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Research Report

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Pre- and Post-Fire Property Values in the Eaton Fire Burn Area

An Evaluation of the Diminution-in-Value Model Used in Southern California Edison's Wildfire Recovery Compensation Program

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About This Report

The Eaton Fire that struck the Altadena area of Los Angeles on January 7, 2025 destroyed over 9,000 structures, with 18 confirmed civilian fatalities. The cause of the fire remains under investigation; however, if its equipment were to be shown to have started the fire, Southern California Edison (SCE) could be exposed to liability for ensuing damages. To speed recovery and avoid lengthy, expensive litigation, SCE has created the Wildfire Recovery Compensation Program (WRCP). The voluntary program will provide expedited settlement offers to parties suffering losses. Offers for owners of the approximately 5,100 single-family homes destroyed in the fire will be based in part on the difference in the value of the property before and after the fire. SCE hired Compass Lexecon, a global economics consulting firm, to develop these estimates. Due to the significance and complexity of the valuation models, SCE requested that RAND independently assess the data and methods used. This report summarizes the results of that review.

SCE provided the funding that made this study possible with the understanding that RAND retained analytic and editorial control. SCE, Compass Lexecon, and a RAND Institute for Civil Justice Advisory Board member who represents Eaton Fire victims, reviewed pre-publication drafts, or parts thereof, and provided comments to the research team. SCE, as well as attorneys who might represent individuals impacted by the Eaton Fire, have previously donated unrestricted funds to the RAND Feinberg Center for Catastrophic Risk Management and Compensation in support of research and activities, and SCE has also donated to other parts of RAND in support of research and activities.

The intended audience of this report includes potential claimants and their lawyers, utility ratepayers, and parties that oversee the California Wildfire Fund that may partially reimburse SCE outlays through the fund. This report may also be of interest to analysts considering how to best evaluate losses for similar programs that might be set up in the future.

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This work was conducted in the Infrastructure and Justice Program of RAND Education, Employment, and Infrastructure, a division of RAND that aims to improve educational opportunity, economic prosperity, and civic life for all. For more information, visit www.rand.org/eei or email eei@rand.org.

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We would like to thank the team at Compass Lexecon for making time available to explain the data and methodologies used in their analysis and for providing the documentation needed to complete our evaluation. We would also like to thank Susan Gates and Michael Mattock, both Senior Economists at RAND, for their expeditious and insightful peer reviews. Helpful comments were also provided by James Anderson and Benjamin Miller at RAND. Lastly, we would like to thank members of the RAND Institute for Civil Justice Advisory Board who commented on portions of the draft report.

Summary

The Eaton Fire that struck the Altadena area of Los Angeles on January 7, 2025 destroyed over 9,000 structures, with 18 confirmed civilian fatalities. The cause of the fire remains under investigation; however, if its equipment were to be shown to have started the fire, SCE could be exposed to liability for damages. To support recovery and reduce the need for extended litigation, SCE established the voluntary Wildfire Recovery Compensation Program (WRCP), offering expedited settlement options to affected owners.

For the approximately 5,100 single-family homes destroyed, settlement amounts will be based in part on the difference in the value of the property before and after the fire. SCE engaged Compass Lexecon, a global economic consulting firm, to develop these estimates. Given the significance and complexity of the valuation models, SCE requested that RAND independently assess the data and methods used. This report summarizes the results of that review.

Compass Lexecon developed models that estimate the pre-fire and post-fire market value, respectively, for single-family residential (SFR) properties where the primary structure was destroyed by the Eaton Fire. The difference between the two estimates is used to estimate the loss in market value of the SFR property due to the fire, which is known as the diminution-in-value (DIV). DIV is used as a starting point by SCE to determine the compensation offer to rebuild the destroyed structure and indirectly to estimate personal property loss. Values generated by the pre-fire model are also used for loss-of-use calculations.

This paper examines:

- whether appropriate data and methods were used to estimate the pre-fire value, post-fire value, and DIV for SFRs destroyed in the Eaton Fire
- the amount of uncertainty in the property value and DIV estimates
- circumstances under which the models may be expected to overestimate or underestimate values.

Our analysis is subject to the following limitations:

- We do not evaluate the accuracy or appropriateness of the formula used to translate DIV into offers for rebuild costs nor the formula that bases loss-of-use compensation on a property's pre-fire value.
- We do not assess whether the WRCP's settlement offers are favorable or unfavorable from the perspective of applicants, other stakeholders, or the public.
- We do not provide guidance on whether claimants should accept or reject offers from the program.

The analysis presented in this report is based on information obtained during interviews with Compass Lexecon and SCE, publicly available WRCP documentation, and supporting documentation provided by Compass Lexecon. During the course of the project, the research

team submitted to Compass Lexecon written requests for statistics on samples, variable definitions, as well as information on model estimation and goodness of fit. Compass Lexecon fully responded to all the requests submitted. The research team did not obtain or review the data files, the detailed machine-learning model output, the estimated property values, or information that would allow us to directly audit the accuracy of information. SCE indicated that it would consider providing those items if we found that we were unable to conduct our analysis effectively without them. Ultimately, Compass Lexecon was able to provide us with information adequate to support the analysis we present in this report.

Findings

Pre-Fire Valuation Model for Destroyed Single-Family Residences

The pre-fire valuations provided by Compass Lexecon are produced using modern analytic methods that incorporate a wide range of property characteristics, including the characteristics that are typically used to estimate property value in automated valuation models (AVMs). AVMs may be familiar to many people through their use by real estate tech firms such as Zillow and Redfin, which provide current estimates of a property's value as part of their suites of public-facing data relating to home sales activity. Compass Lexecon used a supervised machine learning (SML) algorithm to estimate pre-fire values, which is an appropriate choice for this estimation task. The SML model was "trained" on a set of 6,120 property sales between 2020 and 2024 in Altadena, Pasadena, and Sierra Madre. The model was then used to estimate the market value as of December 2024 of the approximately 5,100 SFRs that were destroyed in the Eaton Fire.

Dozens of property characteristics were included as predictors in the pre-fire model. We believe that this set of characteristics either directly or indirectly captures a large share of the characteristics used in the published research literature on housing prices as well as those recommended for use by regulators in conducting remote appraisals.

The characteristics of the sales used to train the model should be comparable to those of the destroyed SFRs. Comparison of these training data and the destroyed SFRs suggests that for the vast majority of destroyed SFRs, the training data comprise an appropriate sample of home sales for modeling pre-fire values of the SFRs destroyed in the Eaton Fire. However, there are some destroyed homes with characteristics outside the range of those in the training data. This will cause the estimated pre-fire values to be less accurate for some properties.

The specific machine learning algorithm used is well suited for this type of task, and the algorithm was optimized by tuning a number of settings to maximize the out-of-sample accuracy of the estimates. It appears unlikely that there are other settings within this class of machine learning algorithms that would result in meaningfully more accurate estimates of the pre-fire values. We examined the relationships between property characteristics, such as house and lot size, and pre-fire value that were identified by the model, and found that they were consistent with a reasonable property valuation model.

The accuracy of the model was checked by comparing the pre-fire estimated value from the model with the actual sale price for the 786 SFRs that were destroyed in the Eaton Fire and had been sold at some point between 2020 and 2024. We found:

- The estimated values are within -9 percent and +11 percent of the actual transaction value for 50 percent of the properties.
- The estimated values are within -17 percent and +25 percent of the actual transaction value for 80 percent of the properties.

While the model appears to work well for about half of properties, there are some with substantial errors of estimation.[1] For example, 10 percent of property values are underestimated by more than 17 percent, while another 10 percent of property values are overestimated by more than 25 percent.

Because the WRCP computes rebuilding costs and loss of personal property as a function of DIV per square foot of the house, it may be useful to look at accuracy on a basis of dollars per square foot of the house. Across the set of destroyed SFR properties with a prior sale in 2020–2024, about half of the pre-fire estimates were within $90 of the actual transaction price per square foot of the house, and half were off by a larger magnitude. However, over- and underestimates on this metric showed a systematic pattern:

- The model almost always overestimates the pre-fire value of properties that sold for less than $600 per square foot of the house.
- The model almost always underestimates the pre-fire value of properties that sold for more than $1,200 per square foot of the house.
- Both over- and underestimates of the approximately 20 percent of properties outside of the $600 to $1200 per square foot of the house range were often large, sometimes larger than $300 per square foot, while errors of estimates for properties inside that range were generally smaller.

Assessment of the Pre-Fire Model

Overall, we find that the pre-fire valuations provided by Compass Lexecon are produced using modern analytic methods and incorporate a wide range of property characteristics, including the characteristics that are typically used to estimate property value in AVMs. Unlike other available AVMs, the Compass Lexecon estimates are based exclusively on historical property transactions of single-family homes in the immediate region of the fire and reflect the

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[1] Estimation errors are the difference between the estimated and actual transaction values. Such overestimates and underestimates are inherent to models of complex processes (e.g., property transactions) because it is infeasible to measure all factors that affect the transaction price, some of which may have to do with the buyer and seller rather than the property itself. While a good model will have smaller estimation errors than a bad one, no model in this setting will be error-free.

buyer preferences in that particular real estate market. Compass Lexecon has shown that estimates from their model are quantitatively very similar to those produced by other commercially available AVMs. We have no reason to believe that any other AVM would be more accurate for determining the pre-fire value of the single-family homes destroyed by the Eaton Fire. Having said that, this method will not be accurate for every destroyed SFR, most notably for the approximately 20 percent of homes outside of the $600 to $1,200 per square foot range described above. We also cannot evaluate how the accuracy of this method compares with a standard property assessment tailored to each individual property (which might include, for example, physical inspection of a property). Such an assessment might be able to take into consideration a larger set of property features as well as the pre-fire property condition.

Post-Fire Valuation Model for Destroyed Single-Family Residences

The post-fire valuation model is based on the transaction prices of 204 SFRs that were destroyed in the Eaton Fire and then sold between February 2025 and mid-August 2025. The model is used to estimate the post-fire value of the approximately 5,100 SFR properties destroyed in the Eaton Fire.

Compass Lexecon relied on a simpler model to estimate post-fire property values, relative to the pre-fire model. Specifically, they used ordinary least squares (OLS) regression, a common statistical technique that, while less flexible than the model used for their pre-fire valuations, has benefits in data-poor settings. We believe this is a reasonable choice in this context due to the nature of the available data, where there have been only a couple hundred post-fire sales of destroyed SFRs, and there are substantially less data documenting differences in these properties.

Compass Lexecon considered a number of property characteristics to include in the post-fire valuation model, and we are satisfied that an appropriate set of characteristics were selected. The 204 properties with post-fire sales generally seemed to be representative of the larger set of destroyed SFRs. However, there are some destroyed SFRs with lot sizes substantially outside the range observed for the properties that have already sold. The post-fire model will likely be less reliable for such properties. We are also satisfied with decisions regarding the variable transformations used in the model (e.g., logging of variables, inclusion of polynomials).

The accuracy of the model was checked by comparing the post-fire sale value estimated by the model with the actual sales values for the 204 SFRs that were destroyed in the Eaton Fire and were sold after the fire. Estimates from the post-fire model had significantly smaller over- and underestimates than those from the pre-fire model for most properties:

- The estimated values are within -7 percent and +6 percent of the actual value for 50 percent of the properties.
- The estimated values are within -12 percent and +18 percent of the actual value for 80 percent of the properties.

There are also properties for which the post-fire model performs less well, with 10 percent of properties underestimated by more than 12 percent and 10 percent overestimated by more than

18 percent. These figures again compare favorably with the pre-fire model. This is to be expected because it is more straightforward to estimate the value of empty lots than lots with structures that can have widely varying attributes.

We find some indication that the post-fire model also tends to overestimate the value of low-value properties and underestimate the value of high-value properties, which is expected for models with any error of estimation. However, the pattern is much less pronounced, and the magnitudes of the under- and overestimation are substantially smaller than in the pre-fire model.

Assessment of the Post-Fire Model

Overall, the methods Compass Lexecon used for developing the post-fire valuation tool were reasonable and consistent with accepted analytic methods for such analyses. We find some indication that the post-fire model tends to overestimate the value of low-value structures and underestimate the value of high-value structures, similar to but much less pronounced than in the pre-fire model estimates.

Diminution-in-Value Estimates

The estimate of the DIV for a property is the difference between the estimated pre-fire and post-fire values. Across the 5,123 destroyed SFRs, estimates of DIV from the Compass Lexecon models vary over a wide range and are negative in some cases. Excluding the top and bottom 1 percent of estimates, estimates run from approximately $200 to $740 per square foot of the house, and the average over all destroyed SFRs is $435 per square foot.

Inaccuracies in the DIV per square foot are almost entirely attributable to inaccuracies in the estimated pre-fire value per square foot. This reflects the fact that the magnitude of over- and underestimates in the pre-fire model is much greater than in the post-fire model when expressed on a price per square footage of the house basis. The accuracy of the DIV estimates thus mirrors that of the pre-fire model. Namely,

- 50 percent of properties will have DIV per square foot of the house within approximately $100 of the change in market value from pre- to post-fire.
- A small number of homes are expected to have larger over- or underestimates, with
  - DIV per square foot of the house overestimated for 10 percent of properties by more than approximately $200.
  - DIV per square foot of the house underestimated for 10 percent of properties by more than approximately $200.

The differences between estimated and actual DIV are expected to show the same pattern as the differences between estimated and actual pre-fire value:

- DIV will typically be overestimated for properties with a true pre-fire value less than $600 per square foot of the house.
- DIV will typically be underestimated for properties with a true pre-fire value of more than $1,200 per square foot of the house.

- Some of these over- or underestimates in DIV could be substantial, and almost all of those large errors are expected to occur for properties whose pre-fire value was unusually large or small on a square foot basis relative to the typical home destroyed by the fire.

Assessment of Diminution-in-Value Estimates

We have no reason to believe that any other AVM would be more accurate for determining DIV of the single-family homes destroyed by the Eaton Fire. When evaluating the accuracy of the DIV estimates, it is important to recognize that not all over- or underestimates of DIV will affect the compensation being offered because under the current proposal the influence of DIV is limited by minimum and maximum values on the offered rebuild cost in dollars per square foot. In addition, we have only evaluated the accuracy of the DIV estimate itself. We have no way to evaluate whether the proposed use of DIV to determine compensation will accurately reflect eventual rebuilding costs or property losses.

Conclusion

The data and methods that were used by Compass Lexecon to estimate the pre-fire, post-fire, and DIV values for SFRs destroyed in the Eaton Fire were appropriate. The analyses used modern statistical methods and, in our judgment, were thoughtfully done and well executed. The estimates for most properties are expected to be as accurate as is feasible based on available data. However, no model is perfect. In this case, the models tend to overestimate values for properties where the true pre-fire value is particularly low and underestimate values where the true pre-fire value is particularly high.

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Chapter 1. Introduction

The Eaton Fire began on the evening of January 7, 2025, in Eaton Canyon in the San Gabriel Mountains. Driven by hurricane-force Santa Ana winds,[2] the wildfire advanced into the unincorporated community of Altadena and portions of Pasadena, ultimately burning 14,021 acres and destroying 9,414 residential, commercial, and other structures.[3] As of the date of this report, the cause of the fire remains under investigation. However, numerous parties including the United States Department of Justice[4] and Los Angeles County[5] have filed lawsuits against SCE alleging SCE's equipment caused the fire. SCE has not admitted fault or liability for the Eaton Fire.

California's legal framework exposes electric utilities to substantial financial liability if their equipment is found to have caused a wildfire. Under the doctrine of inverse condemnation, a public utility, including an investor-owned utility, may be held responsible when its equipment is the cause and origin of a fire, regardless of fault.[6] This doctrine applies a form of strict liability for certain types of damages, meaning that claimants do not need to prove negligence or misconduct; liability may arise even when the utility has followed all applicable safety and operational rules.[7] In recent years, these standards have produced damage awards and settlements totaling billions of dollars in utility-related wildfire cases, creating significant financial risk for utilities and, through potential cost recovery in rates or other mechanisms, for their customers and investors.[8]

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[2] "In the Altadena area specifically, the intensity of the wind increased notably [90 mph in the Eaton Fire area and 65 mph in Altadena] in the hours after ignition and was accompanied by highly variable wind directions." Los Angeles County, *Eaton Fire: Synopsis of Findings and Timeline*, After-Action Review, January 7, 2025. As of October 5, 2025: https://file.lacounty.gov/SDSInter/lac/1192777_AAR_EatonFireSynopsisofFindingsandTimeline.pdf

[3] California Department of Forestry and Fire Protection (CAL FIRE), "Eaton Fire, incident information page," January 7, 2025. As of October 5, 2025: https://www.fire.ca.gov/incidents/2025/1/7/eaton-fire

[4] United States Attorney's Office, Central District of California. As of October 10, 2025: https://www.justice.gov/usao-cdca/pr/united-states-sues-southern-california-edison-co-seeking-tens-millions-dollars-damages

[5] Los Angeles County lawsuit against SCE. As of October 10, 2025: https://file.lacounty.gov/SDSInter/lac/1178568_EatonFireLACountySCEComplaint.pdf

[6] Legislative Analyst's Office, Allocating Wildfire Damages Between Public and Private Entities, Sacramento, CA: Legislative Analyst's Office, June 21, 2019. As of October 5, 2025: https://lao.ca.gov/reports/2019/4079/allocating-wildfire-costs-062119.pdf; *Pac. Bell Tel. Co. v. S. Cal. Edison Co.*, 146 Cal. Rptr. 3d 568, 576 (Cal. Ct. App. 2012), as modified (Sept. 13, 2012).

[7] Legislative Analyst's Office, Allocating Wildfire Damages, 2019, p.5.

[8] Legislative Analyst's Office, Allocating Wildfire Damages, 2019.

To address the threat that liabilities arising out of wildfire events could destabilize the state's major electric utilities and delay compensation to individuals and businesses impacted by utility-caused wildfires, California established the California Wildfire Fund in 2019.[9] The Fund serves as a dedicated source of liquidity to cover eligible claims from catastrophic wildfires caused by participating investor-owned utility companies. It is financed through a combination of utility shareholder contributions, surcharges on electricity ratepayers, and a short-term loan from the State's Pooled Money Investment Account. Access to the Fund is conditioned on a utility meeting specified requirements, and only after the utility has paid a substantial annual "retention" amount (approximately $1 billion for SCE).[10]

Within that framework, SCE is launching a voluntary program to address claims from the Eaton Fire. In July 2025, SCE announced the Wildfire Recovery Compensation Program (WRCP) that will offer compensation to eligible claimants, with program launch planned for fall 2025.[11] The WRCP is designed to provide timely, standardized settlement offers as an alternative to litigation. Participation is voluntary, and claimants who accept settlement offers waive any further Eaton Fire-related claims against SCE.

A central feature of the WRCP is its use of data-driven valuation methodologies to estimate the value of real property losses—particularly for destroyed single-family residences—through the concept of diminution-in-value (DIV). DIV measures the difference between an affected property's market value before and after the fire, forming the basis for multiple offer components within the WRCP. SCE retained the economic consulting firm Compass Lexecon to develop specialized models to produce these values.

Because DIV estimates directly influence compensation offers, there is a broader public interest in ensuring that these estimates are both accurate and fair. If DIV estimates are too low, there is a potential for claimants to receive less than they might otherwise obtain through litigation, which could raise questions of fairness (although the WRCP is designed with other incentives, such as direct claim premiums,[12] reduced transaction costs, and faster payment, that

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[9] California Wildfire Fund, homepage. As of October 5, 2025: https://www.cawildfirefund.com

[10] California Wildfire Fund Administrator, Section 3287 Statutory Report — 2025, January 31, 2025. As of October 5, 2025: https://www.cawildfirefund.com/sites/wildfire/files/documents/2024/section-3287-statutory-report-2025.pdf

[11] Southern California Edison, "Southern California Edison Announces Wildfire Recovery Compensation Program for Eaton Fire Launching This Fall," *SCE Newsroom*, July 24, 2025. As of October 8, 2025: https://newsroom.edison.com/releases/southern-california-edison-announces-wildfire-recovery-compensation-program-for-eaton-fire-launching-this-fall

[12] The Protocol sets forth that "In addition to the economic and non-economic compensation, all Claimants who submit a complete claim will have a Direct Claim Premium included as part of their Settlement Offer at the amount specified for their claim type…" Southern California Edison, *Wildfire Recovery Compensation Program Protocol, Draft for Public Comment*, September 17, 2025, p. 26. As of October 10, 2025: https://download.edison.com/406/files/20258/Wildfire%20Recovery%20Compensation%20Program%20Protocol_Draft01.pdf. The Protocol to which this paper refers is the version as of October 8, 2025.

may make offers attractive relative to prolonged legal proceedings). Conversely, if DIV estimates are too high, those additional costs could ultimately be borne by a range of stakeholders, including utility customers, SCE investors, or, in some possible scenarios, taxpayers.

With these public interest considerations in view, this report examines the methodologies Compass Lexecon used to estimate pre- and post-fire property values for single-family residences and evaluates their reasonableness relative to common alternative methods.[13] The objective is to inform understanding of how the WRCP's core valuation calculations are designed and how they align with prevailing practices in property valuation.

Research Questions and Scope of Analysis

Compass Lexecon developed two models that estimate the pre-fire and post-fire market value, respectively, of single-family residential parcels where the primary structure was destroyed by the Eaton Fire. Used in combination, these models provide the basis for estimating the DIV for affected properties. The WRCP protocol states that it will use DIV as a starting point for compensation offered to cover rebuilding costs and personal property losses. Values generated by the pre-fire model are also used for loss-of-use calculations.

This paper examines:

- whether appropriate data and methods were used to estimate the pre-fire value, post-fire value, and DIV for SFRs destroyed in the Eaton Fire
- the amount of uncertainty in the property value and DIV estimates
- circumstances under which the models may be expected to overestimate or underestimate values.

Our analysis is subject to the following limitations:

- We do not evaluate the accuracy or appropriateness of the formula used to translate DIV into offers for rebuild costs nor the formula that bases loss-of-use compensation on a property's pre-fire value.
- We do not assess whether the WRCP's settlement offers are favorable or unfavorable from the perspective of applicants, other stakeholders, or the public.
- We do not provide guidance on whether claimants should accept or reject offers from the program.

Organization

The remainder of this report is organized as follows:

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[13] We evaluate the models as of October 1, 2025. We do not evaluate subsequent changes, if any, made after that date.

Chapter 2 provides background on the property valuation tools developed by Compass Lexecon, and the methods used in the study. Chapter 3 provides the results of our evaluation of the pre-fire valuation model. Chapter 4 provides the results of our evaluation of the post-fire valuation model. Chapter 5 presents findings on the accuracy of estimated DIV. The report concludes with final observations in Chapter 6 and an appendix that provides background on the types of functional forms that were considered in the post-fire model.

Chapter 2. Background and Methods

Background on the Wildfire Recovery Compensation Program

The WRCP is a voluntary claim resolution framework designed to offer eligible individuals and entities compensation for losses arising from the 2025 Eaton Fire in exchange for waiving Eaton Fire-related claims against SCE.[14]

On September 17, 2025, SCE released for public comment a draft of the Wildfire Recovery Compensation Program Protocol ("Protocol"), which specifies the procedures for determining eligibility, estimating property losses, and formulating settlement offers.[15] The Protocol outlines two participation tracks:

- **Fast Pay**—a streamlined process with reduced documentation requirements, intended to produce a compensation offer within 90 days of the claimant submitting the required materials.
- **Detailed Review**—a more comprehensive process requiring extensive documentation and longer evaluation times to enable a full assessment of the claimant's economic loss.

This paper focuses on methodologies relevant to compensation offers made through the Fast Pay option. Within the Fast Pay framework, the central economic input for residential structure losses in the Eaton Fire area is the affected property's DIV—a measure of the difference between the property's pre-fire market value and its post-fire market value, with the post-fire value typically reflecting residual land value when improvements have been destroyed.

The Protocol's Attachment 3 ("Fast Pay Claim Valuation Methodology") describes the calculation process for owners of destroyed SFRs:

> For single-family residential properties where the primary structure is classified as Destroyed (>50% damage) in the CAL Fire DINS database ("DINS"), SCE will first calculate the value of the lost structure(s) and landscaping. This calculation will use two valuation tools developed by expert economists at Compass Lexecon: (1) a tool that estimates the property's pre-fire value as of the date immediately before the fire, using publicly-available data, and (2) a tool that estimates the property's post-fire value based on its condition after the fire, using actual post-fire lot sales.[16]

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[14] Southern California Edison, "Wildfire Recovery Compensation Program," webpage, undated. As of October 20, 2025: https://energized.edison.com/wildfire-recovery-compensation-program-launching-soon

[15] Southern California Edison, *Wildfire Recovery Compensation Program Protocol, Draft for Public Comment*, September 17, 2025. As of October 10, 2025: https://download.edison.com/406/files/20258/Wildfire%20Recovery%20Compensation%20Program%20Protocol_Draft01.pdf.

[16] Southern California Edison, *Wildfire Recovery Compensation Program Protocol, Draft for Public Comment, Attachment 3, p. 17,* September 17, 2025.

Together, these models provide a data-driven foundation for estimating DIV for each destroyed SFR.

Once the pre-fire value, post-fire value, and resulting DIV for an affected property have been determined, they are each used in particular ways to calculate compensation offers in three main categories:

- rebuild costs as described in the Protocol
- personal property loss
- loss of use.

As noted in Chapter 1, we do not assess the accuracy or appropriateness of how these offer components are calculated using the pre-fire estimate, post-fire estimate, and DIV. As such, we will not describe in detail how these compensation offers are computed. One critical detail, however, is that DIV contributes to the offer for rebuilding costs and personal property solely through estimates of DIV per square foot of the primary structure that was on the lot before the fire (DIV per square foot is then multiple by the square footage of the house to determine the offer). As such, much of our analysis focuses on estimates of DIV per square foot of the house.

When interpreting our results it is important to recognize that possible over- and underestimates in pre-fire, post-fire, and DIV values which we discuss in this report do not always affect compensation offers under the proposed plan in a one-to-one manner. For example, when DIV per square foot of the house is within a certain range, changes in DIV do translate directly into the compensation offer for rebuild costs and personal property loss. However, there are both lower and upper limits on what the WRCP will offer for rebuilding costs and personal property loss on a dollar per square foot basis. Thus, when we discuss the possibility that the DIV per square foot of the house may be $100 too high, it may not affect the offered rebuild cost because the actual DIV per square foot is already above the upper limit. Likewise, a DIV estimate that is $100 per square foot too low will not affect the compensation offer if the actual DIV is below the lower limit. Understanding how our results regarding the accuracy of valuations relate to the compensation offered under the plan for any given property should be based on an analysis specific to the valuations for that property.

Methods Used in This Study

The research team interviewed individuals from SCE who are involved in the design of the WRCP. These discussions provided general information about the program, including its design, objectives, and the intended purpose and scope of the pre-fire and post-fire models. SCE also offered verbal feedback on a prepublication draft of this paper. SCE did not have editorial control over this document. The Summary of the draft report was also reviewed by a plaintiffs' attorney who represents Eaton Fire victims.

The research team also engaged in several video conferences with personnel from Compass Lexecon and SCE. The meetings included technical/statistical experts and programmers from

Compass Lexecon, most often with one or more representatives from SCE as well. These meetings focused on understanding and evaluating the modeling approaches. Topics included:

- data inputs to the supervised machine learning model used for pre-fire property value estimation
- model specification for the pre-fire valuation tool
- Compass Lexecon's validation procedures for the pre-fire model
- input data and regression techniques used for post-fire property value estimation
- Compass Lexecon's validation procedures for the post-fire model
- Compass Lexecon's rationale behind analytic choices.

During the course of the project, the research team submitted written requests to Compass Lexecon for statistics on samples, variable definitions, and information on model estimation and goodness of fit. Compass Lexecon fully responded to all the requests submitted. The research team did not obtain or review the data files, the detailed machine-learning model output, the estimated property values, or information that would allow us to directly audit the accuracy of information. SCE indicated that it would consider providing those items if we found that we were unable to conduct our analysis effectively without them. Ultimately, Compass Lexecon was able to provide us with information adequate to support the analysis we present in this report.

In addition to interviews, the research team reviewed publicly available materials about the WRCP, including the Program Protocol and Compass Lexecon's white paper describing the statistical methods used in model development.[17] The analysis presented in this report is therefore based on information obtained during interviews with SCE and Compass Lexecon, publicly available WRCP documentation, and supporting documentation provided by Compass Lexecon.

One of the objectives of this study was to determine if the model development process and the final models used for estimation of pre- and post-fire property values were appropriate to the data and this estimation task. The standard we used for this assessment was verifying that it avoided common problems with such models and did not use techniques that are known to be worse than alternatives. Thus, we conclude statistical methods are appropriate when we know of no evidence that they are inappropriate. This is a standard of review similar to what is often used in peer review of scientific articles. However, we are not assessing if we think the model could be improved (models can always be improved) or whether the Compass Lexecon methods are better than specific alternative methods of property valuation.

[17] Compass Lexecon, "Estimation of Pre- and Post-Fire Value for Single-Family Residential Parcels," white paper, October 1, 2025.

Chapter 3. Pre-Fire Valuation Model for Destroyed Single-Family Residences

The pre-fire property value for almost all destroyed SFRs is estimated by Compass Lexecon using a common machine learning algorithm, XGBoost.[18] This analytic approach appears to be a good choice for this estimation task, and it produces property valuations that are derived from recent sales transactions in the local real estate market.

This machine learning algorithm may appear to be a mysterious black box; however, it works similarly to methods that property appraisers often use to generate valuations. The algorithm is a type of "tree-based" regression that groups the historical property transactions into categories, called "leaves," based on property transaction features. These features are characteristics like square footage of the primary structure, lot size, age of construction, history of remodeling permits, location, etc. Tree-based regressions create these leaves from the property features in a way that maximizes similarity in sales prices among the properties within each leaf. Once trained, tree-based regression models estimate the value of a new property by determining which leaf it falls into based on its property features, then averaging the sales prices of training transactions in that same leaf. Essentially, tree-based regression sorts the historical property sale data into sets of comparable properties, or "comps," and then averages the values of that set of comps to estimate the value of any given property.

However, an algorithm like XGBoost does not sort each property into a single leaf, nor assign it to a single set of comps. It creates leaves for hundreds or thousands of relatively simple regression trees, each representing a slightly different way to partition properties based on their features into groups with similar sales prices. Each individual tree added to the model builds on the previous trees to allow it to create progressively more fine-grained distinctions among properties. That is to say, the additional trees allow the model to narrow down the set of appropriate comparison properties for any given property to a smaller subset that are more closely matched on both the property features and transaction price. In the Compass Lexecon implementation, they create 2,600 regression trees that each have up to 64 leaves. The price estimate for a given property is a weighted average of historical transactions within the 2,600 leaves into which the property falls. A property in the training data that is very similar to the to-be-estimated property on all of the important property characteristics will be in the same leaf across most of these trees, and thus it will play a large role in creating the price estimate for the to-be-estimated property. Conversely, properties that are quite different will never fall into the

[18] For the burned homes that had previously sold in 2023 or 2024, Compass Lexecon does not use this model to estimate pre-fire value. The value for those homes is based on their prior sale price, inflation adjusted to December 2024 using the Case-Shiller price index for the Los Angeles region.

same leaf and will play no role in the estimate. This process of combining across thousands of regression trees results in price estimates that are much closer to the actual sales prices than estimates relying on a single set of leaves from a single regression tree.

Consistent with best practices, the key features of XGBoost models, including the number of trees and how they were created, were selected using a process called cross-validation in which Compass Lexecon explored a range of different ways to run the algorithm on "training" subsets of the historical data and then evaluated how accurately it estimated the sales prices for "test" historical data which were not used in training. Compass Lexecon then selected the XGBoost settings that gave the most accurate estimates for properties in the test data.

As we discuss below, the key limitations of the approach used to generate pre-fire valuations are tied to the dataset of historical transactions that was used to train the machine learning algorithm, rather than limitations of the algorithm itself. Specifically, there are two broad limitations related to the data: (1) some burned properties may have very few close comparative properties within the historical transactions used to train the model, which may increase the magnitude of over- and underestimates for those unusual properties; and (2) some property characteristics that may increase or decrease market value of a property are not available in the data being used to determine the value. These limitations largely reflect availability of relevant data rather than a flaw in the way it is being analyzed.

Data Used to Develop the Pre-Fire Model

A key challenge in modeling pre-fire property value is assuring that the model's training data are sufficiently representative to accurately estimate market value of the destroyed SFRs. "Sufficiency" implies that the training dataset contains similar-enough properties to each of the destroyed SFRs and that the relevant characteristics for establishing this similarity are observable and represented in the data.

Description of Data Sources Used in the Pre-Fire Model

We begin by summarizing the data sources that were used to develop the analysis dataset for the pre-fire model. We provide a brief summary of each of these and point interested readers to the Compass Lexecon white paper[19] on the DIV model for some additional detail.

1. **ATTOM data**. Basic data on property characteristics and transactions were provided by ATTOM, a major data vendor to the real estate industry. Much of the underlying data for these records comes from county tax assessor rolls and transactions records. ATTOM data are the source of information on property type (e.g., single-family residence), square footage of both residences and parcels, and the presence of amenities such as outbuildings and pools. ATTOM data are also used for transaction prices and dates. The

[19] Compass Lexecon, "Estimation of Pre- and Post-Fire Value for Single-Family Residential Parcels," white paper, October 1, 2025.

transaction history in the provided data included any observed sale between 2015 and summer of 2025. The data also contain indicators for arms-length transactions.

2. **Regrid data**. Data on parcel geographic boundaries were obtained from Regrid, a data vendor that obtains geographic information systems (GIS) data from local assessor offices and aggregates and harmonizes them for its users. Regrid data also include elevation and other parcel-specific factors that were used in the model including a FEMA risk rating, building counts and the square footage of all buildings, and assessor data on property characteristics including presence of heating/cooling, other property amenities, and basic information on construction type and quality of the house.
3. **CAL FIRE damage inspection (DINS) data**. Online damage data from CAL FIRE[20] were used to identify affected parcels including the type of primary structure and the level of damage as well as the presence of and the extent of damage to outbuildings.
4. **National Interagency Fire Center (NIFC) data**. Data from NIFC, a source for authoritative geospatial data collected and disseminated under the interagency Wildland Fire Data Program, were used to define the Eaton Fire perimeter.[21]
5. **Building permit data**. Historical data on building permits and dates of issue were collected via "web scraping" from two sources: Los Angeles County[22] and the City of Pasadena.[23] Compass Lexecon restricted these data to focus on four permit categories: building, mechanical, plumbing, and electrical, and further focused on permits with work descriptions that included "remodel," "renovation," "addition," and "convert" (along with common misspellings of these terms). The permit data were also tagged according to whether the permit was finalized. Building permit data were not available via web scraping for properties in Sierra Madre.
6. **Altadena Historical Society data**. Data on the location of roughly 1,500 Altadena properties with a historic designation were obtained from the Altadena Historical Society.
7. **Case-Shiller Home Price Index data**. The Case-Shiller Home Price Index is a long-running and widely used price index that uses a "repeat sales" approach to track home price changes over time. This index produces an average measure of price changes for the Los Angeles-Long Beach-Anaheim metropolitan statistical area that includes Los Angeles County as well as parts of Orange, Riverside, San Bernardino, and Ventura Counties. This index was used to adjust all historical transaction prices observed between 2015 and 2024 to comparable December 2024 values.[24]

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[20] CAL FIRE, "DINS 2025 Eaton Public View," webpage, January 8, 2025. As of October 6, 2025: https://catalog.data.gov/dataset/dins-2025-eaton-public-view#sec-dates

[21] Wildland Fire Interagency Geospatial Services (WFIGS) Group, "WFIGS Interagency Fire Perimeters to Date," webpage, National Interagency Fire Center ArcGIS Online Organization, 2025. As of October 6, 2025: https://data-nifc.opendata.arcgis.com/pages/wfigs-wildland-fire-perimeters

[22] Los Angeles County, "Los Angeles County Building Permit Viewer," webpage, Geocortex Essentials GIS Viewer, undated. As of October 6, 2025: https://apps.gis.lacounty.gov/Geocortex/Essentials/GISVIEWER/REST/sites/LA_County_BPV/map/mapservices/6/layers/0/datalinks/GISP_Dapts/link

[23] City of Pasadena, "MyPermits Self-Service Portal," webpage, undated. As of October 6, 2025: https://mypermits.cityofpasadena.net/EnerGov_Prod/SelfService#/search

[24] Additional analytic steps, discussed in a later section, were taken to address potential differences between the time trend of home prices in Altadena and those in the broader Los Angeles metro area measured by this index.

8. **U.S. Census Bureau data**. Estimates of small area socioeconomic and demographic characteristics were derived from the U.S. Census Bureau's American Community Survey (ACS) including data on population, population change, housing growth, and median home price. Census provides these data as 5-year averages aggregated to the level of either a census block group—a geography typically containing between 600 and 3,000 people—or, if unavailable due to privacy-related data suppression, at the census tract level—typically containing between 2,500 and 8,000 people. These data represent average characteristics over the period 2019 through 2023 (the most recent data vintage available).[25, 26]

Assessing the Sufficiency of the Data Used for Generating Credible Pre-Fire Valuations

For establishing a definition of relevant characteristics, we look to two primary examples: (1) the types of characteristics commonly used in appraisals, and (2) the types of characteristics used in the academic social science literature concerning hedonic price models that use regression modeling (or potentially other statistical methods) to decompose variations in the price of housing into components attributable to different characteristics of the property. The goal of such modeling is to find measurable characteristics that most effectively explain price variation in often unique properties that would otherwise be difficult to credibly value.

The approach used to generate pre-fire property valuations in the Eaton Fire burn area differs in critical ways, by necessity, from the normal process of performing a property appraisal for the purposes of a property purchase or refinancing. The most common method for supporting the valuation of properties in such transactions is a "traditional appraisal," which involves a physical inspection of the property in question. Conceptually, the modeling approach used here is most closely aligned with the "desktop appraisal" method, which relies on third-party data on comparable sales in lieu of performing an onsite inspection.[27] Federal guidance on the types of data used in forming appraised values advises that the comparable sales "should have similar physical and legal characteristics when compared to the subject property…[including], but not limited to, site, room count, finished area, style, and condition."[28] This guidance also suggests that external factors—a FEMA-designated flood zone is used as an example—should be given consideration as well.

The data used in the pre-fire model substantially exceeds this minimal list of property characteristics and follows the guidance that external factors should be included (the model

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[25] U.S. Census Bureau, "Geography Program Glossary," webpage, April 2022. As of October 6, 2025: https://www.census.gov/programs-surveys/geography/about/glossary.html#par_textimage_4

[26] These data were provided directly to Compass Lexecon for use in the model by Regrid but we discuss them as a distinct data source to make clear that they were derived from primary data collected by the U.S. Census Bureau.

[27] Fannie Mae, "Selling Guide Supplement: Uniform Appraisal Dataset (UAD) 3.6 Policy," September 3, 2025. As of October 6, 2025: https://singlefamily.fanniemae.com/media/42571/display

[28] Fannie May, "Originating & Underwriting: Selling Guide," webpage, September 3, 2025. As of October 6, 2025: https://selling-guide.fanniemae.com/sel/b4-1.3-08/comparable-sales

includes factors like the distance to the fire perimeter, the elevation of the parcel, and the distance to power transmission lines, as well as a FEMA risk rating).

A recent meta-analysis of the social science literature on hedonic modeling from 2023 tabulated the 20 most common variables included in such models from 276 studies conducted from 2005 to 2021.[29] Table 3.1 lists these variables, the share of studies they appear in, and whether they are represented in the pre-fire model, or in certain cases, were not applicable.[30] In all, of the 16 potentially relevant measures in this list (the list of 20 variables minus the four that have no or limited applicability in this setting), we find that the pre-fire model explicitly measures 11 of them and uses what appears to be indirect or proxy measure for two others. The only three that are not included in the model are presence of a fireplace, distance to the nearest park, and whether the property was vacant.

[29] Khoshnoud, Mahsa, G. Stacy Sirmans, and Emily N. Zietz, "The Evolution of Hedonic Pricing Models," *Journal of Real Estate Literature*, Vol. 31, No. 1, 2023. As of October 6, 2025: https://doi.org/10.1080/09277544.2023.2201020

[30] For example, features like basements and property conditions like being under foreclosure or vacant were, to the best of our knowledge, exceedingly rare or possibly absent among the destroyed SFRs.

Table 3.1. Most Common Property Characteristics Used in Studies Estimating Home Value

Property Characteristic	Percent of Studies Using Variable	Represented in Pre-Fire Model
Age of structure	65%	Yes
Square feet of structure	58%	Yes
Number of bathrooms	55%	Yes
Number of bedrooms	53%	Yes
Lot size	44%	Yes
Garage space	36%	No (but presence of garage is measured)
Fireplace	31%	No
Pool	24%	Yes
Time on market	22%	Not applicable
Distance[a]	20%	Yes (distance from fire perimeter)
Vacant	15%	No
Number of stories	15%	Yes
Time trend	15%	Yes
Half baths	13%	Not applicable (measuring baths and full baths is equivalent)
Full baths	10%	Yes
Air conditioning	9%	Yes
Basement	9%	Not applicable[b]
Distance to nearest park	8%	No
Water view / income / property condition	7%	No (but includes limited building quality, renovation permit data)
Foreclosure / golf	7%	Not applicable[c]

SOURCE: Khoshnoud, Sirmans, and Zietz (2023) based on analysis of 276 published research articles and author calculations from Compass Lexecon-provided data.

[a] It is not clear what "distance" indicates in Khoshnoud, Sirmans, and Zietz (2023) but the most likely explanation is distance to a central business district. In the case of the pre-fire model, Altadena itself is a very geographically small area and distance is used to measure houses nearer to and farther from the Eaton Fire perimeter as a way to control for a potentially diminishing comparability (this distance measure is set to zero for all homes within the fire perimeter).

[b] To the best of our knowledge basements are exceedingly rare or possibly entirely absent among the sample of SFRs in the pre-fire model (Crotta, Carol, "Why Basements Are Scarce in Southern California," Los Angeles Times, May 9, 2015. As of October 6, 2025: https://www.latimes.com/home/la-hm-basement-side-20150509-story.html).

[c] There is a municipal golf course within the fire perimeter such that all destroyed SFRs are proximate; it is unclear that any homes were in foreclosure or vacant at the time of the Eaton Fire, and this variable is most likely common to studies focused on the period after the Great Recession, when this was a common condition.

The training data for the pre-fire model comprise a large sample of SFRs from Altadena, as well as homes from two nearby municipalities: Pasadena and Sierra Madre. The parcels included in this sample were all sold at least once between 2020 and 2024. They are all zoned for either SFR or planned urban development use and contained an SFR as the primary structure. This initial sample was trimmed according to the following exclusion criteria:

- Non-arm's length transactions, identified using indicators for this condition provided in the ATTOM property data as well as some additional exclusions for other properties with a transaction price of zero or other indicators for non-arm's length transaction types, were excluded.
- Properties with adjusted transaction prices higher than the 99th percentile of the distribution were excluded (the highest transaction price in the dataset prior to exclusions was $9.9 million).
- Properties with adjusted transaction prices per square foot outside of the range of the 0.5th to 99.5th percentiles were excluded.
- Properties with *either* a lot size or a primary structure square footage outside of the range of the 0.25th to 99.75th percentiles were excluded.

These exclusions removed 155 observations. After these restrictions, the final training data sample was N=6,210.

From the data sources previously described, a large set of variables were taken or constructed for use in the model. In Table 3.2, we list the 12 most empirically important variables used in the pre-fire model according to a measure of the relative importance of each variable in the XGBoost model, along with a brief description of each variable.[31] A full list of the 50 variables appearing in the pre-fire model is contained in the Compass Lexecon white paper.[32]

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[31] This measure of importance is generated by XGBoost during the model training process.

[32] Compass Lexecon, "Estimation of Pre- and Post-Fire Value for Single-Family Residential Parcels," white paper, October 1, 2025.

Table 3.2. Most Important Variables in the Pre-Fire Model

Variable	Description
Square footage	Square footage of primary structure
Distance to fire perimeter	Set to zero for homes inside perimeter, otherwise distance to nearest fire perimeter boundary
Design extras = none	Categorical variable indicating presence of none of pool, spa, miscellaneous, or other
Design extras = pool	Categorical variable indicating presence of a pool
Design extras = pool / miscellaneous	Categorical variable indicating the presence of a pool and miscellaneous additional amenities
Construction quality	A measure from assessor data summarizing construction features and workmanship as a numeric score
Adjusted prior sale price	Prior observed sale price adjusted to December 2024 using Case-Shiller Index for the L.A. metro areaa
Median home price	Value of median home at census block or tract level from ACS 5-year estimates
Lot size	Square footage of parcel
Renovation permit (last 20 years)	Issuance of a renovation-associated permit in the prior 20 years
Renovation permit (last 10 years)	Issuance of a renovation-associated permit in the prior 10 years
Renovation permit (last 5 years)	Issuance of a renovation-associated permit in the prior 5 years

SOURCE: Compass Lexecon tabulations.
[a] During model training, prior sale is the sale preceding the most recent sale recorded between 2020 and 2024. Prior sales are only tracked back through 2015.

Since the pre-fire model generates a valuation estimate by averaging the observed transaction prices of properties in the same set of model leaves as the destroyed SFR, the training data should ideally match or bracket the characteristics of the destroyed SFRs as the model cannot extrapolate values outside those observed in the training data. Additionally, the more frequently the training data contains properties with characteristics that are similar to those of the set of destroyed SFRs, the better the model will perform.

Table 3.3 shows the distribution of key characteristics of both the training sample and the destroyed SFRs.[33] This table serves two purposes. First, to illustrate the level of comparability between the properties used to train the model and the destroyed SFRs. Second, to illustrate the extent to which the limits of data values in the training data bracket the most extreme observed values among the destroyed SFRs, a key consideration for potential model accuracy. For three measures—adjusted transaction price, lot size, and size of the primary structure—we present the values at the mean, minimum, 5th percentile, median, 95th percentile, and the maximum.

[33] Note that the training data include destroyed SFRs that sold between 2020 and 2024.

Table 3.3. Comparing Select Characteristics of the Training Sample and the Destroyed SFRs

Characteristic / Data	Mean	Min	5th percentile	Median	95th percentile	Max	Percent of values missing
Prior transaction adjusted price (dollars)							
Training data	1,622,969	103,718	755,707	1,335,526	3,586,066	8,338,630	66%
Destroyed SFRs	1,478,692	262,798	883,035	1,344,181	2,562,170	5,095,463	75%
Lot size (square feet)							
Training data	10,689	1,473	4,501	8,317	25,041	81,493	0%
Destroyed SFRs	10,790	2,372	5,372	8,368	22,336	1,657,734	0%
Structure size (square feet)							
Training data	1,900	491	884	1,660	3,842	7,544	0%
Destroyed SFRs	1,704	380[a]	862	1,534	3,100	9,555	0%

SOURCE: Compass Lexecon analyst calculations fulfilling RAND data request.
NOTE: The training data sample (N=6,210) is after the exclusions described in text. The destroyed SFRs (N=5,123) are properties where the primary structure was destroyed in the Eaton Fire. Transaction prices reflect adjustment to December 2024 using the Case-Shiller Home Price Index for the L.A. metro area. The prior transaction values are taken from 2015 to 2024. For destroyed SFRs the prior transaction is the most recent observed (adjusted) sale price while in the training dataset it is the second-most recent transaction (the most recent transaction is the outcome the model is trained on). Some destroyed SFRs had a sale in the 2020 to 2024 period and are also in the training dataset. In such cases, the more recent adjusted sale price contributes to the “prior transaction” value for the destroyed SFR data and the previous adjusted sale price contributes to the “prior transaction” value for the training data.
[a] This smallest property based on structure size is part of the set of destroyed SFRs, but Compass Lexecon did not produce a pre-fire estimate for it because it is missing other data used for prediction.

The comparisons in Table 3.3 provide mixed evidence in terms of the extent to which the most extreme values of the training sample data bracket the minimum and maximum among destroyed SFRs. For example, adjusted prior sales prices for the training sample do have minimum and maximum values that are, respectively, below and above the minimum and maximum observed among destroyed SFRs. However, this is not the case for structure size, where the minimum value in the destroyed SFR sample is smaller than the minimum value in the training sample. Additionally, the property with the largest lot size in the destroyed SFR data is roughly 20 times larger than the maximum value in the training sample. Overall, though, 24 of a total of 34 numeric variables used as predictors in the model (71 percent) have values among destroyed SFRs within the minimum or maximum values of the training sample.[34]

Even though the characteristics of the destroyed SFRs fall within the training data for a considerable majority of the numeric variables there are some destroyed SFRs that fall outside the 5th and 95th percentiles of the training data on some characteristics. This is a region where it may become more difficult to find well-matched comparable properties in the training set. On all

[34] This is excluding binary variables that take on a value of 0 or 1 to signify the presence or absence of a feature.

29 numeric variables used as predictive features, there is at least one destroyed SFR that is outside the 5th or 95th percentiles of the training data.

Additional Data Limitations for the Pre-Fire Model

There are further important limitations in the data that are primarily related to an inability to incorporate key factors specific to a home that would, for example, be used in a traditional appraisal approach. Namely, the model is lacking critical details on the condition of the home that would facilitate a greater ability to distinguish properties of particularly high or low quality. For example, certain properties may have been remodeled in a particularly high-quality manner (e.g., granite countertops, high-end appliances, high quality windows and doors) while other properties may be closer to a "teardown" condition. Relatedly, the presence of higher and lower quality amenities beyond the primary structure (landscaping, mature trees, higher quality outbuildings) is also unmeasurable. This is because the data to accurately distinguish these types of differences are not obtainable from third-party sources. As discussed below, this is one reason the pre-fire model will likely tend to overvalue lower-quality properties and undervalue higher-quality properties.

There are a large number of missing values for prior transaction price among properties in both the training sample and destroyed SFRs (66 and 75 percent, respectively). This is due to the fact that transactions are relatively infrequent events, but it is also due to Compass Lexecon only requesting transaction values in a 10-year "look back" window spanning 2015 through 2024 and not including earlier transactions. However, this may not be much of a limitation because it is also the case that errors in the housing price indexes grow over time, so their accuracy decreases when used over a long period.[35] This implies that were the model to use older prior transaction data, the process of adjusting these prices to current prices might yield diminishing returns in terms of improving model valuation estimates.

Assessment

Overall, the preceding comparison of these training data and the destroyed SFRs suggests that for the vast majority of destroyed SFRs, the training data comprise an appropriate sample of home sales for modeling pre-fire value. More specifically, it is unclear that there is a feasible alternative approach to collecting available data that could have yielded a notably better training data sample for the purpose of estimating pre-fire values.

[35] Hayunga, Darren R., Kelley Pace, Shuang Zhu, and Raffaella Calabrese, "Differential Measurement Error in House Price Indices," *The Journal of Real Estate Finance and Economics*, September 11, 2024. As of October 7, 2025: https://doi.org/10.1007/s11146-024-09994-z

Specification of the Pre-Fire Model

One of the data challenges in estimating property values just before the fire began is that the start date of the fire (January 7, 2025) is at the edge of the data used to train the model (transactions in the 2020–2024 period). This means that comparable transaction prices used in the estimate of a given property could be pulled from further back in time than is typical in real estate appraisals. The estimation method used by Compass Lexecon deals with this data limitation in two ways. First, they inflation-adjust all transaction prices in the training data to December 2024 prices using the Case-Shiller housing price index for the Los Angeles region. For example, this adjustment increases the value of transactions made in January 2020 by approximately 50 percent to more closely approximate the properties' December 2024 value. The model they estimate is being trained on these adjusted transaction prices, rather than the actual historical transaction price. Secondly, they include the date of the transaction within the XGBoost model. This effectively further adjusts the prices to better reflect the price changes over this historical period within the local area of Altadena, Pasadena, and Sierra Madre, where local price trends may differ somewhat from the price trends in the broader L.A. region. Essentially, if the price trend in the regional Case-Shiller housing price index does not accurately account for the local price trend, XGBoost will automatically subset the data in a manner that restricts the comparable properties used in the pre-fire value estimates to those transactions closer to the end of the training data period.

As discussed in the Compass Lexecon white paper, the final XGBoost model was first optimized using five-fold cross-validation. Their specific optimization procedure was slightly nonstandard and involved three steps. They first created five separate XGBoost models on five subsets of the data,[36] with each of the five models having tuning parameters optimized to minimize the error of estimation on its respective cross-validation test data. Because each is optimized separately, these five models had slightly different numbers of trees and other XGBoost tuning parameters. They next took the median values of all tuning parameters across the five models (except the number of trees) and trained a single model on 90 percent of the historical data to the number of trees that minimized error of the estimates in a 10 percent test sample; 2,600 trees were determined to be optimal for those tuning parameters using this criterion. A final model was then estimated on all data using the median tuning parameters and 2,600 total trees which was then used for estimating the pre-fire property value of the burned single-family homes.

In optimizing these models, they searched across a range of reasonable values on the tuning parameters of XGBoost that typically matter for minimizing error of estimates. These included

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[36] These subsets were created so that each training set contained 80 percent of the historical transactions and each transaction appeared in four of the five training sets while being omitted from the training set for one of the five. A historical transaction serves as the cross-validation test data point for the model trained on the set where it had been excluded.

the number of trees, the tree depth, the learning rate, the subsampling rate, the minimum error reduction necessary to create an additional leaf, and the minimum number of observations in a leaf. Given this exploration of alternatives, it appears unlikely that there are some other XGBoost settings that would provide meaningfully more accurate estimates of pre-fire property values given the set of historical transactions they used in training. The final tuning parameters included a tree depth of six (which results in trees with up to 64 leaves), 52 percent subsampling, and a learning rate of 0.005; these are very typical parameter values for XGBoost models optimized to minimize cross-validated error of the estimates.

We asked to see figures showing some of the relationships between property characteristics and price that are captured in the final model. These were provided to us, and we generally feel that those relationships are consistent with a reasonable property valuation model. The XGBoost algorithm was run in a way that ensures that price is monotonically increasing with the size of the house and the size of the lot. That means that if you increase the size of the house or the lot while holding all other property features constant, the model never gives a lower estimated value. We also looked at the relationship between transaction date and adjusted price to investigate if the regional Case-Shiller adjustment was appropriate for local area, or if the model needed to apply substantial additional adjustments to account for the local price trend. In general, the model adjusted the local price trend a small amount relative to the substantial inflation adjustment from Case-Shiller. This model adjustment of the time trend suggests that properties in this area may have increased in value slightly slower than in the broader L.A. region, particularly from 2020 through 2022. The fact that the Case-Shiller adjustment works quite well to explain the local price trend eases concerns about inferring pre-fire property valuations from transactions that sometimes occurred several years earlier.

As discussed earlier in the chapter we were also shown figures documenting the relative importance of the predictor variables within the XGBoost model. The model relied most heavily on the square footage of the structure, although a number of other variables also contributed meaningfully, including: a history of building permits, lot size, a set of design or construction features (e.g., having a pool or spa), local area median home price, and adjusted prior sale price (only available when there was a prior sale since 2015). These are property features that one might reasonably expect to influence property valuations. The model also considered distance to the burn area in its valuations; this implies that when getting estimates for burned homes it will rely more heavily on the comparable properties in or near the burn area than those further away.

Accuracy of the Pre-Fire Model

Property-value estimates from the pre-fire model are comparable to those produced by commercially available AVMs.[37] As discussed in the Compass Lexecon white paper, estimated property values from the pre-fire model are very highly correlated with those from commercially available AVMs for the properties within the burn perimeter. The average of the property values for the set of destroyed SFRs estimated by the model is also very similar to, or slightly higher than, the averages from the commercially available AVMs. For typical properties, we see no reason to believe that some other AVM would be more accurate than the one developed for this specific area by Compass Lexecon.

Despite performance that appears to be as good as some other alternatives, there are still going to be properties whose estimated value is meaningfully different from the (inflation-adjusted) price the property actually sold for. Our goal in this section is (1) to give additional information about the accuracy of the model on some additional metrics; (2) to highlight subsets of the properties for which the magnitude of over- and underestimates tend to be larger or smaller, reflecting more or less uncertainty in the estimate; and (3) to highlight subsets of the properties where estimated values from the model were consistently higher or consistently lower than actual transaction prices.

Compass Lexecon provided us with information about the cross-validated error of the estimates for the XGBoost models they developed. This data allows one to assess how close the estimated values are to the actual adjusted transaction values for the historical transactions. For each transaction, this is assessed using the model where that transaction was excluded from training, giving an out-of-sample error of the estimates.[38] In this report we assess these over- or under-estimations using only the 786 training transactions that are of properties where the primary structure later burned, which is a subset of properties to which the valuation model is being applied.

We also look at three different metrics to help better understand the accuracy of the estimates: (1) error of the estimate in dollars computed as the model estimated adjusted price minus actual adjusted sale price, (2) that same difference divided by actual adjusted sale price to express over- and underestimates as a percentage of actual value, and (3) the model estimated adjusted value per square foot of primary structure minus actual adjusted sale price per square

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[37] Examples of such AVMs include those developed by Corelogic, ATTOM data solutions, Quantarium, and Cotality.

[38] Following convention, we refer to the estimated transaction value from the model minus the actual transaction value as the error of estimation. However, there may be considerable randomness in the actual transaction prices because markets are not perfectly efficient. That is to say, even with a hypothetically perfect property assessment, some buyers may pay more than market value (for example if there are multiple interested parties who bid up the property) while others may pay considerably less (for example when the seller needs to sell the property on a tight timeline). What we call error combines both sources of variability: imperfection in the model as well as randomness inherent to the local real estate market. Because of this, it is not reasonable to expect any property valuation to perfectly predict the transaction price—those prices may depend on more than just the property.

foot. Understanding over- and underestimates using this last metric is relevant because it is an important component of SCE's proposed formula for calculating compensation offers.

As can be seen by comparing the 25th percentile and 75th percentile columns of Table 3.4, 50 percent of the estimates are within -9 and +11 percent of the actual adjusted value. Twenty-five percent of properties had values that were underestimated by more than $135,000, by more than 9 percent of actual value, or by more than $92 per square foot. Similarly, 25 percent of properties had a price that was overestimated by more than $135,000, by more than 11 percent of actual value, or by more than $90 per square foot. As can be seen by comparing the 10th and 90th percentile columns of Table 3.4, 80 percent of the estimates are within -17 percent and +25 percent of the actuals.

Table 3.4. Distribution of Over- and Underestimates of Property Value for the Pre-Fire Model

Error Metric	1st percentile	10th percentile	25th percentile	Median	75th percentile	90th percentile	99th percentile
Estimated - Actual	-$672,000	-$294,000	-$135,000	$5,000	$135,000	$282,000	$725,000
As percent of actual	-30%	-17%	-9%	0%	11%	25%	70%
In price per square foot of house	-$408	-$183	-$92	$3	$90	$182	$393

NOTE: Negative errors indicate properties where the pre-fire model underestimated the historical adjusted sale price, positive errors where it overestimates historical adjusted sale price. Percentiles refer to the percentage of all properties with errors more negative than the corresponding values. Actual value is based on prior sales among 786 subsequently destroyed SFRs.

While the model appears to work quite well for over half of the properties, there are also some properties with substantial over- or underestimates of pre-fire value. For example, 1 percent of properties had an underestimated price by more than $672,000, by more than 30 percent of actual value, or by more than $408 per square foot. Similarly, 1 percent of properties had a price that was overestimated by more than $725,000, by more than 70 percent of actual value, or by more than $393 per square foot.

Given that the pre-fire valuation appears to be relatively accurate for many properties but also may be considerably over- or underestimated for others, we have investigated whether we can characterize the types of properties for which the estimates are more or less accurate. When possible, we also try to describe the likely direction of these potential errors.

The largest determinant of accuracy of the estimated value in dollars is the actual value of the property. Estimated property values for high-end properties tend to have larger differences from the actual transaction price than estimates for less expensive properties. For example, the average gap between estimated value and actual transaction price in dollars is perhaps 50 percent larger for a $2 million house relative to a $1 million house.[39] Because of this relationship between accuracy of the estimate and the price of the property, it may be useful to think of accuracy in terms of percentage of the price as well as in absolute dollar terms.

There are several reasons why a given property may have its pre-fire value either overestimated or underestimated. These reasons primarily fall into two groups: (1) some burned properties may have very few close comparative properties within the historical transactions used to train the model; and (2) some property characteristics that may increase or decrease market value of a property are not available in the data being used to determine the value. Regarding the first set of reasons, the XGBoost model in effect divides the training data up based on the property features into subsets with comparable prices. It then calculates an estimate for a given property as a weighted average of the prices of the comparable properties in the training data. However, if a property has unusual features, there may be no close comparable properties in the training set at all. For example, one of the burned properties has a lot size that is much larger than any property sold in the area in the prior five years, and so its value is determined by the average sale price for much smaller properties. The XGBoost model cannot give a property any credit for valuable features (e.g., building size, lot size, number of bedrooms) that are above the range of that feature contained in the training data. The model does not know how much more a 9,000 square foot house is worth relative to a 7,500 square foot house because there are no examples of houses larger than 7,500 square feet in the training data. The larger burned house gets treated the same as the largest houses captured in the training set. Similarly, the model cannot debit any properties that are unusually small, and they are consequently treated like the smallest properties in the training data. The limits of the training distribution across several key features were shown in Table 3.3. To the extent that a property has any feature that is near the maximum of the training data, the value of that unusual property is more likely to be underestimated. To the extent that a property has any feature that is near the minimum of the training data, the value of that unusual property is more likely to be overestimated. Fortunately, the training data for structure size and lot size have good coverage for the vast majority of burned houses, but underestimation becomes of increasing concern for houses greater than 3,100 square feet and lots greater than 19,000 square feet, and overestimation becomes of increasing concern for houses and lots less than 1,000 square feet and 5,500 square feet, respectively (see 5th and 95th percentiles in Table 3.3).

While this first limitation of the data affects only burned properties that are quite unusual, the second problem affects a large number of properties: many features that affect property value cannot be included in the model because the information is not in the training data. The model does not know which properties have granite countertops, covered patios, a 3-car garage, mature trees, extensive landscaping, architectural significance, or new paint. Similarly, it does not know

[39] This approximation is based on inspection of plots of model residuals by transaction price provided by Compass Lexecon to the project team. See Figure B.1.

which properties have extensive termite damage, a crumbling foundation, a leaky roof, or would require significant investment to prepare for a sale. Some of these features might be partially captured in variables like prior sale price (although prior sale is only available for a third of properties that sold between 2020 and 2024) or the number of building permits that have been pulled.[40] However, there is no obvious way to get systematic measures of these important property characteristics across the full region, and they are, thus, not reflected in the pre-fire estimate. Two properties could have similar values on the predictor variables used by the model (same age, size, neighborhood, number of permits, etc.), but one could be in a condition where it is likely to be torn down by its new owners while the other could be considered a premium or luxury property by real estate professionals. Because this dimension is not well captured in the pre-fire model (or any AVM), properties that are toward the "tear down or remodel" end of the continuum are very likely to have their property value overestimated by the model, while the opposite is true at the "luxury" end of the continuum. These biases may be larger for properties that had not sold recently (or had sold in a significantly different condition than they were in at the time of the fire) or had significant work done that was not accurately reflected in the building permits.

One way these biases can be seen in the data is by looking at the error of the estimates (i.e., estimated price minus actual transaction price) as a function of the actual transaction price per square foot of the house, a rough measure of the extent to which the property is a premium property. This information is shown in Figure 3.1. The figure shows that the model overestimated the value for almost every property that actually sold for less than $600 per square foot of the house. It also underestimated the value for almost every property that actually sold for more than $1,200 per square foot of the house.[41] Property owners of destroyed SFRs do not know exactly what the true market price was for their properties at the time of the fire, which means they do not know exactly where along the horizontal axis of this figure their property sits. However, they may have some idea of whether their property is likely to be below average or above average on a price per square foot basis. Knowing that provides a lot of information about whether their property is in the range where the model is more likely to overestimate value, the range where it is more likely to underestimate value, or in the range where the model is relatively accurate. For properties that sold between $600 and $1,200 per square foot of the house, the model is considerably more accurate than implied by overall distributions of over- and underestimates shown earlier in Table 3.4; more than 80 percent of destroyed SFRs in the sample fall into that range.

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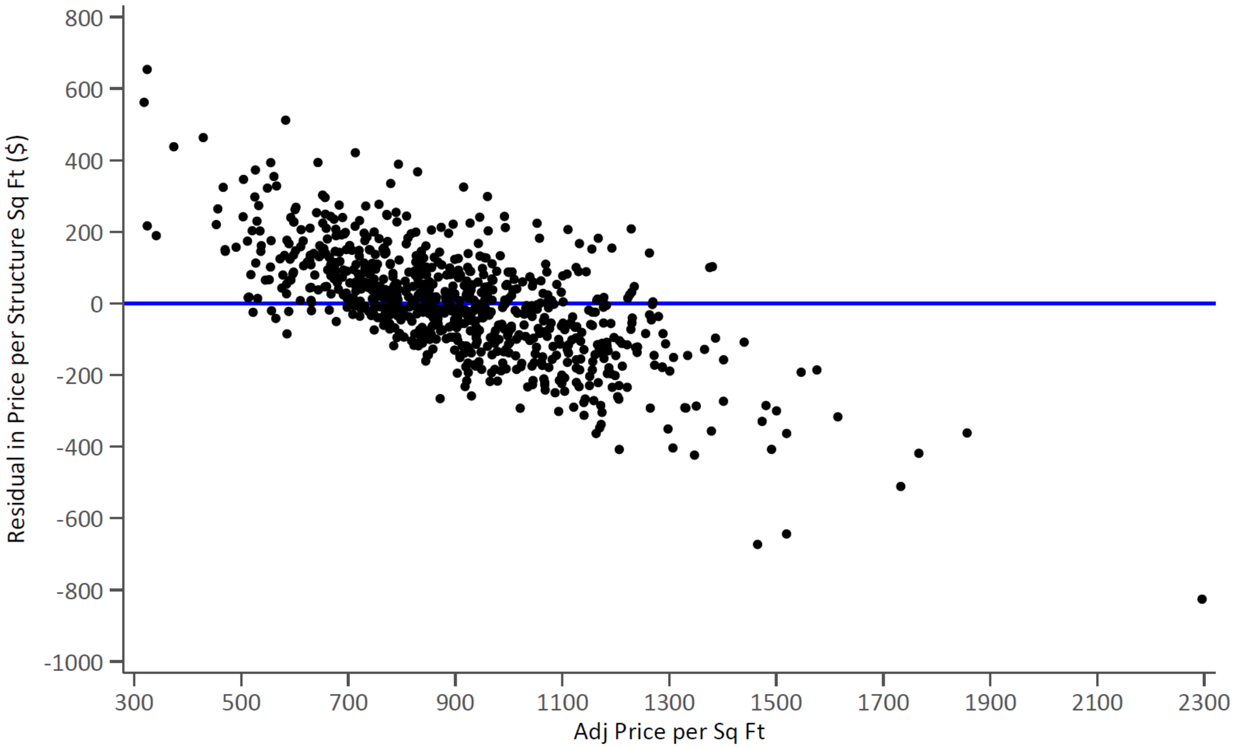
[40] Building permits were available for properties in Altadena and Pasadena but not Sierra Madre.

[41] This phenomenon is caused by regression to the mean. This leads to the residuals of a model (predicted – actual) being negatively correlated with the outcome (e.g., actual sale price). Regression to the mean occurs in any model that is estimated with uncertainty.

Figure 3.1. Out-of-Sample Residuals for Destroyed Properties by Actual Price per Square Foot of House



SOURCE: Figure provided by Compass Lexecon. Used with permission. RAND researchers did not create the plot or have access to the underlying data.
NOTE: Vertical axis values are computed as (model estimated – actual) sales price per square foot for the historical transactions in the training data. Horizontal axis reflects the actual adjusted transaction price per square foot of the house during the 2020–2024 period. Higher residuals indicate properties whose values are overestimated by the model, while lower numbers indicate those whose values were underestimated. Figure is restricted to 786 training properties that later burned in the Eaton Fire.

Summary of Valuations Produced by the Pre-Fire Model

The pre-fire valuations provided by Compass Lexecon are produced using modern analytic methods and incorporate a wide range of property characteristics, including the characteristics that are typically used to estimate property value in AVMs. Unlike other available AVMs, however, the Compass Lexecon estimates are based exclusively on historical property transactions of single-family homes in the immediate region of the fire and reflect the buyer preferences in that particular real estate market. Our analysis of the accuracy of the estimates suggests that the estimated price is within plus or minus 10 percent of the actual transaction price for about half of homes in the burn area sold in the period before the fire. Compass Lexecon presents evidence in their white paper[42] that estimates from their model are quantitatively very

[42] Compass Lexecon, "Estimation of Pre- and Post-Fire Value for Single-Family Residential Parcels," white paper, October 1, 2025.

similar to those produced by other commercially available AVMs. We have no reason to believe that any other AVM would be more accurate for determining the pre-fire value of single-family homes destroyed by the Eaton Fire.

Having said that, the pre-fire model provides estimates that deviate substantially from market value for a subset of properties. Deviations of more than $300,000 occurred for almost 20 percent of properties. These deviations are not entirely random and vary in size and direction based on characteristics of the properties. The direction of the errors is strongly associated with the actual transaction price per square foot of the house. The model tends to overestimate value for homes that are less expensive than average on a price per square foot basis, and underestimates value for homes that are more expensive on average by this metric. Underestimates will be more likely for large properties that lack close comparable properties in the training data and for upscale properties that had not previously been sold in 2020–2024. Overestimates are more likely for exceptionally small properties and for those that were in worse than average condition. These types of over- and underestimates occur with all AVMs to some extent because several key factors that affect price beyond square footage are not available in the datasets used to create the model.[43] We know about these limitations of the Compass Lexecon model because Compass Lexecon shared some model diagnostics and methodological details with us, which is a higher level of transparency than is common for commercial AVMs.

[43] Compass Lexecon also produced figures similar to Figure 3.1 for four different commercial AVMs. These figures show generally similar patterns. However, they are more difficult to interpret than Figure 3.1 because their estimates are not necessarily out of sample, unlike with the Compass Lexecon model, and thus may overestimate the accuracy of those models.

Chapter 4. Post-Fire Valuation Model for Destroyed Single-Family Residences

Compass Lexecon relied on a simpler model to estimate post-fire property values. Specifically, they used ordinary least squares (OLS) regression, a common statistical technique that, while less flexible than the tree-based model used for the pre-fire valuations, has benefits in data-poor settings. We believe this is a reasonable choice in this context due to the nature of the available data. Specifically, there have been only a couple hundred sales of relevant properties (i.e., properties with SFRs that were destroyed by the Eaton Fire). There is also substantially less to differentiate these properties (mostly burned lots) than there is for the properties sold pre-fire. While complex, non-parametric models such as XGBoost thrive in data-rich settings with complex relationships between predictors, they tend to perform poorly when there is insufficient data to distinguish the complex, true relationships from noise. Simple parametric models like OLS make much stronger assumptions about the relationships between the predictors and the outcome (i.e., post-fire property value). While these assumptions are unlikely to perfectly capture the correct relationships, they are often reasonable and can be evaluated. Additionally, they permit extrapolation to observations with values outside of those available in the training data. Given the small number of post-fire transactions, we believe that the use of a simple parametric model is appropriate.

We also emphasize that, based on our current understanding of Compass Lexecon's approach, the DIV estimate will rely on the actual post-fire sale value for the properties that were sold after the fire and the modeled estimate for properties that have yet to sell. The discussion below focuses only on the modeled estimates. We do not consider the appropriateness of substituting post-fire transaction amounts for modeled values, although the modeling results suggest that this will have little impact on the expected DIV.

Data Used to Develop the Post-Fire Model

The analysis sample for the post-fire model is 204 parcels within the Eaton Fire perimeter with destroyed SFRs (defined as a loss of 50 percent or more or the primary structure in the DINS data) that transacted between February and mid-August of 2025. The sample uses data from a subset of the data sources used in the pre-fire model.

The outcome data for the post-fire model is the transaction price for sales of the 204 properties that were destroyed in the Eaton Fire. The post-fire model employs five variables as regressors to explain the variation in these transaction prices. These inputs are:

- **Estimated pre-fire value:** This is the output of the pre-fire model for each property. The purpose of including this variable is to find a way to incorporate a potentially large amount of property details without having to include multiple variables, since the very small number of observations would not allow for this. In this sense, the pre-fire estimate serves as a proxy for multiple characteristics of the particular parcel that might influence its value.

- **Median home price in the census block group or tract:** This variable (that also appears in the pre-fire model) is included to represent the average level of pre-fire property values in the small area (a census block group or tract) in which a property is located.
- **Lot size:** Total area of the property's parcel; theoretically one of the characteristics of a burned SFR-zoned parcel that should be most relevant to value.
- **February or March sale indicator:** This is a binary variable equal to 1 if a post-fire sale occurred in February or March and equal to zero otherwise. The rationale for including this variable is that the earliest sales may have had some unique characteristics related to being especially distressed sales or to being part of an unusual period of initial price discovery among sellers and buyers.
- **Standing outbuildings indicator:** This is a binary variable equal to 1 if DINS data indicates that the property had a largely or completely intact outbuilding remaining.

We note that some may have equity concerns for including a neighborhood-effect variable (i.e., median home price in the census block group or tract), particularly because the average pre-fire home price is not a feature of a lot itself. However, the primary reason for including this variable is that it slightly improves the accuracy of the post-fire property value estimates. Accuracy in these valuations is a primary concern for ensuring fairness in the settlement offers. In addition, we note that the model coefficient on this predictor is such that including it may slightly increase the settlement offers to property owners from lower income neighborhoods.

Some key values from the distributions of three key variables are listed in Table 4.1 along with a set of comparisons between aspects of this sample of 204 parcels that sold in the post-fire period and the full set of damaged SFR parcels within the Eaton Fire perimeter.

Table 4.1. Characteristics of the Post-Fire Transaction Sample and of All Destroyed SFRs

Characteristic	Mean	Min	5th percentile	Median	95th percentile	Max
Post-fire sale price (dollars) (outcome variable; post-fire transaction sample)	646,865	226,000	450,750	600,000	936,350	1,865,000
Lot size (square feet)						
Post-fire transaction sample	9,900	2,400	5,600	8,600	20,100	29,500
Destroyed SFRs	10,800	2,400	5,400	8,400	22,300	1,657,700
Median home price of census block group (millions of dollars)						
Post-fire transaction sample	1.1	0.7	0.7	1.1	1.5	1.8
Destroyed SFRs	1.1	0.7	0.8	1.1	1.8	2.0

Characteristic	Mean	Min	5th percentile	Median	95th percentile	Max
Model estimated pre-fire price (millions of dollars)						
Post-fire transaction sample	1.4	0.6	0.9	1.3	2.2	3.1
Destroyed SFRs	1.4	0.6	0.9	1.3	2.4	4.3

SOURCE: Compass Lexecon calculations.
NOTE: Lot size values for sold parcels are rounded to the nearest hundred square feet. N=5,123 for destroyed SFRs and N=204 for the post-fire transaction sample.

Post-fire sale prices have a mean value of $646,865. The distribution of prices is slightly right skewed with the median value of $600,000 modestly below this mean. The highest value transaction in the data was over $1.8 million. We note that these prices were not adjusted using any inflation or home price index. However, the Consumer Price Index–Shelter in U.S. City[44] average increased by 2 percent for the first seven months of 2025 while the Case-Shiller Los Angeles Home Price Index declined by 1.5 percent, suggesting that underlying macroeconomic pressures on real estate prices indicated by these two measures were near zero.

A comparison of the lot sizes of the post-fire sold-parcel sample and the full set of destroyed SFRs indicates that the sample of 204 parcels is similar to the overall set of destroyed SFRs. That is, the median values are quite close (8,600 square feet versus 8,376) as are the 5th percentile (5,600 versus 5,371) and the 95th percentile (20,100 versus 22,285) values.

Comparing the average median home price at the census block group level suggests that the post-fire sold-parcel sample is a distribution of modestly lower cost homes than the full set of destroyed SFRs. The mean and median values are the same, but the 5th ($0.7 million versus $0.8 million) and 95th ($1.5 million versus $1.8 million) percentiles are both slightly lower.

We also make a comparison between the estimated pre-fire value of the sample of 204 post-fire sales and the full set of destroyed SFRs. This comparison indicates a distribution that matches in terms of value at the mean, the minimum, the 5th percentile, and the median. However, at the 95th percentile, the pre-fire estimated values of the sample of post-fire transactions are slightly lower than the corresponding percentile in the overall sample of destroyed SFRs ($2.2 million versus $2.4 million). The maximum value in the post-fire sample is notably lower than the maximum estimated pre-fire value in the full sample of destroyed SFRs ($3.1 million versus $4.3 million). On balance, this suggests that, as of August of 2025, the properties with the highest pre-fire estimated values have transacted less frequently than properties at the lower to middle portion of the distribution of estimated pre-fire values for all destroyed SFRs.

[44] U.S. Bureau of Labor Statistics, Consumer Price Index for All Urban Consumers: Shelter in U.S. City Average [CUSR0000SAH1], retrieved from FRED, Federal Reserve Bank of St. Louis. As of October 7, 2025: https://fred.stlouisfed.org/series/CUSR0000SAH1

The pace of post-fire lot sales has increased over time—only 20 percent of sales occurred in the first 2 months of the 7.5 months of post-fire sales transaction data. The model variable indicating presence of remaining outbuildings is indicative of a rare scenario in the small sample of post-fire sales. Only 4 percent of the 204 sold parcels were indicated to have a standing outbuilding of any kind.

Assessment

It is difficult to make conclusive claims about the adequacy of the data in the post-fire model since the setting is so highly unusual. However, we held extensive discussions with Compass Lexecon about the available data and how data choices were made under the substantial constraint represented by the small number of observations available to use in generating estimates. The focus on lot size as a primary factor appears sound simply because for many of these properties a cleared lot is likely all that exists. We believe that including both the pre-fire estimate for the property and the average pre-fire property values in the small area around a property is a reasonable approach for approximating a variety of potential characteristics that are either not observable in an available dataset or would require the inclusion of many variables. Both the indicator for sales occurring early in the post-fire period and the indicator for remaining outbuildings are conceptually sound, though, as discussed below, neither has a substantial effect (in terms of either coefficient size or precision) on the model. In summary, we are not aware of any approach to developing a dataset for this purpose that would be meaningfully better than the approach used by Compass Lexecon.

Specification of the Post-Fire Model

Compass Lexecon used OLS regression to estimate post-fire values as a function of the property characteristics described above. Prior to fitting the model, Compass Lexecon applied a log transformation to the outcome variable (post-fire value) and several predictors (modeled pre-fire value, the median pre-fire home price for the census block containing each property, and lot size). The full model[45] assumes logged post-fire value is a linear function of logged estimated pre-fire value from the pre-fire model, logged median home price in the census block group containing the property, whether the property sold in February or March of 2025, the number of remaining outbuildings on the property, and logged lot size of the property.

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[45] In mathematical terms the model is specified as

$$\begin{aligned} log(\text{post-fire value for property } i) = \beta_0 + \beta_1 \times log(\text{modeled pre-fire value for property } i) \\ + \beta_2 \times log(\text{median home price in census block group containing property } i) \\ + \beta_3 \times (\text{indicator for whether property } i \text{ sold in Feb. or Mar. 2025}) \\ + \beta_4 \times (\text{number of remaining outbuildings}) + \beta_5 \times log(\text{lot size of property } i) + \epsilon_i, \end{aligned}$$

where the error terms ϵ_i are independent, identically, and normally distributed (a standard assumption in regression models).

The pre-fire machine learning model XGBoost does not make any specific assumptions about the functional relationships between variables and, as such, researchers do not typically focus on univariate transformations prior to fitting those models. Conversely, OLS makes strong assumptions about the functional relationships between variables, and the results can be very sensitive to variable transformations. Specifically, OLS assumes linear relationships between each variable and the outcome, as modeled. If the post-fire model were fit without the log transformations above, then that would assume that, for example, each square-foot increase in lot size would have the same increase in post-fire value. Given that there is evidence that this assumption is likely violated in this setting, exploring alternative functional relationships between the variables is warranted. See Appendix A for an illustration of how different transformations affect the different implied relationships between variables.

Given that the post-fire model will be used to provide values for lots that are both larger and smaller than any in the training data, it is important that the functional relationship between the variables provides a reasonable estimate outside of the sample (i.e., that it does not unreasonably increase toward infinity or drop below zero). Because lot size was the most influential predictor in the model, Compass Lexecon explored several combinations of transformations on the outcome (untransformed, log) and lot size specifications (linear, quadratic, log, log-quadratic) and ultimately decided to include a logged sale price and logged lot size in the final model.[46] We inspected the implied relationship between lot size and sale price, as well as model fit statistics for a variety of these specifications and were satisfied with this decision based on those results. Compass Lexecon also explored untransformed and logged specifications for the modeled pre-fire value and census block group median home price and reasonably chose the logged specification. In addition, Compass Lexecon evaluated inclusion of some additional variables (e.g. parcel elevation) that did not meaningfully affect the accuracy of the model.

An additional concern in OLS regression is high-leverage outliers. Outliers are points that exist at the extreme ends of the distribution of covariates and often appear detached from the rest of the distribution. These points can exert a high amount of leverage on model predictions (i.e., estimated post-fire values), pulling them upward or downward toward the outlier outcome. In extreme cases this can result in substantially worse fits for the majority of the non-outliers. A common method of identifying overly influential outliers is to run analyses with potential outliers removed and see if the results meaningfully change. Compass Lexecon conducted two outlier sensitivity tests: one that excluded the top five most expensive and bottom five least expensive lots, and another that excluded the top five largest and bottom five smallest lots.

[46] In a quadratic specification explored by Compass Lexecon, both the natural logarithm of lot size and the square of the natural logarithm of lot size are included in the model. The incorporation of a squared term is common in estimation settings where a simple linear relationship may not accurately characterize the true functional form of a relationship. More specifically, the inclusion of this term allows for a relationship with both a slope and a curvature, as would be present if, beyond a point, additional lot size was not associated with a linearly increasing price but instead a price that grew more slowly.

Regression coefficients did not meaningfully change, suggesting that these points are not overly influential. Outliers were thus not dropped during model estimation.

Accuracy of the Post-Fire Model

Compass Lexecon provided us with model coefficients and standard errors presented in Table 4.2 below. The coefficient indicates how the model-estimated value depends on that predictor and the standard errors capture uncertainty in those coefficients.

Table 4.2. Regression Coefficients for the Post-Fire Model

Parameter	Coefficient	Standard Error
Constant	8.271	0.577
Log of pre-fire value	0.177	0.0436
Log of census block group median home price	0.115	0.0438
Indicator if home sold in Feb. or Mar. 2025	-0.007	0.0163
Number of standing outbuildings	0.103	0.0540
Log of lot size	0.442	0.0313

SOURCE: Compass Lexecon calculations.
NOTE: The outcome variable is the natural logarithm of the transaction price. Standard errors were calculated to be robust to heteroskedasticity. N=204.

Unlike XGBoost, the OLS regression model coefficients are directly interpretable, and it is good practice to investigate if those coefficients appear reasonable. In general, all model parameters appear reasonable. While the log transform on both the outcome and some covariates makes more specific comparisons challenging without additional analysis, the signs of all coefficients appear reasonable. One would expect that, all else being equal, a higher pre-fire value, more expensive neighborhood, more standing outbuildings, and larger lots would all contribute to higher post-fire values. All coefficients associated with these predictors are positive, confirming this expected relationship. Additionally, the indicator of whether a home sold in February or March of 2025 (versus later in the year) is essentially zero. This is consistent with there being no significant differences between these two time periods but does not preclude differences within those periods.

Regarding the magnitude of the parameters, we directly compare the predicted effects of 10 percent and 100 percent increases in the predictor value on the outcome (see Table 4.3).[47]

[47] When a model is estimated with the outcome (i.e., sale price) on the log scale, researchers need to be careful in back-transforming estimates to the natural scale (i.e., from log-dollars to dollars). Basic transformation from logged space to real space relies on exponentiating all estimates. However, exp(average[log(y)]) ≠ average[y] if there is any uncertainty in the estimates, so this process often produces biased estimates. Table 4.4 shows that there is indeed bias in the expected value of the property (see "mean" column). However, this bias is very small relative to the

Table 4.3. Post-Fire Model Parameter Effects

Parameter	Coefficient	10% Increase in Predictor	100% Increase in Predictor
Pre-fire value	0.177	1.7%	13.1%
Census block group median home price	0.115	1.1%	8.3%
Lot size	0.442	4.3%	35.8%

SOURCE: Computed from values in Table 4.2.
NOTE: This table provides interpretation for the regression coefficients. For example, a 10 percent increase in estimated pre-fire value would result in a 1.7 percent increase in estimated post-fire value.

As is evident from Table 4.3, the model is much more sensitive to lot size than to each of the other two predictors. Additionally, the marginal effect of adding a single standing outbuilding is a 10.8 percent increase in value. We emphasize, however, that these effects assume all other features are held constant. Given that many of the predictors are correlated, one should interpret these marginal effects with caution (i.e., it is unlikely that a house could double in lot size without also increasing in pre-fire value). The overall model, however, is designed to accommodate these correlations between predictors. These are reasonable estimates that do not appear to result in any strange or unexpected behavior.

While face-validity of model results can help identify potential issues, thorough examination of the model fit statistics is still helpful. For the model reported to us, the post-fire value had an r^2 value of 0.804 in log-space, indicating that the model can explain 80 percent of the total variance in log-transaction price.[48] Table 4.4 shows the distribution of over- and underestimates in dollars, as a percent of the actual sale price, dollars per square foot of the primary structure, and dollars per square foot of the lot. Both the absolute and relative errors of estimates are lower for the post-fire model than the pre-fire model (see Table 3.4 in Chapter 3).

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magnitude of the prediction (for example, the average sales price post-fire is approximately $650,000). As such, we do not believe it is necessary that the estimates be adjusted to minimize bias in dollars, and it is possible that applying such a correction would introduce a bias in the opposite direction when transformed onto a dollars per square foot basis.

[48] r^2 is a standard metric for evaluating model fit. It ranges from 0, indicating a model that does no better than estimating the mean value for all outcomes, to 1, indicating perfect estimation.

Table 4.4. Distribution of Over- and Underestimates of Property Value for the Post-Fire Model

Error Metric	Mean	10th percentile	25th percentile	Median	75th percentile	90th percentile
Estimated - Actual	-$3,938	-$80,588	-$42,142	-$7,470	$34,433	$93,606
As percent of actual	0.6%	-11.5%	-6.8%	-1.3%	6.0%	18.1%
In price per square foot of primary structure[a]	-$2.41	-$56.71	-$26.64	$-4.46	$19.06	$57.56
In price per square foot of lot	-$0.37	-$9.11	-$5.19	-$0.83	$3.95	$8.99

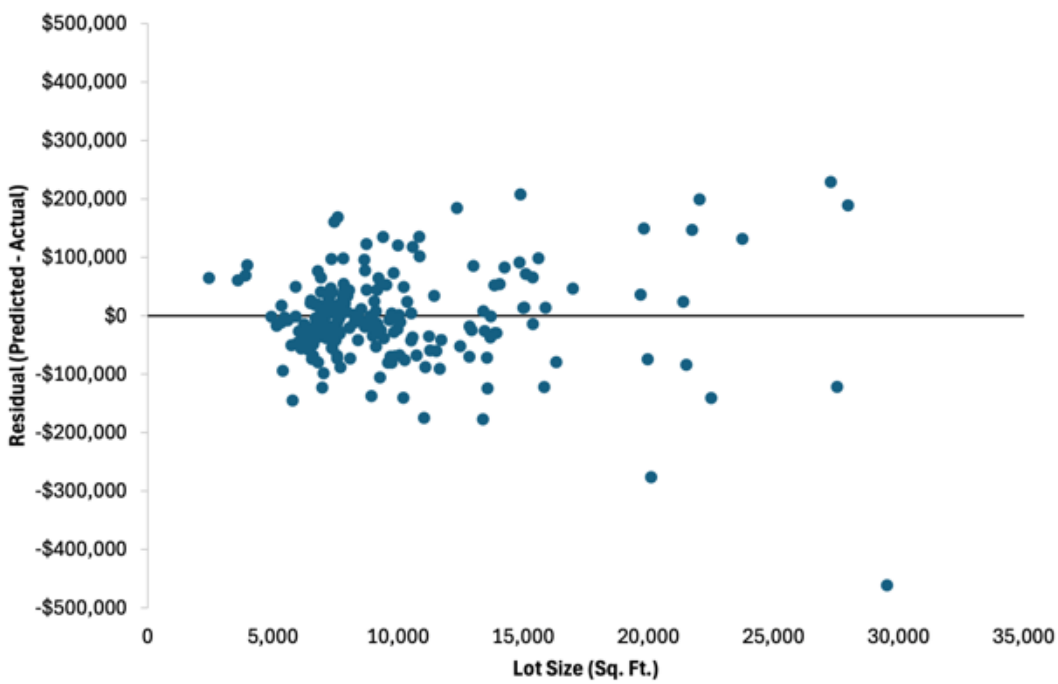
NOTE: Negative errors indicate properties where the post-fire model underestimated the sale price, positive errors where it overestimated sale price. Percentiles refer to the percentage of all properties with errors more negative than the corresponding values. N=204.

[a] We recognize that price per square foot of the primary structure is an unusual metric for a lot with a burned home. We include it here because DIV informs the compensation offer only through DIV/ft^2 of the house. As DIV/ft^2 = pre-fire value/ft^2 – post-fire value/ft^2, the error in the estimated DIV/ft^2 partially depends on the error in estimated post-fire value/ft^2.

As with the pre-fire model, we also explore situations where the post-fire model may have statistical bias (e.g., where one can predict in which direction the error of the estimate will be). This bias is likely induced by relevant features of the property that were either not available to Compass Lexecon or that ultimately were not included in the model. Examples of property features that may not be accounted for are views, proximity to the national forest, degree of post-fire clean-up, and surviving post-fire property features like mature trees, landscaping, and pools. Some neighborhood effects (e.g., views, proximity to the national forest) may be captured imperfectly by the estimated pre-fire valuation, but (1) the pre-fire model itself is blind to some of these features, (2) the pre-fire estimates may over- or underestimate the true pre-fire value, and (3) the relationship between these features and the pre-fire value, which is largely a function of the structure, may not be the same as their relationship with the post-fire value, which is largely a function of the land. As such, although including estimated pre-fire value clearly captures some of these effects (based on the fact that it is one of the larger coefficients), it cannot capture all of them. Median census block group pre-fire home price is also an important feature to capture neighborhood effects beyond those captured by the estimated pre-fire value, but it cannot capture property-specific features. There may also be bias due to extrapolation (e.g., estimating values for burned lots that are much larger or smaller than any included in the training data). However, unlike XGBoost, there is no way to know in which direction these extrapolation errors of estimates will be. It is possible that they will be quite small if the true functional form is accurately modeled, but there is no way to estimate this with the available data.

Figure 4.1 below shows the distribution of residuals as a function of lot size.[49] Given that lot size was included as a predictor in the model, it is unsurprising that the model is unbiased with respect to lot size. However, there is some evidence of increasing variance in the residuals with lot size. Lots between approximately 5,000 and 12,000 square feet generally have over- and underestimates that are smaller in magnitude (i.e., there is a cluster of points near the $0 residual line). Estimates for lots that are larger than approximately 12,000 square feet do not show any systematic bias but are more likely to be farther away from the true sale value. Note that these estimates are in absolute dollars, and errors would likely be smaller for larger properties as a percent of the actual sale price.

Figure 4.1. Post-Fire Over- and Underestimates of Property Value as a Function of Lot Size



SOURCE: Figure provided by Compass Lexecon. Used with permission.
NOTE: Negative residuals indicate properties where the post-fire model underestimated the sale price, positive residuals where it overestimated sale price. N=204.

Finally, we compare residuals (in dollars) to the true transaction price per square foot of the lot (Figure 4.2). Generally, the model overestimates the post-fire value of lots that ultimately sold for less than $50 per square foot and underestimates the value of lots that sold for greater than $80 per square foot. Note that this behavior is expected for models with any error of estimation. These over- and underestimates may be caused by any combination of (1) relevant

[49] The difference between estimates and actuals are typically referred to as residuals when regression techniques are used to statistically estimate the model.

property features that are not present in the model (e.g., views or proximity to amenities), (2) the strict assumptions imposed by OLS, or (3) unobservable transaction characteristics (e.g., seller or buyer motivation).

Figure 4.2. Post-Fire Over- and Underestimates of Property Value as a Function of Price per Square Foot of the Lot

SOURCE: Figure provided by Compass Lexecon. Used with permission.
NOTE: Negative residuals indicate properties where the post-fire model underestimated the sale price, positive residuals where it overestimated sale price. N=204.

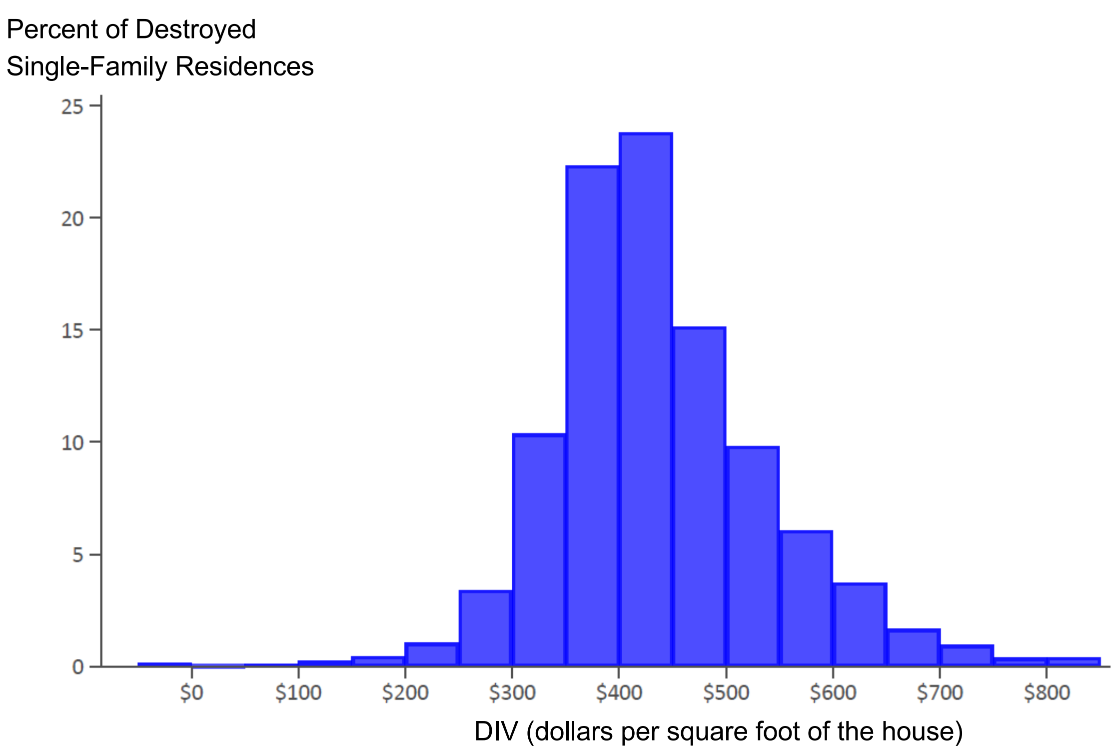
Chapter 5. Accuracy of the Estimated Diminution-in-Value

Within the proposed WRCP Fast Pay compensation track, the pre-fire and post-fire property valuation estimates affect compensation for rebuilding costs and personal property loss only through a computation of the DIV per square foot of the primary structure. The DIV is defined as the pre-fire value minus the post-fire value, and this is then divided by the square footage of the primary structure. In the sections above, we reported the accuracy of the pre-fire and post-fire estimates, however, the proposed settlement offers depend primarily on the accuracy of the DIV per square foot of the house, which depends on both the pre-fire and post-fire estimates.

The distribution of DIV per square foot of the house across destroyed SFRs is shown in Figure 5.1. Across the 5,123 destroyed SFRs,

- the average estimated DIV per square foot of the house was $435
- half of the houses had estimates that fell between $372 and $491 per square foot of the house
- 16 percent have DIV estimates below $350 per square foot, and 13 percent had estimates above $550 per square foot.

Figure 5.1. Distribution of DIV per Square Foot of the House for Destroyed Single-Family Residences



NOTE: Seven properties had a DIV/ft2 less than $0 and 21 properties had a DIV/ft2 greater than $800; these values are included in the leftmost and rightmost columns, respectively.

To directly observe the DIV for a property, it would have had to sell shortly before the fire, then again after the fire. There are only 204 properties that have sold after the fire in the training data, and few of them sold shortly before the fire. For this reason, we cannot directly observe DIV on a large enough sample of destroyed SFRs to determine accuracy. As such, we must derive our estimates for the error in DIV from the errors in the pre- and post-fire models rather than simply subtracting an observed actual value from the estimated value. Because we know the distribution of the over- and underestimates of both the pre-fire and post-fire property values expressed in dollars per square foot of the house, we can approximate the error in DIV per square foot under standard assumptions.[50] The distribution of over- and underestimates suggests that:

- 50 percent of properties will have DIV within approximately \$100 per square foot of the change in market value from pre- to post-fire.
- 25 percent of properties will be overestimated by approximately \$100 per square foot or more.
- 25 percent of properties will be underestimated by approximately \$100 per square foot or more.
- A small proportion of homes are expected to have larger over- or underestimates, with:
  - 10 percent having overestimates of DIV per square foot greater than approximately \$200
  - 10 percent having underestimates of DIV per square foot greater than approximately \$200.[51]

Inaccuracies in the DIV per square foot are almost entirely attributable to inaccuracies in the pre-fire estimated price per square foot. This reflects the fact that the gaps between estimated price and actual transaction price in the pre-fire model are much greater than the gaps in the post-fire model when expressed on a price per square foot of the house basis. This likely occurs because many of the property features that differentiate prices in the pre-fire market were

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[50] The mean of the error distribution in DIV/ft^2 is provided by the following formula: $Avg\_DIV = (Avg\_pre - Avg\_post)$ where *Avg_pre* and *Avg_post* are the average of model errors for the pre- and post-models expressed in dollars per square foot. Assuming that the errors of the two models are independent, the standard deviation of errors in DIV per square foot are $sd\_DIV = (sd\_pre^2 + sd\_post^2)^{0.5}$ where *sd_pre* and *sd_post* are the standard deviations of residuals for the pre- and post-models expressed in dollars per square foot. We can then compute the proportion of the properties that fall within particular error ranges by assuming errors are normally distributed with the computed mean and standard deviation.

[51] To create these distributions of over- and underestimates, we needed to make an assumption about the correlation between errors of the estimates across the two models because it cannot be estimated well in the available data. We assumed a correlation of zero (halfway between highest and lowest possible correlations), however, the estimated error in DIV/ft^2 is very similar across a wide range of reasonable assumptions about this correlation. The error in DIV/ft^2 would change slightly if the errors of estimates across the two models were correlated. For example, if one assumed the residuals were correlated with $r = 0.3$, the size of the errors in estimated DIV/ft^2 would shrink relative to assuming independence; 25 percent of properties would be overestimated by \$101 or more, while another 25 percent of properties would be underestimated by \$97 or more. On the other hand, if one assumed the residuals were correlated with $r = -0.3$ the size of the errors in estimated DIV/ft^2 would grow relative to assuming independence; 25 percent of properties would be overestimated by \$119 or more, while another 25 percent of properties would be underestimated by \$114 or more.

eliminated by the fire, making it easier to estimate the post-fire value accurately even with a model that included only a few predictors.

These over- and underestimates are expected to show the same pattern as shown for errors in the estimates of pre-fire value:

- DIV will almost always be overestimated for properties with a true pre-fire value less than $600 per square foot.
- DIV will almost always be underestimated for homes with a true pre-fire value of more than $1,200 per square foot.
- Some of these over- and underestimates of DIV could be substantial, and almost all of those large errors are expected to occur for properties whose pre-fire value was unusually small or large on a value per square foot basis relative to the typical home damaged by the fire.

The proposed WRCP uses this estimated DIV to determine the compensation offer for rebuilding the structure and for personal property losses. However, not all over- and under-estimates in DIV would affect the compensation being offered under the proposed WRCP because the influence of DIV on the compensation offer is constrained by minimum and maximum values within the current plan. Because of this, determining the extent to which the compensation offer under the plan might have been affected by overestimates or underestimates of DIV requires an analysis specific to each individual property and cannot be inferred solely from our analyses.[52] More generally, as discussed in Chapter 1 when describing the scope of our analysis, we have only evaluated the accuracy of the DIV estimate itself. We have no way to evaluate whether the proposed use of DIV to determine compensation will accurately reflect eventual rebuilding costs.

[52] Specifically, when a property has an estimated DIV/ft^2 and a true DIV/ft^2 that are below the floor set in the proposed compensation plan, any over- or underestimates of these values are irrelevant for the offered compensation. When a property has an estimated DIV/ft^2 and a true DIV/ft^2 that puts it below the floor set in the proposed compensation plan, the rebuilding costs and property loss compensation would be determined by the plan's minimum value. Conversely, when a property has an estimated DIV/ft^2 and a true DIV/ft^2 that puts it above the ceiling set in the proposed compensation plan, any over- or underestimates of these values are irrelevant for the offered compensation. The rebuilding costs and property loss compensation would be determined by that plan's maximum value.

Chapter 6. Conclusion

The broad goals of this report were to investigate:

- whether appropriate data and methods were used to estimate the pre-fire value, post-fire value, and DIV for SFRs destroyed in the Eaton Fire
- the amount of uncertainty in the property value and DIV estimates
- circumstances under which the models may be expected to overestimate or underestimate values.

Our analysis of the information provided by Compass Lexecon suggests that the data and methods that were used to estimate the pre-fire value, post-fire value, and DIV for SFRs destroyed in the Eaton Fire were broadly appropriate. The property characteristics used to generate valuations included the types of variables that are typically used to assess value in AVMs. The training data covered a wide range of properties and generally included properties that were similar to the destroyed SFRs, with the exception of a handful of unusual properties. The statistical models used to generate estimates from the training data were modern and appropriately selected for the task, and the estimation of the models appears to have been well-executed. We do not have any reason to believe that the other commercially available AVMs would produce more accurate estimates of property value for the destroyed SFRs. There is also reason to prefer the Compass Lexecon estimates over other AVMs, which are not as carefully tailored to the local real estate market, and do not generally reveal their data, methods, or performance for outside evaluation. To be clear, we are not claiming that the Compass Lexecon approach is optimal—further refinements in statistical models are always possible—nor that these automated property estimates are generally more accurate than estimates based on standard property appraisal methods tailored to an individual property. Such appraisals typically take into account a broader range of property features and information about property condition, however, such methods may not always be feasible for the destroyed SFRs and may not be possible given the promise of expedited offers by the WRCP.

Fifty percent of the destroyed SFRs are expected to have estimated pre-fire values that are within approximately 10 percent of the true value, and 50 percent are expected to have post-fire values that are within approximately 7 percent of the true value. The effect of these estimates on the settlement offer is primarily through a calculation of DIV per square foot of the house, which represents the loss of market value to the property due to the fire. For the majority of properties, the estimate of DIV per square foot of the house is expected to be within $100 per square foot of the true DIV. However, there will be more substantial over- and underestimates for a small proportion of properties. For example, 20 percent of properties are expected to be off by more than $200 per square foot, with about half of those errors being overestimates and half being underestimates.

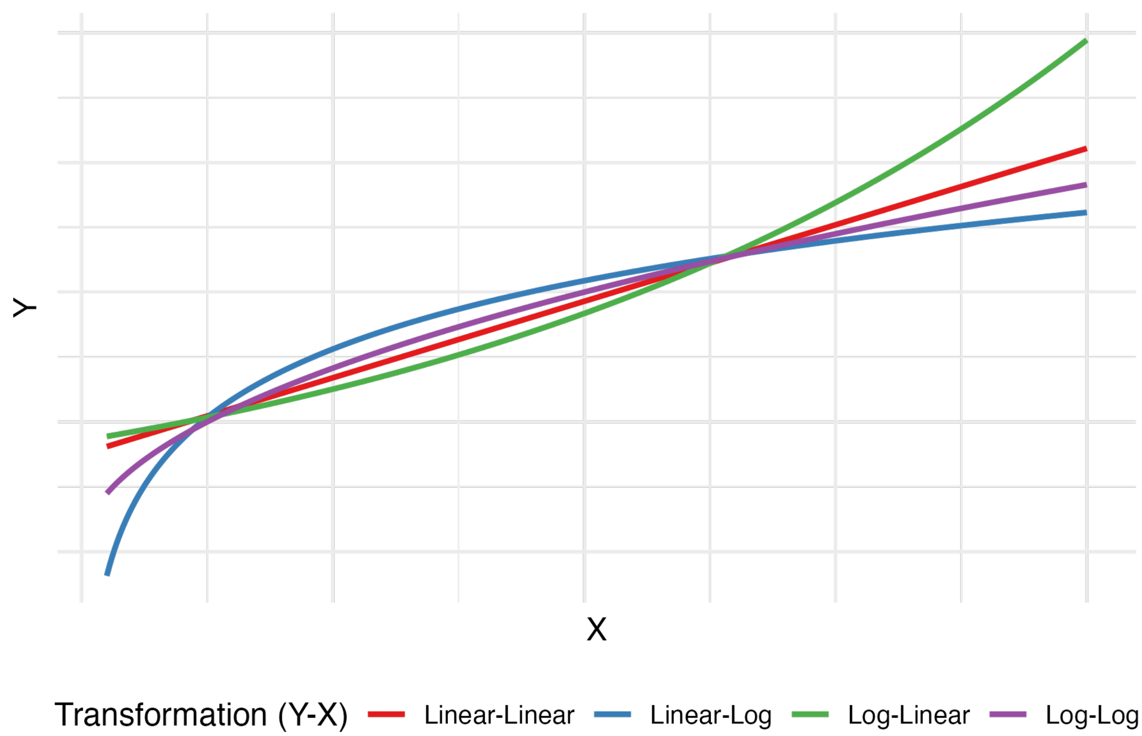
In general, the model tends to underestimate pre-fire value and DIV per square foot of the house for homes that had usually high value per square foot of the house prior to the fire, i.e., homes at the luxury, or high end, of the local market. It tends to overestimate value for homes that had unusually low value per square foot, i.e., homes at the low end of the market or in below-average structural condition.

Fire victims should not interpret our discussion of these errors in estimation as advice about whether they should accept the compensation offered by the WRCP. In part this is because not all over- or underestimates will end up affecting the compensation being offered for rebuilding or personal property loss, and in part because we have not evaluated the true relationship between DIV and rebuilding costs or personal property loss.

Appendix A. Functional Forms in the Post-Fire Model

Different transformations permit different relationships between variables. The figure below shows the predicted relationship between two simulated variables using different transformations of the Y (outcome) and X (predictor) variables (see Figure A.1). As is evident from the figure, different transformations on both the variables matter and can describe different kinds of relationships. In general, these predictions are similar closer to the center of the distribution of predictors but can diverge dramatically on the edges of the distribution, particularly when extrapolating beyond the limits of the dataset used to fit the model.

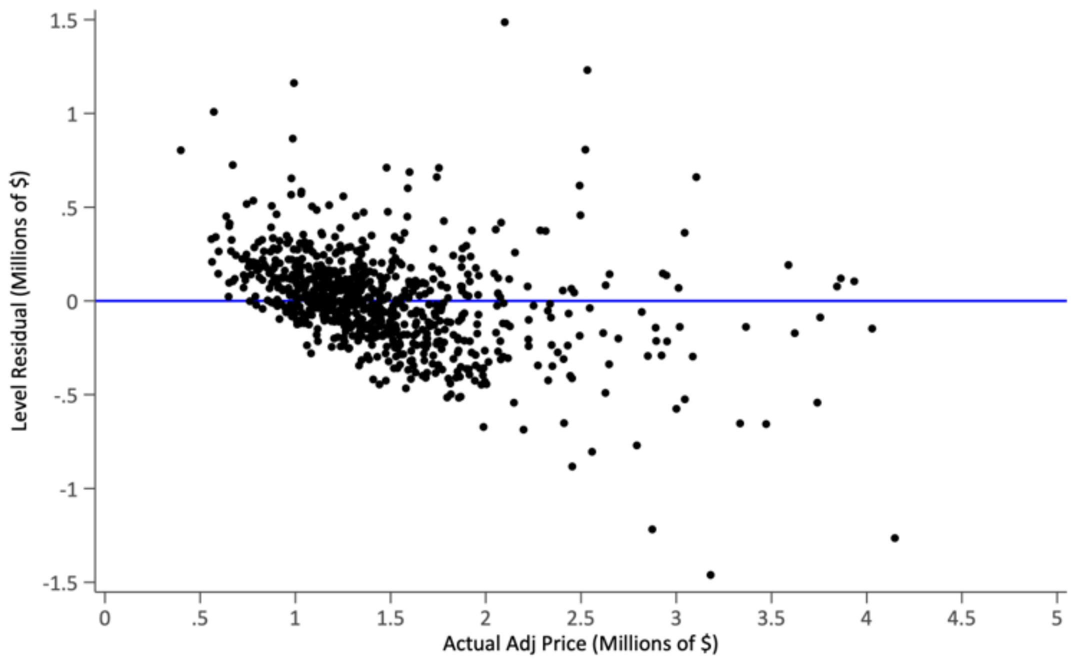
Figure A.1. Example of Different Functional Relationships between the Outcome Y and Predictor X in an OLS Regression



NOTE: These data are simulated from an arbitrary distribution and do not reflect any real dataset associated with the fire evaluations. They are solely designed to illustrate examples of different functional relationships.

Appendix B. Additional Plots of Over- and Underestimates

Figure B.1. Pre-Fire Residual Values as a Function of Actual Sale Price



SOURCE: Figure provided by Compass Lexecon. Used with permission.
NOTE: Negative residuals indicate properties where the pre-fire model underestimated the sale price, positive residuals where it overestimated sale price. All actual prices are Case-Shiller adjusted.

Figure B.2. Post-Fire Residual Values per Square Foot of the House as a Function of Sales Price per Square Foot of the House

SOURCE: Figure provided by Compass Lexecon. Used with permission.
NOTE: Negative residuals indicate properties where the post-fire model underestimated the sale price, positive residuals where it overestimated sale price.

Abbreviations

AVM	Automated Valuation Model
ACS	American Community Survey
DINS	CAL FIRE Damage Inspection Data
DIV	Diminution-in-Value
ft^2	Square Foot/Feet
GIS	Geographic Information Systems
ICJ	RAND Institute for Civil Justice
NIFC	National Interagency Fire Council
OLS	Ordinary Least Squares
SCE	Southern California Edison
SFR	Single-Family Residence
SML	Supervised Machine Learning
UAD	Uniform Appraisal Dataset
WRCP	Wildfire Recovery Compensation Program
WFIGS	Wildland Fire Interagency Geospatial Services

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