INFORMATION DISCLOSURE: APPLICATIONS IN ENERGY ECONOMICS

By

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ABSTRACT

My dissertation titled, "Information Disclosure: Applications in Energy Economics," is comprised of three chapters, each based on a mandatory disclosure policy in Portland, Oregon that requires sellers to obtain and publish a home energy score assessment in real estate listings prior to selling a home. This assessment provides a variety of information about energy efficiency. In chapter 1, I examine the supply of information, studying compliance with the policy. In chapter 2, I examine the demand of information, estimating the premium for energy efficiency. In chapter 3, I evaluate changes in energy efficiency from 1900 to 2020. In doing so, I examine whether current racial disparities in energy costs can be explained by discriminatory housing policies like redlining.

Chapter 1: Is Mandatory Disclosure Really Mandatory? Evidence from Energy Assessments

When buying and selling a home, there is asymmetric information about energy efficiency, as sellers tend to have more information. To address this problem, cities across the United States have begun to adopt mandatory disclosure policies. Similar to other settings with mandatory disclosure, the policy in Portland suffers from non-compliance: 64% of sellers obtain an assessment, and 72% of these sellers publish the assessment (46% overall). To understand the causes of non-compliance, I develop a theoretical model, evaluating the seller's disclosure decision. Using administrative assessment data and proprietary housing transaction data, I test hypotheses from the model. Consistent with the theory of asymmetric information, I show that sellers act strategically, as they are more likely to obtain and publish an assessment if their home is efficient. This behavior was exacerbated with the COVID-19 pandemic when the city reduced enforcement, suspending fines for non-compliance. Surprisingly, there is not full compliance among the most efficient homes. This suggests that there is a coordination problem between sellers and realtors. There is also heterogeneity by realtor, as experienced realtors are more likely to publish the assessment.

Chapter 2: What Energy Information Matters to Home Buyers?

Created by the U.S. Department of Energy, the home energy score is a discrete metric (1–10) of energy efficiency. The score allows buyers to evaluate the energy efficiency level of a home prior to purchase. In this paper, I examine the sales price premium for energy efficiency, as measured by the

score. I estimate a premium of about 0.50% ($2,929) for a one unit increase in the score, which is roughly equivalent to the present discounted value of the corresponding energy cost savings over a 30-year mortgage ($2,734). Since the premium for the score is greater than the energy cost savings, there is not an energy efficiency gap. The premium for the score varies with housing attributes, as it is greater when there is more uncertainty about energy efficiency, for example, in old homes. In addition to the score, the assessment includes other energy metrics like energy consumption, energy costs, and carbon emissions. I find that buyers respond more heavily to the score, as the premium for the score is greater than the other metrics. Since the score is a function of the other metrics, it provides less information than the underlying metrics. Thus, the results suggest that simple discrete metrics may be easier for consumers to comprehend than continuous metrics.

Chapter 3: The Evolution of Energy Efficiency: Impacts (or lack thereof) of Redlining and the Fair Housing Act

While minority households face higher energy costs relative to white households, the mechanisms for this gap are not clear. One possible explanation is differences in the housing stock. In this paper, I examine to what extent the current housing stock is a reflection of past housing policies, especially those that are based on discriminatory behavior like redlining. If the redlining maps were binding, introducing credit constraints, homeowners may not have been able to invest in efficient technologies, like insulation, resulting in lower levels of energy efficiency. Using a difference-in-differences design, I examine the evolution of energy efficiency for homes constructed between 1900 and 2020, focusing on the introduction of the redlining maps. Similarly, I consider the Fair Housing Act of 1968. I find that these housing policies did not impact the gap in energy efficiency between redlined and non-redlined areas. Likewise, using a spatial regression discontinuity design, I find no gap in energy efficiency at the boundaries of these maps. Meanwhile, at the city level, I observe widespread improvements in energy efficiency after the introduction of state building codes in the 1970s, with the majority of improvements coming from insulation.

To my mom who gives me strength.

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PREFACE

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CHAPTER 1

IS MANDATORY DISCLOSURE REALLY MANDATORY? EVIDENCE FROM ENERGY ASSESSMENTS

1.1 Introduction

In a residential setting, sellers tend to have more information than buyers about the energy efficiency level of a home, as they have lived in the home, consuming energy and paying utility bills. While buyers may make assumptions based on observable housing attributes, such as cooling and heating equipment, insulation, and windows, they are unable to measure energy efficiency with accuracy. This asymmetric information causes a variety of issues. Without the disclosure of information, the value of energy efficiency is determined by the average efficiency in the market. If a home is more or less efficient than the average home, then it will result in economic losses or rents, respectively. Ultimately, this may lead to issues of moral hazard in which sellers do not make investments in energy efficiency prior to selling a home, afraid that they will not be able to recoup their investment.[1] Without disclosure, buyers face uncertainty about the energy efficiency level of a home. This uncertainty may lead to sub-optimal sorting behavior in which buyers are unable to purchase homes based on their preferences for energy efficiency.[2] This uncertainty may also lead to sub-optimal investments in energy efficiency after the purchase of a home.[3]

To mitigate these issues, there have been attempts to increase information about energy efficiency. In recent years, cities and states have begun to adopt voluntary and mandatory disclosure policies, requiring sellers to disclose an energy assessment at the time of sale. While the theory of asymmetric information suggests that markets should unravel in the presence of disclosure, this rarely occurs in practice, as there are often issues of non-compliance (Dranove and Jin, 2010; Grossman, 1981; and Milgrom, 1981). In this paper, I examine a mandatory disclosure policy

[1] Myers et al. (2022) show that sellers are more likely to make investments in energy efficiency when they are required to disclose an energy audit at the time of sale.

[2] Brewer (2022) studies sorting behavior in the rental market, finding that renters are more likely to sort into landlord-pay pricing regimes when energy costs are high.

[3] Gilbert et al. (2022) examine two forms of sub-optimal investment behavior in the presence of a rebate program. They find that rebates may induce some homeowners to make investments prematurely that they would otherwise make later in the tenure of their home without a rebate. Meanwhile, other homeowners make investments that are not cost-effective.

in Portland, Oregon. In 2018, the City of Portland established the Home Energy Score program, requiring sellers to obtain and publish a home energy score assessment in real estate listings. Although the program is mandatory, there are rampant rates of non-compliance: only 64% of sellers obtain an assessment, and 72% of these sellers publish the assessment (46% overall). While other disclosure policies also suffer from non-compliance, there is little research that examines the causes.[4]

In this paper, I ask the question: "What factors influence the seller's disclosure decision?" I consider both internal factors that are unique to a home, like energy efficiency and housing attributes, as well as external factors like enforcement. I also consider the realtors in the housing market. In doing so, I examine whether sellers engage in strategic behavior. To motivate the empirical analysis, I construct a two-stage decision model, evaluating the seller's decision to obtain and publish an assessment. From this model, I derive comparative statics, which I use to create hypotheses about these factors. For the empirical analysis, I combine administrative assessment data with proprietary housing transaction data. I measure energy efficiency in terms of the home energy score, which is a discrete metric (1–10) of energy efficiency created by the U.S. Department of Energy. Note that a more efficient home receives a higher score. Since I only observe the score if a seller obtains an assessment, I estimate a predicted score based on observable housing attributes from the real estate listings. In the analysis, I examine strategic behavior in response to the predicted score, actual score, and the difference in the predicted and actual score.

First, I consider the internal factors, exploring issues of selection. I examine selection in terms of energy efficiency and housing attributes like the age and size of a home. I find that sellers engage in strategic behavior at each stage of the disclosure decision. In stage 1, sellers are more likely to obtain an assessment as the predicted score increases. Meanwhile, in stage 2, sellers are more likely to publish the assessment as the actual score increases. While the market does not unravel, these results are consistent with strategic behavior in the presence of asymmetric information, as sellers

[4]For example, the Energy Conservation Audit and Disclosure ordinance in Austin, Texas had a compliance rate of 62% over the first 2.5 years of the ordinance (c.f. http://www.austintexas.gov/edims/document.cfm?id=192556). And, following the energy performance certificate mandate in the European Union, Germany had a compliance rate of about 60% (see Frondel et al., 2019).

of the most efficient homes have a greater incentive to disclose the energy efficiency level of their home. Surprisingly, I find that there is not full compliance among the most efficient homes. While this may occur for several reasons, it possibly suggests that there is a coordination problem between sellers and realtors. Not only do sellers act strategically based on the predicted and actual scores, but they also act strategically based on the difference in these scores. I find that sellers are less likely to publish the assessment if the score is over-predicted (i.e., predicted score > actual score). These results suggest three things: (1) sellers perceive that there are differential gains to disclosing an assessment; (2) sellers have some prior information about the energy efficiency level of their home, and they decide to obtain an assessment based on that information; and (3) the assessment provides additional information to sellers, and they decide to publish the assessment based on that information. In terms of the housing attributes, I show that there is selection in stage 1 but not stage 2. For example, sellers are more likely to obtain an assessment for old homes, where there is greater uncertainty about the energy efficiency level of a home.

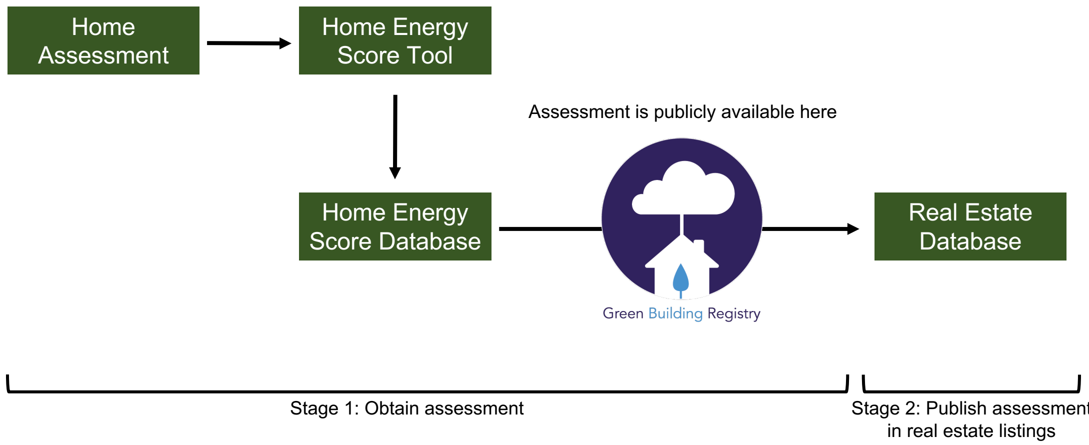
Next, I consider the external factors, focusing primarily on enforcement. In the theoretical model, I show that sellers are less likely to disclose an assessment when enforcement decreases. I examine this empirically using the COVID-19 pandemic as a natural experiment. During the pandemic, the City of Portland announced that they would reduce enforcement and suspend fines for non-compliance. Consistent with the model, I find that sellers are less likely to disclose an assessment during the pandemic without enforcement. I show that this result is driven by strategic behavior. While sellers with high scores are equally likely to disclose an assessment during the pandemic, sellers with low scores are less likely to disclose an assessment during the pandemic. A similar result holds for the difference in the predicted and actual score, as sellers are less likely to disclose an assessment during the pandemic when the score is over-predicted. These results suggest that strategic behavior is exacerbated without enforcement. Finally, I examine heterogeneity by realtors. I find that experienced realtors are more likely to publish the assessment.

With this paper, I contribute to a nascent literature on mandatory disclosure policies in the energy sector. When the policy was established in Portland, there were two other cities in the

United States that had a similar policy: Austin, Texas and Berkeley, California. Since these policies are not widespread, there is little research on their impact. While recent research examines the policy in Austin (Cassidy, 2023; and Myers et al., 2022), most other research examines policies abroad, for example, energy performance certificates in Europe (Aydin et al., 2018; Frondel et al., 2019; and Fuerst et al., 2015). Although the focus of each of these papers is the capitalization of energy efficiency, few look at non-compliance. Myers et al. (2022), for example, contend that sellers may not be fully informed about the energy efficiency level of their home, contributing to non-compliance. Thus, more research is needed to understand the causes of non-compliance. This will become increasingly important as cities and states continue to adopt mandatory disclosure policies in the future.[5]

My paper fills this void, tackling issues of non-compliance. In doing so, I make several contributions. First, I construct a two-stage decision model, evaluating the seller's disclosure decision. While other policies only require sellers to obtain an assessment, this policy also requires sellers to publish the assessment in real estate listings. By looking at both of these stages, I am able to elicit additional information about strategic behavior. I show that sellers act strategically in each stage, as they are more likely to disclose an assessment if their home is efficient. Second, I examine the causes of non-compliance, considering the role of external factors. I show that sellers are more likely to engage in strategic behavior when there is a reduction in enforcement. Meanwhile, I find heterogeneity across realtors. To the best of my knowledge, my paper is the first to consider the role of realtors. Third, I use a comprehensive proxy of energy efficiency. Since the home energy score is based on home assets rather than consumer behavior, it provides consumers with more accurate information than other proxies of energy efficiency. For example, consider utility bills, which are often disclosed at the time of sale. While these bills provide information about historical energy consumption, they do not fully reflect energy efficiency, since they cannot separate heterogeneous consumption between households.

Figure 1.1: Stages of Disclosure



Notes: The figure illustrates the two stages of disclosure. Stage 1 requires sellers to obtain a home energy score assessment. And, stage 2 requires sellers to publish the assessment in real estate listings.

1.2 Background

The Home Energy Score program requires sellers in Portland to (1) obtain a home energy score assessment and (2) publish the assessment in real estate listings prior to selling a home. The seller is responsible for the cost of obtaining an assessment, which typically ranges from $100 to $250 depending on the assessor.[6] Meanwhile, the fine for non-compliance is $500.[7] This fine is assessed to sellers. While the program is mandatory for all homes, a seller may obtain an exemption in extreme cases, for example, a foreclosure.[8]

Figure 1.1 illustrates the two stages of disclosure. Stage 1 requires a seller to obtain an assessment. During an assessment, an assessor walks through a home, documenting home assets like insulation. These assets go into an engineering calculator that produces estimates of energy use. Upon completion of an assessment, it is stored in a central database by the U.S. Department of Energy, denoted in the figure as the home energy score database. Earth Advantage, a non-profit

[5]Following the policy in Portland, other cities in the metropolitan area have adopted a similar policy.

[6]Low-income households (i.e., households with income at or below 60 percent of median family income) qualify for a free assessment.

[7]The City of Portland may issue additional fines for every subsequent 180-day period in which the violation continues (see Bureau of Planning and Sustainability, City of Portland, 2017).

[8]A seller may obtain an exemption if any of the following apply: foreclosure sale; trustee's sale; deed-in-lieu of foreclosure sale; pre-foreclosure sale where sales price is less than current mortgage; sale at public auction; under control of court appointed receiver; subject to notice of default; deemed uninhabitable due to casualty; condemned by action of government; or compliance would cause undue hardships on seller (see Bureau of Planning and Sustainability, City of Portland, 2017).

organization in Portland, collects these assessments and provides them to the public via the Green Building Registry. This registry is an online portal that allows people to search for an assessment by street address. Stage 2 then requires a seller to publish the assessment in real estate listings, which are stored in a real estate database. The assessment remains publicly available in the registry, regardless of whether a seller publishes the assessment. If a seller chooses to withhold their assessment from real estate listings for whatever reason, a buyer can still access the assessment through the registry. I observe data at two points: (1) home energy score database; and (2) real estate database. As a result, I am able to construct individual measures of compliance for obtaining and publishing an assessment.

The home energy score assessment is a nationally accredited assessment created by the U.S. Department of Energy. The assessment presents a variety of information regarding residential energy use (see appendix figure A.1). I focus on the home energy score, since it is the metric that is emphasized in the real estate listings. The home energy score is a discrete metric (1–10) of energy efficiency, with a score of 10 representing the most efficient home. The score is based on home assets, including physical housing attributes, like the age and size of a home, and other products like cooling and heating equipment, insulation, and windows.[9] The score is an absolute measure of energy efficiency, since it is not normalized by the size of a home. Because of this, a larger home will receive a lower score, as it requires more energy to heat and cool the area of the home, and vice versa. Since the score does not take into consideration consumer behavior, it provides an "apples-to-apples" comparison between homes without concerns of heterogeneous consumption. Thus, the score is more comprehensive than other proxies of energy efficiency, like utility bills, which are commonly used in disclosure settings.

1.3 Data

To conduct this analysis, I combine two sources of data. First, I obtain the housing data from the Regional Multiple Listing Service (RMLS). I prefer the RMLS database to other real estate databases, such as CoreLogic or Zillow, because it is the only database that has a field for the home

[9] About 50 home assets go into the engineering calculator that produces the score. For additional details about these assets, see U.S. Department of Energy (2017).

energy score. A link to the assessment is often provided as well. In addition, the data in the RMLS is used to populate other real estate platforms such as Redfin and Trulia. Thus, the information from the assessment is publicly disseminated to prospective buyers, becoming a housing attribute that enters into their purchasing decision. This data set includes 39,439 housing transactions in Portland from 2018 to 2021. It contains the general set of housing attributes (e.g., acres, bathrooms, bedrooms, sqft, and year of construction) as well as the score.[10] Appendix table A.1 presents the summary statistics for these attributes. The housing outcome of interest is sales price, which has a mean of $604,254. Second, I obtain the home energy score data from Earth Advantage, which maintains the Green Building Registry. This data set includes 31,157 assessments in Portland from 2018 to 2021. It contains the score and other assessment information like the date of the assessment.

I combine these data sets, merging on street address. For each housing transaction, I select the most recent assessment, if any, that occurs prior to the close date.[11] This allows me to measure whether a seller obtains an assessment. Of the 39,439 housing transactions, 25,048 (64%) transactions occur when the seller obtains an assessment. Next, I measure whether the seller publishes the assessment in the real estate listings. Now, 18,142 (46%) transactions occur when the seller publishes the assessment.

In this analysis, I study strategic behavior in the disclosure of assessments, particularly with respect to the score. The data is limiting in the fact that I only observe the score when a seller obtains an assessment. In other words, I do not observe the score when a seller does not obtain an assessment. The score, however, is correlated with housing attributes (see appendix table A.2). For example, newer and smaller homes tend to be more efficient. To examine whether sellers engage in strategic behavior when deciding to obtain an assessment, I construct a predicted score based on observable housing attributes from the real estate listings. First, I estimate the following equation

[10]Because of data limitations, I only consider the number of full baths.

[11]Through this process, I successfully match 23,886 (77%) assessments to a housing transaction. The following are reasons why an assessment may not have matched successfully: there are discrepancies in the address field across the two data sets; there are multiple assessments for a single home; the assessment occurred after the close date; the home was sold by owner; and the home has yet to be transacted.

for the subset of transactions with an assessment:

$$Score_{it} = \gamma X_i + \alpha_t + \varepsilon_{it} \tag{1.1}$$

where X_i is a vector of housing attributes and α_t is a quarter of sample fixed effect. I include a flexible set of housing attributes. In addition to the housing attributes listed in appendix table A.1, I include third degree polynomials of the continuous attributes and interact the continuous attributes with sqft. I also include a set of binary variables that contain key words (e.g., "insulation") from the property description. These attributes explain about 50% of the variation in the score, as measured by adjusted R^2. Next, I extract these estimates to obtain the fitted value of the score for the full sample of transactions. This fitted value is the predicted score.

Appendix figure A.2 displays the distribution of the predicted and actual scores for the subset of transactions with an assessment. While the average score is the same for the actual and predicted scores (4.38), the distributions vary. The prediction process reduces the number of extreme scores (e.g., 1 and 10), centering the scores closer to the mean. As a result, the variance of the predicted score is less than the actual score (2.90 vs 5.83). Next, I calculate the difference in the predicted and actual score. Here, a positive value indicates that the score is over-predicted, as the predicted score is greater than the actual score, and vice versa. Appendix figure A.3 displays the distribution of this difference. The prediction process is fairly accurate, as 85% of the predicted scores are within 2 units from the actual score.

1.4 Stylized Facts

1.4.1 Compliance

As documented previously, there are rampant rates of non-compliance. About 64% of sellers obtain an assessment. Of these sellers, 72% publish the assessment in real estate listings. In total, less than half of the sellers (46%) publish the assessment and remain in compliance with the program. Because there is non-compliance, it allows me to study the factors that influence disclosure and, in doing so, examine whether sellers act strategically. I consider two types of factors, which I refer to as internal and external factors. Internal factors are determined by the home. These include energy efficiency and housing attributes. Meanwhile, external factors, like enforcement, are determined outside of the home and are experienced similarly across the entire market.

First, I examine the internal factors. These factors allow me to explore issues of selection. Appendix table A.3 presents the summary statistics separated by disclosure status. From these unconditional means, it appears that sellers sort in each stage of disclosure. In stage 1, sellers are more likely to obtain an assessment if their predicted score is higher. The average predicted score is 4.38 for sellers who obtain an assessment and 3.67 for sellers who do not. Meanwhile, in stage 2, sellers are more likely to publish the assessment if their actual score is higher. Here, the average score is 4.44 for sellers who publish the assessment and 4.21 for sellers who do not. Sellers also appear to sort based on housing attributes. For example, in stage 1, sellers with newer homes are less likely to obtain an assessment. In stage 2, however, sellers do not appear to sort based on housing attributes. Since many of the housing attributes are correlated, I study this sorting behavior in more detail later in the analysis.

Next, I examine the external factors. Appendix figure A.4 documents changes in the compliance rate across time. The figure also highlights the periods of enforcement. To increase the public's perception of the program, the City of Portland did not issue fines for non-compliance for the first year and a half of the program. While enforcement was essentially "turned off" during this time period, it was not communicated to the public. As a result, the perceived threat of the fine was still present. This may partially explain why the compliance rate did not change at the end of 2019 when the city announced that they would "turn enforcement on" and issue fines.[12] With the COVID-19 pandemic, the city announced that they would reduce enforcement and suspend fines. During the pandemic, the compliance rate decreased by about 15 percentage points. After the city reinstated fines in 2021, the compliance rate increased, though not fully back to the baseline that was observed prior to the pandemic.

Lastly, I consider the role of realtors. The decision to obtain an assessment is linked to realtors, especially if some realtors are risk adverse and do not want sellers to be caught in violation of the

[12]c.f. https://www.pdxhes.com/blog/2019/9/20/sellers-start-receiving-fines-this-month-for-missing-home-energy-score

policy. The same applies for publishing the assessment. In addition, realtors are responsible for inputting the score into the real estate listings. Thus, it is likely that compliance varies by realtor. Panel (a) of appendix figure A.5 displays the density plot of compliance across realtors. Here, I restrict the set of realtors to the top quartile (8^+ transactions). While the mass of realtors is skewed left, there is quite a bit of variation. Given this variation, it is likely the case that realtors hold individual beliefs about enforcement and the probability of being caught in violation. Alternatively, they may hold beliefs about the value of disclosure. To further understand realtor behavior, I examine differences by realtor experience. I use the number of transactions as proxy of experience. Panel (b) plots the average compliance rate across realtors separated by the number of transactions. Here, I bin transactions by increments of 10. Initially, the compliance rate increases with the number of transactions, both for obtaining and publishing an assessment. In terms of obtaining an assessment, the compliance rate remains relatively unchanged after 10 transactions. This may be the case because sellers are responsible for obtaining an assessment. Meanwhile realtors are responsible for publishing the assessment in the real estate listings. In terms of publishing the assessment, however, the compliance rate continues to increase with the number of transactions. These results suggest that there are systematic differences in compliance by realtor activity. This may be partially explained by economies of scale. For example, if a realtor belongs to a large real estate agency, they are likely to have greater access to resources, working with other professionals and staff. In this case, it is likely that additional time will be allocated to the listing, resulting in fewer reporting errors.

1.4.2 Premium for Energy Efficiency

In this section, I explore the relationship between energy efficiency and sales price using revealed preference methods. While the following estimates are not causal, they provide suggestive evidence that energy efficiency is positively correlated with price. In other words, there is a premium for energy efficiency. This premium is greater when the assessment is published in real estate listings.

Here, I am interested in the actual score, since it is the score that buyers observe in real estate listings. As such, I restrict the analysis to transactions where the seller obtains an assessment. I estimate the following hedonic price model:

$$ln(Price_{irtz}) = \beta_1 Score_i + \gamma X_i + \alpha_{tz} + \alpha_r + \varepsilon_{irtz} \tag{1.2}$$

for home i sold by realtor r in quarter of sample t and zip code z. $Score_i$ represents the actual score. X_i is a vector of housing attributes.[13] To control for temporal and spatial variation, I include a quarter of sample by zip code fixed effect α_{tz}. I also control for variation within realtor using a realtor fixed effect α_r. To examine whether the premium is linear in the score, I estimate a similar equation with a set of binary indicators for the individual scores.

The estimates are presented in panel (a) of appendix table A.4. Column (4) is the preferred specification because it has the most inclusive set of controls and fixed effects. The estimates, however, are stable across other specifications with less comprehensive sets of fixed effects. The estimate of the score is 0.0050. Hence, a one unit increase in the score is associated with a 0.50% ($2,929) increase in price.[14] This premium is roughly equivalent to the corresponding energy cost savings over a 30-year mortgage ($2,729). To obtain this estimate, I regress energy costs on the score.[15] For a one unit increase in the score, energy costs decrease by about $145. I then calculate the present discounted value of the energy cost savings using the average 30-year mortgage fixed rate from 2018 to 2021 (3.6 percent). While the estimate of the premium is not causal, these results suggest that the valuation of the score is reasonable, as it is only 7% greater than its corresponding energy cost savings. Panel (a) of appendix figure A.6 plots the estimates from the binary case. While there are non-linearities, the premium is approximately linear in the score. Thus, I assume the price is linear in the theoretical model.

The previous estimation implicitly assumes that the premium for energy efficiency is the same, regardless of whether the assessment is published or not. This, however, is unlikely to be the case. First, the score is available to a wider audience of buyers when the assessment is published. In this case, the score is more likely to enter into a buyer's purchasing decision. Second, there may be transaction or search costs associated with accessing the assessment when it is not published.

[13] In the remainder of the analysis, I use the set of attributes in appendix table A.1 unless otherwise specified.
[14] The average sales price is $585,801 for the set of homes with an assessment.
[15] I measure energy costs by the expected annual energy costs that are presented in the assessment.

Because of this, I examine whether the premium is greater when the assessment is published. To do so, I estimate a similar hedonic price model, now interacting $Score_i$ with $Publish_i$, which is an indicator for publishing the assessment:

$$ln(Price_{irtz}) = \beta_1 Score_i + \beta_2 Publish_i + \beta_3 Score_i \times Publish_i + \gamma X_i + \alpha_{tz} + \alpha_r + \varepsilon_{irtz} \quad (1.3)$$

Note that β_1 measures the premium for the score when the assessment is not published and β_3 measures the additional premium when the assessment is published. Thus, $\beta_1 + \beta_3$ measures the total premium when the assessment is published. Meanwhile, β_2 measures the gap in the premium at the intercept.[16] Again, I estimate a similar equation, replacing the score with binary indicators for the score.

The estimates are presented in panel (b) of appendix table A.4. First, I consider the specification in column (3), which does not include the realtor fixed effect. Here, the estimate of the score is 0.0031. Hence, a one unit increase in the score is associated with a 0.31% ($1,816) increase in price when the assessment is not published. The estimate of the interaction term is 0.0023. This suggests that there is an additional premium for the score when the assessment is published ($1,347). In total, a one unit increase in the score is associated with a 0.54% ($3,163) increase in price when the assessment is published. Although the estimate of publishing the assessment is not statistically significant, the negative sign suggests that the intercept is lower when the assessment is published. Panel (b) of appendix figure A.6 plots the estimates from the binary case. Although not statistically different, the premium from publishing an assessment is less than not publishing for a score of 1. This suggests that there may be a penalty for publishing a low score. The premium for publishing an assessment tends to be greater than not publishing for other scores. While there are non-linearities, the premiums are approximately linear in the score.

Next, I consider the specification in column (4), which includes the realtor fixed effect. Here, a one unit increase in the score is associated with a 0.41% ($2,402) increase in price when the assessment is not published. Meanwhile, a one unit increase in the score is associated with a 0.54% ($3,163) increase in price when the assessment is published. Now, however, the estimate of the

[16]Since the score is between 1 and 10, the intercept is never reached.

interaction term (0.0013) is not statistically significant. As these estimates control for within realtor variation, the results suggest that, for a given realtor, the decision to publish the assessment has little impact on the premium. This may be the case, for example, if individual realtors consistently publish or do not publish the assessment. These results suggest that the premium is greater when the assessment is published, though it is driven by differences across realtors at the market level. In addition, there is a penalty for publishing the assessment at low scores. The incentive to publish the assessment is thus dependent on the energy efficiency level of a home. This relationship is reflected in the payoff structure in the following theoretical model.

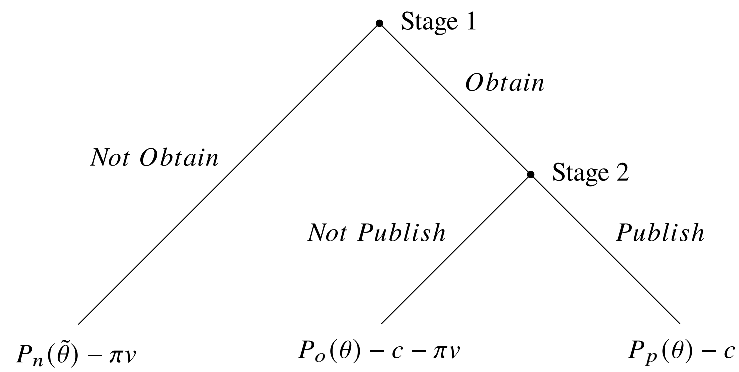
1.5 Two-Stage Decision Model

In this section, I develop a two-stage decision model, looking at the seller's decision to obtain and publish an assessment. The model is evaluated in terms of the seller's payoff from decision j:

$$j = \begin{cases} n & \text{if the seller does not obtain an assessment} \\ o & \text{if the seller obtains but does not publish an assessment} \\ p & \text{if the seller obtains and publishes an assessment} \end{cases}$$

The payoff includes the price (premium) for energy efficiency that the seller receives when selling a home. Similar to the rest of the analysis, energy efficiency is evaluated in terms of the home energy score. Let θ_i be the actual score for home i. This is observed by the buyer when the seller obtains an assessment. Meanwhile, let X_i be the set of observable housing attributes from the real estate listing. Thus, the price for energy efficiency is $P_{ij}(\theta_i, X_i)$ when the seller obtains an assessment. If the seller does not obtain an assessment, the actual score is not known by the buyer. Instead, the buyer makes a prediction of the score based on the housing attributes. Let $\tilde{\theta}$ be the predicted score. Thus, the price for energy efficiency is $P_{in}(\tilde{\theta}, X_i)$ when the seller does not obtain an assessment. For simplicity, I write the prices as $P_n(\tilde{\theta})$ and $P_j(\theta)$ for $j = o, p$. The payoff also includes the cost of the assessment as well as the expected cost of non-compliance. If the seller obtains an assessment, they face an assessment cost c. Meanwhile, the fine for non-compliance is v, and the probability of being caught in violation is π. Practically, π can be measured by the degree of enforcement. Taken together, the expected cost of non-compliance is πv.

Figure 1.2: Decision Tree



Notes: The figure illustrates the seller's decision tree. In stage 1, the seller decides whether to obtain an assessment. In stage 2, the seller decides whether to publish the assessment in real estate listings.

Figure 1.2 illustrates the seller's decision tree. In stage 1, the seller decides whether to obtain an assessment ($Obtain$) or not ($Not\ Obtain$). If the seller does not obtain an assessment, they face the expected cost of non-compliance. Thus, their payoff is

$$P_n(\tilde{\theta}) - \pi v$$

If the seller obtains an assessment, they continue to stage 2 where, upon reviewing the results of the assessment, they decide whether to publish the assessment in real estate listings ($Publish$) or not ($Not\ Publish$). In both cases, the seller faces the cost of the assessment. If the seller does not publish the assessment, they also face the expected cost of non-compliance. Thus, if the seller does not publish the assessment, their payoff is

$$P_o(\theta) - c - \pi v$$

Meanwhile, if the seller publishes the assessment, their payoff is

$$P_p(\theta) - c$$

1.5.1 Stage 2: Publish Assessment

The seller's optimal decision is solved by backwards induction. Beginning with stage 2, the seller decides whether to publish the assessment after observing the actual score from the assessment.

The seller will publish the assessment if the payoff from publishing is greater than the payoff from not publishing. Thus,

$$\begin{aligned} &P_p(\theta) - c \geq P_o(\theta) - c - \pi v \implies \\ &\underbrace{P_p(\theta) - P_o(\theta) + \pi v}_{\text{LHS}} \geq 0 \end{aligned} \tag{1.4}$$

The left hand side (LHS) of the equation represents the net benefit from publishing the assessment. The LHS can be separated into two terms. First is the gap in prices $P_p(\theta) - P_o(\theta)$, which captures the additional premium that the seller receives from publishing the assessment. This gap is not guaranteed to be positive for all scores. A negative gap may occur, for example, if the market penalizes inefficient homes with a low (or even negative) price. The second term is the expected cost of non-compliance. Since the LHS represents the net benefit of publishing the assessment, this term can be interpreted as the avoided cost of non-compliance. Given an interior solution, there exists θ^* such that $P_p(\theta^*) = P_o(\theta^*) - \pi v$.[17] Assuming that the marginal price of publishing the assessment is greater than not publishing ($\frac{\partial P_p}{\partial \theta} > \frac{\partial P_o}{\partial \theta}$), this solution is unique. This was previously observed in section 1.4.2. Note that θ^* is the threshold score that determines the set of scores for which the seller will publish the assessment. The seller will publish the assessment if the score exceeds the threshold score ($\theta \geq \theta^*$), as the net benefit of publishing is greater than not publishing. The converse is true if the score is below the threshold score ($\theta < \theta^*$).

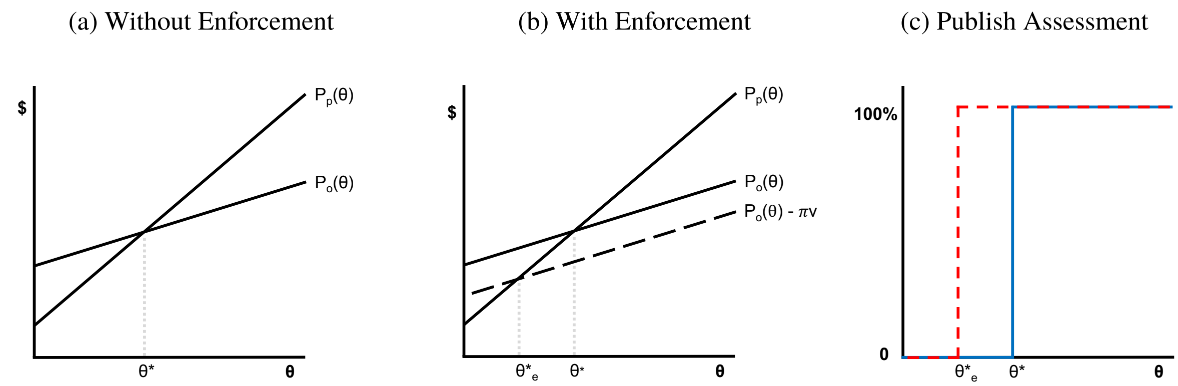
To examine how the expected cost of non-compliance influences the seller's decision to publish the assessment, I totally differentiate equation (1.4) with respect to πv. I then calculate the following:

$$\begin{aligned} \frac{\partial \theta^*}{\partial \pi v} &= \frac{-1}{\frac{\partial P_p(\theta^*)}{\partial \theta^*} - \frac{\partial P_o(\theta^*)}{\partial \theta^*}} \\ &< 0 \end{aligned}$$

As long as the marginal price of publishing the assessment is greater than not publishing, then this comparative static is negative. If θ^* decreases, as observed here, then the probability that the seller publishes the assessment increases. Thus, the probability that the seller publishes the assessment

[17]Note that there may be a corner solution if $P_p(\theta) \gtrless P_o(\theta) - \pi v$ for all θ.

Figure 1.3: Interior Solution



Notes: The figure illustrates the interior solution for publishing the assessment. Panel (a) is the case without enforcement, and panel (b) is the case with enforcement. Panel (c) is the cumulative density function of publishing the assessment. θ^* is the threshold score without enforcement and θ_e^* is the threshold score with enforcement.

increases when the expected cost of non-compliance increases. This is displayed graphically in figure 1.3. In panel (a), I consider the case when the expected cost of non-compliance is zero. This may occur, for example, when there is no enforcement. Here, the threshold score occurs at θ^*. In panel (b), the expected cost of non-compliance is non-zero. This occurs when there is enforcement. Since the expected cost of non-compliance is fixed for all θ, it shifts the payoff of not publishing the assessment down and the new threshold score occurs at $\theta_e^* < \theta^*$. As illustrated in panel (c), this shifts the cumulative density function to the left, making the seller more likely to publish the assessment.

1.5.2 Stage 1: Obtain Assessment

Now, in stage 1, the seller must decide whether to obtain an assessment without observing the actual score. While the seller does not observe the score, they know its distribution. The seller will obtain an assessment if the expected payoff from obtaining is greater than the payoff from not obtaining. Note that the expected payoff from obtaining an assessment accounts for pooling in stage 2.

Let $f(\theta)$ and $F(\theta)$ be the probability density function and cumulative density function for θ, respectively. Recall that the seller publishes the assessment if the actual score exceeds the threshold score ($\theta > \theta^*$). Thus, $F(\theta^*) = \mathbb{P}(\theta \leq \theta^*)$ is the probability that the seller does not publish the assessment. Likewise, $1 - F(\theta^*)$ is the probability that the seller publishes the assessment. If the seller obtains an assessment in stage 1, their payoff is the expected payoff from stage 2. Thus, the payoff from obtaining an assessment is,

$$\begin{aligned} &F(\theta^*)\Big[P_o\Big(\mathbb{E}(\theta|\theta \le \theta^*)\Big) - c - \pi v\Big] + (1 - F(\theta^*))\Big[P_p\Big(\mathbb{E}(\theta|\theta > \theta^*)\Big) - c\Big] \implies \\ &F(\theta^*)\Big[P_o\Big(\mathbb{E}(\theta|\theta \le \theta^*)\Big) - \pi v\Big] + (1 - F(\theta^*))\Big[P_p\Big(\mathbb{E}(\theta|\theta > \theta^*)\Big)\Big] - c \end{aligned} \tag{1.5}$$

This payoff assumes that the price is linear in θ.[18] This was observed in section 3.2. For simplicity, define $\bar{\theta}_o \equiv \mathbb{E}(\theta|\theta \le \theta^*)$ and $\bar{\theta}_p \equiv \mathbb{E}(\theta|\theta > \theta^*)$. Thus, $\bar{\theta}_o$ is the expected score conditional on not publishing the assessment, and $\bar{\theta}_p$ is the expected score conditional on publishing the assessment. Again, the seller will obtain an assessment if the expected payoff from obtaining is greater than the payoff from not obtaining. Thus,

$$\begin{aligned} &F(\theta^*)\Big[P_o(\bar{\theta}_o) - \pi v\Big] + (1 - F(\theta^*))\Big[P_p(\bar{\theta}_p)\Big] - c \ge P_n(\tilde{\theta}) - \pi v \implies \\ &\underbrace{F(\theta^*)\Big[P_o(\bar{\theta}_o)\Big] + (1 - F(\theta^*))\Big[P_p(\bar{\theta}_p) + \pi v\Big] - c - P_n(\tilde{\theta})}_{\text{LHS}} \ge 0 \end{aligned} \tag{1.6}$$

Now, the LHS of the equation represents the net benefit from obtaining an assessment. Note that the seller does not face the expected cost of non-compliance when they publish the assessment. Because of this, the expected cost of non-compliance does not affect the payoffs one-to-one, as the relative difference is $1 - F(\theta^*)$. Thus, $(1 - F(\theta^*))\,\pi v$ can be interpreted as the avoided cost of non-compliance, weighted by the probability of publishing the assessment.

Next, I examine how the cost of the assessment and expected cost of non-compliance influence the seller's decision to obtain an assessment. In particular, I calculate the marginal net benefit

[18] The expected price for energy efficiency from obtaining an assessment is

$$\int_{-\infty}^{\theta^*} P_o(\theta) f(\theta) d(\theta) + \int_{\theta^*}^{\infty} P_p(\theta) f(\theta) d(\theta) = F(\theta^*)\Big[\mathbb{E}\Big((P_o(\theta|\theta \le \theta^*)\Big)\Big] + (1 - F(\theta^*))\Big[\mathbb{E}\Big(P_p(\theta|\theta > \theta^*)\Big)\Big]$$

Assuming that the price is linear in θ, then the expected price becomes

$$\begin{aligned} &F(\theta^*)\Big[\mathbb{E}\Big(P_o(\theta|\theta \le \theta^*)\Big)\Big] + (1 - F(\theta^*))\Big[\mathbb{E}\Big(P_p(\theta|\theta > \theta^*)\Big)\Big] \\ = \ &F(\theta^*)\Big[P_o\Big(\mathbb{E}(\theta|\theta \le \theta^*)\Big)\Big] + (1 - F(\theta^*))\Big[P_p\Big(\mathbb{E}(\theta|\theta > \theta^*)\Big)\Big] \end{aligned}$$

from obtaining an assessment (LHS) with respect to the cost of the assessment and expected cost of non-compliance. To do so, I totally differentiate equation (1.6) with respect to c and πv, respectively:

1. Cost of assessment (c):

$$\begin{aligned} \frac{\partial LHS}{\partial c} &= -1 \\ &< 0 \end{aligned}$$

2. Expected cost of non-compliance (πv):[19]

$$\begin{aligned} \frac{\partial LHS}{\partial \pi v} = \quad & \underbrace{(1 - F(\theta^*))}_{\text{"Direct Effect"}} + \\ & \underbrace{\frac{\partial(1 - F(\theta^*))}{\partial \pi v}\Big[P_p(\bar{\theta}_p) - P_o(\bar{\theta}_o) + \pi v\Big]}_{\text{"Publish Effect"}} \quad + \\ & \underbrace{F(\theta^*)\frac{\partial P_o(\bar{\theta}_o)}{\partial \pi v} \quad + \quad (1 - F(\theta^*))\frac{\partial P_p(\bar{\theta}_p)}{\partial \pi v}}_{\text{"Price Effect"}} \\ = \quad & \underbrace{(+)}_{\text{"Direct Effect"}} \quad + \quad \underbrace{(+)}_{\text{"Publish Effect"}} \quad + \quad \underbrace{(-)}_{\text{"Price Effect"}} \\ \gtreqless \quad & 0 \end{aligned}$$

Since $\frac{\partial LHS}{\partial c} < 0$, the seller is less likely to obtain an assessment if the cost of the assessment increases. Since $\frac{\partial LHS}{\partial \pi v} \gtreqless 0$, the result is ambiguous if the expected cost of non-compliance increases. To better understand how the expected cost of non-compliance impacts the net benefit from obtaining an assessment, I separate the effect into three parts. First is the "direct effect," which measures the change in the net benefit as a result of a change in the avoided cost of non-compliance, weighted by the initial probability of publishing the assessment. By definition, the direct effect is

[19]For the derivation of this comparative static, please see the theory appendix.

positive for all scores. This effect is displayed graphically in panel (a) of appendix figure A.10 in the theory section.[20] Second is the "publish effect," which measures the change in the net benefit as a result of a change in the probability of publishing the assessment. This effect can be separated into two parts: the gap in expected prices $\frac{\partial(1-F(\theta^*))}{\partial \pi v}\left[P_p(\bar{\theta}_p) - P_o(\bar{\theta}_o)\right]$ and the avoided cost of non-compliance $\frac{\partial(1-F(\theta^*))}{\partial \pi v}\left[\pi v\right]$. As observed in stage 2, the seller is more likely to publish the assessment when the expected cost of non-compliance increases ($\frac{\partial(1-F(\theta^*))}{\partial \pi v} > 0$). Given an interior solution, the gap in the expected prices is positive, since $\bar{\theta}_p > \theta^* > \bar{\theta}_o$. The avoided cost of non-compliance is also positive. Thus, the publish effect is positive. This effect is displayed in panel (b). Third is the "price effect," which measures the change in the net benefit as a result of a change in the expected prices, weighted by the initial probabilities. Here, the expected prices decrease because the threshold score decreases, resulting in the seller publishing the assessment for lower scores. Thus, the price effect is negative. This effect is displayed in panel (c). As long as the sum of the direct effect and publish effect are greater than the price effect, then the aggregate effect is positive. In this case, the seller is more likely to obtain an assessment when the expected cost of non-compliance increases.

In the following section, I test these comparative statics in the data. Since I do not observe the cost of the assessment, I am unable to test whether the probability of obtaining an assessment increases following an increase in the cost of the assessment. Thus, I focus on the expected cost of non-compliance, which I evaluate in terms of a reduction in enforcement. Based on these comparative statics, a seller should be less likely to obtain and publish an assessment with a reduction in enforcement. The former assumes that the aggregate effect in stage 1 is positive.

1.6 Disclosure Results

With the stylized facts and conceptual framework from the theoretical model, I turn to the data to test the hypotheses. First, I examine whether sellers act strategically based on internal factors like energy efficiency and housing attributes. Second, I examine whether external factors like enforcement influence the seller's disclosure decision.

[20]Note that, in this graphical representation, I implicitly assume that the score follows a uniform distribution. The results are generalizable to other distributions.

1.6.1 Internal Factors

In this section, I expand on the stylized facts, looking at selection based on internal factors like energy efficiency and housing attributes.

1.6.1.1 Energy Efficiency

First, I examine disclosure with respect to energy efficiency. Panel (a) of appendix figure A.7 plots the compliance rate for obtaining an assessment by the predicted score. The compliance rate varies dramatically across scores, ranging from about 40 to 80 percentage points. Consistent with the theory of asymmetric information, sellers are more likely to obtain an assessment when the predicted score increases. This may be the case if sellers perceive that there is a penalty for low scores. By not obtaining an assessment, a seller with a low score can mask their home as an average home, receiving a higher premium. Conditional on obtaining an assessment, panel (c) plots the compliance rate for publishing the assessment by the actual score. Here, the compliance rate ranges between about 70 and 80 percentage points. Similarly, sellers are more likely to publish the assessment as the score increases. In contrast to the theory, there is not full compliance among the most efficient homes, as only 80% of sellers publish the assessment with a score of 10. One possible explanation for why this occurs is that there exists a coordination problem between sellers and realtors.[21] Since a seller is responsible for obtaining an assessment, then there may be a lack of communication where a seller does not share the assessment with their realtor. Meanwhile, panel (e) plots the compliance rate for publishing the assessment by the difference in the predicted and actual score. Recall that a score is over-predicted if the difference is positive and under-predicted if the difference is negative. Sellers are less likely to publish the assessment as the difference increases. This may be the case if, upon obtaining an assessment, sellers do not publish the assessment because the actual score is less than the predicted score. As long as buyers have the same prediction, then sellers have an incentive to withhold their score from real estate listings.

[21] Other explanations include: (1) there are transaction costs associated with publishing an assessment; (2) a realtor has little experience and does not know about the program; and (3) a realtor does not perceive that the score provides value to the seller in the form of a premium.

I examine the relationship between energy efficiency and disclosure more carefully, estimating the following equation:

$$Disclose_{irtz} = \beta_1 Score_i + \gamma X_i + \alpha_{tz} + \alpha_r + \varepsilon_{irtz} \tag{1.7}$$

where $Disclose_{irtz}$ is an indicator for disclosing an assessment. I estimate this equation for obtaining and publishing an assessment. When estimating the decision to obtain an assessment, $Score_i$ represents the predicted score. Meanwhile, when estimating the decision to publish the assessment, $Score_i$ either represents the actual score or the difference in the predicted and actual score.

These estimates are presented in appendix table A.5. Again, column (4) is the preferred specification. Panel (a) displays the results for obtaining an assessment. Here, a one unit increase in the predicted score is associated with a 8.28 percentage point (12.94%) increase in the probability of obtaining an assessment. Panels (b) and (c) display the results for publishing the assessment with respect to the actual score and the difference in the predicted and actual score, respectively. Here a one unit increase in the actual score is associated with a 0.59 percentage point (0.92%) increase in the probability of publishing the assessment. Meanwhile, a one unit increase in the difference in the predicted and actual score is associated with a 0.57 percentage point (0.89%) decrease in the probability of publishing the assessment. Together, these results provide evidence that sellers act strategically across both stages of disclosure, as they are more likely to obtain and publish an assessment if their home is efficient. This relationship is stronger in stage 1. Thus, these results suggest that sellers decide to obtain an assessment based on ex-ante knowledge about energy efficiency.

1.6.1.2 Housing Attributes

Next, I examine disclosure with respect to housing attributes. The degree to which the score provides buyers with additional information about energy efficiency depends on the variance of the housing attributes. When the variance is small, the score provides little information, as there are fewer deviations from the mean. The converse is true when the variance is large. In the following chapter, I show that the premium is greater when there is more uncertainty about energy efficiency. In this case, sellers have a greater incentive to disclose an assessment because their expected payoff is greater. I study uncertainty, looking at the age and size of a home. To do so, I subset the year of construction into 10-year bins. The 1900 bin includes all homes constructed before or during 1900. The 1910 bin includes all homes constructed between 1901 and 1910. And so on. Similarly, I subset the size of a home into 250 sqft bins. I measure variance in terms of the variance of residuals from the following regression:

$$Score_i = \gamma X_i + \varepsilon_i \tag{1.8}$$

where X_i is a vector of housing attributes minus the attribute of interest. For example, when looking at the age of a home, I do not include the year of construction. I estimate this equation individually for each bin. I do so for both the predicted and actual score.

Panel (a) of appendix figure A.8 displays the mean and variance of the actual score by year of construction. The average score tends to increase with year of construction. This is expected given building codes and advancements in technology. Given this more standardized form of construction, newer homes tend to have a smaller variance. This is similarly the case for the predicted score, though to a lesser degree (see panel (b)). Similarly, panel (c) displays the mean and variance of the actual score by sqft. The average score tends to decrease with sqft. This is expected given the score is an absolute measure of energy efficiency and is not normalized by the size of a home. Because of this, the variance is smaller for both small and large homes. This is similarly the case for the predicted score (see panel (d)). Given the hypothesis around uncertainty, sellers should be more likely to disclose an assessment for old and mid-size homes, since there is more uncertainty about energy efficiency.

To test this, I estimate an equation similar to equation (1.7), including binary indicators for the year of construction and sqft bins. Panels (a) and (b) of appendix figure A.9 plot the estimates for obtaining and publishing an assessment by year of construction, respectively. In stage 1, the results are consistent with the hypothesis, as sellers are more likely to obtain an assessment for older homes. Thus, sellers sort in stage 1 by the age of a home. This is not the case in stage 2, as sellers publish the assessment at similar rates, regardless of the size of a home. Panels (c) and (d) plot the estimates for sqft. In stage 1, the results are not consistent with the hypothesis, as sellers are more likely to obtain an assessment for larger homes. While sellers appear to sort in stage 1 by the size of a home, it is not necessarily done strategically. Meanwhile, sellers do not sort in stage 2. Together, these results suggest that sellers decide to obtain an assessment based on housing attributes. Upon obtaining an assessment, however, sellers do not decide to publish the assessment based on these attributes.

1.6.2 External Factors: Enforcement

In the previous section, I show that sellers act strategically based on energy efficiency. In this section, I examine whether the degree to which sellers engage in strategic behavior varies with external factors like enforcement. In the theoretical model, I show that sellers are more likely to obtain and publish an assessment if enforcement increases and vice versa.

I study compliance following a reduction in enforcement with the COVID-19 pandemic. As previously discussed, the City of Portland reduced enforcement and suspended fines for non-compliance in 2020 with the onset of the pandemic. This was later reversed in 2021. During the pandemic, sellers are less likely to obtain an assessment without enforcement (see appendix figure A.4). While this follows from the theory, I cannot fully separate whether this is an "enforcement effect" or a "pandemic effect" or a combination of the two. Due to the perceived health risk, some sellers may have been unwilling to invite an assessor into their home during the pandemic. This is reflected in the pandemic effect. This is not a problem, however, when considering the decision to publish the assessment, since these sellers have already obtained an assessment. Similarly, sellers are less likely to publish the assessment during the pandemic without enforcement.

This reduction in compliance is the result of strategic behavior if sellers are less likely to obtain and publish an assessment for low scores. I test this in the data, comparing the pre-pandemic compliance rate in 2019 with enforcement to the post-pandemic compliance rate in 2020 without enforcement. Panel (b) of appendix figure A.7 plots the compliance rate for obtaining an assessment by the predicted score. Pre-pandemic, compliance is consistent with strategic behavior, as sellers are more likely to obtain an assessment as the score increases. This behavior is exacerbated post-pandemic without enforcement. Relative to pre-pandemic compliance, sellers with high scores are equally likely to obtain an assessment post-pandemic. Whereas, sellers with low scores are less likely to obtain an assessment post-pandemic. For some scores, the gap in the pre-pandemic and post-pandemic compliance rate is as much as 17 percentage points. Conditional on obtaining an assessment, panel (d) plots the compliance rate for publishing the assessment by the actual score. Now, there is little to no strategic behavior pre-pandemic. There is strategic behavior, however, post-pandemic. Similar to the first stage, sellers with high scores are about equally likely to publish the assessment post-pandemic while sellers with low scores are less likely to publish the assessment post-pandemic. Here, the gap in the compliance rate is as much as 15 percentage points. Meanwhile, panel (f) plots the compliance rate for publishing the assessment by the difference in the predicted and actual score. Again, there is little to no strategic behavior pre-pandemic. Meanwhile, compliance is consistent with strategic behavior post-pandemic. Here, sellers are less likely to publish the assessment as the difference in the predicted and actual score increases.

To examine the role of enforcement in more detail, I estimate the following equation, interacting the score with enforcement:

$$Disclose_{irtz} = \beta_1 Score_i + \beta_2 Post_{it} + \beta_3 Score_i \times Post_{it} + \gamma X_i + \alpha_z + \alpha_r + \varepsilon_{irz} \tag{1.9}$$

where $Post_{it}$ is an indicator for post-pandemic. While β_1 measures the association between the score and pre-pandemic compliance (with enforcement), β_3 measures the change in this association post-pandemic (without enforcement). Thus, β_2 measures the gap in the probability of obtaining and publishing an assessment at the intercept.

The estimates are presented in appendix table A.6. Panel (a) displays the results for obtaining an assessment by the predicted score. Pre-pandemic, a one unit increase in the score is associated with a 7.42 percentage point (11.59%) increase in the probability of obtaining an assessment. And, post-pandemic, a one unit increase in the score is associated with a 8.47 percentage point (13.23%) increase in the probability of obtaining an assessment. Panels (b) and (c) display the results for publishing the assessment by the actual score and the difference in the predicted and actual score, respectively. As suggested in the previous figures, there is no strategic behavior pre-pandemic, as there are null effects. There is, however, strategic behavior post-pandemic. For example, a one unit increase in the score is associated with a 1.02 percentage point (1.41%) in the probability of publishing the assessment. Meanwhile, a one unit increase in the difference in the predicted and actual score is associated with a 1.16 percentage point (1.61%) decrease in the probability of publishing the assessment. Together, these results suggest that sellers act more strategically without enforcement at all stages of the decision making process. In stage 1, sellers are more likely to obtain an assessment as the predicted score increases. Similarly, in stage 2, sellers are more likely to publish the assessment as the actual score increases. Meanwhile, sellers are less likely to publish the assessment as the difference in the predicted and actual score increases. These results are congruent with the hypotheses from the theoretical model. For example, consider stage 2, where a seller decides to publish the assessment. Without enforcement, a seller publishes the assessment for fewer scores than the case with enforcement (see figure 1.3). This is observed in the aggregate, as sellers are less likely to publish the assessment without enforcement, withholding low scores from real estate listings.

1.7 Conclusion

When purchasing a home, buyers have little ex-ante knowledge about energy efficiency. One common method to address this problem of asymmetric information is voluntary and mandatory disclosure policies. While these policies cause the market to unravel in theory, this unraveling process rarely occurs in practice. Instead, there are often issues of non-compliance. In this paper, I study a mandatory disclosure policy that requires sellers to obtain and publish an assessment in real estate listings prior to selling a home. Because there is non-compliance, this research setting provides a unique opportunity to study the factors that influence disclosure and, in doing so, examine whether sellers act strategically.

To understand how the factors influence disclosure, I construct a two-stage decision model, examining the seller's decision to obtain and publish an assessment. I then test hypotheses from this model using administrative assessment data and proprietary housing transaction data. I observe selection on energy efficiency, as sellers are more likely to disclose an assessment if their home is efficient. This strategic behavior is exacerbated without enforcement. These results suggest that sellers have ex-ante knowledge about energy efficiency. In addition, I observe selection on housing attributes in stage 1 but not stage 1. For example, sellers with old homes are more likely to obtain an assessment, as there is greater uncertainty in such homes. Lastly, I find heterogeneity in compliance by realtors. Thus, the decision to disclose an assessment is likely a multi-agent decision between a seller and their realtor. More work is necessary to examine the extent to which realtors are involved with the disclosure decision and what mechanisms influence their decision.

Ultimately, these results may help policymakers better refine mandatory disclosure policies in the future. If the goal of these polices is to achieve full compliance, then this is most readily done through enforcement and the fine for non-compliance. In this paper, I show that sellers respond dramatically to changes in enforcement, as they are less likely to disclose an assessment without enforcement. Since there is not full compliance during the period of enforcement, it suggests two things: (1) the fine is not a large enough threat to induce sellers to comply with the policy; and (2) sellers do not believe that they will be caught in violation of the policy. While policymakers can increase the fine infinitely, it may be politically untenable to do so. Thus, they will need to determine an optimal fine, weighing the benefits and costs of the assessment. Although the focus of this paper is energy efficiency, these findings can be abstracted to other settings of asymmetric information (e.g., durable goods, education, food, healthcare, and labor markets).

CHAPTER 2

WHAT ENERGY INFORMATION MATTERS TO HOME BUYERS?

2.1 Introduction

Energy efficiency is often considered a win-win opportunity, as it not only reduces carbon emissions, but it also saves people money, given the product is cost-effective. Research suggests that investment in such products has not been optimal under a cost-effective framework. This underinvestment of energy efficient products has led many economists to refer to this phenomenon as the "energy efficiency gap." Allcott and Wozny (2014), for example, find that people are only willing to pay $0.76 for a $1 of discounted fuel savings in the automobile sector. In theory, this relationship should be one-to-one. While other explanations for the existence of the energy efficiency gap have been proposed, asymmetric information is often cited.[1]

When buying and selling a home, sellers tend to have more information than buyers about energy efficiency. Without the disclosure of information, buyers cannot effectively examine the energy efficiency level of a home. Consequently, energy efficiency may not be accurately capitalized into a home's sales price. This creates a moral hazard issue if sellers do not make cost-effective investments in energy efficiency prior to selling their home for fear that they will not be able to recoup their investment at the time of sale. Meanwhile, after the purchase of a home, buyers may not be able to identify cost-effective energy efficient products, further contributing to the energy efficiency gap. To mitigate this problem, there have been attempts to increase information through voluntary and mandatory disclosure policies.

In this paper, I examine a mandatory disclosure policy in Portland, Oregon. Established in 2018, the Home Energy Score program requires sellers in Portland to publish a home energy score assessment in real estate listings prior to selling a home. The home energy score is a discrete metric (1–10) of energy efficiency created by the U.S. Department of Energy. Likened to a "miles-per-gallon" rating, this score allows buyers to examine the energy efficiency level of a home, reducing

[1]Other explanations include principal-agent issues, credit constraints, learning-by-using, regulatory failures, and behavioral anomalies (Gillingham and Palmer, 2014).

asymmetric information between buyers and sellers. With such information publicly available, energy efficiency is better capitalized into sales price, encouraging sellers to make cost-effective investments. While there is evidence of capitalization of energy efficiency for specific products, like insulation (Cassidy, 2023), few studies have looked at the overall energy efficiency level of a home. My research helps fill this void, as I examine the premium for the home energy score. Since there are alternative energy metrics (e.g., expected annual energy consumption, energy costs, and carbon emissions) that are presented in the assessment, I further examine the premium for the score in relation to these metrics.

There are two other cities in the United States that have similar mandatory disclosure policies: Austin, Texas and Berkeley, California. Recent research looks at the Energy Conservation Audit and Disclosure (ECAD) ordinance in Austin. Cassidy (2023) examines the capitalization of energy efficiency for the following home assets: attic insulation, duct insulation, duct leakage, and HVAC. Using repeat sales transactions, the author finds that capitalization is greater for the home assets that are difficult to observe without the disclosure ordinance. Myers et al. (2022) take a more holistic approach, creating a proxy of energy efficiency (i.e., kWh/sqft) for the entire home. Using a difference-in-differences model, they show that capitalization is greater for homes subject to the disclosure ordinance.

Although similar in many respects, there are several differences between the policies in Austin and Portland. First, Austin's audit is limited in scope, reporting only a few home assets, some of which are difficult to interpret without prior construction and/or engineering knowledge. Portland's assessment is much more informative, as it presents a variety of energy metrics (e.g., home energy score) in addition to the home assets. Second, the policy in Austin allows for more exemptions. For example, a home is exempt from the policy if it was constructed within ten years from the time of sale.[2] In Portland, all homes are required to publish an assessment, regardless of the year of construction. Third, and probably most important, is the timing of the requirement. While the policy in Austin requires sellers to share the audit with buyers upon request, typically during

[2]In addition, a home is exempt if it has undergone energy efficiency upgrades through Austin Energy programs within the past ten years.

the option period, the policy in Portland requires sellers to publish the assessment upfront in real estate listings. If an audit/assessment is provided to buyers in real estate listings, then they may be more likely to consider energy efficiency as a housing attribute, similar to sqft, when making their purchasing decision. If, on the other hand, an audit/assessment is provided to buyers during the option period, then they may be less likely to consider energy efficiency as a housing attribute, as they have already initiated the contract. Thus, energy efficiency may be more likely to be capitalized into sales price when the audit/assessment is published in real estate listings.

Other papers that examine mandatory disclosure policies are based outside of the United States, with most papers studying energy performance certificates in Europe. The energy performance certificate is an alphabetical label (A–G) indicating the energy efficiency level of a home. Fuerst et al. (2015) show that there exists a premium for energy efficiency in England, as homes with a more efficient label tend to have a greater sales price. Meanwhile, Aydin et al. (2018) find evidence of a premium for the overall energy efficiency level of a home but not its label in the Netherlands.[3] Lastly, Frondel et al. (2019) examine the change in sales price going from a voluntary to mandatory disclosure scheme in Germany. Under a mandatory disclosure scheme, the sales price decreases for homes that did not disclose an energy performance certificate under the previous voluntary disclosure scheme. Since these homes tend to be less efficient, their results suggest that there are selection issues with voluntary disclosure policies. While there is little research on mandatory disclosure policies, there is much more research on voluntary disclosure policies, especially for energy audits and certificates (Bond and Devine, 2016; Bruegge et al., 2016; Deng et al., 2012; Kahn and Kok, 2014; Walls et al., 2017; and Zheng et al., 2012). Walls et al. (2017), for example, find a premium for Energy Star and other local certifications in Austin, Portland, and the Research Triangle (i.e., Chapel Hill, Durham, and Raleigh, North Carolina).

This paper contributes to the discussion of the energy efficiency gap in the housing market. To the best of my knowledge, my paper is the first paper to estimate the premium for energy efficiency in the form of the home energy score. I find that a one unit increase in the score is associated

[3]They use a regression discontinuity design to examine the change in the premium at the label cutoffs.

with a 0.50% ($2,929) increase in sales price. This result holds across a variety of specifications. To determine whether there is an energy efficiency gap, I calculate the present discounted value of an equivalent stream of energy cost savings over a 30-year mortgage ($2,734). Note that the premium for the score is 7% greater than the stream of energy cost savings, implying that there is not an energy efficiency gap. I then perform a series of heterogeneity analyses, examining how the premium varies with housing attributes and time of sale. I find that the premium is greater when there is more uncertainty about energy efficiency, for example, in old homes. Meanwhile, I find that the premium does not vary with quarter of sample or season. Given recent changes in residential energy consumption following the COVID-19 pandemic, this result is surprising. Lastly, I examine the premium for the score in relation to alternative energy metrics like energy consumption. When the energy metrics are considered individually, I show that the score has the greatest premium. And, when the energy metrics are considered jointly, I show that there is still a premium for the score — 0.46% ($2,695) — even though all of the variation in energy efficiency is captured through the alternative energy metrics. This result suggests that simple discrete metrics, like the score, may be more salient to buyers and easier to comprehend than continuous energy metrics like energy consumption. These results have direct policy implications, as more cities and states pursue similar policies.

2.2 Background

The Home Energy Score program requires sellers to obtain and publish a home energy score assessment in real estate listings prior to selling a home. This assessment, created by the U.S. Department of Energy, provides consumers with a variety of information regarding residential energy use (see appendix figure B.1). Of particular interest is the home energy score, which is a discrete metric (1–10) that indicates the energy efficiency level of a home. Note that a more energy efficient home that consumes less energy receives a higher score. The score is described as an asset rating score because it is based entirely on the home's assets (see appendix figure B.2). These assets include physical housing attributes, like the age and size of a home, as well as other energy-related products like insulation.[4] By construction, the score does not take into consideration heterogeneous consumption from behavioral choices (e.g., preferences for heating and cooling) and electrical load (e.g., appliances and lighting). Instead, the engineering calculator applies multiple modeling assumptions.[5] Because of this, the score is a comprehensive proxy of energy efficiency, removing consumer behavior that is difficult to separate in other proxies like utility bills.

The following describes the process in which the score is created. During an assessment, an assessor walks through a home documenting the home assets. These assets are entered into an engineering calculator, which is used to estimate expected annual energy consumption, measured in terms of British Thermal Units (MBTU). The score is based on a subset of energy consumption, that is, consumption from heating, cooling, and hot water use. This continuous metric is then converted into the score with thresholds defined by the U.S. Department of Energy (see appendix figure B.3). These thresholds vary by weather station, allowing homes to be compared across climate zones.[6] One caveat of the score is that it is an absolute measure of energy efficiency. Since the score is not normalized by the size of a home, a larger home will receive a lower score because it requires more energy to heat and cool the area of the home. As long as buyers account for the size of a home when evaluating the score, it should not influence the premium for the score.

2.3 Data

For this analysis, I combine two sources of data. First, I obtain the housing data from the Regional Multiple Listing Service (RMLS). This data set includes 39,439 housing transactions in Portland from 2018 to 2021. It contains the general set of housing attributes (e.g., acres, bathrooms, bedrooms, sqft, and year of construction) as well as the score. The housing outcome of interest is sales price. Second, I obtain the home energy score data from Earth Advantage, a non-profit organization in Portland that serves as the data aggregator for the Home Energy Score program. This data set includes 31,157 assessments in Portland from 2018 to 2021. It contains information

[4]About 50 home assets go into the engineering calculator that produces the score. For additional details about these assets, see U.S. Department of Energy (2017)

[5]Modeling assumptions include the following: occupancy; appliance fuel type; building length and width aspect ratio; thermostat settings; and electrical load (see U.S. Department of Energy, 2017).

[6]The weather stations are identified in accordance with TMY3 weather data. There are three weather stations that service Portland: Portland Hillsboro; Portland International Airport; and Portland Troutdale.

on each energy metric.

I combine these data sets, merging on street address. For each housing transaction, I select the most recent assessment that occurs prior to the close date. In doing so, I observe the same energy metrics that were present at the time of sale. As documented in the previous chapter, this program suffers from non-compliance. Of the 39,439 housing transactions, 25,048 (64%) transactions occur when a seller obtains an assessment. Thus, I restrict the sample to these 25,048 transactions. Appendix table B.1 presents the summary statistics for the housing attributes from this sample. The average sales price in this sample is $585,801.

Appendix table B.2 presents the summary statistics for the energy metrics. The home energy score is constructed in such a way that a score of 5 represents the "average home."[7] In this sample, however, the average score is 4.38, as the distribution is skewed right (see appendix figure B.4). This is likely the case because the housing stock in Portland is old with an average year of construction of 1949. Since older homes are constructed with weaker building codes and less efficient technology, they will consume more energy and receive a lower score unless it has been retrofitted. Appendix figure B.5 presents a more detailed distribution of the score, displaying the underlying running variable: expected annual energy consumption for heating, cooling, and hot water use (MBTU). The figure also documents the score thresholds. With these types of scoring variables, one common threat to empirical analysis is strategic manipulation of the running variable. In this setting, it may occur if an assessor manipulates the home assets that go into the engineering calculator to receive a higher score. In practice, manipulation typically results in bunching near the score thresholds. This, however, does not appear to be an issue, as there is not consistent bunching around the thresholds.

Appendix table B.2 also provides information on the alternative energy metrics: energy consumption, energy costs, and carbon emissions. In this sample, average energy consumption is 145 MBTU, energy costs is $1,568, and carbon emissions is 5.5 metric tons. While energy costs and carbon emissions are based on energy consumption, there is variation between these metrics

[7]As previously mentioned, the score thresholds vary by weather station, accounting for local climate conditions. Thus, the "average home" is unique to the weather station.

depending on the fuel type and utility.[8] There is also variation between the score and these metrics (see appendix figure B.6). While each metric generally decreases with respect to the score, there is significant overlap in the metrics across scores. For example, consider energy consumption. The range includes 150 MBTU for scores 1 – 9. This occurs because the score is based on a subset of expected annual energy consumption — heating, cooling, and hot water use. On average, these end uses contribute about 56% of total energy consumption. While a home may be efficient in terms of heating, cooling, and hot water use, it may be inefficient in all other end uses. Since the score does not consider all end uses, as is the case for the alternative metrics, the score does not provide a complete picture of energy efficiency relative to the other metrics.

2.4 Empirical Setting and Results

In this section, I examine the relationship between energy efficiency and sales price. While the following estimates do not have causal interpretation, it is not a concern, since I do not attempt to measure the capitalization of energy efficiency. Instead, I focus on the premium for the home energy score, comparing it to the premium for the alternative energy metrics. In doing so, I examine how buyers respond to different energy metrics.

2.4.1 Home Energy Score

First, I consider the home energy score, since it is the primary emphasis of the assessment. I estimate the premium for the score using the following hedonic price model:

$$ln(Price_{irtz}) = \beta_1 Score_i + \gamma X_i + \alpha_{tz} + \alpha_r + \varepsilon_{irtz} \tag{2.1}$$

where $Price_{irtz}$ is the sales price for home i sold by realtor r in quarter t and zip code z.[9] $Score_i$ represents the home energy score. Meanwhile, X_i is a vector of housing attributes. To control for temporal and spatial variation, I include a quarter by zip code fixed effect α_{tz}. I also control for variation within realtor using a realtor fixed effect α_r. This equation assumes that price is linear in the score. To examine non-linearities, I also estimate an equation with a set of binary indicators for

[8]Note that there are two electric utility companies that service Portland: Pacific Power and Portland General Electric. Since these utilities have different resource mixes, they also have different carbon intensities.

[9]I measure quarter by the quarter of sample.

the individual scores.

These estimates are presented in panel (a) of appendix table B.3. While column (4) is the preferred specification, as it has the most inclusive set of controls and fixed effects, the estimates are stable across other specifications. The estimate of the score is 0.0050. Hence, a one unit increase in the score is associated with a 0.50% ($2,929) increase in price. Appendix figure B.7 presents the point estimates from the binary equation, evaluated relataive to a score of 1. While there are non-linearities, the premium tends to increase with the score. To better understand the relationship between the score and sales price, I conduct a series of heterogeneity analyses.

2.4.1.1 Heterogeneity Analysis: Housing Attributes

First, I consider heterogeneity by housing attributes. Since the score is based on home assets, like the age and size of a home, it is highly correlated with housing attributes. This is observed in appendix table B.4, which presents summary statistics for the housing attributes by the score. I study this correlation for three attributes: age (year of construction); size (sqft); and property condition. In particular, I examine how the premium for the score varies with these attributes. Note that the premium reflects the amount of information provided by the score. And, the amount of information is dependent on the variance of the score. If the variance is zero (i.e., all homes receive the same score), then the score provides no information to buyers. In this case, the premium should be zero. If, the variance is non-zero, then the score provides information to buyers, with the amount of information increasing with the variance. In this case, the premium should increase with the variance.

Appendix figure B.8 plots the mean and variance of the score with respect to these housing attributes. As seen in panel (a), the average score tends to increase with year of construction. This is expected given changes in building codes and technology. Meanwhile, the variance of the score tends to decrease with year of construction, likely the result of the standardization of construction with building codes. Since the variance in old homes is greater than new homes, the score provides more information for old homes. Thus, the premium should be greater for old homes. As seen in panel (b), the average score tends to decrease with sqft. This is expected because the score is not normalized by the size of a home. Recall that a larger home will require more energy to heat and cool the area of the home and thus receive a lower score. Now, the variance has an inverted u-shape relationship. Since the variance in mid-size homes is greater than small and large homes, the score provides more information for mid-size homes. Thus, the premium should be greater for mid-size homes. Lastly, panel (c) plots the average score by property condition. As expected, the average score for new homes is high and the variance is low. While resale and remodeled homes have similar averages, the variance of remodeled homes is less than resale homes. This is expected if a home is retrofitted when it is remodeled. Thus, the premium should be greater for resale homes followed by remodeled and new homes. The premium for fixer and restored homes is somewhat ambiguous, since these homes attract a niche set of consumers, with many of these homes being purchased as "project" homes to potentially be flipped. In this case, sellers may not care about energy efficiency if they plan on remodeling in the future.

I test these hypotheses, estimating a similar equation as before, now interacting the score with the housing attributes. I separate year of construction into 10-year bins and sqft into 250ft bins. These estimates are presented in appendix figure B.9. Consistent with the hypotheses, the premium tends to be greater for old and mid-size homes. For the property condition, the premium is positive and statistically significant for resale and remodeled homes. As hypothesized, the premium is smaller for remodeled homes. While the estimate for new homes is not significant, the premium is negative, suggesting that there is a penalty for an increase in the score. This may be the case because there are large increasing costs for making improvements in energy efficiency. Since new homes tend to be more efficient, a marginal increase in the score may come at a cost of other desirable attributes. Together, these results suggest that the consumer valuation of the score is dependent on the housing attributes of a home.

2.4.1.2 Heterogeneity Analysis: Time of Sale

Next, I consider heterogeneity by the time of sale. I examine two forms of heterogeneity: (1) quarter of sample; and (2) season. The quarter of sample measures temporal changes in the premium over the duration of the program. This premium may change, for example, if consumer preferences change. As an example, consider the COVID-19 pandemic. While the pandemic had many effects on the housing market, one effect is the emergence and persistence of stay-at-home work opportunities. As people spent more time at home, residential energy consumption increased, resulting in greater expenditures on energy consumption (Benatia and Gingas, 2021; Brewer, 2023; and Cicala, 2023). With additional expenditures, energy consumption may have become more salient to homeowners, causing them to change their preferences for energy efficiency. Thus, the premium may increase during the pandemic. Meanwhile, the premium may fluctuate throughout the year with seasonal changes, perhaps from projection bias (Busse et al., 2012; and Busse et al., 2015).[10] If buyers act rationally, maximizing expected future utility, then the premium should not be dependent on the season. Buyers, however, may overweight their preferences for energy efficiency during the winter and summer when the demand for energy is at its peak. Thus, the premium may be greater during these seasons.

I account for these temporal changes, estimating a similar equation, now interacting the score with an indicator for the time of sale:

$$y_{itz} = \beta_T Score_i \times T + \gamma X_i + \alpha_{tz} + \alpha_r \varepsilon_{irtz} \tag{2.2}$$

where T is the indicator for time of sale. I estimate this equation individually for the quarter of sample and season. These estimates are presented in appendix figure B.10. Panel (a) plots the premium by quarter of sample. While the premium varies by quarter, the estimates are not statistically different than the reference group of 2018-Q1. The premium for the reference group is 0.50%, similar to what is observed in the aggregate. These results suggest that the preferences for energy efficiency did not change during the pandemic. Meanwhile, panel (b) plots the estimates by season. While the premium varies by season, the estimates are not statistically different. These results suggest that there is not a projection bias during the winter and summer. Rather, buyers appear to value energy efficiency similarly throughout the year.

[10] Busse et al. (2012) find that home buyers are willing to pay more for central air when the demand for air conditioning increases. Similarly, Busse et al. (2015) find that car buyers are more likely to buy a convertible on a sunny day.

2.4.2 Alternative Energy Metrics

Since the assessment also presents alternative energy metrics, I examine whether the premium for energy efficiency varies across these metrics. To do so, I first estimate the premium for each alternative energy metric from the following equation:

$$ln(Price_{irtz}) = \beta_1 Energy\ Metric_i + \gamma X_i + \alpha_{tz} + \alpha_r + \varepsilon_{irtz} \tag{2.3}$$

where $Energy\ Metric_i \in$ *(Energy Consumption (MBTU), Energy Costs ($), and Carbon Emissions (Metric Ton))*. Since each of these metrics have different units of measurement, they are not directly comparable to the score. To obtain comparable estimates, I estimate the following equation:

$$Energy\ Metric_i = \lambda_0 + \lambda_1 Score_i + \varepsilon_i \tag{2.4}$$

where λ_1 represents the score equivalence, that is, the change in $Energy\ Metric_i$ with respect to the score. This coefficient is then used to rescale β_1 from equation (2.3). Thus, the rescaled estimate of $Energy\ Metric_i$ is

$$\begin{aligned}\beta_1^* &= \frac{\Delta ln(Price_{irtz})}{\Delta Energy\ Metric_i} \times \frac{\Delta Energy\ Metric_i}{\Delta Score_i} \\ &= \beta_1 \times \lambda_1\end{aligned}$$

Appendix table B.3 presents the rescaled estimates. As an example, consider energy consumption, where β_1 is -0.0003. Meanwhile, λ_1 is -12.81. Hence, a one unit increase in the score translates to a 12.81 MBTU decrease in energy consumption. The rescaled estimate of energy consumption is thus

$$\begin{aligned}\beta_1^* &= \beta_1 \times \lambda_1 \\ &= -0.0003 \times -12.81 \\ &= 0.0040\end{aligned}$$

Hence, a 12.81 decrease in MBTU, equivalent to a one unit increase in the score, is associated with a 0.40% increase in price. Recall, the premium for the score is 0.50%. Thus, the premium for energy consumption is 20% less than the premium for the score. Similarly, the rescaled estimates of energy costs and carbon emissions are 0.37% and 0.36%, respectively (see panels (c) and (d)).

These premiums are 26% and 28% less than the premium for the score. These results suggest that consumers respond more heavily to the score, as the score has the greatest individual premium.

Equation (2.3) assumes that each energy metric is observed individually. In practice, however, these metrics are observed jointly in the assessment. Thus, I examine the premium for these metrics jointly, estimating the following equation:

$$ln(Price_{irtz}) = \beta_1 Score_i + \beta_2 Energy\ Metric_i + \gamma X_i + \alpha_{tz} + \alpha_r + \epsilon_{irtz} \tag{2.5}$$

for *Energy Metric*$_i$ $\in$ (*Energy Consumption (MBTU), Energy Costs (\$), and Carbon Emissions (Metric Ton)*). Appendix table B.5 presents these joint estimates. Panel (a) considers the case when the score is presented alongside energy consumption. This yields a similar estimate as before, as the estimate of the score is 0.0046 and statistically significant. Holding energy consumption constant, a one unit increase in the score is associated with a 0.46% ($2,695) increase in price. This result is surprising, since energy consumption offers a complete picture of energy efficiency. The score, however, offers an incomplete picture of energy efficiency, since it is based on a subset of energy consumption. If the premium for the score manifests solely through its relation to energy efficiency, then the score should have no additional impact, as all of the variation in energy efficiency is already accounted for in the form of energy consumption. Alternatively, the rescaled estimate of energy consumption is 0.0005 and is not statistically significant. As there is substantial variation in energy consumption within scores, it is surprising that energy consumption is not internalized into price. A similar result occurs when considering the score with energy costs (see panel (b)) and carbon emissions (see panel (c)). Here, the premium for the score is 0.42% ($2,460) and 0.45% ($2,636), respectively.

I then consider all energy metrics jointly, estimating the following equation:

$$\begin{aligned} ln(Price_{irtz}) = &\beta_1 Score_i + \beta_2 Energy\ Consumption_i + \beta_3 Energy\ Costs_i + \\ &\beta_4 Carbon\ Emissions_i + \gamma X_i + \alpha_{tz} + \alpha_r + \epsilon_{irtz} \end{aligned} \tag{2.6}$$

These estimates are presented in panel (d) of appendix table B.5. A similar result occurs, as the premium for the score is 0.46% ($2,695). Collectively, these results suggest that there may be a salience effect, as buyers are willing to pay a premium for the score when they are presented with more complete information in the form of the alternative energy metrics. Thus, simple discrete metrics, like the score, may be more informative to buyers than continuous metrics like energy consumption.

2.4.3 Is there an Energy Efficiency Gap?

In this section, I examine whether there exists an energy efficiency gap. I measure the gap in terms of the difference between the upfront premium for the score and an equivalent stream of energy cost savings. If this value is negative, then a gap is present, as consumers undervalue the score relative to energy cost savings. Meanwhile, if this value is positive, then a gap is not present, as consumers overvalue the score relative to energy cost savings.

To determine whether a gap is present, I perform the following back-of-the-envelope calculation. Recall from appendix table B.3, a one unit increase in the score translates to a $145.29 decrease in energy costs. This can be interpreted as energy cost savings. I then calculate the present discounted value of this energy costs savings. I assume a 30-year time horizon in accord with standard mortgage terms. For the discount rate, I use the average 30-year mortgage fixed-rate between 2018 and 2021 (3.6%). This yields a present discounted value of $2,734. Since this stream of energy cost savings is less than the upfront premium for the score ($2,929), then a gap is not present. Instead, consumers slightly overvalue the score, as the premium for the score is 7% greater than the stream of energy cost savings. Although this difference is relatively small, I consider three possible explanations for why the score may be overvalued. First, the score may be correlated with unobserved housing attributes and thus the estimate may be biased upward. Second, the score may serve as a signaling mechanism, such as social status, and thus the estimate may be biased upward. Third, buyers may have a different internal discount rate. Consequently, I calculate the implied discount rate, that is, the rate at which the premium is rationalized based on consumer behavior. Here, the implied discount rate for a 30-year time horizon is 3.0%. And, the implied discount rate for a 100-year time horizon is 4.9%.[11] These results suggest that there is not an energy efficiency

[11] Myers et al. (2022) perform a similar analysis using a 100-year expected lifetime of a home. My estimate is

gap in this setting, as buyers value the score similarly to the future stream of energy cost savings.

2.5 Conclusion

As the energy efficiency gap persists, researchers and policymakers continue to search for ways to close the gap. Since asymmetric information is a driving factor of the gap, voluntary and mandatory disclosure policies have garnered a lot of attention in recent years. I examine a mandatory disclosure policy in Portland, Oregon. With this policy, home buyers have access to a wide variety of information regarding residential energy use in the form of the home energy score assessment. I examine how buyers engage with this information when purchasing a home and whether such information can help eliminate this gap.

In this paper, I examine whether there is a premium for energy efficiency. I further examine whether the premium varies across different energy metrics. I focus on the home energy score, which is a discrete metric (1-10) of energy efficiency. I estimate a 0.50% ($2,929) premium for a one unit increase in the score. As the corresponding energy cost savings ($2,734) is less than this premium, it suggests that there is not an energy efficiency gap. Instead, there is a slight overvaluation of energy efficiency. Next, I show that this premium varies with housing attributes. For example, the premium is greater in old homes, where there is more uncertainty about energy efficiency. I also show that the premium does not vary with the time of sale. Lastly, I compare the premium for the score to the premium for alternative energy metrics, like energy consumption, looking at how buyers respond to different energy metrics. While the alternative energy metrics provide more information than the score, buyers respond more heavily to the score. When the metrics are considered individually, the premium for the alternative energy metrics are 20% – 28% less than the premium for the score. Meanwhile, when the metrics are considered jointly, buyers pay a premium for the score even though all of the variation in energy efficiency is captured through the alternative energy metrics. Since the score provides less information than the alternative energy metrics, then buyers may make sub-optimal purchasing decisions, unable to align their preferences for energy efficiency. At the same time, discrete metrics, like the score, may be easier to interpret

within the range of their estimates.

than continuous metrics like energy efficiency. Thus, a trade-off emerges between the content and comprehension of information.

Since the focus of the research on mandatory disclosure policies has been on the capitalization effects of energy efficiency, more work is necessary to examine the greater impact of these policies. While these papers find evidence of capitalization at the time of sale, little is known about homeowners after the purchase of a home. Myers et al. (2022) find that new homeowners are more likely to receive energy efficiency rebates after the introduction of a disclosure policy. A similar study can be done here with this policy. Since the assessment provides recommendations of cost-effective energy efficiency investments, one can examine whether homeowners are more likely to make such investments with the policy. This would provide more insight into the energy efficiency gap.

CHAPTER 3

THE EVOLUTION OF ENERGY EFFICIENCY: IMPACTS (OR LACK THEREOF) OF REDLINING AND THE FAIR HOUSING ACT

3.1 Introduction

Racial disparities are well-documented in the energy sector, as minority households face higher energy costs relative to white households. While this gap has been decreasing over time, black households continue to face higher energy costs today, even after controlling for observable characteristics (Lyubich, 2020). Not only do they face higher energy costs, but they also spend a greater share of their income on energy consumption (Kontokosta, et al., 2020). Together, this contributes to higher rates of energy insecurity, as households are unable to meet their energy needs (Hernández et al., 2016). And, in the extreme, households are required to make trade-offs between basic necessities, asking the question: "heat or eat?" (Bhattacharya, et al, 2003).

Such racial disparities extend beyond energy costs, as they are also present in discussions of pollution exposure, with minority households experiencing higher exposure risk. While this may occur for a variety of reasons, such as source siting (Pastor et al., 2001) and "coming to the nuisance" (Depro et al., 2013), recent research points to housing discrimination. For example, Christensen et al. (2022) document discriminatory behavior in the rental market. They show that the choice set is restricted for minority households, as they are less likely to receive a response from a rental inquiry in low-exposure areas. This impacts residential sorting, directing minority households to high-exposure areas. Hausman and Stolper (2021) suggest that this kind of sorting behavior can also occur in instances of "hidden information." If buyers sort on observable characteristics that are correlated with pollution, then disparities may arise without knowledge of exposure risk. In a similar vein, minority households may disproportionately sort into inefficient homes and thus face higher energy costs.

Today, the quality of the housing stock remains dependent on historical housing practices, especially those that are based on discriminatory behavior. In the 1930s, the Home Owners' Loan Corporation (HOLC) constructed maps for urban cities, assigning grades to residential areas based on perceived risk: A – "Best"; B – "Still Desirable"; C – "Definitely Declining"; and D – "Hazardous." Since the D areas were outlined in the color red, this practice is now commonly referred to as *redlining*. These maps recommended that lending access be restricted in redlined (i.e., high-risk) areas, determined in part by the racial composition of the neighborhood. They described redlined areas as "characterized by detrimental influences in a pronounced degree, undesirable population or an infiltration of it" (University of Richmond, 2022a).[1] While insurance and mortgage lending was limited in redlined areas, there is debate about whether this was the result of the maps themselves or existing discriminatory behavior (Fishback et al., 2020; and Fishback et al. 2021). Since redlined areas were often drawn around neighborhoods with a greater share of low-income and minority households, the maps may simply reflect existing discrimination and residential sorting.

If the HOLC maps were binding and introduced additional credit constraints, then it is possible that some homeowners may not have been able to invest in efficient technologies, like insulation, resulting in lower levels of energy efficiency. If true, a gap in energy efficiency between redlined and non-redlined areas may emerge or widen after the introduction of the maps. The practice of redlining was banned in 1968 with the Fair Housing Act, which prohibited racial discrimination in the housing market. In theory, the act removed credit constraints that were in place as a result of redlining. Similarly, if true, the gap in energy efficiency may close after the act.

In this paper, I examine the question: "To what extent is the current housing stock a reflection of these past housing polices, bearing the qualities that were present at the time of construction?" To do so, I consider the housing stock in Portland, Oregon. Looking at homes constructed between 1900 and 2020, I evaluate the evolution of energy efficiency, focusing on the introduction of the redlining

[1]The following is more detailed language describing the HOLC grades: "HOLC described A areas as hot spots... where good mortgage lenders with available funds are willing to make their maximum loans... - perhaps up to 75-80 percent of appraisal. HOLC described B areas as still good but not as hot as A areas. They are neighborhoods where good mortgage lenders will have a tendency to hold commitments 10-15 percent under the limit, or around 65 percent of appraisal. C neighborhoods were characterized by obsolescence [and] infiltration of lower grade population. Good mortgage lenders are more conservative in C areas and hold commitments under the lending ratio for the A and B areas. HOLC described D areas as characterized by detrimental influences in a pronounced degree, undesirable population or an infiltration of it. They recommended lenders refuse to make loans in these areas or only on a conservative basis" (University of Richmond, 2022a).

maps and the Fair Housing Act. I measure energy efficiency in terms of expected annual energy consumption from electricity and gas (MBTU). This measure comes from the home energy score assessment, a nationally accredited assessment created by the U.S. Department of Energy. In this assessment, expected energy consumption is based strictly on home assets, like insulation, and is therefore not contaminated by consumer behavior that varies between occupants.[2] Thus, expected energy consumption is a comprehensive proxy of energy efficiency and is preferred to other proxies of energy efficiency, like utility bills, that cannot separate consumer behavior. This information is widely available in Portland, since the city requires homeowners to obtain an assessment prior to selling a home. Not only does the data include expected energy consumption, but also the home assets that go into its calculation. Because of this, I am able to decompose changes in energy efficiency with respect to these home assets.

I address this research question using a difference-in-differences and event study design, comparing homes that were constructed in redlined and non-redlined areas before and after the introduction of the redlining maps and Fair Housing Act. First, I examine changes in the home assets. While the composition of homes is different between redlined and non-redlined areas, I find that these assets evolve along similar paths. Second, I examine changes in energy efficiency. I show that these polices had no impact on the evolution of energy efficiency between redlined and non-redlined areas. As a robustness check, I also consider the role of urban renewal projects on energy efficiency. Commonly sited in redlined areas, urban renewal projects displaced households with new construction during the 1960s and 1970s. As a result, homes constructed within an urban renewal project area may be more energy efficient. To account for this, I further separate redlined areas by urban renewal projects. This yields no significant changes. As an additional robustness check, I examine the frequency in which homes are renovated, finding no difference between homes in redlined and non-redlined areas. Together, the results suggest that, while the composition of homes varies between redlined and non-redlined areas, the housing stock evolved similarly across the market.

[2]For additional details regarding the home assets, including a full list of the assets used in the calculation of expected energy consumption, see U.S. Department of Energy (2017).

I supplement this difference-in-differences design with a spatial regression discontinuity design, looking at the gap in energy efficiency across the boundaries of the redlining maps. This captures a more localized effect, since homes located near the boundary of a redlined area should be similar in construction. To do so, I construct buffers around redlined areas, comparing the energy efficiency level of homes on both sides of the boundary. Consistent with the previous findings, I show that there is no gap in energy efficiency between redlined and non-redlined areas across these boundaries. While I observe null effects, the results are interesting, since they do not align with what some scholars believe to be a cause of the racial disparities present with energy costs. These findings suggest that scholars may need to direct their search elsewhere for such causes.

Lastly, I examine temporal changes in energy efficiency at the city level, looking at trends across the market. Prior to 1940, energy efficiency remains fairly unchanged. Between 1940 and 1970, energy efficiency improves marginally. I show that much of this improvement comes from fixed home assets. I define fixed assets as those that are typically determined at the time of construction and are not chosen with considerations of energy efficiency. These assets include: area (sqft); basement; bedrooms; and stories. After 1970, energy efficiency improves dramatically. Now, however, the fixed home assets cannot explain this improvement. Instead, I show that the entirety of this improvement comes from insulation, especially ceiling and wall insulation. I attribute this result to the introduction of state building codes in the 1970s.

This paper makes four contributions. First, I add to the discussion of the impacts of redlining. While Fishback et al. (2020) and Fishback et al. (2021) caution the use of the HOLC maps to identify the causal impact of redlining, many studies examine the correlation between the grades and a variety of outcomes: credit (Aaronson et al., 2021b); crime (Anders, 2019); environmental (Hoffman et al., 2020; Lane et al., 2022; and Nardone et al., 2020c); health (Krieger et al., 2020; Mujahida et al., 2021; Nardone et al., 2020a; and Nardone et al., 2020b); and housing (Aaronson et al., 2021a; Appel and Nickerson, 2016; and Krimmel, 2020) among others. With a difference-in-differences design, I am able to credibly examine the causal impact of redlining on energy efficiency, comparing homes constructed before and after the introduction of the maps. I show that, while the composition of homes varies by grade, the maps themselves had no impact on the gap in energy efficiency between redlined and non-redlined areas. These findings are consistent with the arguments brought forth by Fishback and coauthors. Second, by using this difference-in-differences design, I can also examine the impacts of the Fair Housing Act. Similarly, I show that the Fair Housing Act had no impact on the gap in energy efficiency. Together, these results suggest that differences in the composition of homes are the result of existing housing conditions, not these housing policies. Third, by looking at homes located near the boundary of redlined areas, I am able to estimate a more localized effect. I observe similar findings with a spatial regression discontinuity design, as there is no gap in energy efficiency across the boundaries of the maps.[3] And, fourth, I examine general trends in energy efficiency at the city level. While energy efficiency improves over time, the majority of the improvements occur after 1970. I show that these improvements are the result of changes in insulation, driven by the introduction of state building codes. Similar to other work looking at the impacts of building codes on energy consumption (Jacobsen and Kotchen, 2013; and Levinson, 2016) and natural hazards (Simmons et al., 2018; and Baylis and Boomhower, 2021), these findings support the effectiveness of targeted building codes.

3.2 Background

With the decline in household income during the Great Depression, many homeowners became delinquent on their mortgage. To address the ensuing foreclosure crisis, the New Deal introduced multiple housing programs under the Federal Home Loan Bank Board. Established in 1933, the Home Owners' Loan Corporation (HOLC) purchased existing loans, refinancing them over a 15-year period. To determine the level or risk for these loans, the HOLC established more than 200 field offices across the nation, working with local professionals (Fishback et al., 2020). They then conducted surveys, collecting information on buildings, inhabitants, and mortgage availability among other characteristics. From these survey documents, they constructed maps, assigning grades to residential areas based on perceived risk. The survey documents recommended that mortgage commitments should be held lower in high-risk areas, with some loans to be refused in

[3]Many of the redlining papers cited above consider a spatial regression discontinuity design.

redlined areas altogether (University of Richmond, 2022a). The maps were created during 1937 – 1940, after the HOLC finished refinancing loans in 1936 (Fishback et al., 2013). Thus, the maps likely reflect previous lending patterns rather than guidelines for future lending.

Because of this, Fishback et al. (2020) and Fishback et al. (2021) caution the use of these maps to examine the causal impacts of redlining. In particular, Fishback et al. (2020) argue that the maps merely highlighted existing segregation, noting, "The vast majority of black households were redlined, not due to biased map construction, but instead because decades of disadvantage and discrimination had already pushed them in to the core of economically distressed neighborhoods." Fishback et al. (2021) examine the role of the Federal Housing Administration (FHA), which actively restricted insurance and lending access in low-income and minority neighborhoods. Established in 1934, the FHA insured private loans and financed new construction. Since legislation required that the FHA insure loans that were "economically sound," they too were concerned about the level of risk, constructing maps of their own.[4] The FHA continued to discriminate on the basis of race until the 1960s, at which time the maps were destroyed. Consequently, the authors argue that the HOLC maps had little impact on lending access. Instead, they suggest that restrictions in lending access is attributable to the FHA. My findings mirror these criticisms, as I show that the introduction of the maps had little to no impact on the development of the housing stock.

3.3 Data

To conduct this analysis, I combine two main sources of data. First, I obtain the redlining data from the University of Richmond's Mapping Inequality program. This program provides the historical HOLC documents, including the maps (see appendix figure C.1) and survey documents (see appendix figure C.2), which describe each residential area in terms of its buildings, inhabitants, mortgage availability, and other characteristics. Created in 1938, the map for Portland contains 16, 29, 36, and 9 areas with A, B, C, and D grades, respectively. The University of Richmond also maintains the Renewing Inequality program, which documents federally funded urban renewal projects. In Portland, there are two primary urban renewal projects: Albina Neighborhood and

[4]Unlike the HOLC maps, which are stored at the National Archive, the FHA maps were destroyed.

South Auditorium. Together, these projects displaced about 600 households. These projects were sited predominantly in C and D areas (see appendix figure C.3).

Second, I obtain the home energy score assessment data from Earth Advantage, a non-profit organization in Portland. This data set includes 31,157 assessments obtained in Portland from 2018 to 2021. This data set records expected energy consumption as well as the home assets that go into its calculation. The data set records additional information on the property, such as address, which I geocode to obtain latitude and longitude. I then match the coordinates to the HOLC map. Since the map does not span the entire city, only 18,223 (58%) assessments are matched to a grade. In total, there are 1,053, 4,976, 10,411, and 1,783 assessments in A, B, C, and D areas, respectively.

Appendix table C.1 presents summary statistics by HOLC grade. Looking at the raw data, it appears as if homes located in high-risk areas (i.e., C and D) are more energy efficient, as they consume less energy. This can partially be explained by differences in home assets. I separate home assets into fixed assets and choice assets. Fixed assets are assets that are typically determined at the time of construction. These assets include: area (e.g., conditioned floor, floor, roof, and window); bedrooms; ceiling height; exterior wall; foundation; orientation; primary fuel type; stories; and year of construction. While some of these assets may change at a future date with an addition and/or remodel, they are rarely done with considerations of energy efficiency. Such changes are also very costly. Meanwhile, choice assets are assets that need not be determined at the time of construction, as they can later be retrofitted by a homeowner. These assets include: cooling and heating equipment; ducts; insulation; and window type. Moreover, these assets are often installed with considerations of energy efficiency. Thus, if a homeowner wants to improve the energy efficiency level of their home, it is most readily done through changes in the choice assets.

Panel (a) of appendix table C.1 presents the fixed assets. The size of the home directly impacts expected energy consumption, as a larger home requires more energy to cool and heat the area of the home. This is observed in the data, as conditioned floor area is smaller for homes located in D areas (1,957 sqft) than A areas (3,097 sqft). The presence of a basement similarly impacts consumption. With a conditioned basement, additional energy is required to cool and heat the basement; whereas, with an unconditioned basement, additional energy is required, as heat leaks from the ground floor to the basement. Relative to A areas, homes in D areas are less likely to have a basement (69% vs 75%). The exterior wall also impacts consumption, as products have different R-values.[5] Relative to A areas, homes in D areas are more likely to be built with efficient products such as wood and vinyl (94% vs 75%). This is likely the case because these products are cheaper than brick and stucco. Similarly, panel (b) of appendix table C.1 presents the choice assets. While the majority of homes (84%) have a central furnace, cooling equipment varies by grade. For example, 43% of homes have cooling equipment in D areas as compared to 63% in A areas. Given differences in the above assets, it is not surprising that consumption is lower in high-risk areas. There are, however, similarities between grades. The majority of homes in the sample (78%) have double or triple pane windows. Since double pane windows were not commonly installed until the 1970s, this suggests that many homes installed them after construction, replacing old windows. Insulation also varies little by grade.

In my main specification, I examine the evolution of energy efficiency from 1900 to 2020. To do so, I sort homes by year of construction, placing them into ten-year bins. The 1900 bin includes all homes constructed before or during 1900. The 1910 bin includes all homes constructed between 1901 and 1910. And so on. Panel (a) of appendix figure C.4, plots expected energy consumption by year of construction separated by grade. Consumption tends to decrease with year of construction, regardless of the grade. Within year of construction, there is substantial variation between grades, as consumption tends to be lower in high-risk areas. Again, much of this variation can be explained by the fixed assets. As seen in panel (b), the conditioned floor area is much smaller in high-risk areas.

My alternative empirical specification measures localized differences in energy efficiency at the boundaries of redlined areas. To do so, I construct buffers (e.g., 0.1, 0.2, and 0.3 miles) around each redlined area, selecting all homes within such buffers (see appendix figure C.5).[6] As documented in appendix table C.2, expected energy consumption increases with the size of the buffer. Next, I

[5]The R-value is a measure of resistance to heat flow. A product is more efficient if it has a higher R-value.
[6]Note, a distance of 0 corresponds to homes located in a redlined area.

calculate the distance between a home and the boundary of the nearest redlined area.[7] This distance takes a positive value if a home is located in a redlined area and a negative value if it is located in a non-redlined area. I also construct a categorical variable, assigning each home to the boundary of the nearest redlined area. This allows me to consider boundary fixed effects, comparing homes located near the same redlined area.

3.4 Empirical Setting and Results

As previously documented, high-risk areas have lower expected energy consumption. This, however, may be the result of differences in the composition of homes. Thus, I examine whether the fixed assets can explain this difference entirely. To do so, I consider a naive model, looking at the correlation between consumption and these grades. I estimate the following equation:

$$MBTU_{ig} = \sum_{g \in B,C,D} \beta_g + \gamma X_i + \varepsilon_{ig} \tag{3.1}$$

where $MBTU_{ig}$ is expected energy consumption for home i in grade g. I estimate a unique β for each grade $g \in \{B, C, D\}$. I control for the fixed assets, represented by the vector X_i. Appendix table C.3 reports these estimates. Column (1) presents the unconditional means, which are observed in the summary statistics. Relative to A areas, homes in D areas consume 24.5 less MBTU. Column (2) then presents the conditional means, controlling for the fixed assets. Now, homes in D areas consume 4.9 less MBTU. While the magnitude decreases with the addition of the fixed assets, these assets alone cannot explain the difference between grades. This suggests that the choice assets or other unobserved characteristics make up the remainder of this difference.

3.4.1 Difference-in-Differences and Event Study

In this section, I examine the evolution of the housing stock, measuring temporal changes between redlined and non-redlined areas.

3.4.1.1 Fixed Assets

First, I examine changes in the composition of homes, looking at the fixed assets. To do this, I use an event study design. In my research setting, time is determined by the year of construction.

[7] I measure distance to the edge of the redlined area, not the centroid of the redlined area.

I compare the fixed assets of homes constructed before and after the introduction of the redlining maps and Fair Housing Act.[8] In particular, I estimate the following event study equation for each fixed asset separately:

$$Y_{igt} = \alpha_g + \alpha_t + \sum_{\substack{t=1900 \\ t\neq 1940}}^{2020} \beta_t \boldsymbol{I}[g = D] + \varepsilon_{igt} \tag{3.2}$$

where Y_{igt} is the fixed asset for home i located in grade g and constructed in year t. Here, the grade takes on two values, redlined (D) and non-redlined ($-D$) areas.[9] I include grade and year of construction fixed effects, represented by α_g and α_t, respectively. The coefficients of interest, β_t, capture differential changes in redlined areas. The reference group is 1940, the period in which the maps were introduced. These event study estimates are presented in appendix figure C.6 for the following fixed assets: area (sqft); basement; bedrooms; and stories. I focus on these assets because they are central to the structure of a home and are costly to change after construction. Thus, absent an addition and/or remodel, these assets reflect the structure of the home at the time of construction. I find that these assets change little after the introduction of the maps. While the size of a home increases after the Fair Housing Act, much of this increase occurs after 2000, long after the act was passed. A similar change occurs with the number of stories.

To aggregate these dynamic treatment effects, I use a difference-in-differences design, pooling across three time periods (i.e., $\leq$ 1940, 1941-1970, and 1971-2020). I estimate the following difference-in-differences equation for each fixed asset separately:

$$\begin{aligned} Y_{it} =& \alpha + \beta_1 D_i + \beta_2 Post_{i,1940} + \beta_3 Post_{i,1970} + \\ & \beta_4 D_i \times Post_{i,1940} + \beta_5 D_i \times Post_{i,1970} + \varepsilon_{it} \end{aligned} \tag{3.3}$$

where D_i is an indicator, equal to 1 if a home is located in a redlined area. $Post_{i,1940}$ and $Post_{i,1970}$ are indicators, equal to 1 if a home is constructed in [1941, 1970] and [1971, 2020], respectively.

[8]This event study design is similar to the one used by Baylis and Boomhower (2021) who measure the impact of building codes on wildfire survival.

[9]Note that C areas are most similar to D areas. In some cases, the survey documents explicitly state that, if it was not for the racial composition of an area, such areas would have received a grade of C rather than D. Thus, as a robustness check, I estimate a similar equation, reducing the control group to C areas. This produces similar results as the main specification.

While β_2 and β_3 capture general trends following the introduction of the maps and Fair Housing Act, β_4 and β_5 capture differential trends in redlined areas. Appendix table C.4 reports these difference-in-differences estimates. These estimates confirm that, with the exception of the number of bedrooms, the fixed assets do not change differentially after the introduction of the maps. While the fixed assets tend to increase more in redlined areas after the Fair Housing Act, much of this increase occurs after 2000 and is thus not reflective of the act.

3.4.1.2 Energy Efficiency

Next, I examine changes in energy efficiency, as measured by expected energy consumption. I estimate a similar event study equation, controlling for the fixed assets, where Y_{igt} is MBTU. Panel (a) of appendix figure C.7 presents these estimates. Prior to the introduction of the maps in 1940, there are no pre-trends, as the estimates are centered around zero. After 1940, the estimates remain relatively unchanged. I then estimate a difference-in-differences equation. Panel (a) of appendix table C.5 reports these estimates. Columns (1) and (2) present the unconditional and conditional means, respectively. My preferred specification is column (2), as it accounts for the fixed assets. While consumption decreases by 3.6 MBTU between 1940 and 1970 in aggregate, it does not change differentially between redlined and non-redlined areas. A similar result occurs after 1970, now to a greater degree, as consumption decreases by 36.3 MBTU in aggregate. Together, these results suggest that these housing policies had no impact on the evolution of energy efficiency between redlined and non-redlined areas.

These difference-in-differences estimates represent the treatment effects as long as homes in non-redlined areas serve as a valid control group. This identifying assumption can be separated into two parts. First, the parallel trends assumption suggests that, prior to treatment, both redlined and non-redlined areas follow similar trends. This is observed in the event study estimates. Second, there must be no unobserved factors that influence expected energy consumption differentially between redlined and non-redlined areas, occurring over the same time period. While there are unobserved factors that influence consumption (e.g., building codes), many of these factors occur equally across the market. And, while I cannot preclude all factors that influence consumption in redlined areas, I consider the impact of urban renewal projects, which occur simultaneously with treatment. These projects, commonly sited in redlined areas, displaced households during the 1960s and 1970s. As a robustness check, I estimate similar event study and difference-in-differences equations, separating redlined areas by urban renewal projects:

$$\begin{aligned} Y_{it} = \alpha + \beta_1 \textit{URP: No}_i + \beta_2 \textit{URP: Yes}_i + \beta_3 Post_{i,1940} + \beta_4 Post_{i,1970} + \\ \beta_5 \textit{URP: No}_i \times Post_{i,1940} + \beta_6 \textit{URP: Yes}_i \times Post_{i,1940} + \\ \beta_7 \textit{URP: No}_i \times Post_{i,1970} + \beta_8 \textit{URP: Yes}_i \times Post_{i,1970} + \gamma X_i + \varepsilon \end{aligned} \tag{3.4}$$

where $\textit{URP: Yes}_i$ is an indicator, equal to 1 if a home is located in a redlined area as well as an urban renewal project area. Conversely, $\textit{URP: No}_i$ is an indicator, equal to 1 if a home is located in a redlined area but not an urban renewal project area. Panel (b) of appendix figure C.7 presents the event study estimates. While there are minor differences by year of construction, the majority of these point estimates are not statistically different. As seen in Panel (b) of appendix table C.5, the difference-in-differences estimates are similar as before, yielding no significant changes. Thus, the presence of urban renewal projects is not a threat to my identification.

Another threat to my identification is the nature and frequency of housing transactions. I observe a home in the data set if (1) the home survives to the sample period, (2) the home sells during the sample period, and (3) the homeowner obtains an assessment.[10] This introduces bias if selection across these processes varies by HOLC grade. To address the issue of survival, I examine the frequency in which homes are demolished. To do this, I combine demolition records with housing units.[11] I find similar demolition rates across grades, with 1.7 and 1.9 demolitions per 100 housing units in redlined and non-redlined areas, respectively. In a similar vein, I examine the frequency in which homes are remodeled. Now, I use housing transactions, which document the property condition of a home.[12] Similarly, there is little difference, as 26% and 25% of homes are remodeled in redlined and non-redlined areas, respectively. Alternatively, using a difference-in-differences design, I show that there is no difference in the probability that a home is remodeled

[10]Note that a homeowner may receive a home energy score assessment without selling their home. This, however, is seldom the case.

[11]I obtain demolition records from the City of Portland and housing units from the U.S. Census.

[12]I obtain housing transactions from the Regional Multiple Listing Service.

between redlined and non-redlined areas (see panel (a) of appendix table C.6). And, using a triple difference-in-differences design, I show that there is no gap in energy efficiency between remodeled homes in redlined and non-redlined areas (see panel (b) of appendix table C.6). Together, these results suggest that homes are renovated at similar rates between redlined and non-redlined areas, easing concerns of differential rates of gentrification.

3.4.1.3 Choice Assets

Lastly, I consider changes in the choice assets. As seen in the following section, insulation explains the majority of the changes in energy efficiency over time. Thus, I focus on insulation here. Again, I estimate similar event study and difference-in-differences equations, controlling for the fixed assets. Appendix figure C.8 presents the event study estimates by type of insulation: ceiling; floor; roof; and wall. The estimates are relatively constant over time, regardless of the type of insulation. Appendix table C.7 reports the difference-in-differences estimates. While insulation levels increase dramatically after 1970, there are only minor differences between redlined and non-redlined areas. This widespread increase in insulation coincides with the introduction of state building codes during the 1970s. These results suggest that building codes are not only effective at improving energy efficiency, but also ensure that the improvements are experienced the same across the market, regardless of existing socio-economic conditions.

3.4.2 Spatial Regression Discontinuity

The previous section examines the evolution of the housing stock, looking at temporal changes in home assets and energy efficiency. In this section, I examine spatial differences at a more localized level. By looking exclusively at homes located near the boundary of a redlined area, I am able to measure discontinuous changes in energy efficiency across such boundaries. I estimate the following spatial regression discontinuity equation separately for the individual bandwidths (e.g., 0.1, 0.2, and 0.3 miles):

$$MBTU_{ib} = \beta_1 D_i + \beta_2 (x_i - x_0) + \beta_3 D_i \times (x_i - x_0) + \gamma X_i + \alpha_b + \varepsilon \qquad (3.5)$$

where $MBTU_{ib}$ is expected energy consumption for home i located near the boundary of redlined area b. Again, D_i is an indicator for a home located in a redlined area. The boundary of a redlined area is represented by x_0. As such, $x_i - x_0$ is the distance between a home and the nearest redlined area. This distance takes a positive value if the home is located in a redlined area and a negative value if it is located in a non-redlined area. I control for acute spatial differences, including a fixed effect α_b that assigns each home to the boundary of the nearest redlined area. By doing so, I compare consumption within a set of homes located near the same redlined area. I allow for different linear trends on each side of the boundary, as measured by β_2 and β_3. The coefficient of interest, β_1, captures the discontinuous change in consumption at the boundary. Appendix figure C.9 presents the regression discontinuity estimates, plotting average consumption. Regardless of the size of the bandwidth, consumption does not change at the boundary. This is confirmed in appendix table C.8, as the estimates of D_i are not significant. These results provide further evidence that these maps had no impact on energy efficiency, even at a localized level.

3.4.3 General Trends in Energy Efficiency

In this section, I aggregate expected energy consumption to the city level, documenting general trends in energy efficiency across the market. Panel (a) of appendix figure C.10, documents changes in consumption relative to 1900. To better understand the mechanisms behind these changes, I condition on (1) fixed assets as well as (2) fixed and choice assets, plotting residualized consumption. Prior to 1940, consumption remains relatively unchanged. Between 1940 and 1970, consumption decreases by 6.7 MBTU. Here, the fixed assets can explain about 55% of this reduction. After 1970, consumption decreases by 30.5 MBTU. The fixed assets can no longer explain this reduction. Instead, the reduction is the result of the choice assets. The choice assets can explain about 77% of this reduction, with the remainder coming from unobserved characteristics. The question remains: what is driving this reduction?

In panel (b) of appendix figure C.10, I examine the reduction in expected energy consumption more carefully, conditioning on various sets of choice assets. When conditioning on all but insulation, the estimates are no different than the unconditional means. This result suggests that choice assets, such as cooling and heating equipment, ducts, and window type, do not contribute to this reduction. Rather, insulation contributes to the entirety of this reduction. I further condition by type of insulation. In doing so, I find that this reduction is driven by wall insulation followed by ceiling insulation.[13] This reduction coincides with the introduction of building codes, as Oregon adopted minimum standards for ceiling and wall insulation in 1973. While these estimates are not causal, they provide strong suggestive evidence that targeted building codes can be effective at reducing consumption and thereby improving energy efficiency.

3.5 Conclusion

While racial disparities are well-documented in the energy sector, with minority households facing higher energy costs relative to white households, few studies have attempted to explain this gap. One possible mechanism for this gap is differences in the housing stock. Although Lyubich (2020) explores the role of housing characteristics, such as year of construction, the author is unable to control for a comprehensive set of characteristics, including energy efficiency. I help fill this void, looking at the evolution of energy efficiency in the housing stock. As today's housing stock is influenced by historical housing policies, I examine the impact of redlining and the Fair Housing Act on energy efficiency.

To do this, I use a difference-in-differences design, measuring the gap in energy efficiency between redlined and non-redlined areas before and after the introduction of the redlining maps and the Fair Housing Act. I find that these housing policies had no impact on the evolution of energy efficiency. In other words, the introduction of the maps did not create nor widen the gap in energy efficiency between redlined and non-redlined areas. Similarly, the Fair Housing Act did not close the gap. Likewise, with a spatial regression discontinuity design, I find no gap in energy efficiency between redlined and non-redlined areas across the boundaries of the map. These results suggest that the practice of redlining did not create additional disparities in energy efficiency. This is consistent with recent research by Fishback et al. (2020) and Fishback et al. (2021) who argue that the maps did not influence lending access. Rather, they are a reflection of existing discriminatory

[13]After conditioning on wall and ceiling insulation, floor and roof insulation provide little additional improvement.

behavior.

Finally, I aggregate the analysis to the city level, measuring general trends in energy efficiency across the market. The majority of the improvements in energy efficiency occur after 1970. I show that these improvements can be explained almost entirely by insulation, in particular, ceiling and wall insulation. These improvements coincide with the introduction of state building codes, supporting the effectiveness of targeted building codes. These findings also suggest that insulation may be the most effective solution when retrofitting a home. Ultimately, these findings can help policymakers direct resources to state and federal programs, like the Weatherization Assistance Program, that provide insulation to existing homes.

One limitation of this paper is data availability, as information about energy efficiency is lacking at local, state, and national levels. Because of this, many studies use historical energy consumption from utility bills as a proxy of energy efficiency. Notwithstanding the issues of utility bills as a proxy, these bills are difficult to collect across multiple service territories. As a result, many studies focus on small geographical areas. While I use a novel data set, measuring energy efficiency by expected energy consumption from a nationally accredited assessment, this paper focuses on a single city. These assessments are made available by the Home Energy Score program, which requires homeowners to obtain an assessment prior to selling a home. Since this program applies to homeowners in Portland, I am restricted to homes within Portland for my analysis. Thus, to examine the external validity of these findings, it will require a concerted effort to improve data availability and access at a larger geographical scale. Ultimately, this may require uniform standards of reporting across local, state, and national jurisdictions.[14]

In this paper, I strictly consider the built environment, looking at energy efficiency in the housing stock. More work is necessary to examine how individuals interact within this environment. For example, what does current sorting behavior look like? Are low-income and minority households disproportionately sorting into inefficient homes? Does information provision affect sorting behavior? If so, does it promote equity or exacerbate existing disparities? Answers to these questions

[14] As an example, other cities in Oregon have adopted similar programs as Portland, so too requiring homeowners to obtain a home energy score assessment.

can help develop more effective policies while targeting energy efficiency rebate programs.

BIBLIOGRAPHY

[1] Aaronson, Daniel, Daniel Hartley, and Bhashkar Mazumder. 2021a. "The Effects of the 1930s HOLC 'Redlining' Maps." *American Economic Journal: Economic Policy* 13 (4): 355-392.

[2] Aaronson, Daniel, Jacob Faber, Daniel Hartley, Bhashkar Mazumder, and Patrick Sharkey. 2021b. "The Long-run Effects of the 1930s HOLC 'Redlining' Maps on Place-based Measures of Economic Opportunity and Socioeconomic Success." *Regional Science and Urban Economics* 86(2021): 2-15.

[3] Allcott, Hunt and Nathan Wozny. 2014. "Gasoline Prices, Fuel Economy, and the Energy Paradox." *The Review of Economics and Statistics* 96(5): 779-795.

[4] Anders, John. 2019. "The Long Run Effects of De Jure Discrimination in the Credit Market: How Redlining Increased Crime." *Working Paper*.

[5] Appel, Ian and Jordan Nickerson. 2016. "Pockets of Poverty: The Long-term Effects of Redlining." *Working Paper*.

[6] Aydin, Erdal, Dirk Brounen, and Nils Kok. 2018. "Information Asymmetry and Energy Efficiency: Evidence from the Housing Market." *Working Paper*.

[7] Baylis, Patrick and Judson Boomhower. 2021. "Mandated vs. Voluntary Adaptation to Natural Disasters: The Case of U.S. Wildfires." *NBER Working Paper* 29621.

[8] Benatia, David and Samuel Gingras. 2021. "Reaching New Lows? The Pandemic's Consequences for Electricity Markets." *USAEE Working Paper* No. 20-454

[9] Bhattacharya, Jayanta, Thomas DeLeire T, Steven Haider, and Janet Currie. 2003. "Heat or Eat? Cold-weather Shocks and Nutrition in Poor American Families." *American Journal of Public Health* 93(7): 1149-54.

[10] Bond, Shaun, and Avis Devine. 2016. "Certification Matters: Is Green Talk Cheap Talk?" *The Journal of Real Estate Finance and Economics* 52(2): 117-140.

[11] Brewer, Dylan. 2022. "Equilibrium Sorting and Moral Hazard in Residential Energy Contracts." *Journal of Urban Economics* 129: 1-22.

[12] Brewer, Dylan. 2023. "Changes in Electricity use following COVID-19 Stay-at-Home Behavior." *Economics of Energy & Environmental Policy* (Forthcoming).

[13] Bruegge, Chris, Carmen Flores, and Jaren Pope. 2016. "Does the Housing Market Value Energy Efficient Homes? Evidence from the Energy Star Program." *Regional Science and Urban Economics* 57: 63-76.

[14] Bureau of Planning and Sustainability, City of Portland. 2017. "Administrative Rules – Residential Energy Performance Rating and Disclosure."

[15] Busse, Meghan, Devin Pope, Jaren Pope, and Jorge Silva-Risso. 2015. "The Psychological Effect of Weather on Car Purchases." *Quarterly Journal of Economics* 130(1): 371-414.

[16] Busse, Meghan, Devin Pope, Jaren Pope, and Jorge Silva-Risso. 2012. "Projection Bias in the Car and Housing Markets" *NBER Working Paper* 18212.

[17] Cassidy, Alecia. 2023. "How Does Mandatory Energy Efficiency Disclosure Affect Housing Prices?" *Journal of the Association of Environmental and Resource Economists* (Forthcoming).

[18] Christensen, Peter, Ignacio Sarmiento-Barbieri, and Christopher Timmins. 2022. "Housing Discrimination and the Toxics Exposure Gap in the United States: Evidence from the Rental Market." *Review of Economics and Statistics* (Forthcoming).

[19] Cicala, Steve. 2023. "Powering Work From Home." *Journal of Urban Economics: Insight* 133.

[20] Deng, Yongheng, Zhiliang Li, and John Quigley. 2012. "Economic Returns to Energy-Efficient Investments in the Housing Market: Evidence from Singapore." *Regional Science and Urban Economics* 42: 506-515.

[21] Depro, Brooks, Christopher Timmins, and Maggie O'Neil. 2015. "White Flight and Coming to the Nuisance: Can Residential Mobility Explain Environmental Injustice?" *Journal of the Association of Environmental and Resource Economists* 2(3): 439-468.

[22] Dranvoe, David and Ginger Zhe Jin. 2010. "Quality Disclosure and Certification: Theory and Practice." *Journal of Economic Literature* 48(4): 935-963.

[23] Fishback, Price, Jessica LaVoice, Allison Shertzer, and Randall Walsh. 2020. "Race, Risk, and the Emergence of Federal Redlining." *NBER Working Paper* 28146.

[24] Fishback, Price, Jonathan Rose, and Kenneth Snowden. 2013. "Well Worth Saving: How the New Deal Safeguarded Home Ownership." *Chicago: University of Chicago Press*.

[25] Fishback, Price, Jonathan Rose, Kenneth Snowden, and Thomas Storrs. 2021. "New Evidence on Redlining by Federal Housing Programs in the 1930s." *NBER Working Paper* 29244.

[26] Frondel, Manuel Andreas Gerster, and Colin Vance. 2019. "The Power of Mandatory Quality Disclosure: Evidence from the German Housing Market." *Journal of the Association of Environmental and Resource Economists* 7(1): 181-208.

[27] Fuerst, Franz, Pat McAllister, Anupam Nanda, and Peter Wyatt. 2015. "Does energy efficiency matter to home-buyers? An Investigation of EPC Ratings and Transaction Prices in England."

Energy Economics 48: 145-156.

[28] Gilbert, Ben, Jacob LaRiviere, and Kevin Novan. 2022. "Uncertainty and Additionality in Energy Efficiency Programs." *Journal of Environmental Economics and Management* (Forthcoming).

[29] Gillingham, Kenneth and Karen Palmer. 2014. "Bridging the Energy Efficiency Gap: Policy Insights from Economic Theory and Empirical Evidence." *Review of Environmental Economics and Policy* 8(1): 18-38.

[30] Grossman, Sanford. 1981. "The Information Role of Warranties and Private Disclosure about Product Quality." *The Journal of Law and Economics* 24(3): 461-483.

[31] Hausman, Catherine and Samuel Stolper. 2021 "Inequality, Information Failures, and Air Pollution." *Journal of Environmental Economics and Management* 110(2021): 1-16.

[32] Hernández, Diana, Yang Jiang, Daniel Carrión, Douglas Phillips, and Yumiko Aratanib. 2016. "Housing Hardship and Energy Insecurity among Native-born and Immigrant Low-income Families with Children in the United States." *Journal of Children and Poverty* 22(2): 77-92.

[33] Hoffman, Jeremy, Vivek Shandas, and Nicholas Pendleton. 2020. "The Effects of Historical Housing Policies on Resident Exposure to Intra-Urban Heat: A Study of 108 US Urban Areas." *Climate* 8(12): 1-15.

[34] Jacobsen, Grant and Mathhew Kotchen. 2013. "Are Building Codes Effective at Saving Energy? Evidence from Residential Billing Data in Florida." *The Review of Economics and Statistics* 95(1): 34–49.

[35] Kahn, Matthew, and Nils Kok. 2014. "The Capitalization of Green Labels in the California Housing Market." *Regional Science and Urban Economics* 47: 25-34.

[36] Kontokosta, Constantine, Vincent Riena, and Bartosz Bonczak. 2020. "Energy Cost Burdens for Low-income and Minority Households." *Journal of the American Planning Association* 86(1): 89–105.

[37] Krieger, Nancy, Gretchen Van Wye, Mary Huynh, Pamela Waterman, Gil Maduro, Wenhui Li, Charon Gwynn, Oxiris Barbot, and Mary Bassett. 2020. "Structural Racism, Historical Redlining, and Risk of Preterm Birth in New York City, 2013–2017." *American Journal of Public Health* 110(7): 1046-1053.

[38] Krimmel, Jacob. 2020. "Persistence of Prejudice: Estimating the Long Term Effects of Redlining." *Working Paper*.

[39] Lane, Haley, Rachel Morello-Frosch, Julian Marshall, and Joshua Apte. 2022. "Historical

Redlining Is Associated with Present-Day Air Pollution Disparities in U.S. Cities." *Evinronmental Science and Technology Letters* 9(4): 345-350.

[40] Levinson, Arik. 2016. "How Much Energy Do Building Energy Codes Save? Evidence from California Houses." *American Economic Revew* 106(10): 2867–2894.

[41] Lyubich, Eva. 2020. "The Race Gap in Residential Energy Expenditures." *Energy Institute Working Paper* 306.

[42] Milgrom, Paul. 1981. "Good News and Bad News: Representation Theorems and Applications." *Bell Journal of Economics* 12(2): 380-391.

[43] Mujahida, Mahasin, Xing Gao, Loni Tabb, Colleen Morris, and Tene Lewis. 2021. "Historical Redlining and Cardiovascular Health: The Multi-ethnic Study of Atherosclerosis" *Proceedings of the National Academy of Sciences* 118(51): 1-8.

[44] Myers, Erica, Steven Puller, and Jeremy West. 2022. "Mandatory Energy Efficiency Disclosure in Housing Markets." *American Economic Journal: Economic Policy* 14(4): 453-87.

[45] Nardone, Anthony, Joan Casey, Rachel Morello-Frosch, Mahasin Mujahid, John Balmes, and Neeta Thakur. 2020a. "Associations between Historical Residential Redlining and Current Age-adjusted Rates of Emergency Department Visits due to Asthma Across Eight Cities in California: An Ecological Study." *Lancet Planet Health* 4(1): 24-31.

[46] Nardone, Anthony, Joey Chiang, and Jason Corburn. 2020b. "Historic Redlining and Urban Health Today in U.S. Cities." *Environmental Justice* 13(4): 109-119.

[47] Nardone, Anthony, Kara Rudolph, Rachel Morello-Frosch, and Joan Casey. 2020c. "Redlines and Greenspace: The Relationship between Historical Redlining and 2010 Greenspace across the United States." *Environmental Health Perspectives* 129(1): 1-9.

[48] Pastor, Manuel, Jim Sadd, and John Hipp. 2001. "Which Came First? Toxic Facilities, Minority Move-in and Environmental Justice." *Journal of Urban Affairs* 23(1): 1-21.

[49] Simmons, Kevin, Jeffrey Czajkowski, and James Done. 2018. "Economic Effectiveness of Implementing a Statewide Building Code: The Case of Florida." *Land Economics* 94 (2): 155-174.

[50] University of Richmond. 2022a. "Mapping Inequality."
https://dsl.richmond.edu/panorama/redlining/loc=5/39.1/-94.58

[51] University of Richmond. 2022b. "Renewing Inequality."
https://dsl.richmond.edu/panorama/renewal/view=0/0/1viz=cartogram

[52] U.S. Department of Energy. 2017. "Home Energy Score Scoring Methodology."

[53] Walls, Margaret, Karen Palmer, Todd Gerrarden, and Xian Bak. 2017. "Is Energy Efficiency Capitalized into Home Prices? Evidence from Three U.S. Cities." *Journal of Environmental Economics and Management* 82: 104-124.

[54] Zheng, Siqi, Jing Wu, Matthew Kahn, and Yongheng Deng. 2012. "The Nascent Market for "Green" Real Estate in Beijing." *European Economic Review* 56:5 974-984.

APPENDIX A

CHAPTER 1 APPENDIX

Table A.1: Summary Statistics - Housing Attributes

Attribute	**Mean (Standard Deviation)**	**N**
Sales Price	604,254	39,439
	(293,893)	
Year of Construction	1956	39,439
	(67)	
Sqft	2,171	39,430
	(972)	
# of Bedrooms	3.33	39,439
	(0.94)	
# of Baths	1.95	39,439
	(0.80)	
# of Stories	2.04	39,439
	(0.77)	
# of Garages	1.34	39,439
	(0.89)	
Acres	0.21	37,781
	(0.77)	
Property Condition		39,439
New	0.06	
Fixer	0.04	
Remodel	0.21	
Restored	0.02	
Other	0.67	
Cooling System		39,439
Central Air	0.43	
Heat Pump	0.05	
Wall / Window Unit	0.03	
Other	0.06	
None	0.11	
Missing	0.33	
Heating System		39,439
Forced Air	0.89	
Baseboard	0.02	
Heat Pump	0.01	
Wall Furnace	0.01	
Other	0.08	
Fuel Type		39,439
Gas	0.73	
Electric	0.11	
Electric and Gas	0.11	
Other	0.05	
Observations	39,439	

Notes: The table reports the mean (standard deviation in parentheses) of the housing attributes for the full sample of homes transacted in Portland from 2018 to 2021.

Table A.2: Summary Statistics - Housing Attributes by Home Energy Score

	Home Energy Score									
Characteristic	1	2	3	4	5	6	7	8	9	10
Sales Price	670,027	607,227	587,946	575,788	552,582	556,717	538,547	557,238	577,137	575,040
	(364,932)	(296,812)	(249,296)	(260,924)	(213,287)	(210,841)	(190,110)	(209,243)	(216,306)	(173,835)
Year of Construction	1939	1943	1945	1946	1948	1952	1957	1967	1974	1976
	(26)	(26)	(28)	(29)	(55)	(50)	(83)	(80)	(41)	(93)
Sqft	2,579	2,259	2,168	2,053	1,954	1,902	1,826	1,824	1,879	1,810
	(1,199)	(990)	(885)	(856)	(774)	(752)	(695)	(697)	(713)	(663)
# of Bedrooms	3.54	3.31	3.29	3.16	3.10	3.06	3.08	3.08	3.15	3.05
	(0.98)	(0.85)	(0.88)	(0.87)	(0.85)	(0.87)	(0.85)	(0.83)	(0.86)	(0.88)
# of Baths	1.98	1.83	1.83	1.79	1.77	1.81	1.82	1.91	1.96	1.95
	(0.90)	(0.80)	(0.78)	(0.75)	(0.71)	(0.73)	(0.69)	(0.71)	(0.67)	(0.68)
# of Stories	2.32	2.15	2.13	2.05	1.99	2.00	1.98	2.00	2.03	2.07
	(0.87)	(0.84)	(0.83)	(0.81)	(0.78)	(0.71)	(0.69)	(0.68)	(0.66)	(0.66)
# of Garages	1.22	1.19	1.22	1.20	1.19	1.15	1.13	1.11	1.06	0.87
	(0.93)	(0.85)	(0.86)	(0.85)	(0.83)	(0.79)	(0.77)	(0.71)	(0.69)	(0.65)
Acres	0.20	0.19	0.17	0.16	0.16	0.15	0.13	0.13	0.12	0.13
	(0.34)	(0.39)	(0.19)	(0.13)	(0.15)	(0.17)	(0.11)	(0.11)	(0.11)	(0.37)
Property Condition										
New	0.00	0.00	0.00	0.00	0.01	0.01	0.03	0.08	0.15	0.25
Fixer	0.07	0.05	0.04	0.02	0.02	0.02	0.01	0.01	0.01	0.00
Remodel	0.21	0.22	0.24	0.25	0.24	0.26	0.26	0.23	0.20	0.18
Restored	0.03	0.03	0.03	0.03	0.02	0.03	0.02	0.01	0.02	0.02
Other	0.69	0.70	0.70	0.70	0.70	0.69	0.67	0.66	0.62	0.56
Cooling System										
Central Air	0.38	0.39	0.43	0.42	0.42	0.42	0.39	0.39	0.34	0.26
Heat Pump	0.04	0.03	0.03	0.04	0.05	0.05	0.07	0.09	0.09	0.16
Wall / Window Unit	0.04	0.04	0.04	0.03	0.03	0.04	0.03	0.03	0.03	0.04
Other	0.02	0.03	0.03	0.03	0.03	0.04	0.05	0.10	0.13	0.19
None	0.14	0.14	0.13	0.13	0.13	0.11	0.11	0.11	0.10	0.07
Missing	0.39	0.37	0.34	0.36	0.34	0.34	0.34	0.29	0.31	0.29
Heating System										
Forced Air	0.82	0.85	0.91	0.91	0.93	0.92	0.90	0.86	0.85	0.74
Baseboard	0.04	0.03	0.02	0.02	0.01	0.00	0.00	0.00	0.00	0.00
Heat Pump	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.03
Wall Furnace	0.01	0.01	0.00	0.01	0.00	0.00	0.01	0.00	0.01	0.00
Other	0.12	0.09	0.06	0.06	0.05	0.06	0.07	0.13	0.13	0.22
Fuel Type										
Gas	0.64	0.69	0.75	0.75	0.78	0.78	0.79	0.74	0.74	0.65
Electric	0.17	0.13	0.09	0.09	0.08	0.08	0.10	0.12	0.12	0.13
Electric and Gas	0.11	0.11	0.10	0.11	0.10	0.11	0.10	0.11	0.09	0.14
Other	0.09	0.08	0.07	0.05	0.04	0.03	0.02	0.03	0.04	0.08
Observations	4,036	2,362	3,174	4,046	3,499	2,823	2,097	1,614	821	576
(%)	(16)	(9)	(13)	(16)	(14)	(11)	(8)	(6)	(3)	(2)

Notes: The table reports the mean (standard deviation in parentheses) of the housing attributes for homes transacted with an assessment in Portland from 2018 to 2021. The statistics are separated by the home energy score.

Table A.3: Summary Statistics - Housing Attributes by Disclosure Status

	Disclose Assessment					
	Obtain Assessment			Publish Assessment		
Attribute	Yes	No	p-value	Yes	No	p-value
Home Energy Score	4.38	—	—	4.44	4.21	<0.01
	(2.42)	—		(2.42)	(2.39)	
Home Energy Score (Predicted)	4.38	3.67	<0.01	4.41	4.33	<0.01
	(1.70)	(1.64)		(1.72)	(1.67)	
Sales Price	585,801	636,372	<0.01	586,366	584,317	0.59
	(264,112)	(337,164)		(259,822)	(275,077)	
Year of Construction	1949	1969	<0.01	1949	1950	0.12
	(49)	(87)		(44)	(62)	
Sqft	2,096	2,303	<0.01	2,102	2,079	0.08
	(922)	(1,040)		(925)	(913)	
# of Bedrooms	3.22	3.53	<0.01	3.21	3.24	0.01
	(0.90)	(0.98)		(0.89)	(0.91)	
# of Baths	1.85	2.12	<0.01	1.85	1.86	0.23
	(0.77)	(0.83)		(0.77)	(0.76)	
# of Stories	2.09	1.96	<0.01	2.11	2.04	<0.01
	(0.79)	(0.71)		(0.80)	(0.79)	
# of Garages	1.17	1.62	<0.01	1.16	1.22	<0.01
	(0.83)	(0.92)		(0.82)	(0.86)	
Acres	0.16	0.29	<0.01	0.16	0.17	0.04
	(0.23)	(1.26)		(0.23)	(0.21)	
Property Condition						
New	0.02	0.12	<0.01	0.02	0.03	<0.01
Fixer	0.03	0.05	<0.01	0.03	0.04	<0.01
Remodel	0.24	0.18	<0.01	0.24	0.23	0.63
Restored	0.03	0.01	<0.01	0.03	0.03	0.01
Other	0.68	0.64	<0.01	0.69	0.67	0.01
Cooling System						
Central Air	0.40	0.48	<0.01	0.40	0.39	0.06
Heat Pump	0.05	0.05	0.25	0.05	0.04	<0.01
Wall / Window Unit	0.03	0.02	<0.01	0.03	0.04	0.01
Other	0.04	0.08	<0.01	0.04	0.05	0.08
None	0.12	0.08	<0.01	0.12	0.13	0.39
Missing	0.35	0.29	<0.01	0.35	0.35	0.28
Heating System						
Forced Air	0.88	0.89	<0.01	0.89	0.88	0.06
Baseboard	0.02	0.02	0.24	0.02	0.02	0.05
Heat Pump	0.01	0.01	0.98	0.01	0.01	0.57
Wall Furnace	0.01	0.01	0.73	0.01	0.01	0.69
Other	0.08	0.07	<0.01	0.08	0.08	0.37
Fuel Type						
Gas	0.73	0.74	0.49	0.74	0.71	<0.01
Electric	0.11	0.11	0.50	0.11	0.12	0.021
Electric and Gas	0.11	0.11	0.10	0.10	0.11	<0.01
Other	0.05	0.05	0.006	0.05	0.06	0.28
Observations	25,048	14,391		18,142	6,906	
(%)	(64)	(36)		(72)	(28)	

Notes: The table reports the mean (standard deviation in parentheses) of the housing attributes for the full sample of homes transacted in Portland from 2018 to 2021. The statistics are separated by disclosure status.

Table A.4: Estimates - Premium

	ln(Price)			
	(1)	(2)	(3)	(4)
Panel A				
Actual Score	0.0082***	0.0051***	0.0049***	0.0050***
	(0.0019)	(0.0009)	(0.0009)	(0.0009)
Observations	24,540	24,540	24,540	24,540
Adjusted R^2	0.70	0.84	0.84	0.86
F-test	2,291	5,653	3,363	3,219
Panel B				
Actual Score	0.0067***	0.0036***	0.0031***	0.0041***
	(0.0011)	(0.0012)	(0.0009)	(0.0011)
Publish	-0.0141**	-0.0050	-0.0059	-0.0079
	(0.0060)	(0.0061)	(0.0052)	(0.0062)
Actual Score × Publish	0.0021*	0.0020*	0.0023**	0.0013
	(0.0012)	(0.0098)	(0.0010)	(0.0012)
Observations	24,540	24,540	24,540	24,540
Adjusted R^2	0.70	0.84	0.84	0.86
F-test	2,556	44,081	38,342	33,015
Controls	✓	✓	✓	✓
Fixed Effect: Quarter		✓		
Fixed Effect: Zip Code		✓		
Fixed Effect: Quarter × Zip Code			✓	✓
Fixed Effect: Realtor				✓

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Notes: The table reports the estimates from the hedonic price models. *Actual Score* represents the score observed in the assessment. *Publish* is an indicator for publishing the assessment in real estate listings. Robust standard errors are reported in parentheses, clustered by zip code.

Table A.5: Estimates - Disclosure

	Disclose Assessment			
	(1)	(2)	(3)	(4)
Panel A: Obtain Assessment				
Predicted Score	0.1419***	0.0946***	0.0938***	0.0828***
	(0.0147)	(0.0072)	(0.0072)	(0.0061)
Observations	37,781	37,781	37,781	37,781
Adjusted R^2	0.24	0.42	0.42	0.52
F-test	806	145	111	304
Panel B: Publish Assessment				
Actual Score	0.0097***	0.0089***	0.0092***	0.0059***
	(0.0011)	(0.0011)	(0.0011)	(0.0009)
Observations	24,540	24,540	24,540	24,540
Adjusted R^2	0.01	0.02	0.02	0.36096
F-test	92	37	87	1,024
Panel C: Publish Assessment				
Difference	-0.0090***	-0.0085***	-0.0088***	-0.0057***
	(0.0012)	(0.0012)	(0.0013)	(0.0012)
Observations	24,540	24,540	24,540	24,540
Adjusted R^2	0.01	0.02	0.02	0.36
F-test	128	39	104	1,140
Controls	✓	✓	✓	✓
Fixed Effect: Quarter		✓		
Fixed Effect: Zip Code		✓		
Fixed Effect: Quarter × Zip Code			✓	✓
Fixed Effect: Realtor				✓

*p<0.1; **p<0.05; ***p<0.01

Notes: The table reports the estimates from the linear probability models for disclosure. *Predicted Score* represents the score predicted by the housing attributes. *Actual Score* represents the the score observed in the assessment. And, *Difference* is the difference in the predicted and actual score. Robust standard errors are reported in parentheses, clustered by zip code.

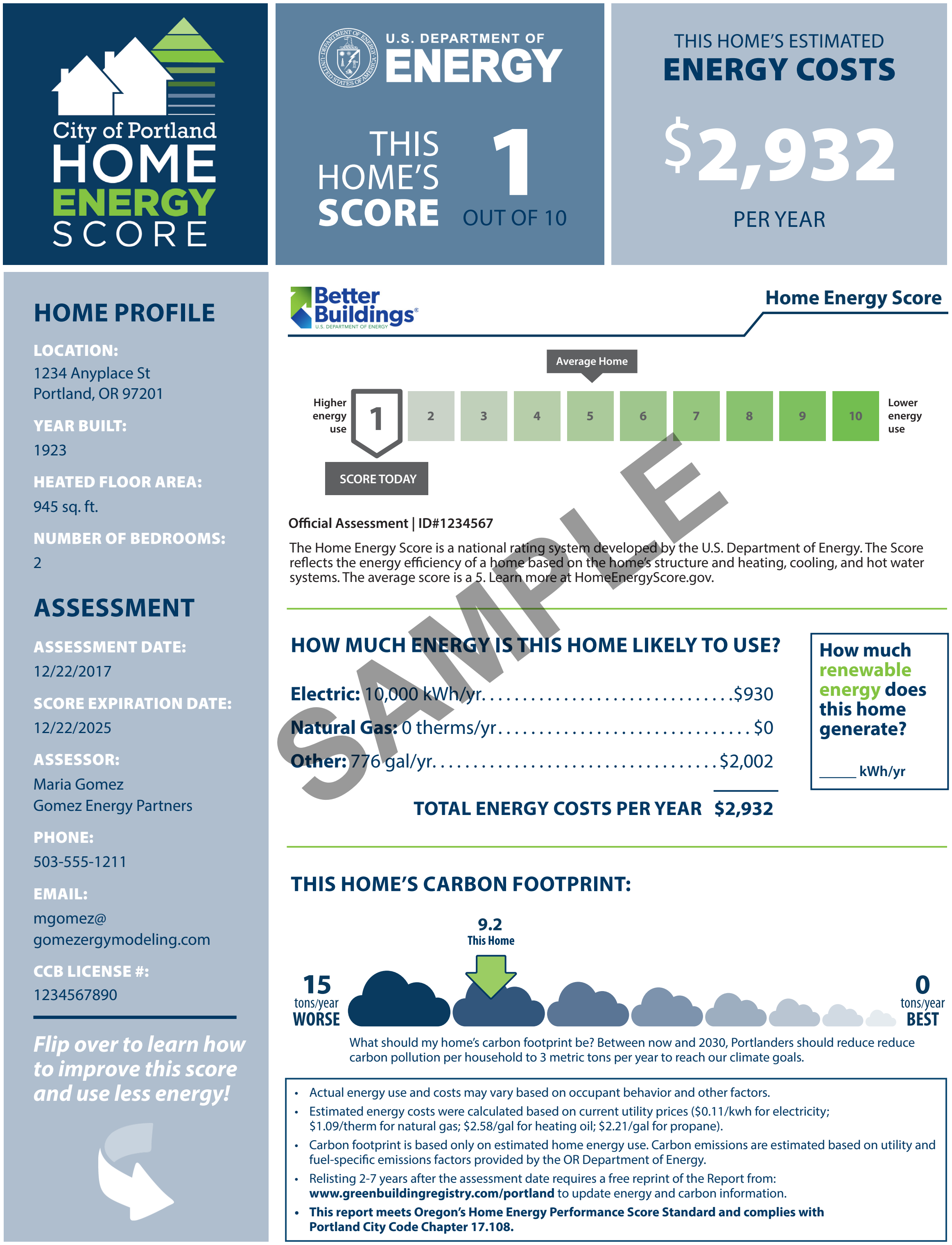
Table A.6: Estimates - Disclosure by Enforcement

	Disclose Assessment		
	(1)	(2)	(3)
Panel A: Obtain Assessment			
Predicted Score	0.1297***	0.0873***	0.0742***
	(0.0170)	(0.0069)	(0.0073)
Post	-0.2109***	-0.2359***	-0.2043***
	(0.0435)	(0.0374)	(0.0385)
Predicted Score × Post	0.0140**	0.0182***	0.0105*
	(0.0064)	(0.0052)	(0.0055)
Observations	18,343	18,343	18,343
Adjusted R^2	0.25	0.39	0.51
F-test	2,128	459	155
Panel B: Publish Assessment			
Actual Score	0.0042**	0.0034*	0.0003
	(0.0019)	(0.0020)	(0.0034)
Post	-0.1584***	-0.1583***	-0.1543***
	(0.0172)	(0.0173)	(0.0211)
Actual Score × Post	0.0108***	0.0108***	0.0099***
	(0.0029)	(0.0029)	(0.0035)
Observations	11,817	11,817	11,817
Adjusted R^2	0.02	0.03	0.41
F-test	1,076	1,110	374
Panel C: Publish Assessment			
Difference	-0.0037	-0.0033	-0.0008
	(0.0028)	(0.0029)	(0.0040)
Post	-0.1109***	-0.1110***	-0.1110***
	(0.0092)	(0.0091)	(0.0105)
Difference × Post	-0.0126***	-0.0127***	-0.0108**
	(0.0042)	(0.0042)	(0.0049)
Observations	11,817	11,817	11,817
Adjusted R^2	0.02	0.03	0.41
F-test	845	882	84
Controls	✓	✓	✓
Fixed Effect: Zip Code		✓	✓
Fixed Effect: Realtor			✓

*p<0.1; **p<0.05; ***p<0.01

Notes: The table reports the estimates from the linear probability models for disclosure. *Predicted Score* represents the score predicted by the housing attributes. *Actual Score* represents the the score observed in the assessment. And, *Difference* is the difference in the predicted and actual score.   is an indicator for the period without enforcement during the pandemic. Robust standard errors are reported in parentheses, clustered by zip code.

Figure A.1: Sample Home Energy Score Assessment



City of Portland HOME ENERGY SCORE

U.S. DEPARTMENT OF ENERGY

THIS HOME'S SCORE 1 OUT OF 10

THIS HOME'S ESTIMATED ENERGY COSTS

$2,932 PER YEAR

HOME PROFILE

LOCATION:
1234 Anyplace St
Portland, OR 97201

YEAR BUILT:
1923

HEATED FLOOR AREA:
945 sq. ft.

NUMBER OF BEDROOMS:
2

ASSESSMENT

ASSESSMENT DATE:
12/22/2017

SCORE EXPIRATION DATE:
12/22/2025

ASSESSOR:
Maria Gomez
Gomez Energy Partners

PHONE:
503-555-1211

EMAIL:
mgomez@
gomezergymodeling.com

CCB LICENSE #:
1234567890

Flip over to learn how to improve this score and use less energy!

Better Buildings — U.S. DEPARTMENT OF ENERGY

Home Energy Score

Average Home

Higher energy use 1 2 3 4 5 6 7 8 9 10 Lower energy use

SCORE TODAY

SAMPLE

Official Assessment | ID#1234567

The Home Energy Score is a national rating system developed by the U.S. Department of Energy. The Score reflects the energy efficiency of a home based on the home's structure and heating, cooling, and hot water systems. The average score is a 5. Learn more at HomeEnergyScore.gov.

HOW MUCH ENERGY IS THIS HOME LIKELY TO USE?

Electric: 10,000 kWh/yr. $930

Natural Gas: 0 therms/yr. $0

Other: 776 gal/yr. $2,002

TOTAL ENERGY COSTS PER YEAR $2,932

How much renewable energy does this home generate?

____ kWh/yr

THIS HOME'S CARBON FOOTPRINT:

9.2 This Home

15 tons/year WORSE

0 tons/year BEST

What should my home's carbon footprint be? Between now and 2030, Portlanders should reduce reduce carbon pollution per household to 3 metric tons per year to reach our climate goals.

- Actual energy use and costs may vary based on occupant behavior and other factors.
- Estimated energy costs were calculated based on current utility prices ($0.11/kwh for electricity; $1.09/therm for natural gas; $2.58/gal for heating oil; $2.21/gal for propane).
- Carbon footprint is based only on estimated home energy use. Carbon emissions are estimated based on utility and fuel-specific emissions factors provided by the OR Department of Energy.
- Relisting 2-7 years after the assessment date requires a free reprint of the Report from: **www.greenbuildingregistry.com/portland** to update energy and carbon information.
- **This report meets Oregon's Home Energy Performance Score Standard and complies with Portland City Code Chapter 17.108.**

Figure A.1 (cont'd)

Score today:	Score with improvements:*	Estimated **energy savings** with improvements:	Estimated **carbon reduction** with improvements:
1	9	$1,672 PER YEAR	57% PER YEAR

TACKLE ENERGY WASTE TODAY!

Enjoy the rewards of a comfortable, energy efficient home that saves you money.

- [x] Get your home energy assessment. Done!
- [ ] Choose energy improvements from the list of recommendations below.

  Need help deciding what to do first? Non-profit Enhabit offers free 15-minute phone consults with expert home advisors. Call 855-870-0049.
- [ ] Select a contractor (or two, for comparison) and obtain bids.

  Checkout **www.energytrust.org/findacontractor** or call toll free **1-866-368-7878**.
- [ ] Explore financing options at **www.enhabit.org** or **www.energytrust.org**.

* PRACTICAL ENERGY IMPROVEMENTS | COMPLETE NOW OR LATER

To achieve the "score with improvements," all recommended improvements listed below must be completed. Improvements all have a simple payback of ten years or less and may be eligible for mortgage financing. For a more detailed explanation of costs and payback, please get a bid from a contractor.

FEATURE	TODAY'S CONDITION	RECOMMENDED IMPROVEMENTS
Attic insulation	Ceiling insulated to R-0	Insulate to R-38 or R-49 if code requires it
Attic insulation	Ceiling insulated to R-19	Insulate to R-38 or R-49 if code requires it
Duct insulation	Un-insulated	Insulate to R-8
Duct sealing	Un-sealed	Reduce leakage to a maximum of 10% of total airflow
Envelope/Air Sealing	Not professionally air sealed	Professionally air seal
Heating Equipment	Oil furnace 60% AFUE	Upgrade to ENERGY STAR
Heating Equipment	Natural Gas/Propane Furnace	Upgrade to ENERGY STAR
Wall insulation	Insulated to R-0	Fully insulate wall cavities
Water Heater	Standard electric tank	Upgrade to ENERGY STAR, minimum 2.76 EF (Energy Factor)
Windows	Multiple types	Upgrade to ENERGY STAR
Air Conditioner	None	
Basement wall insulation	None	
Floor insulation	Insulated to R-0	
Foundation wall insulation	None	
Skylights	None	
Cathedral ceiling	None	
Solar PV	None	Visit www.energytrust.org/solar to learn more

YOU CAN DO IT YOURSELF!

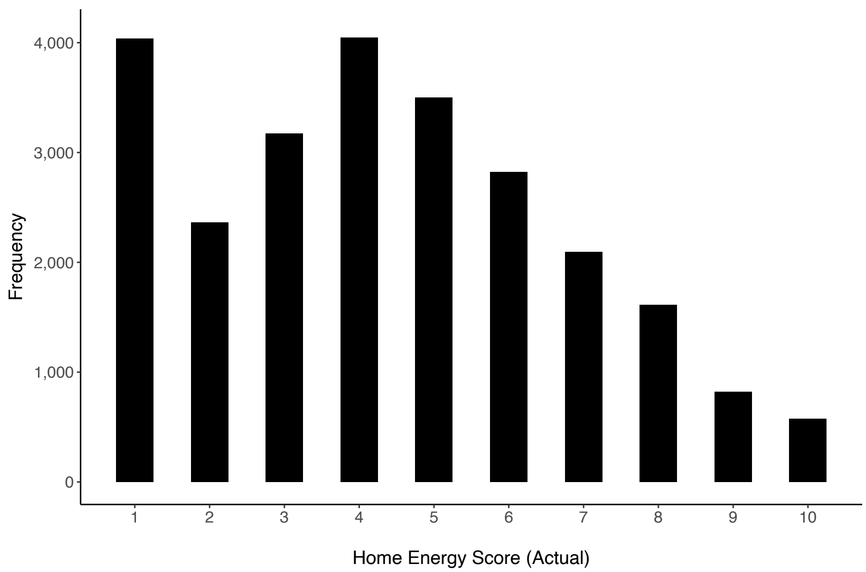
Looking for low-cost ways to cut energy waste, boost your comfort and lower your energy bills? Visit the resources below to learn about easy changes you can make today:

www.energytrust.org/tips and **www.communityenergyproject.org/services**

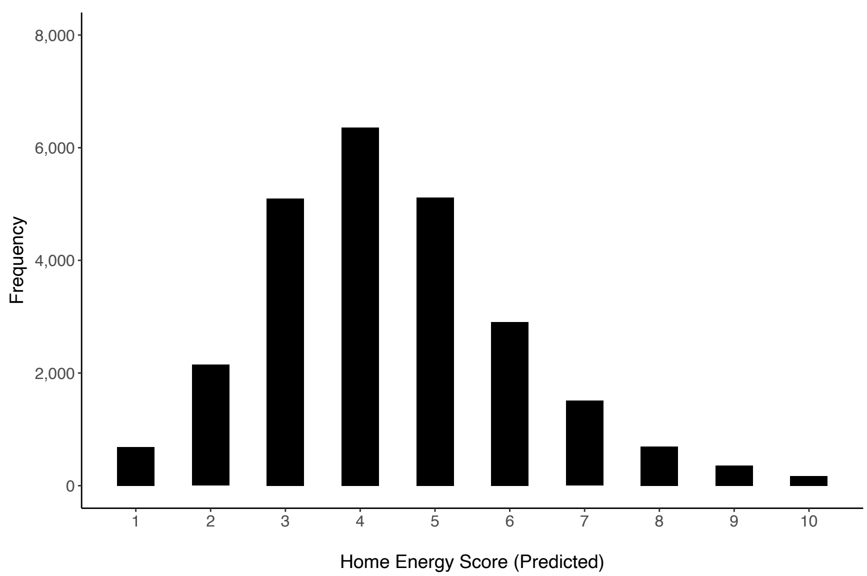
Notes: The figure presents a sample report of the home energy score assessment.

Figure A.2: Distribution - Home Energy Score

(a) Actual Score



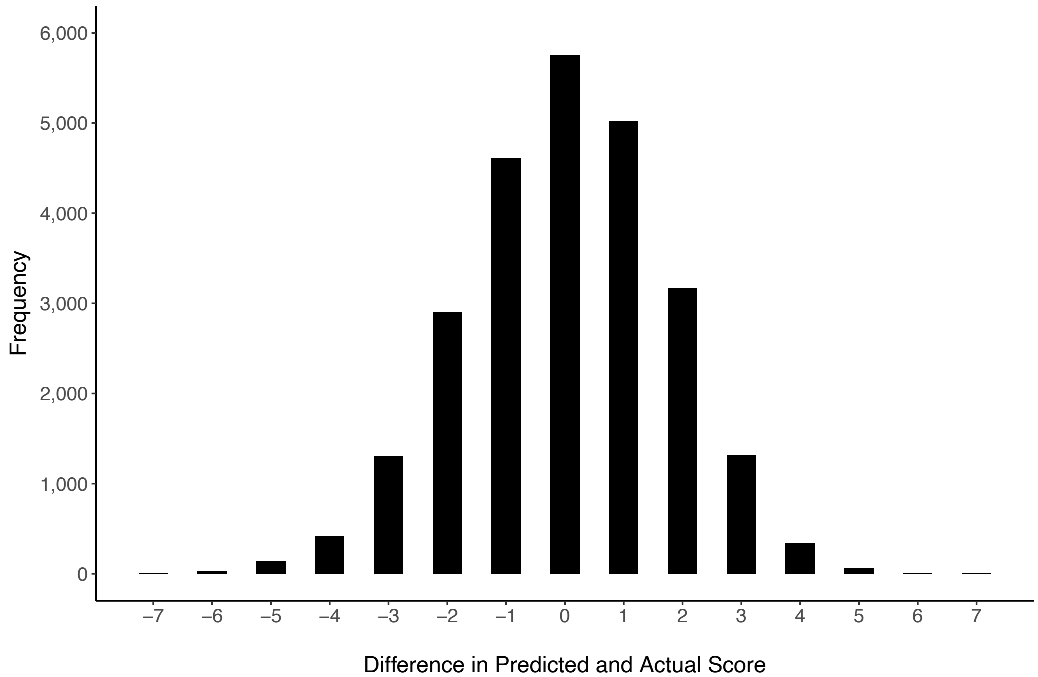
(b) Predicted Score



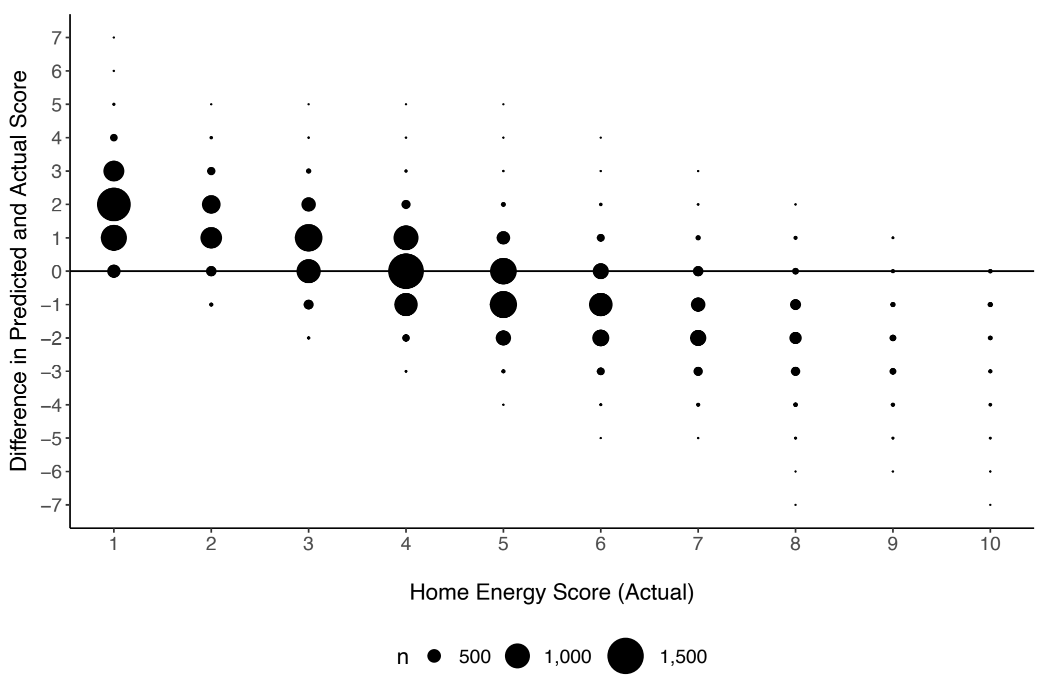
Notes: The figure presents the distribution of the home energy score. Panel (a) and (b) present the results for the actual and predicted score, respectively.

Figure A.3: Distribution - Difference in the Predicted and Actual Score

(a) Distribution

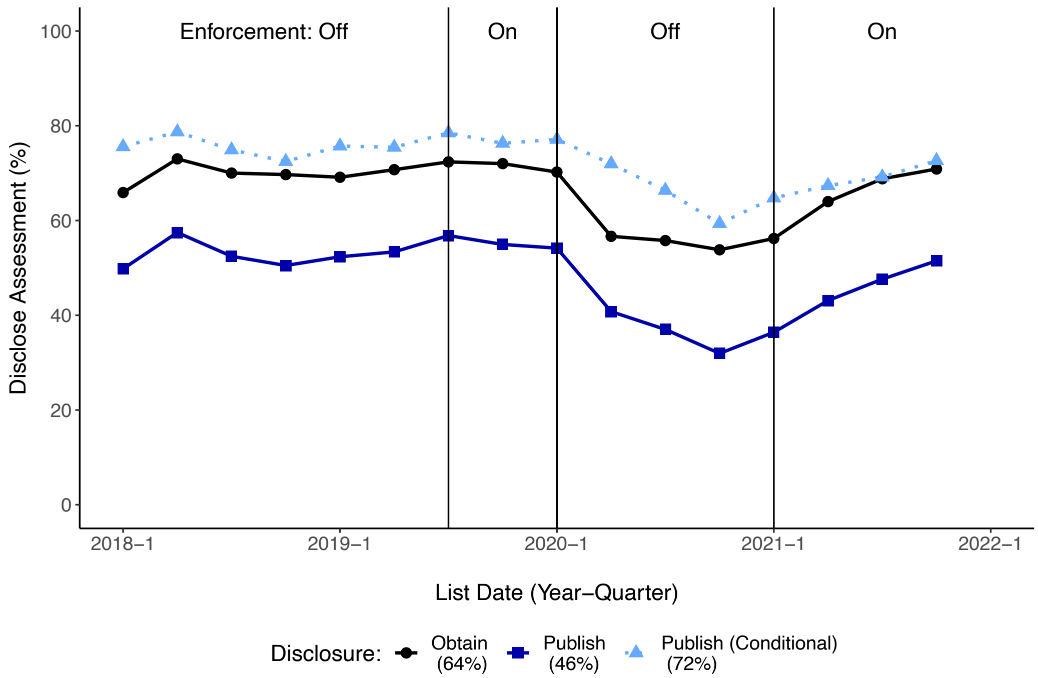


(b) Distribution by Home Energy Score



Notes: The figure presents the distribution of the the difference in the predicted and actual score. Panel (a) presents the aggregate distribution, and panel (b) presents the distribution separated by the actual score.

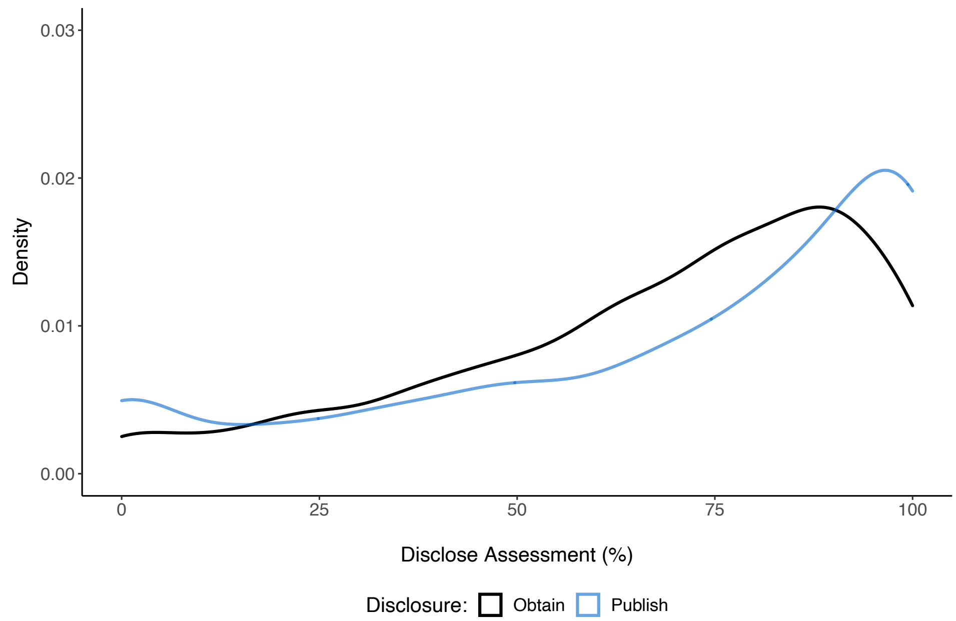
Figure A.4: Compliance Rate



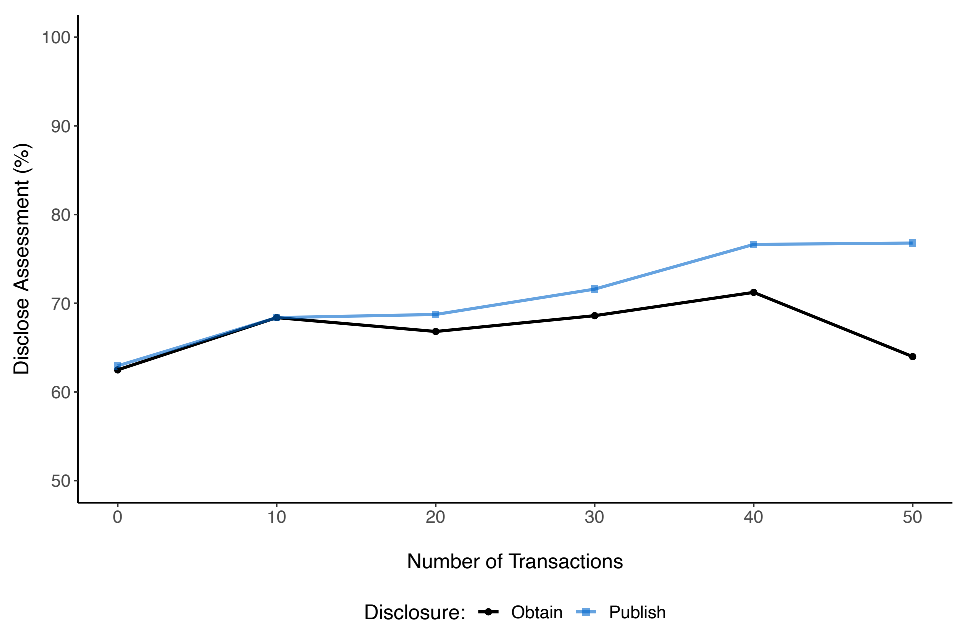
Notes: The figure plots the compliance rate throughout the duration of the program. *Obtain* and *Publish* represent obtaining and publishing an assessment, respectively. *Publish (Conditional)* represents publishing the assessment conditional on obatining an assessment. The figure also documents the periods of enforcement.

Figure A.5: Realtors

(a) Density Plot of Compliance



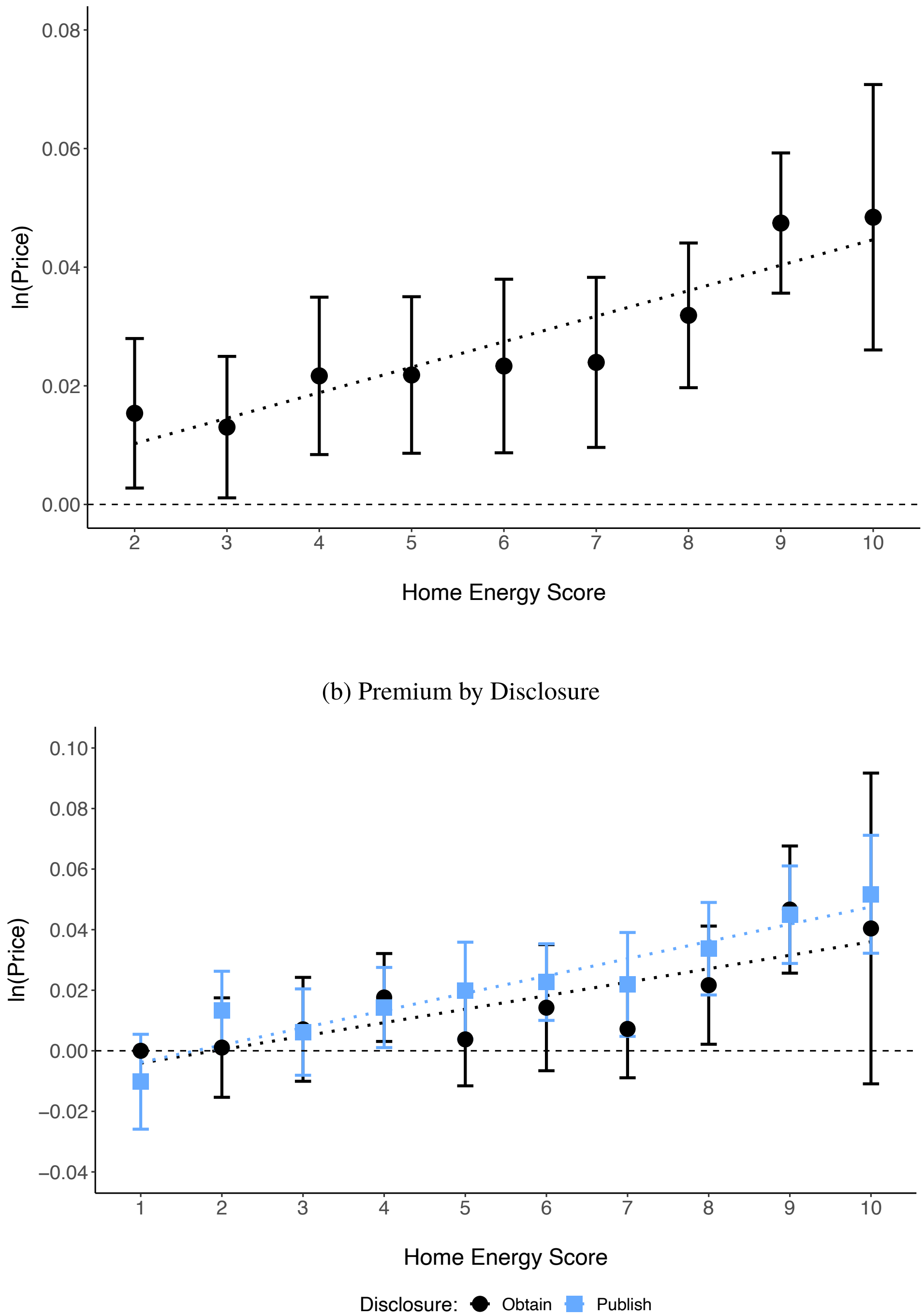
(b) Compliance by Number of Transactions



Notes: Panel (a) is the density plot of compliance for realtors within the top quartile of transactions (8^{+}). Panel (b) plots the average compliance rate among realtors for designated bins of transactions. The 0 bin includes realtors with 1-9 transactions. The 10 bin includes realtors with 10-19 transactions and so on. The 50 bin includes all realtors with 50 or more transactions.

Figure A.6: Estimates - Premium (Binary)

(a) Premium

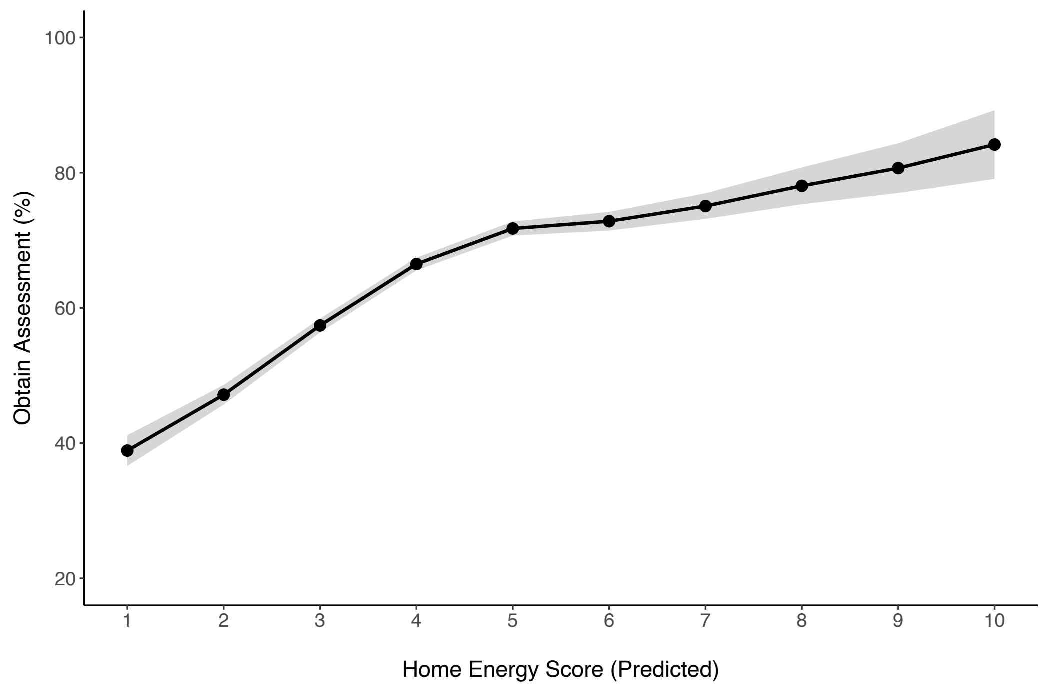


(b) Premium by Disclosure

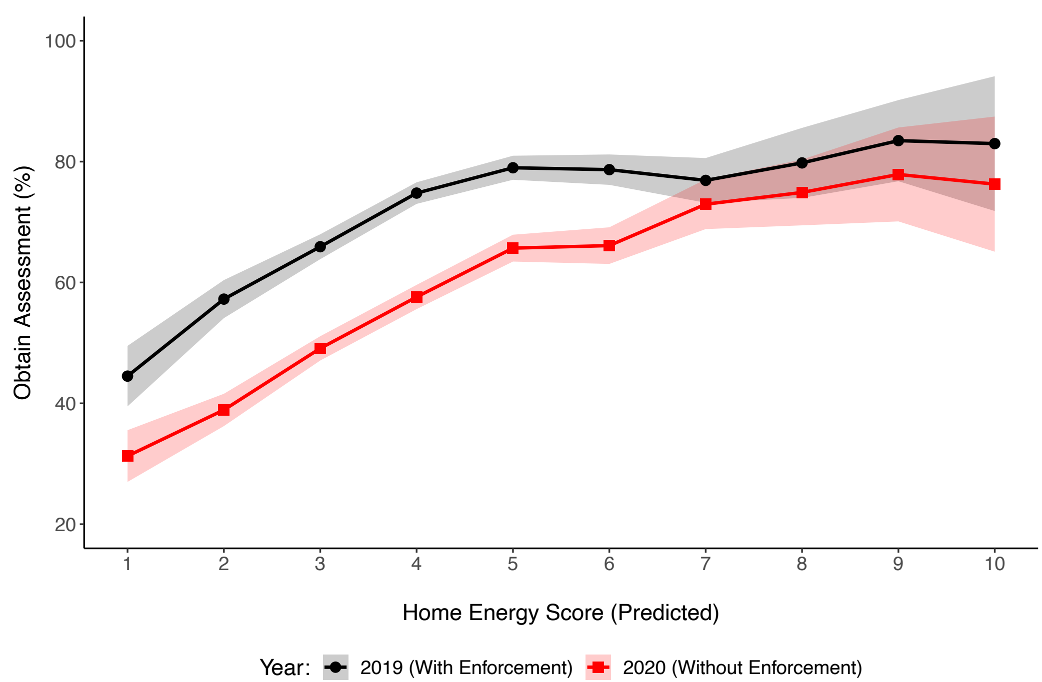
Notes: Panel (a) plots the estimates of the premium for the score by the individual scores. The reference case is a score of 1. Meanwhile, panel (b) plots the estimates of the premium separated by disclosure status.

Figure A.7: Compliance Rate by Home Energy Score

(a) Obtain Assessment



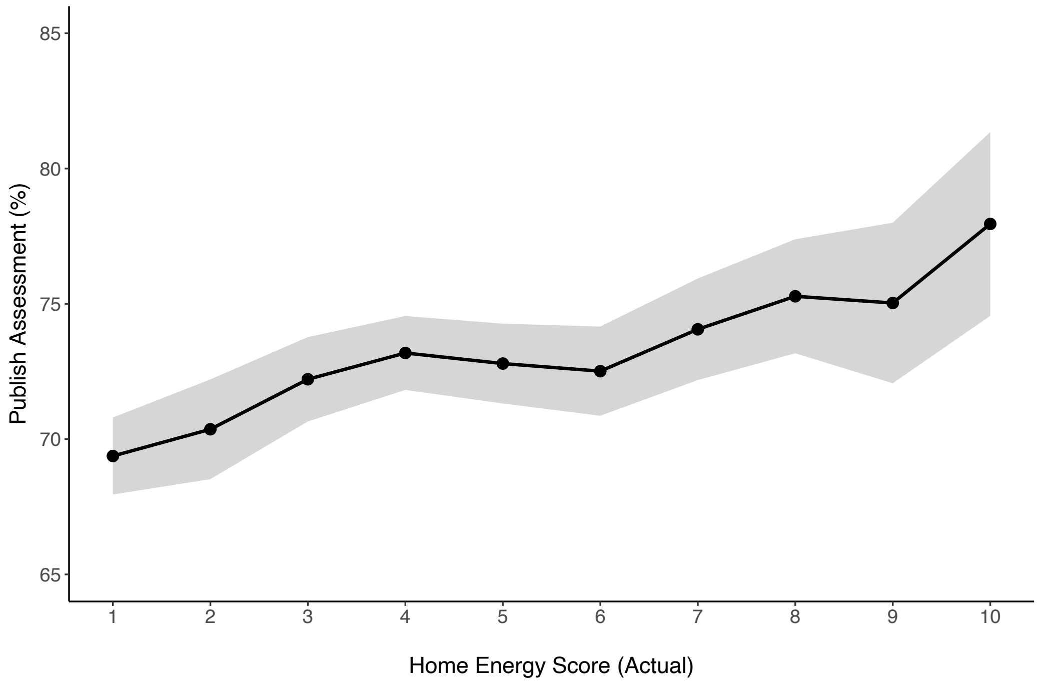
(b) Obtain Assessment by Enforcement



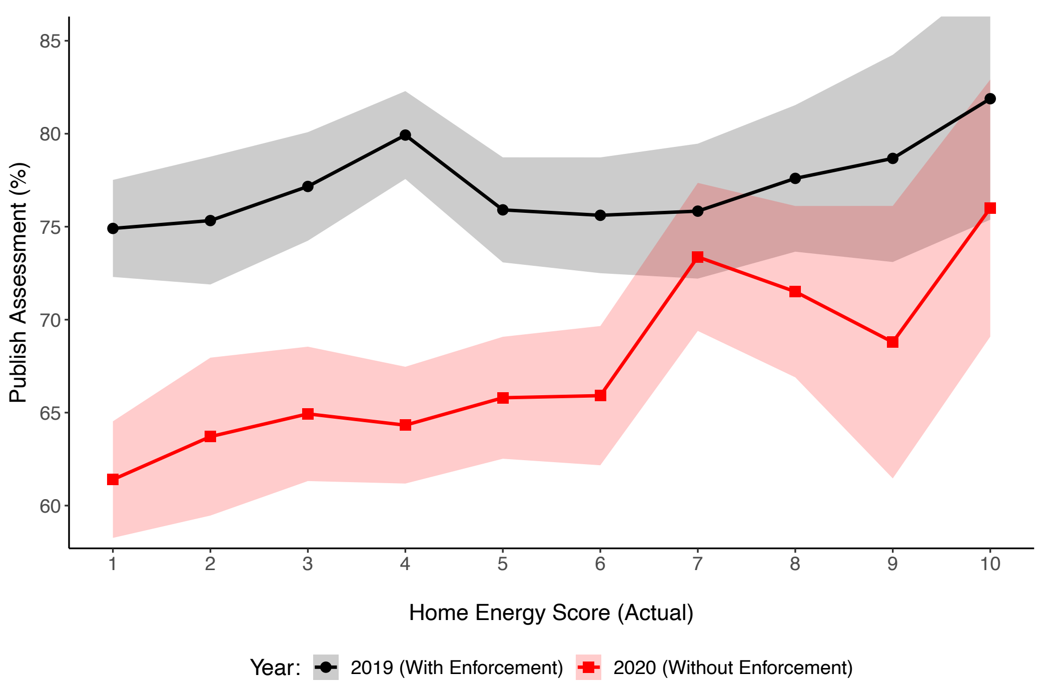
Notes: Panel (a) plots the share of sellers that obtain an assessment separated by the predicted score. The 95% confidence interval is displayed in gray. Panel (b) further separates by periods of enforcement. The 95% confidence intervals are displayed in gray and red for 2019 and 2020, respectively.

Figure A.7 (cont'd)

(c) Publish Assessment (Actual)



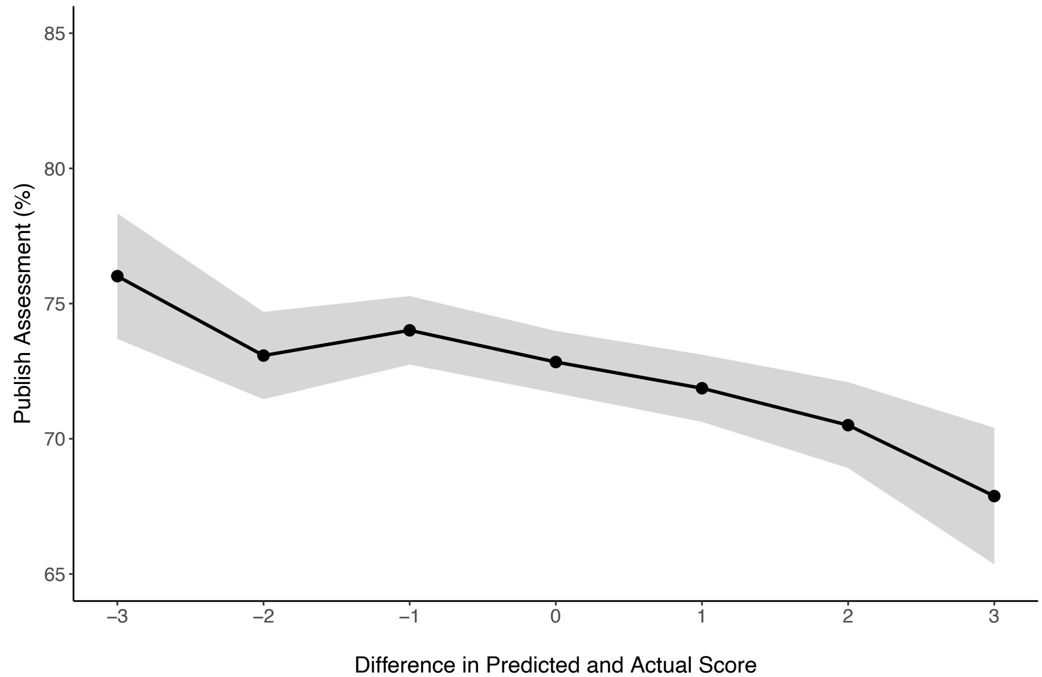
(d) Publish Assessment by Enforcement (Actual)



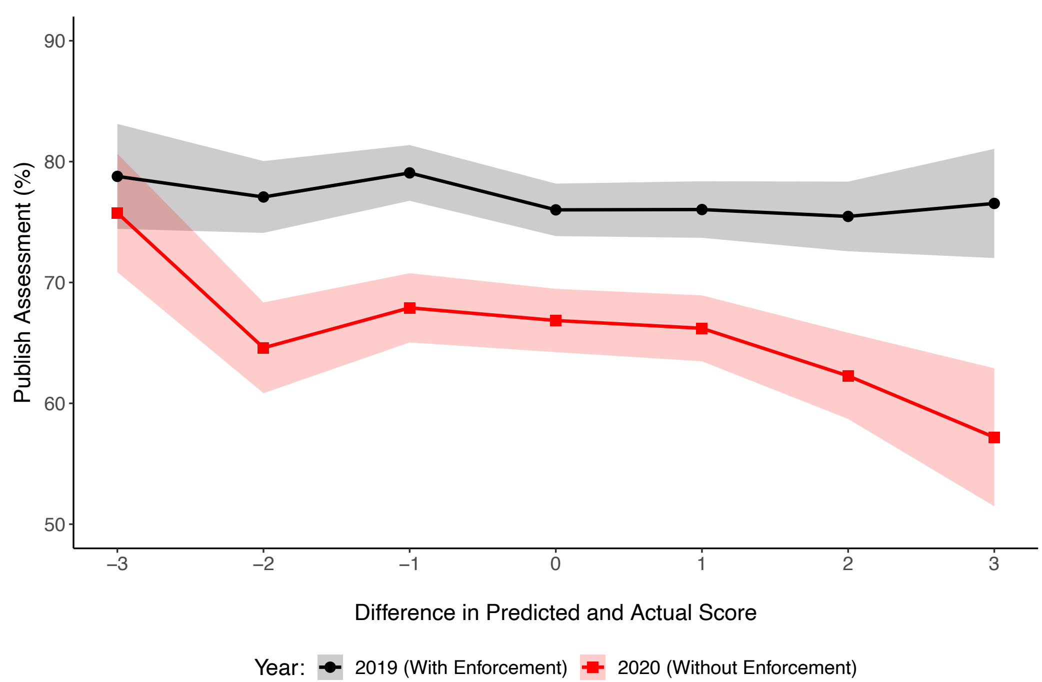
Notes: Panel (c) plots the share of sellers that publish an assessment conditional on obtaining an assessment separated by the actual score. The 95% confidence interval is displayed in gray. Panel (d) further separates by periods of enforcement. The 95% confidence intervals are displayed in gray and red for 2019 and 2020, respectively.

Figure A.7 (cont'd)

(e) Publish Assessment (Difference)



(f) Publish Assessment by Enforcement (Difference)

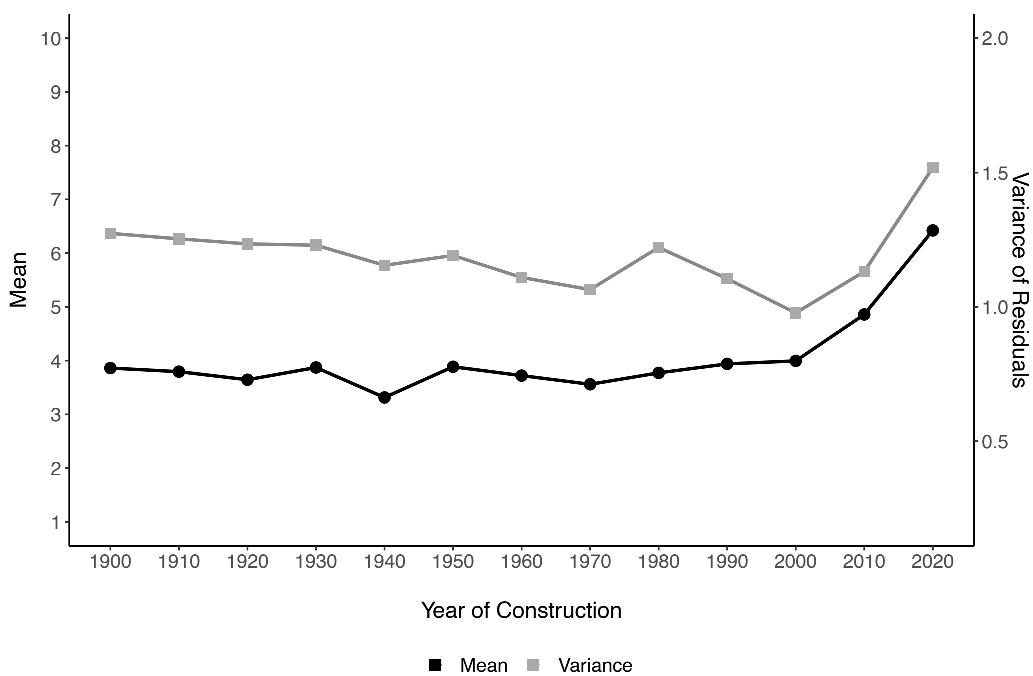


Notes: Panel (e) plots the share of sellers that publish an assessment conditional on obtaining an assessment separated by the difference in the predicted and actual score. The 95% confidence interval is displayed in gray. Panel (f) further separates by periods of enforcement. The 95% confidence intervals are displayed in gray and red for 2019 and 2020, respectively.

Figure A.8: Home Energy Score by Housing Attributes

(a) Actual Score by Year of Construction

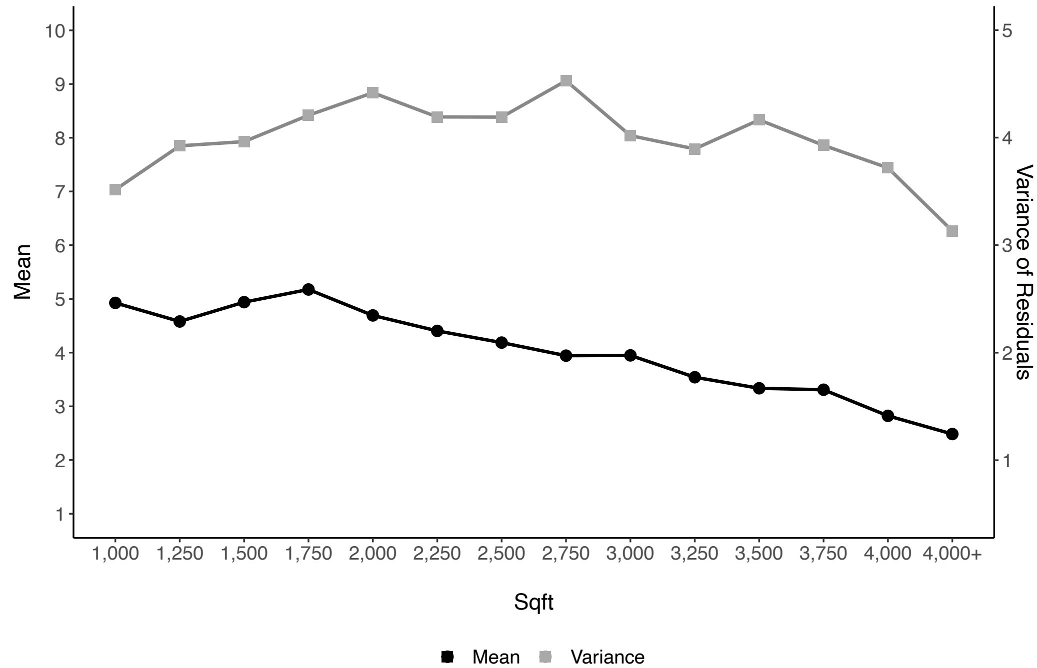
(b) Predicted Score by Year of Construction



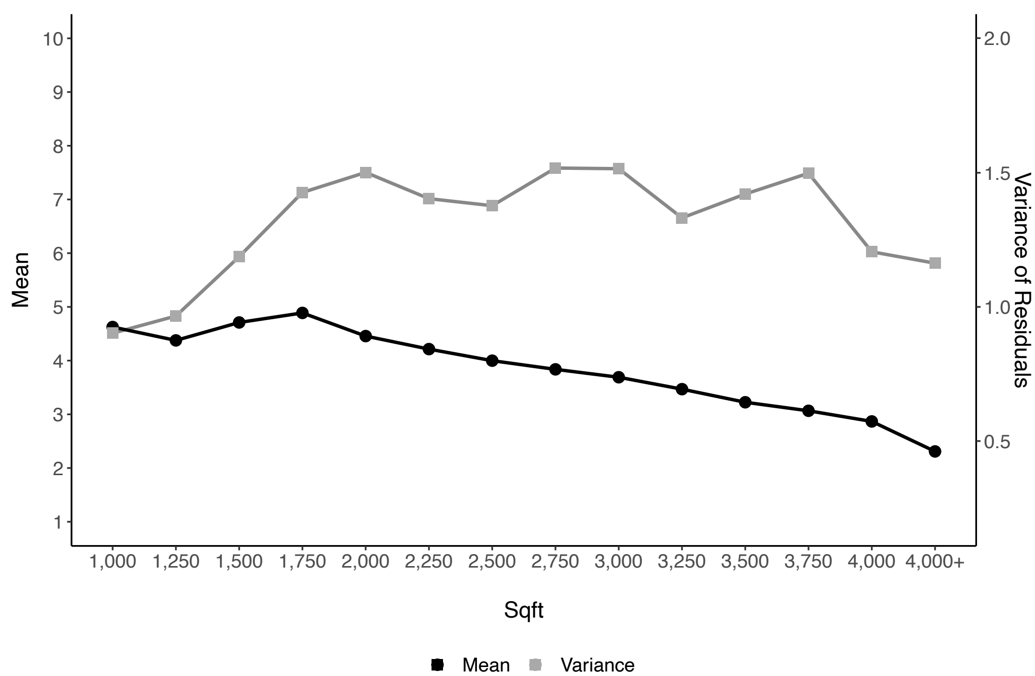
Notes: The figure plots the mean home energy score (black) and variance (gray) of residuals separated by housing attributes. Panels (a) and (b) present the results for the actual and predicted score by year of construction.

Figure A.8 (cont'd)

(c) Actual Score by Sqft



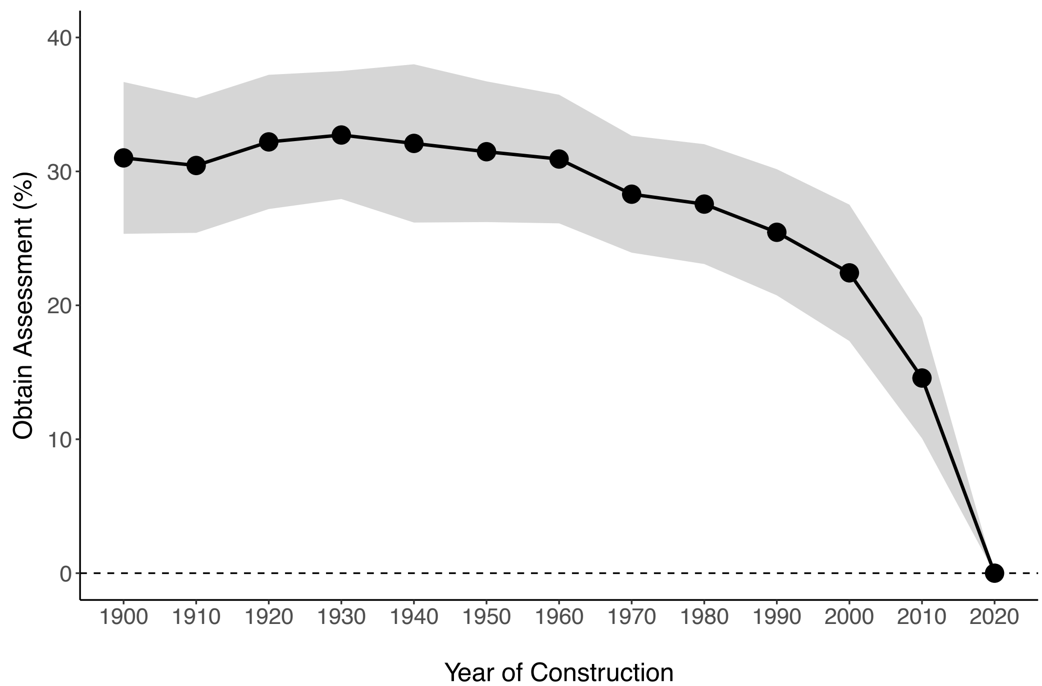
(d) Predicted Score by Sqft



Notes: The figure plots the mean home energy score (black) and variance (gray) of residuals separated by housing attributes. Panels (c) and (d) present the results for the actual and predicted score by sqft.

Figure A.9: Estimates - Disclosure by Housing Attributes

(a) Obtain Assessment by Year of Construction

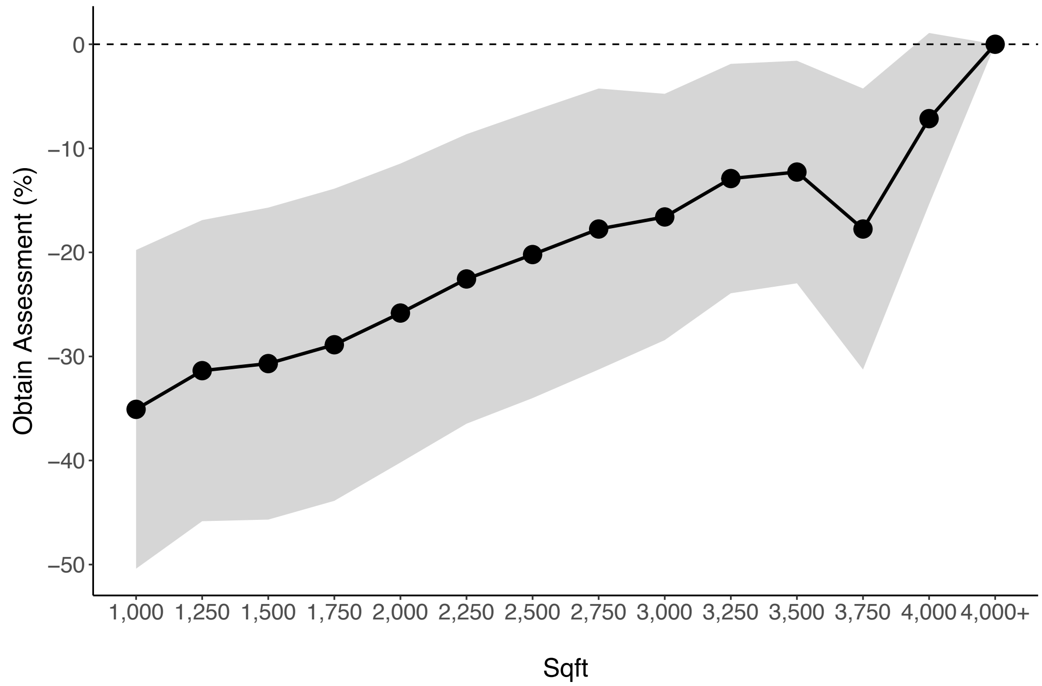


(b) Publish Assessment by Year of Construction

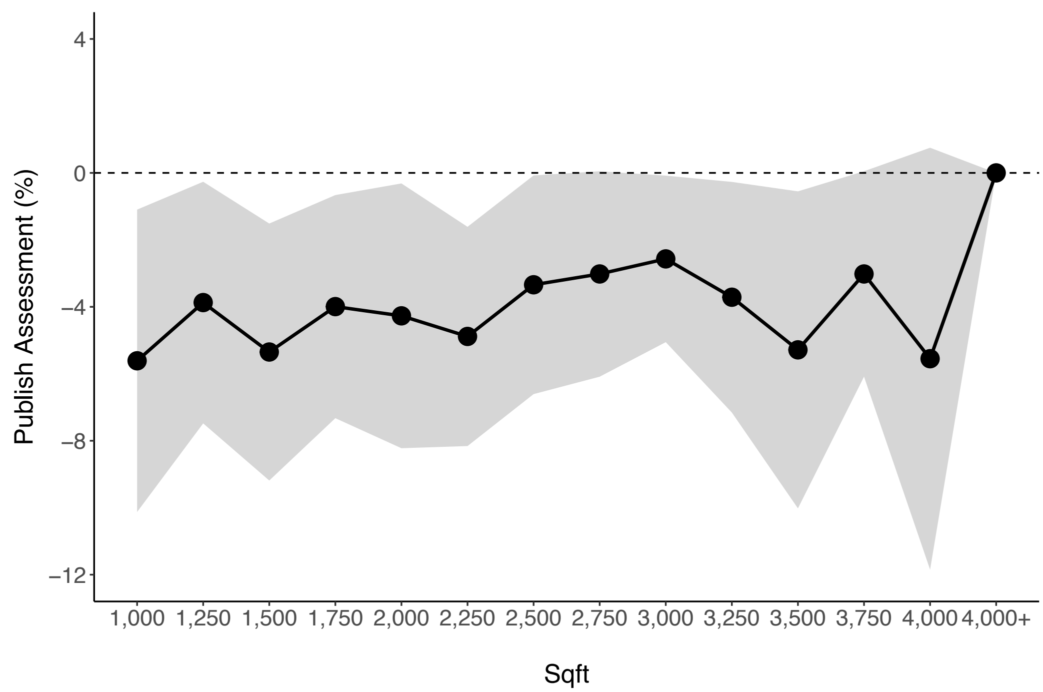
Notes: The figure plots the estimates for disclosure separated by housing attributes. Panels (a) and (b) plots the estimates for obtaining and publishing an assessment by year of construction.

Figure A.9 (cont'd)

(c) Obtain Assessment by Sqft



(d) Publish Assessment by Sqft



Notes: The figure plots the estimates for disclosure separated by housing attributes. Panels (c) and (d) plots the estimates for obtaining and publishing an assessment by sqft.

THEORY

In this section, I derive the comparative static for the expected cost of non-compliance in stage 1 where a seller decides whether to obtain an assessment. The following information is used to determine the sign of the the comparative static:

1. $\dfrac{\partial \theta^*}{\partial \pi v} < 0$ (This result is derived in stage 2)
2. $\dfrac{\partial (1 - F(\theta^*))}{\partial \theta^*} < 0$ (By definition of the CDF)
3. $\dfrac{\partial P_o(\bar{\theta_o})}{\partial \bar{\theta_o}} > 0$ and $\dfrac{\partial P_p(\bar{\theta_p})}{\partial \bar{\theta_p}} > 0$ (Since $P_o(\theta)$ and $P_p(\theta)$ are increasing functions)
4. $\dfrac{\partial \bar{\theta_o}}{\partial \theta^*} > 0$ and $\dfrac{\partial \bar{\theta_p}}{\partial \theta^*} > 0$ (By definition of the conditional expectation)

Comparative static for the expected cost of non-compliance (πv):

$$\frac{\partial LHS}{\partial \pi v} = F(\theta^*)\frac{\partial P_o(\bar{\theta}_o)}{\partial \bar{\theta}_o}\frac{\partial \bar{\theta}_o}{\partial \theta^*}\frac{\partial \theta^*}{\partial \pi v} + P_o(\bar{\theta}_o)\frac{\partial F(\theta^*)}{\partial \theta^*}\frac{\partial \theta^*}{\partial \pi v} \quad +$$

$$(1 - F(\theta^*))\frac{\partial P_p(\bar{\theta}_p)}{\partial \bar{\theta}_p}\frac{\partial \bar{\theta}_p}{\partial \theta^*}\frac{\partial \theta^*}{\partial \pi v} + P_p(\bar{\theta}_p)\frac{\partial(1 - F(\theta^*))}{\partial \theta^*}\frac{\partial \theta^*}{\partial \pi v} \quad +$$

$$(1 - F(\theta^*))\frac{\pi v}{\partial \pi v} + \pi v\frac{\partial(1 - F(\theta^*))}{\partial \theta^*}\frac{\partial \theta^*}{\partial \pi v}$$

$$= \underbrace{(1 - F(\theta^*))}_{\text{"Direct Effect"}} +$$

$$\underbrace{\frac{\partial(1 - F(\theta^*))}{\partial \theta^*}\frac{\partial \theta^*}{\partial \pi v}\Big[P_p(\bar{\theta}_p) - P_o(\bar{\theta}_o) + \pi v\Big]}_{\text{"Publish Effect"}} \quad +$$

$$\underbrace{F(\theta^*)\Big[\frac{\partial P_o(\bar{\theta}_o)}{\partial \bar{\theta}_o}\frac{\partial \bar{\theta}_o}{\partial \theta^*}\frac{\partial \theta^*}{\partial \pi v}\Big] \quad + \quad (1 - F(\theta^*))\Big[\frac{\partial P_p(\bar{\theta}_p)}{\partial \bar{\theta}_p}\frac{\partial \bar{\theta}_p}{\partial \theta^*}\frac{\partial \theta^*}{\partial \pi v}\Big]}_{\text{"Price Effect"}}$$

$$= \underbrace{(+)}_{\text{"Direct Effect"}} \quad +$$

$$\underbrace{(-)(-)\Big[(+) - (+) + (+)\Big]}_{\text{"Publish Effect"}} \quad +$$

$$\underbrace{(+)\Big[(+)(+)(-)\Big] + (+)\Big[(+)(+)(-)\Big]}_{\text{"Price Effect"}}$$

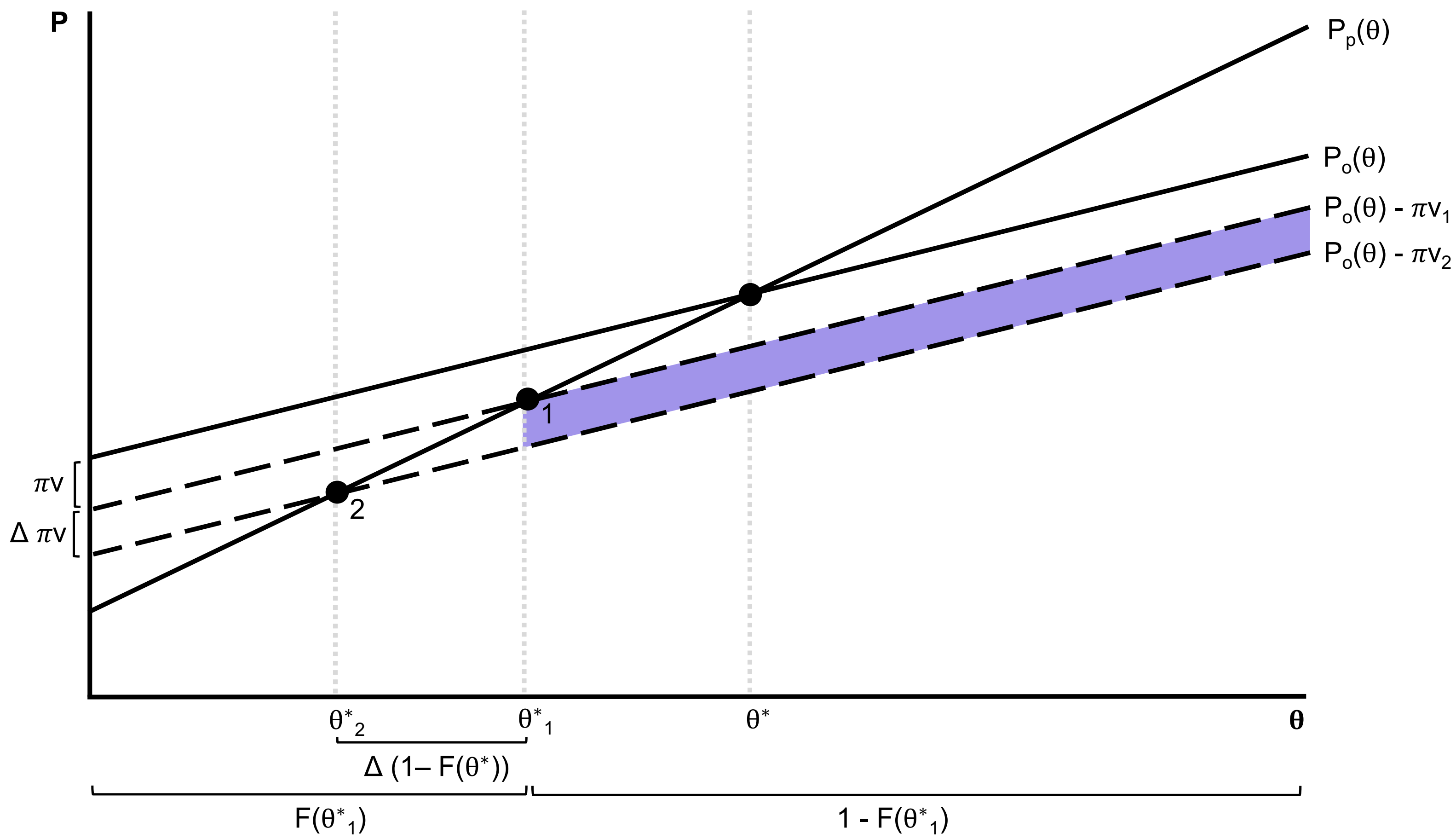
Since $P_p(\bar{\theta}_p) > P_o(\bar{\theta}_o)$ then $P_p(\bar{\theta}_p) - P_o(\bar{\theta}_o) > 0$

$$= \underbrace{(+)}_{\text{"Direct Effect"}} + \underbrace{(+)}_{\text{"Publish Effect"}} + \underbrace{(-)}_{\text{"Price Effect"}}$$

$$\gtreqless \quad 0$$

Figure A.10: Change in the Expected Cost of Non-Compliance

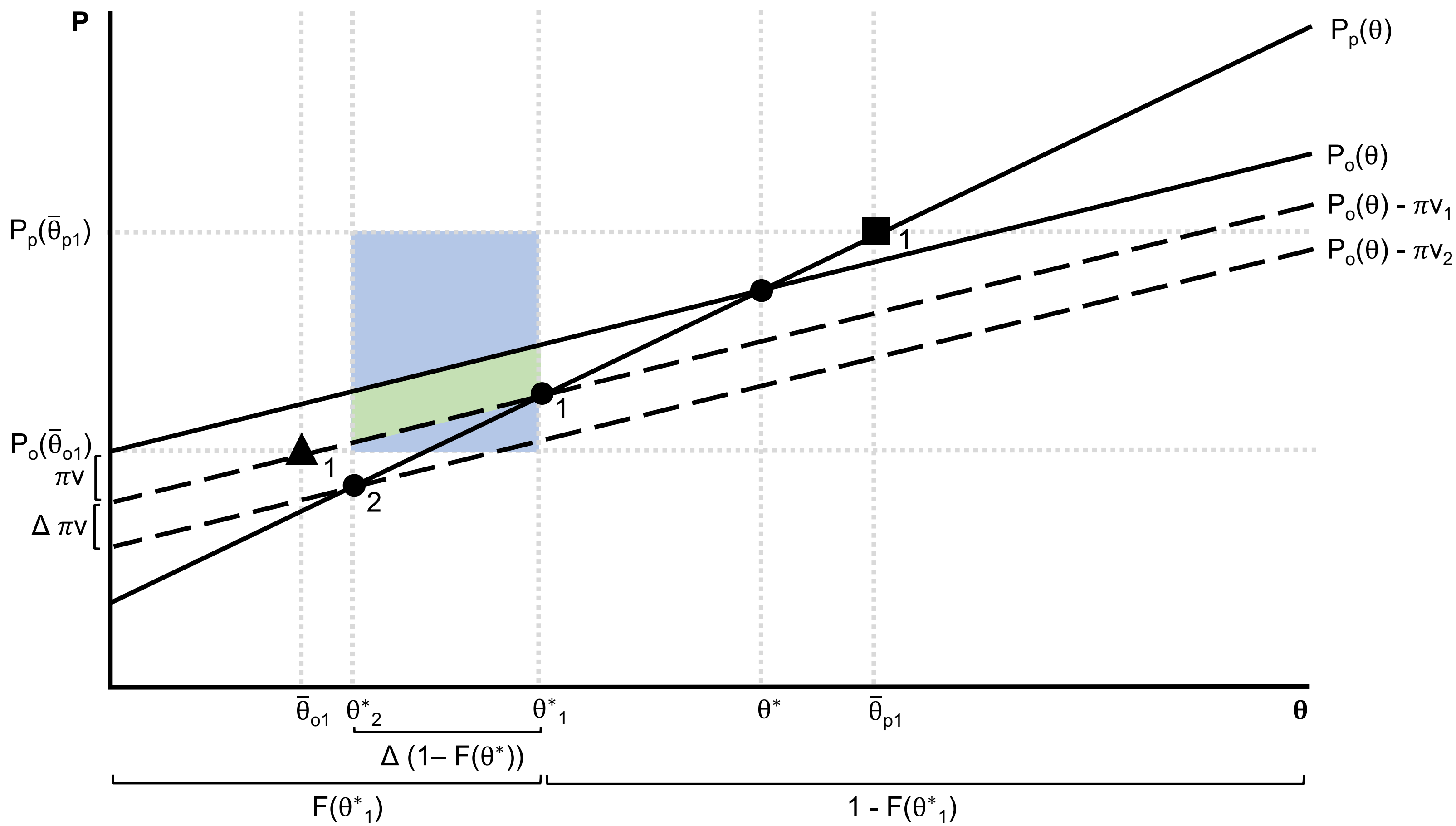
(a) Direct Effect



Notes: The figure illustrates a change in the expected cost of non-compliance. Panel (a) is the direct effect. The purple shaded area measures the change in avoided cost of non-compliance, weighted by the initial probability of publishing the assessment. This area is positive

Figure A.10 (cont'd)

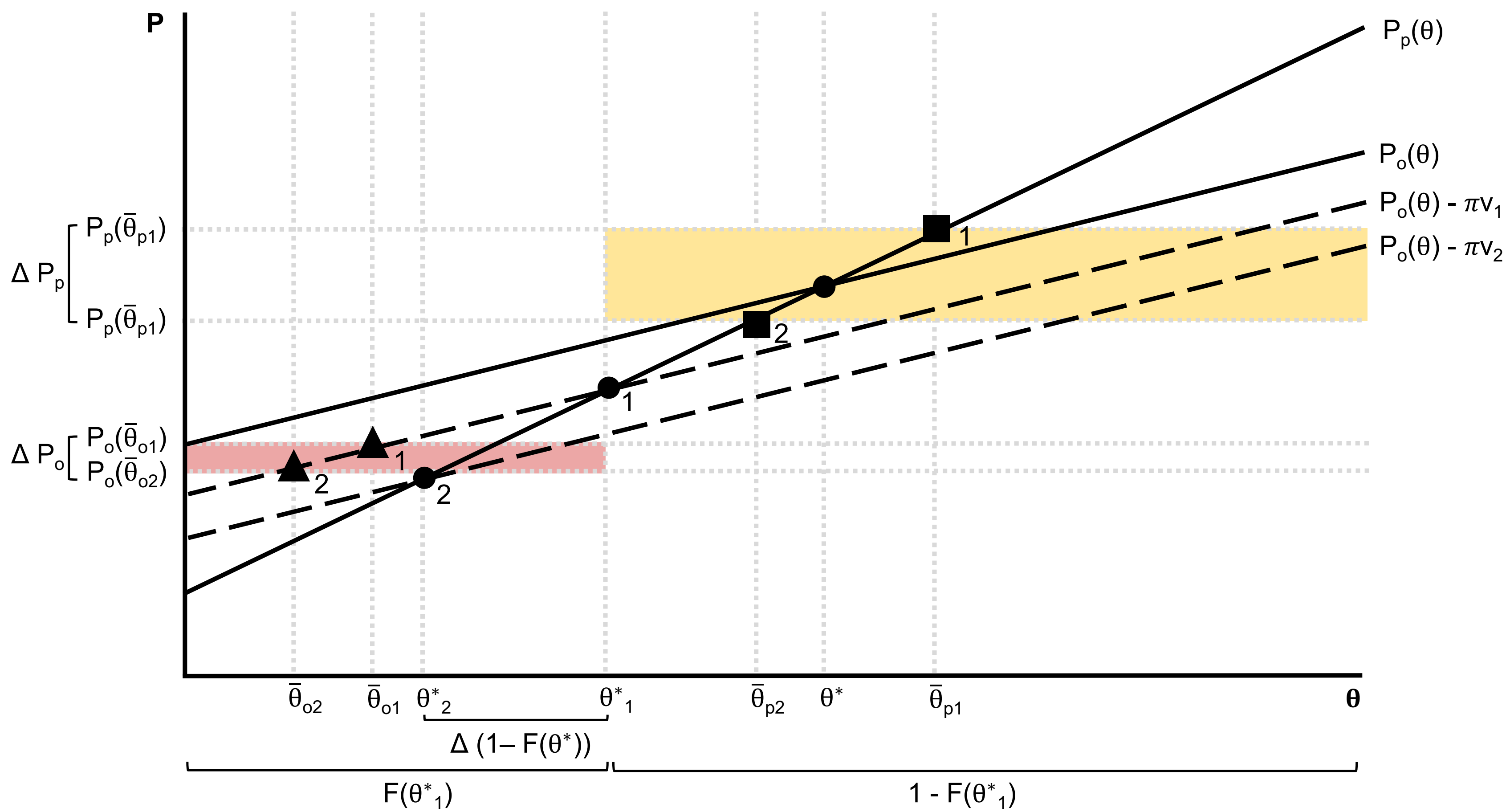
(b) Publish Effect



Notes: Panel (b) is the publish effect. The green shaded area measures the change in the probability of publishing the assessment in terms of avoided costs. Meanwhile, the blue shaded area measures the change in the probability of publishing the assessment in terms of the price gap in expected prices. Both of these areas are positive.

Figure A.10 (cont'd)

(c) Price Effect



Notes: Panel (c) is the price effect. The red and yellow shaded areas measure the change in expected prices, weighted by the initial probabilities. Both of these shaded areas are negative.

APPENDIX B

CHAPTER 2 APPENDIX

Table B.1: Summary Statistics - Housing Attributes

Attribute	**Mean (Standard Deviation)**	**N**
Sales Price	585,801	25,048
	(264,112)	
Year of Construction	1949	25,048
	(49)	
Sqft	2,096	25,048
	(922)	
# of Bedrooms	3.22	25,048
	(0.90)	
# of Baths	1.85	25,048
	(0.77)	
# of Stories	2.09	25,048
	(0.79)	
of Garages	1.17	25,048
	(0.83)	
Acres	0.16	24,540
	(0.23)	
Property Condition		
Fixer	0.03	25,048
New	0.02	25,048
Remodel	0.24	25,048
Resale	0.68	25,048
Restored	0.03	25,048
Cooling System		
Central Air	0.40	25,048
Heat Pump	0.05	25,048
Wall / Window Unit	0.03	25,048
Other	0.04	25,048
None	0.12	25,048
Missing	0.35	25,048
Heating System		
Forced Air	0.88	25,048
Baseboard	0.02	25,048
Heat Pump	0.01	25,048
Wall Furnace	0.01	25,048
Other	0.08	25,048
Fuel Type		
Gas	0.73	25,048
Electric	0.11	25,048
Electric and Gas	0.11	25,048
Other	0.05	25,048
Observations	25,048	

Notes: The table reports the mean (standard deviation in parentheses) of the housing attributes for the sample of homes transacted with an assessment in Portland from 2018 to 2021.

Table B.2: Summary Statistics - Energy Metrics

Characteristic	**Mean (Standard Deviation)**	**N**
Score	4.38	25,408
	(2.42)	
Energy Consumption (MBTU)	145	25,408
	(39)	
Energy Costs ($)	1,568	25,408
	(475)	
Carbon Emissions (Metric Ton)	5.54	25,408
	(1.71)	
Observations	25,408	

Notes: The table reports the mean (standard deviation in parentheses) of the energy metrics for homes transacted with an assessment in Portland from 2018 to 2021.

Table B.3: Estimates - Premium by Energy Metric (Individual)

	ln(Price)			
	(1)	(2)	(3)	(4)
Panel A				
Score	0.0082***	0.0051***	0.0049***	0.0050***
	(0.0019)	(0.0009)	(0.0009)	(0.0009)
Panel B				
Energy Consumption (MBTU)	-0.0007***	-0.0003***	-0.0003***	-0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Rescaled Energy Consumption (MBTU)	0.0085***	0.0039***	0.0036***	0.0040***
	(0.0017)	(0.0009)	(0.0009)	(0.0010)
Rescaling Parameter (λ): -12.81				
Panel C				
Energy Costs ($)	-0.00007***	-0.00003***	-0.00002***	-0.00003***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Rescaled Energy Costs ($)	0.0102***	0.0037***	0.0036***	0.0037***
	(0.0014)	(0.0008)	(0.0008)	(0.0009)
Rescaling Parameter (λ): -145.29				
Panel D				
Carbon Emissions (Metric Ton)	-0.0182***	-0.0069***	-0.0065***	-0.0070***
	(0.0030)	(0.0018)	(0.0018)	(0.0019)
Rescaled Carbon Emissions (Metric Ton)	0.0094***	0.0036***	0.0034***	0.0036***
	(0.0015)	(0.0010)	(0.0010)	(0.0010)
Rescaling Parameter (λ): -0.52				
Controls	✓	✓	✓	✓
Fixed Effect: Quarter		✓		
Fixed Effect: Zip Code		✓		
Fixed Effect: Quarter × Zip Code			✓	✓
Fixed Effect: Realtor				✓
Observations	24,540	24,540	24,540	24,540

*p<0.1; **p<0.05; ***p<0.01

Notes: *Score* represents the home energy score. The rescaling parameter (λ) is obtained from regressing the alternative energy metric (e.g., energy consumption, energy costs, and carbon emissions) on the score. The rescaled estimate is then the original estimate multiplied by this parameter. Robust standard errors are reported in parentheses, clustered by zip code.

Table B.4: Summary Statistics - Housing Attributes by Home Energy Score

	Home Energy Score									
Characteristic	1	2	3	4	5	6	7	8	9	10
Sales Price	670,027	607,227	587,946	575,788	552,582	556,717	538,547	557,238	577,137	575,040
	(364,932)	(296,812)	(249,296)	(260,924)	(213,287)	(210,841)	(190,110)	(209,243)	(216,306)	(173,835)
Year of Construction	1939	1943	1945	1946	1948	1952	1957	1967	1974	1976
	(26)	(26)	(28)	(29)	(55)	(50)	(83)	(80)	(41)	(93)
Sqft	2,579	2,259	2,168	2,053	1,954	1,902	1,826	1,824	1,879	1,810
	(1,199)	(990)	(885)	(856)	(774)	(752)	(695)	(697)	(713)	(663)
# of Bedrooms	3.54	3.31	3.29	3.16	3.10	3.06	3.08	3.08	3.15	3.05
	(0.98)	(0.85)	(0.88)	(0.87)	(0.85)	(0.87)	(0.85)	(0.83)	(0.86)	(0.88)
# of Baths	1.98	1.83	1.83	1.79	1.77	1.81	1.82	1.91	1.96	1.95
	(0.90)	(0.80)	(0.78)	(0.75)	(0.71)	(0.73)	(0.69)	(0.71)	(0.67)	(0.68)
# of Stories	2.32	2.15	2.13	2.05	1.99	2.00	1.98	2.00	2.03	2.07
	(0.87)	(0.84)	(0.83)	(0.81)	(0.78)	(0.71)	(0.69)	(0.68)	(0.66)	(0.66)
# of Garages	1.22	1.19	1.22	1.20	1.19	1.15	1.13	1.11	1.06	0.87
	(0.93)	(0.85)	(0.86)	(0.85)	(0.83)	(0.79)	(0.77)	(0.71)	(0.69)	(0.65)
Acres	0.20	0.19	0.17	0.16	0.16	0.15	0.13	0.13	0.12	0.13
	(0.34)	(0.39)	(0.19)	(0.13)	(0.15)	(0.17)	(0.11)	(0.11)	(0.11)	(0.37)
Property Condition										
New	0.00	0.00	0.00	0.00	0.01	0.01	0.03	0.08	0.15	0.25
Fixer	0.07	0.05	0.04	0.02	0.02	0.02	0.01	0.01	0.01	0.00
Remodel	0.21	0.22	0.24	0.25	0.24	0.26	0.26	0.23	0.20	0.18
Restored	0.03	0.03	0.03	0.03	0.02	0.03	0.02	0.01	0.02	0.02
Other	0.69	0.70	0.70	0.70	0.70	0.69	0.67	0.66	0.62	0.56
Cooling System										
Central Air	0.38	0.39	0.43	0.42	0.42	0.42	0.39	0.39	0.34	0.26
Heat Pump	0.04	0.03	0.03	0.04	0.05	0.05	0.07	0.09	0.09	0.16
Wall / Window Unit	0.04	0.04	0.04	0.03	0.03	0.04	0.03	0.03	0.03	0.04
Other	0.02	0.03	0.03	0.03	0.03	0.04	0.05	0.10	0.13	0.19
None	0.14	0.14	0.13	0.13	0.13	0.11	0.11	0.11	0.10	0.07
Missing	0.39	0.37	0.34	0.36	0.34	0.34	0.34	0.29	0.31	0.29
Heating System										
Forced Air	0.82	0.85	0.91	0.91	0.93	0.92	0.90	0.86	0.85	0.74
Baseboard	0.04	0.03	0.02	0.02	0.01	0.00	0.00	0.00	0.00	0.00
Heat Pump	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.03
Wall Furnace	0.01	0.01	0.00	0.01	0.00	0.00	0.01	0.00	0.01	0.00
Other	0.12	0.09	0.06	0.06	0.05	0.06	0.07	0.13	0.13	0.22
Fuel Type										
Gas	0.64	0.69	0.75	0.75	0.78	0.78	0.79	0.74	0.74	0.65
Electric	0.17	0.13	0.09	0.09	0.08	0.08	0.10	0.12	0.12	0.13
Electric and Gas	0.11	0.11	0.10	0.11	0.10	0.11	0.10	0.11	0.09	0.14
Other	0.09	0.08	0.07	0.05	0.04	0.03	0.02	0.03	0.04	0.08
Observations	4,036	2,362	3,174	4,046	3,499	2,823	2,097	1,614	821	576
(%)	(16)	(9)	(13)	(16)	(14)	(11)	(8)	(6)	(3)	(2)

Notes: The table reports the mean (standard deviation in parentheses) of the housing attributes for homes transacted with an assessment in Portland from 2018 to 2021. The statistics are separated by the home energy score.

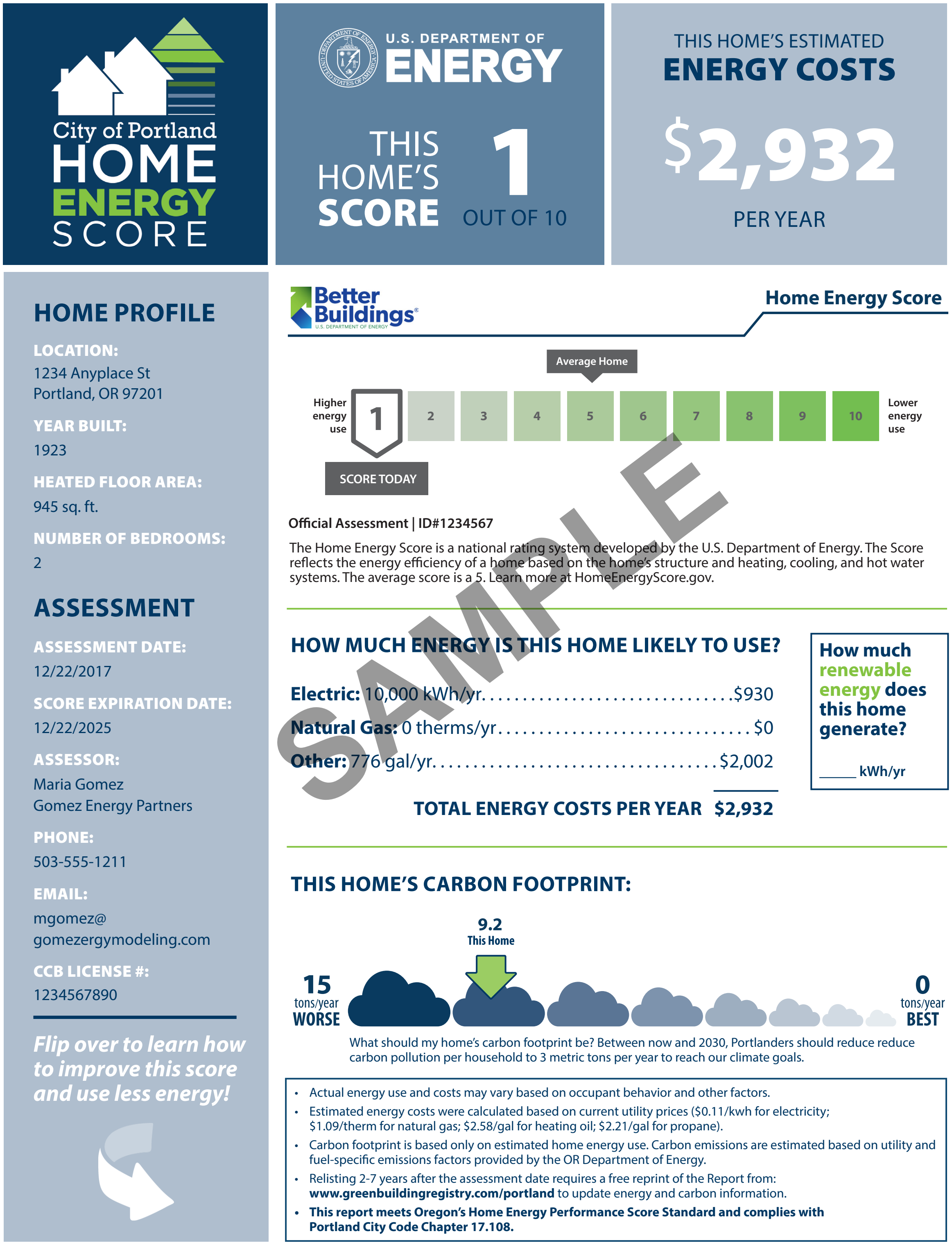
Table B.5: Estimates - Premium by Energy Metric (Joint)

	ln(Price)			
	(1)	(2)	(3)	(4)
Panel A				
Score	0.0082***	0.0051***	0.0049***	0.0050***
	(0.0019)	(0.0009)	(0.0009)	(0.0009)
Panel B				
Score	0.0021	0.0054***	0.0055***	0.0046***
	(0.0022)	(0.0008)	(0.0009)	(0.0008)
Rescaled Energy Consumption (MBTU)	0.0068***	-0.0003	-0.0007	0.0005
	(0.0018)	(0.0010)	(0.0011)	(0.0012)
Panel C				
Score	0.0013	0.0044***	0.0042***	0.0042***
	(0.0022)	(0.0008)	(0.0008)	(0.0008)
Rescaled Energy Costs ($)	0.0110***	0.0009	0.0008	0.0010
	(0.0015)	(0.0009)	(0.0009)	(0.0009)
Panel D				
Score	-0.0005	0.0047***	0.0047***	0.0045***
	(0.0019)	(0.0009)	(0.0009)	(0.0009)
Rescaled Carbon Emissions (Metric Ton)	0.0097***	0.0005	0.0002	0.0007
	(0.0015)	(0.0011)	(0.0012)	(0.0012)
Panel E				
Score	0.0025	0.0053***	0.0054***	0.0046***
	(0.0019)	(0.0009)	(0.0009)	(0.0009)
Rescaled Energy Consumption (MBTU)	-0.0148***	-0.0030*	-0.0036**	-0.0012
	(0.0014)	(0.0015)	(0.0017)	(0.0019)
Rescaled Energy Costs ($)	0.0126***	0.0022**	0.0027**	0.0015
	(0.0016)	(0.0011)	(0.0011)	(0.0011)
Rescaled Carbon Emissions (Metric Ton)	0.0089***	0.0006	0.0004	0.0002
	(0.0019)	(0.0016)	(0.0017)	(0.0018)
Controls	✓	✓	✓	✓
Fixed Effect: Quarter		✓		
Fixed Effect: Zip Code		✓		
Fixed Effect: Quarter × Zip Code			✓	✓
Fixed Effect: Realtor				✓
Observations	24,540	24,540	24,540	24,540

*p<0.1; **p<0.05; ***p<0.01

Notes: *Score* represents the home energy score. Robust standard errors are reported in parentheses, clustered by zip code.

Figure B.1: Sample Home Energy Score Assessment



City of Portland HOME ENERGY SCORE

U.S. DEPARTMENT OF ENERGY

THIS HOME'S SCORE **1** OUT OF 10

THIS HOME'S ESTIMATED **ENERGY COSTS**

$2,932 PER YEAR

HOME PROFILE

LOCATION:
1234 Anyplace St
Portland, OR 97201

YEAR BUILT:
1923

HEATED FLOOR AREA:
945 sq. ft.

NUMBER OF BEDROOMS:
2

ASSESSMENT

ASSESSMENT DATE:
12/22/2017

SCORE EXPIRATION DATE:
12/22/2025

ASSESSOR:
Maria Gomez
Gomez Energy Partners

PHONE:
503-555-1211

EMAIL:
mgomez@
gomezergymodeling.com

CCB LICENSE #:
1234567890

Flip over to learn how to improve this score and use less energy!

Better Buildings U.S. DEPARTMENT OF ENERGY

Home Energy Score

Average Home

Higher energy use | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | Lower energy use

SCORE TODAY

SAMPLE

Official Assessment | ID#1234567

The Home Energy Score is a national rating system developed by the U.S. Department of Energy. The Score reflects the energy efficiency of a home based on the home's structure and heating, cooling, and hot water systems. The average score is a 5. Learn more at HomeEnergyScore.gov.

HOW MUCH ENERGY IS THIS HOME LIKELY TO USE?

Electric: 10,000 kWh/yr. $930
Natural Gas: 0 therms/yr. $0
Other: 776 gal/yr. $2,002

TOTAL ENERGY COSTS PER YEAR $2,932

How much renewable energy does this home generate?

_____ kWh/yr

THIS HOME'S CARBON FOOTPRINT:

9.2 This Home

15 tons/year WORSE

0 tons/year BEST

What should my home's carbon footprint be? Between now and 2030, Portlanders should reduce reduce carbon pollution per household to 3 metric tons per year to reach our climate goals.

- Actual energy use and costs may vary based on occupant behavior and other factors.
- Estimated energy costs were calculated based on current utility prices ($0.11/kwh for electricity; $1.09/therm for natural gas; $2.58/gal for heating oil; $2.21/gal for propane).
- Carbon footprint is based only on estimated home energy use. Carbon emissions are estimated based on utility and fuel-specific emissions factors provided by the OR Department of Energy.
- Relisting 2-7 years after the assessment date requires a free reprint of the Report from: **www.greenbuildingregistry.com/portland** to update energy and carbon information.
- **This report meets Oregon's Home Energy Performance Score Standard and complies with Portland City Code Chapter 17.108.**

Figure B.1 (cont'd)

Score today:	Score with improvements:*	Estimated **energy savings** with improvements:	Estimated **carbon reduction** with improvements:
1	**9**	**$1,672** PER YEAR	**57%** PER YEAR

TACKLE ENERGY WASTE TODAY!

Enjoy the rewards of a comfortable, energy efficient home that saves you money.

- [x] Get your home energy assessment. Done!
- [ ] Choose energy improvements from the list of recommendations below.

  Need help deciding what to do first? Non-profit Enhabit offers free 15-minute phone consults with expert home advisors. Call 855-870-0049.
- [ ] Select a contractor (or two, for comparison) and obtain bids.

  Checkout **www.energytrust.org/findacontractor** or call toll free **1-866-368-7878**.
- [ ] Explore financing options at **www.enhabit.org** or **www.energytrust.org**.

* PRACTICAL ENERGY IMPROVEMENTS | COMPLETE NOW OR LATER

To achieve the "score with improvements," all recommended improvements listed below must be completed. Improvements all have a simple payback of ten years or less and may be eligible for mortgage financing. For a more detailed explanation of costs and payback, please get a bid from a contractor.

FEATURE	TODAY'S CONDITION	RECOMMENDED IMPROVEMENTS
Attic insulation	Ceiling insulated to R-0	Insulate to R-38 or R-49 if code requires it
Attic insulation	Ceiling insulated to R-19	Insulate to R-38 or R-49 if code requires it
Duct insulation	Un-insulated	Insulate to R-8
Duct sealing	Un-sealed	Reduce leakage to a maximum of 10% of total airflow
Envelope/Air Sealing	Not professionally air sealed	Professionally air seal
Heating Equipment	Oil furnace 60% AFUE	Upgrade to ENERGY STAR
Heating Equipment	Natural Gas/Propane Furnace	Upgrade to ENERGY STAR
Wall insulation	Insulated to R-0	Fully insulate wall cavities
Water Heater	Standard electric tank	Upgrade to ENERGY STAR, minimum 2.76 EF (Energy Factor)
Windows	Multiple types	Upgrade to ENERGY STAR
Air Conditioner	None	
Basement wall insulation	None	
Floor insulation	Insulated to R-0	
Foundation wall insulation	None	
Skylights	None	
Cathedral ceiling	None	
Solar PV	None	Visit www.energytrust.org/solar to learn more

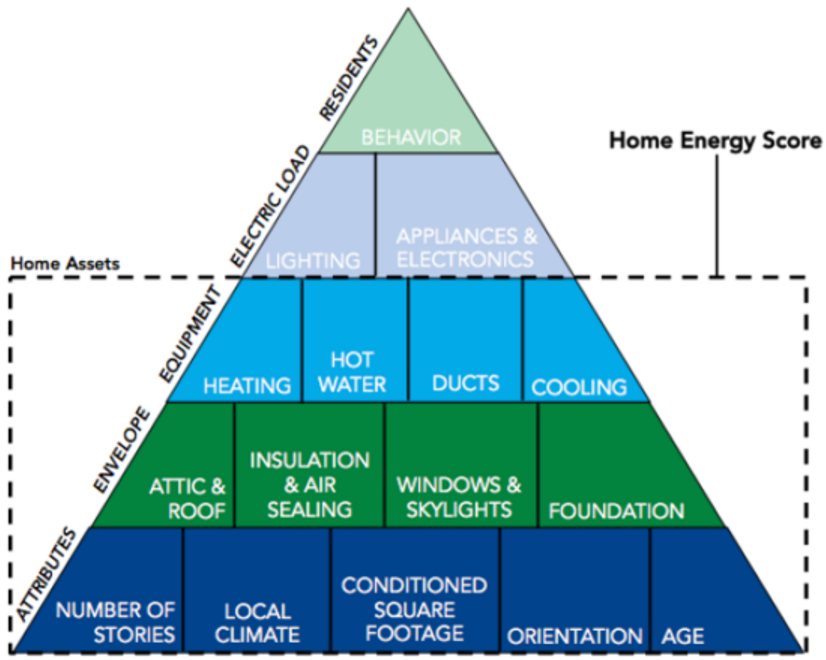
YOU CAN DO IT YOURSELF!

Looking for low-cost ways to cut energy waste, boost your comfort and lower your energy bills? Visit the resources below to learn about easy changes you can make today:

www.energytrust.org/tips and **www.communityenergyproject.org/services**

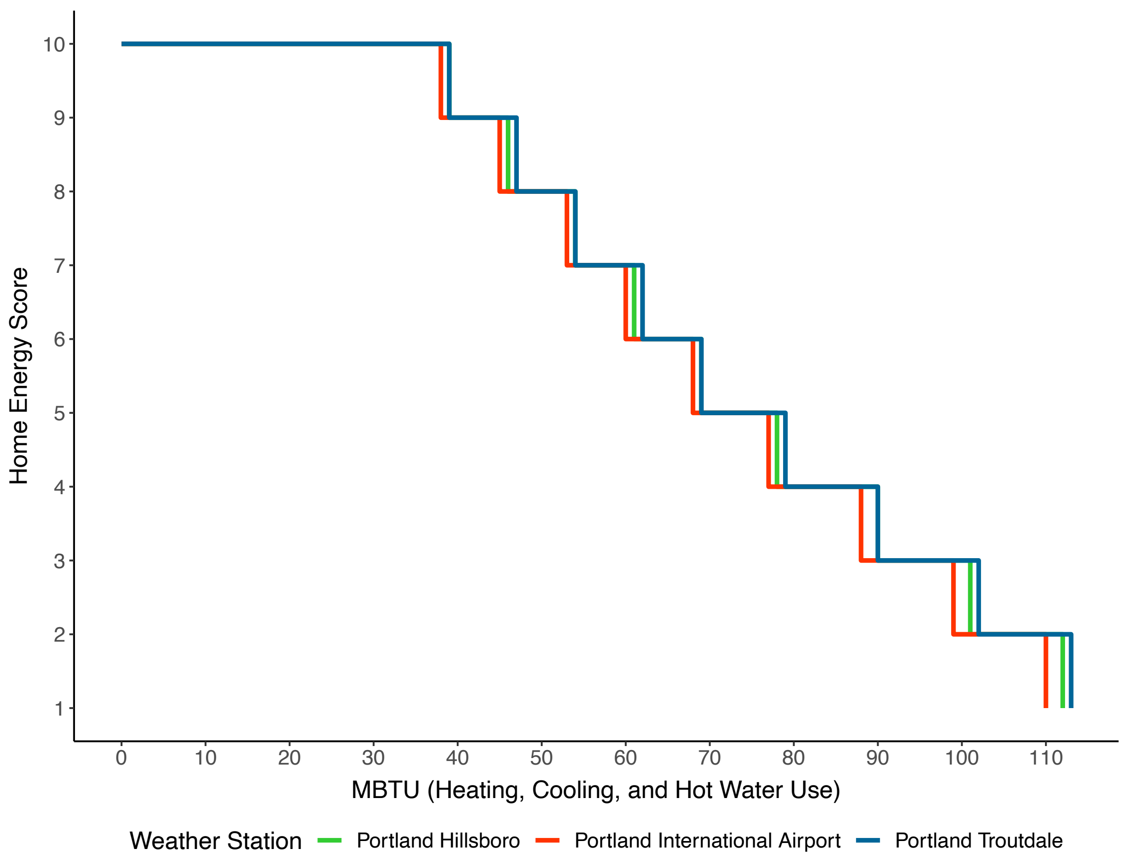
Notes: The figure presents a sample report from the home energy score assessment.

Figure B.2: Home Assets



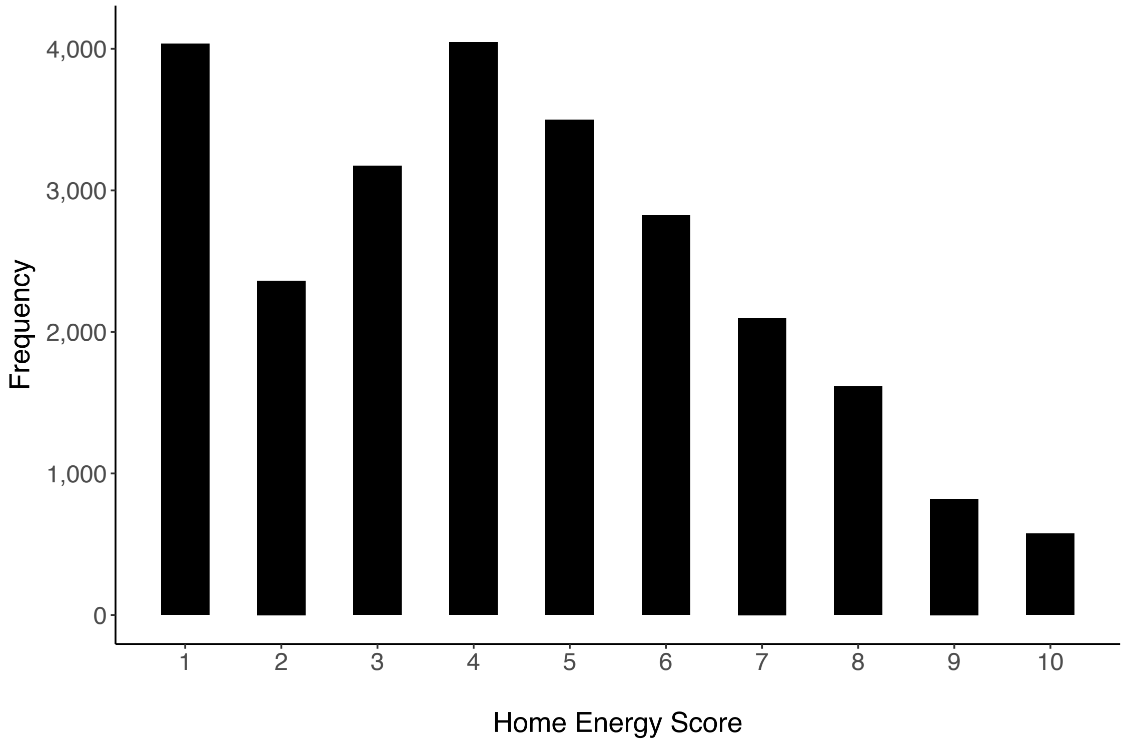
Notes: The figure documents the home assets associated with the home energy score (see US Department of Energy, 2017). About 50 home assets go into the calculation of the score.

Figure B.3: Home Energy Score Thresholds



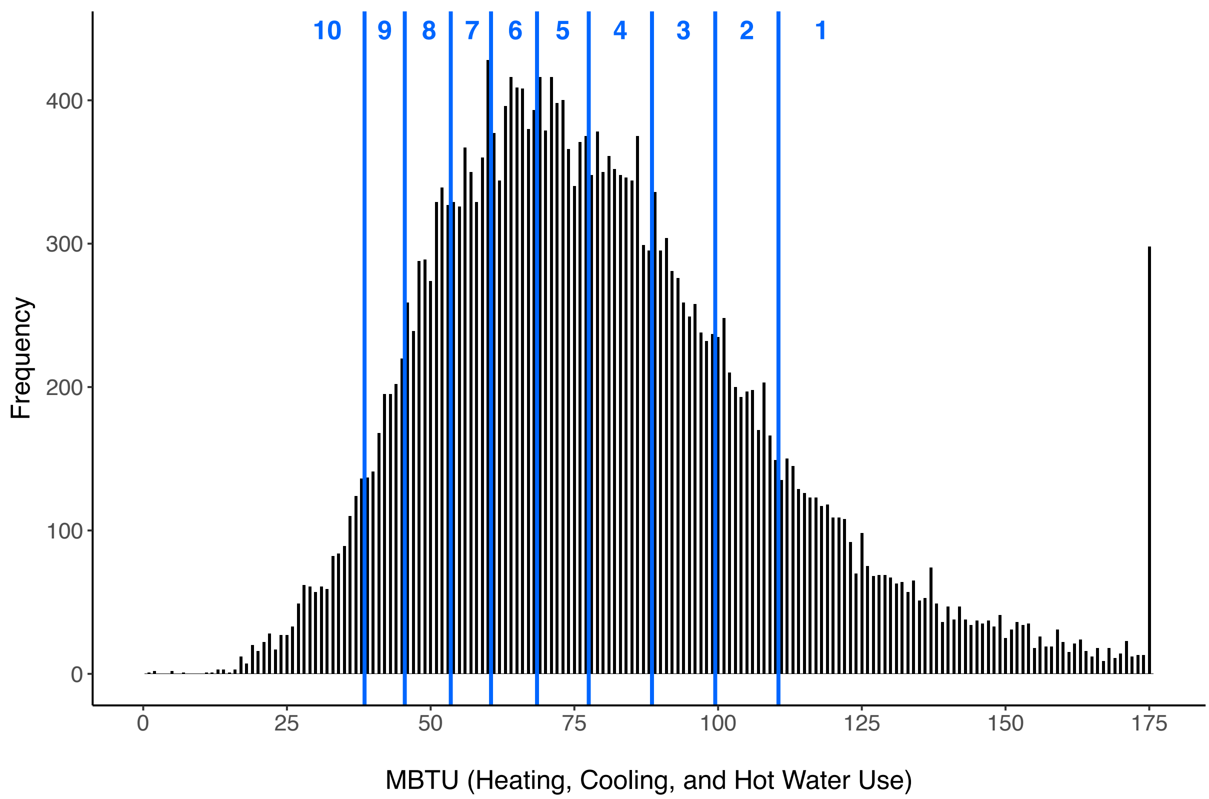
Notes: The figure plots the mapping of the home energy score from expected annual energy consumption for heating, cooling, and hot water use (MBTU). The thresholds vary by weather station, accounting for regional climatic conditions. The majority of assessments (86%) are located within the Portland International Airport weather station.

Figure B.4: Distribution - Home Energy Score



Notes: The figure is a histogram of the home energy score.

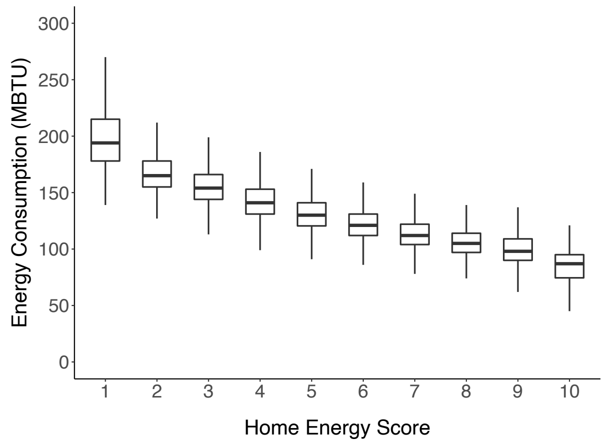
Figure B.5: Distribution - Energy Consumption (MBTU)



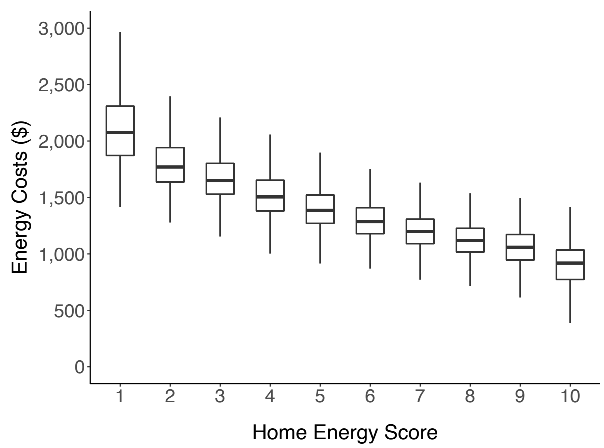
Notes: The figure is a histogram of energy consumption for heating, cooling, and hot water use (MBTU) for the weather station, Portland International Airport. The vertical blue lines represent the home energy score thresholds. Energy consumption is capped at 175 MBTU.

Figure B.6: Box Plots - Alternative Energy Metrics

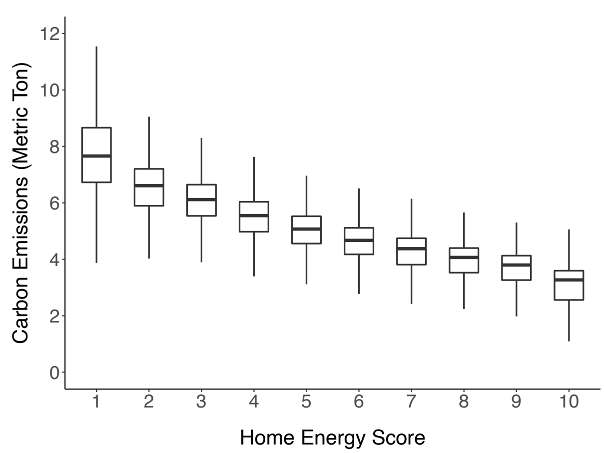
(a) Energy Consumption



(b) Energy Costs

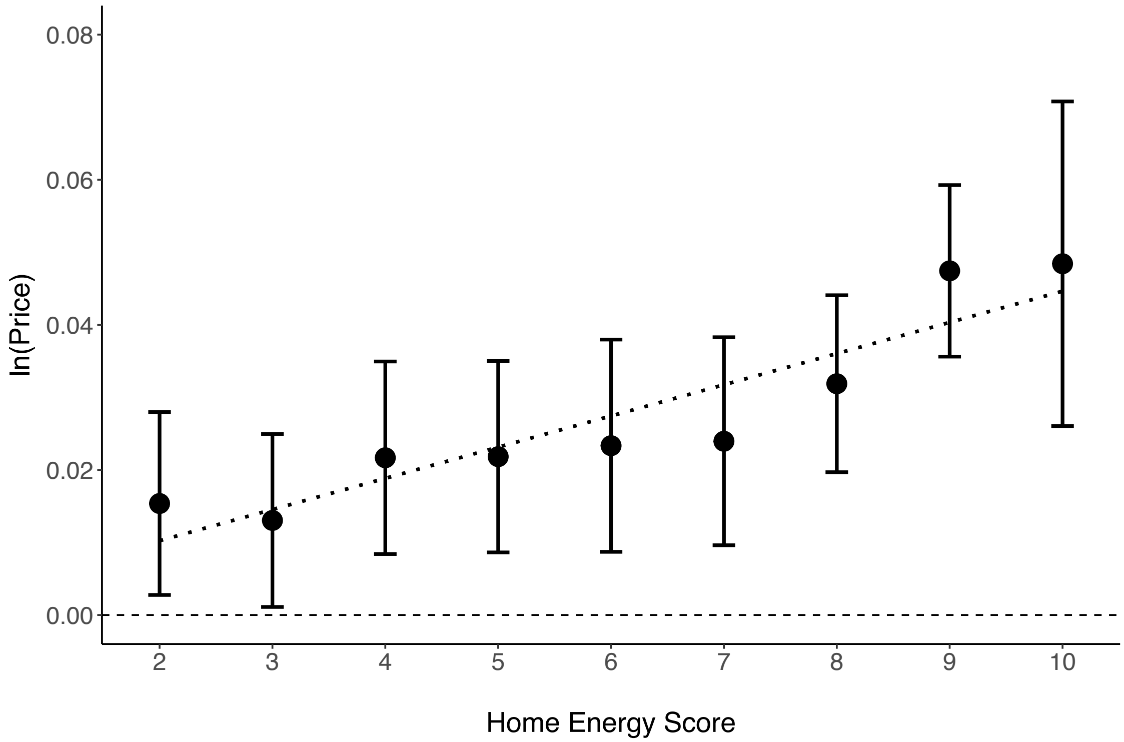


(c) Carbon Emissions



Notes: The figure presents box plots for the following energy metrics with respect to the home energy score: (a) energy consumption; (b) energy costs; and (c) carbon emissions.

Figure B.7: Estimates - Premium (Binary)

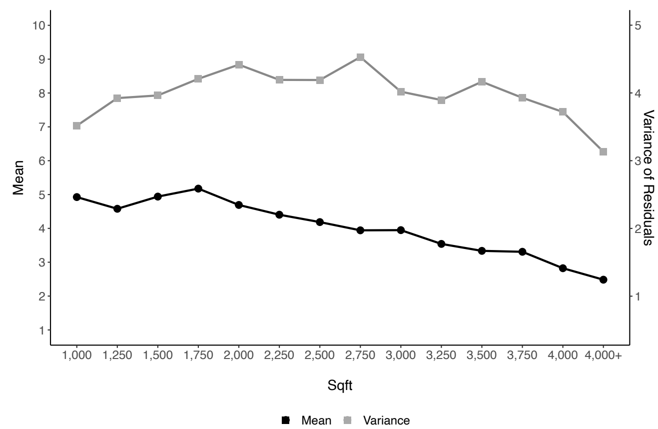


Notes: The figure plots the premium for binary indicators of the score. The dotted line is a linear trend.

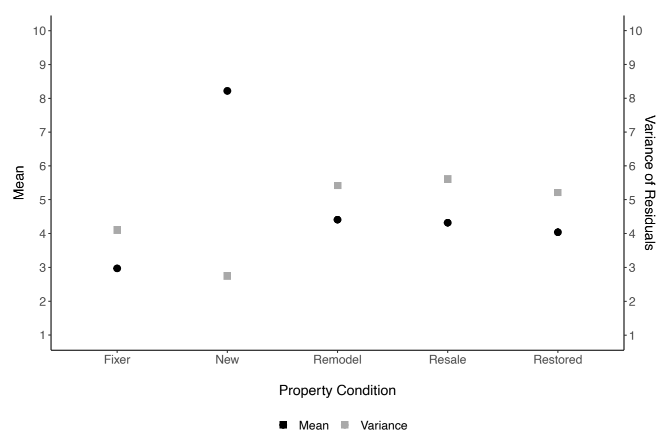
Figure B.8: Home Energy Score by Housing Attributes

(a) Year of Construction

(b) Sqft



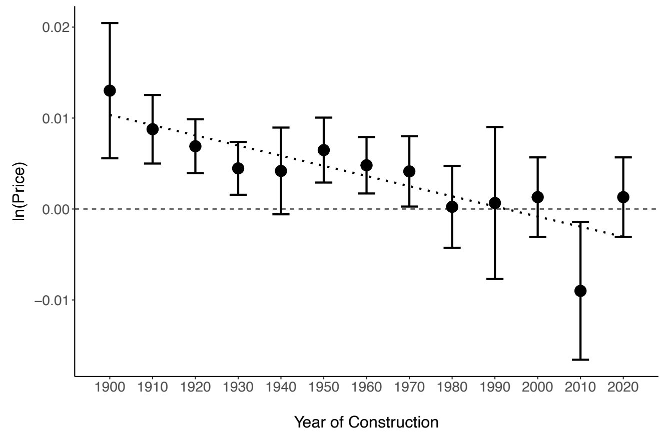
(c) Property Condition



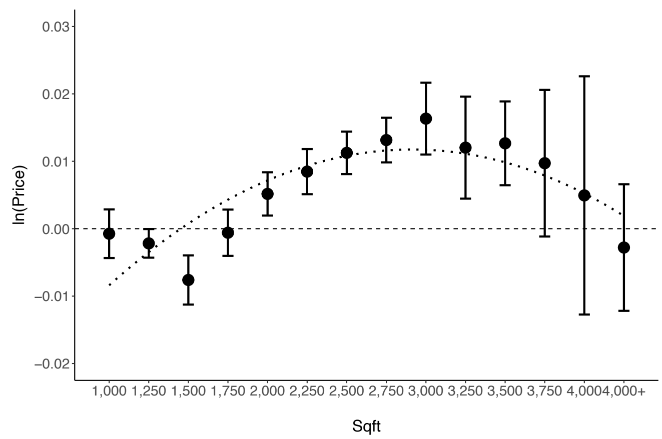
Notes: The figure plots the mean home energy score (black) and variance of residuals (gray) with respect to the following housing attributes: (a) age (year of construction); (b) size (sqft); and (c) property condition.

Figure B.9: Estimates - Premium by Housing Attributes

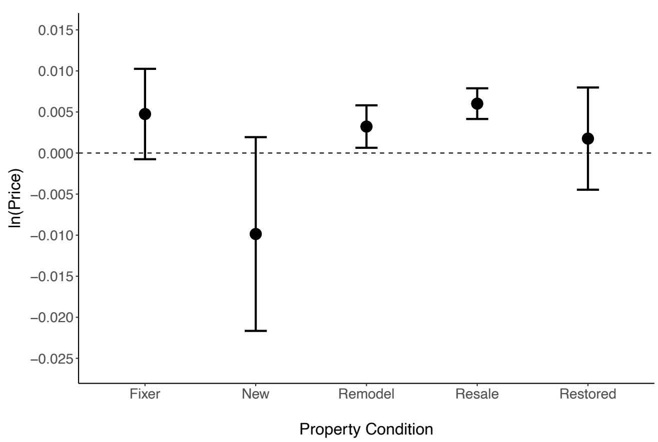
(a) Year of Construction



(b) Sqft

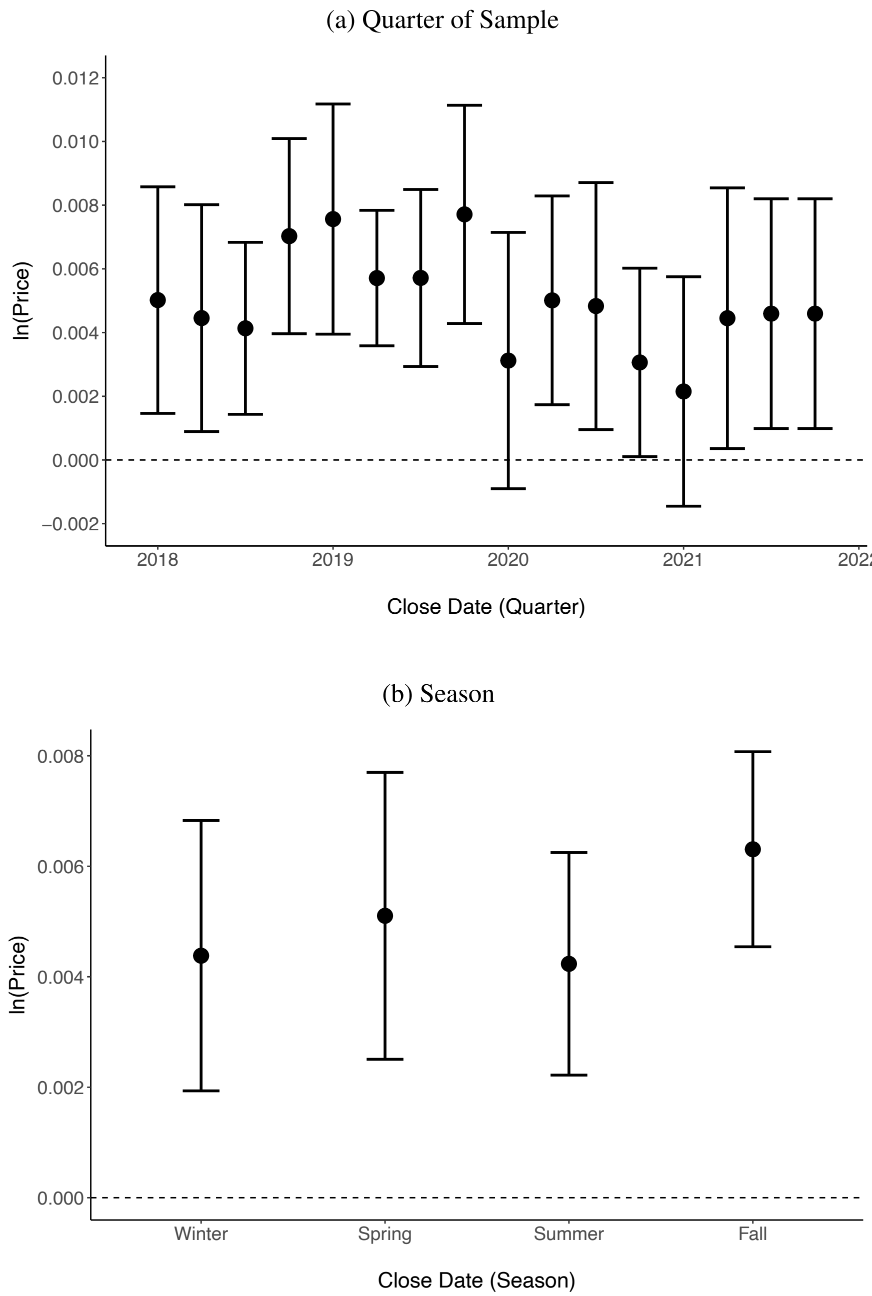


(c) Property Condition



Notes: The figure plots the premium for the home energy score with respect to the following housing attributes: (a) age (year of construction); (b) size (sqft); and (c) property condition. In panel (a), the dotted line is a linear trend. And, in panel (b), the dotted line is a quadratic trend.

Figure B.10: Estimates - Premium by Time of Sale



Notes: The figure plots the premium for the home energy score with respect to the time of sale: (a) quarter of sample and (b) season.

APPENDIX C

CHAPTER 3 APPENDIX

Table C.1: Summary Statistics - Home Assets by HOLC Grade

	HOLC Grade				
Characteristic	A	B	C	D	**Overall**
Energy Consumption (MBTU)	101	85	76	77	80
Panel A: Fixed Assets					
Year of Construction	1942	1939	1949	1942	1945
Bedrooms	3.63	3.24	2.92	3.04	3.06
Ceiling Height (Ft)	8.29	8.10	8.12	8.33	8.15
Stories	2.05	1.84	1.61	1.96	1.73
Area (Sqft)					
Conditioned Floor	3,097	2,256	1,678	1,957	1,945
Floor	1,399	1,075	962	916	1,014
Roof	1,259	975	891	836	930
Window	405	268	201	238	234
Exterior Wall					
Wood	0.73	0.81	0.82	0.87	0.82
Vinyl	0.02	0.08	0.11	0.07	0.09
Aluminum	0.02	0.04	0.04	0.03	0.04
Stucco	0.15	0.04	0.01	0.01	0.03
Brick	0.07	0.02	0.01	0.02	0.02
Foundation					
Basement (Conditioned)	0.65	0.65	0.41	0.51	0.50
Basement (Unconditioned)	0.10	0.14	0.13	0.18	0.14
Crawl (Vented)	0.13	0.14	0.37	0.17	0.27
Crawl (Unvented)	0.07	0.04	0.05	0.07	0.05
Orientation					
North	0.15	0.17	0.21	0.21	0.19
South	0.14	0.17	0.21	0.20	0.19
East	0.22	0.29	0.24	0.27	0.26
West	0.26	0.29	0.24	0.29	0.26
Primary Fuel					
Electric	0.09	0.09	0.19	0.15	0.15
Natural Gas	0.88	0.87	0.77	0.83	0.81
Panel B: Choice Assets					
Insulation					
Ceiling	23.06	20.68	22.88	22.83	22.29
Floor	5.70	5.17	7.62	8.43	6.92
Wall	5.92	5.45	6.75	7.66	6.44
Roof	3.15	2.53	1.96	2.90	2.27
Cooling					
None	0.37	0.49	0.58	0.57	0.54
Central	0.54	0.43	0.29	0.32	0.35
Window	0.02	0.03	0.04	0.03	0.04
Heat Pump	0.05	0.03	0.03	0.03	0.03
Mini Split	0.03	0.03	0.05	0.05	0.04
Heating					
Furnace	0.84	0.88	0.81	0.84	0.84
Heat Pump	0.05	0.03	0.03	0.03	0.03
Mini Split	0.02	0.03	0.05	0.05	0.04
Baseboard	0.01	0.02	0.10	0.07	0.07
Boiler	0.08	0.03	0.01	0.01	0.02
Ducts					
Insulated	0.21	0.19	0.31	0.24	0.26
Sealed	0.16	0.15	0.18	0.19	0.17
Window Type: Double/Triple Pane	0.72	0.73	0.82	0.76	0.78
Observations	1,053	4,976	10,411	1,783	18,223
(%)	5.78	27.31	57.13	9.78	100.00

Notes: The table presents summary statistics (i.e., mean) of the home assets separated by HOLC grade.

Table C.2: Summary Statistics - Home Assets by Distance to Redlined Area

	Distance (Mile)				
Characteristic	0	0.1	0.2	0.3	**Overall**
Energy Consumption (MBTU)	77	79	85	85	80
Panel A: Fixed Assets					
Year of Construction	1942	1941	1941	1939	1941
Bedrooms	3.04	3.03	3.16	3.23	3.10
Ceiling Height (Ft)	8.33	8.29	8.27	8.24	8.29
Stories	1.96	1.95	1.99	1.94	1.96
Area (Sqft)					
Conditioned Floor	1,957	2,023	2,199	2,352	2,102
Floor	916	939	1,003	1,069	970
Roof	836	842	907	979	882
Window	238	245	275	285	257
Exterior Wall					
Wood	0.87	0.85	0.86	0.81	0.85
Vinyl	0.07	0.05	0.06	0.06	0.06
Aluminum	0.03	0.04	0.04	0.04	0.03
Stucco	0.01	0.03	0.03	0.06	0.03
Brick	0.02	0.02	0.02	0.03	0.02
Foundation					
Basement (Conditioned)	0.51	0.52	0.54	0.63	0.54
Basement (Unconditioned)	0.18	0.19	0.17	0.14	0.17
Crawl (Vented)	0.17	0.16	0.15	0.12	0.16
Crawl (Unvented)	0.07	0.07	0.07	0.06	0.07
Orientation					
North	0.21	0.20	0.18	0.18	0.19
South	0.20	0.24	0.20	0.17	0.20
East	0.27	0.27	0.28	0.27	0.27
West	0.29	0.24	0.26	0.26	0.27
Primary Fuel					
Electric	0.15	0.14	0.12	0.10	0.13
Natural Gas	0.83	0.83	0.84	0.86	0.84
Panel B: Choice Assets					
Insulation					
Ceiling	22.83	22.16	21.38	21.80	22.19
Floor	8.43	7.59	6.66	5.72	7.33
Wall	7.66	6.60	6.20	6.41	6.90
Roof	2.90	3.34	2.87	3.25	3.05
Cooling					
None	0.57	0.57	0.52	0.51	0.54
Central	0.32	0.34	0.40	0.39	0.36
Window	0.03	0.02	0.02	0.03	0.03
Heat Pump	0.03	0.04	0.04	0.04	0.04
Mini Split	0.05	0.04	0.02	0.03	0.04
Heating					
Furnace	0.84	0.83	0.86	0.87	0.85
Heat Pump	0.03	0.04	0.04	0.04	0.04
Mini Split	0.05	0.04	0.02	0.03	0.04
Baseboard	0.07	0.06	0.05	0.02	0.05
Boiler	0.01	0.03	0.03	0.03	0.02
Ducts					
Insulated	0.24	0.20	0.20	0.19	0.21
Sealed	0.19	0.18	0.17	0.16	0.18
Window Type: Double/Triple Pane	0.76	0.72	0.71	0.73	0.74
Observations	1,783	880	907	970	4,540
(%)	39.27	19.38	19.98	21.73	100.00

Notes: The table presents summary statistics (i.e., mean) of the home assets separated by distance to the boundary of a redlined area.

Table C.3: Estimates - Energy Consumption by HOLC Grade

	Energy Consumption (MBTU)	
	(1)	(2)
B	-16.22***	-2.31*
	(1.09)	(0.92)
C	-24.97***	-2.57**
	(1.04)	(0.93)
D	-24.46***	-4.85***
	(1.25)	(1.08)
Controls: Fixed Assets		✓
Observations	18,223	18,223

*p<0.1; **p<0.05; ***p<0.01

Notes: The table presents estimates for expected energy consumption by HOLC grade. B, C, and D are indicators for a home located in the respective grades.

Table C.4: Difference-In-Differences Estimates - Fixed Assets

	Fixed Assets			
	Area (Sqft)	Basement	Bedrooms	Stories
D	-109.71***	-0.01	-0.06*	0.07***
	(27.42)	(0.01)	(0.03)	(0.02)
Post_{1940}	-520.52***	-0.24***	-0.28***	-0.50***
	(16.33)	(0.01)	(0.02)	(0.01)
Post_{1970}	-275.37***	-0.54***	0.07***	0.20***
	(17.32)	(0.01)	(0.02)	(0.01)
D × Post_{1940}	-83.17	0.02	-0.30***	0.01
	(83.16)	(0.04)	(0.09)	(0.05)
D × Post_{1970}	191.60***	0.06**	0.01	0.27***
	(48.82)	(0.03)	(0.05)	(0.03)
Observations	18,148	18,148	18,148	18,148

*p<0.1; **p<0.05; ***p<0.01

Notes: The table presents the difference-in-differences estimates for the following fixed assets: conditioned floor area (sqft), basement (conditioned), bedrooms, and stories. D is an indicator for a home located in a redlined area. $Post_{1940}$ and $Post_{1970}$ are indicators for a home constructed in [1941,1970] and [1971,2020], respectively.

Table C.5: Difference-In-Differences Estimates - Energy Consumption

	Energy Consumption (MBTU)	
	(1)	(2)
Panel A: Redlined Areas		
D	-2.07**	0.89
	(0.96)	(0.83)
$Post_{1940}$	-7.18***	-3.59***
	(0.57)	(0.55)
$Post_{1970}$	-30.71***	-36.32***
	(0.61)	(0.66)
D × $Post_{1940}$	-1.93	-0.04
	(2.92)	(2.50)
D × $Post_{1970}$	-0.85	-1.35
	(1.71)	(1.48)
Panel B: Redlined Areas by Urban Renewal Project Status		
URP: No	-1.40	0.85
	(1.34)	(1.12)
URP: Yes	-2.71**	0.92
	(1.31)	(1.13)
$Post_{1940}$	-7.18***	-3.59***
	(0.57)	(0.55)
$Post_{1970}$	-30.71***	-36.32***
	(0.61)	(0.66)
URP: No × $Post_{1940}$	0.61	1.42
	(3.85)	(3.29)
URP: No × $Post_{1970}$	-0.27	0.018
	(2.63)	(2.26)
URP: Yes × $Post_{1940}$	-5.64	-2.00
	(4.39)	(3.77)
URP: Yes × $Post_{1970}$	-0.90	-2.12
	(2.17)	(1.86)
Controls: Fixed Assets		✓
Observations	18,148	18,148

*p<0.1; **p<0.05; ***p<0.01

Notes: The table presents the difference-in-differences estimates for expected energy consumption. *D* is an indicator for a home located in a redlined area. *URP: Yes* and *URP: No* are indicators for a home located in a redlined area that is and is not contained within an urban renewal project, respectively. $Post_{1940}$ and $Post_{1970}$ are indicators for a home constructed in [1941,1970] and [1971,2020], respectively.

Table C.6: Difference-In-Differences Estimates - Remodel

	Remodel	
	(1)	(2)
Panel A		
D	0.0154	0.0151
	(0.0153)	(0.0153)
$Post_{1940}$	-0.0037	0.0020
	(0.0090)	(0.0102)
$Post_{1970}$	-0.1103***	-0.1194***
	(0.0106)	(0.0131)
D × $Post_{1940}$	-0.0589	-0.0534
	(0.0564)	(0.0560)
D × $Post_{1970}$	0.0155	0.0146
	(0.0357)	(0.0356)

	Energy Consumption (MBTU)	
	(1)	(2)
Panel B		
D	-2.841**	-0.2094
	(1.201)	(1.014)
$Post_{1940}$	-6.504***	-3.115***
	(0.7005)	(0.6463)
$Post_{1970}$	-30.38***	-39.21***
	(0.7776)	(0.7964)
Remodel	-4.607***	-5.307***
	(0.7505)	(0.6317)
D × $Post_{1940}$	4.453	4.759
	(4.267)	(3.574)
D × $Post_{1970}$	-1.098	-2.562
	(2.670)	(2.244)
D × Remodel	0.6005	1.255
	(2.270)	(1.900)
$Post_{1940}$ × Remodel	0.6738	1.220
	(1.365)	(1.143)
$Post_{1970}$ × Remodel	11.76***	14.16***
	(1.869)	(1.571)
D × $Post_{1940}$ × Remodel	-5.230	-8.014
	(9.031)	(7.558)
D × $Post_{1970}$ × Remodel	1.483	1.061
	(6.011)	(5.032)
Controls: Fixed Assets		✓
Observations	18,148	18,148

*p<0.1; **p<0.05; ***p<0.01

Notes: Panel (a) presents the difference-in-differences estimates for remodel. Panel (b) presents the triple difference-in-differences estimates for expected energy consumption. D is an indicator for a home located in a redlined area. $Post_{1940}$ and $Post_{1970}$ are indicators for a home constructed in [1941,1970] and [1971,2020], respectively. And, $Remodel$ is an indicator for a home that is remodeled.

Table C.7: Difference-In-Differences Estimates - Insulation

	Insulation			
	Ceiling	Floor	Roof	Wall
D	-0.53	0.26	-0.22	0.23
	(0.43)	(0.25)	(0.20)	(0.16)
Post_{1940}	2.71^{***}	0.54^{***}	0.16	0.60^{***}
	(0.29)	(0.17)	(0.13)	(0.11)
Post_{1970}	17.89^{***}	11.20^{***}	-0.26^{*}	9.29^{***}
	(0.34)	(0.20)	(0.16)	(0.13)
$\text{D} \times \text{Post}_{1940}$	-2.41^{*}	-0.04	0.18	-1.14^{**}
	(1.30)	(0.77)	(0.60)	(0.49)
$\text{D} \times \text{Post}_{1970}$	0.12	1.30^{***}	0.22	0.23
	(0.78)	(0.45)	(0.36)	(0.29)
Controls: Fixed Assets	✓	✓	✓	✓
Observations	18,147	17,550	18,147	17,827

*p<0.1; **p<0.05; ***p<0.01

Notes: The table presents the difference-in-differences estimates for insulation. D is an indicator for a home located in a redlined area. $Post_{1940}$ and $Post_{1970}$ are indicators for a home constructed during [1941,1970] and [1971,2020], respectively.

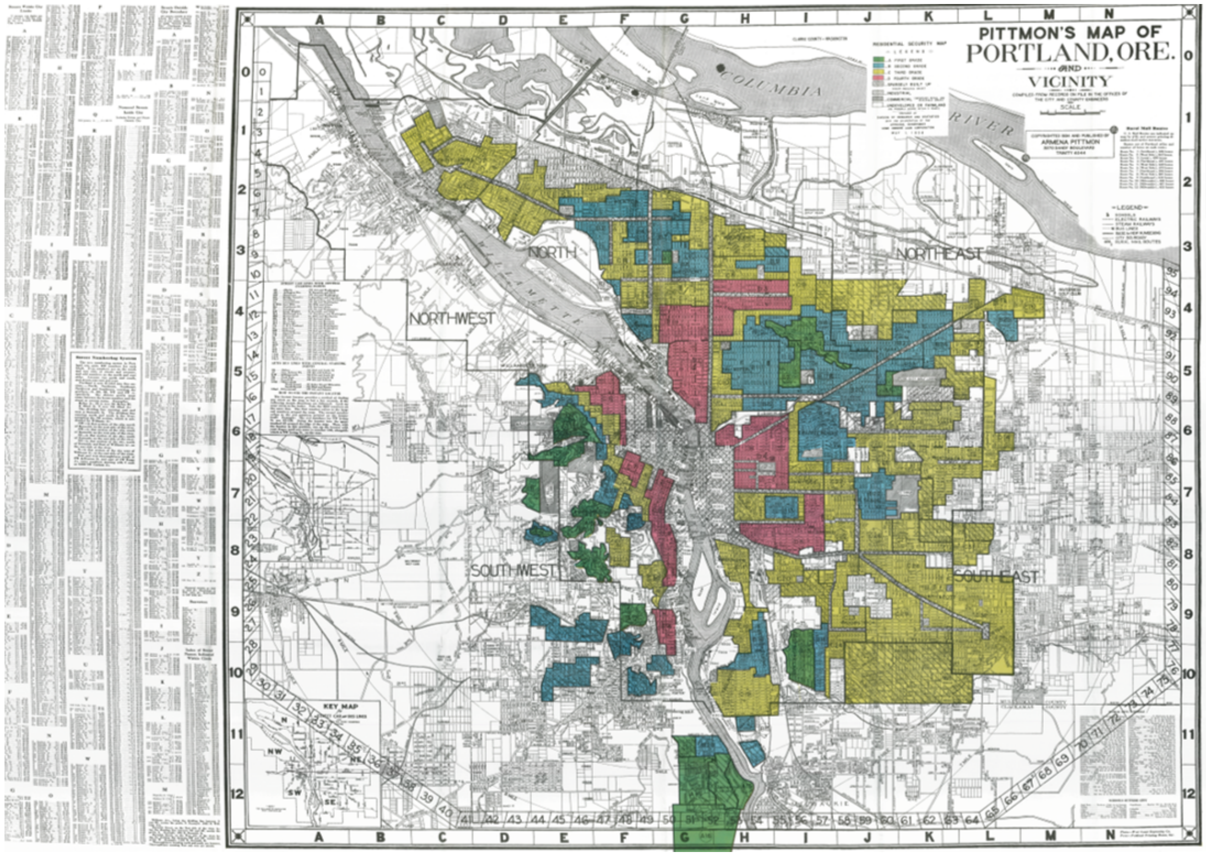
Table C.8: Spatial Regression Discontinuity Estimates - Energy Consumption

	Energy Consumption (MBTU)					
	(1)	(2)	(3)	(4)	(5)	(6)
D	2.29	2.35	0.16	0.99	-2.21	-1.31
	(3.29)	(2.67)	(2.08)	(1.59)	(2.41)	(1.64)
$(x - x_0)$	-0.045*	-0.017	-0.037**	-0.014**	-0.017	-0.00
	(0.02)	(0.023)	(0.01)	(0.01)	(0.01)	(0.00)
D $\times$ $(x - x_0)$	0.03	-0.01	0.05**	0.013	0.03	0.00
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)
Controls: Fixed Assets		✓		✓		✓
Fixed Effect: Boundary	✓	✓	✓	✓	✓	✓
Bandwidth						
0.1 Mile	✓	✓				
0.2 Mile			✓	✓		
0.3 Mile					✓	✓
Observations	2,056	2,056	3,461	3,461	4,503	4,503

*p<0.1; **p<0.05; ***p<0.01

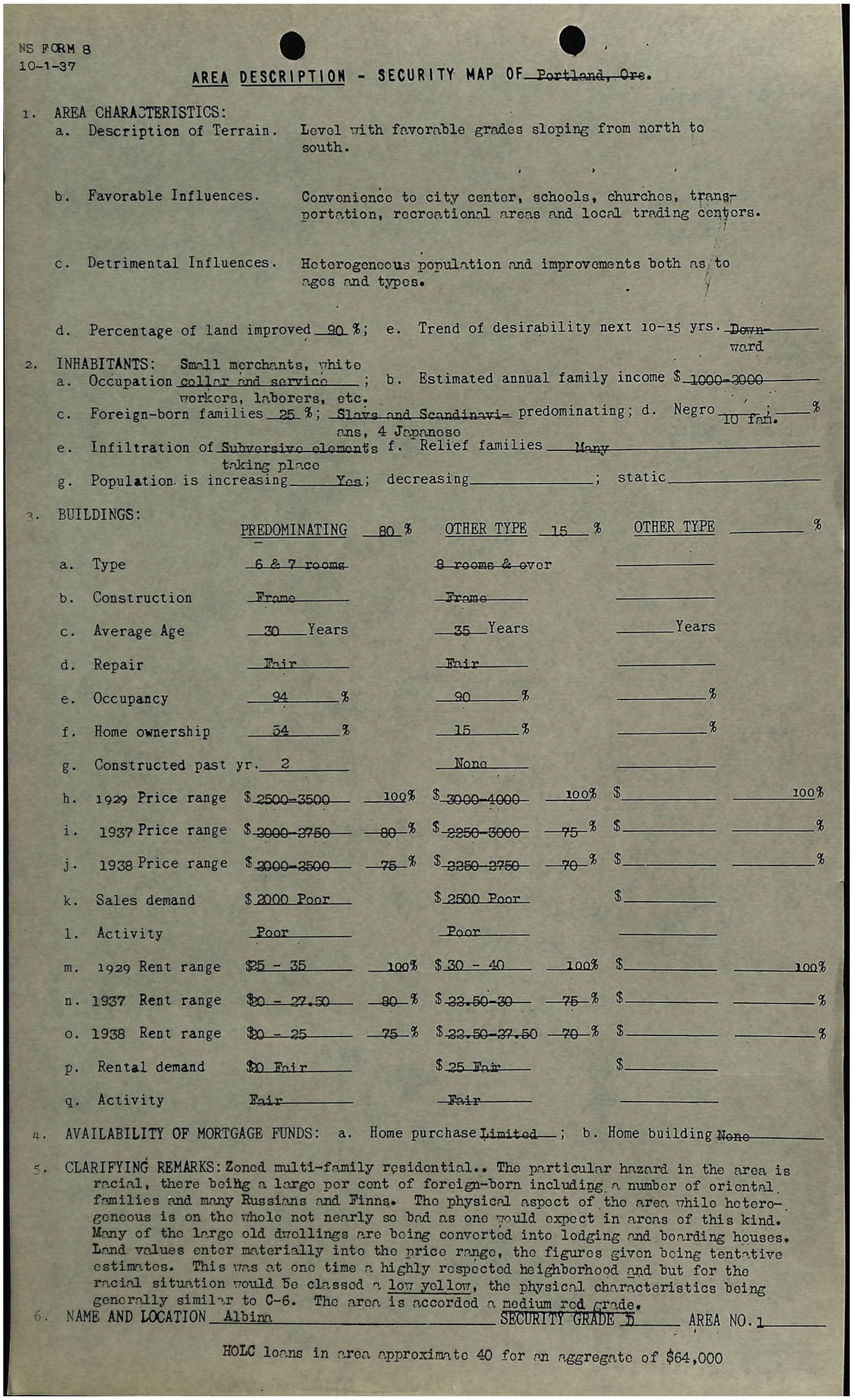
Notes: The table presents the spatial regression discontinuity estimates for energy consumption. D is an indicator for a home located in a redlined area. $(x - x_0)$ denotes the distance to the boundary of the nearest redlined area. Standard errors are clustered at this boundary.

Figure C.1: HOLC Map



Notes: The figure displays the historical HOLC map of Portland, established in 1938. The HOLC grades — A, B, C, and D — are denoted by the colors green, blue, yellow, and red, respectively.

Figure C.2: HOLC Survey Document



NS FORM 8
10-1-37

AREA DESCRIPTION - SECURITY MAP OF Portland, Ore.

1. AREA CHARACTERISTICS:
   a. Description of Terrain. Level with favorable grades sloping from north to south.
   b. Favorable Influences. Convenience to city center, schools, churches, transportation, recreational areas and local trading centers.
   c. Detrimental Influences. Heterogeneous population and improvements both as to ages and types.
   d. Percentage of land improved 90 %; e. Trend of desirability next 10-15 yrs. Downward
2. INHABITANTS:
   a. Occupation Small merchants, white collar and service workers, laborers, etc.; b. Estimated annual family income $ 1000-2000
   c. Foreign-born families 25 %; Slavs and Scandinavians, 4 Japanese predominating; d. Negro 10 fam. ; %
   e. Infiltration of Subversive elements taking place f. Relief families Many
   g. Population is increasing Yes; decreasing ; static
3. BUILDINGS:

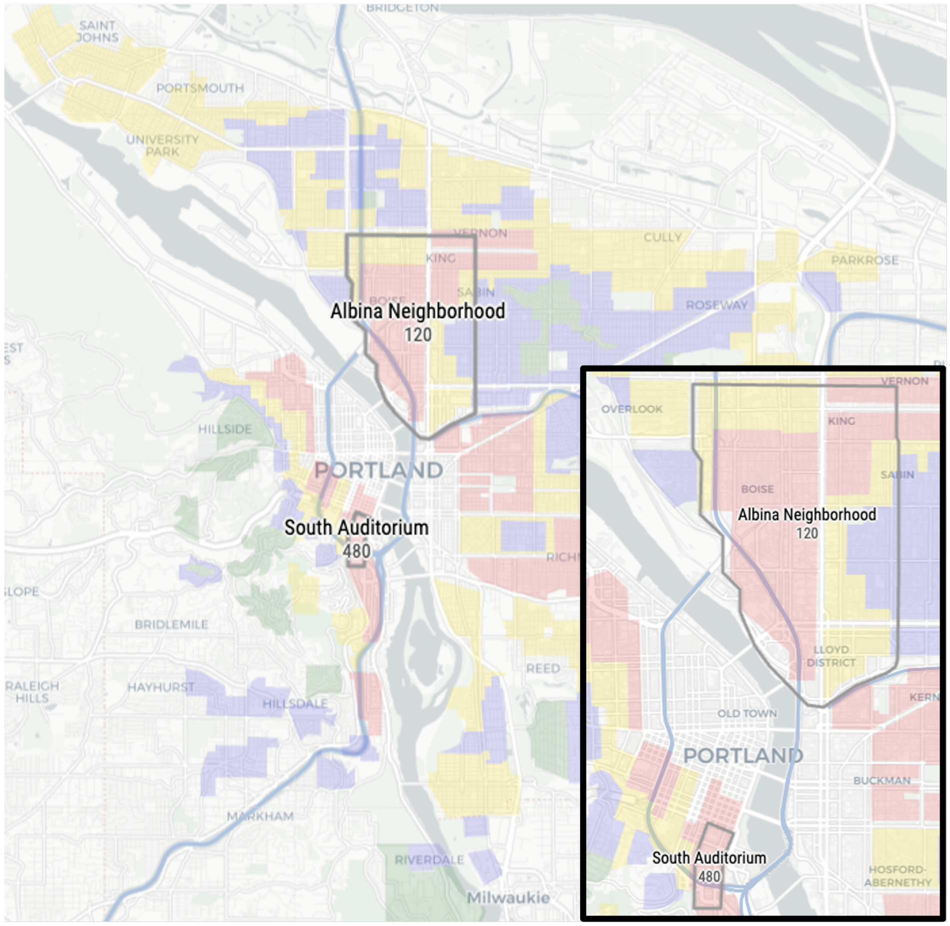
	PREDOMINATING	80 %	OTHER TYPE	15 %	OTHER TYPE	%
a. Type	6 & 7 rooms		8 rooms & over			
b. Construction	Frame		Frame			
c. Average Age	30 Years		35 Years		Years	
d. Repair	Fair		Fair			
e. Occupancy	94 %		90 %		%	
f. Home ownership	54 %		15 %		%	
g. Constructed past yr.	2		None			
h. 1929 Price range	$ 2500-3500	100%	$ 3000-4000	100%	$	100%
i. 1937 Price range	$ 2000-2750	80 %	$ 2250-3000	75 %	$	%
j. 1938 Price range	$ 2000-2500	75 %	$ 2250-2750	70 %	$	%
k. Sales demand	$ 2000 Poor		$ 2500 Poor		$	
l. Activity	Poor		Poor			
m. 1929 Rent range	$25 - 35	100%	$ 30 - 40	100%	$	100%
n. 1937 Rent range	$20 - 27.50	80 %	$ 22.50-30	75 %	$	%
o. 1938 Rent range	$20 - 25	75 %	$ 22.50-27.50	70 %	$	%
p. Rental demand	$20 Fair		$ 25 Fair		$	
q. Activity	Fair		Fair			

4. AVAILABILITY OF MORTGAGE FUNDS: a. Home purchase Limited; b. Home building None
5. CLARIFYING REMARKS: Zoned multi-family residential.. The particular hazard in the area is racial, there being a large per cent of foreign-born including a number of oriental families and many Russians and Finns. The physical aspect of the area while heterogeneous is on the whole not nearly so bad as one would expect in areas of this kind. Many of the large old dwellings are being converted into lodging and boarding houses. Land values enter materially into the price range, the figures given being tentative estimates. This was at one time a highly respected neighborhood and but for the racial situation would be classed a low yellow, the physical characteristics being generally similar to C-6. The area is accorded a medium red grade.
6. NAME AND LOCATION Albina SECURITY GRADE D AREA NO. 1

HOLC loans in area approximate 40 for an aggregate of $64,000

Notes: The figure displays the historical HOLC survey document for the redlined area — D2. The document includes information on the area's buildings, inhabitants, mortgage availability, and other characteristics.

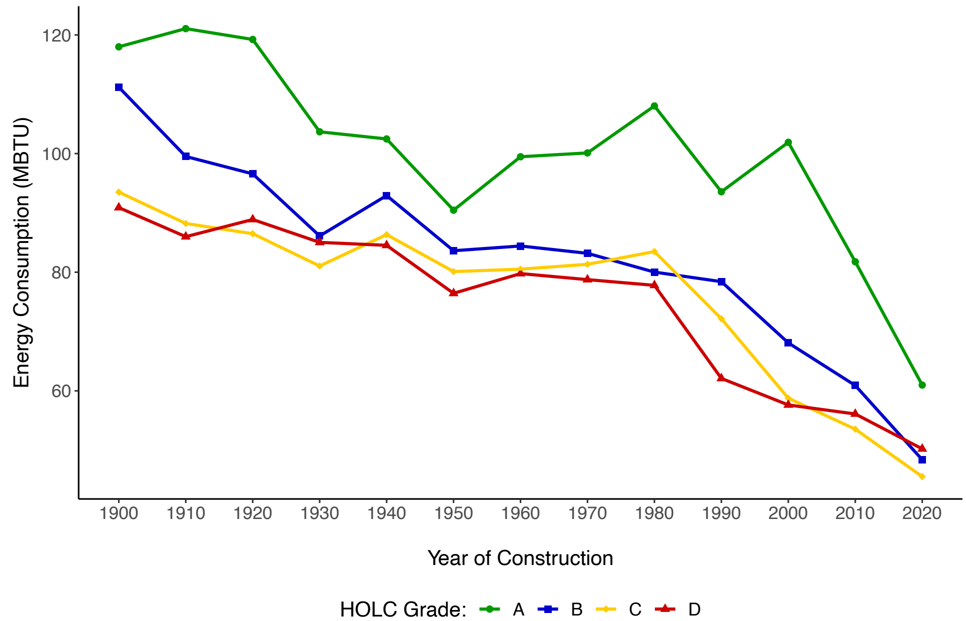
Figure C.3: Urban Renewal Projects



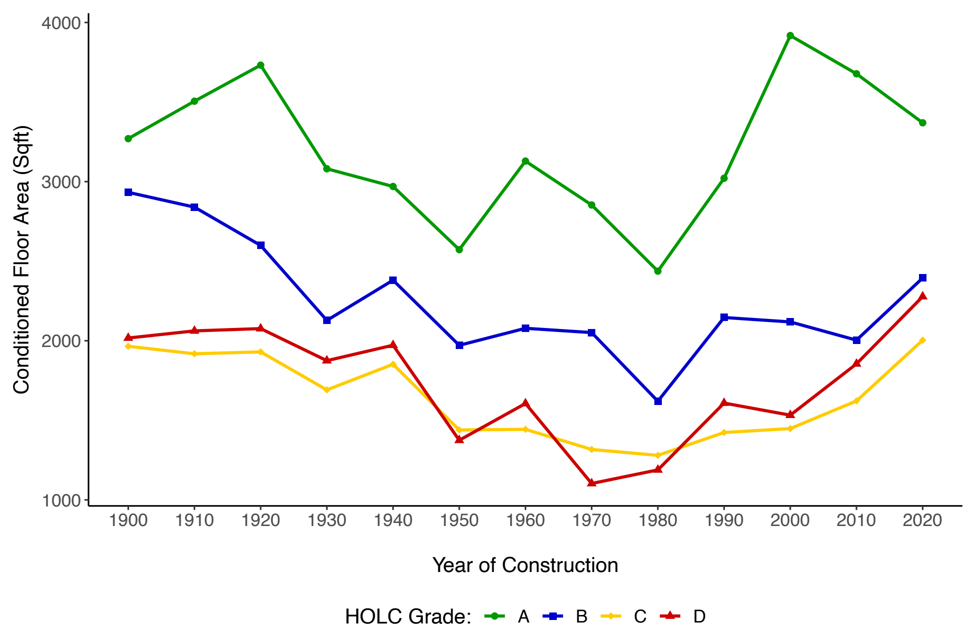
Notes: The figure displays the urban renewal projects that displaced families in Portland during the 1960s and 1970s (see University of Richmond, 2022b). These projects — the Albina Neighborhood and South Auditorium — are outlined in gray. The figure also displays the HOLC grades — A, B, C, and D — denoted by the colors green, blue, yellow, and red, respectively.

Figure C.4: Trends by Year of Construction

(a) Energy Consumption (MBTU)

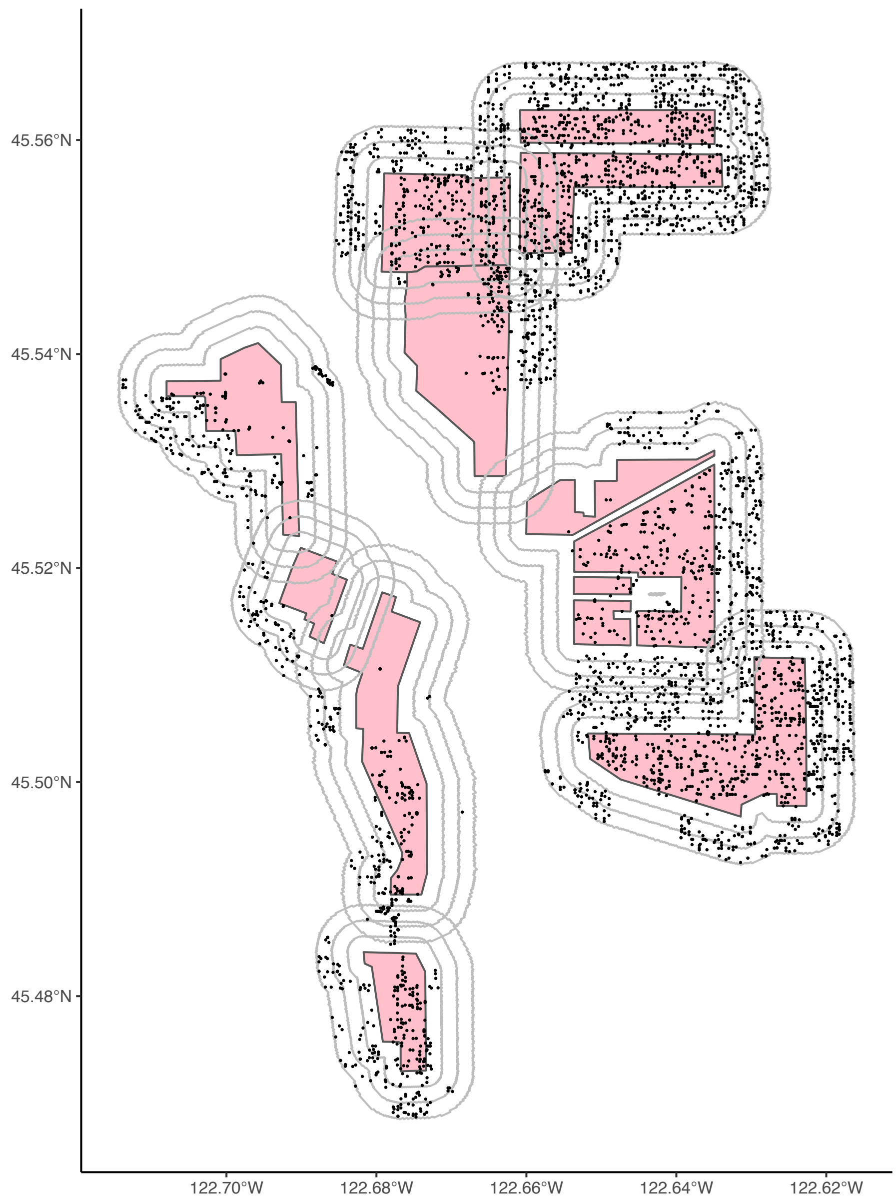


(b) Conditioned Floor Area (Sqft)



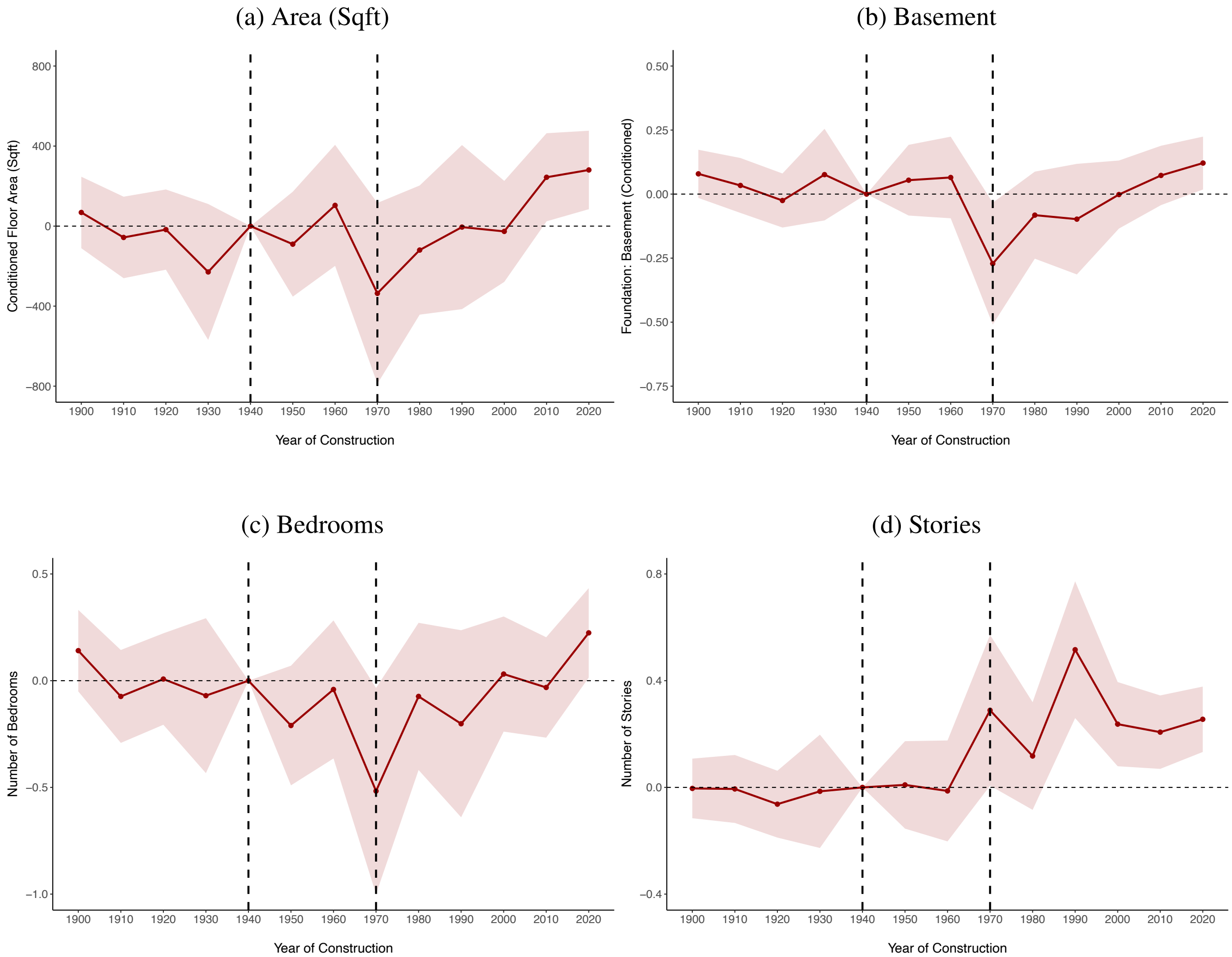
Notes: Panel (a) plots the average home energy score by year of construction separated by HOLC grade. Similarly, Panel (b) plots the average conditioned floor area (sqft). The HOLC grades — A, B, C, and D — are denoted by the colors green, blue, yellow, and red, respectively.

Figure C.5: Redlined Areas and Buffers



Notes: The figure plots homes with a home energy score assessment located in a redlined area or its respective buffers — 0.1, 0.2, and 0.3 miles. The redlined areas and buffers are denoted by the colors red and gray, respectively. The black points are homes.

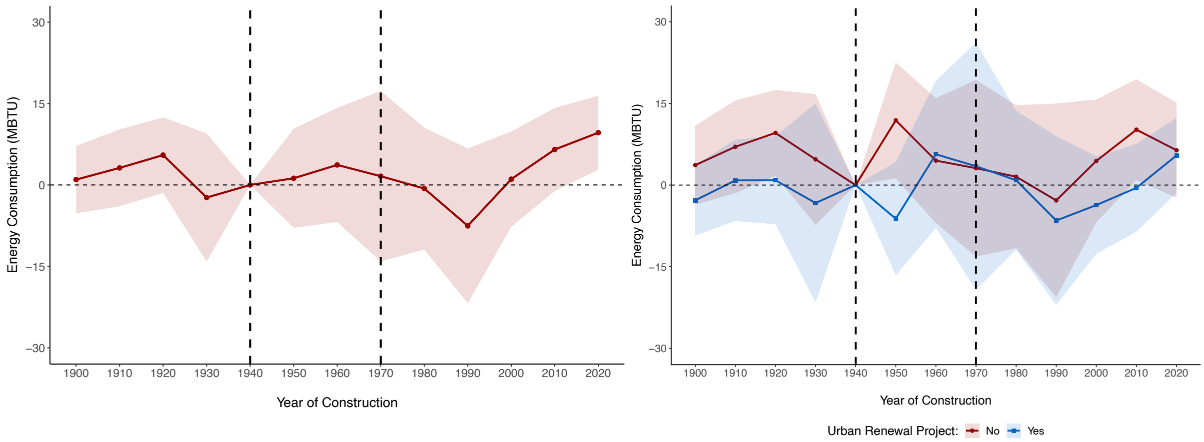
Figure C.6: Event Study Estimates - Fixed Assets



Notes: The figure plots the event study estimates for the fixed assets. Panels (a), (b), (c), and (d) plot the estimates for conditioned floor area (sqft), basement, bedrooms, and stories, respectively.

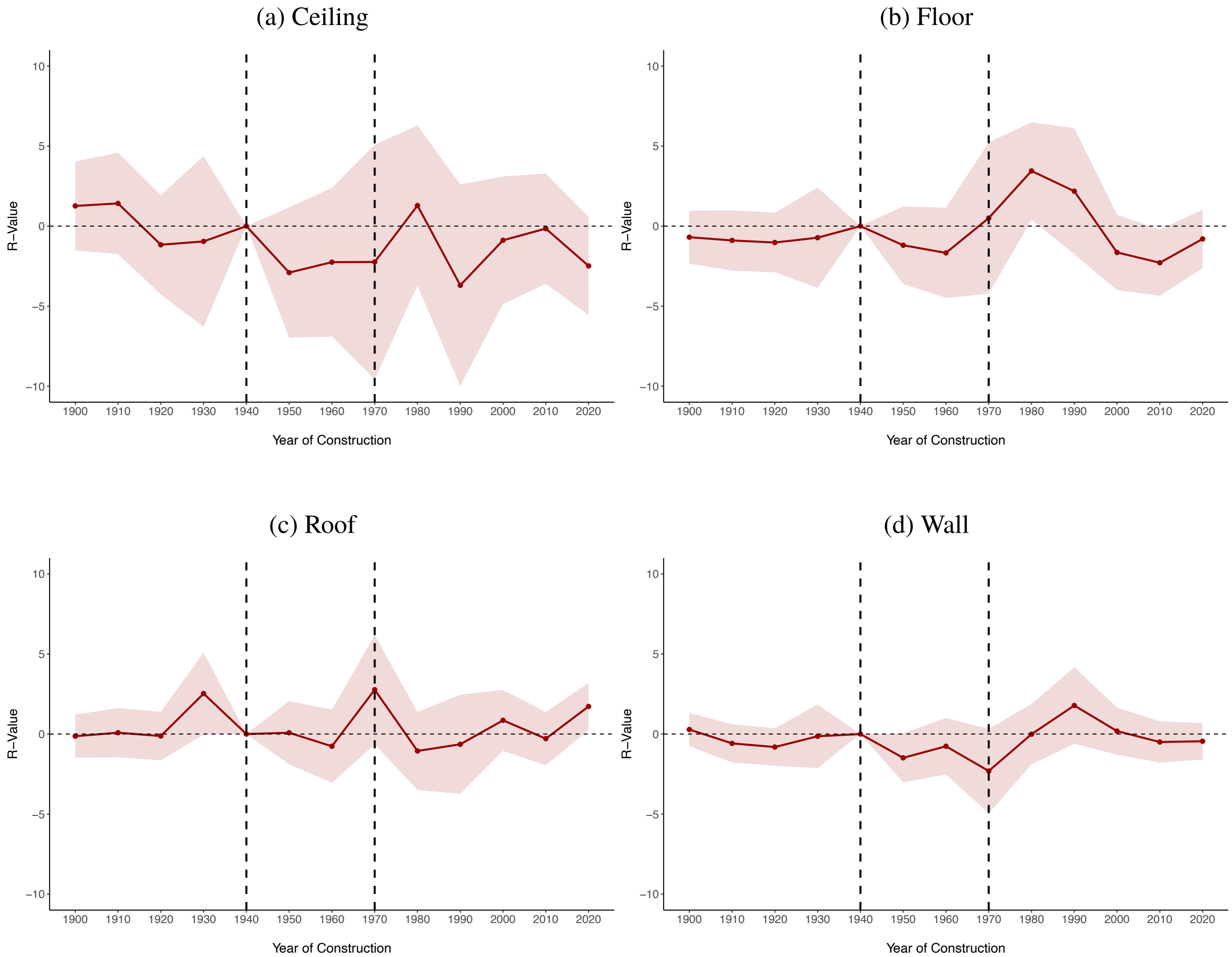
Figure C.7: Event Study Estimates - Energy Consumption

(a) Redlined Areas (b) Urban Renewal Projects



Notes: The figure plots the event study estimates for expected energy consumption. In panel (a), treatment is redlined areas. In panel (b), treatment is separated into redlined areas that are and are not contained in an urban renewal project.

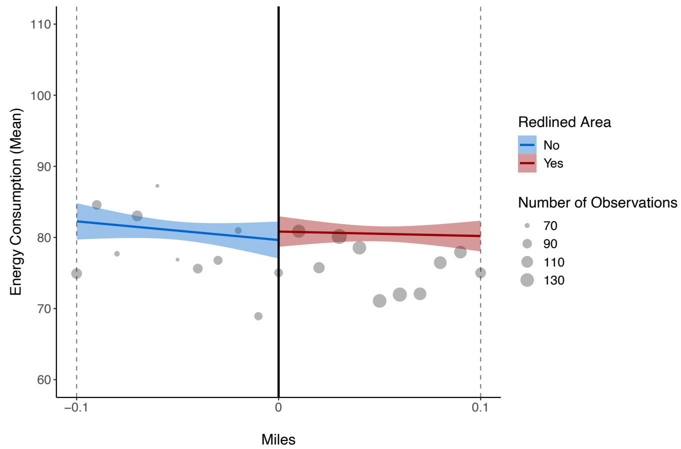
Figure C.8: Event Study Estimates - Insulation



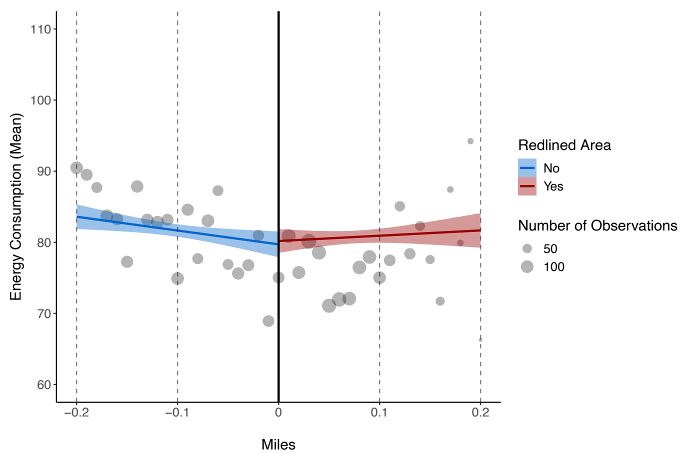
Notes: The figure plots the event study estimates for insulation. Panels (a), (b), (c), and (d) plot the estimates for ceiling, floor, roof, and wall insulation, respectively.

Figure C.9: Spatial Regression Discontinuity Estimates - Energy Consumption

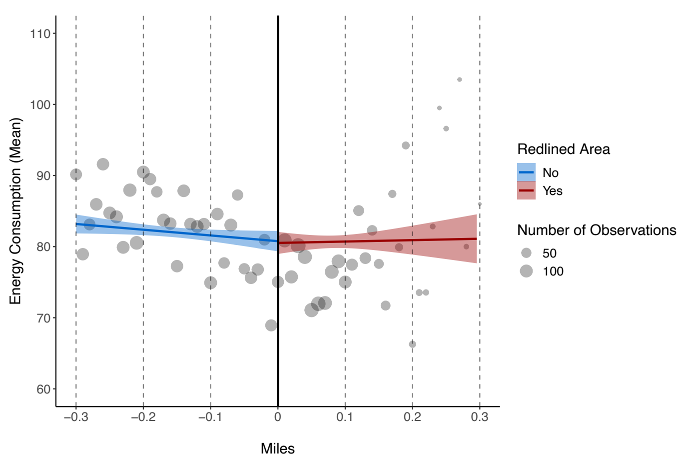
(a) Bandwidth: 0.1 Miles



(b) Bandwidth: 0.2 Miles



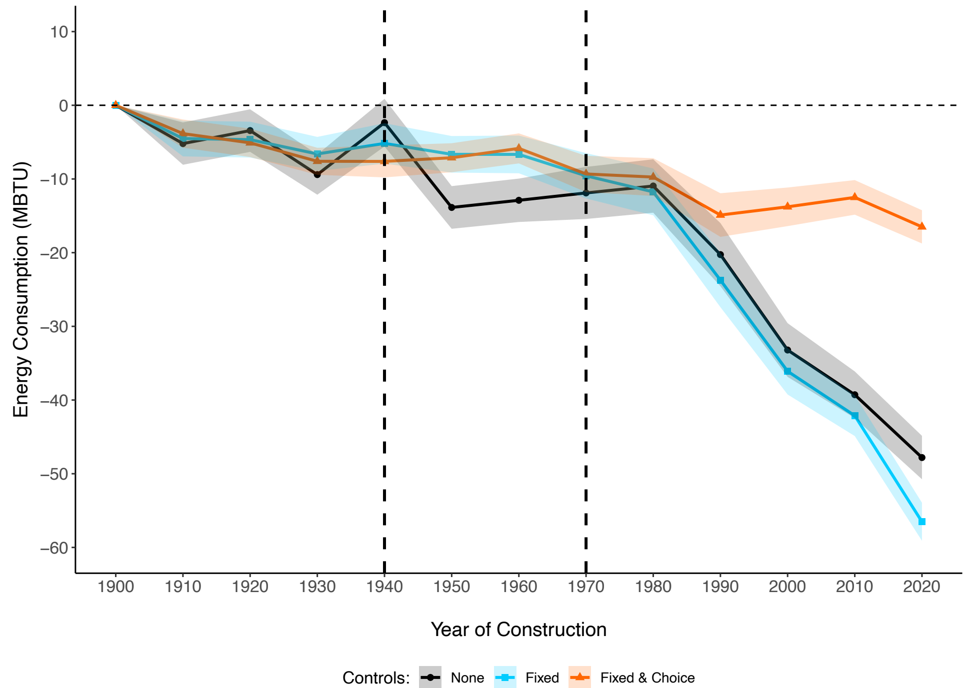
(c) Bandwidth: 0.3 Miles



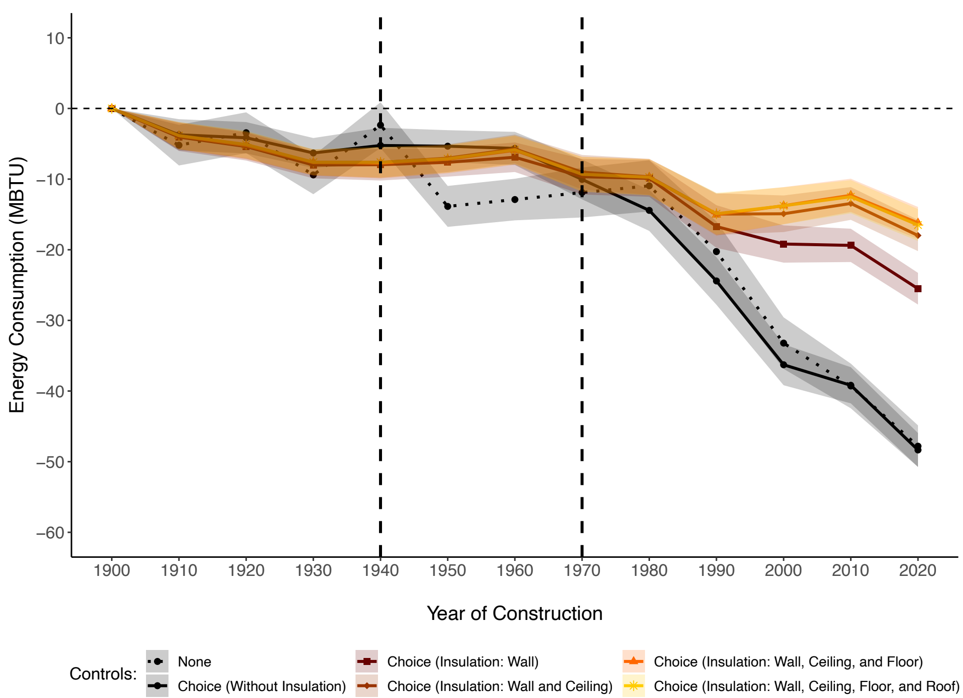
Notes: The figure plots the spatial regression discontinuity estimates for expected energy consumption. Panels (a), (b), and (c) plot the estimates with a bandwidth of 0.1, 0.2, and 0.3 miles, respectively.

Figure C.10: Changes in Energy Consumption by Year of Construction

(a) Fixed and Choice Assets



(b) Choice Assets (With and Without Insulation)



Notes: The figure plots the change in expected energy consumption by year of construction relative to the reference group, 1900. In panel (a), I condition on the fixed and choice assets. In panel (b), I separate the choice assets by insulation.