Equilibrium Effects of Energy Efficiency Disclosure in Housing Markets

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Abstract

Building energy efficiency is crucial for identifying energy-saving potential, yet such information was not publicly available in the past. This paper examines the equilibrium effects of a regulation in New York City that mandates increased public access to building energy efficiency information. I find that the effectiveness of disclosure policies in achieving desired market outcomes hinges significantly on the salience of the information disclosed. My findings suggest that enhancing the salience of building energy efficiency disclosures leads to the emergence of energy efficiency premiums and incentivizes buildings to make energy efficiency improvements. Particularly, luxury buildings exhibit more pronounced responses. I develop and estimate an equilibrium model of demand for homes and building energy efficiency, as well as buildings' choices of energy efficiency levels. The results indicate that the increase in housing prices attributable to energy efficiency improvements significantly exceeds the savings in energy bills.

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1 Introduction

Improving Energy efficiency is a key strategy to achieve energy use reduction goals and combat the challenges of climate change. In the United States, buildings are significant energy consumers, accounting for 40% of the nation's total energy usage, with residential and commercial sectors contributing 21% and 18%, respectively (the U.S. Energy Information Administration, 2021). However, until recently, information about the energy consumption and efficiency of buildings remained largely hidden from the public eye. Today, an increasing number of local and state governments are actively adopting policies to enhance transparency in building energy efficiency. These policies require owners of both residential and commercial properties to consistently measure and disclose data about their energy consumption to the public. Notably, since 2010, a total of 21 municipalities and states across the United States have embraced these policies, specifically targeting residential buildings (National Association of State Energy Officials, 2022).

The debate over energy benchmarking and disclosure policies is multifaceted. On one hand, proponents argue that these policies bring about several notable benefits. They claim that these policies may allow the housing market to better assess the value of energy efficiency by providing detailed energy consumption data. Moreover, information regarding building energy use helps owners identify opportunities for energy efficiency improvements. Furthermore, information interventions are considered a low-cost policy tool to incentivize property owners to invest in energy-saving upgrades, compared to subsidies for energy efficiency improvements. On the other hand, critics challenge the effectiveness of these policies, questioning whether mandatory disclosures are sufficient to significantly improve market outcomes (Winston (2008), Ho et al. (2019)).

To bridge the gap between these perspectives, this study investigates the equilibrium effects of increased public access to energy efficiency information on housing prices, home-buyer decisions, and building responses. It employs a combination of causal analysis and a model of demand and supply of building energy efficiency to quantify the impacts of energy disclosure policies in New York City. New York City is one of the first cities in the United States to mandate the annual measurement and public disclosure of energy usage for large buildings. Disclosure requirements in NYC were phased in gradually, leading to changing policy stringency since their introduction. The mandate for online disclosure began in 2013. However, there was a policy change in late 2017 with the goal of enhancing the salience of energy efficiency measures by requiring buildings to prominently display energy efficiency ratings at their entrances. This study leverages the 2017 policy change to identify the impact of increased salience on the housing market.

To study how the policy change, which enhances the salience of energy efficiency, affects the equilibrium valuation of energy efficiency in housing prices, I use New York City's building energy efficiency disclosure data set from 2011 to 2021. This data contain detailed energy consumption information and the Energy Star score[1] for buildings under disclosure requirements. I link the data with the complete home sale records from New York City between 2010 and 2021, which provide transaction prices, exact street addresses, apartment specifics, and building characteristics. To analyze supply-side responses, I merge this data with a data set on building work in NYC between 2011 and 2021, which enables me to assess buildings' investments in improving energy efficiency in response to the change in disclosure requirements.

My empirical analysis delivers three key findings. First, the enhanced salience of energy efficiency information disclosure leads to increases in the equilibrium prices of building energy efficiency. Prior to the mandated disclosure, and even in the first few years after the disclosure became available online, there were no premiums for achieving higher energy efficiency. However, a significant shift occurred in 2017 with the introduction of the requirement to prominently display the score near the building entrance. Since then, each one-point increase in the Energy Star score[2] corresponds to a 0.14% increase in

[1] The Energy Star score ranges from 1 to 100 and is calculated using weather-normalized Source Energy Use Intensity (EUI), adjusting for climate differences. It evaluates energy efficiency relative to similar buildings nationwide, considering factors like size and location.

[2] One standard deviation of the Energy Star score is around 30 points.

the sale price of apartment units. Second, in response to the enhanced disclosure requirements, building owners are increasingly investing in energy efficiency improvements to obtain a higher Energy Star score. I find that buildings have reduced their energy use intensities by up to 10% since 2017. Third, I document heterogeneous responses among different types of buildings. Upscale buildings show more substantial premiums and greater improvements compared to affordable buildings.

Motivated by the empirical findings, I develop and estimate a model of the demand and supply of energy efficiency. On the demand side, households consider the price, the building's Energy Star rating, energy bills, and other building characteristics. However, a building's Energy Star rating may not be easily noticeable by households and thus may fail to be taken into account in their valuation. Enhancing the salience of building energy efficiency raises the awareness of households about the true energy efficiency level of the building and changes their willingness to pay. On the supply side, buildings choose their Energy Star scores to maximize profits, which are composed of capitalization gains, savings in energy bills, and investment costs.

The model highlights two sources of inefficiencies arising from information frictions. First, household choices can be distorted by their perceived value of a product feature, which depends on the feature's salience. Second, buildings may lack incentives to improve their energy efficiency if the benefits of such improvements do not outweigh the costs. Thus, enhancing the salience of building energy efficiency, if it leads to improved market attractiveness and increased market valuation, could reduce these inefficiencies by incentivizing investment in energy efficiency. However, this might also increase inefficiencies if the price premiums for energy efficiency exceed its actual benefits.

I use the model to quantify the impact of the proposal that requires prominent disclosure of a building's Energy Star score in New York City. I find that the capitalization of building energy efficiency into the equilibrium housing prices is mainly driven by the increase in households' willingness to pay for a higher Energy Star score when it becomes more noticeable. I further benchmark the increase in housing prices with its benefits. I find that every one-point increase in the Energy Star score results in an approximate post-tax capital gain of $112,000 for a building after 2017. At a discount rate of 5%, the corresponding perpetual savings in energy bills amount to $33,000, while the upper bound of perpetual reduced social costs is approximately $28,000. Note that the price increase significantly exceeds the benefits from actual savings in bills and reduced social cost of carbon.

This paper makes significant contributions to several strands of literature. First, it aligns with a broad body of work examining the value of information provision, as demonstrated in prior research such as Jin and Leslie (2003), Ho et al. (2019), Hastings and Weinstein (2008), Dranove and Jin (2010), Barahona et al. (2020), Bollinger et al. (2011), Andrabi et al. (2017), and Dai and Luca (2020). Existing research has investigated the effects of mandatory disclosure, as shown in Greenstone et al. (2006), and voluntary disclosure, as Lewis (2011) and Guo and Zhao (2009). Information disclosure has far-reaching implications for various market participants, changing sellers' behavior, as in Jin and Leslie (2009), and shaping consumers' beliefs through learning, as indicated by Chernew et al. (2008). Prior research has primarily emphasized the benefits of information disclosure, such as how quality certification can rectify information asymmetry market failures, as highlighted in Elfenbein et al. (2015), and how it raises consumer awareness, as discussed in Li et al. (2016). This paper contributes by identifying how increasing the visibility and prominence of information can shape the equilibrium effects of information disclosure. It quantifies the causal impact of enhancing the visibility of disclosure on energy efficiency premiums and provides evidence of the energy efficiency improvement responses on the building side.

Second, this paper extends the literature examining the impacts of energy efficiency regulations and contributes to the broader field of energy information studies. It speaks to research works on how energy and environmental information affects consumers' demand, as in Barwick et al. (2019), Houde (2018), Jessoe and Rapson (2014), and Graff Zivin and Neidell (2009). In addition, it directly relates to the literature on the capitalization of energy efficiency in the housing market, akin to Myers et al. (2022), Aydin et al. (2020), Kahn and Kok (2014), Koirala et al. (2014), Fesselmeyer (2018) (Singapore), Jensen et al. (2016) (Denmark), and Holtermans and Kok (2019) (CRE). Moreover, it adds to the studies that examine how energy efficiency labeling induces supply-side responses, as demonstrated in Chegut et al. (2019), Deng and Wu (2014), and Tomar (2023). This paper's unique contribution to this body of work lies in quantifying the equilibrium impacts of energy efficiency policies.

Furthermore, this paper contributes to the literature on the optimal design of disclosure policies, as in prior studies like Weil et al. (2006), Hui et al. (2022), and Vatter (2022). Two of the most relevant studies include Cassidy (2023) and Ghosh et al. (2023). Cassidy (2023) shows that disclosure of less observable energy-efficiency features has a much stronger correlation with sale prices, compared to disclosure of more easily observed features. Ghosh et al. (2023) also find that salience is the key for the disclosure to generate energy efficiency premiums. What distinguishes this paper is that it benchmarks the increase in housing prices against the actual energy savings and investment costs. The finding that the increase in housing prices significantly exceeds the actual cost savings provides new evidence of overreaction to enhanced salience in the real estate market. Additionally, this paper makes an extra contribution by shedding light on the heterogeneous responses among households and buildings to energy efficiency information disclosure policies. This insight underscores the critical need for policymakers to account for these distributional effects in order to strike a balance between effectiveness and equity when formulating and implementing information disclosure programs.

The remainder of the paper is organized as follows. Section 2 describes the policy background and the data. Section 3 presents the empirical analysis. Section 5 introduces an empirical model and details the estimation process. Section 7 concludes.

2 Policy Background and Data

2.1 Policy Background

Over the years, energy efficiency has emerged as a central concern in the United States, driven by a combination of environmental, economic, and social factors. The recognition of the environmental impact of energy consumption, particularly in terms of greenhouse gas emissions and their contribution to climate change, has underscored the need for more sustainable energy practices. Simultaneously, rising energy costs and the pursuit of economic competitiveness have placed energy efficiency at the forefront of corporate and government agendas.

New York City was among the first cities in the U.S. to tackle energy efficiency challenges and establish disclosure requirements for buildings. The aim was to enhance transparency and accountability in building energy usage, thereby encouraging owners to adopt energy-efficient practices. The focus on building energy efficiency stems from the recognition that buildings are significant contributors to energy consumption and greenhouse gas emissions, making the implementation of policies to monitor and improve energy efficiency in buildings paramount.

New York City made the first move in December 2009, introducing Local Law 84 (LL84) in response to growing concerns over energy consumption and sustainability. LL84 mandated that owners of buildings with a gross floor area exceeding 50,000 square feet (hereafter referred to as "large buildings") must record their energy and water consumption annually, a process known as energy benchmarking. These benchmarking results were then required to be submitted to the U.S. Environmental Protection Agency (EPA) Portfolio Manager by May 1 of the following year, with the results published online by the NYC Department of Finance by September 1. Benchmarking for large buildings commenced in 2010, and the disclosure requirements for multifamily properties were enforced in 2013. Non-compliance with the ordinance carried a penalty fine of up to $2,000 per year, underlining the city's commitment to driving energy efficiency improvements.

To facilitate the assessment of a building's energy efficiency performance, the disclosure information began including the Energy Star score in 2015. When the building submits its benchmarking results, the benchmarking tool known as Portfolio Manager calculates an Energy Star score for it. This calculation primarily relies on a building's energy use intensity (EUI) and adjusts for variations due to weather conditions. It then compares the building's EUI to that of similar national average buildings in terms of size, location, number of occupants, number of PCs, and etc. Consequently, the Energy Star score serves as a comprehensive indicator of a building's energy efficiency, with a range of 1 to 100, where higher scores indicate better energy performance. In September 2016, Local Law 84 was amended by Local Law 133 (LL133), reducing the benchmarking and disclosure threshold to 25,000 square feet for mid-size buildings. Benchmarking for these buildings started in 2017, with the first disclosure for mid-size multifamily properties taking place in May 2018.

Despite the implementation of disclosure laws, public awareness about these measures is not as high as desired. Findings from a 2015 New York State Energy Research and Development Authority (NYSERDA) survey show that over half of the tenants remain uninformed about energy efficiency policies. To address this issue, Local Law 33 was passed in December 2017, requiring buildings to prominently exhibit their energy efficiency ratings and scores at their main entrances. This requirement was set to take effect from October 2020, as part of a strategy to enhance public engagement with building energy efficiency.

The introduction of the amended energy efficiency policy in late 2017 gained significant attention from the media, which effectively informed the public about the importance of energy efficiency. This increase in exposure has played a crucial role in raising public awareness and emphasizing the significance of visible Energy Star scores. With the policy coming into full effect in late 2020, it has captured the public's interest in energy efficiency and has substantially improved their awareness.

Placing the Energy Star score prominently near the building entrance carries substantial significance compared to online disclosure alone. While online disclosure provides access to important information, it often relies on individuals actively seeking out the data. In contrast, displaying the score at a visible location near the entrance serves as a powerful advertising and awareness tool. The prominent display of the Energy Star score can influence the decisions of both tenants and property investors. Tenants are more likely to choose energy-efficient buildings, as they translate into lower utility bills and greater comfort. For investors, energy-efficient buildings can signify reduced operational costs and increased property value, further incentivizing building owners to invest in improving energy efficiency.

2.2 Data

2.2.1 Building Energy Efficiency Disclosure Data

To capture changes in energy consumption by buildings, I collect the data set of Energy and Water Data Disclosure from NYC OpenData. The data tracks the benchmarking results and energy efficiency ratings for buildings subject to the disclosure requirements in NYC from 2010 to 2021. In this data set, each building is identifiable by its Borough-Block-Lot (BBL), which allows me to link the disclosure data set to the housing transaction data set. The data set includes various aspects of energy usage, including source Energy Use Intensity (source EUI)[3], site Energy Use Intensity (EUI)[4], electricity consumption, total carbon emissions, the use of specific fuels (e.g., Fuel No. 2, Fuel No. 4, Fuel No. 5&6),

[3]Source EUI (kBtu/sqft) is a metric that follows the heat and electricity used at a specific site all the way back to their initial raw sources. It takes into consideration the energy losses that occur during the production, transmission, and delivery of that energy to the building. Source EUI also performs a conversion, equating primary energy sources (such as raw fuel like natural gas or fuel oil) and secondary energy sources (like energy products such as electricity or heat) into equivalent units of raw fuel required to generate one unit of energy consumed on-site.

[4]Site EUI (kBtu/sqft) represents the quantity of heat and electricity consumed by a building, as indicated in its annual utility bills, divided by the total square footage of the building area.

and total water consumption. Starting in 2015, the Energy Star score starts to be available for disclosure. Appendix Figure A.1 presents a geographic distribution of these disclosed buildings. I supplement the data set with additional historical energy prices by category specific to New York State from the Environmental Impact Assessment (EIA). It allows me to calculate the utility bills for the buildings in the sample.[5]

2.2.2 Home Sale and Deeds Data

To investigate the effects of the disclosure policy change on real estate prices, I complement the building energy use disclosure data by collecting the complete data set of housing transactions in NYC between 2010 and 2021 from the NYC Department of Finance's Rolling Sales files. Each transaction record identifies apartments by their apartment number and the buildings by a unique identifier known as Borough-Block-Lot (BBL). The data set includes detailed characteristics of apartments and buildings. Apartment characteristics include the transaction price, gross square footage, and date of sale. Building characteristics include the exact street address, building age, number of residential units, number of floors, the building's total gross floor area, primary use, and tax class.

2.2.3 Building Job Filing Application Data

To examine the upgrades buildings are making for energy efficiency, I further compile a data set that documents building responses to such improvements. The data is collected from the Department of Building (DOB), DOB NOW - Building, and DOB NOW - Electrical. It covers job applications for various construction, alteration, and demolition activities within NYC properties from 2010 to 2021. Each record corresponds to a building's application for specific work, indicating the type of work undertaken, such as

[5] I include natural gas, electricity, fuel oil No.2 (home heating oil), fuel oil No.4 (transition oil), and fuel oil No.5 & No.6 (residual oil) in the calculation of energy bill expenses. As nearly half of the buildings in the sample do not report their water usage, water usage has not been included in the energy expense calculations. Additionally, Panel (f) in Appendix Figure A.2 indicates a 10% to 20% decrease in building water usage over the years. This suggests that the calculated energy bills serve as a conservative estimate of actual spending on energy and water usage.

boiler installations, HVAC projects, and electrical work, along with a detailed description of the proposed construction tasks. Notably, this data set provides an uncommon chance to observe project costs. It also provides information about the dates of filing and permit approvals for the applications. The buildings in the data set can be identified by their BBL codes, enabling linkage to the aforementioned data sets. [6]

2.2.4 Property Valuation and Assessment Data

To assess the impact of the disclosure policy change on the assessed market value of buildings, I additionally collect data on estimated rental income, expenses, net operating income, and market value for residential cooperative and condominium buildings in New York City from 2010 to 2022. Each building is uniquely identifiable in the data set using its BBL code. [7]

2.2.5 Sample Construction and Descriptive Statistics

To examine the impact of energy efficiency disclosure policies on housing prices and building improvements in energy efficiency, I construct a sample by linking the energy disclosure data set with the transaction data set, job application data set, and property valuation data set using the buildings' BBL codes. I focus on buildings that began disclosing their Energy Star score before 2017 and had housing transactions between 2015 and 2021. The complete sample consists of 135,449 transactions across 3,351 buildings.

Summary statistics for the primary building energy disclosure in the full sample are presented in Panel A of Table 1. The average residential building in the sample inhabits

[6] NYC mandates that buildings submit an application and obtain permits for construction work prior to commencement. Before 2016, all such applications were submitted directly to the Department of Buildings (DOB). Since 2016, however, applications for building work have been processed through DOB NOW. DOB NOW - Building covers job applications for a wide range of work types, whereas electrical work within buildings needs a separate application process through DOB NOW - Electrical.

[7] In compliance with New York State regulations, the NYC Department of Finance assesses the value of residential cooperative and condominium buildings by referencing income and expense statements from rental buildings that share similar characteristics, including factors such as unit count, size, age, proximity, and number of stories.

120 households, with an Energy Star score of 58, and produces 817 mtCO_2e of CO_2 every year. On average, each building spends $387,000 on utility bills. When translated to annual per-household energy expenditure, this equals around $3,225.

Panel B of Table 1 shows the summary statistics for the apartment variables in the full sample. The average apartment sells at $1.02 million with 1120 square feet. A typical building experiences 14 transactions annually.

Panel C of Table 1 provides a snapshot of building work undertaken for energy efficiency improvements. Between 2010 and 2021, the buildings in the sample have completed a total of 2,296 projects related to energy efficiency upgrades. On average, each project incurs a cost of $174,000. The most frequently employed measures for improving buildings' energy efficiency include upgrades to heating, ventilation, and air conditioning (HVAC) systems, the replacement of boilers, and converting to natural gas.

To illustrate the evolution of the Energy Star score distribution over time, I present a binned scatter plot that compares the Energy Star scores for buildings in 2015 to those in 2021 in Figure 1a. Most of the data points lie to the right of the 45-degree line, suggesting that many buildings have seen an increase in their Energy Star ratings over this period.

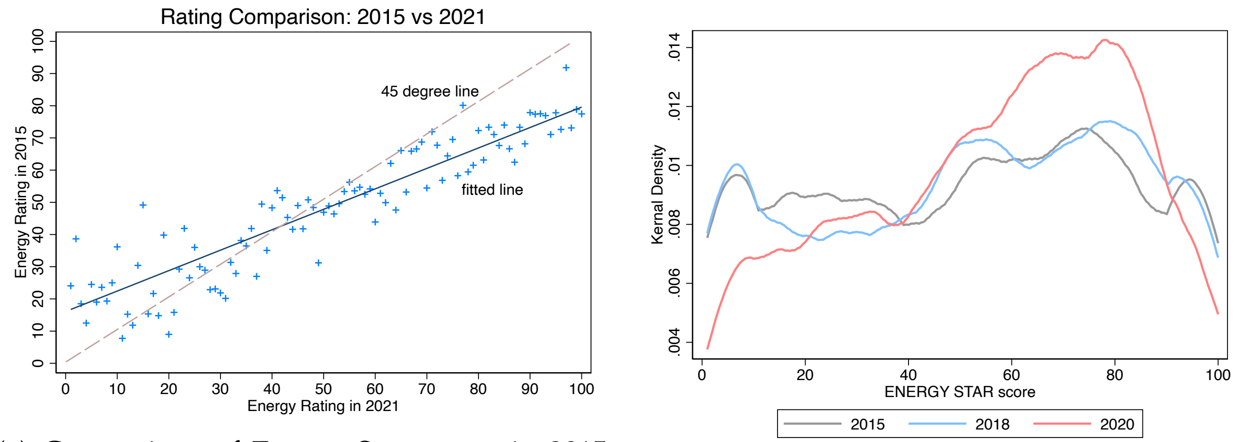
Furthermore, Figure 1b provides snapshots of the Energy Star score distributions for buildings in 2015, 2018, and 2020. It plots the kernel density curves in corresponding years Between 2015 and 2018, there was a decrease in density for scores ranging from 20 to 40, accompanied by an increase for scores between 40 and 60, as well as scores above 80. In the 2020 data, when compared to previous years, there is a notable decrease in the kernel density that is predominantly below 40, along with an increase within the range of 40 to 80. This shift signals significant improvements in energy efficiency over time.

Table 1: Summary Statistics

	Mean	SD	Min	Max	Median	Observations
Table A: Building Characteristics and Energy Use for Residential Buildings						
Year Built	1948.006	26.95004	1800	2017	1942	40212
Building Floors	10.88247	7.943515	1	78	7	40212
Number of Residential Units	120.6004	197.5335	20	8749	82	40206
Energy Star Score	58.09234	28.67386	1	100	63	24974
Energy Bills (USD/year)	386774.4	7488519	1583.177	6.24e+08	173932	40212
Building Gross Floor Area (sqft)	142549.1	215728.8	25403	8942176	95707	40212
Electricity (kWh)	950620.5	3857437	87.3	2.06e+08	470586.9	40212
Natural Gas (kBtu)	1.42e+07	6.09e+08	0	4.95e+10	4126764	40212
No.2 Fuel Oil (kBtu)	1515043	3478367	0	1.08e+08	0	40212
No.4 Fuel Oil (kBtu)	1262413	3860027	0	1.05e+08	0	40212
No.5 & No.6 Fuel Oil (kBtu)	1663498	4140040	0	1.04e+08	0	40212
Water (kGal)	15385.19	98573.26	.7	3423222	4717.65	29774
CO2 Emissions (MTCO2e)	816.9737	1378.512	13.34	19438.24	504.2	40212
Table B: Apartment Transactions in Buildings						
Sale Price (USD)	1018119	1233345	133500	1.03e+07	615000	135449
Sale Price Per SQFT(USD/sqft)	858.6841	835.5063	37.11786	57692.31	646.0975	135437
Apt. Gross Floor Area (sqft)	1119.366	504.7447	104	7768	1010.657	135437
Transactions	13.9503	18.66141	1	182	8	135449
Table C: Building Investments in Energy Efficiency Upgrade						
Initial Cost	147651.6	304014.2	1000	5769987	64000	2296
Total Costs	173763.8	314512.7	3750	6418900	88300	2296
Boiler Replacement	.0170649	.1324023	0	2	0	39672
Fuel Burning Work	.0138889	.1176757	0	2	0	39672
Solar Panel	.0017897	.1161151	0	21	0	39672
Upgrade Fuel Oil	.0044868	.06721	0	2	0	39672
Gas Work	.0163844	.1325833	0	3	0	39672
Heat Pump Upgrade	.0010083	.0317376	0	1	0	39672
Furnance Upgrade	.0000252	.0050206	0	1	0	39672
Lighting Upgrade	.0037558	.0639898	0	2	0	39672
Insulation Upgrade	.0002521	.0158748	0	1	0	39672
Fuel Work	.0154517	.1239539	0	2	0	39672
Heating Upgrade	.0193335	.1409528	0	2	0	39672
Cooling Upgrade	.003655	.0624001	0	3	0	39672
Ventilation Upgrade	.0033525	.059098	0	2	0	39672
Waterheating Upgrade	.001462	.0388626	0	2	0	39672
HVAC Upgrade	.033903	.1903498	0	3	0	39672

Notes: The sample used in calculating summary statistics consists of buildings that started to disclose their ENERGY STAR rating before 2017.

Figure 1: Energy Star score Change In Response to Building Work



(a) Comparison of Energy Star scores in 2015 and 2021

(b) ENERY STAR Score Distribution

Notes: The sample consists of buildings that started Energy Star score disclosure by 2015 and continued consistently through 2021.

3 Empirical Analysis

This section presents empirical evidence of the impact of the energy efficiency disclosure policies on home sale prices and building energy efficiency changes.

The findings reveal three key facts. First, transaction prices of residential units in energy-efficient buildings started to increase after the policy proposing prominent disclosure was passed. Second, in response to the proposed policy on prominent disclosure, building owners take steps to improve their buildings' energy efficiency. Third, the responses to these changes, in terms of both demand and supply, are especially significant among upscale buildings.

3.1 Capitalization of Building Energy Efficiency into Housing Prices

3.1.1 The Effects of Building Energy Efficiency on Apartment Sale Prices

I use an event-study design to quantify the impact of the policy that proposes to enhance the prominence of disclosure on energy efficiency premiums and estimate the following regression specification.

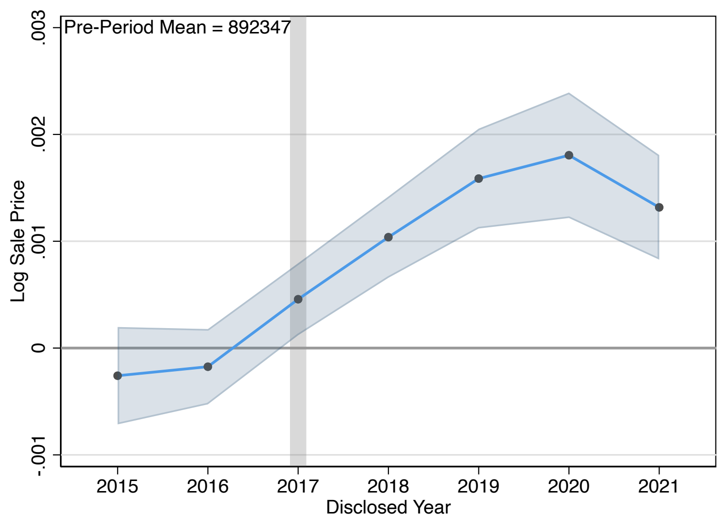
$$\ln p_{ijt} = \alpha + \sum_t \beta_t T_t \times e_{jt} + \rho b_{jt} + \alpha_i + \lambda_t + \gamma_q + \epsilon_{ijt} \tag{1}$$

where p_{ijt} denotes the transaction price for apartment unit i in building j sold in year t; T_t are a set of time dummies for the years disclosed, ranging from 2015 to 2021; and e_{jt} is a measure of energy efficiency for building j in year t. In the regression, I also include apartment fixed effects α_i, calendar year fixed effects λ_t, and quarter-of-the-year fixed effects γ_q to control for seasonality. The standard errors are clustered at the building level to address potential correlations within the same buildings. Additionally, the regression includes b_{jt}, which represents the log of yearly energy bill expenses per unit in building j for year t.

The coefficients of interest are $\{\beta_t\}_t$, which capture the effects of building energy efficiency on housing prices over time. In this regression, an observation is a home sale transaction in year t. Since the requirement to display these scores prominently applies to all buildings previously mandated to disclose them online, there is no control group of buildings that disclosed their scores but are exempt from the requirement for prominent display. Identification of the effect of the prominent display policy is thus primarily due to time series variation in whether the policy regarding the salience of disclosure requirements is passed. In addition, I include apartment fixed effects to control for time-invariant characteristics of these repeatedly sold apartments. The inclusion of the apartment fixed effects results in a sample of 47,590 transactions for the regression, as compared to the original full sample of 135,449 home sale transactions in buildings that started the disclosure before 2017.

Figure 5 displays the results from estimating Equation (1), using the Energy Star score, which has been available since 2015, as the measure of building energy efficiency e_{jt} in the regression. In the years 2015 and 2016, the coefficients are small and do not significantly differ from zero. However, beginning in 2017, apartments start to exhibit a premium for energy efficiency. A one-point increase in a building's Energy Star score leads to an increase in housing prices by up to 0.18%. This suggests that enhancing the prominence of disclosure is key to driving housing price responses. Table 2 summarizes the results

Figure 2: The Effect of Energy Star score on Housing Prices



Notes: This figure presents the coefficients γ_t of the event study regression from Equation 1. The sample comprises 47,590 transactions from the repeated sale of apartments in 3,306 buildings, which started disclosing their Energy Star score before 2017 when the policy proposal that required prominent displays near building entrances was passed.

from estimating Equation 1, with the years grouped into two periods: 2015–2017 and 2018–2021. The results indicate that since 2018, a one-point increase in the Energy Star score corresponds to a 0.14% rise in sale prices, as shown in Column (1). Additionally, I perform two robustness checks: Column (2) replaces calendar year fixed effects with fixed effects for building vintage groups organized by calendar year.[8] In Column (3), instead of apartment fixed effects, I include controls for the size of the sold unit, a penthouse dummy, and building fixed effects. This addresses the concern that apartment fixed effects may limit the sample to units sold multiple times, potentially biasing the results

[8]The vintage groups are categorized into: pre-war buildings (constructed before 1940), post-war buildings (constructed between 1940 and 1980), modern buildings (constructed between 1980 and 2010 before the introduction of the disclosure policy), and new buildings constructed post-2010. This approach offers an alternative way to control for time-related variables, considering diverse price trends across different building vintages.

compared to units sold only once. The outcomes reported in Columns (2) and (3) support the main finding, showing that a one-point increase in the Energy Star score is linked to a 0.1% increase in housing prices after 2017. In Appendix A.2.1, I show that the 2017 policy change also results in a 0.02% increase in both the net operating income and the assessed market value of residential condominiums or cooperatives.

The average sale price for an apartment in NYC was approximately $890k before 2017. Since then, each one-point increase in the Energy Star score has resulted in a nearly $1246 increase in housing prices. Importantly, the coefficient on energy bills is not statistically different from zero, suggesting that it is the energy efficiency score itself, rather than the potential for energy cost savings, that primarily drives the energy efficiency premiums.

Table 2: The Effect of Increased Salience on the ratio of Home Sale Prices to Energy Star Scores

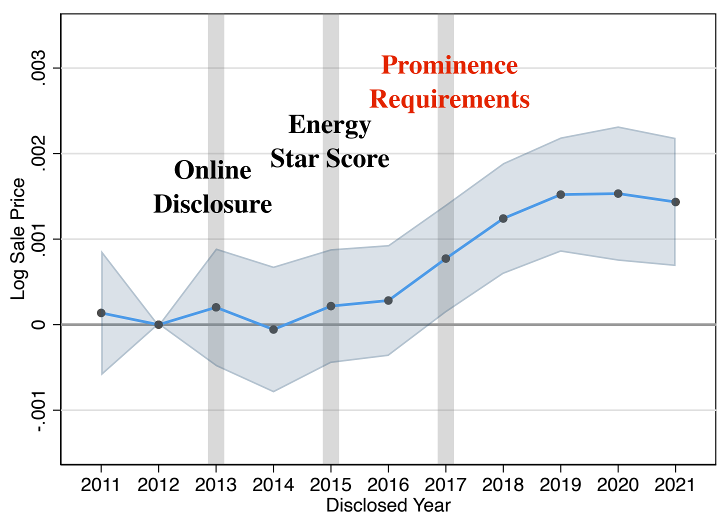
VARIABLES	(1) Log Sale Price	(2) Log Sale Price	(3) Log Sale Price
2015-2017×ES Score	0.00003	0.00009	-0.00018
	(0.00013)	(0.00013)	(0.00012)
2018-2021×ES Score	0.00141***	0.00109***	0.00105***
	(0.00017)	(0.00017)	(0.00017)
Log Energy Bills	-0.00306	-0.00365	-0.00513
	(0.00874)	(0.00760)	(0.00717)
Apartment FE	X	X	
Calendar Year FE	X		X
Calendar Quarter FE	X	X	X
Building Vintage X Calendar Year FE		X	
Apartment Characteristics			X
Property FE			X
Observations	47,590	47,590	127,619
R-squared	0.96610	0.96709	0.82497

Notes: In the regression, I cluster the standard errors by building with Huber-White standard errors Stars denote significance levels: 99 percent confidence level (***), 95 percent confidence level (**), and 90 percent confidence level (*).

To further investigate the effect of disclosure on the price-energy-efficiency ratio, I construct an additional proxy measure of building energy efficiency. This involves calculating the percentile rank of weather-normalized source Energy Use Intensities (EUI) for buildings, with data available extending back to 2011, prior to the mandate for disclosure. Figure 3 presents the estimation result of Equation 1 using the percentile rank of the building's weather-normalized source EUI as e_{jt}. I normalize the coefficient of 2012 interacted with the energy efficiency measure e_{jt} to be zero. The results indicate that before the disclosure requirement, the price-energy-efficiency ratio was nearly zero. Furthermore, the disclosure's impact on this ratio appears to be minimal. Moreover, it reinforces the baseline result that the premiums for energy efficiency in buildings only became significant starting in 2017, which aligns with the increased salience and public awareness of building energy efficiency.

In Appendix A.5, I develop a micro-founded model that rationalizes the findings that we do not observe energy efficiency premiums up until energy efficiency becomes notably salient.

Figure 3: The Effects of Percentile Ranks of Building Weather Normalized Source EUI on Housing Prices



Notes: The sample consists of all residential transactions in New York City from 2015 to 2021, within buildings that initiated Energy Star score disclosure before 2017, prior to the policy proposal mandating prominent displays near building entrances.

3.1.2 Heterogeneity by Building Characteristics

To investigate the heterogeneous responses in prices to the policy that enhances the salience of energy efficiency among different property types, I categorize buildings into groups based on quartiles of average sale prices, building size, floor rise, and vintage. The estimating regression is as follows

$$\ln p_{ijt} = \alpha + \sum_{o} \sum_{t} \beta_{ot} T_t \times e_{jt} \times O_j + \rho b_{jt} + \alpha_i + \lambda_{ot} + \gamma_q + \epsilon_{ijt} \tag{2}$$

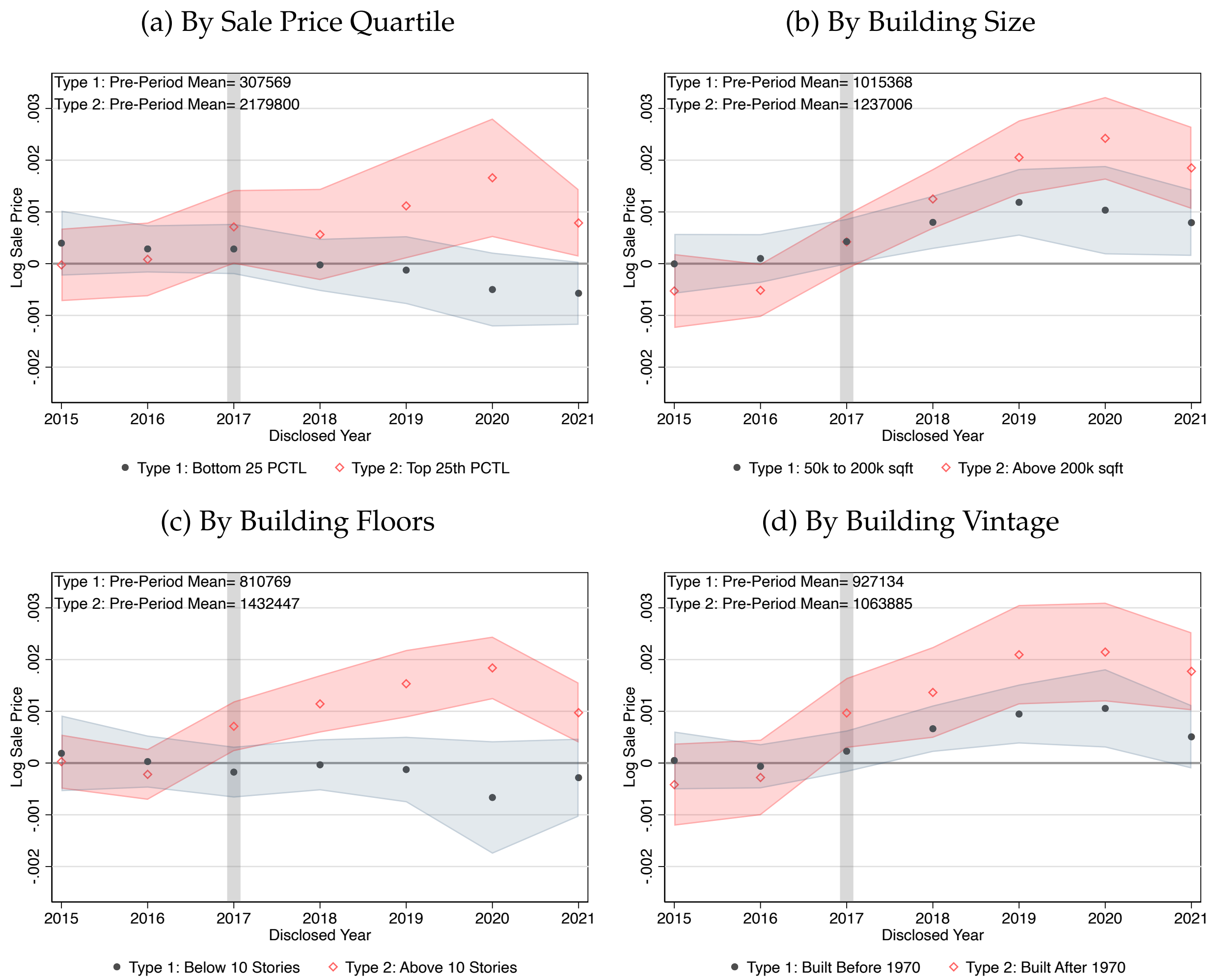
where o indexes the type of properties; O_j represents indicator dummies for each property type to which building j belongs; α_j denotes the building fixed effects. I also include the fixed effects for property type by calendar year λ_{ot} to control for differential trends among different property types. The rest of the variables are defined as in Equation 1.

The coefficients of interest, β_{ot}, reflect the change in housing prices for every one-point increase in the Energy Star score, differentiated by property type and year. As depicted in Figure 4, the findings suggest that luxury, larger, taller, and newer properties tend to exhibit higher energy efficiency premiums. For these property types, each one-point increase in the Energy Star score is associated with an increase in housing prices of up to 0.21%. High-SES individuals are more likely to purchase apartments in these types of properties. This result provides indirect evidence of a greater increase in the value placed on energy efficiency by high-SES households in response to the policy that proposed to raise the salience of energy efficiency.

3.2 Changes in Energy Use

To assess whether buildings responded to the policy that enhances prominence by making energy efficiency improvements, I estimate the changes in their energy use over time

Figure 4: Heterogeneity in Energy Efficiency Premiums by Property Type



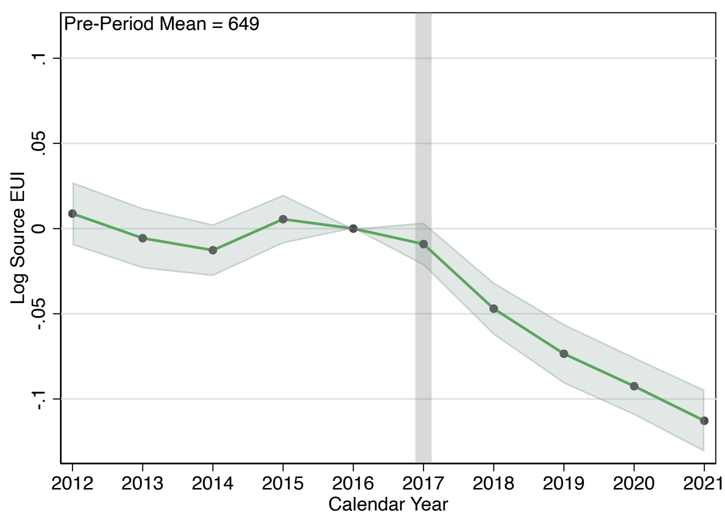
Notes: The sample consists of all residential transactions in New York City from 2015 to 2021, within buildings that initiated Energy Star score disclosure before 2017.

using the following event-study design:

$$\ln y_{jt} = \alpha + \sum_{t} \beta_t T_t + \lambda_j + \epsilon_{jt} \tag{3}$$

where j indexes building, and t denotes year. T_t denote calendar year fixed effects and λ_j are building fixed effects. The estimated $\{\beta_t\}_t$ capture the changes in the energy use within a building over years. Identification of these coefficients relies on the time-series variation in whether the policy proposal aimed at enhancing the salience of energy efficiency was passed. The coefficient for the year 2016 is normalized to zero. The results are displayed in Figure 5. Before 2017, the average weather-normalized Source Energy Use Intensity (EUI)[9] for a building in the sample was 649 kBtu/sqft. Since 2017, there has been a 10% drop in the weather-normalized source EUI.

Figure 5: Changes in Building Energy Use



Notes: The sample consists of buildings that started Energy Star score disclosure by 2015 and continued consistently through 2021.

I further examine the heterogeneous responses of buildings to improvements in energy efficiency. Figure 6 demonstrates that buildings characterized as luxurious, taller,

[9]Weather-normalized Source EUI adjusts the metric of Source EUI for the impact of weather patterns on energy use.

and more modern initially had higher energy use intensity. However, these buildings have shown a more substantial decrease in their weather-normalized source EUI in the post-period. It is noteworthy that these types of properties also experienced a more substantial increase in housing prices following the implementation of the policy aimed at enhancing the salience of energy efficiency. This suggests that high-end buildings are more responsive to the change in the disclosure requirements.

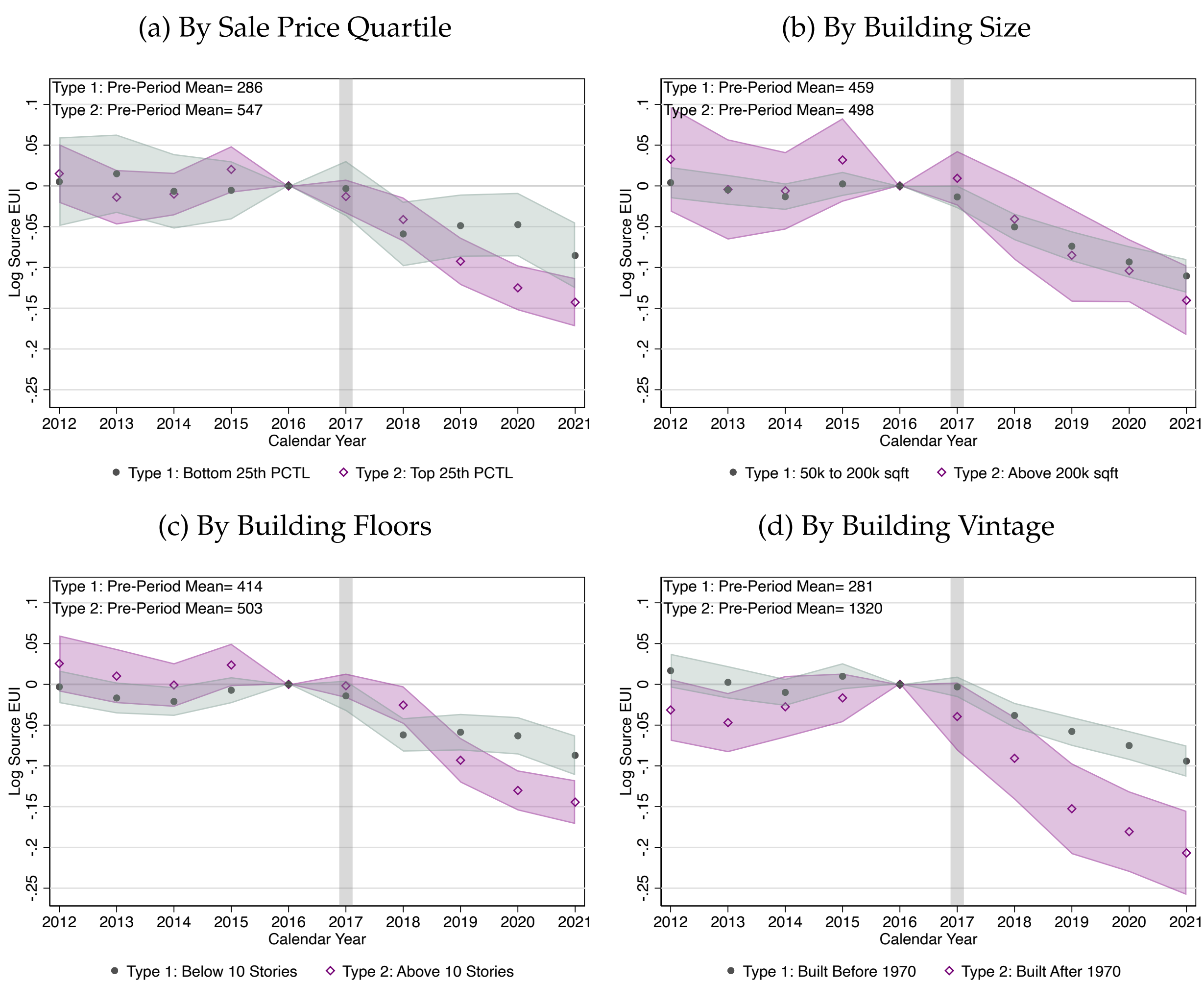
Figure 6: Heterogeneity in Energy Efficiency Improvements by Property Type

(a) By Sale Price Quartile

(b) By Building Size

(c) By Building Floors

(d) By Building Vintage



Notes: The sample consists of buildings that started Energy Star score disclosure by 2015 and continued consistently through 2021.

4 Empirical Model

This section introduces a model of demand and supply for building energy efficiency. Using this model, I aim to quantify the policy's effect on changes in willingness to pay, consumer welfare, and energy efficiency consumption.

4.1 Demand Model

To model the choices of residential buildings by home-buying households, I adopt methods from Berry, Levinsohn and Pakes (2004) and Bayer, Ferreira and Mcmillan (2007). I aggregate the home sale transactions to the building level. A market t is defined by the calendar year. There is a continuum of risk-neutral home-buyers $i \in \mathcal{I}_t$ in year t. There are $\mathcal{J}_t$ multifamily buildings in year t indexed by $j \in \mathcal{J}_t$. The utility of purchasing an apartment unit in building j in market t for home buyer i is:

$$u_{ijt} = \delta_{jt} + \epsilon_{ijt} \qquad \text{where} \quad \delta_{jt} = -\alpha p_{jt} + X'_{jt}\beta + \gamma e_{jt} + \phi b_{jt} + \delta_{T(t)} + \xi_{jt} \tag{4}$$

where δ_{jt} denotes the average utility derived from purchasing an apartment unit in building j in market t. p_{jt} denotes the natural logarithm of the average transaction prices for home sales in building j in market t, and X_{jt} is a matrix of observable building characteristics and its neighborhood characteristics in market t [10]. Additionally, e_{jt} represents the building's Energy Star score, and b_{jt} denotes the annual energy bills per apartment in building j in year t, expressed in thousands of dollars. Each building is thus characterized by $(p_{jt}, X_{jt}, e_{jt}, b_{jt})$. $\delta_{T(t)}$ are year fixed effects, ξ_{jt} is an unobserved demand shock to building j in market t, and ϵ_{ijt} is the idiosyncratic preference for building j in year t that is Extreme Value Type I distributed. The parameter α governs the households' price sensitivity.

[10] Building-level characteristics include average apartment size, building age, the square of building age, number of floors, and building size; neighborhood characteristics include population density, the proportion of the population with college degrees, median household income

However, information about a building's energy efficiency may not be easily noticeable by prospective home buyers. Their buying decisions are often based on perceived building energy efficiency, which can sometimes differ from the true energy efficiency levels. As a consequence, a prospective home buyer may not necessarily maximize their utility. Based on these subjective beliefs, a prospective home buyer chooses building j to maximize their perceived utility $\widetilde{u}_{ijt}$:

$$\max_{j} \widetilde{u}_{ijt} = -\alpha p_{jt} + X'_{jt}\beta + \gamma \widetilde{e}_{jt} + \phi b_{jt} + \delta_{T(t)} + \xi_{jt} + \epsilon_{ijt} \tag{5}$$

where $\widetilde{e}_{jt}$ denotes the households perceived building energy efficiency. In this sense, $\widetilde{\delta}_{jt} = -\alpha p_{jt} + X'_{jt}\beta + \gamma \widetilde{e}_{jt} + \phi b_{jt} + \delta_{T(t)} + \xi_{jt}$. e_{jt} is the true Energy Star score that building j receives in the year. However, households may fail to recall the Energy Star scores when such information is disclosed in a hidden place or when the awareness of the households regarding building energy efficiency is not high. When the frequency that the prospective buyer gets exposed to such information is low, then the households may take into account a wrong value for building energy efficiency in their expected utility function. The disclosure policies can change $\widetilde{e}_{jt}$ and thus change the households' perceived utility from building energy efficiency.

Under the assumption that ϵ_{ijt} follows a Type I extreme-value distribution, the market share of building j in year t is

$$s_{jt} = \frac{exp(\widetilde{\delta}_{jt})}{1 + \sum_{j'} exp(\widetilde{\delta}_{j't})} \tag{6}$$

To estimate how changes in disclosure requirements have changed preferences for building's Energy Star score, I interact three time period dummies with the building's

Energy Star score e_{jt} and estimated the following demand model:

$$\begin{aligned} u_{ijt} = &-\alpha p_{jt} + X'_{jt}\beta + \phi b_{jt} + \delta_{T(t)} + \xi_{jt} \\ &+ \gamma_1 \mathbf{1}\{t < 2017\} e_{jt} + \gamma_2 \mathbf{1}\{2017 \leq t < 2020\} e_{jt} + \gamma_3 \mathbf{1}\{t \geq 2020\} e_{jt} \end{aligned}$$

The evolution of $\frac{\gamma_\tau}{\alpha}$, where $\tau \in \{1, 2, 3\}$, captures the variation in the average marginal willingness to pay (MWTP) by households under different disclosure regimes.

4.1.1 Estimation

I estimate the demand model using the generalized method of moments. The estimation moment equation is given by

$$E[\xi_{jt} Z_{jt}] = 0 \tag{7}$$

where ξ_{jt} denotes the unobservable demand shocks as in Equation 4 and Z_{jt} are the three set of instruments that I describe below.

4.1.2 Price Instruments

To address the potential correlation between home sale price p_{jt} and unobserved quality of buildings ξ_{jt}, I construct three sets of instruments.

First, I construct differentiation instruments following the approach proposed by Gandhi and Houde (2019). The set of instruments consists of differences in the housing characteristics between a building and its rival buildings. It captures how isolated a building is relative to other buildings in the market t in the characteristic space. The distance of building j and other building j' in the characteristic space in the same market t can be measured as

$$z_{jt}^{(x)} = \sum_{j' \neq j} (x_{jt} - x_{j't})^2 \tag{8}$$

I construct the set of instruments $Z1_{jt} = \{z_{jt}^{(x)}, z_{jt}^{(x)} \bigotimes z_{jt}^{(x)'}, z_{jt}^{(x)} \bigotimes d_{jt}\}$, where x_{jt} denotes the physical attributes of building j [11], x_{jt} includes building stories, building area, average apartment size, building age., d_{jt} denotes its census block group level demographics[12], and $\bigotimes$ denotes the Kronecker product of two matrices. Then I select the top 15 most significant instruments in the first stage, denoted as z_{jt}^{a}, to construct a price predictor given by $\hat{p}_{jt} = E[p_{jt}|x_{jt}, z_{jt}^{a}]$.

In the next step, I generate an additional set of instruments $\{z_{jt}^{(\hat{p})}, z_{jt}^{(\hat{p})} \bigotimes z_{jt}^{(x)}, z_{jt}^{(\hat{p})} \bigotimes d_{jt}\}$. Then I obtain the top 15 instruments that are the most significant in the first stage as the first set of instruments $Z1_{jt}$.

The second set of instruments $Z2_{jt}$ consists of the number of apartment units available for sale in the same Census-Block-Group as the building j to capture the intensity of competition that building j faces. This consists of the second set of instruments $Z2_{jt}$.

The third set of instruments consists of measures of buildings' energy efficiency and utility bills prior to the mandate for disclosure in 2013. These predicted measures are uncorrelated with the current demand shocks. To be specific, I calculate the percentile ranks of the building's weather-normalized source EUI, and the estimated energy bills in 2012 to be included in the third set of instruments $Z3_{jt}$.

Then I obtain the complete set of instruments $Z_{jt} = \{Z1_{jt}, Z2_{jt}, Z3_{jt}\}$. The F-statistics for the first-stage regression is approximately 509.

[11] Physical building characteristics here include average apartment sizes, building floor rise, building gross floor area, and the age of building.

[12] d_{jt} includes census block group level population, median household income, and the share of population with college degrees.

Coefficients	Notations	Estimates	Std. Errors
Price	α	-1.4044***	0.013
$\mathbf{1}\{t < 2017\}$Energy Star Score	γ_1	0.0009*	0.0006
$\mathbf{1}\{2017 \leq t < 2020\}$Energy Star Score	γ_2	0.0011***	0.0004
$\mathbf{1}\{t \geq 2020\}$Energy Star Score	γ_2	0.0015***	0.0005
Energy Bill ($\times 10e3$)	ϕ	0.1169***	0.0057
Building Floor Rise	β_1	0.028***	0.0012
Building Gross Floor Area ($\times 1e-6$)	β_2	2.653***	0.0499
Building Age	β_3	-0.2585***	0.0102
Building Age Square	β_4	0.0198***	0.0008
Population Share of College Degrees	β_5	1.933***	0.0535
Median Household Income	β_6	0.0000*	0.0000

Table 3: Demand Model Estimates of Interest

4.2 Results

In this section, I present the results for the estimated demand parameters in Table 3. The average marginal willingness to pay (MWTP) for an Energy Star score can be calculated as $-\frac{\gamma_t}{\alpha}$. Note that before 2017, the MWTP for an Energy Star score was only approximately 0.06%, and it increased to approximately 0.17%. This result suggests that the MWTP for an Energy Star score increases by 0.1% when the salience of disclosure increases. This finding aligns with the empirical analysis, indicating that the increase in equilibrium prices for energy efficiency due to enhanced salience is primarily driven by the increase in MWTP.

4.3 Supply Model

I assume that building owners can choose Energy Star score e_j for the building to maximize their expected profits:

$$\pi_j(e_j) = \underbrace{N_j P_j(e_j)(1-\tau)}_{\text{Post-tax Market Value}} + \underbrace{B_j(e_j)}_{\text{Energy Savings}} - \underbrace{C_j(e_j)}_{\text{Investment cost}} \tag{9}$$

where N_j denotes the number of residential units in building j, and P_j is the level of apartment price per unit in building j in year t. τ captures the capital gain tax rate. B_j denotes the life-time energy savings for building j in year t, and is a function of its building energy efficiency e_j; C_j is the investment cost associated with improving building energy efficiency.

Assuming a discount rate of 5%, the perpetual energy savings for building j, denoted as B_j, can be converted to the discounted sum of annual energy savings, represented as $\frac{b_j}{0.05}$. The derivative of the profit function for building j with respect to the Energy Star score is given by:

$$\frac{\partial \pi_j}{\partial e_j} = N_j P_j \frac{\partial \log(P_j)}{\partial e_j}(1-\tau) + \frac{b_j}{0.05}\frac{\partial \log(b_j)}{\partial e_j} - \frac{\partial C_j}{\partial e_j} \tag{10}$$

The first component has already been calculated in Section 3.1. The value of $\frac{\partial \log(P_j)}{\partial e_j}$ is close to zero before 2017, and it increases to approximately 0.14% after 2017. The average building, denoted as j, has a total of 120 units, each with a sale price of \$892,000. In New York City, the capital gains tax rate is around 25%. Thus, a building can realize a total of approximately \$112,000 in terms of energy efficiency premiums for a one-point improvement in the Energy Star score. The remaining tasks are to calculate the marginal benefit in terms of savings in energy expenditure and the marginal cost of energy efficiency improvements, which are described below.

4.3.1 Energy Savings from Energy Efficiency Improvements

To quantify the private benefits of energy savings and social benefits of reduced social costs of carbon from building energy efficiency improvement, I estimate the following regression:

$$\ln y_{jt} = \alpha + \sum_t \beta_t T_t \times e_{jt} + \alpha_j + \lambda_t + \epsilon_{jt} \tag{11}$$

where y_{jt} is the outcomes of interest, including the annual energy bills and total CO_2 emissions for building j in year t. In the regression, I control for building-specific characteristics (building fixed effects, α_j) and temporal trends (calendar year fixed effects, λ_t). The coefficients $\{\beta_t\}_t$ capture the relationship between the Energy Star scores and the two key variables—energy bills and CO_2 emissions—across different years.

The estimated $\{\beta_t\}_t$ are presented in Table 4. Column 1 of this table indicates that a one-point increase in the Energy Star score corresponds to a 0.43% reduction in energy bills. To provide context, the annual energy bills for a building amount to approximately \$386,774.4, as shown in Panel A of Table 1. Consequently, the average savings in annual energy bills per building are estimated to be around \$1,663. Considering that each multifamily building in our sample contains an average of 120 units, a one-point increase in the Energy Star score translates to an annual energy cost savings of about \$14 per apartment. Assuming a discount rate of 5%, this results in a perpetual value of approximately \$33,200 in utility savings at the building level and \$280 at the apartment level for each one-point increase in the Energy Star score.

In addition to the energy savings benefit for buildings, there is also a significant social benefit from the reduced social cost of carbon associated with increased building energy efficiency. Column 2 of Table 4 demonstrates that an increase of one point in the Energy Star score results in a reduction of 0.9% in a building's carbon dioxide (CO_2) emissions. The social cost of carbon is estimated to be in the range of \$43/$mtCO_2e$ to \$190/$mtCO_2e$ annually [13]. Panel A of Table 1 indicates that the average building in the sample emits 817$mtCO_2e$. This means that an incremental one-point improvement in the Energy Star

[13] Under the Trump administration, the social cost of carbon was determined at around \$43 per metric ton of CO_2 emissions $mtCO_2e$. The Biden administration revised the estimate to be approximately \$51/$mtCO_2e$. In November 2022, the Environmental Protection Agency proposed an increase to \$190/$mtCO_2e$.

score can lead to a yearly reduction in the social cost of carbon by anywhere from \$316 to \$1,397. When calculated with a 5% discount rate, this amounts to a continuous societal benefit ranging from \$6,320 to \$27,940.

Table 4: The Benefits of Increases in Energy Star scores

	(1)	(2)
VARIABLES	Log Energy Bills	Log Total CO2
UNIT	USD/yr	mtCO2/yr
2015 × ES Score	-0.00430***	-0.00871***
	(0.00021)	(0.00025)
2016 × ES Score	-0.00486***	-0.00907***
	(0.00020)	(0.00023)
2017 × ES Score	-0.00456***	-0.00864***
	(0.00017)	(0.00021)
2018 × ES Score	-0.00444***	-0.00944***
	(0.00016)	(0.00023)
2019 × ES Score	-0.00384***	-0.00942***
	(0.00017)	(0.00023)
2020 × ES Score	-0.00373***	-0.00781***
	(0.00018)	(0.00024)
2021 × ES Score	-0.00435***	-0.00835***
	(0.00020)	(0.00024)
2022 × ES Score	-0.00445***	-0.00906***
	(0.00022)	(0.00031)
Observations	62,514	62,514
R-squared	0.90162	0.83645
Property FE	X	X

Notes: The sample in the regression consists of buildings that started disclosure Energy Star scores before 2017 and continued to disclose building energy efficiency annually till 2021. Stars denote significance levels: 99 percent confidence level (***), 95 percent confidence level (**), and 90 percent confidence level (*).

4.3.2 Cost of Building Energy Efficiency Improvements

In this section, I first demonstrate how building work leads to increases in Energy Star scores and then proceed to estimate a marginal cost curve for building energy efficiency improvements.

In this context, I define energy efficiency-related building work[14] as activities that involve replacing boilers or burners, upgrading HVAC, lighting, heating, fuel, and electrical systems, or conducting work related to natural gas.

I begin by estimating the change in Energy Star scores following jobs within buildings aimed at improving energy efficiency using the following dynamic difference-in-differences (DID) design:

$$r_{jt} = \alpha + \sum_{\tau \neq -1} \beta^{\tau} D_t^{\tau} + \alpha_j + \epsilon_{jt} \tag{12}$$

where D_t^{τ} is a dummy for τ years relative to the first year in which building j undergoes an energy-efficiency upgrade in year t; α_j denotes building fixed effects. The coefficients $\{\beta^{\tau}\}_{\tau}$ captures the change in the Energy Star score τ years relative to the year before the permit is received for energy efficiency upgrade work. The coefficient for the period before the energy efficiency upgrade work, β^{-1}, is normalized to zero.

Results of the estimated $\{\beta^{\tau}\}_{\tau}$ from Equation 12 are presented in Panel (a) of Figure 7. These specific types of building work lead to an increase of at least 5 points in Energy Star scores within one year. As shown in Panel C of Table 1, the average total cost of building work aimed at improving the Energy Star score is approximately \$174,000. This suggests that a one-point increase in Energy Star rating costs \$35,000 on average for a building.

I further estimate the return on investment for building energy efficiency improvement projects in terms of changes in the Energy Star score in Appendix A.3. The results indicate that every one percent increase in investment cost leads to approximately a one-point increase in the Energy Star score.

In addition, I present a detailed breakdown of the effects and returns of different types of building work on Energy Star scores in Appendix A.4. Boiler replacement, HVAC

[14] Typical building work aimed at energy efficiency upgrades includes improving insulation, upgrading lighting and heating, ventilation, and air conditioning (HVAC) systems, installing heat pumps, or converting to natural gas or electric power (NYSERDA Residential Statewide Baseline Study Volume 2: Multifamily Report)

Figure 7: Energy Star score Change In Response to Building Work

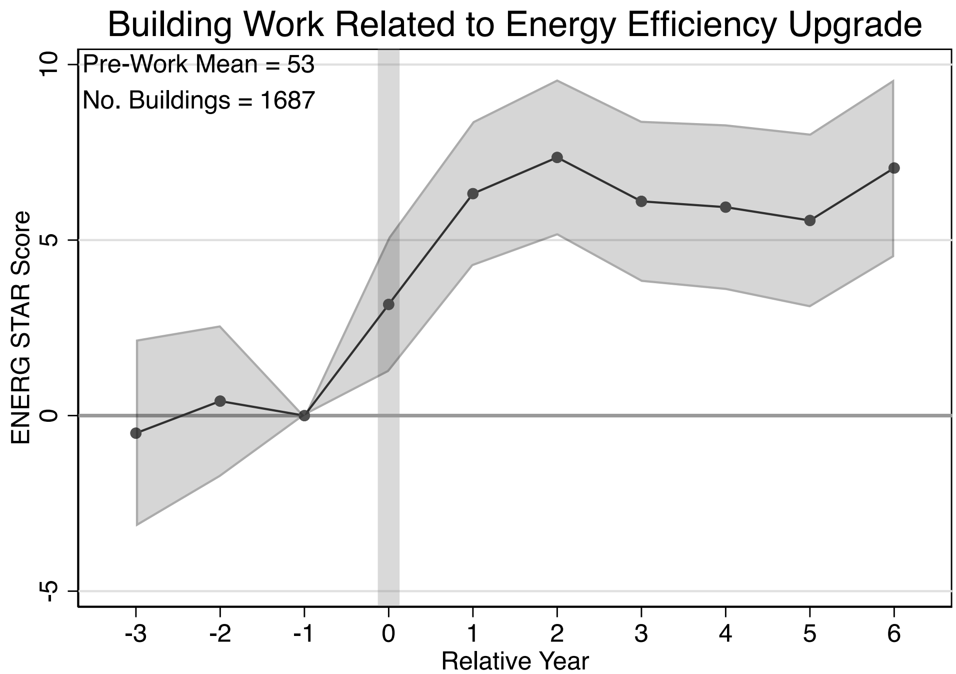


Figure 8: The Changes in Energy Star score

upgrades, and gas work are identified as the top three most significant types of jobs for improving building energy efficiency.

4.4 Equilibrium Effects of Enhancing the Prominence of Building Energy Efficiency Disclosure

In this section, I calculate the marginal benefits and costs of energy efficiency improvements under different information disclosure frameworks. As shown in Equation 10, the key aspects of a building's profits consist of capitalization gains in the housing market, savings in energy bills, and investment costs. Additionally, the reduced social cost of carbon is also considered if the building is concerned about the social impact of improved energy efficiency.

Capitalization Gains from Housing Price Increases. The results in Section 3.1 suggest that the value of $\frac{\partial \log(P_j)}{\partial e_j}$ is close to zero before 2017, and it increases to approximately 0.14% after 2017. The buildings can realize a total of approximately \$112k in terms of post-tax energy efficiency premiums.

Savings in Energy Bills. The relationship between the Energy Star score and energy bills remains constant before and after the policy change aimed at improving the salience of energy efficiency. Column 1 of Table 4 indicates that energy savings due to a one-point increase in the Energy Star score, $\frac{\partial \log(b_j)}{\partial e_j}$, is equal to 0.43%, which are equal to savings in annual energy bills per building of around \$1,663. At a discount rate of 5%, this corresponds to a perpetual value of approximately \$33,200 in utility savings at the building level for each one-point increase in the Energy Star score.

Reduced Social Cost of Carbon. Column 2 of Table 4 demonstrates that an increase of one point in the Energy Star score results in a reduction of 0.9% in a building's carbon dioxide (CO_2) emissions. This means that an incremental one-point improvement in the Energy Star score can lead to a yearly reduction in the social cost of carbon by anywhere from \$316 to $\$1,397$. At a 5% discount rate, this amounts to a perpetual societal benefit ranging from $\$6,320$ to $\$27,940$.

Energy Efficiency Improvement Investment Cost. Figure 7 indicates that the marginal cost of building work to improve energy efficiency is approximately \$35,000 on average for a one-point increase in the Energy Star score.

Taking these estimates together, note that before the policy change in 2017, which enhanced the salience of disclosure, the investment costs of improving energy efficiency outweigh the benefits from savings in energy bills, undermining the incentives for buildings to improve their energy efficiency. However, since 2017, the value of energy efficiency began to be reflected in housing prices, creating incentives for buildings to invest in improving their energy efficiency. Nevertheless, the post-tax capitalization of the Energy Star score, represented by a substantial \$112,000, greatly exceeds both the actual savings of \$33,000 in energy bills and the upper bound of the reduced social cost of \$28,000. This result suggests that the enhanced salience of disclosure leads to an overreaction in the housing market.

5 Conclusion

In this paper, I investigate the equilibrium impacts of building energy efficiency disclosure policies on two critical aspects: energy efficiency premiums and building responses to energy efficiency improvements. The empirical analysis in this study delivers three main findings. First, the implementation of building energy efficiency disclosure regulations becomes effective in generating energy efficiency premiums, particularly when these regulations enhance the visibility of the disclosed information. Second, the enhanced salience of disclosed building energy efficiency information serves as a strong incentive for buildings to invest in enhancing their energy efficiency. Third, upscale buildings exhibit greater responsiveness to such policies, with more pronounced positive outcomes in terms of energy premiums and energy efficiency improvements.

I develop and estimate an equilibrium model of supply and demand for apartment units and energy efficiency and use it to estimate households' willingness to pay for energy efficiency under different information disclosure regimes. The key findings from this study indicate that the change in the equilibrium prices of building energy efficiency are mainly driven by the increase in households' willingness to pay when the salience of building energy efficiency improves. In addition, the appreciation of housing prices incentivizes building owners to make investments to improve their building energy efficiency. However, the increase in housing prices due to increases in buildings' Energy Star score outweighs the sum of savings in energy bills and the reduced social cost of carbon.

Governments have increasingly employed information disclosure as a policy tool to address market failures related to information frictions and enhance product quality within markets. In the context of the housing market, a growing number of local governments have embraced building energy efficiency disclosure as a means to promote energy efficiency, particularly in response to concerns about climate change.

This paper demonstrates the crucial role of information salience in generating energy efficiency premiums in housing prices and encouraging building investments. However, several questions remain for future research. First, while enhanced disclosure salience leads to energy efficiency premiums, it raises housing prices beyond cost savings. Second, upscale buildings respond more to information interventions, prompting consideration of alternative policies for improving energy efficiency in affordable buildings. Third, discount rates play a pivotal role in shaping households' perceived value of long-term benefits from energy efficiency improvements.

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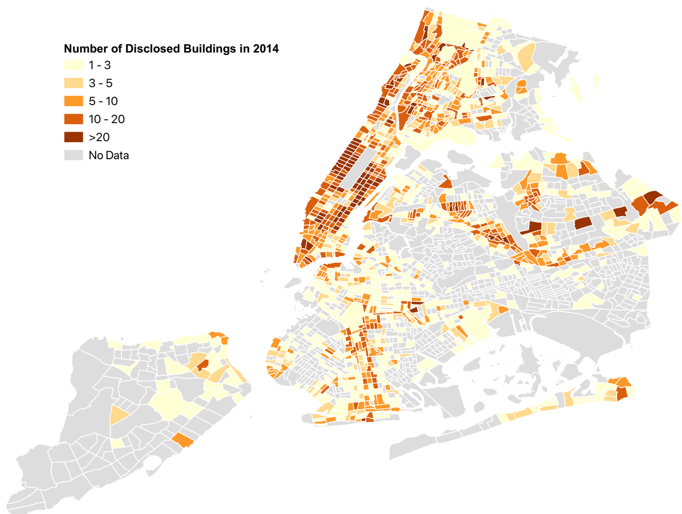
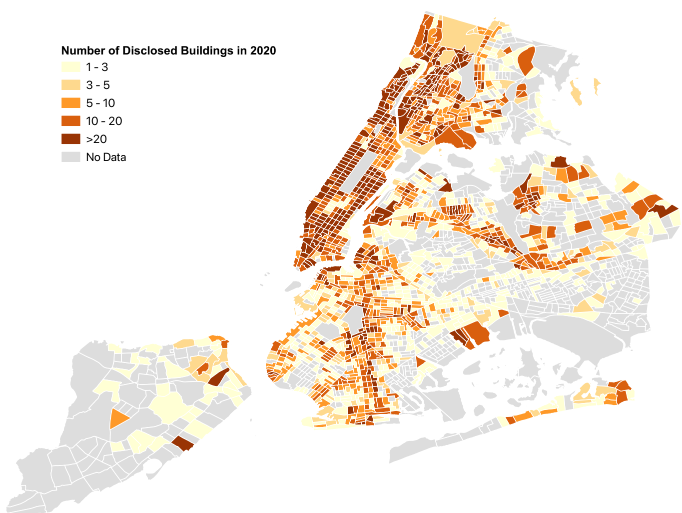
A Appendix

A.1 The Geographical Distribution of Disclosed Buildings



(a) 2014



(b) 2020

Figure A.1: Geographic Distribution of Disclosed Buildings

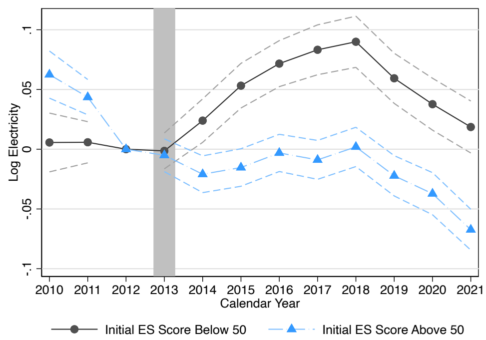
A.2 The Changes in Building Energy Use

This section presents the change in building energy use by category. I split the buildings into two groups based on whether the first disclosed Energy Star score for the building is below or above 50.

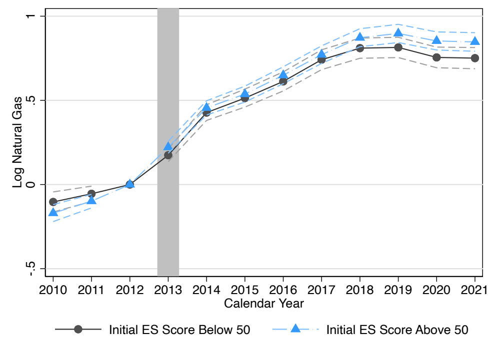
I estimate how the energy use of the buildings change over time with the following event study design:

$$\ln y_{jt} = \alpha + \sum_t \beta_t T_t \times O_j + \lambda_j + \epsilon_{jt} \tag{13}$$

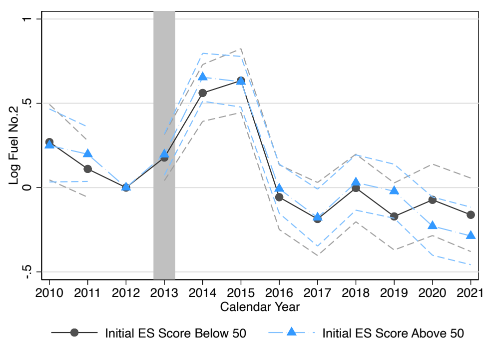
In this regression, j represents the building, and t signifies the year. T_t stands for a time dummy for each year, while O_j indicates whether the initial Energy Star score that building j receives is above or below 50. The coefficient on the dummy variable for the year 2012 is normalized to zero. I control for building fixed effects λ_j, allowing the estimated β_{t_t} to capture changes in the energy use within a building over the years. The changes in various building-level energy categories, including electricity use, natural gas consumption, fuel oil types No.2, No.4, No.5, and No.6, total water usage, CO_2 emissions, as well as weather-normalized site and source energy use intensity (EUI), are presented in the following figure.



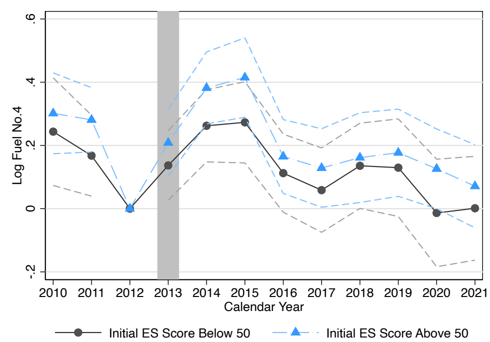
(a) Electricity (kWh)



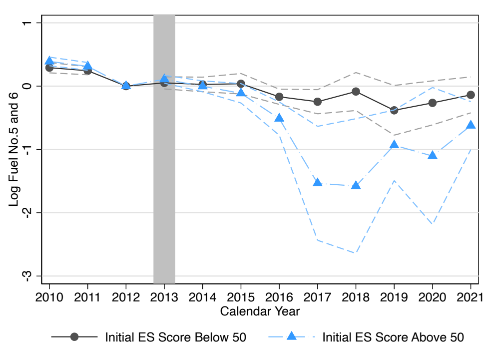
(b) Natural Gas (kBtu)



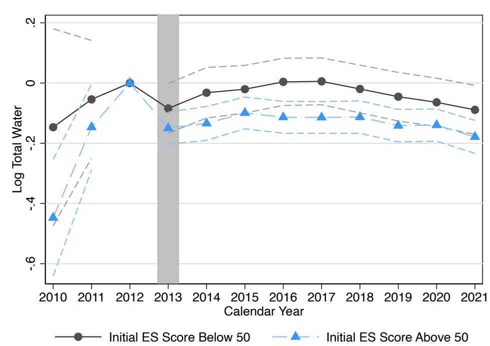
(c) Fuel Oil No.2 (kBtu)



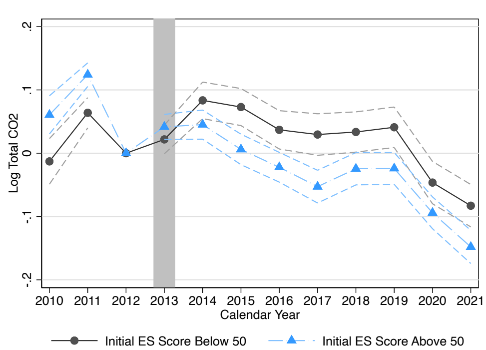
(d) Fuel Oil No.4 (kBtu)



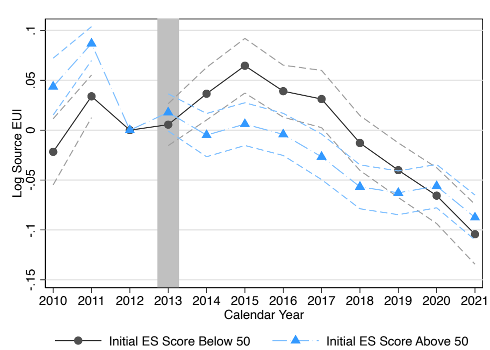
(e) Fuel Oil No.5 & No. 6 (kBtu)



(f) Total Water Use (kGal)



(g) Total CO_2 Emissions (MtCO_2e)



(h) Weather Normd.Source EUI (kBtu/sqft)

Figure A.2: Changes in Building Energy Use

A.2.1 The Impacts on Building Market Values

I investigate the effects of Energy Star score on the values of residential properties with the following specification.

$$y_{jt} = \alpha + \sum_{\tau} \beta_{\tau} T_t^{\tau} \times r_{jt} + b_{jt} + \alpha_j + \lambda_{nt} + \epsilon_{jt} \tag{14}$$

where τ denotes the time period, r_{jt} represents the building-level Energy Star score disclosed in year t; b_{jt} denotes the logarithm of the annual energy bills for building j in year t; α_j and λ_{nt} denote the building fixed effects and census tract by calendar year fixed effects, respectively.

Table A.1 summarizes energy efficiency premiums in market values for residential properties. While higher Energy Star scores have no effect on market values from 2015 to 2017, a one-unit increase in Energy Star score from 2018 onward leads to a 0.023% increase in market values. For condos or coops, starting in 2018, a one-unit increase in Energy Star score results in a 0.019% increase in estimated gross rental income, necessitates a 0.015% increase in expenses, leads to a 0.021% increase in net operating income, and results in a 0.021% appreciation in market value.

Table A.1: The Capitalization of Energy Star scores on Residential Property Values

VARIABLES	(1) Log Market Value	(2) Log Rental Income	(3) Log Expense	(4) Log NOI	(5) Log Market Value
2015-2017×ES Score	-0.00003	0.00001	0.00002	-0.00002	-0.00004
	(0.00007)	(0.00005)	(0.00008)	(0.00007)	(0.00006)
2018-2022×ES Score	0.00023***	0.00019***	0.00015*	0.00021***	0.00021***
	(0.00007)	(0.00006)	(0.00008)	(0.00007)	(0.00006)
Log Energy Bill	0.00512	0.00167	0.00311	0.00011	-0.00593*
	(0.00407)	(0.00270)	(0.00392)	(0.00375)	(0.00323)
Observations	57,297	40,741	40,741	40,741	40,741
R-squared	0.989142	0.99048	0.97649	0.98738	0.99350
Property FE	X	X	X	X	X
Census Tract X Year FE	X	X	X	X	X

Notes: Column (1) presents the impacts of Energy Star scores on the market values of all residential properties. Columns (2) to (5) present the effects of Energy Star scores on the market outcomes for all condos or coops. In the regression, I cluster the standard errors by building with Huber-White standard errors. Stars denote significance levels: 99 percent confidence level (***), 95 percent confidence level (**), and 90 percent confidence level (*).

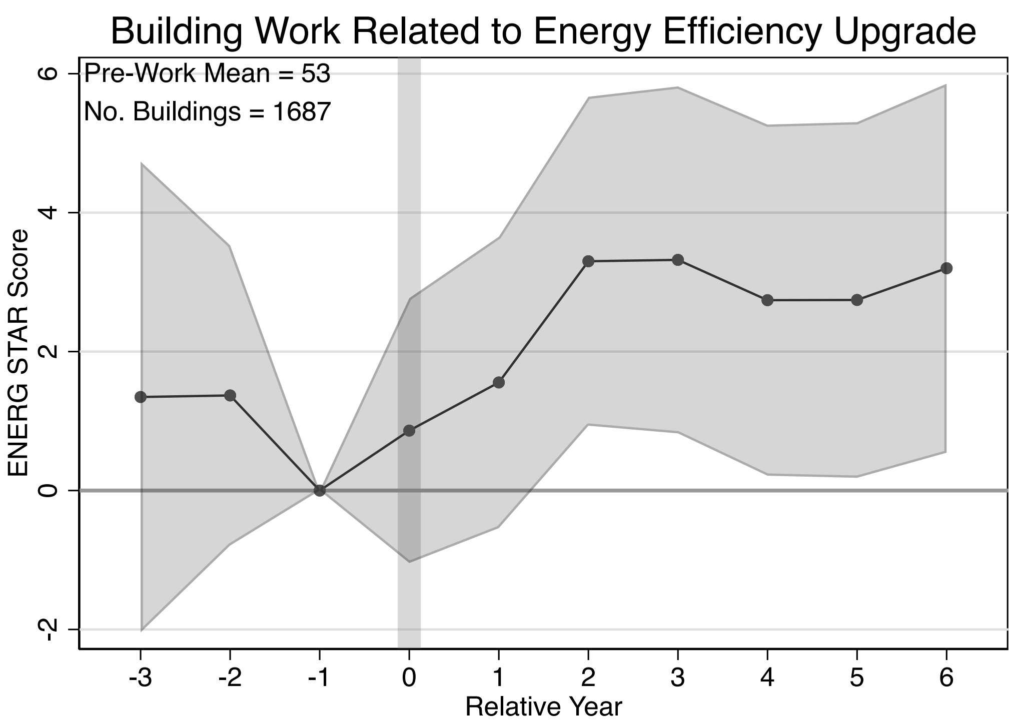
A.3 The Returns of Building Work Costs on Energy Star Scores

I further investigate the returns on investment for building work aimed at improving building energy efficiency with the following event study:

$$r_{jt} = \alpha + \sum_{\tau \neq -1} \beta^{\tau} D_t^{\tau} + \sum_{\tau \neq -1} \gamma^{\tau} D_t^{\tau} \times c_j + \alpha_j + \lambda_t + \epsilon_{jt} \tag{15}$$

where c_j represents the log of building work expenses, and λ_t corresponds to calendar year fixed effects. The estimated γ^{τ} quantifies the change in Energy Star scores resulting from a 1% increase in annual building work expenses. As depicted in Panel (b) of Figure A.3, a 1% rise in building work expenses leads to a three-point increase in Energy Star scores within one year after the investment.

Figure A.3: The Returns of Building Work Investment



Notes: This figure presents the coefficients γ^{τ} of the event study regression from Equation 15. The sample comprises energy-efficiency improvement projects between 2011 and 2021 for 1,687 buildings which started disclosing their Energy Star score before 2017 and have transactions of apartment units between 2015 and 2021.

A.4 The Effects of Building Work on Energy Star score by Building Work Type

I assess how different types of building work changes Energy Star score with the event study design

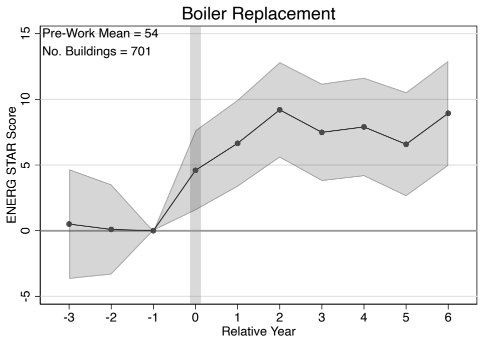
$$r_{jt} = \alpha + \beta^{\tau} D_t^{\tau} + \alpha_j + \epsilon_{jt} \tag{16}$$

where D_t^{τ} denotes the year relative to the first year that a building j conducts energy-efficiency upgrade work. α_j denotes the building fixed effects. β^{τ} captures the change in the Energy Star score τ years since the first year energy efficiency upgrade building work applications are submitted in year t. I normalize the coefficient β^{τ} to be zero in the period before the building work, i.e., $\beta^{-1} = 0$.

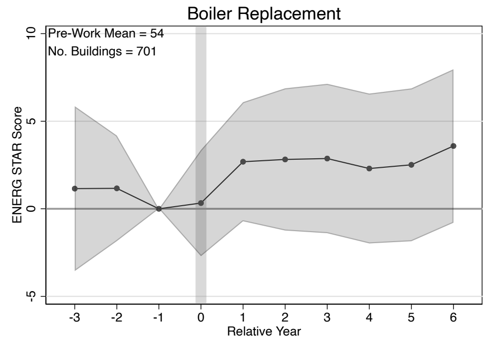
I further investigate the returns of investment of building work related to building energy efficiency improvement with the following event study

$$r_{jt} = \alpha + \beta^{\tau} D_t^{\tau} + \gamma^{\tau} D_t^{\tau} \times c_{jt} + \alpha_j + \lambda_t + \epsilon_{jt} \tag{17}$$

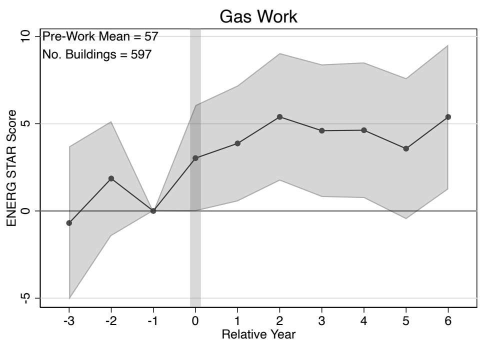
where c_{jt} denotes the log of the building work expenses, and λ_t represents the calendar year fixed effects. The estimated γ^{τ} captures the change in Energy Star score for a 1% increase in building work expenses every year.



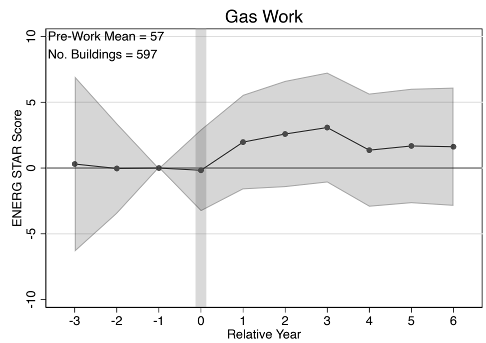
(a) Boiler Replacement



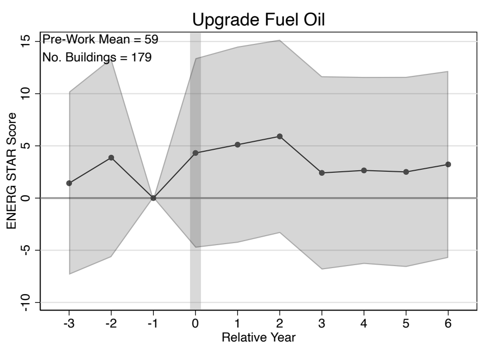
(b) The Returns of Boiler Replacement



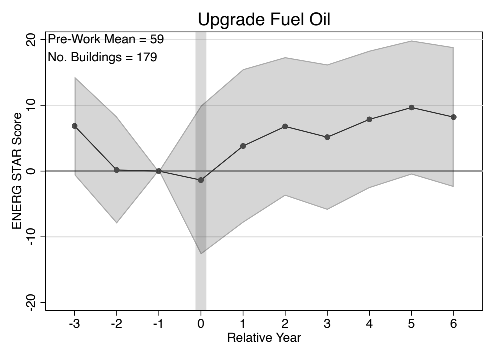
(c) Gas Work



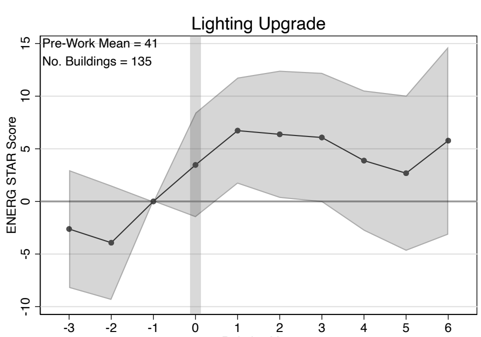
(d) The Returns of Gas Work



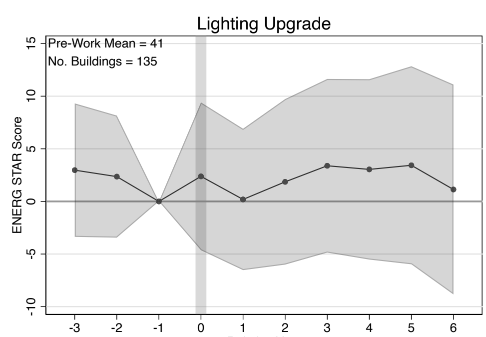
(e) Upgrade Fuel Oil



(f) The Returns of Fuel Oil Upgrade

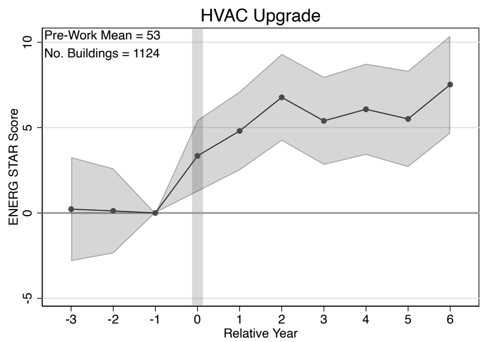


(g) Lighting Upgrade

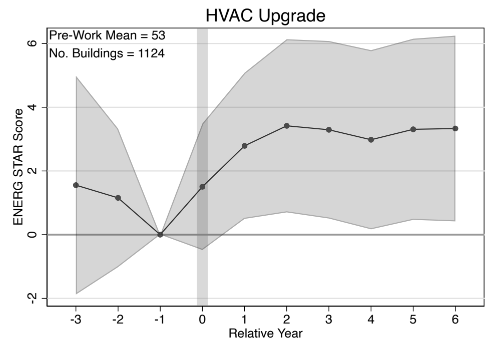


(h) The Returns of Lighting Upgrade

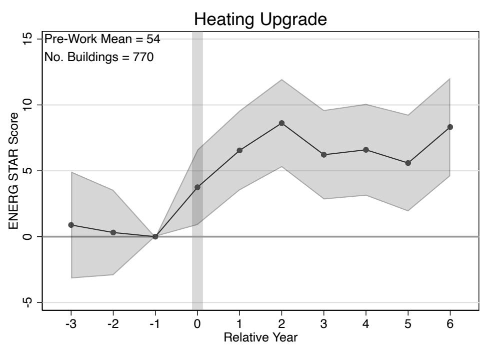
Figure A.4: The Returns of Building Work by Type



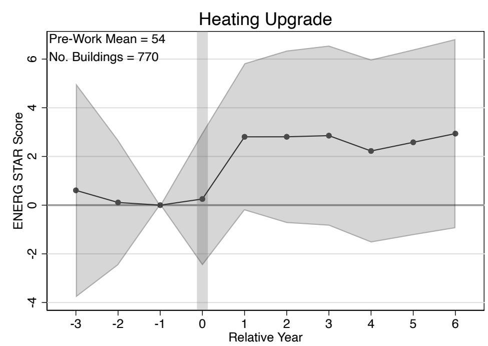
(a) HVAC Upgrade



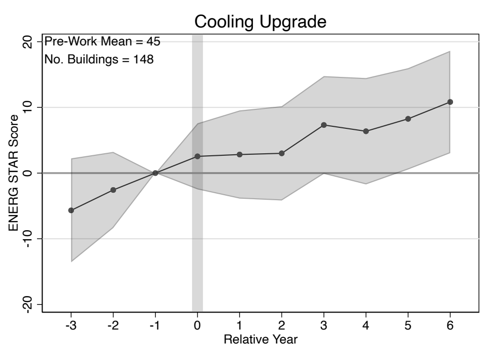
(b) The Returns of HVAC Upgrade



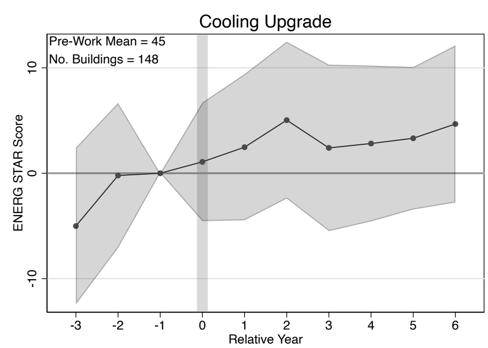
(c) Heating Upgrade



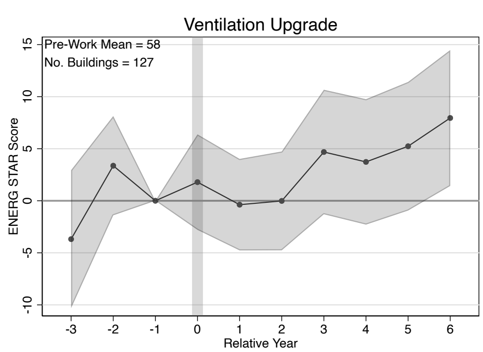
(d) The Returns of Heating Upgrade



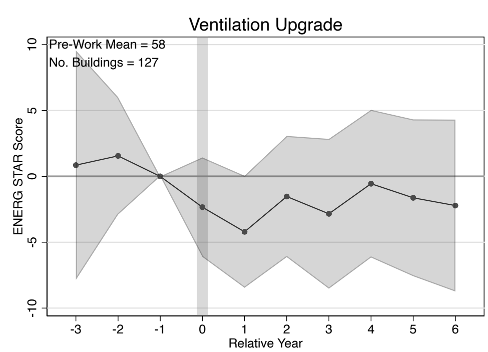
(e) Cooling Upgrade



(f) The Returns of Cooling Upgrade



(g) Ventilation Upgrade



(h) The Returns of Ventilation Upgrade

Figure A.5: The Returns of Building Work by Type (Continued)

A.5 Stylized Model

In this subsection, I describe a stylized model of the decision-making process. The model provides a framework that integrates both belief updating and attention. The aim of the model is to help explain the changes in prices of energy efficiency over the years.

There exists a representative, risk-neutral decision maker (hereafter referred to as DM) who chooses buildings based on their energy efficiency, denoted as q, and pays a price p. A building is characterized by its energy efficiency and its price, i.e., (q, p). The intrinsic value of the building to the DM is formalized as:

$$V = q - p \tag{18}$$

However, due to information frictions, the true energy efficiency of the building is not fully observable to the DM. Instead, the DM is able to observe signals about the building's energy efficiency. The information set consists of a collection of signals that the DM has received and processed. Based on the available information set, the DM solves a de facto value maximization problem:

$$\max E[V|S] = E[q|S] - p \tag{19}$$

An outside option exists where $(p_0, q_0) = (0, 0)$. The DM's choice set comprises $C = \{(p, q), (0, 0)\}$. The willingness to pay (WTP) for the building's energy efficiency q can then be expressed as:

$$\begin{aligned} WTP(q|(p,q)) &= \sup p \\ s.t. \quad E[V(p,q)|S] &\geq E[V(0,0)|S] \end{aligned}$$

The expected value of the outside option is normalized to be zero, $E[V(0,0)|S] = 0$. Therefore, the WTP is captured by the expected quality conditional on the information set, i.e., $WTP(q|(p,q)) = E[q|S]$.

Assume that the energy efficiency for building j is represented by a binary indicator $e_j \in \{H, L\}$, which denotes whether the building's energy efficiency level is high (H) or low (L). There are four periods, denoted as $t \in \{0, 1, 2, 3\}$. In each period, the DM observes a signal $s_{jt} \in [1, 100]$ that provides information about the building's energy efficiency. A signal s_{jt} closer to 100 is more indicative of high energy efficiency H, while a signal closer to 1 is more indicative of low energy efficiency L.

Given the signal, the Bayesian DM forms beliefs about the energy efficiency, q, of a building. We denote the DM's belief about the inherent energy efficiency of building j at time t as π_t. Here, π_0 denotes the DM's prior belief about the building's energy efficiency. Assume that the prior beliefs π_0 follow the beta family of distributions, specifically $\pi_0 \sim \beta(x, x)$, which is a symmetric distribution. The beta distribution naturally arises as a continuous probability distribution in this context. Subsequently, the DM evaluates the building based on the expected energy efficiency conditional on their readily available information set and the price.

Two primary information frictions cause the expected building quality, conditional on one's information set, to deviate from rational expectations. First, signals conveying building energy efficiency may be bundled with noises. Second, the DM might not consistently recall these signals, leading to their omission during considerations. The progression of energy efficiency policies over the years represents a dual process: diminishing noise interference and enhancing awareness.

The DM's attention to the signal plays a crucial role in influencing the DM's decision-making process. Assume that in each period, a signal s_t has a corresponding probability r_t of being recalled by the DM and thus taken into consideration during the process of belief updating. The recall probability r_t has significant real-world implications. It can be thought of as an increasing function of the intensity of signal exposure: the more often the DM is exposed to the signal, the more likely it is that the DM will recall the signals observed. To put this into context, before 2017, households could only get exposed to building Energy Star scores by navigating lengthy reports online. Since this could be viewed as a daunting task, the frequency at which the DM was exposed to such information was low. This translates to a very low recall probability in such a period. The passage of a policy at the end of 2017, which proposed increasing the visual prominence of building energy efficiency, sparked intense discussions and attracted media attention. The substantial media coverage provided the DM with a second channel of exposure to building energy information, simultaneously improving the DM's recall probability of the building's energy efficiency, even though the prominence requirements were not yet in place. Finally, after the policy was implemented in 2020, the DM gained a third channel of exposure to the building's energy efficiency. This triple exposure significantly increased the recall probability of the current signal.

In subsequent periods, the upadted beliefs about the energy efficiency of building j follow the new beta distributions:

$$\pi_t \sim \beta(x + \sum_t r_t s_t, x + 100 \sum_t r_t - \sum_t r_t s_t)$$

The mean of the distribution of beliefs in period 3 is equal to the expected value building energy efficiency conditional on the signals $S = \{s_1, s_2, s_3\}$ observed in the past:

$$E[\pi_3] = E[q|S] = \frac{x + r_1 s_1 + r_2 s_2 + r_3 s_3}{2x + 100(r_1 + r_2 + r_3)} \tag{20}$$

In the section above, I abstracted from the noise associated with the signals the Decision Maker (DM) observes every period. Such noise in the signal might arise for various reasons, one being that the observable building energy efficiency measure is less interpretable. This scenario can be visualized as a situation where only itemized energy usage is disclosed, making it challenging for households to transform the disclosed data into a precise measure of building energy efficiency. Now, assume that the signal related to building energy efficiency observed by the DM closely aligns with the true energy efficiency but has noise added: $s_t = s + e_t$. I postulate that the noise term e_t is normally distributed with a mean of zero and a standard deviation of σ_t, denoted as $e_t \sim \mathcal{N}(0, \sigma_t^2)$.

When the signals are noisy, the mean of the belief distribution in period 2 corresponds to the expected value of building energy efficiency conditional on previously observed signals $S = \{s_1, s_2\}$:

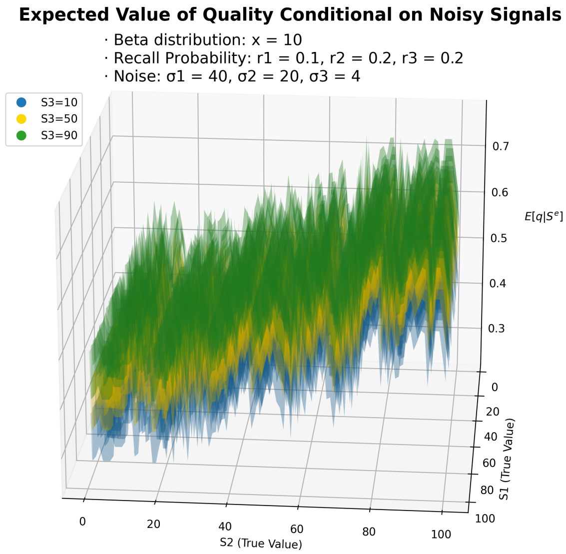
$$E[\pi_3] = E[q|S^e] = \frac{x + r_1 s_1^e + r_2 s_2^e + r_3 s_3^e}{2x + 100(r_1 + r_2 + r_3)} = \frac{x + r_1(s_1 + e_1) + r_2(s_2 + e_2) + r_3(s_3 + e_3)}{2x + 100(r_1 + r_2 + r_3)}$$

Figure A.6 displays simulated outcomes for the expected quality of buildings based on noisy signals, denoted as $E[q|S^e]$, in the third period. These simulations visualize how the marginal willingness to pay (WTP) changes with the most recent signal of quality, s_3, conditional on earlier signals. A comparison between panels (a) and (d) illustrates that both reduced signal noise and increased awareness increase the marginal WTP for high-quality signals.

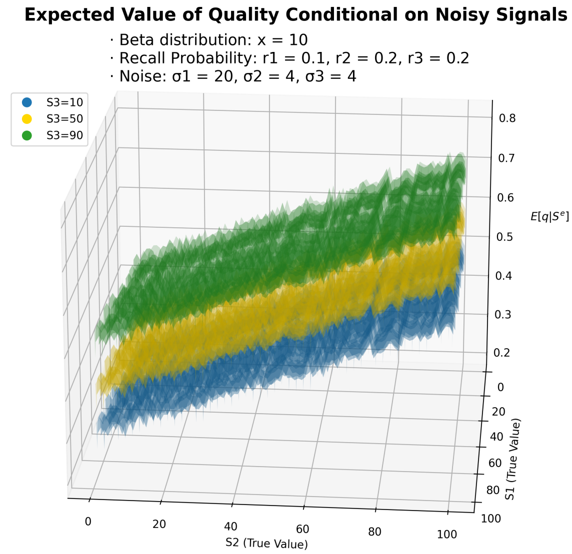
In Panel (a), $\sigma_1 = 40$, $\sigma_2 = 20$, and $\sigma_3 = 4$. The choice of σ_1 mirrors the period from 2010 to 2013. During this time, the DM had limited public access to building energy data and had to rely on unverified sources. Additionally, available data covered only a subset of buildings, preventing a broad comparison and understanding of building energy efficiency. This limitation prevented the DM from a comprehensive comparison and understanding of energy efficiency across the building stock. The choice of σ_2 here is to emulate the period from 2013 to 2015, when online disclosures with detailed energy usage data were introduced, but there was no clear metric for energy efficiency. This development facilitated comparisons yet required DMs to interpret raw data, resulting in moderate signal noise. Subsequently, in the 2015-2017 window, the integration of Energy Star scores into disclosures significantly diminished signal noise. Thus I further reduce the value of σ_3.

In Panel (b), signal variances are further reduced to $\sigma_1 = 20$, $\sigma_2 = 4$, and $\sigma_3 = 4$, with low recall probabilities set at $r_1 = 0.1$, $r_2 = 0.2$, and $r_3 = 0.2$, representing the period of reduced signal noise coupled with lower recall probabilities. Notably, as signals become clearer, the DM is less likely to have a diminished WTP for buildings with signals of better quality compared to inferior ones.

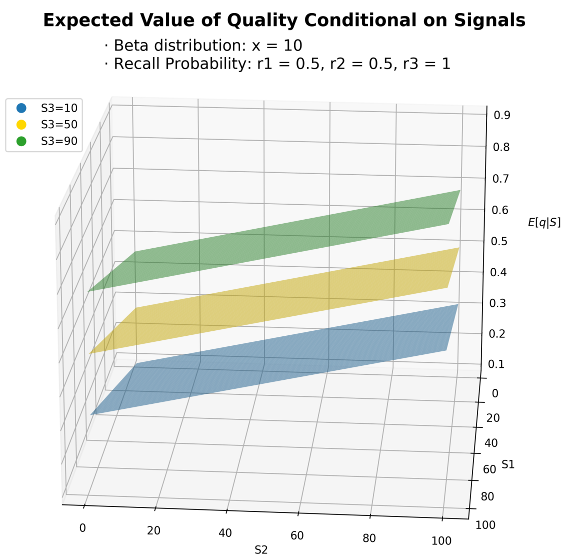
Transitioning from Panel (c) to Panel (d), I shift the focus to examine the effect of higher recall probabilities—indicative of increased public awareness—on the DM's WTP for the quality in the equilibrium. In these scenarios, the noise variances are deliberately chosen to be zero. Panel (c) sets recall probabilities at $r_1 = 0.5$, $r_2 = 0.5$, and $r_3 = 1$, while Panel (d) sets them at 1 for all periods. Comparing these two panels reveals that increasing public awareness of the signal correlates with an increased WTP. However, in scenarios where there is no further enhancement in public awareness, despite high-quality signals still commanding a higher valuation and WTP, the magnitude of WTP for quality is marginally smaller compared to periods of growing public awareness.



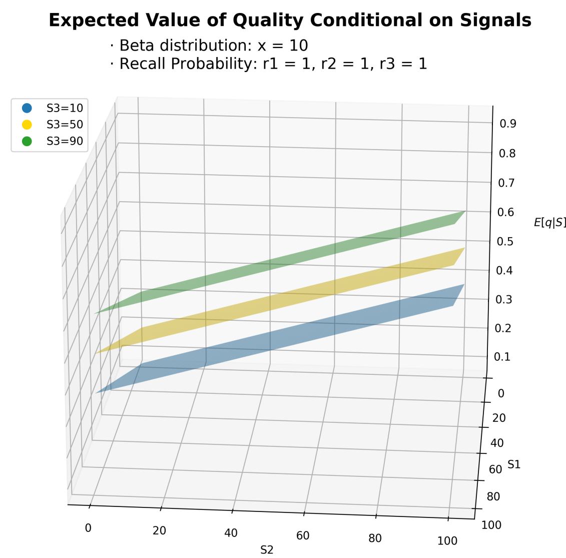
(a) Large Noise, Low Recall Probability: (2010-2013)



(b) Reduced Noise, Low Recall Probability: (2013-2015-2017)



(c) Minimal Noise, Increased Recall Probability: (2017-2010)



(d) Minimal Noise, High Recall Probability: (2021 onwards)

Figure A.6: Expected Value of Quality Conditional on Signals