.52	16.66	3.98
$A+B+AC$	B + B + B	0.50	4.24	6.37	2	3	4	2.54	16.63	4.25
$A+B+AC$	B + B + B	0.75	4.68	5.47	2	3	4	2.35	17.22	4.30
$A+B+AC$	B + B + B	1	5.29	6.06	2	3	4	2.40	16.94	4.23
$A+B+AC$	B + B + S	0.10	2.79	6.25	2	3	3.99	1.85	16.79	3.50
$A+B+AC$	B + B + S	0.25	2.81	5.46	2	3	4	1.83	16.56	3.42
$A+B+AC$	B + B + S	0.50	3.38	5.63	2	2.99	4	1.78	16.17	3.88
$A+B+AC$	B + B + S	0.75	3.14	4.78	2	2.99	3.99	1.76	15.88	4.17
$A+B+AC$	B + B + S	1	3.61	5.58	2	3	4	1.72	16.31	4.11
$A+B+AC$	B + S + B	0.10	2.92	5.24	2	3	3.98	1.86	17.12	4.45
$A+B+AC$	B + S + B	0.25	2.93	5.42	2	3	4	1.90	17.41	4
$A+B+AC$	B + S + B	0.50	3.37	5.17	2	2.98	3.99	1.88	17.39	4.15
$A+B+AC$	B + S + B	0.75	3.77	4.54	2	2.96	4	1.82	16.88	3.75
$A+B+AC$	B + S + B	1	3.75	4.36	2	2.98	4	1.78	16.44	3.75
$A+B+AC$	B + S + S	0.10	2.82	6.21	2	3	4	1	16.84	3.50
$A+B+AC$	B + S + S	0.25	2.83	5.30	2	3	4	1.01	16.70	3.84
$A+B+AC$	B + S + S	0.50	2.77	4.88	1.97	2.99	4	1.02	15.99	4.07
$A+B+AC$	B + S + S	0.75	2.06	3.84	1.97	2.98	3.97	1.03	15.80	3.90
$A+B+AC$	B + S + S	1	2.77	3.59	1.96	3	4	1.13	15.05	4.21
$A+B+AC$	S + B + S	0.10	2.75	6.09	1.99	3	4	1	17.27	3.55
$A+B+AC$	S + B + S	0.25	2.47	5.03	1.98	3	3.99	1	16.22	3.70
$A+B+AC$	S + B + S	0.50	2.47	4.08	2	2.99	4	1.02	17.05	3.93
$A+B+AC$	S + B + S	0.75	2.17	4.02	1.98	3	3.98	1.05	16.16	4.14
$A+B+AC$	S + B + S	1	2.15	3.44	1.97	3	3.99	1.08	16.43	4.05
$A+B+AC$	S + S + S	0.10	3.06	5.46	2	3	3.98	1.50	16.66	3.56
$A+B+AC$	S + S + S	0.25	3.58	5.29	2	3	4	1.41	17.28	4.41
$A+B+AC$	S + S + S	0.50	2.25	3.86	2	2.99	4	1.24	16.86	4.25
$A+B+AC$	S + S + S	0.75	2.49	3.61	1.97	2.98	4	1.33	16.76	4.27
$A+B+AC$	S + S + S	1	2.02	2.66	1.99	2.97	3.96	1.25	14.81	3.82

Table 8: Number of Significant Effects for Antiviral Drug Experiment in Xu et al. (2014)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
A	B	0.10	1	1.50	1.33	1.49	1.57	1	1.53	1.65
A	B	0.25	1.16	1.62	1.44	1.77	1.84	1	1.68	1.95
A	B	0.50	1.30	1.54	1.38	1.63	1.75	1	1.63	2.01
A	B	0.75	1.33	1.51	1.39	1.64	1.72	1	1.72	2.14
A	B	1	1.26	1.43	1.25	1.48	1.59	1.05	1.62	2.46
A	S	0.10	1.22	1.50	1.32	1.68	1.87	1	1.64	2.02
A	S	0.25	1.37	1.50	1.35	1.53	1.58	1.01	1.55	1.80
A	S	0.50	1.51	1.45	1.32	1.55	1.68	1.14	1.58	1.99
A	S	0.75	1.36	1.29	1.32	1.49	1.53	1.23	1.50	2.28
A	S	1	1.40	1.25	1.34	1.42	1.57	1.19	1.47	2.51
$A+B$	B + B	0.10	2	2.69	2	2.47	2.70	1.89	3.62	2.45
$A+B$	B + B	0.25	2.14	2.55	2	2.39	2.57	1.91	3.53	2.58
$A+B$	B + B	0.50	2.35	2.51	2	2.34	2.48	1.84	3.24	2.62
$A+B$	B + B	0.75	2.49	2.66	2	2.46	2.69	1.83	3.40	2.87
$A+B$	B + B	1	2.69	2.75	2	2.53	2.78	1.84	3.51	3.07
$A+B$	B + S	0.10	2.03	2.55	2	2.38	2.55	1.02	3.35	2.64
$A+B$	B + S	0.25	2.24	2.63	2	2.44	2.63	1.01	3.50	2.69
$A+B$	B + S	0.50	2.31	2.38	1.85	2.24	2.45	1.01	2.99	2.58
$A+B$	B + S	0.75	1.88	2.05	1.64	1.94	2.14	1.02	2.18	2.50
$A+B$	B + S	1	1.93	1.95	1.54	1.95	2.08	1.10	2.17	2.93
$A+B$	S + S	0.10	2.26	2.53	2	2.40	2.54	1.42	3.40	2.71
$A+B$	S + S	0.25	2.48	2.54	1.97	2.37	2.51	1.31	3.10	2.63
$A+B$	S + S	0.50	2.42	2.29	1.79	2.19	2.40	1.28	2.56	2.69
$A+B$	S + S	0.75	1.87	1.76	1.51	1.88	2.03	1.30	1.92	2.69
$A+B$	S + S	1	1.41	1.28	1.39	1.55	1.64	1.34	1.48	2.63
$A+AB$	B + B	0.10	2	2.47	2	2.36	2.63	1.90	3.26	2.34
$A+AB$	B + B	0.25	2.23	2.64	2	2.39	2.73	1.81	3.36	2.55
$A+AB$	B + B	0.50	2.36	2.31	2	2.25	2.51	1.89	3.24	2.67
$A+AB$	B + B	0.75	2.41	2.56	2	2.37	2.74	1.83	3.24	2.98
$A+AB$	B + B	1	2.42	2.39	2	2.34	2.62	1.82	3.06	3.09
$A+AB$	B + S	0.10	1.96	2.48	2	2.34	2.63	1.02	3.68	2.66
$A+AB$	B + S	0.25	2.07	2.31	1.97	2.23	2.40	1	3.25	2.50
$A+AB$	B + S	0.50	1.94	2.11	1.78	2.05	2.20	1	2.45	2.39
$A+AB$	B + S	0.75	1.81	1.98	1.63	1.95	2.11	1.02	1.86	2.66
$A+AB$	B + S	1	1.49	1.46	1.34	1.56	1.66	1.06	1.60	2.60
$A+AB$	S + S	0.10	2.32	2.59	2	2.40	2.70	1.31	3.31	2.86
$A+AB$	S + S	0.25	2.45	2.51	2	2.40	2.65	1.31	3.26	3.12
$A+AB$	S + S	0.50	2.13	1.88	1.78	2.12	2.27	1.26	2.40	2.70
$A+AB$	S + S	0.75	1.63	1.39	1.52	1.80	1.86	1.23	1.88	2.55
$A+AB$	S + S	1	1.76	1.25	1.43	1.60	1.69	1.40	1.75	2.75

Table 8: Number of Significant Effects for Antiviral Drug Experiment in Xu et al. (2014)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$A+B+AB$	B + B + B	0.10	3	3.64	2	3	3.45	2.74	3.80	3.16
$A+B+AB$	B + B + B	0.25	3.12	3.62	2	3	3.46	2.65	3.85	3.28
$A+B+AB$	B + B + B	0.50	3.71	3.86	2	3	3.53	2.69	3.77	3.66
$A+B+AB$	B + B + B	0.75	3.53	3.58	2	3	3.47	2.55	3.82	3.64
$A+B+AB$	B + B + B	1	3.53	3.58	2	2.98	3.44	2.59	3.73	3.83
$A+B+AB$	B + B + S	0.10	2.96	3.65	2	3	3.47	1.89	3.70	3.30
$A+B+AB$	B + B + S	0.25	3.34	3.76	2	3	3.55	1.86	3.88	3.55
$A+B+AB$	B + B + S	0.50	3.13	3.35	2	2.86	3.30	1.90	3.55	3.49
$A+B+AB$	B + B + S	0.75	3.05	3.08	2	2.72	2.99	1.89	3.49	3.25
$A+B+AB$	B + B + S	1	2.85	2.92	2	2.60	2.86	1.91	3.34	3.21
$A+B+AB$	B + S + B	0.10	3	3.49	2	3	3.38	1.87	3.88	3.12
$A+B+AB$	B + S + B	0.25	3.26	3.57	2	3	3.42	1.87	3.69	3.30
$A+B+AB$	B + S + B	0.50	3.38	3.32	2	2.85	3.28	1.84	3.57	3.44
$A+B+AB$	B + S + B	0.75	2.90	2.91	2	2.58	2.85	1.85	3.33	3.14
$A+B+AB$	B + S + B	1	2.80	2.84	2	2.53	2.97	1.92	3.45	3.34
$A+B+AB$	B + S + S	0.10	3	3.60	2	3	3.43	1.01	3.66	3.40
$A+B+AB$	B + S + S	0.25	3.55	3.54	2	2.96	3.37	1	3.55	3.53
$A+B+AB$	B + S + S	0.50	2.88	2.98	1.91	2.57	2.96	1.01	3.12	3.12
$A+B+AB$	B + S + S	0.75	2.20	2.44	1.82	2.31	2.56	1.03	2.62	2.93
$A+B+AB$	B + S + S	1	2.11	2.01	1.58	1.93	2.12	1.14	2.07	2.75
$A+B+AB$	S + S + S	0.10	3.21	3.56	2	3	3.38	1.74	3.97	3.52
$A+B+AB$	S + S + S	0.25	3.58	3.45	2	2.97	3.35	1.41	3.58	3.71
$A+B+AB$	S + S + S	0.50	2.89	2.70	1.90	2.42	2.73	1.31	2.93	3.14
$A+B+AB$	S + S + S	0.75	2.24	2.04	1.69	2.09	2.38	1.40	2.36	3.12
$A+B+AB$	S + S + S	1	1.73	1.56	1.51	1.74	1.90	1.53	1.85	2.88
$A+B+C$	B + B + B	0.10	3	3.94	2	3	3.57	2.69	5.79	3.49
$A+B+C$	B + B + B	0.25	3.13	3.79	2	3	3.56	2.61	5.63	3.55
$A+B+C$	B + B + B	0.50	3.85	3.88	2	3	3.53	2.69	5.51	3.70
$A+B+C$	B + B + B	0.75	3.89	3.89	2	3	3.59	2.71	5.43	3.89
$A+B+C$	B + B + B	1	3.77	3.76	2	3	3.50	2.58	5.46	3.88
$A+B+C$	B + B + S	0.10	2.99	3.71	2	3	3.51	1.89	5.41	3.30
$A+B+C$	B + B + S	0.25	3.30	3.70	2	2.99	3.46	1.89	5.39	3.49
$A+B+C$	B + B + S	0.50	3.49	3.51	2	2.91	3.30	1.85	5.11	3.48
$A+B+C$	B + B + S	0.75	3.45	3.40	2	2.77	3.22	1.86	4.48	3.41
$A+B+C$	B + B + S	1	2.83	2.85	2	2.56	2.80	1.91	3.80	3.07
$A+B+C$	B + S + S	0.10	2.99	3.66	2	3	3.46	1.02	5.48	3.45
$A+B+C$	B + S + S	0.25	3.57	3.70	2	2.98	3.49	1	5.24	3.49
$A+B+C$	B + S + S	0.50	3.17	3.21	1.93	2.64	3.15	1	4.02	3.38
$A+B+C$	B + S + S	0.75	2.45	2.55	1.81	2.32	2.52	1.03	2.74	2.85
$A+B+C$	B + S + S	1	2.02	2.30	1.69	2.09	2.33	1.18	2.38	3.06

Table 8: Number of Significant Effects for Antiviral Drug Experiment in Xu et al. (2014)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$A+B+C$	S + S + S	0.10	3.27	3.67	2	3	3.47	1.66	5.50	3.50
$A+B+C$	S + S + S	0.25	3.87	3.73	2	2.98	3.51	1.58	5.29	3.84
$A+B+C$	S + S + S	0.50	3.22	3.14	1.94	2.62	2.95	1.43	3.53	3.36
$A+B+C$	S + S + S	0.75	1.87	1.90	1.61	1.94	2.13	1.39	2.20	2.82
$A+B+C$	S + S + S	1	1.60	1.60	1.53	1.78	1.96	1.62	1.84	2.84
$A+B+AC$	B + B + B	0.10	3	3.62	2	3	3.49	2.64	4.62	3.18
$A+B+AC$	B + B + B	0.25	3.18	3.56	2	3	3.40	2.53	4.60	3.29
$A+B+AC$	B + B + B	0.50	3.58	3.71	2	3	3.45	2.48	4.79	3.61
$A+B+AC$	B + B + B	0.75	3.57	3.49	2	3	3.41	2.54	4.49	3.63
$A+B+AC$	B + B + B	1	3.60	3.59	2	3	3.40	2.54	4.53	3.72
$A+B+AC$	B + B + S	0.10	2.97	3.56	2	3	3.46	1.80	4.90	3.10
$A+B+AC$	B + B + S	0.25	3.29	3.51	2	3	3.41	1.86	5	3.15
$A+B+AC$	B + B + S	0.50	3.42	3.33	2	2.84	3.21	1.86	4.36	3.40
$A+B+AC$	B + B + S	0.75	2.93	3.03	2	2.62	2.96	1.87	3.77	3.17
$A+B+AC$	B + B + S	1	2.81	2.90	2	2.57	2.82	1.82	3.54	3.16
$A+B+AC$	B + S + B	0.10	2.97	3.56	2	3	3.41	1.86	5.07	3.03
$A+B+AC$	B + S + B	0.25	3.32	3.60	2	2.99	3.45	1.87	4.94	3.16
$A+B+AC$	B + S + B	0.50	3.29	3.30	2	2.73	3.24	1.84	4.40	3.39
$A+B+AC$	B + S + B	0.75	2.96	3.04	2	2.65	3.03	1.83	3.86	3.28
$A+B+AC$	B + S + B	1	2.66	2.73	1.99	2.45	2.74	1.85	3.37	3.07
$A+B+AC$	B + S + S	0.10	3.01	3.63	2	3	3.43	1.01	5.79	3.42
$A+B+AC$	B + S + S	0.25	3.47	3.56	1.99	2.98	3.41	1	5.22	3.50
$A+B+AC$	B + S + S	0.50	2.73	2.87	1.89	2.61	2.88	1.01	3.83	3.06
$A+B+AC$	B + S + S	0.75	1.94	2.27	1.69	2.14	2.32	1.01	2.41	2.81
$A+B+AC$	B + S + S	1	2.01	2.13	1.62	1.91	2.16	1.14	1.85	2.93
$A+B+AC$	S + B + S	0.10	3.04	3.72	2	3	3.47	1	3.65	3.13
$A+B+AC$	S + B + S	0.25	3.23	3.37	1.96	2.97	3.36	1	3.33	3.18
$A+B+AC$	S + B + S	0.50	2.80	2.87	1.83	2.75	3.04	1	3.15	3.30
$A+B+AC$	S + B + S	0.75	2.06	2.13	1.62	2.19	2.49	1.02	2.50	3.04
$A+B+AC$	S + B + S	1	1.83	1.75	1.47	2.01	2.20	1.07	2.32	2.64
$A+B+AC$	S + S + S	0.10	3.20	3.55	2	3	3.40	1.52	4.52	3.48
$A+B+AC$	S + S + S	0.25	3.61	3.51	1.98	2.94	3.37	1.49	4.39	3.67
$A+B+AC$	S + S + S	0.50	2.60	2.49	1.79	2.53	2.86	1.30	3.18	3.16
$A+B+AC$	S + S + S	0.75	2.11	1.84	1.62	2.02	2.19	1.36	2.30	2.89
$A+B+AC$	S + S + S	1	1.85	1.56	1.56	1.81	1.98	1.39	2.15	2.97
$A+A_q$	B + B	0.10	2	2.56	2	2.41	2.67	1.85	2.65	2.57
$A+A_q$	B + B	0.25	2.10	2.56	2	2.39	2.66	1.83	2.52	2.61
$A+A_q$	B + B	0.50	2.37	2.36	2	2.29	2.50	1.86	2.53	2.63
$A+A_q$	B + B	0.75	2.45	2.43	2	2.32	2.56	1.78	2.55	2.80
$A+A_q$	B + B	1	2.56	2.54	2	2.37	2.72	1.78	2.60	2.91

Table 8: Number of Significant Effects for Antiviral Drug Experiment in Xu et al. (2014)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$A+A_q$	B + S	0.10	1.99	2.39	2	2.26	2.60	1.08	2.63	2.36
$A+A_q$	B + S	0.25	2.25	2.41	2	2.29	2.55	1.04	2.61	2.52
$A+A_q$	B + S	0.50	2.28	2.33	1.89	2.22	2.48	1.02	2.47	2.73
$A+A_q$	B + S	0.75	2.03	2.01	1.69	2.06	2.27	1.05	2.21	2.59
$A+A_q$	B + S	1	1.75	1.80	1.62	1.82	2.03	1.15	2.06	2.84
$A+A_q$	S + S	0.10	2.19	2.53	2	2.37	2.59	1.47	2.52	2.55
$A+A_q$	S + S	0.25	2.51	2.47	1.99	2.29	2.47	1.22	2.44	2.79
$A+A_q$	S + S	0.50	2.39	1.95	1.88	2.17	2.40	1.19	2.50	2.55
$A+A_q$	S + S	0.75	1.90	1.53	1.65	1.88	1.97	1.19	1.86	2.48
$A+A_q$	S + S	1	1.81	1.25	1.56	1.76	1.87	1.35	1.87	2.65
$A+A_q+B+B_q$	B + B + B + B	0.10	4	4.40	2	3	4	2.65	4.30	4.09
$A+A_q+B+B_q$	B + B + B + B	0.25	4.09	4.52	2	3	4	2.82	4.62	4.16
$A+A_q+B+B_q$	B + B + B + B	0.50	4.53	4.62	2	3	4	2.81	4.56	4.20
$A+A_q+B+B_q$	B + B + B + B	0.75	4.75	4.56	2	3	4	2.95	4.56	4.30
$A+A_q+B+B_q$	B + B + B + B	1	4.60	4.49	2	2.98	4	2.64	4.34	4.36
$A+A_q+B+B_q$	B + B + B + S	0.10	4	4.61	2	3	4	2.46	4.48	3.99
$A+A_q+B+B_q$	B + B + B + S	0.25	4.30	4.54	2	3	4	2.55	4.47	4.05
$A+A_q+B+B_q$	B + B + B + S	0.50	4.51	4.42	2	3	3.93	2.49	4.40	3.96
$A+A_q+B+B_q$	B + B + B + S	0.75	4.18	4.22	2	3	3.77	2.28	4.38	3.92
$A+A_q+B+B_q$	B + B + B + S	1	4.19	4.06	1.99	3	3.66	2.32	4.40	4.07
$A+A_q+B+B_q$	B + B + S + S	0.10	4	4.58	2	3	4	1.84	4.54	4.12
$A+A_q+B+B_q$	B + B + S + S	0.25	4.39	4.50	2	2.96	4	1.82	4.52	4.11
$A+A_q+B+B_q$	B + B + S + S	0.50	4.36	4.07	2	2.79	3.89	1.84	4.52	4.01
$A+A_q+B+B_q$	B + B + S + S	0.75	3.43	3.26	2	2.68	3.49	1.82	3.85	3.83
$A+A_q+B+B_q$	B + B + S + S	1	3.03	2.93	2	2.53	3.21	1.80	3.41	3.50
$A+A_q+B+B_q$	B + S + B + S	0.10	4	4.58	2	3	4	1.89	4.56	4.04
$A+A_q+B+B_q$	B + S + B + S	0.25	4.51	4.68	2	3	4	1.93	4.79	4.08
$A+A_q+B+B_q$	B + S + B + S	0.50	4.53	4.36	2	3	3.86	1.92	4.43	4.23
$A+A_q+B+B_q$	B + S + B + S	0.75	3.99	3.95	2	2.97	3.60	1.93	4.04	3.91
$A+A_q+B+B_q$	B + S + B + S	1	3.54	3.61	2	2.92	3.43	1.96	4.06	3.78
$A+A_q+B+B_q$	B + S + S + S	0.10	4.02	4.45	2	3	4	1.11	4.32	4.08
$A+A_q+B+B_q$	B + S + S + S	0.25	4.39	4.29	2	2.99	4	1.03	4.42	4.23
$A+A_q+B+B_q$	B + S + S + S	0.50	4.03	3.64	1.99	2.89	3.77	1.02	4.17	3.98
$A+A_q+B+B_q$	B + S + S + S	0.75	3.18	2.92	1.88	2.76	3.35	1.14	3.62	3.50
$A+A_q+B+B_q$	B + S + S + S	1	2.56	2.50	1.77	2.47	2.85	1.23	3.14	3.21
$A+A_q+B+B_q$	S + S + S + S	0.10	4.20	4.64	2	3	4	1.81	4.67	4.11
$A+A_q+B+B_q$	S + S + S + S	0.25	4.58	4.32	2	2.94	3.99	1.22	4.61	4.41
$A+A_q+B+B_q$	S + S + S + S	0.50	4.13	3.22	1.98	2.75	3.68	1.22	4.18	4.16
$A+A_q+B+B_q$	S + S + S + S	0.75	3.27	2.17	1.92	2.52	3.12	1.29	3.39	3.48
$A+A_q+B+B_q$	S + S + S + S	1	2.35	1.63	1.78	2.10	2.55	1.38	2.60	3.10

Table 8: Number of Significant Effects for Antiviral Drug Experiment in Xu et al. (2014)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$A+AB+A_q$	B + B + B	0.10	3	3.47	2	3	3.29	2.59	4.43	3.09
$A+AB+A_q$	B + B + B	0.25	3.01	3.31	2	3	3.23	2.36	4.29	3.17
$A+AB+A_q$	B + B + B	0.50	3.35	3.38	2	3	3.31	2.49	4.23	3.46
$A+AB+A_q$	B + B + B	0.75	3.35	3.35	2	3	3.28	2.51	4.44	3.55
$A+AB+A_q$	B + B + B	1	3.53	3.41	2	3	3.28	2.42	4.40	3.62
$A+AB+A_q$	B + B + S	0.10	3	3.42	2	3	3.33	1.89	4.07	3.10
$A+AB+A_q$	B + B + S	0.25	3.25	3.43	2	3	3.31	1.91	4.07	3.30
$A+AB+A_q$	B + B + S	0.50	3.33	3.30	2	2.93	3.24	1.87	4.20	3.52
$A+AB+A_q$	B + B + S	0.75	3.13	3.13	2	2.83	3.14	1.78	3.79	3.50
$A+AB+A_q$	B + B + S	1	2.99	3.01	1.99	2.68	3.02	1.89	3.50	3.50
$A+AB+A_q$	B + S + B	0.10	2.90	3.56	2	3	3.41	1.85	4.44	3.40
$A+AB+A_q$	B + S + B	0.25	3.03	3.37	2	3	3.28	1.79	4.47	3.40
$A+AB+A_q$	B + S + B	0.50	3.13	3.22	2	2.82	3.13	1.76	3.45	3.36
$A+AB+A_q$	B + S + B	0.75	2.81	2.89	2	2.61	2.96	1.83	3.04	3.20
$A+AB+A_q$	B + S + B	1	2.68	2.65	2	2.47	2.71	1.82	2.64	3.05
$A+AB+A_q$	B + S + S	0.10	2.98	3.31	2	3	3.23	1.04	4.51	3.22
$A+AB+A_q$	B + S + S	0.25	3.42	3.40	2	2.99	3.29	1.01	4.17	3.54
$A+AB+A_q$	B + S + S	0.50	2.98	3.03	1.98	2.72	3.03	1.01	3.40	3.33
$A+AB+A_q$	B + S + S	0.75	2.11	2.31	1.84	2.24	2.37	1.04	2.48	2.85
$A+AB+A_q$	B + S + S	1	1.85	2.11	1.71	2.10	2.35	1.18	2.07	3.06
$A+AB+A_q$	S + S + S	0.10	3.10	3.35	2	3	3.28	1.41	4.47	3.29
$A+AB+A_q$	S + S + S	0.25	3.47	3.27	2	2.99	3.22	1.34	4.23	3.73
$A+AB+A_q$	S + S + S	0.50	3.10	2.45	1.96	2.68	3.04	1.31	3.35	3.32
$A+AB+A_q$	S + S + S	0.75	2.63	1.78	1.88	2.33	2.69	1.25	2.56	3.17
$A+AB+A_q$	S + S + S	1	2.11	1.39	1.70	1.98	2.12	1.38	2.22	2.79
$A+AB+C+C_q$	B + B + B + B	0.10	4	4.48	2	3	4	3.15	4.81	4.08
$A+AB+C+C_q$	B + B + B + B	0.25	4.06	4.52	2	3	4	2.97	4.67	4.15
$A+AB+C+C_q$	B + B + B + B	0.50	4.43	4.58	2	3	4	2.97	4.84	4.38
$A+AB+C+C_q$	B + B + B + B	0.75	4.98	4.78	2	3	4	3.31	4.85	4.70
$A+AB+C+C_q$	B + B + B + B	1	4.68	4.44	2	2.99	4	3.24	4.82	4.51
$A+AB+C+C_q$	B + B + B + S	0.10	4	4.62	2	3	4	2.66	4.94	4.15
$A+AB+C+C_q$	B + B + B + S	0.25	4.32	4.51	2	3	4	2.55	4.86	4.27
$A+AB+C+C_q$	B + B + B + S	0.50	4.37	4.40	2	3	3.94	2.54	4.76	4.27
$A+AB+C+C_q$	B + B + B + S	0.75	4.18	4.16	2	3	3.84	2.60	4.51	4.23
$A+AB+C+C_q$	B + B + B + S	1	4.38	4.23	1.98	3	3.78	2.46	4.40	4.39

Table 8: Number of Significant Effects for Antiviral Drug Experiment in Xu et al. (2014)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$A+AB+C+C_q$	B + B + S + S	0.10	4	4.66	2	2.99	4	1.89	5.20	4.06
$A+AB+C+C_q$	B + B + S + S	0.25	4.58	4.47	2	2.93	4	1.86	5.11	4.31
$A+AB+C+C_q$	B + B + S + S	0.50	4.18	3.70	2	2.71	3.86	1.82	5.10	4.21
$A+AB+C+C_q$	B + B + S + S	0.75	3.68	3.47	2	2.72	3.56	1.86	4.43	3.92
$A+AB+C+C_q$	B + B + S + S	1	2.84	2.76	2	2.41	3.03	1.83	3.60	3.44
$A+AB+C+C_q$	B + S + B + B	0.10	3.95	4.46	2	3	4	2.51	4.53	3.94
$A+AB+C+C_q$	B + S + B + B	0.25	4.18	4.43	2	3	3.94	2.52	4.62	3.92
$A+AB+C+C_q$	B + S + B + B	0.50	4.23	4.14	2	3	3.77	2.47	4.67	3.80
$A+AB+C+C_q$	B + S + B + B	0.75	3.89	3.84	2	3	3.56	2.45	4.43	3.86
$A+AB+C+C_q$	B + S + B + B	1	3.75	3.71	1.99	3	3.53	2.43	4.33	3.95
$A+AB+C+C_q$	B + S + B + S	0.10	4.01	4.74	2	3	4	1.90	5.26	4.08
$A+AB+C+C_q$	B + S + B + S	0.25	4.47	4.50	2	3	4	1.97	5.03	4.23
$A+AB+C+C_q$	B + S + B + S	0.50	4.28	4.10	2	3	3.79	1.92	4.46	4.16
$A+AB+C+C_q$	B + S + B + S	0.75	3.77	3.76	2	2.91	3.43	1.85	4	3.93
$A+AB+C+C_q$	B + S + B + S	1	3.12	3.28	1.99	2.81	3.24	1.90	3.66	3.65
$A+AB+C+C_q$	B + S + S + S	0.10	4	4.68	2	3	4	1.05	5.63	4.17
$A+AB+C+C_q$	B + S + S + S	0.25	4.52	4.36	2	3	3.99	1	5.52	4.32
$A+AB+C+C_q$	B + S + S + S	0.50	4.16	3.47	1.97	2.88	3.71	1	4.57	4
$A+AB+C+C_q$	B + S + S + S	0.75	3.33	2.70	1.84	2.71	3.19	1.06	3.75	3.55
$A+AB+C+C_q$	B + S + S + S	1	2.51	2.22	1.67	2.39	2.69	1.19	2.87	3.12
$A+AB+C+C_q$	S + S + B + B	0.10	4	4.80	2	3	4	1.84	5.06	3.98
$A+AB+C+C_q$	S + S + B + B	0.25	4.32	4.53	2	3	3.97	1.83	4.48	3.98
$A+AB+C+C_q$	S + S + B + B	0.50	4.18	3.89	2	2.82	3.68	1.82	4.22	3.83
$A+AB+C+C_q$	S + S + B + B	0.75	3.31	3.06	2	2.57	3.31	1.88	3.56	3.55
$A+AB+C+C_q$	S + S + B + B	1	2.93	2.70	2	2.46	2.87	1.82	3.04	3.31
$A+AB+C+C_q$	S + S + B + S	0.10	4	4.50	2	3	4	1.03	4.36	4.09
$A+AB+C+C_q$	S + S + B + S	0.25	4.51	4.50	2	3	3.97	1.01	4.47	4.28
$A+AB+C+C_q$	S + S + B + S	0.50	4.28	3.60	1.97	2.92	3.74	1.02	4.50	4.24
$A+AB+C+C_q$	S + S + B + S	0.75	2.98	2.77	1.85	2.42	2.95	1.06	3.17	3.43
$A+AB+C+C_q$	S + S + B + S	1	1.86	2.09	1.68	2.11	2.33	1.17	2.37	3.02
$A+AB+C+C_q$	S + S + S + S	0.10	4.22	4.59	2	3	4	1.65	4.76	4.19
$A+AB+C+C_q$	S + S + S + S	0.25	4.46	4.32	2	2.97	3.98	1.31	4.60	4.39
$A+AB+C+C_q$	S + S + S + S	0.50	3.93	3.19	1.97	2.71	3.60	1.38	4.10	4.03
$A+AB+C+C_q$	S + S + S + S	0.75	3.03	2.25	1.84	2.41	2.78	1.29	2.94	3.52
$A+AB+C+C_q$	S + S + S + S	1	2.59	1.87	1.71	2.18	2.51	1.46	2.55	3.35

Table 9: Number of Significant Effects for Wood Pulp Experiment in Chipman et al. (1997)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
A	B	0.10	1	2.36	1.94	2.97	3.97	1	11.79	1.43
A	B	0.25	1.05	2.48	1.97	2.98	3.96	1	12.51	2.11
A	B	0.50	1.30	2.08	1.94	2.95	3.90	1	12.05	2.53
A	B	0.75	1.50	1.83	1.94	2.95	3.94	1.01	12.41	2.70
A	B	1	1.77	2.11	1.99	2.97	3.93	1.13	11.94	2.94
A	S	0.10	1.07	1.77	1.92	2.96	3.91	1	11.95	2.55
A	S	0.25	1.49	2.01	1.98	2.97	3.96	1.12	12.03	3.57
A	S	0.50	1.80	1.64	1.97	2.96	3.99	1.07	11.31	3.52
A	S	0.75	1.77	1.62	1.99	2.98	3.97	1.13	11.81	3.43
A	S	1	2.56	1.42	1.98	2.93	3.97	1.09	12.42	3.15
$A+B$	B + B	0.10	2	3.37	2	3	3.99	1.92	13.60	2.21
$A+B$	B + B	0.25	2.11	3.62	2	2.99	3.98	1.90	13.20	2.63
$A+B$	B + B	0.50	2.61	3.35	2	2.94	3.93	1.86	13.19	2.99
$A+B$	B + B	0.75	2.71	2.97	2	2.97	3.98	1.67	13.66	3.17
$A+B$	B + B	1	2.27	2.54	1.99	2.96	3.95	1.55	12.65	2.62
$A+B$	B + S	0.10	1.87	3.63	2	2.97	3.95	1.02	13.63	2.35
$A+B$	B + S	0.25	1.73	2.63	2	2.98	4	1	12.31	2.73
$A+B$	B + S	0.50	1.58	2.77	1.95	2.98	3.99	1.05	13.52	2.91
$A+B$	B + S	0.75	1.55	2.51	1.98	2.99	3.94	1.02	12.30	2.95
$A+B$	B + S	1	1.79	1.94	1.91	2.95	3.97	1.07	12.73	2.81
$A+B$	S + S	0.10	2.10	3.16	2	2.98	3.96	1.43	12.56	2.94
$A+B$	S + S	0.25	2.32	2.80	1.98	2.98	3.99	1.19	12.49	3.74
$A+B$	S + S	0.50	1.86	2.06	1.98	2.97	3.97	1.13	12.22	3.67
$A+B$	S + S	0.75	2.05	1.46	1.96	2.98	3.96	1.06	11.46	3.53
$A+B$	S + S	1	1.81	1.63	1.94	2.93	3.91	1.11	11.28	2.77
$A+AB$	B + B	0.10	2	2.94	2	2.96	3.94	1.91	13.21	2.16
$A+AB$	B + B	0.25	2.09	2.96	2	2.95	3.93	1.92	12.72	2.42
$A+AB$	B + B	0.50	2.39	2.98	2	2.95	3.96	1.76	12.70	2.98
$A+AB$	B + B	0.75	2.74	2.80	2	2.97	3.93	1.56	13.25	3.06
$A+AB$	B + B	1	2.60	2.93	2	2.97	3.94	1.61	12.81	2.95
$A+AB$	B + S	0.10	1.87	3	2	2.93	3.97	1.01	12.94	2.29
$A+AB$	B + S	0.25	1.72	2.89	1.99	2.98	3.97	1	13.38	2.56
$A+AB$	B + S	0.50	1.57	2.44	1.97	2.94	3.98	1	12.36	2.92
$A+AB$	B + S	0.75	1.64	2.57	1.94	2.98	3.96	1.05	12.82	3.09
$A+AB$	B + S	1	1.49	2.05	1.94	2.93	3.95	1.12	12.69	2.64
$A+AB$	S + S	0.10	2.08	2.94	2	2.92	3.95	1.38	13.09	2.69
$A+AB$	S + S	0.25	2.39	2.44	1.98	2.97	3.97	1.19	13.28	3.56
$A+AB$	S + S	0.50	2.23	1.68	1.99	2.96	3.96	1.09	11.30	3.73
$A+AB$	S + S	0.75	1.91	1.54	1.97	2.95	3.91	1.05	11.30	3.29
$A+AB$	S + S	1	1.87	1.42	1.96	2.94	3.95	1.15	12.03	3.13

Table 9: Number of Significant Effects for Wood Pulp Experiment in Chipman et al. (1997)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$A+B+AB$	B + B + B	0.10	3	4.25	2	3	3.99	2.15	13.45	3.08
$A+B+AB$	B + B + B	0.25	3.15	4.22	2	3	3.99	2.06	13.55	3.30
$A+B+AB$	B + B + B	0.50	3.56	4.50	2	3	3.99	1.94	12.71	3.40
$A+B+AB$	B + B + B	0.75	3.74	3.86	2	3	4	1.75	12.80	3.32
$A+B+AB$	B + B + B	1	3.33	3.17	2	3	4	1.69	13.03	2.93
$A+B+AB$	B + B + S	0.10	2.75	4.26	2	3	3.98	1.97	13.96	2.85
$A+B+AB$	B + B + S	0.25	2.64	3.52	2	3	3.95	1.89	13.12	3.06
$A+B+AB$	B + B + S	0.50	2.56	3.39	2	2.99	3.95	1.79	13.40	3.16
$A+B+AB$	B + B + S	0.75	2.73	3.27	2	2.99	3.99	1.69	12.51	3.28
$A+B+AB$	B + B + S	1	2.76	3.28	2	2.99	4	1.69	13.47	3.05
$A+B+AB$	B + S + B	0.10	2.67	4.48	2	3	3.99	1.86	13.47	2.81
$A+B+AB$	B + S + B	0.25	2.50	3.74	2	3	3.99	1.85	13.97	2.98
$A+B+AB$	B + S + B	0.50	2.59	3.36	2	2.99	3.98	1.73	13.32	3.16
$A+B+AB$	B + S + B	0.75	2.56	2.72	1.99	2.96	3.98	1.66	13.55	3.15
$A+B+AB$	B + S + B	1	2.57	2.73	1.98	3	3.98	1.44	12.80	2.91
$A+B+AB$	B + S + S	0.10	2.65	4.11	2	3	4	1	14.16	2.97
$A+B+AB$	B + S + S	0.25	2.04	3.29	1.99	2.98	3.96	1	13.27	2.87
$A+B+AB$	B + S + S	0.50	1.85	2.75	1.98	2.96	3.95	1	12.51	3.29
$A+B+AB$	B + S + S	0.75	1.85	2.49	1.94	2.91	3.92	1.05	11.84	3.07
$A+B+AB$	B + S + S	1	1.96	2.04	1.98	2.93	3.90	1.04	11.53	2.72
$A+B+AB$	S + S + S	0.10	2.99	4.36	2	3	4	1.29	13.42	3.36
$A+B+AB$	S + S + S	0.25	2.68	3.35	2	2.99	3.99	1.23	13.72	4
$A+B+AB$	S + S + S	0.50	1.89	2.02	1.99	3	4	1.10	12.46	3.83
$A+B+AB$	S + S + S	0.75	1.66	1.70	1.96	2.97	3.94	1.16	11.69	3.50
$A+B+AB$	S + S + S	1	2.60	1.67	1.97	2.97	3.94	1.02	11.43	3.32
$A+B+C$	B + B + B	0.10	3.26	4.71	2	3	4	2.71	8.01	4.21
$A+B+C$	B + B + B	0.25	3.56	3.80	2	3	3.98	2.24	7.22	3.94
$A+B+C$	B + B + B	0.50	3.95	2.95	2	3	4	2.05	8.79	3.65
$A+B+C$	B + B + B	0.75	4.06	3.29	2	3	3.99	1.83	10.34	3.21
$A+B+C$	B + B + B	1	3.87	3.07	2	2.99	4	1.69	10.77	2.67
$A+B+C$	B + B + S	0.10	2.67	4.58	2	3	4	1.88	12.50	2.98
$A+B+C$	B + B + S	0.25	2.64	4.30	2	3	3.98	1.91	11.63	3.15
$A+B+C$	B + B + S	0.50	2.78	3.94	2	3	3.98	1.81	12.54	3.19
$A+B+C$	B + B + S	0.75	2.86	2.99	2	2.99	3.97	1.74	12.99	3.14
$A+B+C$	B + B + S	1	2.36	2.89	2	3	3.97	1.51	12.88	2.50
$A+B+C$	B + S + S	0.10	2.47	3.72	2	3	3.99	1.01	4.38	3.39
$A+B+C$	B + S + S	0.25	1.94	3.40	2	3	4	1.01	10.62	3.33
$A+B+C$	B + S + S	0.50	1.72	2.60	1.98	3	4	1.03	12.29	3.22
$A+B+C$	B + S + S	0.75	1.57	2.16	1.96	2.99	3.95	1.01	11.84	2.92
$A+B+C$	B + S + S	1	1.72	2.01	1.96	2.97	3.95	1.11	12.38	2.89

Table 9: Number of Significant Effects for Wood Pulp Experiment in Chipman et al. (1997)

Model	Size	σ	Lasso	Method 1	Method 2 $h=2$	Method 2 $h=3$	Method 2 $h=4$	Dantzig selector	LARS	Nonneg-Garotte
$A+B+C$	S + S + S	0.10	3.18	3.57	2	3	3.98	1.50	8.85	4.27
$A+B+C$	S + S + S	0.25	2.79	2.61	2	3	4	1.13	11.58	4.06
$A+B+C$	S + S + S	0.50	2.12	1.85	1.97	2.98	3.90	1.13	10.36	3.61
$A+B+C$	S + S + S	0.75	1.86	2.03	1.98	2.97	3.96	1.15	11.77	3.40
$A+B+C$	S + S + S	1	1.87	1.62	1.97	2.95	3.97	1.07	12.03	2.95
$A+B+AC$	B + B + B	0.10	3	4.32	2	3	3.99	1.95	13.17	2.89
$A+B+AC$	B + B + B	0.25	3.24	4.31	2	3	3.98	2.08	13.26	3.05
$A+B+AC$	B + B + B	0.50	3.71	4.15	1.99	3	3.98	1.80	13.85	3.27
$A+B+AC$	B + B + B	0.75	3.43	3.75	2	3	3.99	1.78	12.96	3.23
$A+B+AC$	B + B + B	1	2.95	3.12	1.99	3	4	1.66	13.01	2.62
$A+B+AC$	B + B + S	0.10	2.69	4.42	2	3	3.99	1.91	14.27	2.65
$A+B+AC$	B + B + S	0.25	2.60	3.95	2	3	3.99	1.87	13.70	2.79
$A+B+AC$	B + B + S	0.50	2.54	3.35	2	2.98	3.97	1.87	13.25	3.21
$A+B+AC$	B + B + S	0.75	2.73	3.76	2	3	3.98	1.72	13.07	3.03
$A+B+AC$	B + B + S	1	2.46	2.95	1.99	2.97	3.97	1.52	13	2.73
$A+B+AC$	B + S + B	0.10	2.61	4.08	2	3	3.99	1.89	12.89	2.71
$A+B+AC$	B + S + B	0.25	2.51	3.74	2	3	3.98	1.80	13.29	2.85
$A+B+AC$	B + S + B	0.50	2.53	3.03	2	2.96	3.98	1.72	13.52	3.11
$A+B+AC$	B + S + B	0.75	2.77	2.88	2	2.95	3.96	1.50	13.66	3.20
$A+B+AC$	B + S + B	1	2.66	2.57	2	2.96	3.97	1.43	12.99	2.68
$A+B+AC$	B + S + S	0.10	2.41	3.93	2	3	4	1.01	13.70	2.86
$A+B+AC$	B + S + S	0.25	1.91	3.37	2	3	3.98	1	14.60	2.79
$A+B+AC$	B + S + S	0.50	1.60	2.31	1.97	2.94	3.95	1.01	12.51	2.92
$A+B+AC$	B + S + S	0.75	1.62	2.18	1.97	2.98	3.97	1.06	12.05	3.06
$A+B+AC$	B + S + S	1	1.57	1.95	1.95	2.96	3.92	1.06	11.83	2.74
$A+B+AC$	S + B + S	0.10	2.58	3.85	2	3	3.97	1.01	13.03	2.53
$A+B+AC$	S + B + S	0.25	1.99	2.79	1.97	3	3.98	1.04	13.71	2.97
$A+B+AC$	S + B + S	0.50	1.77	2.18	1.96	2.99	3.97	1.03	13.19	2.77
$A+B+AC$	S + B + S	0.75	1.62	2.08	1.98	2.97	3.97	1.03	13.10	2.81
$A+B+AC$	S + B + S	1	1.98	2.01	1.93	2.99	3.98	1.12	11.97	2.50
$A+B+AC$	S + S + S	0.10	2.99	3.71	2	3	3.99	1.34	13.46	3.45
$A+B+AC$	S + S + S	0.25	2.16	2.64	1.98	2.99	3.98	1.27	13.69	3.87
$A+B+AC$	S + S + S	0.50	2.03	1.94	1.98	2.97	3.96	1.10	12.76	3.67
$A+B+AC$	S + S + S	0.75	1.95	1.57	1.99	2.96	3.94	1.08	10.77	3.37
$A+B+AC$	S + S + S	1	2.10	1.41	1.99	2.98	3.99	1.06	11.07	3.02
$A+E$	B + B	0.10	2	3.55	2	2.98	4	1.91	13.76	2.14
$A+E$	B + B	0.25	2.15	3.53	2	2.96	3.97	1.94	12.66	2.48
$A+E$	B + B	0.50	2.44	3.77	2	3	3.98	1.82	13.79	2.95
$A+E$	B + B	0.75	2.41	3.40	2	2.97	3.95	1.73	13.22	2.58
$A+E$	B + B	1	2.68	3.06	2	2.99	4	1.61	13.40	2.52

Table 9: Number of Significant Effects for Wood Pulp Experiment in Chipman et al. (1997)

Model	Size	σ	Lasso	Method 1	Method 2 $h=2$	Method 2 $h=3$	Method 2 $h=4$	Dantzig selector	LARS	Nonneg-Garotte
$A+E$	B + S	0.10	1.85	3.50	2	2.99	3.99	1.03	12.76	2.32
$A+E$	B + S	0.25	1.66	3.13	2	2.96	3.95	1.03	13.72	2.58
$A+E$	B + S	0.50	1.52	2.24	1.94	2.97	3.95	1.02	13.12	2.68
$A+E$	B + S	0.75	1.37	2.11	1.95	2.97	3.98	1.04	13.08	3.06
$A+E$	B + S	1	2.01	2.12	1.96	2.97	3.92	1.08	12.57	2.51
$A+E$	S + B	0.10	1.86	3.46	2	2.99	3.99	1.03	13.17	2.25
$A+E$	S + B	0.25	1.70	3.14	1.99	2.96	4	1.02	13.18	2.47
$A+E$	S + B	0.50	1.66	2.56	1.95	2.97	3.96	1.02	12.51	2.78
$A+E$	S + B	0.75	1.76	2.20	1.94	2.94	3.97	1.04	12.67	2.94
$A+E$	S + B	1	2	2.50	1.93	2.91	3.99	1.08	13.03	2.72
$A+E$	S + S	0.10	2.08	3.27	2	2.98	3.99	1.38	13.42	2.76
$A+E$	S + S	0.25	1.95	2.69	1.97	2.98	3.99	1.21	13.72	3.59
$A+E$	S + S	0.50	2.58	1.95	1.98	2.96	4	1.16	12.44	3.39
$A+E$	S + S	0.75	2.14	1.66	1.96	2.97	3.97	1.12	11.35	3.30
$A+E$	S + S	1	2.03	1.72	1.97	2.94	3.94	1.12	10.19	3.14
$A+E+E^2$	B + B + B	0.10	3	4.30	2	3	4	2.48	13.36	3.02
$A+E+E^2$	B + B + B	0.25	3.02	4.25	2	3	4	2.12	13.43	2.97
$A+E+E^2$	B + B + B	0.50	3.35	4.28	2	3	3.98	2.22	13.52	2.96
$A+E+E^2$	B + B + B	0.75	3.34	3.39	2	3	4	2.08	13.25	2.78
$A+E+E^2$	B + B + B	1	3.17	2.77	2	3	3.99	1.92	13.89	2.35
$A+E+E^2$	B + B + S	0.10	2.59	4.17	2	3	3.99	1.89	12.70	2.89
$A+E+E^2$	B + B + S	0.25	2.54	4.14	2	2.99	4	1.89	13.70	3.03
$A+E+E^2$	B + B + S	0.50	2.76	3.65	2	2.98	3.99	1.81	13.51	2.88
$A+E+E^2$	B + B + S	0.75	2.82	3.06	2	3	4	1.80	13.95	2.65
$A+E+E^2$	B + B + S	1	2.91	2.83	2	2.96	3.96	1.64	13.18	2.62
$A+E+E^2$	B + S + S	0.10	2.39	4.06	2	3	4	1.34	13.22	2.88
$A+E+E^2$	B + S + S	0.25	2.08	2.09	2	3	3.97	1.13	13.48	2.57
$A+E+E^2$	B + S + S	0.50	1.96	2.09	2	3	3.99	1.14	13.91	3
$A+E+E^2$	B + S + S	0.75	2.17	2.26	1.99	2.97	3.96	1.16	12.60	3
$A+E+E^2$	B + S + S	1	2.18	2.22	2	3	4	1.25	12.81	2.71
$A+E+E^2$	S + B + B	0.10	2.51	4.60	2	3	3.97	1.92	13.20	2.87
$A+E+E^2$	S + B + B	0.25	2.50	3.99	2	3	3.98	1.80	13.82	2.95
$A+E+E^2$	S + B + B	0.50	2.49	2.93	2	2.98	3.96	1.48	12.46	2.70
$A+E+E^2$	S + B + B	0.75	2.60	2.61	2	2.95	3.95	1.45	12.58	2.57
$A+E+E^2$	S + B + B	1	2.78	2.04	1.99	2.99	3.97	1.44	12.85	2.09
$A+E+E^2$	S + B + S	0.10	2.45	4.85	2	3	4	1	13.84	2.92
$A+E+E^2$	S + B + S	0.25	2.15	3.33	2	3	4	1.02	13.11	2.74
$A+E+E^2$	S + B + S	0.50	1.82	2.67	1.98	2.95	3.94	1.09	13.30	2.86
$A+E+E^2$	S + B + S	0.75	2.02	2.19	1.96	2.94	3.98	1.13	13.88	2.98
$A+E+E^2$	S + B + S	1	2.36	2.08	1.95	2.97	3.97	1.11	12.80	2.58

Table 9: Number of Significant Effects for Wood Pulp Experiment in Chipman et al. (1997)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$A+E+E^2$	S + S + S	0.10	2.86	4.24	2	3	4	1.64	13.82	3.19
$A+E+E^2$	S + S + S	0.25	3	2.57	2	2.99	4	1.33	13.57	3.64
$A+E+E^2$	S + S + S	0.50	2.35	1.86	1.97	2.97	3.98	1.17	12.81	3.42
$A+E+E^2$	S + S + S	0.75	2.57	1.73	1.95	2.97	3.98	1.19	12.25	3.08
$A+E+E^2$	S + S + S	1	1.95	1.41	1.95	2.92	3.91	1.07	11.73	2.85
$A+E+EI$	B + B + B	0.10	3	4.45	2	3	3.98	1.17	9.96	2.93
$A+E+EI$	B + B + B	0.25	3.05	4.60	2	3	4	1.12	7.93	2.90
$A+E+EI$	B + B + B	0.50	3.43	3.89	2	3	3.99	1.10	9.99	2.55
$A+E+EI$	B + B + B	0.75	3.30	3.61	2	3	3.98	1.15	10.25	2.21
$A+E+EI$	B + B + B	1	2.83	3.41	2	2.99	3.96	1.21	10.65	1.91
$A+E+EI$	B + B + S	0.10	2.86	4.23	2	3	3.98	1.86	14.61	2.84
$A+E+EI$	B + B + S	0.25	2.57	4.04	2	3	3.97	1.89	14.15	2.77
$A+E+EI$	B + B + S	0.50	2.78	3.77	2	3	4	1.78	13.54	2.62
$A+E+EI$	B + B + S	0.75	2.56	3.69	2	2.97	3.96	1.69	13.94	2.70
$A+E+EI$	B + B + S	1	2.44	3.04	2	2.99	4	1.46	13.14	2.31
$A+E+EI$	B + S + S	0.10	2.30	4.22	2	3	3.99	1	14.45	3.04
$A+E+EI$	B + S + S	0.25	1.67	3.06	1.99	3	3.99	1	13.76	2.44
$A+E+EI$	B + S + S	0.50	1.67	2.40	1.99	3	3.98	1	13.07	2.66
$A+E+EI$	B + S + S	0.75	1.58	2.15	1.97	2.99	3.99	1.04	13.10	2.75
$A+E+EI$	B + S + S	1	1.98	2.25	1.95	2.96	3.92	1.05	12.75	2.50
$A+E+EI$	S + B + B	0.10	2.74	4.52	2	3	3.99	1	8.21	2.32
$A+E+EI$	S + B + B	0.25	2.75	3.80	2	3	3.99	1	9.67	2.35
$A+E+EI$	S + B + B	0.50	3.05	3.45	2	2.95	3.94	1.06	7.40	2.42
$A+E+EI$	S + B + B	0.75	2.83	3	2	2.98	3.99	1.04	9.50	2.19
$A+E+EI$	S + B + B	1	2.70	2.45	2	3	3.95	1.09	10.02	2.05
$A+E+EI$	S + B + S	0.10	2.78	4.45	2	3	4	1	14.79	2.69
$A+E+EI$	S + B + S	0.25	2.28	3.96	2	2.99	4	1.01	14.71	2.78
$A+E+EI$	S + B + S	0.50	1.96	3.08	2	3	3.98	1.02	14.10	2.80
$A+E+EI$	S + B + S	0.75	2.18	2.29	1.96	2.94	3.93	1.09	12.56	2.67
$A+E+EI$	S + B + S	1	1.81	2.12	1.99	2.97	3.99	1.11	13.38	2.49
$A+E+EI$	S + S + S	0.10	2.91	3.94	2	3	3.99	1.05	10.48	3.44
$A+E+EI$	S + S + S	0.25	2.10	2.82	2	2.99	3.98	1.07	11.40	3.30
$A+E+EI$	S + S + S	0.50	2.27	1.77	2	3	3.99	1.09	11.58	3.50
$A+E+EI$	S + S + S	0.75	2.21	1.55	1.97	3	4	1.07	10.83	3.10
$A+E+EI$	S + S + S	1	2.26	1.41	1.99	2.95	3.95	1.11	12.38	3.14

Table 9: Number of Significant Effects for Wood Pulp Experiment in Chipman et al. (1997)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h = 2$	$h = 3$	$h = 4$	selector		Garotte
$A + E + AE$	B + B + B	0.10	3	4.29	2	3	3.98	2.66	13.33	2.98
$A + E + AE$	B + B + B	0.25	3.08	4.54	2	3	3.97	2.65	14.17	3.16
$A + E + AE$	B + B + B	0.50	3.59	4.12	2	3	4	2.42	13.56	3.36
$A + E + AE$	B + B + B	0.75	3.74	3.97	2	2.99	3.99	2.33	13.58	3.14
$A + E + AE$	B + B + B	1	3.54	3.71	2	2.99	3.95	2.14	12.99	2.73
$A + E + AE$	B + B + S	0.10	2.75	4.53	2	3	3.98	1.95	13.08	2.98
$A + E + AE$	B + B + S	0.25	2.69	3.76	2	2.98	3.99	1.87	14.14	2.83
$A + E + AE$	B + B + S	0.50	2.80	3.45	2	3	4	1.85	13.65	2.93
$A + E + AE$	B + B + S	0.75	2.75	3.31	2	2.98	3.99	1.68	14.16	2.80
$A + E + AE$	B + B + S	1	2.62	3.15	1.99	2.97	3.99	1.64	13.52	2.38
$A + E + AE$	B + S + S	0.10	2.66	4.18	2	3	3.99	1.01	13.20	3.12
$A + E + AE$	B + S + S	0.25	2.09	3.03	1.99	3	3.98	1.01	13.13	2.88
$A + E + AE$	B + S + S	0.50	1.81	2.41	1.99	2.98	3.98	1.01	13.33	3.03
$A + E + AE$	B + S + S	0.75	1.77	2.45	1.95	2.99	3.97	1.05	13.44	3.06
$A + E + AE$	B + S + S	1	1.60	2.06	1.99	2.99	3.96	1.13	12.47	2.67
$A + E + AE$	B + S + B	0.10	2.68	4.47	2	3	3.99	1.99	13.71	2.91
$A + E + AE$	B + S + B	0.25	2.48	3.77	2	3	3.98	1.95	13.10	2.73
$A + E + AE$	B + S + B	0.50	2.29	3.10	2	2.95	3.98	1.86	13.46	2.93
$A + E + AE$	B + S + B	0.75	2.69	3.08	2	2.97	3.98	1.66	12.94	3.02
$A + E + AE$	B + S + B	1	2.82	2.39	1.99	2.98	3.97	1.56	13.32	2.80
$A + E + AE$	S + B + B	0.10	2.75	4.33	2	3	4	2	13.82	2.73
$A + E + AE$	S + B + B	0.25	2.71	4.11	2	3	3.99	1.93	13.94	2.67
$A + E + AE$	S + B + B	0.50	3.17	3.23	2	2.97	3.99	1.85	13.34	2.79
$A + E + AE$	S + B + B	0.75	3.23	3.15	2	2.94	4	1.70	13.64	2.93
$A + E + AE$	S + B + B	1	2.99	2.60	2	2.94	3.97	1.45	13.27	2.43
$A + E + AE$	S + B + S	0.10	2.76	4.42	2	3	3.95	1.15	12.70	3.07
$A + E + AE$	S + B + S	0.25	2.69	4.01	2	2.99	3.99	1.05	13.20	2.99
$A + E + AE$	S + B + S	0.50	2.32	3.06	1.98	2.99	4	1.08	12.30	2.90
$A + E + AE$	S + B + S	0.75	2.21	2.25	1.98	2.95	3.97	1.15	13.13	2.98
$A + E + AE$	S + B + S	1	1.99	2.03	1.98	3	3.97	1.18	13.40	2.58
$A + E + AE$	S + S + S	0.10	3.01	4.40	2	3	3.97	1.76	14.05	3.40
$A + E + AE$	S + S + S	0.25	2.81	3.29	2	2.99	4	1.42	13.72	3.78
$A + E + AE$	S + S + S	0.50	2.49	1.99	2	2.99	3.95	1.15	13.19	3.60
$A + E + AE$	S + S + S	0.75	1.75	1.88	1.98	2.99	3.94	1.14	12.42	3.13
$A + E + AE$	S + S + S	1	1.83	1.57	1.98	2.99	3.93	1.09	11.70	3.22

Table 10: Number of Significant Effects for Ceramics Experiment in Yuan (1998)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
A	B	0.10	1	1.50	1.38	1.59	1.67	1	1.40	1.52
A	B	0.25	1.04	1.78	1.40	1.79	1.91	1	1.59	1.82
A	B	0.50	1.30	1.68	1.43	1.84	2.06	1	1.70	2.21
A	B	0.75	1.28	1.65	1.40	1.63	1.77	1	1.40	2.40
A	B	1	1.39	1.70	1.41	1.66	1.83	1.03	1.54	2.77
A	S	0.10	1.25	1.75	1.38	1.80	1.96	1	1.68	1.95
A	S	0.25	1.41	1.71	1.40	1.71	1.85	1.01	1.57	2.01
A	S	0.50	1.59	1.52	1.46	1.72	1.91	1.10	1.63	2.63
A	S	0.75	1.38	1.31	1.37	1.59	1.66	1.15	1.50	2.52
A	S	1	1.59	1.32	1.39	1.54	1.67	1.26	1.62	2.50
B	B	0.10	1	1.76	1.48	1.76	1.85	1	1.53	1.77
B	B	0.25	1.05	1.54	1.33	1.60	1.71	1	1.48	1.72
B	B	0.50	1.28	1.56	1.37	1.56	1.65	1	1.42	2.07
B	B	0.75	1.34	1.60	1.38	1.65	1.76	1	1.51	2.55
B	B	1	1.47	1.77	1.50	1.83	1.96	1.07	1.63	2.79
B	S	0.10	1.20	1.65	1.49	1.61	1.68	1	1.44	1.83
B	S	0.25	1.42	1.59	1.39	1.66	1.74	1.01	1.54	2.22
B	S	0.50	1.42	1.52	1.47	1.69	1.73	1.24	1.59	2.67
B	S	0.75	1.53	1.30	1.37	1.57	1.62	1.22	1.51	2.50
B	S	1	1.43	1.37	1.44	1.65	1.79	1.34	1.76	2.48
$A+B$	B + B	0.10	2	2.75	2	2.42	2.72	1.90	3.38	2.29
$A+B$	B + B	0.25	2.08	2.69	2	2.50	2.71	1.81	3.27	2.61
$A+B$	B + B	0.50	2.24	2.77	2	2.53	2.80	1.82	3.28	2.73
$A+B$	B + B	0.75	2.37	2.60	2	2.35	2.69	1.82	3.24	2.92
$A+B$	B + B	1	2.49	2.91	2	2.54	2.83	1.74	3.16	3.16
$A+B$	B + S	0.10	1.90	2.76	2	2.49	2.73	1	3.34	2.44
$A+B$	B + S	0.25	2.30	2.82	2	2.51	2.75	1	3.33	2.68
$A+B$	B + S	0.50	2.19	2.53	1.83	2.37	2.56	1	2.63	2.78
$A+B$	B + S	0.75	1.74	2.08	1.66	1.98	2.25	1	2.08	2.75
$A+B$	B + S	1	1.38	1.75	1.45	1.82	1.93	1.05	1.64	2.75
$A+B$	S + S	0.10	2.22	2.70	2	2.47	2.69	1.33	3.21	2.58
$A+B$	S + S	0.25	2.50	2.75	2	2.51	2.76	1.26	3.18	2.81
$A+B$	S + S	0.50	2.32	2.34	1.79	2.41	2.65	1.20	2.29	3.02
$A+B$	S + S	0.75	1.74	1.70	1.56	1.90	2.12	1.26	1.86	2.83
$A+B$	S + S	1	1.55	1.52	1.47	1.70	1.80	1.30	1.69	2.60
$A+AB$	B + B	0.10	2	2.55	2	2.31	2.59	1.84	3.01	2.23
$A+AB$	B + B	0.25	2.05	2.48	2	2.34	2.59	1.83	3.09	2.53
$A+AB$	B + B	0.50	2.33	2.64	2	2.39	2.76	1.78	3.27	2.71
$A+AB$	B + B	0.75	2.58	2.51	2	2.32	2.66	1.83	3.11	2.82
$A+AB$	B + B	1	2.56	2.59	1.99	2.41	2.69	1.83	3.22	3.08

Table 10: Number of Significant Effects for Ceramics Experiment in Yuan (1998)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$A+AB$	B + S	0.10	1.91	2.69	2	2.42	2.75	1	3.41	2.49
$A+AB$	B + S	0.25	2.07	2.65	1.99	2.41	2.66	1	3.18	2.72
$A+AB$	B + S	0.50	2.15	2.42	1.85	2.25	2.57	1	2.52	2.83
$A+AB$	B + S	0.75	1.77	2.10	1.65	2.03	2.27	1	1.94	2.67
$A+AB$	B + S	1	1.62	1.82	1.52	1.78	2.03	1.06	1.79	3.04
$A+AB$	S + S	0.10	2.16	2.50	2	2.31	2.66	1.40	3.09	2.55
$A+AB$	S + S	0.25	2.48	2.66	2	2.41	2.68	1.31	3.02	2.69
$A+AB$	S + S	0.50	2.22	2.27	1.82	2.23	2.52	1.18	2.49	2.99
$A+AB$	S + S	0.75	1.68	1.60	1.59	1.94	2.01	1.24	1.83	2.82
$A+AB$	S + S	1	1.57	1.28	1.49	1.69	1.83	1.22	1.79	2.74
$B+AB$	B + B	0.10	2	2.67	2	2.44	2.71	1.86	3.69	2.39
$B+AB$	B + B	0.25	2.07	2.64	2	2.47	2.76	1.94	3.65	2.74
$B+AB$	B + B	0.50	2.29	2.63	2	2.43	2.74	1.90	3.52	2.75
$B+AB$	B + B	0.75	2.42	2.61	2	2.37	2.64	1.92	3.52	2.86
$B+AB$	B + B	1	2.37	2.51	2	2.36	2.56	1.82	3.44	3.12
$B+AB$	B + S	0.10	1.98	2.56	2	2.38	2.65	1.01	3.50	2.43
$B+AB$	B + S	0.25	2.27	2.63	1.99	2.40	2.70	1	3.31	2.62
$B+AB$	B + S	0.50	1.99	2.20	1.80	2.16	2.41	1	2.46	2.72
$B+AB$	B + S	0.75	1.66	1.98	1.64	1.91	2.10	1.02	1.99	2.87
$B+AB$	B + S	1	1.53	1.82	1.48	1.77	2	1.09	1.63	3.02
$B+AB$	S + S	0.10	2.26	2.62	2	2.39	2.59	1.35	3.48	2.59
$B+AB$	S + S	0.25	2.46	2.55	2	2.37	2.72	1.36	3.17	2.76
$B+AB$	S + S	0.50	2.30	1.89	1.85	2.19	2.52	1.21	2.29	2.88
$B+AB$	S + S	0.75	1.85	1.58	1.66	1.99	2.10	1.22	1.81	2.91
$B+AB$	S + S	1	1.76	1.46	1.62	1.83	2.01	1.29	1.79	2.71
$A+B+AB$	B + B + B	0.10	3	3.75	2	3	3.51	2.73	3.58	3.06
$A+B+AB$	B + B + B	0.25	3.03	3.56	2	3	3.40	2.59	3.49	3.34
$A+B+AB$	B + B + B	0.50	3.34	3.67	2	3	3.50	2.65	3.48	3.61
$A+B+AB$	B + B + B	0.75	3.36	3.62	2	3	3.42	2.48	3.57	3.60
$A+B+AB$	B + B + B	1	3.49	3.77	2	2.99	3.47	2.59	3.58	3.77
$A+B+AB$	B + B + S	0.10	2.98	3.57	2	3	3.43	1.87	3.26	3.18
$A+B+AB$	B + B + S	0.25	3.09	3.80	2	3	3.51	1.87	3.32	3.47
$A+B+AB$	B + B + S	0.50	3.18	3.59	2	2.85	3.35	1.85	3.32	3.46
$A+B+AB$	B + B + S	0.75	2.86	3.14	2	2.73	3.05	1.84	3.18	3.19
$A+B+AB$	B + B + S	1	2.77	3.16	2	2.66	3.08	1.84	3.22	3.49
$A+B+AB$	B + S + B	0.10	2.95	3.84	2	3	3.49	1.91	3.67	3.21
$A+B+AB$	B + S + B	0.25	3.20	3.61	2	3	3.43	1.85	3.70	3.36
$A+B+AB$	B + S + B	0.50	2.95	3.29	2	2.81	3.18	1.88	3.28	3.29
$A+B+AB$	B + S + B	0.75	2.81	3.09	2	2.64	3.03	1.75	3.27	3.19
$A+B+AB$	B + S + B	1	2.62	2.87	2	2.57	2.86	1.83	3.04	3.22

Table 10: Number of Significant Effects for Ceramics Experiment in Yuan (1998)

Model	Size	σ	Lasso	Method 1	Method 2 $h=2$	Method 2 $h=3$	Method 2 $h=4$	Dantzig selector	LARS	Nonneg-Garotte
$A+B+AB$	B + S + S	0.10	3	3.69	2	3	3.46	1	3.46	3.22
$A+B+AB$	B + S + S	0.25	3.43	3.64	2	2.98	3.43	1	3.30	3.47
$A+B+AB$	B + S + S	0.50	2.88	3.09	1.97	2.64	3.13	1	3.25	3.30
$A+B+AB$	B + S + S	0.75	1.94	2.59	1.83	2.37	2.69	1.03	2.46	2.99
$A+B+AB$	B + S + S	1	1.89	2.16	1.65	2.14	2.37	1.08	2.14	3.02
$A+B+AB$	S + B + B	0.10	3	3.68	2	3	3.48	1.96	3.55	3.20
$A+B+AB$	S + B + B	0.25	3.28	3.64	2	2.99	3.40	1.89	3.59	3.41
$A+B+AB$	S + B + B	0.50	3.03	3.32	2	2.83	3.23	1.85	3.52	3.44
$A+B+AB$	S + B + B	0.75	3.02	3.36	2	2.75	3.21	1.85	3.34	3.42
$A+B+AB$	S + B + B	1	2.74	2.91	2	2.55	2.93	1.85	3.35	3.38
$A+B+AB$	S + B + S	0.10	3	3.64	2	3	3.47	1.06	3.26	3.32
$A+B+AB$	S + B + S	0.25	3.38	3.52	2	2.96	3.35	1	3.40	3.50
$A+B+AB$	S + B + S	0.50	3.27	3.39	1.97	2.80	3.22	1	3.31	3.48
$A+B+AB$	S + B + S	0.75	2.40	2.67	1.86	2.46	2.71	1.05	2.75	3.26
$A+B+AB$	S + B + S	1	2.12	2.32	1.70	2.16	2.48	1.18	2.19	3.20
$A+B+AB$	S + S + S	0.10	3.17	3.66	2	3	3.44	1.75	3.61	3.42
$A+B+AB$	S + S + S	0.25	3.39	3.52	2	2.96	3.35	1.46	3.61	3.46
$A+B+AB$	S + S + S	0.50	2.88	2.86	1.91	2.57	2.87	1.31	2.75	3.36
$A+B+AB$	S + S + S	0.75	2.08	2.10	1.73	2.15	2.28	1.26	2.12	3.18
$A+B+AB$	S + S + S	1	1.80	1.67	1.62	1.91	1.99	1.35	1.77	2.98
$A+B+C$	B + B + B	0.10	3	3.82	2	3	3.51	2.56	5.52	3.17
$A+B+C$	B + B + B	0.25	3.07	3.69	2	3	3.47	2.60	5.40	3.44
$A+B+C$	B + B + B	0.50	3.48	3.89	2	3	3.58	2.63	5.37	3.57
$A+B+C$	B + B + B	0.75	3.68	3.90	2	3	3.57	2.57	5.41	3.70
$A+B+C$	B + B + B	1	3.59	3.73	2	3	3.46	2.52	5.08	3.62
$A+B+C$	B + B + S	0.10	2.96	3.86	2	3	3.57	1.78	5.46	3.16
$A+B+C$	B + B + S	0.25	3.23	3.81	2	2.98	3.55	1.78	5.21	3.49
$A+B+C$	B + B + S	0.50	3.41	3.58	2	2.88	3.46	1.82	4.28	3.47
$A+B+C$	B + B + S	0.75	2.95	3.26	2	2.74	3.12	1.79	3.47	3.31
$A+B+C$	B + B + S	1	2.72	3.03	1.99	2.62	2.90	1.75	3.42	3.29
$A+B+C$	B + S + S	0.10	2.90	3.69	2	3	3.46	1	5.37	3.27
$A+B+C$	B + S + S	0.25	3.30	3.77	2	2.98	3.53	1	4.52	3.63
$A+B+C$	B + S + S	0.50	2.84	3.10	1.91	2.63	3.01	1	3.11	3.21
$A+B+C$	B + S + S	0.75	2.26	2.54	1.79	2.37	2.76	1	2.57	3.14
$A+B+C$	B + S + S	1	1.76	2.21	1.64	2.08	2.42	1.07	2.14	3.26
$A+B+C$	S + S + S	0.10	3.25	3.83	2	3	3.56	1.63	5.28	3.47
$A+B+C$	S + S + S	0.25	3.85	3.83	2	2.98	3.59	1.42	4.88	3.70
$A+B+C$	S + S + S	0.50	2.83	2.97	1.89	2.60	3.05	1.27	2.95	3.39
$A+B+C$	S + S + S	0.75	2.20	2.19	1.72	2.13	2.38	1.32	2.25	3.05
$A+B+C$	S + S + S	1	1.55	1.65	1.45	1.77	1.93	1.48	1.71	2.89

Table 10: Number of Significant Effects for Ceramics Experiment in Yuan (1998)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$A+B+AC$	B + B + B	0.10	3	3.78	2	3	3.45	2.63	4.65	3.23
$A+B+AC$	B + B + B	0.25	3.07	3.77	2	3	3.55	2.56	4.68	3.42
$A+B+AC$	B + B + B	0.50	3.38	3.80	2	3	3.48	2.52	4.85	3.51
$A+B+AC$	B + B + B	0.75	3.42	3.66	2	3	3.48	2.59	4.53	3.51
$A+B+AC$	B + B + B	1	3.36	3.53	2	2.99	3.39	2.39	4.48	3.52
$A+B+AC$	B + B + S	0.10	2.96	3.68	2	3	3.47	1.85	4.65	3.21
$A+B+AC$	B + B + S	0.25	3.30	4	2	2.99	3.60	1.83	4.76	3.44
$A+B+AC$	B + B + S	0.50	3.14	3.55	2	2.85	3.35	1.80	3.76	3.26
$A+B+AC$	B + B + S	0.75	2.75	3.20	2	2.72	3.14	1.87	3.39	3.19
$A+B+AC$	B + B + S	1	2.72	3.03	2	2.63	2.96	1.80	3.19	3.30
$A+B+AC$	B + S + B	0.10	2.95	3.92	2	3	3.60	1.89	4.93	3.17
$A+B+AC$	B + S + B	0.25	3.21	3.54	2	3	3.41	1.86	4.70	3.27
$A+B+AC$	B + S + B	0.50	3.06	3.31	2	2.79	3.21	1.83	4.16	3.25
$A+B+AC$	B + S + B	0.75	2.80	3	2	2.57	3	1.77	3.32	3.15
$A+B+AC$	B + S + B	1	2.71	2.88	2	2.55	2.85	1.86	3.29	3.15
$A+B+AC$	B + S + S	0.10	2.99	3.62	2	3	3.43	1	5.50	3.24
$A+B+AC$	B + S + S	0.25	3.30	3.74	2	2.98	3.48	1	4.98	3.41
$A+B+AC$	B + S + S	0.50	2.63	3.07	1.94	2.66	2.94	1	3.37	3.10
$A+B+AC$	B + S + S	0.75	2.29	2.63	1.80	2.36	2.63	1	2.48	3.04
$A+B+AC$	B + S + S	1	1.72	2.16	1.56	2.02	2.26	1.05	1.97	2.93
$A+B+AC$	S + B + S	0.10	3.02	3.90	2	3	3.57	1.03	3.45	3.23
$A+B+AC$	S + B + S	0.25	3.48	3.68	2	2.98	3.46	1	3.35	3.39
$A+B+AC$	S + B + S	0.50	3.06	3.39	1.97	2.84	3.23	1	3.19	3.37
$A+B+AC$	S + B + S	0.75	2.23	2.61	1.78	2.46	2.81	1.03	2.59	3.20
$A+B+AC$	S + B + S	1	1.89	2.27	1.63	2.12	2.37	1.08	2.27	3.10
$A+B+AC$	S + S + S	0.10	3.21	3.72	2	3	3.48	1.48	4.58	3.27
$A+B+AC$	S + S + S	0.25	3.56	3.68	2	3	3.49	1.37	4.26	3.62
$A+B+AC$	S + S + S	0.50	2.73	2.73	1.91	2.69	3.02	1.32	2.96	3.36
$A+B+AC$	S + S + S	0.75	1.95	2.02	1.70	2.11	2.25	1.36	1.96	2.87
$A+B+AC$	S + S + S	1	1.65	1.60	1.60	1.95	2.26	1.37	2.11	3.01
$B+B_q$	B + B	0.10	2	2.68	2	2.45	2.76	1.66	2.35	2.17
$B+B_q$	B + B	0.25	2.03	2.59	2	2.38	2.59	1.70	2.38	2.31
$B+B_q$	B + B	0.50	2.28	2.57	2	2.40	2.62	1.59	2.24	2.57
$B+B_q$	B + B	0.75	2.35	2.58	2	2.38	2.61	1.60	2.26	2.75
$B+B_q$	B + B	1	2.41	2.52	2	2.39	2.79	1.56	2.40	2.94

Table 10: Number of Significant Effects for Ceramics Experiment in Yuan (1998)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$B+B_q$	B + S	0.10	2	2.73	2	2.54	2.78	1.27	2.14	2.48
$B+B_q$	B + S	0.25	2.33	2.66	2	2.42	2.71	1.07	2.37	2.63
$B+B_q$	B + S	0.50	2.10	2.39	2	2.34	2.51	1.03	2.18	2.60
$B+B_q$	B + S	0.75	2.18	2.28	1.88	2.25	2.56	1.05	2.34	2.98
$B+B_q$	B + S	1	2.07	2.17	1.74	2.14	2.38	1.17	2.29	3.19
$B+B_q$	S + S	0.10	2.18	2.70	2	2.39	2.67	1.32	2.40	2.43
$B+B_q$	S + S	0.25	2.55	2.67	2	2.49	2.76	1.04	2.44	2.82
$B+B_q$	S + S	0.50	2.32	2.09	1.97	2.27	2.45	1.13	2.09	2.70
$B+B_q$	S + S	0.75	2.31	1.68	1.86	2.20	2.40	1.08	2.38	3.04
$B+B_q$	S + S	1	2.04	1.35	1.74	2.02	2.27	1.21	2.15	2.92
$B+B_q+C+C_q$	B + B + B + B	0.10	4	4.90	2	3	4	1.71	4.44	4
$B+B_q+C+C_q$	B + B + B + B	0.25	4.09	4.72	2	3	4	1.76	4.88	4.04
$B+B_q+C+C_q$	B + B + B + B	0.50	4.23	4.73	2	3	4	1.66	4.98	4.13
$B+B_q+C+C_q$	B + B + B + B	0.75	4.61	4.97	2	3	4	1.74	4.90	4.25
$B+B_q+C+C_q$	B + B + B + B	1	4.87	5.10	2	3	4	1.83	4.91	4.27
$B+B_q+C+C_q$	B + B + B + S	0.10	4	4.80	2	3	4	1.83	6.18	3.99
$B+B_q+C+C_q$	B + B + B + S	0.25	4.19	4.65	2	3	4	2.01	6.46	4.01
$B+B_q+C+C_q$	B + B + B + S	0.50	4.48	4.73	2	3	3.99	1.99	6.24	4
$B+B_q+C+C_q$	B + B + B + S	0.75	4.33	4.47	2	3	3.90	2.15	5.31	3.98
$B+B_q+C+C_q$	B + B + B + S	1	4.04	4.30	2	3	3.75	2.03	4.72	3.78
$B+B_q+C+C_q$	B + B + S + S	0.10	4	4.55	2	3	4	1.65	4.85	4
$B+B_q+C+C_q$	B + B + S + S	0.25	4.17	4.56	2	2.99	4	1.55	5.30	3.99
$B+B_q+C+C_q$	B + B + S + S	0.50	4.25	3.89	2	2.82	3.94	1.53	5.04	3.83
$B+B_q+C+C_q$	B + B + S + S	0.75	3.56	3.58	2	2.69	3.77	1.63	4.16	3.58
$B+B_q+C+C_q$	B + B + S + S	1	3.38	3.25	2	2.53	3.39	1.45	3.30	3.31
$B+B_q+C+C_q$	B + S + B + S	0.10	4.03	4.87	2	3	4	1.98	7.27	4.04
$B+B_q+C+C_q$	B + S + B + S	0.25	4.44	4.74	2	3	4	1.95	7.27	4.19
$B+B_q+C+C_q$	B + S + B + S	0.50	4.50	4.60	2	3	3.96	1.93	5.59	4.09
$B+B_q+C+C_q$	B + S + B + S	0.75	4.16	4.14	2	2.99	3.86	1.97	4.92	3.90
$B+B_q+C+C_q$	B + S + B + S	1	3.79	3.90	1.99	2.93	3.61	2.04	4.43	3.81
$B+B_q+C+C_q$	B + S + S + S	0.10	4.01	4.82	2	3	4	1.03	7.49	4.05
$B+B_q+C+C_q$	B + S + S + S	0.25	4.40	4.33	2	2.98	4	1.01	6.95	4.05
$B+B_q+C+C_q$	B + S + S + S	0.50	4.29	3.66	1.98	2.82	3.85	1.02	5.28	3.90
$B+B_q+C+C_q$	B + S + S + S	0.75	3.20	3.21	1.88	2.84	3.70	1.05	3.89	3.83
$B+B_q+C+C_q$	B + S + S + S	1	2.63	2.69	1.83	2.61	3.28	1.13	3.11	3.54
$B+B_q+C+C_q$	S + S + S + S	0.10	4.11	5	2	3	4	1.15	4.81	4.05
$B+B_q+C+C_q$	S + S + S + S	0.25	4.81	4.62	2	2.99	4	1.09	5.03	4.14
$B+B_q+C+C_q$	S + S + S + S	0.50	4.72	3.77	2	2.94	3.88	1.08	4.81	3.94
$B+B_q+C+C_q$	S + S + S + S	0.75	3.24	2.42	1.93	2.70	3.45	1.15	3.46	3.69
$B+B_q+C+C_q$	S + S + S + S	1	3	2.14	1.88	2.55	3.03	1.23	2.75	3.46

Table 10: Number of Significant Effects for Ceramics Experiment in Yuan (1998)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$B+BC+B_q$	B + B + B	0.10	3	3.53	2	3	3.38	2.03	4.13	3.04
$B+BC+B_q$	B + B + B	0.25	3.10	3.46	2	3	3.36	1.89	4.45	3.11
$B+BC+B_q$	B + B + B	0.50	3.20	3.39	2	3	3.35	1.99	4.34	3.26
$B+BC+B_q$	B + B + B	0.75	3.43	3.65	2	3	3.42	1.83	4.73	3.36
$B+BC+B_q$	B + B + B	1	3.61	3.51	2	2.99	3.32	1.90	4.41	3.49
$B+BC+B_q$	B + B + S	0.10	3	3.69	2	3	3.44	1.86	4.20	3.16
$B+BC+B_q$	B + B + S	0.25	3.15	3.47	2	3	3.31	1.94	5.17	3.18
$B+BC+B_q$	B + B + S	0.50	3.41	3.56	2	2.99	3.37	1.78	4.82	3.33
$B+BC+B_q$	B + B + S	0.75	3.20	3.31	2	2.85	3.31	1.81	4.19	3.35
$B+BC+B_q$	B + B + S	1	3.12	3.08	2	2.77	3.08	1.91	3.82	3.35
$B+BC+B_q$	B + S + B	0.10	2.75	3.47	2	3	3.34	1.61	4.40	3.18
$B+BC+B_q$	B + S + B	0.25	2.83	3.37	2	2.95	3.33	1.57	4.53	3.12
$B+BC+B_q$	B + S + B	0.50	2.76	3.20	2	2.79	3.11	1.55	3.26	2.99
$B+BC+B_q$	B + S + B	0.75	2.55	2.90	2	2.62	3.03	1.58	2.63	3.05
$B+BC+B_q$	B + S + B	1	2.59	2.77	2	2.51	2.93	1.63	2.61	3.31
$B+BC+B_q$	B + S + S	0.10	3.03	3.59	2	3	3.42	1.20	5.45	3.18
$B+BC+B_q$	B + S + S	0.25	3.32	3.48	2	2.96	3.39	1.07	4.91	3.32
$B+BC+B_q$	B + S + S	0.50	2.89	3.25	1.99	2.76	3.22	1.08	3.09	3.32
$B+BC+B_q$	B + S + S	0.75	2.40	2.86	1.92	2.56	2.91	1.08	2.71	3.20
$B+BC+B_q$	B + S + S	1	1.99	2.36	1.80	2.29	2.48	1.21	2.31	3.32
$B+BC+B_q$	S + S + S	0.10	3.21	3.55	2	3	3.38	1.24	4.78	3.16
$B+BC+B_q$	S + S + S	0.25	3.66	3.37	2	2.96	3.33	1.16	4.57	3.38
$B+BC+B_q$	S + S + S	0.50	3.22	2.64	1.99	2.71	3.06	1.11	3.04	3.16
$B+BC+B_q$	S + S + S	0.75	2.31	1.86	1.90	2.42	2.78	1.14	2.48	3.10
$B+BC+B_q$	S + S + S	1	2.02	1.61	1.68	2.18	2.45	1.29	2.12	3.11
$B+BC+D+D_q$	B + B + B + B	0.10	4	4.70	2	3	4	1.60	4.78	4.02
$B+BC+D+D_q$	B + B + B + B	0.25	4.03	4.68	2	3	4	1.58	4.80	4.06
$B+BC+D+D_q$	B + B + B + B	0.50	4.25	4.54	2	3	4	1.57	4.52	4.13
$B+BC+D+D_q$	B + B + B + B	0.75	4.63	4.52	2	3	4	1.58	4.72	4.23
$B+BC+D+D_q$	B + B + B + B	1	4.56	4.52	2	3	4	1.78	4.77	4.16
$B+BC+D+D_q$	B + B + B + S	0.10	4	4.64	2	3	4	2.67	4.85	3.99
$B+BC+D+D_q$	B + B + B + S	0.25	4.29	4.74	2	3	4	2.71	4.77	4.02
$B+BC+D+D_q$	B + B + B + S	0.50	4.52	4.61	2	3	3.95	2.58	4.68	4.01
$B+BC+D+D_q$	B + B + B + S	0.75	4.37	4.30	2	3	3.87	2.44	4.82	3.99
$B+BC+D+D_q$	B + B + B + S	1	4.20	4.07	2	3	3.78	2.34	4.41	4.03

Table 10: Number of Significant Effects for Ceramics Experiment in Yuan (1998)

Model	Size	σ	Lasso	Method 1	Method 2			Dantzig	LARS	Nonneg-
					$h=2$	$h=3$	$h=4$	selector		Garotte
$B+BC+D+D_q$	B + B + S + S	0.10	4.01	4.52	2	3	4	1.91	4.70	4.04
$B+BC+D+D_q$	B + B + S + S	0.25	4.31	4.54	2	3	4	1.89	4.82	4.10
$B+BC+D+D_q$	B + B + S + S	0.50	3.86	4.13	2	2.97	3.92	1.86	4.71	3.76
$B+BC+D+D_q$	B + B + S + S	0.75	3.87	3.86	2	2.84	3.71	1.77	4.55	3.73
$B+BC+D+D_q$	B + B + S + S	1	3.38	3.42	2	2.80	3.58	1.87	4.25	3.63
$B+BC+D+D_q$	B + S + B + B	0.10	3.75	4.75	2	3	4	1.50	6.25	3.39
$B+BC+D+D_q$	B + S + B + B	0.25	3.93	4.59	2	3	3.95	1.64	5.91	3.60
$B+BC+D+D_q$	B + S + B + B	0.50	3.84	4.14	2	3	3.75	1.70	4.62	3.67
$B+BC+D+D_q$	B + S + B + B	0.75	3.79	3.94	2	3	3.56	1.83	4.47	3.58
$B+BC+D+D_q$	B + S + B + B	1	3.56	3.77	2	3	3.55	1.69	4.29	3.63
$B+BC+D+D_q$	B + S + B + S	0.10	3.97	4.72	2	3	4	1.91	6.46	4.08
$B+BC+D+D_q$	B + S + B + S	0.25	4.31	4.49	2	3	3.94	1.90	6.17	4
$B+BC+D+D_q$	B + S + B + S	0.50	4.07	3.93	2	3	3.70	1.83	4.87	3.86
$B+BC+D+D_q$	B + S + B + S	0.75	3.78	3.94	2	2.97	3.62	1.78	4	3.83
$B+BC+D+D_q$	B + S + B + S	1	3.74	3.67	2	2.91	3.39	1.82	3.73	3.80
$B+BC+D+D_q$	B + S + S + S	0.10	4.01	4.76	2	3	4	1	5.31	4.07
$B+BC+D+D_q$	B + S + S + S	0.25	4.34	4.47	2	3	3.99	1	5.03	4.07
$B+BC+D+D_q$	B + S + S + S	0.50	3.88	3.97	2	2.99	3.77	1	3.89	3.74
$B+BC+D+D_q$	B + S + S + S	0.75	3.12	3.23	1.97	2.83	3.39	1.09	3.51	3.60
$B+BC+D+D_q$	B + S + S + S	1	2.52	2.69	1.88	2.58	3.04	1.09	2.81	3.38
$B+BC+D+D_q$	S + S + B + B	0.10	3.86	4.86	2	3	4	1.53	4.65	3.56
$B+BC+D+D_q$	S + S + B + B	0.25	3.83	4.42	2	2.99	3.95	1.56	4.62	3.45
$B+BC+D+D_q$	S + S + B + B	0.50	3.49	3.77	2	2.85	3.54	1.57	3.80	3.31
$B+BC+D+D_q$	S + S + B + B	0.75	2.99	3.49	2	2.79	3.32	1.62	3.20	3.13
$B+BC+D+D_q$	S + S + B + B	1	2.82	3.06	2	2.65	3.15	1.58	2.79	3.29
$B+BC+D+D_q$	S + S + B + S	0.10	4.03	4.58	2	3	4	1.31	4.94	4.02
$B+BC+D+D_q$	S + S + B + S	0.25	4.48	4.55	2	3	3.99	1.34	4.64	4.08
$B+BC+D+D_q$	S + S + B + S	0.50	3.74	3.79	1.99	2.89	3.58	1.20	3.90	3.72
$B+BC+D+D_q$	S + S + B + S	0.75	2.97	3.09	1.98	2.62	3.12	1.20	3.23	3.43
$B+BC+D+D_q$	S + S + B + S	1	2.55	2.67	1.84	2.54	2.95	1.29	2.65	3.50
$B+BC+D+D_q$	S + S + S + S	0.10	4.18	4.61	2	3	4	1.13	4.72	4.07
$B+BC+D+D_q$	S + S + S + S	0.25	4.43	4.19	2	3	3.93	1.08	4.64	4.10
$B+BC+D+D_q$	S + S + S + S	0.50	3.79	3.28	2	2.93	3.63	1.11	3.71	3.80
$B+BC+D+D_q$	S + S + S + S	0.75	2.86	2.35	1.94	2.65	3.04	1.07	2.82	3.44
$B+BC+D+D_q$	S + S + S + S	1	2.46	1.67	1.87	2.35	2.68	1.14	2.29	3.25