

Predicting costs

10/25/2019

1. Overview

The agency estimates project costs internally prior to public bidding openings.

Model variation in those bids a couple of ways and try to find ways to improve upon the original estimates before future bidding openings. (Compare basic statistical methods with what are called “regularization” alternatives.)

Project-level data includes a number of characteristics. Economic and demographic variables are specific to national and regional economic and labor market conditions. City of New York building permits can help proxy for activity in the broader regional construction market. ENR’s cost index serves as proxy for broader hard construction costs.

The goal here is to bridge exploration of the agency’s data with potential exogenous predictors, some of which the internal estimation process may underestimate or inadvertently miss. If those predictors can add measurable value to the agency’s cost estimation methods it may inform potential changes in engineers’ estimation methods.

2. Data.

Project data, called “bids” here, come from the Engineering Department. Economic and demographic indicators are specific to Greater New York (18 counties on both sides of the Hudson River) and come from the Planning and Regional Development Department; underlying data is from Oxford Economics.

Construction data is better from some parts of the region than others, but Jersey City’s construction data is not yet as dependable as the City of New York’s. NYC dominates regional construction anyway and it’s justifiable for now to use its permitting data as somewhat representative of the broader regional construction market.

Prices of construction materials and labor already figure directly into the agency’s internal cost estimation, and this analysis borrows the same index for predictive powers despite uncertainty regarding whether its implicit presence in agency estimates helps or hurts its role in any multivariable treatments. It is likely of second-order importance for now.

One variable of interest is the actual bidding process. Institutional discussions and earlier modeling suggests the bidding process may influence actual project costs. Limits placed on the range of bidders could, for example, on average and holding other things constant, increase the average (and lowest qualifying) bid - this is basic microeconomics. I’ll simplify the bidding format variable by making it binary: “public” for projects without significant constraints and “other” for ones closed to firms that don’t qualify, such as large enterprises. First I’ll clean that variable a bit to consolidate categories very close in spirit.

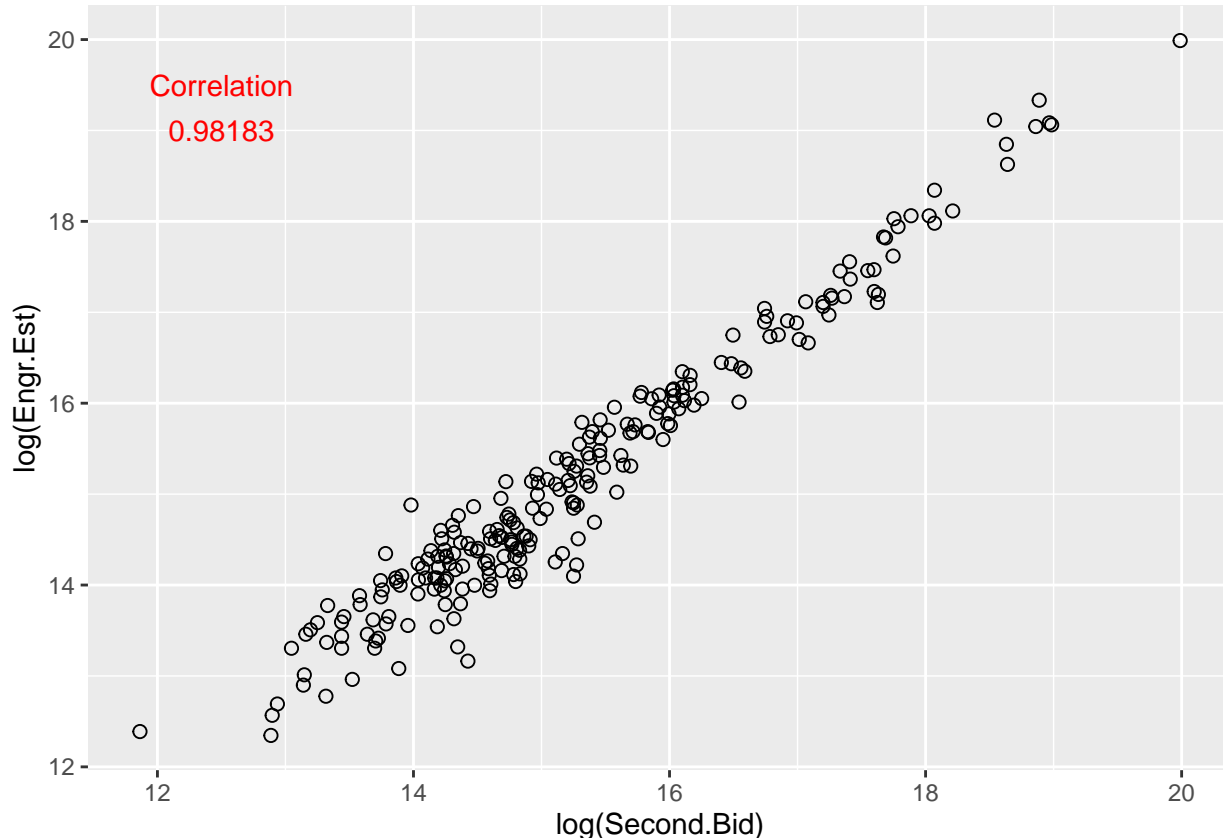
Earlier work suggests there isn’t major variation across the individual developing the in-house estimate and unique employee (estimator) identifiers are omitted from this review.

Agency projects last for months or years and actual costs do not exist for many of the observations, which at just over 260 projects already creates minor dimensionality concerns given the number of potential predictive variables. The second-lowest qualifying bid provides a reasonable target for evaluating internal estimates. The accuracy metric referenced through the exploratory discussion below and appendix plots represents a ratio of that second-lowest bid over the estimate, both in dollars. A 1 would represent a case where the internal estimate (denominator) precisely matched the second-lowest bid; a 0.94 would mean the bidder bid 94 cents for every dollar estimated internally, et cetera.

3. Exploratory analysis.

Why might developing a controlled multivariate model will be worth it? The average gap between bids and estimates is less than \$900,000, or around 5% (the average project bid was \$15 million).

How much inconsistency does that represent?

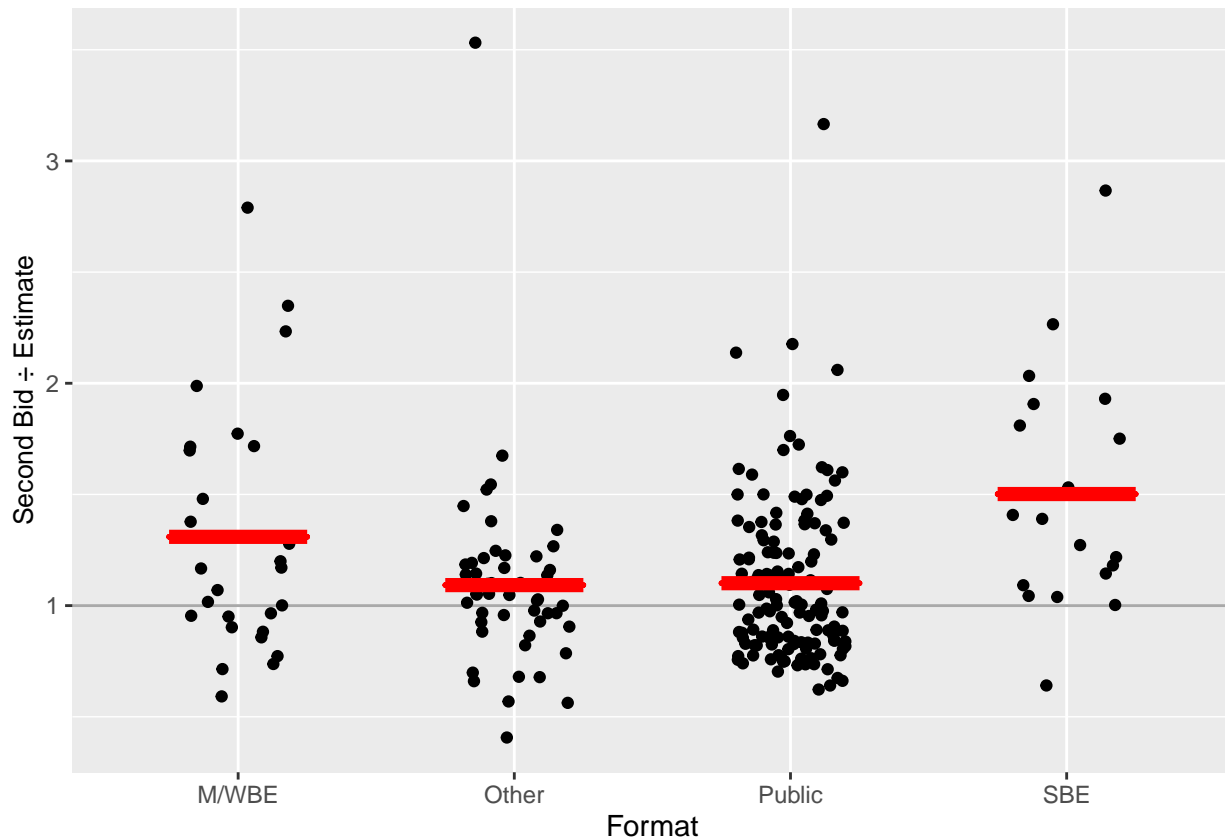


The in-house engineers' guesses predict more than 98% of the variation in second-lowest bids. Some of the remaining variation may be explained by institutional guesswork.

Uncontrolled bivariate relationships provide easy clues as to predictors' potential role in more controlled multivariate relationships. Plots for this exploratory work are in the appendix at the end of the document; all use the definition of "accuracy" defined a few paragraphs above.

- Location may matter: projects that span the Hudson River seem to come in, on average, higher than expected. Projects that span the Hudson River wind up costing (with respect to estimates) more, on average, than ones plunked squarely in either New York or New Jersey.
- The bidding process can be constrained or open, with potential ramifications on the ability to estimate costs. (Visualization for that relationship is just below these bullet points. Plots for the other bullet points can be found in the appendix, along with corresponding test statistics.)
- The signal is stronger regarding the type of project, which has an identifiable (if yet uncontrolled) relationship with estimating accuracy. Of three categories — infrastructure, paving, building — the agency appears to predict paving projects the best. Note: the story changes when considering the lowest bid, where paving projects' relationship to estimates varies significantly.
- Outliers for PATH and TB&T push the average accuracy metric up for each, otherwise there's little apparent difference across departments.
- Strong signals emerge that projects of medium size (in dollar terms) may be less evasive than much larger or smaller projects.

Bidding process (format).



The implication of project size may provide the most valuable results. One might have expected the largest or smallest projects to be the toughest to predict - particularly the very smallest projects. But it's the projects ranging from the 40th to 70th percentiles that seem to be the most challenging.

4. Modeling and prediction

Try and use exogenous covariates to predict an alternative engineering estimate, without using the second lowest bid information, that might be closer to the low bid. (Note: when projects only attracted one bid, that bid is used instead of a second-lowest bid. There are few of these projects in the data set.)

The data set carries dimensionality challenges, with a number of variables (absolutely and relative to the number of observations). It includes mostly continuous variables but also a number of qualitative factors, both ordinal and nominal and all treated categorically without conversion to binary subvariables - the modeling processes used here do that automatically.

4a. Base model (manual selection).

Interpretation: specification was manual and intuitive. Given the fact that estimators' already try and take much of this information into account, however, a model with even a handful of extra covariates could represent overfitting - trying to hard.

Note: ensure the accuracy variable calculated earlier is dropped before modeling or introduce some dual (reverse) causality, which could confuse models. Note: when a number appears in the output without context, it is likely an information criterion (and AIC), which may or may not provide value post-modeling.

Split data into training / test sets. And, just for modeling purposes, remove the accuracy metric. One would split randomly with cross-sectional data and since this effort aims to help predict temporally, split by date — use projects (n=213) from 2015 through the first quarter of 2019 to train models and projects (n=26) since the end of March to test them. That's not many projects for testing but the real test will come as another quarter or two of data rolls in.

Choose a handful of potential predictors and build a linear model. Go with the original estimate (always included) and (1) regional construction-specific employment, (2) bidding process (public or other), (3) typeology (infrastructure, building, or paving), (4) construction permits (lagged by one quarter), (5) construction costs (indexed), and (6) project size, with project dollars (from the second bid) categorized in deciles.

```
base = lm(Second.Bid ~ Engr.Est + Employment.in.construction + Format2 + Typeology + permits_1 + cci + quantile, data = train)
```

```
options(scipen=999)
summary(base)
```

```
##
## Call:
## lm(formula = Second.Bid ~ Engr.Est + Employment.in.construction +
##     Format2 + Typeology + permits_1 + cci + quantile, data = train)
##
## Residuals:
```

	Min	1Q	Median	3Q	Max
	-71511141	-965914	101910	928757	36057047

```
##
## Coefficients:
```

	Estimate	Std. Error	t value
(Intercept)	6480575.50070	18102711.09948	0.358
Engr.Est	0.92614	0.01558	59.460
Employment.in.construction	-145346.86493	162525.05467	-0.894
Format2Public	-1087152.85330	1048463.94815	-1.037
TypeologyInfra	-1884496.88779	1196782.47632	-1.575
TypeologyPaving	-1750022.03616	1469411.68848	-1.191
permits_1	34.58965	99.17871	0.349
cci	4503.02581	5979.35994	0.753
quantile.L	1615261.82377	1859239.37672	0.869
quantile.Q	-925988.08752	1801313.89445	-0.514
quantile.C	-787744.58376	1652165.94976	-0.477
quantile^4	-1459907.57205	1578328.58201	-0.925
quantile^5	-1612438.69112	1526686.15560	-1.056
quantile^6	-1520076.57709	1490945.78988	-1.020
quantile^7	-769296.64776	1507402.60790	-0.510
quantile^8	-318579.79071	1497814.39145	-0.213
quantile^9	125894.52031	1512632.20799	0.083

```
##
##                                Pr(>|t|)
## (Intercept)                    0.721
## Engr.Est                       <0.0000000000000002 ***
## Employment.in.construction      0.372
## Format2Public                   0.301
## TypeologyInfra                  0.117
## TypeologyPaving                 0.235
## permits_1                       0.728
## cci                             0.452
## quantile.L                      0.386
## quantile.Q                      0.608
```

```
## quantile.C                                0.634
## quantile^4                                0.356
## quantile^5                                0.292
## quantile^6                                0.309
## quantile^7                                0.610
## quantile^8                                0.832
## quantile^9                                0.934
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6880000 on 196 degrees of freedom
## Multiple R-squared:  0.9731, Adjusted R-squared:  0.9709
## F-statistic: 443.2 on 16 and 196 DF,  p-value: < 0.00000000000000022
```

The equation above throws a decent amount of information at the engineering estimate and tries to predict the second bid. If the result is noticeably closer to the low qualifying bid than the original estimate, you can use the delta as a post-estimation fudge factor to adjust the final estimate.

What is the summary of the predicted values? How does it compare to the summary of second-lowest bids? Looking at the two summaries, the original engineering estimate and the enhanced prediction do appear to be significantly (statistically) different.

Maybe something more robust can come with a little creativity.

4b. Shrinkage and automated variable selection.

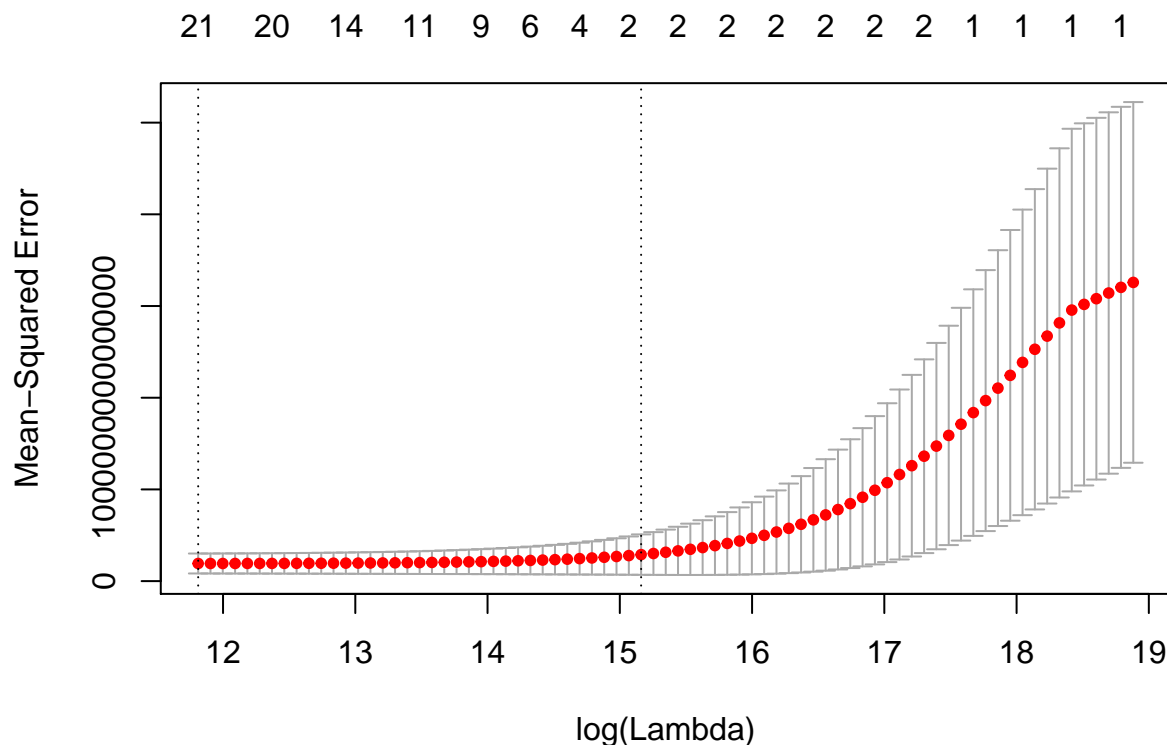
Traditional methodology — tossing variables that made intuitive sense into a model and evaluating outcomes — might have identified a few reliable predictors. But it fell short and, even if it had, specification problems and covariate bias would have challenged the results. A survival method may help — automated variable selection can weed out weaker variables and identify one or more key items to help prediction. Regularization processes penalize variables that threaten to introduce more uncertainty than predictive power to a model. Regularization modeling builds atop ordinary least squares regression, which fits a curve to data that minimizes the distance between the curve and any given point in the data set. Traditional least squares modeling can be prone to overfitting — reading too much signal from what is essentially meaningless noise and providing a tool that creates a poor fit for data that, while tied to the underlying process being modeled, was absent during the fitting process; this presents obvious challenges for prediction.

Regularization begins with the least squares method and adds a penalty. That penalty term is guided by a tuning parameter that essentially works as a dimmer switch — it can be cranked up to increase the penalty or down all the way to zero, which effectively turns off the penalty and produces the same results one would get from ordinary least squares. The tuning parameter is represented by the lambda in the second equation for error estimation (both from Hastie and Tibshirani):

$$\sum_{i=1}^n \left(y_i - \beta_0 - \sum_{j=1}^p \beta_j x_{ij} \right)^2$$

$$\sum_{i=1}^n \left(y_i - \beta_0 - \sum_{j=1}^p \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^p \beta_j^2$$

Run cross-validation to pick the tuning parameter. Cross-validation runs modeling processes iteratively by resampling the data — splitting it into a series of tranches used systematically as training and test sets. The fit with the lowest test error identifies the tuning parameter:



(Note:

to help here with manageability and reproducibility, adopt some of the modeling software’s basic assumptions (10 folds, standardized coefficients, use of mean squared error as an evaluation metric, et cetera).)

This analysis uses a blended regularization penalty that falls between ridge and lasso (the “alpha” is set at 0.25).

The tuning parameter that gets chosen isn’t actually the one associated with the model exhibiting the lowest test error, but with the one coinciding with a sister model (with the lowest test error plus a standard error). If a few models’ test errors are within a standard error of one another, default to the simplest of the group.

The result suppresses all but a pair of predictors: project size and bidding process.

(Very technical note: this regularization process actually carries the prospect of increasing bias and, in the process, dulling coefficients’ reflection of the real world relationship between the processes being modeled. (It can introduce or exacerbate bias.) Regularization is often run with a penalty that, prior to tuning, sums squared coefficients or their absolute values, the second of which is responsible for forcing weak predictors completely out of the model. Performing analysis with the latter shrunk all covariates (aside from the engineer’s estimate) to zero, suppressing them completely. This is a harsh variable selection process but it might’ve been expected given the original estimates’ proven strength. It doesn’t leave enough clues for anyone to offer potential improvements. A little fine-tuning to the penalty combines the regularization treatments and gives the model a little leash, identifying predictors that survive as the model gets further from ordinary least squares without disappearing.)

```
##
## Call:  glmnet(x = x, y = train2[, 5], alpha = blend, lambda = cv$lambda.1se)
##
##      Df    %Dev  Lambda
## [1,]   2 0.9642 3841000
```

Predict using the model and the test data.

4c. Evaluate regularization.

Compare this error with a basic OLS regression using all potential covariates; regularized iterations can be compared with it. Turning the tuning parameter (the dimmer switch) off makes it easy.

Errors (test) for regularization and ordinary models, respectively:

```
## [1] 108096691053724
```

```
## [1] 221388743444856
```

Regularization not only reduced error for the model built using pre-Q2 2019 projects, but that model then provides a stronger fit using the withheld projects. And consider the implications for interpretability. Regress using the full data set:

```
## 45 x 1 sparse Matrix of class "dgCMatrix"
##                                     1
## (Intercept)                    -195436.1940822
## Engr.Est                        0.7918784
## Loc                             .
## LD                              .
## Typeology                       .
## Consumer.price.index            .
## Employment.in.communications     .
## Employment.in.construction       .
## Employment.in.education.and.health .
## Employment.in.financial.and.business.services .
## Employment.in.financial.services .
## Employment.in.government         .
## Employment.in.other.services     .
## Employment.in.production.industries .
## Employment.in.professional.services .
## Employment.in.real.estate        .
## Employment.in.retail              .
## Employment.in.transport.services .
## Employment.in.wholesale           .
## Output.in.communications          .
## Output.in.construction            .
## Output.in.financial.services      .
## Output.in.government              .
## Output.in.retail                  .
## Output.in.education.and.health    .
## Output.in.financial.and.business.services .
## Output.in.other.services          .
## Output.in.production.industries   .
## Output.in.professional.services   .
## Output.in.real.estate             .
## Output.in.transport.services      .
## Output.in.wholesale               .
## Personal.disposable.income..nominal .
## Personal.disposable.income..real  .
## Personal.income..nominal          .
## Retail.sales..nominal              .
## Retail.sales..real                 .
## Total.employment                  .
## Total.office.based.employment     .
## Total.output                       .
```

```
## Total.population .
## permits_1 .
## cci .
## Format2 -296428.0885529
## quantile 563323.5228778
```

5. Discussion.

This suggests some room for targeted efforts to add value to the average engineer’s estimate, since it already correlated very highly with targets. The most obvious predictor is project size, which isn’t too surprising given the exploratory work done earlier. The bidding process, or “format” using the Engineering Department’s terminology, was the other predictor to survive the elimination process.

Both project size and format represent avenues for post-estimation adjustments that could improve accuracy.

Next steps include looking for best practices regarding post-estimation adjustments for project cost by size and/or bidding process. Here are bivariate, uncontrolled relationship parameters between bids and project size:

Both project size and bidding process.

```
summary(lm(bids$Second.Bid ~ bids$Engr.Est + bids$quantile_2 + bids$quantile_3 + bids$quantile_4 + bids$quantile_5 + bids$quantile_6 + bids$quantile_7 + bids$quantile_8 + bids$quantile_9 + bids$quantile_10 + bids$Format2))

##
## Call:
## lm(formula = bids$Second.Bid ~ bids$Engr.Est + bids$quantile_2 +
##     bids$quantile_3 + bids$quantile_4 + bids$quantile_5 + bids$quantile_6 +
##     bids$quantile_7 + bids$quantile_8 + bids$quantile_9 + bids$quantile_10 +
##     bid$Format2)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -66020099  -1045742     2436   1103502   55721829
##
## Coefficients:
##              Estimate      Std. Error t value
## (Intercept)    488675.00994    1605759.01267    0.304
## bids$Engr.Est      0.87662      0.01595   54.951
## bids$quantile_2    791015.17010    2292756.80139    0.345
## bids$quantile_3    934316.84027    2284488.75004    0.409
## bids$quantile_4   1127432.95204    2277086.14599    0.495
## bids$quantile_5   1631907.82549    2302051.43451    0.709
## bids$quantile_6   1912392.64304    2312352.66824    0.827
## bids$quantile_7   1647636.51108    2335865.63069    0.705
## bids$quantile_8   2023216.93254    2297074.48384    0.881
## bids$quantile_9   4849006.58402    2313358.62170    2.096
## bids$quantile_10  2744328.46517    2920208.31396    0.940
## bid$Format2Public -1979709.18023    1072747.07110   -1.845
##
##              Pr(>|t|)
## (Intercept)      0.7612
## bids$Engr.Est    <0.0000000000000002 ***
## bids$quantile_2      0.7304
## bids$quantile_3      0.6829
```



```
## bids$quantile_4          0.6210
## bids$quantile_5          0.4791
## bids$quantile_6          0.4091
## bids$quantile_7          0.4813
## bids$quantile_8          0.3794
## bids$quantile_9          0.0372 *
## bids$quantile_10         0.3483
## bid$Format2Public        0.0663 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7790000 on 227 degrees of freedom
## Multiple R-squared:  0.9653, Adjusted R-squared:  0.9636
## F-statistic: 573.6 on 11 and 227 DF,  p-value: < 0.00000000000000022
```

Project size only.

```
summary(lm(bids$Second.Bid ~ bids$Engr.Est + bids$quantile_2 + bids$quantile_3 + bids$quantile_4 + bids$quantile_5 + bids$quantile_6 + bids$quantile_7 + bids$quantile_8 + bids$quantile_9 + bids$quantile_10))
```

```
##
## Call:
## lm(formula = bids$Second.Bid ~ bids$Engr.Est + bids$quantile_2 +
##     bids$quantile_3 + bids$quantile_4 + bids$quantile_5 + bids$quantile_6 +
##     bids$quantile_7 + bids$quantile_8 + bids$quantile_9 + bids$quantile_10)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -64927474  -490838    31601   573534  56729942
##
## Coefficients:
##              Estimate      Std. Error t value      Pr(>|t|)
## (Intercept)   76048.34661  1598483.07814    0.048      0.9621
## bids$Engr.Est    0.87692     0.01604   54.685 <0.0000000000000002
## bids$quantile_2 -34059.25935  2260576.56828   -0.015      0.9880
## bids$quantile_3  191658.26895  2260597.38380    0.085      0.9325
## bids$quantile_4  467164.92654  2260635.79910    0.207      0.8365
## bids$quantile_5  724044.57116  2260706.51997    0.320      0.7491
## bids$quantile_6  921683.48531  2261008.27650    0.408      0.6839
## bids$quantile_7  491236.92917  2262088.51151    0.217      0.8283
## bids$quantile_8 1195745.54423  2264742.28422    0.528      0.5980
## bids$quantile_9  4099789.39909  2289440.33695    1.791      0.0747
## bids$quantile_10 2003942.85274  2907737.97455    0.689      0.4914
##
## (Intercept)
## bids$Engr.Est ***
## bids$quantile_2
## bids$quantile_3
## bids$quantile_4
## bids$quantile_5
## bids$quantile_6
## bids$quantile_7
## bids$quantile_8
## bids$quantile_9 .
```

```
## bids$quantile_10
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7831000 on 228 degrees of freedom
## Multiple R-squared:  0.9648, Adjusted R-squared:  0.9632
## F-statistic: 624.1 on 10 and 228 DF,  p-value: < 0.00000000000000022
```

Bidding process only.

```
summary(lm(bids$Second.Bid ~ bids$Engr.Est + bid$Format2))
```

```
##
## Call:
## lm(formula = bids$Second.Bid ~ bids$Engr.Est + bid$Format2)
##
## Residuals:
```

	Min	1Q	Median	3Q	Max
	-66472801	-1517706	-297907	819629	52848010

```
##
## Coefficients:
```

	Estimate	Std. Error	t value
(Intercept)	1955717.34653	801987.88596	2.439
bids\$Engr.Est	0.88527	0.01107	79.945
bid\$Format2Public	-1711217.97112	1017025.82578	-1.683

```
##
## Pr(>|t|)
```

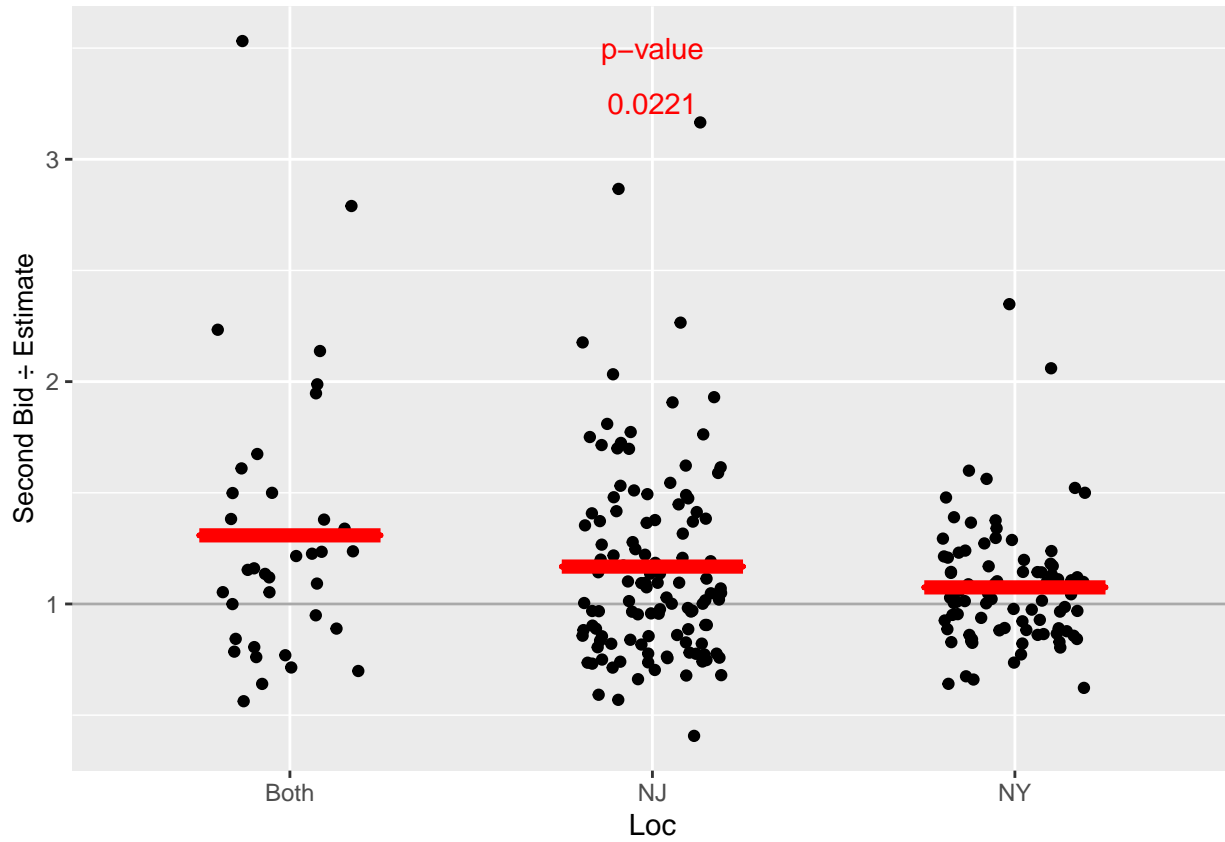
(Intercept)	0.0155 *
bids\$Engr.Est	<0.0000000000000002 ***
bid\$Format2Public	0.0938 .

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7733000 on 236 degrees of freedom
## Multiple R-squared:  0.9644, Adjusted R-squared:  0.9641
## F-statistic: 3199 on 2 and 236 DF,  p-value: < 0.00000000000000022
```

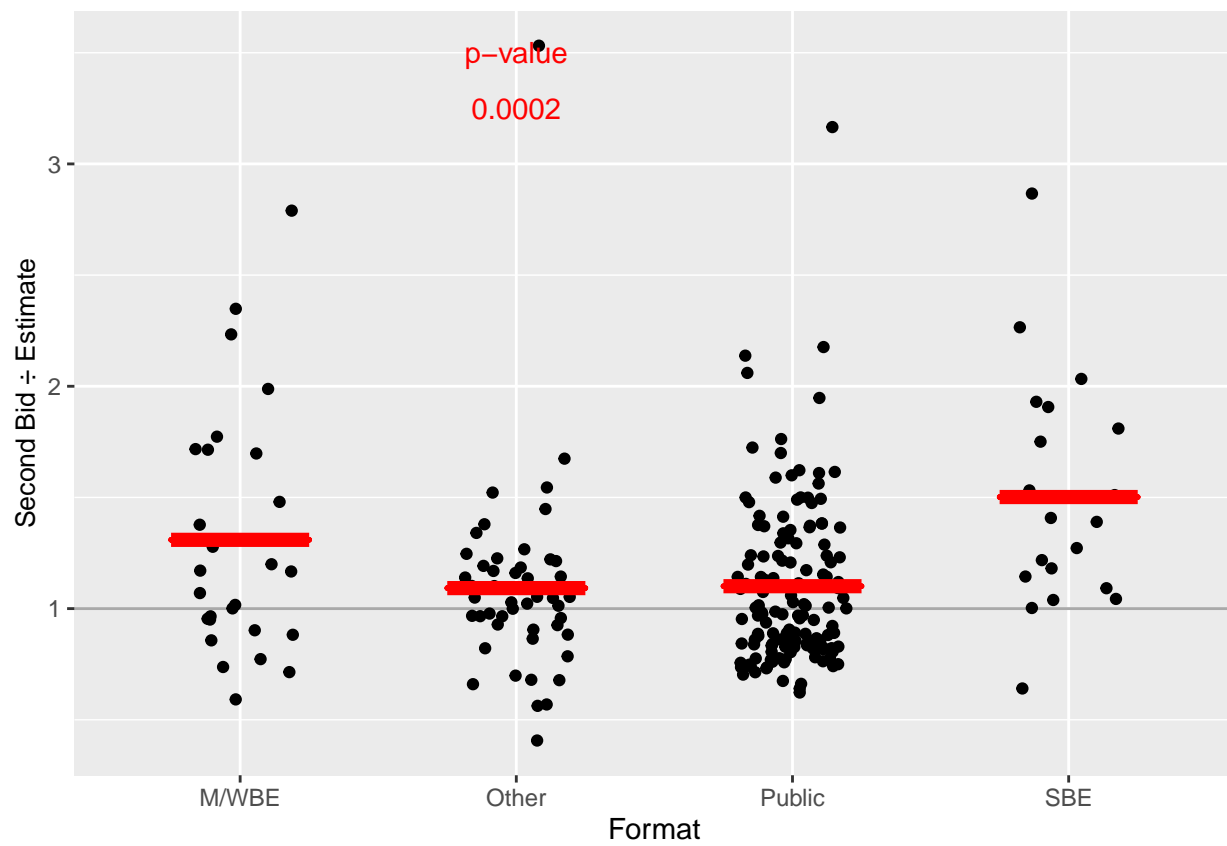
Appendix: exploratory work.

Plots and output from earlier exploratory bivariate work are below. Each considers a potential predictor's relationship to the agency's cost estimation accuracy, defined here as the second-lowest bid over the internal agency estimate.

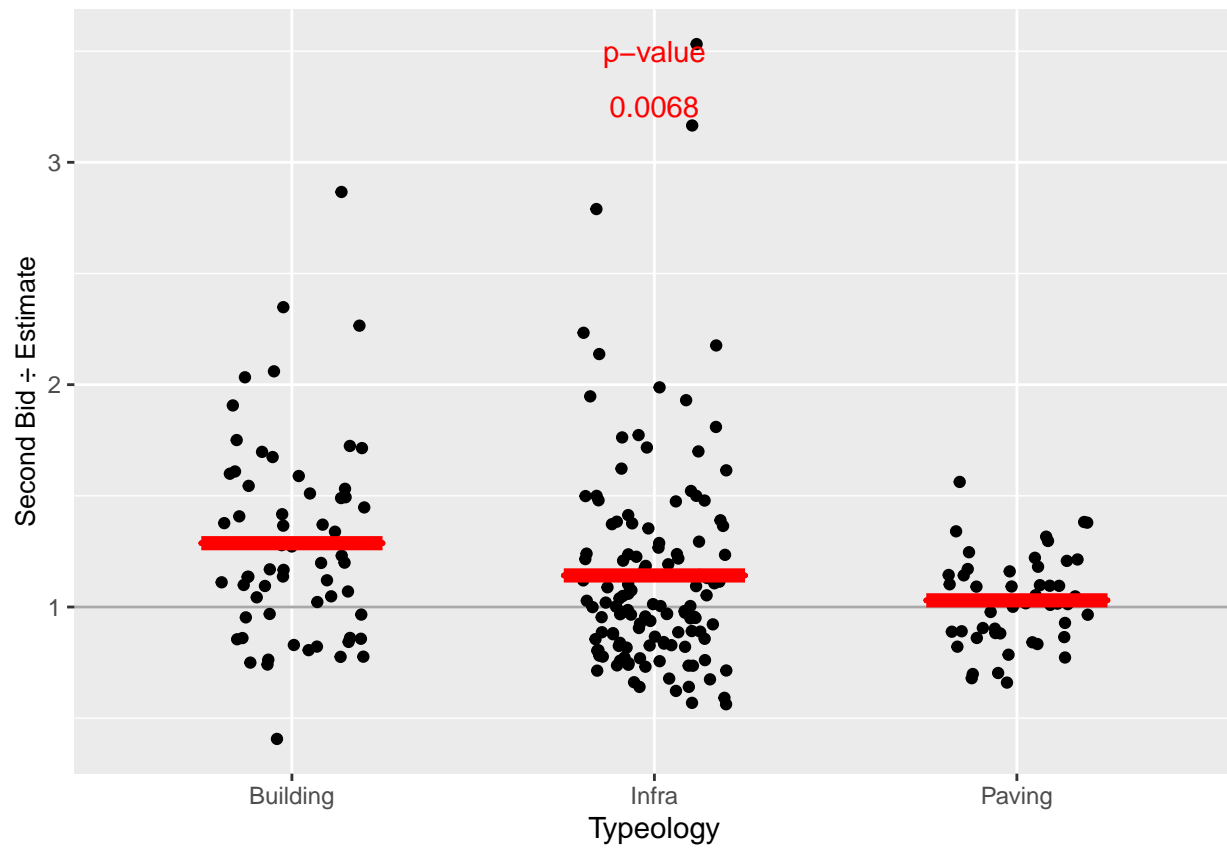
Location.



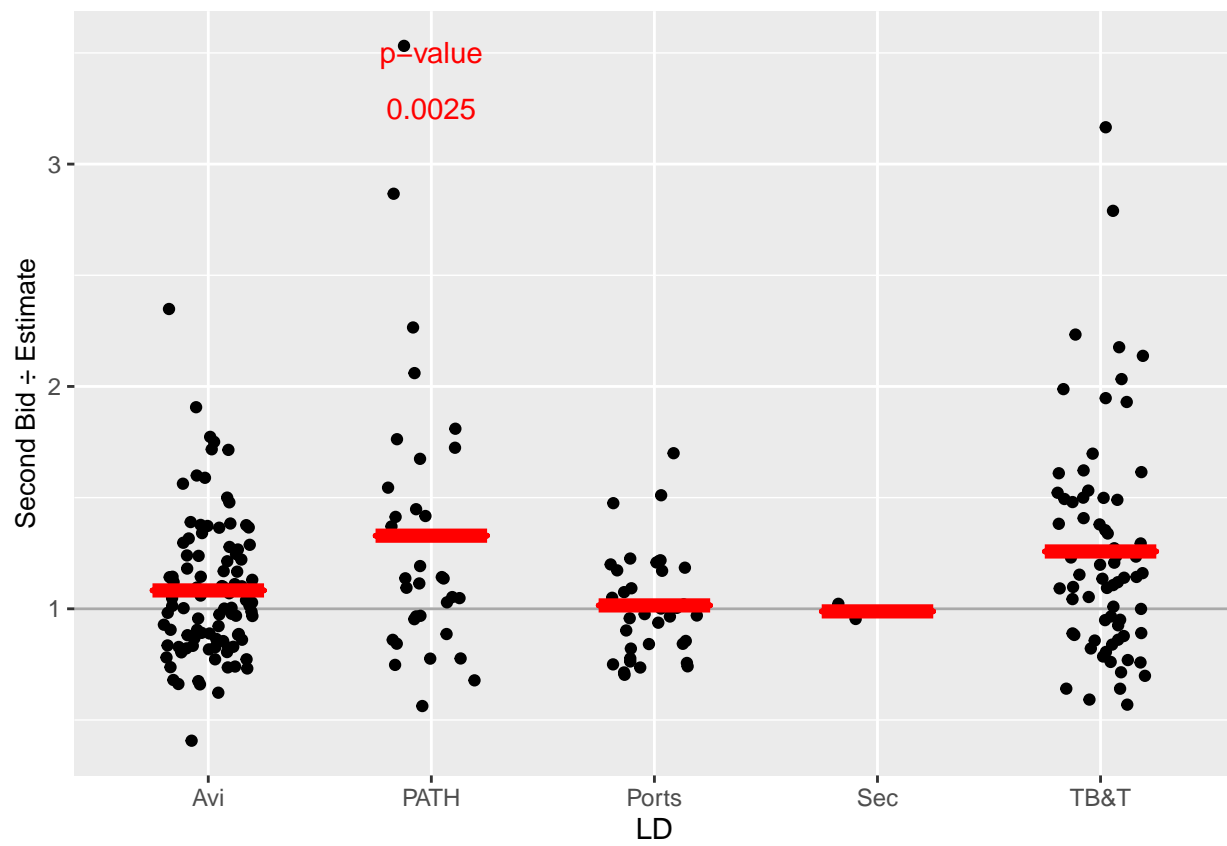
Bidding process (“format”).



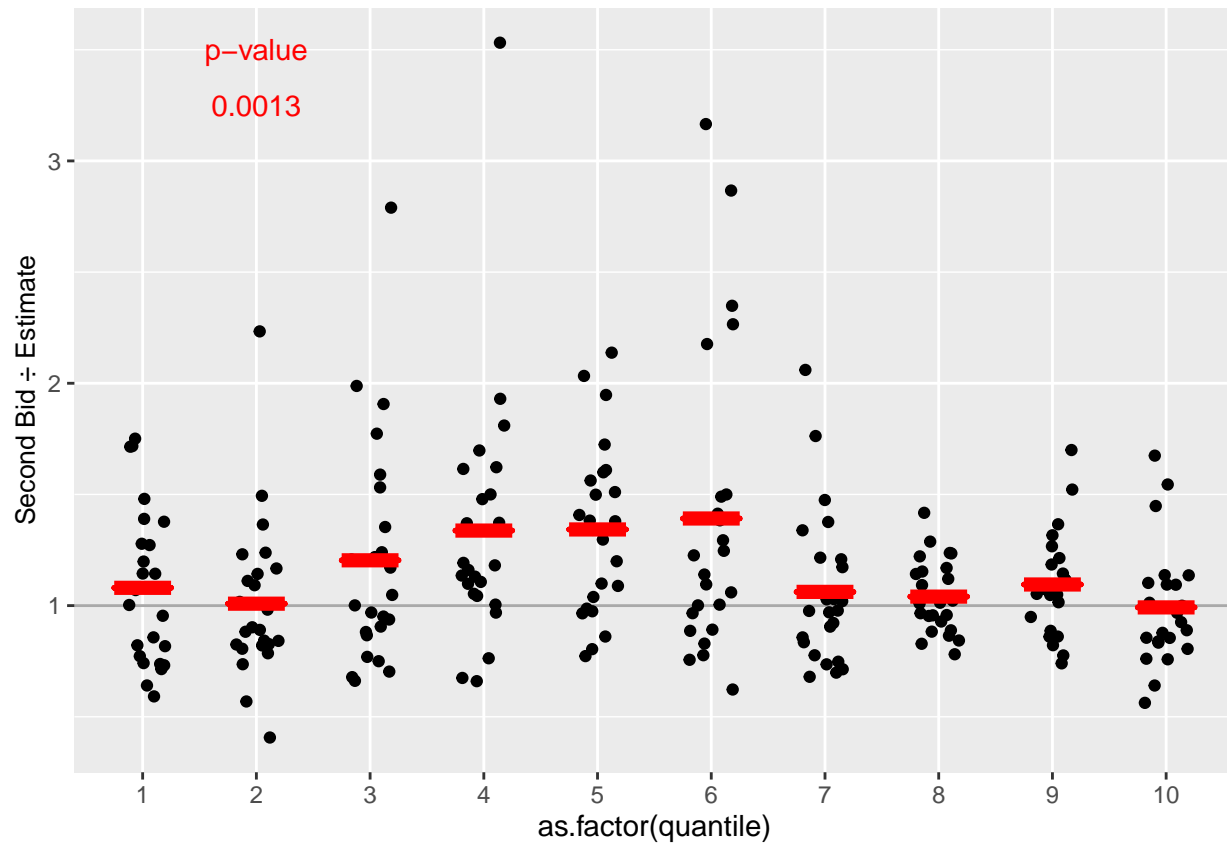
Project typeology.



Department.



Project size (dollars bid).



Project size (dollars) with number of bidders.

