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COST ESTIMATES FOR THE SEISMIC RETROFIT OF FEDERALLY OWNED AND LEASED BUILDINGS

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ABSTRACT

Presidential Executive Order 13717, *Establishing a Federal Earthquake Risk Management Standard*, encourages federal agencies to "enhance resilience…[to] future earthquakes" by evaluating and retrofitting existing federal buildings based on current existing building codes. We develop a methodology for predicting seismic retrofit costs based on observable building characteristics and the desired performance standard. Our approach is to train a series of regression models on a database collected for FEMA 156, *Typical Costs for the Seismic Rehabilitation of Existing Buildings*. The models vary in the level of data required; e.g., a decision-maker may not have information on building construction type. We use prediction error to quantify the effect of data availability on estimates.

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ABSTRACT

Presidential Executive Order 13717, *Establishing a Federal Earthquake Risk Management Standard*, encourages federal agencies to "enhance resilience…[to] future earthquakes" by evaluating and retrofitting existing federal buildings based on current existing building codes. We develop a methodology for predicting seismic retrofit costs based on observable building characteristics and the desired performance standard. Our approach is to train a series of regression models on a database collected for FEMA 156, *Typical Costs for the Seismic Rehabilitation of Existing Buildings*. The models vary in the level of data required; e.g., a decision-maker may not have information on building construction type. We use prediction error to quantify the effect of data availability on estimates.

Introduction

Presidential Executive Order 13717 (EO 13717), Establishing a Federal Earthquake Risk Management Standard, encourages agencies to "enhance resilience…[to] future earthquakes by evaluating and retrofitting existing federal buildings based on current existing building codes. To ensure resilience, EO 13717 suggests that agencies go beyond the minimum life safety performance standard. However, while guidance on evaluation and retrofit practices is readily available (e.g., ASCE/SEI 41-13 [1] and FEMA 547 [2]), a standard approach to estimating seismic retrofit costs does not exist. Moreover, the absence of easily obtainable estimates can make seismic retrofits, especially beyond the minimum of life safety, a prohibitive option for decision makers.

We present a methodology for estimating seismic retrofit costs based on observable

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building characteristics (such as building construction type, age, and area) and the desired performance standard. Our approach relies on using a database collected for FEMA 156 [3] and FEMA 157 [4], hereafter FEMA 156/157, to train linear regression models to predict retrofit costs. The data is freely available, making our approach to estimating retrofit costs a viable and easy to implement option for decision makers.

Moreover, we quantify the cost of data limitations in terms of prediction error. Decision makers may not have access to, or the ability to collect, the data required for prediction; e.g., determining building type for a large building inventory may be infeasible. Our approach provides decision makers with guidance in prioritizing data collection for making retrofit cost predictions, with a direct measure in dollars of the trade-off from using less data.

The paper is structured as follows. We first provide some background on FEMA 156/157 and briefly describe the methodology. We then describe the data, presenting select summary statistics. This is followed by the main results, including estimates of prediction error and an application that compares retrofit costs for different performance standards. Finally, we conclude with a discussion of limitations and future directions.

Methodology

Seismic retrofit costs vary with a building's unique characteristics, such as building construction type, age, and area, as well as the desired performance standard. The most obvious, and perhaps most reliable, approach to estimating retrofit costs is to hire a consulting engineering or construction firm with the appropriate expertise. However, this is both time consuming and expensive, especially for large building inventories.

An alternative to collecting such *primary data* is to estimate retrofit costs based on *secondary data* on retrofits for other buildings. Naturally, an estimate based on retrofits for other buildings will be less accurate than an estimate made specifically for the building of interest. Nevertheless, using secondary data is relatively inexpensive and thus offers both a feasible approach and a reasonable frame of reference for cost estimates.

In NIST TN 1973, *A Methodology for Estimating Retrofit Costs* [5], we develop a methodology based on secondary data. The data was originally collected for FEMA 156/157, *Typical Costs of Seismic Rehabilitation of Existing Buildings* [3, 4]. The FEMA 156/157 reports present both a unique data collection effort and a set of methods for estimating retrofit costs using this data.

According to FEMA 156/157, the data set represents actual or estimated ("by an experienced design professional") retrofit project costs and contains extensive information on building characteristics. Importantly, the data is "validated" through follow-ups with survey respondents, and assigned a quality control rating (or "quality factor") to ensure that each response is "objective and reliable." Cost estimates with low quality factors are removed from the data set, with the intent to improve the overall quality of the data. The final database contains 2088 cost estimates.

Moreover, FEMA 156/157 present three options for estimating retrofit costs, differing in their data requirements. All three options estimate the mean structural retrofit cost, conditional on some observable characteristics. Option 1 estimates the mean cost conditional on building type, while Option 2 estimates the mean cost conditional on building type, building seismicity, and desired performance standard. Option 3 estimates the mean cost conditional on additional building characteristics and is thus presented as a linear regression model. The coefficients from a regression fit to the database can be used to predict costs.[4]

Our approach differs in two critical dimensions. First, we do not use the entire database to fit the regression. We split the data into a training set of size n to estimate the coefficients, and a test set of size m to estimate the prediction error. This approach provides a plausible estimate of prediction error and allows decision makers to compare different models by their accuracy.

Second, our model specification differs from Option 3 in FEMA 156/157. We use building type fixed effects rather than fitting a regression separately for each building type. In NIST TN 1973 [5], we show that this approach can reduce prediction error (defined as Mean Square Error).[5] We also include information on whether the building is deemed historic since retrofits are likely to be very different for historic and non-historic buildings. Most importantly, we model retrofit costs using a Generalized Linear Model (GLM).[6] Let $Y \equiv \log(E[C])$, where $E[C]$ is the expected cost per square foot.[7] Our **main model** is

$$Y = \beta_0 + \beta_1 Area + \beta_2 Age + \beta_3 Stories + \beta_4 Occup + \beta_5 Hist + \gamma + \eta + \delta + \zeta \qquad (1)$$

where *Area* is building area in square feet; *Age* is building age in years; *Stories* is the number of above and below ground stories; *Occup* is building occupancy during the retrofit; *Hist* is a categorical variable denoting the building's historic status; γ is the building type fixed effect; η is the seismicity fixed effect; δ is the performance standard fixed effect; and $\zeta \equiv \eta \times \delta$ is the interaction of seismicity and performance.

While the implications of *Area*, *Age*, *Stories*, and *Hist* are straightforward, the rest of the predictors merit further discussion. *Occup* denotes whether the building occupants remain in place during construction (IP), are temporarily relocated to another part of the building during construction (TR), or whether the building is vacant during construction (V). In terms of construction costs, IP is the most expensive option, because construction takes place around the occupants, while V is the least expensive. Building type denotes the building model type (e.g., Unreinforced Masonry, or URM). Seismicity, which refers to the seismic hazard at the building site, is discussed in the next section, Data.

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[4] More precisely, Option 3 estimates a linear regression, separately for each building type, on a *synthetic* version of the original database. More details and a comparison with our approach, including the danger of overfitting on the synthetic data, are given in NIST TN 1973 [5].

[5] Technically, for consistency with FEMA 156/157 [3, 4], we group similar building model types together rather than using all building types directly. See NIST TN 1973 [5] for more details.

[6] In contrast, the approach illustrated in NIST TN 1973 [5] models the log of retrofit costs, $\log(C)$, a standard linear model as in FEMA 156/157 [3, 4].

[7] We use log to refer to the natural logarithm.

The performance standards, chosen by the decision maker, are defined as follows in FEMA 156 [3]:

- Life Safety (LS): Allows for unrepairable damage as long as life is not jeopardized and egress routes are not blocked.

- Damage Control (DC): Protects some feature or function of the building beyond life-safety, such as protecting building contents or preventing the release of toxic material.

- Immediate Occupancy (IO): Allows only minimal post-earthquake damage and disruption, with some nonstructural repairs and cleanup done while the building remains occupied and safe.

These definitions suggest that Damage Control is equivalent to Life Safety plus *nonstructural* improvements and is more likely to correspond with current Life Safety standards (e.g., as defined in RP-8 [6]).

Note that Eq. 1 only specifies the first element of a GLM, the model for expected cost, E[C]. The model links the mean, E[C], to the predictors through the log function; that is, the mean is modeled as $E[C] = exp(X\beta)$, where X is the matrix of predictors. The second element of a GLM is the distribution of C. Since C should be nonnegative, and the distribution of C is unlikely to be symmetric, we assume that C follows a Gamma distribution. One advantage of this specification is that it does not assume constant variance.[8]

We use Root Mean Square Error (RMSE) as our measure of out-of-sample prediction error. Let $\hat{\beta}$ denote the coefficients obtained in the training step. The RMSE is estimated from the test set as follows:

$$RMSE \equiv \left(\frac{1}{m}\sum_{i=1}^{m}\left(exp(\hat{\beta}^T x_i) - C_i\right)^2\right)^{\frac{1}{2}} \tag{2}$$

Note that we estimate RMSE on the original scale of the response variable, C. Thus, RMSE as defined in Eq. 2 is directly interpretable as prediction error in dollars per square foot.

Data

A version of the data collected for FEMA 156/157 is freely available online through FEMA's Seismic Rehabilitation Cost Estimator (SRCE), a web-based app for estimating retrofit costs that is no longer maintained.[9] Similarities and differences between the data presented in FEMA 156/157 and the data available through SRCE are discussed in NIST TN 1973 [5].

The data set, hereafter the SRCE data, contains 1978 cost estimates for buildings in the United States and Canada. Although the data contains extensive information on building

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[8] The variance of C_i for observation i is modeled as proportional to V(E[C_i]).

[9] See https://www.fema.gov/media-library/assets/documents/30220.

characteristics, it represents a snapshot into retrofit costs in the early 1990s and is thus outdated. Nevertheless, the absence of reliable and comprehensive data on seismic retrofits makes this database an attractive option.

Costs are normalized, to account for variation across time and location, to 1993 US dollars (USD) for construction in the state of California. The adjustment factors, derived from the Engineering News Record's Building Cost Index (BCI), are included in the SRCE data. In order to obtain approximate *current* costs, we obtained historical BCI values to construct an adjustment factor that normalizes costs to 2016 USD for national average construction costs.

The SRCE data also contains information on the seismic hazard the building faces: its seismicity. The measure used, loosely based on peak ground acceleration, is derived from an outdated hazard map. To better approximate seismic hazard for current building inventories, we assign an updated measure of seismicity, derived from the 2014 US Geological Survey (USGS) National Seismic Hazard Maps, to the buildings in the SRCE data.[10]

Table 1 below presents select summary statistics for the SRCE data used in this paper, including cost (in 2016 USD), area, age, and number of stories. It is worth noting that the summary statistics suggest the distribution of cost is not symmetric. Moreover, the buildings are relatively short, in terms of number of stories, and therefore may not be representative of buildings in the United States. Further summary statistics are presented in NIST TN 1973 [5].

Table 1. Summary statistics for SRCE data: cost per square foot and select building characteristics (N = 1716).

	Cost per sq ft (sq m)	**Area 1000 sq ft (sq m)**	**Age years**	**Stories**
Minimum	0.50 (3.1)	0.2 (0.0)	0	1
Mean	49.58 (320.1)	64.8 (6.0)	44	3
Median	26.71 (172.4)	25 (2.3)	40	2
Maximum	1688.54 (18175.94)	1430.3 (132.9)	153	38
Standard deviation	78.97 (849.78)	109.1 (10.1)	22	3

Note that our sample size is 1716 and not 1978, the size of the SRCE data. This is because we drop data for Canadian buildings, as well as other minor restrictions.[11] We use a

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[10] Since the SRCE data only includes state and county location information, we use a population-weighted county average of peak ground acceleration with a 10 % probability of exceedance in 50 years. See NIST TN 1973 [5] for more details.

[11] Given that our objective is to estimate retrofit costs for federal buildings, we restrict the SRCE data to include only those buildings located in the United States. See NIST TN 1973 [5] for a discussion of the other restrictions on the SRCE data, as well as an application that uses the Canadian building data as an additional test set.

75/25 % split on our sample of the SRCE data to obtain our training and test sets, resulting in a training set of size $n = 1287$ and a test set of size $m = 429$.

Results

We use the training set described in the last section to fit our main model, Eq. 1, as well as versions of Eq. 1 that do not use all the predictors. Table 2 presents actual cost and predicted cost for the test data, as well as prediction error, in 2016 USD. In addition to the main model, Eq. 1, we train versions of the main model that do not include information on: building age ("No age"); building type ("No bldg type"); number of stories ("No stories"); and combinations of these cases. For ease of comparison, the last column presents the percentage change in RMSE relative to the main model for the cases subject to data limitations.

Table 2. Predicted cost and RMSE in 2016 USD per sq ft (sq m) for Main model, Eq. 1, and the model subject to data limitations.

Model	**Predicted cost per sq ft (sq m)**	**RMSE**	**RMSE relative to main model**
Actual cost	44.60 (480.07)	-	-
Main model	57.67 (620.81)	54.25 (583.91)	0 %
No age	59.40 (639.37)	56.55 (608.76)	4.26 %
No bldg type	58.15 (625.98)	55.24 (594.66)	1.84 %
No stories	58.05 (624.89)	54.12 (582.59)	-0.23 %
No age, stories	59.66 (642.16)	56.23 (605.25)	3.66 %
No age, stories, bldg type	60.01 (646.01)	55.99 (602.65)	3.21 %

The RMSE may be interpreted as the variation of the true values around our predictions. Thus, for instance, under the main model, true cost per square foot is within one standard deviation of our predicted mean, 57.67 ± 54.25, since 44.60 lies in the interval (3.42, 111.92). Note that this deviation is expressed in the same units, dollars per square foot. While the true cost is within one standard deviation of the prediction, the magnitude of the RMSE represents a large degree of uncertainty around the prediction. Thus, in dollar terms, our prediction interval suggests true retrofit costs could be 6 times smaller or twice as large as predicted cost.

Lower values of RMSE imply better prediction. Omitting data on number of stories does not appear to impact prediction error. In fact, RMSE *decreases,* though the change is negligible. In all other cases, prediction error increases. Surprisingly, building age appears to be more important as a predictor of cost than building type.[12] These results suggest that building age and stories are sufficiently correlated with building type to serve as proxies in cases where building

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[12] In contrast, our results in NIST TN 1973 [5] suggest building type is the most important predictor.

type is not available.

The cost predictions in Table 2 are averaged across all building types and performance standards in the test set. To better illustrate our approach, we use the trained main model, Eq. 1, to make predictions for a particularly vulnerable building type, Unreinforced Masonry (URM), broken down by performance standard. This provides a simple way for a decision maker to compare how retrofit costs increase with stricter performance standards.

In Table 3, we present cost predictions for URM buildings by performance standard. Our predictions assume that the building is not historic and that occupancy during construction is TR. We use the test set average values for *Area*, *Age*, *Stories*, and seismicity.

Table 3. Predicted cost and RMSE in 2016 USD per sq ft (sq m) by performance standard for URM buildings; based on Main model, Eq. 1.

Performance	**Mean cost per sq ft (sq m)**	**Predicted cost per sq ft (sq m)**	**RMSE**
LS	19.07 (205.25)	29.27 (315.09)	10.20 (109.83)
DC	25.55 (274.93)	37.68 (405.62)	12.14 (130.69)
IO	25.27 (2271.88)	46.95 (505.43)	21.70 (233.54)

Predicted costs are larger than actual costs. Moreover, the difference between DC and IO (and between LS and IO) is predicted to be larger than in the test data. However, one interpretation is that predicted costs are *conservative*, erring on the side of caution.

Consistent with the results in Table 2, actual costs for each performance standard are within one standard deviation of our predictions. In the case of LS and DC, actual cost is exactly one standard deviation below our predicted mean. One critical difference between these predictions and the aggregate predictions presented in Table 2 is that prediction error is much smaller relative to the predicted value; in the case of LS, it is almost three times smaller. In contrast, prediction error in Table 2 is roughly the same magnitude as the predicted value.

While the predicted mean values are not directly in line with actual values, RMSE provides an adequate measure of predictive uncertainty. Moreover, this approach provides a sensible starting point for estimating retrofit costs, especially for large building inventories. This example also illustrates the importance of breaking predictions down by building type and performance standard.

Finally, it is worth noting that the larger prediction error for DC and IO is likely due to the relative amount of observations with performance standard LS in the SRCE data. In our training set, for instance, 610 observations are for performance standard LS, compared to 334 for DC and 201 for IO.

Conclusion

In a forthcoming report, we apply our methodology to obtain retrofit cost estimates for federal buildings. While the methodology is developed to obtain the federal estimates, it is applicable to any building inventory. The major caveat is that the data is rather outdated. Our cost adjustments provide a suitable approximation to current retrofit costs, but predictive accuracy could be improved with more recent data.

We focus on predicting construction costs. The FEMA data includes non-construction costs (e.g., permits, fees, and relocation costs), which can easily be incorporated in a model to predict *total cost*. More importantly, our focus on construction costs ignores *indirect* costs, such as loss of productivity during a retrofit. Construction projects may also impose externalities on neighbors, from noise and disruption to traffic. Nevertheless, obtaining reasonable construction cost estimates is an important first step. In future work, we attempt to quantify both direct and indirect costs of seismic retrofits.

References

1. American Society of Civil Engineers (ASCE). *Seismic evaluation and retrofit of existing buildings*. 2014; ASCE/SEI 41-13.
2. Federal Emergency Management Agency (FEMA). *Techniques for the seismic evaluation of existing buildings*. 2006; FEMA 547.
3. Federal Emergency Management Agency (FEMA). *Typical costs for seismic rehabilitation of existing buildings, Volume 1: Summary*. 1994; FEMA 156.
4. Federal Emergency Management Agency (FEMA). *Typical costs for seismic rehabilitation of existing buildings, Volume 2: Supporting documentation*. 1995; FEMA 157.
5. Fung JF, Butry DT, Sattar S, McCabe SL. A methodology for estimating seismic retrofit costs. *NIST Technical Note 1973*. 2017; NIST TN-1973. DOI: https://doi.org/10.6028/NIST.TN.1973
6. Holmes W, Bonowitz D, Cagley J, Poland C. *Standards of seismic safety for existing federally owned and leased buildings – ICSSC Recommended Practice 8.* 2011; NISTGCR-11-917-12 (RP-8).