

Penalized-Constrained Regression

Combining Regularization and Domain Constraints for Cost Estimation

Kevin Joy

Max Watstein

2026-02-13

Table of contents

Abstract	2
1 Introduction	3
2 Motivating Example	4
2.1 The Learning Curve Problem	4
2.2 Example Scenario	4
3 Theoretical Foundation	6
3.1 Regularization: Optimality of Ridge Penalty	6
3.2 Constrained Methods: Superior Performance Under Misspecification	6
4 Framework	6
4.1 Penalized-Constrained Regression (PCReg) Model	6
4.1.1 Objective Function	6
4.1.2 Model Specification	7
4.1.3 Cross Validation (CV) for Hyperparameter Selection	7
4.2 Model Diagnostics	8
4.2.1 In-Sample Fit Statistics	8
4.2.2 Generalized Degrees of Freedom (GDF)-adjusted fit statistics	8
4.2.3 Bootstrap Confidence Intervals	9
5 Example Scenario Revisited with PCReg	9
5.1 PCReg_GCV Model Specification	9
5.2 Model Diagnostics	10
6 Simulation Study	12
6.1 Siumulation Design	12
6.2 Example Scenario	12
7 Key Findings	16
7.1 Finding 1a: PCReg Significantly Outperforms OLS When Coefficients Are Unreasonable	16
7.2 Finding 1b: PCReg Performs Comparably When OLS Coefficients Are Reasonable .	16
7.3 Summary: Win Rates by Coefficient Reasonableness	16

7.4	Finding 2: OLS-LearnOnly Performs Poorly Outside Training Range	17
7.4.1	Finding 3: Coefficient Bias Analysis	18
7.5	Finding 4: Parameter Effects on Model Performance	18
8	Recommendations: When to Use PCReg	21
8.1	Software	21
8.2	Summary	21
	References	21
A	Appendix A: Simulation Details	23
A.1	Data Generation Process	23
A.2	Model Specifications	23
B	Appendix B: Full Results (All Models)	24
C	Appendix C: Software Documentation	25
C.1	Installation	25
C.2	Basic Usage	25
C.3	Citation	25
D	Appendix D: Cross Validation Methods	26
D.1	Overview	26
D.2	K-Fold Cross Validation	26
D.2.1	Methodology	26
D.2.2	Algorithm	26
D.2.3	Choice of K	26
D.2.4	Advantages	26
D.2.5	Disadvantages	26
D.3	Generalized Cross Validation (GCV)	27
D.3.1	Motivation	27
D.3.2	Mathematical Formulation	27
D.3.3	Degrees of Freedom Adjustment	27
D.3.4	GCV as LOO Approximation	27
D.3.5	Advantages	28
D.3.6	Disadvantages	28
D.4	Assumptions and Limitations	28
D.4.1	Common Assumptions (Both K-Fold and GCV)	28
D.4.2	Specific to K-Fold CV	28
D.4.3	Specific to GCV	28
D.5	Comparison and Recommendations	28
D.5.1	Practical Guidance for Cost Estimation	29
D.6	Implementation in PCReg	29
D.7	References for Cross Validation	30

Abstract

Small datasets with intercorrelation pose serious challenges to the stability of coefficients generated by Ordinary Least Squares (OLS) regression. A motivating example in cost estimating is Learning Curve with Rate Effect analysis, where datasets are typically small, the lot midpoint (Learning) is correlated to lot quantity (Rate) as production ramps up, and slopes are expected to be $\leq 100\%$. Lasso, Ridge, and Elastic Net regularization methods address multicollinearity by penalizing coefficients. Separately, constrained optimization methods can impose explicit restrictions on coefficient values when prior knowledge about their behavior is known—such as bounding slopes within a known range. This paper investigates the combined effects of penalized regularization methods and constrained optimization. We explore how to assess model stability and goodness-of-fit using likelihood-free diagnostic techniques suited to optimization-based regressions, such as cross-validation for generalization error.

1 Introduction

While developing Cost Estimating Relationships (CERs) for small datasets (5-30 data points), a recurring pattern emerged. The regression models often showed strong fit statistics with high R^2 and low standard error, but nonsensical coefficients. Coefficients often had wrong signs, implausible magnitudes, and poor p-values. As Department of Defense (DoD) analysts, this story may feel all too familiar.

Intercorrelated datasets are a frequent presence in cost analysis, causing regression models to misbehave. This is especially true for Learning Curve with Rate Effect analysis, where datasets are typically small and the lot midpoint is usually correlated to lot quantity. Traditional remedies for multicollinearity can be insufficient for learning curve datasets. Increasing sample size is infeasible as it requires waiting years for additional production lots and cost data to become available. Dropping explanatory variables, such as rate effect, leads to model misspecification that ignores a fundamental cost driver. This issue is compounded when predicting outside the relevant range which is very common. Even when these remedies are employed, OLS can still produce implausible coefficients with the wrong signs, such as learning curve slopes $>100\%$. Regularization techniques like Ridge, Lasso, and Elastic Net can help stabilize estimates, but they don't guarantee plausible coefficients. Constrained optimization can enforce domain knowledge, but without regularization, it may not solve the underlying multicollinearity problem. This paper explores the combination of penalized regularization and constrained optimization to address both challenges.

For our research, we reviewed existing literature on multicollinearity, regularization, constrained optimization, and learning theory. Drawing on these foundations, we developed the Penalized-Constrained Regression (PCReg) framework, which integrates Elastic Net penalties with domain-knowledge coefficient constraints. We then used Monte Carlo simulation to evaluate PCReg's accuracy estimating the true parameters and compared its performance against OLS across a range of sample sizes and collinearity conditions, measuring both coefficient recovery and out-of-sample prediction accuracy.

This paper develops and validates Penalized-Constrained Regression for cost estimation, providing:

1. **PCReg Python Package** PCReg application in Python
2. **PCReg Excel Template** PCReg application in Excel
3. **Cross Validation framework** for hyperparameter selection without data splitting
4. **Practical Guidance** for when to use PCReg and how to assess model fit

2 Motivating Example

2.1 The Learning Curve Problem

The motivating example for this research is the learning curve with rate effect:

$$\text{Average Unit Cost} = T_1 \cdot (\text{Lot Midpoint})^b \cdot (\text{Lot Quantity})^c \cdot \varepsilon$$

where: T_1 = theoretical first unit cost

b = learning slope in log space

c = rate slope in log space

ε = multiplicative error

b and c are both slopes in log space. When transformed to unit space, they become the learning curve slope (LCS = 2^b) and the rate effect (2^c), both typically ranging from 70-100%. As DoD programs ramp up production from Engineering Manufacturing Development (EMD) to Full Rate Production (FRP), lot midpoint (the learning predictor) becomes highly correlated with lot quantity (the rate predictor). By definition LCS and Rate Effect are $\leq 100\%$, meaning costs strictly decrease with cumulative production or lot quantity.

If estimated LCS or Rate Effect are $>100\%$ this is often an indicator of multicollinearity or that other explanatory variables such as supply chain disruptions or diseconomies of scale are missing and need to be modeled, not a violation of the definition. Once these factors are properly modeled as separate explanatory variables, estimated LCS and Rate Effect should be $\leq 100\%$, consistent with their definition. It is the analyst's responsibility to ensure the model is properly specified and includes all relevant cost drivers.

2.2 Example Scenario

We demonstrate the "Learning Curve Problem" using the following dataset which was generated by our Simulation Study ***insert cross reference**.

Table 1: Motivating example training dataset.

lot_midpoint	lot_quantity	observed_cost
11.694	30.000	44.822
44.592	30.000	43.961
79.598	40.000	42.172
129.251	60.000	39.040
226.613	140.000	38.229
414.709	241.000	26.349
713.347	360.000	22.446
1076.104	360.000	21.463
1437.463	360.000	24.394
1812.743	390.000	24.922

Using OLS, we get the following results:

Metric	OLS
T_1	114
Learning Rate	100.8%
Rate Effect	82.5%

Dep. Variable:	np.log(observed_cost)	R-squared:	0.913			
Model:	OLS	Adj. R-squared:	0.888			
Method:	Least Squares	F-statistic:	36.74			
Date:	Fri, 13 Feb 2026	Prob (F-statistic):	0.000194			
Time:	20:29:50	Log-Likelihood:	10.537			
No. Observations:	10	AIC:	-15.07			
Df Residuals:	7	BIC:	-14.17			
Df Model:	2					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
Intercept	4.7335	0.180	26.328	0.000	4.308	5.159
np.log(lot_midpoint)	0.0115	0.069	0.168	0.872	-0.151	0.174
np.log(lot_quantity)	-0.2771	0.102	-2.704	0.030	-0.519	-0.035
Omnibus:	10.496			Durbin-Watson:	1.701	
Prob(Omnibus):	0.005			Jarque-Bera (JB):	4.527	
Skew:	1.380			Prob(JB):	0.104	
Kurtosis:	4.801			Cond. No.	48.8	

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

We see find that by using OLS this example dataset yields invalid coefficients, specifically a LCS of 100.8% which violates our definition of LCS being $\leq 100\%$. But otherwise this is a good fit with strong R^2 (0.91) and significant F-statistic. This is a common pattern in cost estimating where OLS produces good fit statistics but implausible coefficients. The next section introduces the Penalized-Constrained Regression (PCReg) framework which addresses this issue by combining regularization penalties with domain-knowledge constraints to stabilize coefficient estimates while ensuring they remain within plausible ranges.

3 Theoretical Foundation

3.1 Regularization: Optimality of Ridge Penalty

Theobald-Farebrother Theorem ([Theobald 1974](#); [farebrother1976further?](#)): For any OLS problem, there exists a ridge parameter $\lambda^* > 0$ such that the ridge estimator has strictly lower mean squared error (MSE) than OLS. This result holds for population MSE (true prediction risk), not merely training error. The optimal λ^* depends on unknown population parameters, which cross-validation estimates empirically.

3.2 Constrained Methods: Superior Performance Under Misspecification

James, Paulson, and Rusmevichientong (2020) demonstrated that penalized and constrained (PAC) methods remain superior to unconstrained alternatives even when constraints are imperfectly specified within the Website Advertising domain:

“PAC and relaxed PAC are surprisingly robust to random violations in the constraints... they were still both superior to their unconstrained counterparts for all values [of constraint error] and all settings.”

4 Framework

The Penalized-Constrained Regression (PCReg) framework applies the theoretical and experimental foundations to the cost estimation domain. PCReg consists of two major components: - the penalized-constrained regression model and - the model diagnostics

4.1 Penalized-Constrained Regression (PCReg) Model

The Penalized-Constrained Regression (PCReg) Model integrates regularization penalties (L1 and L2) with domain-knowledge box-constraints ($\theta_{\text{lower}} \leq \theta \leq \theta_{\text{upper}}$) to stabilize coefficient estimates, while ensuring they remain within plausible ranges.

4.1.1 Objective Function

The objective function minimized by PCReg combines a loss function with regularization penalties subject to coefficient bounds:

$$\text{Objective: } \arg \min_{\theta} \underbrace{\sum_{i=1}^n L(y_i, \hat{y}_i)}_{\text{Loss}} + \underbrace{\lambda \left[\alpha \|\theta\|_1 + \frac{1-\alpha}{2} \|\theta\|_2^2 \right]}_{\text{Elastic Net Penalty}}$$

Subject to: $\theta_{\text{lower}} \leq \theta \leq \theta_{\text{upper}}$ (componentwise bounds)

where: $L(y_i, \hat{y}_i)$ = loss function (e.g., SSE, SSPE)

$\lambda \geq 0$ = regularization strength

$\alpha \in [0, 1]$ = L1/L2 mixing parameter

$\|\theta\|_1 = \sum_j |\theta_j|$ (Lasso penalty)

$\|\theta\|_2^2 = \sum_j \theta_j^2$ (Ridge penalty)

The lower and upper bounds (θ_{lower} and θ_{upper}) can be set to achieve loose bounds or tight bounds for the coefficient:

- **Loose bounds** (e.g., 70-100%): Wide range which allows flexibility while preventing egregious coefficient violations
- **Tight bounds** (e.g., 85-95%): Narrower range which incorporates strong prior knowledge but risks over-constraining coefficients

4.1.2 Model Specification

The users can specify the following components of the PCReg model:

- **Prediction function:** Defaults to linear (`X @ coef + intercept`), but supports custom non-linear functions
- **Loss function:** Sum of Squared Percentage Errors (SSPE, default), Sum of Squared Errors (SSE), Mean Squared Error (MSE), or custom loss functions
- **Coefficient bounds:** Componentwise constraints that encode domain knowledge (e.g., learning curve slopes between -1 and 0)
- **Penalty exclusion:** Option to exclude specific coefficients from regularization while still applying bounds
- **Optimizer:** Defaults to SLSQP for constrained optimization

The framework maximizes flexibility and collapses to known regression techniques in special cases:

- OLS when prediction function is linear, `alpha=0`, and bounds are not specified
- Ridge when prediction function is linear, `alpha>0` and `l1_ratio=0`
- Lasso when prediction function is linear, `alpha>1` and `l1_ratio=1`
- Elastic Net when prediction function is linear, `alpha>0` and `0 < l1_ratio < 1`
- Constrained regression when bounds are specified but `alpha=0`

4.1.3 Cross Validation (CV) for Hyperparameter Selection

Finding the optimal penalty parameters for penalized-constrained regression requires testing different values rather than using a formula. Cross Validation (CV) is a method that evaluates how well a model predicts new data by testing it on observations not used during training. The CV process evaluates all combinations of user-specified penalties (λ) and L1 ratio values (α) to find the hyperparameters that produce the best out-of-sample predictions.

Traditional K-Fold CV splits the training data into K subsets, repeatedly training on K-1 subsets and validating on the remaining one. For small datasets, this approach further reduces the already limited training sample size.

We implement both K-Fold CV and Generalized Cross Validation (GCV), with GCV as the default for small datasets. GCV approximates leave-one-out cross validation using a mathematical formula rather than actually splitting data (Golub, Heath, and Wahba 1979). It estimates prediction error based on training residuals adjusted by model complexity (degrees of freedom), making it efficient for small samples. For each combination of penalty parameters, the GCV score is calculated as:

$$GCV = \frac{n \cdot RSS}{(n - df)^2}$$

where: RSS = residual sum of squared errors

n = number of observations

df = effective degrees of freedom

The optimal penalty parameters are those that minimize the GCV score.

4.2 Model Diagnostics

The flexibility of penalized-constrained regression means goodness of fit statistics cannot guarantee classical inference (p-values and F-statistic) apply due to supporting coefficient bounds, regularization penalties, custom loss functions and custom prediction functions. No single inference framework covers all scenarios. When coefficients are at bounds (from constraints or L1 penalties), classical theory breaks down. Additionally, introducing custom loss and prediction functions require specifying their corresponding distributional assumptions as in Generalized Linear Models. We therefore focus on fit statistics that are robust and informative across model specifications:

4.2.1 In-Sample Fit Statistics

Standard in-sample fit measures remain valid across all model configurations, including R^2 (coefficient of determination), SSE (sum of squared errors), RMSE (root mean squared error), MAE (mean absolute error), MAPE (mean absolute percentage error), and residual diagnostics.

4.2.2 Generalized Degrees of Freedom (GDF)-adjusted fit statistics

Classical degrees of freedom ($df = n - p$) assumes unconstrained estimation. GDF suggests that optimization based models ought to lose degrees of freedom to take into account the constraints. We implement both Gaines, Kim, and Zhou (2018) and Hu (2010) GDF formulas to properly adjust fit statistics (SEE, SPE, Adjusted R^2) and account for the effective model complexity.

Gaines et al. (2018) Formula (Default): Gaines, Kim, and Zhou (2018) derive degrees of freedom for constrained Lasso by counting only constraints that are actually binding at the solution:

$$GDF_{\text{Gaines}} = n - |\text{Active predictors}| - |\text{Equality constraints}| - |\text{Binding inequality constraints}|$$

where n is the sample size and active predictors are non-zero coefficients. This reflects the intuition that non-binding constraints don't reduce effective degrees of freedom.

Hu (2010) Alternative Formula: Hu (2010) proposes a more conservative approach where *all specified constraints* count against degrees of freedom, regardless of whether they bind:

$$GDF_{Hu} = n - p - (\# \text{ Constraints}) + (\# \text{ Redundancies})$$

where p is the total number of estimated parameters (including intercept if fitted). Hu's method always reduces GDF when constraints are specified, making it appropriate for ZMPE-type CERs where constraints fundamentally shape the solution.

4.2.3 Bootstrap Confidence Intervals

Standard bootstrap confidence intervals can be misleading for penalized regression (Goeman 2025), as they assume interior solutions and no regularization bias. Our framework addresses this by computing **both** constrained and unconstrained bootstrap resampling:

- **Constrained bootstrap:** Resamples data and refits the model *with* the specified bounds and regularization (penalized-constrained estimation), quantifying coefficient stability under the imposed modeling constraints
- **Unconstrained bootstrap:** Resamples data and fits OLS *without* bounds or penalization (pure unconstrained estimation), showing coefficient variability in the absence of constraints and regularization. This serves as a baseline for comparison.

5 Example Scenario Revisited with PCReg

Given the framework for PCReg we can now model the same motivational example but now using **Penalized-Constrained Regression with Generalized Cross-Validation** (PCReg_GCV). This specification combines the theoretical foundations with practical hyperparameter selection.

5.1 PCReg_GCV Model Specification

The PCReg_GCV specification applies the framework to our learning curve problem with the following configuration:

```
# Define the nonlinear prediction function
def prediction_fn(X, params):
    """Learning curve with rate effect: T1 * (midpoint^b) * (quantity^c)"""
    T1, b, c = params
    return T1 * (X[:, 0] ** b) * (X[:, 1] ** c)

# Configure PCReg_GCV model
pc_gcv = pcreg.PenalizedConstrainedCV(
    coef_names=['T1', 'b', 'c'],
    bounds={'T1': (0, None), 'b': (-0.5, 0), 'c': (-0.5, 0)},
    prediction_fn=prediction_fn,
    fit_intercept=False,
    x0=[100, -0.1, -0.1],
    selection='gcv',           # Generalized Cross-Validation
    loss='sspe',               # Sum of Squared Percentage Errors
    penalty_exclude=['T1'],    # Don't penalize the intercept
    n_jobs=1
)
```

```
# Fit the model
pc_gcv.fit(X_train, y_train)
```

Key Specification Details:

- **Coefficients:** T_1 (first unit cost), b (learning slope), c (rate slope)
- **Bounds:** $T_1 > 0$, $-0.5 \leq b \leq 0$, $-0.5 \leq c \leq 0$
- **Penalty Selection:** GCV automatically selects optimal λ without data splitting
- **Loss Function:** SSPE minimizes percentage errors (appropriate for cost data)
- **Penalty Exclusion:** T_1 is not penalized (only slopes are regularized)

Table 3: Comparison of OLS and PCReg_GCV coefficient estimates

Metric	OLS	PCReg_GCV
T_1	114	100
Learning Rate	100.8%	97.4%
Rate Effect	82.5%	87.3%

Table 4: Comparison of OLS and PCReg_GCV coefficient Specification

Specification	OLS	PCReg_GCV
loss function	MSE	SSPE
prediction function	Linear	Nonlinear (Learning Curve)
lambda (penalty)	N/A	1.0000
alpha (L1 ratio)	N/A	0.50

5.2 Model Diagnostics

We were able to find a reasonable solution with PCReg_GCV that satisfies our domain knowledge constraints (LCS and Rate Effect $\leq 100\%$), but we still need to determine if it's a good fit to the data. The PCReg_GCV model includes bootstrap diagnostics to assess coefficient stability and the impact of constraints. Comparing constrained and unconstrained bootstrap distributions reveals the impact of constraints on coefficient stability. Large divergence indicates constraints are actively shaping the solution, while similar distributions suggest the data naturally satisfies the constraints.

Bootstrap Results Summary

Constrained Bootstrap (with bounds and regularization):

- **T1:** Mean = 93.98, Std = 10.41, 95% CI = [68.63, 100.00]
- **b:** Mean = -0.0658, Std = 0.0425, 95% CI = [-0.1806, -0.0110]
- **c:** Mean = -0.1497, Std = 0.0597, 95% CI = [-0.2275, -0.0000]

Unconstrained Bootstrap (no bounds, alpha=0):

- **T1:** Mean = 109.20, Std = 14.03, 95% CI = [99.99, 140.81]
- **b:** Mean = -0.0059, Std = 0.0704, 95% CI = [-0.1781, 0.1105]

- c: Mean = -0.2493, Std = 0.0903, 95% CI = [-0.3988, -0.0545]

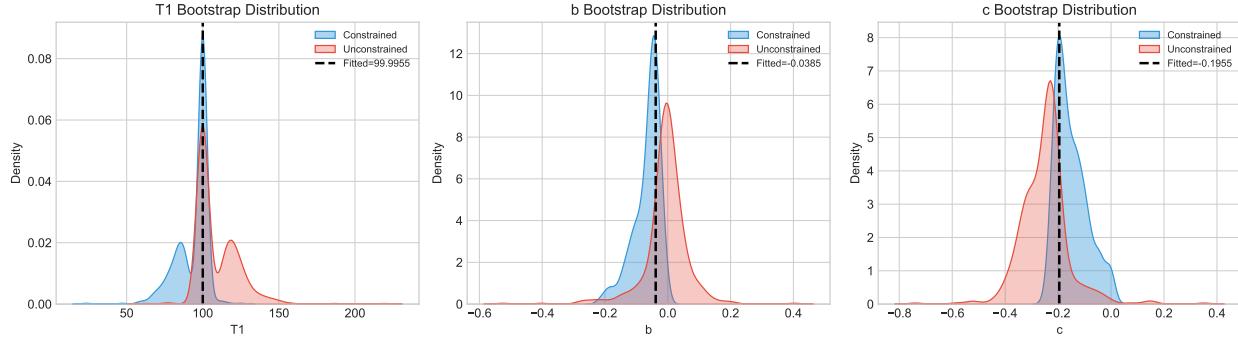


Figure 1: Bootstrap coefficient distributions comparing constrained (blue) vs unconstrained (red) estimation. Vertical lines show fitted values. Constraints reduce variance and keep estimates within economically plausible ranges.

Key Diagnostic Insights:

1. **Constraints at bounds:** When bootstrap samples frequently hit constraint boundaries, the data is “pulling” towards implausible values—exactly when constraints help most.
2. **Variance reduction:** Constrained bootstrap typically shows tighter distributions, reducing coefficient uncertainty at the cost of some bias.
3. **Divergence indicates constraint impact:** Large differences between constrained and unconstrained means show the constraints are actively shaping the solution.

Note on Bootstrap for Penalized Regression: The R `penalized` package (Goeman 2025) documentation warns that standard bootstrap can be problematic for penalized regression due to the biased nature of penalized estimates and potential boundary solutions. Our dual bootstrap approach addresses this by explicitly comparing **constrained** (penalized-constrained) vs **unconstrained** (OLS) resampling, providing transparent inference about both the stability of the constrained solution and the impact of imposing constraints. This is more informative than attempting to construct classical confidence intervals that assume properties (unbiasedness, interior solutions) not satisfied by penalized-constrained estimators.

An interactive HTML diagnostic report with full bootstrap distributions has been saved to `output_v2/pcreg_diagnostic_report.html`.

6 Simulation Study

We performed a Monte Carlo simulation study evaluate PCReg and compare with traditional OLS.

6.1 Siumulation Design

Table 5: Simulation study factorial design. $81 \text{ combinations} \times 100 \text{ replications} = 8,100 \text{ scenarios}$.

Factor	Levels
Sample size (n_lots)	5, 10, 30
CV error	0.01, 0.1, 0.2
Learning rate	85%, 90%, 95%
Rate effect	80%, 85%, 90%

For each scenario, we:

1. **Randomly selected a quantity profile** from the SAR database (actual defense program procurement histories)
2. **Generated simulated average unit costs** using the learning curve model (`?@eq-learning-curve`) with the scenario's true parameters
3. **Added multiplicative lognormal noise** with the specified coefficient of variation (CV)
4. **Split data:** First n lots for training, remaining lots for test

This approach ensures realistic lot structures (varying quantities, realistic ramp-up patterns) while controlling the true underlying parameters. Note that the number of test lots varies by scenario depending on the program's total lot history. Some programs have many available lots beyond training, others have few or none. This variability is acceptable as it reflects real-world conditions.

6.2 Example Scenario

We return to the example scenario which was introduce in *insert cross reference*. Below we see the scenario specifications which generated our example scenario dataset.

Table 6: Example scenario parameters

Parameter	Value
Training lots	10
Test lots	20
True T_1	100
True Learning Rate	95.0%
True Rate Effect	90.0%
Predictor Correlation	0.95
CV Error	0.1

Here is the example dataset with training and test lots (training data matches the dataset shown earlier in **insert crossreference*):

Table 7: Motivating example dataset with training and test lots.

lot_type	lot_midpoint	lot_quantity	observed_cost	true_cost
train	11.694	30	44.822	49.71
train	44.592	30	43.961	45.022
train	79.598	40	42.172	41.287
train	129.251	60	39.040	37.451
train	226.613	140	38.229	31.586
train	414.709	241	26.349	27.811
train	713.347	360	22.446	25.136
train	1076.1	360	21.463	24.382
train	1437.46	360	24.394	23.865
train	1812.74	390	24.922	23.176
test	2208.26	400	—	22.752
test	2669.38	525	—	21.526
test	3231.51	600	—	20.798
test	3789.4	512	—	21.056
test	4320.37	550	—	20.627
test	4866.8	542	—	20.491
test	5408.09	540	—	20.343
test	5955.19	554	—	20.12
test	6509.39	554	—	19.988
test	7063.56	554	—	19.868
test	7615.72	550	—	19.779
test	8165.84	550	—	19.677
test	8715.95	550	—	19.583
test	9266.04	550	—	19.494
test	9816.12	550	—	19.411
test	10366.2	550	—	19.333
test	10916.3	550	—	19.259
test	11466.3	550	—	19.189
test	12016.4	550	—	19.123
test	12556.5	530	—	19.168

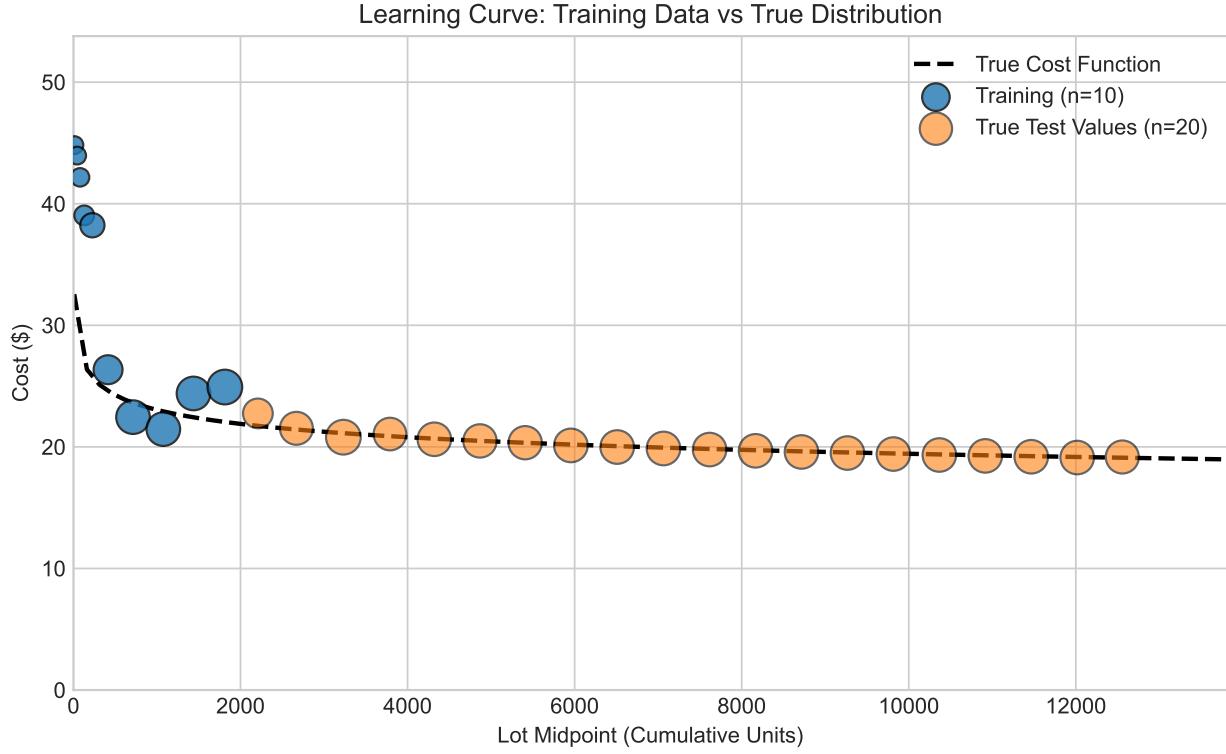


Figure 2: Learning curve data with `python n_train` training lots (blue) and the true underlying cost distribution (dashed line). Point sizes reflect lot quantities. The goal is to predict the true relationship, not just fit the noisy observations.

Table 8: Comparison of estimation methods. PCReg has lower Train R² due to added bias from constraints, but better Test MAPE when predicting the true underlying relationship.

Metric	True	OLS	OLS-LearnOnly	PCReg
T_1	100	114	79	100
Learning Rate	95.0%	100.8%	89.2%	97.4%
Rate Effect	90.0%	82.5%	—	87.3%
Valid Coefficients	Yes	NO	Yes	Yes
Train R ²	—	0.912	0.796	0.907
Test MAPE (vs True)	—	9.8%	8.4%	3.9%

Key Insight: OLS achieves a *lower* Train R² OLS (0.912) than PCReg (0.907). This is expected, penalties and constraints add bias to the training fit. However, this bias *improves* out-of-sample prediction, as shown by the lower Test MAPE against the true distribution.

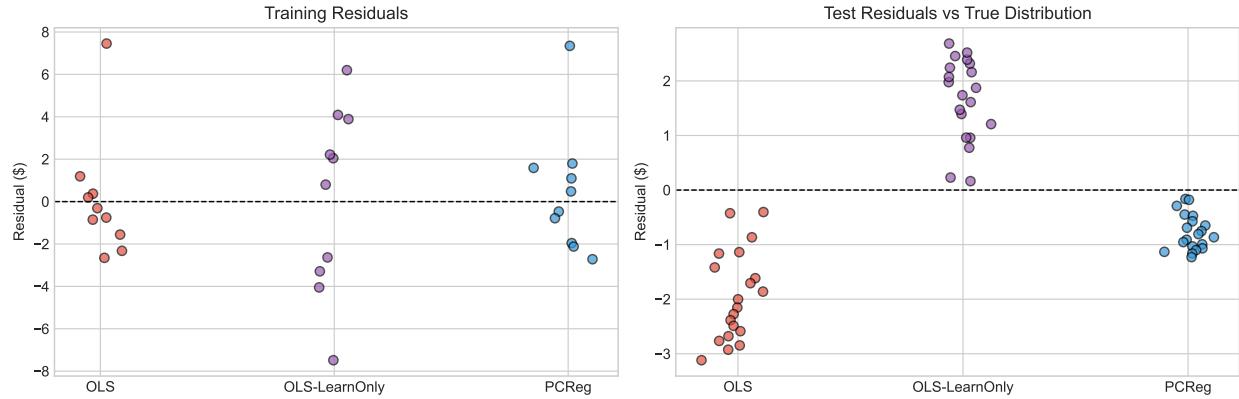


Figure 3: Residuals for each model on training data (left) and against true test values (right). PCReg shows larger training residuals but smaller errors when predicting the true underlying relationship.

7 Key Findings

Across 8,100 simulation scenarios, OLS produced economically unreasonable coefficients (learning curve or rate effect outside 70-100%) in **16.7%** of cases (1,355 scenarios).

7.1 Finding 1a: PCReg Significantly Outperforms OLS When Coefficients Are Unreasonable

When OLS produces unreasonable coefficients, PCReg wins **78.7%** of scenarios on Test MAPE.

Metric	OLS Mean	PCReg Mean	OLS Median	PCReg Median
Test MAPE	0.2862	0.1456	0.2094	0.1179
T1 APE	66.5658	0.5108	0.5694	0.3418
LC Abs Error	0.1182	0.0483	0.0943	0.0489
RC Abs Error	0.3548	0.1219	0.2347	0.1

: Performance comparison when OLS produces unreasonable coefficients (n=1,355). Lower values are better. {#tbl-unreasonable}

Statistical Significance: Wilcoxon signed-rank test confirms PCReg significantly outperforms OLS on Test MAPE ($p < \text{nan}$).

7.2 Finding 1b: PCReg Performs Comparably When OLS Coefficients Are Reasonable

When OLS produces reasonable coefficients, OLS “wins” on Test MAPE in **66.3%** of scenarios. However, the performance differences are negligible in practical terms.

Metric	OLS Mean	PCReg Mean	OLS Median	PCReg Median
Test MAPE	0.0549	0.061	0.0253	0.0298
T1 APE	0.1628	0.1562	0.0623	0.0709
LC Abs Error	0.0156	0.0154	0.007	0.007
RC Abs Error	0.0304	0.0353	0.0153	0.0172

: Performance comparison when OLS produces reasonable coefficients (n=6,745). {#tbl-reasonable}

Key Insight: When OLS coefficients are reasonable, the mean Test MAPE difference is only **0.61 percentage points** (11.1% relative difference). While statistically detectable (Wilcoxon $p=\text{nan}$), this difference is negligible in practice. OLS’s occasional large errors (visible in the heavy right tail) inflate the mean, but the median performance is nearly identical.

7.3 Summary: Win Rates by Coefficient Reasonableness

Table 11: PCReg win rates against OLS by coefficient reasonableness

OLS Coefficients	N Scenarios	PCReg Win Rate (Test MAPE)
Reasonable (70-100%)	6,745	33.7%
Unreasonable (<70% or >100%)	1,355	78.7%
Overall	8,100	41.2%

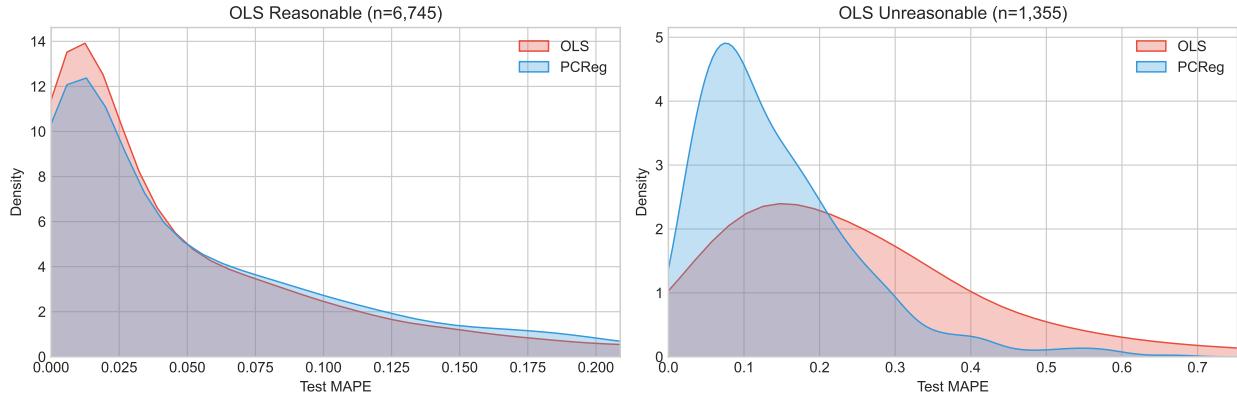


Figure 4: Distribution of Test MAPE for OLS vs PCReg, stratified by whether OLS produced reasonable coefficients. When unreasonable (right), OLS shows a heavy right tail of large errors that PCReg avoids.

7.4 Finding 2: OLS-LearnOnly Performs Poorly Outside Training Range

OLS with only the learning variable (OLS-LearnOnly) ignores the rate effect, which leads to poor extrapolation:

Table 12: Average Test MAPE by model

Model	Mean Test MAPE
OLS-LearnOnly	15.9%
OLS	9.9%
PCReg	7.7%

OLS-LearnOnly has worse Test MAPE than full OLS in **63.9%** of scenarios. While simplifying the model may seem appealing, omitting the rate effect leads to systematic prediction errors outside the training range.

PCReg outperforms OLS-LearnOnly on Test MAPE in **67.9%** of all scenarios:

- When OLS coefficients are **reasonable**: PCReg wins **70.9%**
- When OLS coefficients are **unreasonable**: PCReg wins **52.8%**

Across all scenarios, PCReg outperforms OLS on Test MAPE in **41.2%** of cases, indicating a consistent predictive advantage even when OLS is competitive.

7.4.1 Finding 3: Coefficient Bias Analysis

Constraints introduce bias in coefficient estimates. We analyze whether this bias is systematic and how it affects prediction:

Table 13: Coefficient bias statistics (Estimated - True). Mean/Median near 0 indicates unbiased estimation; lower Std indicates more stable estimates.

	Coefficient	Statistic	OLS	PCReg
0	\$T_1\$	Mean	1108.37	-3.58
1	\$T_1\$	Median	-0.22	-2.73
2	\$T_1\$	Std	69135.60	46.12
3	\$b\$	Mean	-0.0002	-0.0078
4	\$b\$	Median	-0.0002	-0.0017
5	\$b\$	Std	0.11	0.05
6	\$c\$	Mean	-0.0023	0.03
7	\$c\$	Median	0.0003	0.01
8	\$c\$	Std	0.29	0.12

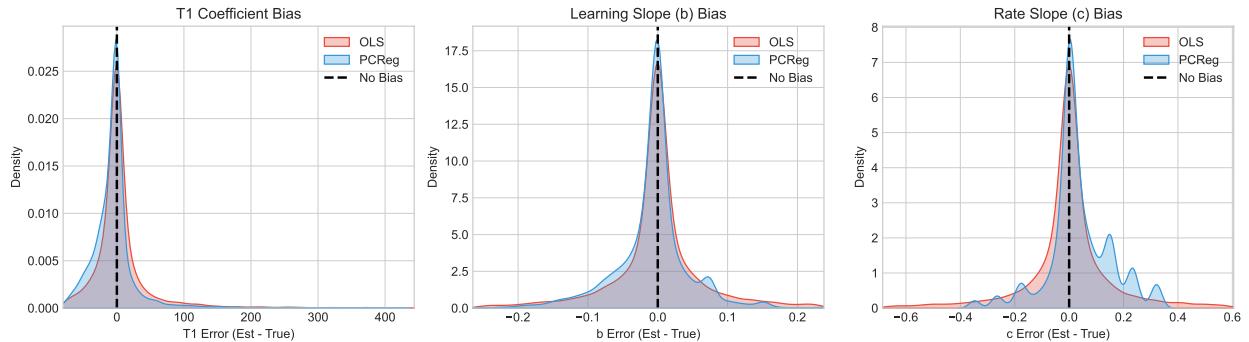


Figure 5: Distribution of coefficient errors by model (1st-99th percentile). Vertical line at 0 indicates no bias. PCReg shows tighter distributions despite some bias, leading to lower variance in predictions.

Key Insight: While OLS is theoretically unbiased (mean errors near 0), it has high variance—the distribution is wide. PCReg may have slight bias but much lower variance, leading to better overall prediction accuracy (the classic bias-variance tradeoff).

7.5 Finding 4: Parameter Effects on Model Performance

Beyond coefficient reasonableness, several design factors systematically influence when PCReg outperforms OLS. We examine sample size, predictor correlation, and noise level.

By OLS Coefficient Reasonableness:

OLS Coefficients	N	PCReg Win Rate	OLS Mean MAPE	PCReg Mean MAPE
Unreasonable	1355	78.7%	28.6%	14.6%

OLS Coefficients	N	PCReg Win Rate	OLS Mean MAPE	PCReg Mean MAPE
Reasonable (70-100%)	6745	33.7%	5.5%	6.1%

By Sample Size (n_lots):

Sample Size	N	PCReg Win Rate	% OLS Unreasonable	OLS Mean MAPE	PCReg Mean MAPE
5	2700	56.9%	32.0%	16.2%	10.7%
10	2700	46.5%	16.8%	7.4%	6.4%
30	2700	20.2%	1.4%	3.7%	4.8%

By Predictor Correlation:

Correlation	N	PCReg Win Rate	% OLS Unreasonable	OLS Mean MAPE	PCReg Mean MAPE
<0.80	3187	31.8%	8.5%	6.7%	6.5%
0.80-0.90	873	52.9%	22.1%	10.3%	7.7%
0.90-0.95	2204	38.9%	15.2%	9.8%	7.6%
>0.95	1416	56.5%	35.0%	14.5%	8.7%

By Noise Level (CV Error):

CV Error	N	PCReg Win Rate	% OLS Unreasonable	OLS Mean MAPE	PCReg Mean MAPE
0.01	2700	36.7%	0.1%	0.9%	1.0%
0.1	2700	43.3%	16.2%	9.4%	8.1%
0.2	2700	43.7%	33.9%	19.6%	14.1%

Key Observations:

- Sample Size Effect:** As sample size decreases, OLS becomes less stable. With n=5 lots, PCReg wins **56.9%** of scenarios compared to **20.2%** at n=30. The rate of unreasonable OLS coefficients also increases from **1.4%** to **32.0%** as sample size decreases.
- Correlation Effect:** Higher predictor correlation destabilizes OLS. At correlation >0.95, PCReg wins **56.5%** of scenarios versus **31.8%** at lower correlations. This is the multicollinearity effect. When predictors are highly correlated, OLS coefficient estimates become unstable and constraints provide crucial stability.
- Noise Level Effect:** Higher CV error increases the advantage of PCReg. With more noise, OLS has greater difficulty separating learning and rate effects, leading to more unreasonable coefficient estimates.

4. **Compounding Effects:** These factors interact—small samples with high correlation and high noise represent the most challenging scenarios for OLS, where PCReg provides the greatest benefit.

8 Recommendations: When to Use PCReg

Practical Decision Rules:

1. If OLS produces unreasonable coefficients (LC or RC outside 70-100%): Use PCReg, it significantly outperforms OLS in these scenarios
2. For small samples ($n = 5$ or 10 lots) with noisy data: Prefer PCReg, it wins 60-67% of scenarios
3. For large samples ($n = 30$ lots): OLS is generally preferred, it wins ~80% of scenarios
4. For intermediate cases: Either method is acceptable; PCReg provides insurance against unreasonable coefficients with minimal downside

Bottom line: The difference between OLS and PCReg is typically small and can be controlled by explicitly defining loose constraints and arbitrarily small penalties.

8.1 Software

The penalized-constrained Python package was developed specifically for the cost estimating community. As of this paper’s publication, the software is in active development but has achieved stable functionality.

Installation: While we anticipate release to PyPI for convenient installation via `pip install penalized-constrained`, the package is currently available via GitHub. To install from the development repository:

```
pip install git+https://github.com/frankij11/Penalized-Constrained-Regression.git
```

For quick-start guides and basic usage examples, see the package documentation on GitHub or Section C in the appendices.

A key advantage of this framework is that **PCReg collapses to OLS** when no constraints are defined, no penalties are applied ($=0$), and a linear functional form is used. This allows analysts to use a single, cohesive library for all regression analysis. From standard OLS to fully constrained penalized models with custom prediction functions all without switching tools or workflows. This library is designed to integrate seamlessly Python’s scikit-learn data science workflows and allow machine learning techniques to solve for optimal parameters.

8.2 Summary

Our simulation study demonstrates that PCReg provides meaningful advantages in small-sample, high-noise scenarios where OLS is most likely to produce unreasonable coefficients, while large samples favor standard OLS. The constraints introduce beneficial bias that reduces prediction variance—a classic bias-variance tradeoff that works in the analyst’s favor when data are limited. With GCV enabling reliable hyperparameter selection using as few as 5 observations and OLS-LearnOnly’s poor extrapolation performance reinforcing that omitting the rate effect oversimplifies the problem, analysts have clear guidance: match the method to the sample size and data quality, with PCReg serving as effective insurance when uncertainty is high.

References

Craven, Peter, and Grace Wahba. 1978. “Smoothing Noisy Data with Spline Functions: Estimating the Correct Degree of Smoothing by the Method of Generalized Cross-Validation.” *Numerische*

- Mathematik* 31: 377–403. <https://doi.org/10.1007/BF01404567>.
- Gaines, Brian R., Jeongyoun Kim, and Hua Zhou. 2018. “Algorithms for Fitting the Constrained Lasso.” *Journal of Computational and Graphical Statistics* 27 (4): 861–71. <https://doi.org/10.1080/10618600.2018.1473777>.
- Goeman, Jelle J. 2025. *Penalized: L1 (Lasso and Fused Lasso) and L2 (Ridge) Penalized Estimation in GLMs and in the Cox Model*. <https://CRAN.R-project.org/package=penalized>.
- Golub, Gene H., Michael Heath, and Grace Wahba. 1979. “Generalized Cross-Validation as a Method for Choosing a Good Ridge Parameter.” *Technometrics* 21 (2): 215–23. <https://doi.org/10.1080/00401706.1979.10489751>.
- Hastie, Trevor, Robert Tibshirani, and Jerome Friedman. 2009. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. 2nd ed. Springer. <https://doi.org/10.1007/978-0-387-84858-7>.
- Hu, Shu-Ping. 2010. “Generalized Degrees of Freedom for Constrained CERs.” PRT-191. Tecolote Research.
- James, Gareth M., Courtney Paulson, and Paat Rusmevichientong. 2020. “Penalized and Constrained Optimization: An Application to High-Dimensional Website Advertising.” *Journal of the American Statistical Association* 115 (529): 107–22. <https://doi.org/10.1080/01621459.2019.1609970>.
- Stone, Mervyn. 1974. “Cross-Validatory Choice and Assessment of Statistical Predictions.” *Journal of the Royal Statistical Society: Series B (Methodological)* 36 (2): 111–47.
- Theobald, C. M. 1974. “Generalizations of Mean Square Error Applied to Ridge Regression.” *Journal of the Royal Statistical Society: Series B* 36 (1): 103–6.

A Appendix A: Simulation Details

A.1 Data Generation Process

For each of the 8,100 scenarios:

1. **Select quantity profile:** Randomly sample a defense program from the SAR database with sufficient lot history
2. **Extract lot structure:** Use actual procurement quantities and calculate lot midpoints
3. **Generate true costs:** Apply learning curve model with scenario parameters
4. **Add noise:** Multiply true costs by lognormal error: $Y_{obs} = Y_{true} \cdot e^\epsilon$ where $\epsilon \sim N(-\sigma^2/2, \sigma^2)$
5. **Split data:** First n lots for training, **all remaining lots** for test (variable test set size)

A.2 Model Specifications

Table 18: Models compared in main paper

Model	Description	Constraints
OLS	Standard log-log OLS	No
OLS_LearnOnly	OLS with learning variable only	No
PCReg_GCV	GCV-selected penalty + constraints	Yes

B Appendix B: Full Results (All Models)

Table 19: Overall model performance across all 8,100 scenarios. Lower Test MAPE is better.

Model	Test MAPE	Test SSPE	b Error	c Error	R2
PCReg_GCV_Tight	0.0561	0.0861	0.0200	0.0337	0.852
PCReg_ConstrainOnly	0.0764	0.2052	0.0354	0.0791	0.877
PCReg_GCV	0.0773	0.2074	0.0338	0.0827	0.871
PCReg_GCV_LogMSE	0.0778	0.2832	0.0341	0.0776	0.877
PCReg_CV	0.0794	0.2538	0.0353	0.0814	0.862
BayesianRidge	0.0801	0.4595	0.0360	0.0886	0.882
PCReg_AICc	0.0808	0.2171	0.0349	0.0913	0.863
RidgeCV	0.0952	0.9362	0.0481	0.1216	0.896
LassoCV	0.0957	0.9767	0.0428	0.1082	0.858
OLS	0.0994	0.9727	0.0520	0.1319	0.897
OLS_LearnOnly	0.1592	0.9543	0.0827	0.2361	0.789

C Appendix C: Software Documentation

C.1 Installation

```
pip install penalized-constrained
```

C.2 Basic Usage

```
import penalized_constrained as pcreg
import numpy as np

model = pcreg.PenalizedConstrainedCV(
    coef_names=['T1', 'b', 'c'],
    bounds={
        'T1': (0, None),          # T1 must be positive
        'b': (-0.5, 0),           # Learning rate 70-100%
        'c': (-0.5, 0)            # Rate effect 70-100%
    },
    prediction_fn=lambda X, p: p[0] * X[:,0]**p[1] * X[:,1]**p[2],
    loss='sspe',
    selection='gcv'
)
model.fit(X_train, y_train)
```

C.3 Citation

```
@inproceedings{joy2026pcreg,
    title={Penalized-Constrained Regression: Combining Regularization
           and Domain Constraints for Cost Estimation},
    author={Joy, Kevin and Watstein, Max},
    booktitle={ICEAA Professional Development \& Training Workshop},
    year={2026}
}
```

D Appendix D: Cross Validation Methods

D.1 Overview

Cross Validation (CV) is a resampling technique used to evaluate how well a statistical model generalizes to independent data. In the context of penalized-constrained regression, CV helps us select optimal penalty parameters (λ and α) that balance model fit against overfitting. This appendix provides technical details on the CV methods implemented in our framework.

D.2 K-Fold Cross Validation

D.2.1 Methodology

K-Fold CV divides the training data into K roughly equal-sized subsets (folds). The model is trained K times, each time using $K-1$ folds for training and the remaining fold for validation. The CV score is the average prediction error across all K validation folds.

D.2.2 Algorithm

For each candidate penalty parameter value:

1. Partition training data into K folds: $D = \{F_1, F_2, \dots, F_K\}$
2. For each fold $k = 1, \dots, K$:
 - Train model on $D \setminus F_k$ (all data except fold k)
 - Predict on validation fold F_k
 - Calculate validation error: $E_k = \sum_{i \in F_k} L(y_i, \hat{y}_i)$
3. Compute CV score: $CV_K = \frac{1}{K} \sum_{k=1}^K E_k$
4. Select penalty parameters that minimize CV_K

D.2.3 Choice of K

- **K=5 or K=10:** Common choices balancing bias and variance
- **Leave-One-Out (LOO, K=n):** Minimum bias but high computational cost and high variance
- **Smaller K:** Less computation, higher bias (less training data per fold), lower variance
- **Larger K:** More computation, lower bias (more training data per fold), higher variance

D.2.4 Advantages

- Directly estimates out-of-sample prediction error
- Straightforward interpretation
- Well-established in machine learning literature
- Provides robust estimates when data is sufficient

D.2.5 Disadvantages

- Reduces effective training sample size (uses only $(K - 1)/K$ of data per fold)
- Problematic for small datasets ($n < 20$)
- Computationally expensive (requires K model fits per penalty value)
- Can have high variance when K is large or n is small
- May produce unstable penalty selection with small samples

D.3 Generalized Cross Validation (GCV)

D.3.1 Motivation

GCV (Golub, Heath, and Wahba 1979; Craven and Wahba 1978) was developed to approximate Leave-One-Out (LOO) cross validation without the computational burden of fitting n separate models. For small datasets common in cost estimation ($n=5-20$), GCV provides penalty selection without further reducing the training sample.

D.3.2 Mathematical Formulation

GCV estimates the prediction error using the full training data and a degrees-of-freedom adjustment:

$$\text{GCV} = \frac{n \cdot \text{RSS}}{(n - \text{df})^2}$$

where:

- n = sample size
- $\text{RSS} = \sum_{i=1}^n (y_i - \hat{y}_i)^2$ = residual sum of squares on training data
- df = effective degrees of freedom (Generalized Degrees of Freedom, GDF)

The penalty parameters that minimize GCV are selected as optimal.

D.3.3 Degrees of Freedom Adjustment

The denominator $(n - \text{df})^2$ penalizes model complexity. For penalized-constrained regression, we use the Gaines et al. (2018) GDF formula:

$$\text{df} = |\text{Active predictors}| + |\text{Equality constraints}| + |\text{Binding inequality constraints}|$$

This accounts for the effective number of parameters after accounting for regularization and active constraints.

D.3.4 GCV as LOO Approximation

GCV approximates the LOO cross validation score:

$$\text{LOO} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i^{(-i)})^2$$

where $\hat{y}_i^{(-i)}$ is the prediction for observation i from a model trained without observation i .

The key approximation is:

$$y_i - \hat{y}_i^{(-i)} \approx \frac{y_i - \hat{y}_i}{1 - h_i}$$

where h_i is the leverage (diagonal element of the hat matrix). GCV replaces individual leverages with the average: $h_i \approx \text{df}/n$.

D.3.5 Advantages

- **No data splitting:** Uses full training sample, crucial for small datasets
- **Efficient computation:** Single model fit per penalty value (vs. K fits for K-Fold)
- **Deterministic:** No randomness from fold assignments
- **Asymptotically equivalent to LOO:** Converges to LOO as n increases
- **Optimal for small samples:** Maintains training power when n < 20

D.3.6 Disadvantages

- Requires differentiable loss and prediction functions to compute GDF
- Approximation quality depends on leverage uniformity
- Less intuitive than K-Fold CV
- May be unstable if GDF calculation is unreliable
- Not applicable to all model types (works well for penalized regression)

D.4 Assumptions and Limitations

D.4.1 Common Assumptions (Both K-Fold and GCV)

1. **Independence:** Observations are independent and identically distributed (i.i.d.)
 - Violation: Time series data, clustered data, or spatial correlation
 - Impact: CV may underestimate prediction error
2. **Stationarity:** The data generation process remains stable
 - Violation: Non-stationary processes or regime changes
 - Impact: Past data may not predict future well
3. **Representative samples:** Training data represents the population of interest
 - Violation: Selection bias, small unrepresentative samples
 - Impact: Selected penalties may not generalize
4. **No data leakage:** Validation data must be truly held out
 - Violation: Feature engineering on full dataset before CV
 - Impact: Overly optimistic error estimates

D.4.2 Specific to K-Fold CV

- **Sufficient data:** Requires enough observations to create meaningful folds (typically n > 50 for K=10)
- **Balanced folds:** Folds should be representative of full dataset

D.4.3 Specific to GCV

- **Smooth loss function:** GCV derivation assumes differentiable loss
- **Accurate GDF:** Requires reliable degrees of freedom calculation
- **Linear-like behavior:** Works best for models with relatively smooth penalty effects

D.5 Comparison and Recommendations

Table 20: Comparison of K-Fold CV and GCV

Criterion	K-Fold CV	GCV	Recommendation
Sample size $n < 10$	Poor	Good	Use GCV
Sample size $10 < n < 20$	Fair	Good	Prefer GCV
Sample size $20 < n < 50$	Good	Good	Either acceptable
Sample size $n \geq 50$	Good	Good	Prefer K-Fold (more robust)
Computational cost	High (K fits)	Low (1 fit)	GCV faster
Interpretability	High	Moderate	K-Fold clearer
Deterministic	No (random folds)	Yes	GCV if reproducibility critical

D.5.1 Practical Guidance for Cost Estimation

1. **Small samples ($n=5-15$ lots):** Use GCV (default in our implementation)
 - Preserves full training data
 - More stable penalty selection
 - Computationally efficient
2. **Medium samples ($n=15-30$ lots):** Either method acceptable
 - GCV for consistency with small-sample cases
 - K-Fold ($K=5$) for more conservative penalty selection
3. **Large samples ($n>30$ lots):** Use K-Fold CV ($K=10$)
 - More robust to model assumptions
 - Direct estimate of out-of-sample error
 - Standard practice in machine learning
4. **When GDF is unreliable:** Fall back to K-Fold CV
 - Non-differentiable loss functions
 - Highly constrained solutions with uncertain active set

D.6 Implementation in PCReg

The `PenalizedConstrainedCV` class supports both methods:

```
# GCV (default for small datasets)
model_gcv = pcreg.PenalizedConstrainedCV(
    selection='gcv', # Generalized Cross Validation
    ...
)

# K-Fold CV
model_kfold = pcreg.PenalizedConstrainedCV(
    selection='cv', # K-Fold Cross Validation
    cv_folds=5,     # Number of folds (default=5)
    ...
)
```

The implementation automatically handles: - GDF calculation for GCV - Stratified fold assignment

for K-Fold CV - Grid search over penalty parameter space - Selection of optimal penalty values

D.7 References for Cross Validation

Key papers on cross validation methods:

- Golub, Heath, and Wahba (1979): Original GCV formulation
- Craven and Wahba (1978): Theoretical foundations of GCV
- Stone (1974): Cross-validatory choice of prediction rules
- Hastie, Tibshirani, and Friedman (2009): Comprehensive treatment in Section 7.10