Essays in Valuation of Non-Market Environmental Impacts

by

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ABSTRACT OF THE DISSERTATION

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In my dissertation, I measure the value of non-market amenities such as environmental quality using the hedonic pricing method in all three chapters.

In Chapter 2, the study examines the price premium from Korea's Energy Efficiency Grade Label. The Korean government recently began energy certification of televisions, providing a setting to analyze a possible price effect of the new label. Hedonic regression results seem to show that a price premium exists for products with the Energy Efficiency Grade Label. However, potential unobserved heterogeneity is a concern. Difference-in-difference and fixed-effects models are used to capture the net effect of the label by controlling for time and product differences. The results suggest that any price premium does not result from the energy efficiency label itself. Instead, energy-efficient products already had higher prices before the introduction of the energy efficiency label. The finding turns our attention to the importance of careful design of labeling programs.

In Chapter 3, using the publicly available housing transaction data in Korea, the study estimates a fixed-effects model to examine the impact of industrial park openings on the housing market in Korea. This study contributes to the literature

in three ways. First, the availability of multiple transactions within apartment complexes makes it feasible to carry out a fixed-effects estimation and address unobserved heterogeneity across apartment complexes. Second, I trace the effect on housing values from the announcement stage to actual operation stage of industrial parks. Third, although most previous studies analyze U.S. housing market, I examine the Korean housing market. I find that people in general have positive expectations about parks opening at the time of announcement, but they do not want to be located in close proximity to the park. Furthermore, the housing price effects of announcement and actual start of operation differ. Local households react positively to the news of industrial park openings and remain positive by the time parks begin operation, but households in close proximity to industrial parks react relatively less positively at the time of announcement, and the decline in price premium becomes greater once parks begin operation.

In Chapter 4, I examine the price effect of the Fukushima nuclear accident on the Korean housing market. The Fukushima nuclear disaster triggered by the earthquake and tsunami was an unfortunate accident that is recorded as the worst nuclear accident since the Chernobyl accident. Given the proximity of South Korea to Japan, Koreans were particularly more concerned about the severity of the accident and its environmental and health impacts. Uncertain events such as the Fukushima nuclear accident may cause households to re-evaluate the likelihood of environmental hazard and decrease the values of housing units that are located near the facilities. Current study analyzes how the Korean housing market responds to the Fukushima nuclear disaster, using publicly available housing transactions data. The study compares the prices of apartments located in the nuclear plant-possessing districts with those of the apartments located in adjacent districts. The results indicate that in reaction to the news of disaster in Japan, housing prices decreased radically in those districts with nuclear power plants.

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Dedication

To my family.

Table of Contents

Abstract . . . . **ii**

Acknowledgements . . . . **iv**

List of Figures . . . . **viii**

List of Tables . . . . **ix**

I. Introduction **1**

II. Is There a Price Premium on Energy Efficiency Labels? Evidence from the Introduction of a Label **3**

2.1. Introduction 3

2.2. Previous Literature 7

2.3. Data 9

2.4. Models and Results 10

2.4.1. Difference-in-Difference Estimation 12

2.4.2. Fixed-Effects Estimation 14

2.5. Policy Implications 15

2.6. Concluding Remarks 17

III. Housing Prices and Environmental Hazard: The Effects of Industrial Park Openings in Korea **26**

3.1. Introduction 26

3.2. Background Information 30

3.3. Measuring Exposure to Environmental Risks 31

3.3.1. Industrial Parks 31

3.3.2. Housing Transaction Data 32

3.3.3. Measuring Exposure to Environmental Risks 32

3.4. Empirical Methodology 34

3.5. Results 35

3.5.1. Announcement Date vs. Start-of-Operation Date 36

3.5.2. Premium on Locating Farther Away from the Park 37
3.5.3. Houses That Experienced Multiple Industrial Park Openings . 38
3.5.4. Toxicity of Industrial Parks 39
3.5.5. Results with Other Controls 41
3.6. Conclusion 41
IV. The Effect of the Fukshima Nuclear Accident on the Korean Housing Market 51
4.1. Introduction 51
4.2. Background Information 53
4.3. Data 55
4.3.1.Nuclear Plants in Korea 55
4.3.2. Housing Transaction Data 55
4.3.3. Measuring Exposure to Nuclear Risks 55
4.4. Empirical Methodology 56
4.5. Results 58
4.6. Conclusion 59
Bibliography 62

List of Figures

Figure 1 (2.1) 19
Figure 2 (2.4) 24
Figure 3 (3.3) 44
Figure 4 (3.3) 45

List of Tables

Table 1 (2.1) 19
Table 2 (2.2) 20
Table 3 (2.3) 21
Table 4 (2.4) 22
Table 5 (2.4) 23
Table 6 (2.4) 25
Table 7 (3.1) 43
Table 8 (3.3) 46
Table 9 (3.5) 47
Table 10 (3.5) 48
Table 11 (3.5) 49
Table 12 (3.5) 50
Table 13 (4.3) 60
Table 14 (4.5) 61

Chapter 1

Introduction

The value of non-market good such as environmental quality is difficulty to quantify because the good is not traded in conventional markets. In my dissertation, I measure the value environmental quality using the hedonic pricing method in all three chapters.

Chapter 2 examines the price premium from Korea's Energy Efficiency Grade Label. The Korean government recently began energy certification of televisions, providing a setting to analyze a possible price effect of the new label. Hedonic regression results seem to show that a price premium exists for products with the Energy Efficiency Grade Label. However, potential unobserved heterogeneity is a concern. Difference-in-difference and fixed-effects models are used to capture the net effect of the label by controlling for time and product differences. The results suggest that any price premium does not result from the energy efficiency label itself. Instead, energy-efficient products already had higher prices before the introduction of the energy efficiency label. The finding turns our attention to the importance of careful design of labeling programs.

In Chapter 3, using the publicly available housing transaction data in Korea, the study estimates a fixed-effects model to examine the impact of industrial park openings on the housing market in Korea. This study contributes to the literature in three ways. First, the availability of multiple transactions within apartment complexes makes it feasible to carry out a fixed-effects estimation and address unobserved heterogeneity across apartment complexes. Second, I trace the effect on housing values from the announcement stage to actual operation stage of industrial parks. Third, although most previous studies analyze U.S. housing market, I examine the Korean housing market. I find that people in general have positive expectations about parks opening at the time of announcement, but they do not want to be located in close proximity to the park. Furthermore, the housing price effects of announcement and actual start of operation differ. Local households react positively to the news of industrial park openings and remain positive by the time parks begin operation, but households in close proximity to industrial parks react relatively less positively at the time of announcement, and the decline in price premium becomes greater once parks begin operation.

Chapter 4 examines the price effect of the Fukushima nuclear accident on the Korean housing market. The Fukushima nuclear disaster triggered by the earthquake and tsunami was an unfortunate accident that is recorded as the worst nuclear accident since Chernobyl. Given the proximity of South Korea to Japan, Koreans were particularly more concerned about the severity of the accident and its environmental and health impacts. Uncertain events such as the Fukushima nuclear accident may cause households to re-evaluate the likelihood of environmental hazard and decrease the values of housing units that are located near the facilities. Current study analyzes how the Korean housing market responds to the Fukushima nuclear disaster, using publicly available housing transactions data. The study compares the prices of apartments located in the nuclear plant-possessing districts with those of the apartments located in adjacent districts. The results indicate that in reaction to the news of disaster in Japan, housing prices decreased radically in those districts with nuclear power plants.

Chapter 2

Is There a Price Premium on Energy Efficiency Labels? Evidence from the Introduction of a Label

2.1. Introduction

Environmental labeling is intended to help consumers take environmental matters into account when making purchasing decisions and to encourage firms to produce environment-friendly goods to satisfy consumer demand. Such programs are usually administered by a third party, such as the government.

Kotchen (2013) describes how environmental labeling can alleviate two market distortions. One is incomplete or asymmetric information. While a seller is aware of the environmental friendliness of the good, a buyer cannot observe it and therefore cannot make an informed decision. Labeling helps narrow this information gap between the buyer and the seller by providing information about products' environmental impacts. Environmental labels are certified through third-party assessment so that buyers are assured that information on the label is accurate and credible.

The other market distortion is related to the public good aspects of environmental quality. Environmental labeling may attenuate free-riding by helping to establish a private mechanism to provide the public good. Consumers may engage in impure altruism, where their voluntary contributions to the provision of a public good are motivated not only by an interest in the welfare of the society, but also by satisfaction from the act of giving (Andreoni, 1990).

The Energy Efficiency Grade Label is a Korean eco-labeling program similar to the US Energy Star program (US Environmental Protection Agency, Energy Star, 2012). This mandatory labeling program is administered by the Korea Energy Management Corporation (KEMC). The energy labeling program may enable consumers to identify which products are energy-saving and might encourage manufacturers to use energy-efficient technology and environment-friendly components. The Energy Efficiency Grade Label was first applied to refrigerators in 1992. Now, the label certifies over 40 product categories, including air conditioners, automobiles, and washing machines. (KEMC, 2012).

As televisions constitute 17 percent of energy usage by households, it was essential that televisions be included in the Energy Efficiency Grade Label program. Internationally coherent system to measure energy efficiency did not exist until 2010, when IEC (International Electrotechnical Commission) 62087 established an agreement in measurement of energy efficiency. IEA (International Energy Agency) advised that every country institutes energy labels for televisions. The Korean government followed suit and started the energy certification on televisions in July 2012. (Ministry of Knowledge Economy, 2011)

Based on average TV viewing hours by household, the agency calculates average wattage usage of each product and certifies the product with the Energy Efficiency Grade Label following the guidelines provided by the program. Certified products are rated at a level of energy efficiency. Level 1 products are the most energy-efficient and Level 5 products are the least energy-efficient of the certified products. Table 1 describes how levels were determined, and this information was released to the public in May 2011, approximately a year before the labeling program started in July 2012. If a product fails to meet minimum standards for certification, then the manufacturer must remove the product from the market within 90 days. Because this study was carried out one month after levels were first assigned to televisions, those models that failed to receive certification remained on the market. The study takes advantage of such timing to look at the price effect of the energy efficiency label.

Figure 1 is an example of an Energy Efficiency Grade Label for televisions. On the label, the following information is provided: level of energy efficiency, wattage usage per 1 $\sqrt{m^2}$, amount of CO_2 emissions per hour, model of television, and yearly energy cost. Before the labeling began, consumers were provided the information on average energy usage only. The labeling program provides new information not only on average energy usage, but also on average CO_2 emissions, average yearly monetary costs, and, most importantly, level of energy efficiency.[1] Newell and Siikamaki (2014) show that labels that give a suggested grade to a model encourage energy-efficient behavior of consumers. In this respect, by providing new information to the consumers, labels may elicit energy-efficient behavior.

Another environmental certification in Korea is the Eco-label, which is given to products that are environmentally less harmful during the manufacturing, consumption and disposal stages. This labeling program also began in 1992 and currently applies to over 120 product categories (Korean Environmental Industry and Technology Institute (KEITI), 2012). The Eco-label is the most widespread environmental certification in Korea. The Eco-label is different from the Energy Efficiency Grade Label in that the Eco-label considers the overall harmful emissions from the manufacturing stage to the disposal stage, while the Energy Efficiency Grade Label considers only the energy-saving aspect.

This paper investigates the effect of the Energy Efficiency Grade Label on the price of televisions in Korea by comparing prices of products that did receive the label and products that failed to receive the label. The fact that this label began to certify televisions in July 2012 motivated the current analysis. Price data is collected

[1] In the case of offline retail stores, the label is attached to the model, so the consumers were able to see the level of efficiency for each model. For online shopping websites, once shoppers click on a webpage with a list of televisions, each model's level of energy efficiency is provided with a separate banner and, when they click on a specific model to see a detailed description of the model, information on the level of energy efficiency is provided again, along with wattage usage, amount of CO_2 emissions per hour, and yearly energy cost. Based on this note, consumers are able to differentiate relatively easily the level of energy efficiency of one model from another.

before and after the adoption of the energy label. Because televisions are also certified by the Eco-label, the paper controls for the effect of the Eco-label on price and studies the price effects of the two labels separately.

Hedonic regression results show that, controlling for other observable attributes of televisions, higher prices are observed for televisions that received the Energy Efficiency Grade Label. However, there is no price premium for the Eco-label. If the energy label is what caused higher prices, the different price premiums for the two labels may exist because households have higher willingness-to-pay for energy-efficient products, but not for environment-friendly products in general.

Additionally, difference-in-difference estimation and fixed-effects estimation are carried out to capture the genuine "treatment" effect of the energy labeling program. The purpose is to address potential unobserved differences in product attributes between labeled and unlabeled televisions. The results suggest that the true effect of the label is close to zero and not statistically significant. Energy-efficient products may have higher quality in diverse dimensions and therefore have higher prices.

The finding that the label has zero effect cautions against faults of the labeling program. The two main goals of labeling programs are the following. The first is to induce energy-efficient behavior on the part of consumers. This leads to the second goal: to give incentives to manufacturers to produce energy-efficient products. The Korean energy label program seems to have used excessively lenient standards when rating energy efficiency of televisions, which made it difficult for consumers to differentiate energy efficiency of models. On a different but related note, announcing the standards too early may have offered time for manufacturers to produce models that satisfy requirements for certification. The strategic behavior of manufacturers combined with absence of rigid standards may have caused a price effect of the label to disappear.

Although numerous hedonic studies have looked for price premiums from environmental certifications, this study is the first to look at the effect of the new adoption of a label. Drawing on this opportunity, this study attempts to address endogeneity problems by using a difference-in-difference method and fixed-effects estimation, which are novel approaches in the hedonic pricing literature. This is also one of the few studies to look at a non-US environmental label. The study's findings contribute to the literature by cautioning that not all eco-labeling programs are successful.

The following section reviews the literature. Section 2 explains the data, Section 3 describes the models and the results, Section 4 explains policy implications of the findings, and we conclude in Section 4.

2.2. Previous Literature

The price premium on environmental labels has been an active research topic. Many studies have approached this issue using stated preference methods (Blend and van Ravenswaay (1999), Sammer and Wustenhagen (2006), and Ward et al. (2011)). However, what consumers say they are willing to buy when they are answering a survey may not coincide with what they actually purchase. Bjorner et al. (2004) is one of very few papers that used a large set of data on actual purchases; they found that an eco-label is a critical factor in determining both the consumer's choice and the product price. The current study is one of very few studies that uses actual data on consumer behavior. Using repeated price data from two periods, I find that the apparent price premium does not exist after all.

The most common approach to assessing the value of environmental certification is hedonic regression. Rosen (1974) argued that, in a market with differentiated goods, the price function is determined by the meeting of the value function set by consumers and the offer function set by producers, and the resulting price function captures the implicit values placed on each attribute of the good. Hence, this method uses a revealed preference approach to identify the factors that determine price and consequently the values that consumers place on product attributes. Also, data can be obtained readily because the information requirements are only the price and other important characteristics of the product of interest that may affect consumer behavior (Galarraga et al., 2011). Numerous studies have found a price premium on products with an environmental label using this method. Some examples are environment-friendly electricity (Roe et al., 2001), apparel products with organic fiber (Nimon and Beghin, 1999), eco-labeled paper towels (Srinivasan and Blomquist, 2009), and Energy Star- and LEED (Leadership in Energy and Environmental Design)-certified buildings (Eichholtz et al., 2009 and Fuerst and McAllister, 2011).

A problem with hedonic analysis is the possibility of omitted variable bias. Although there have been numerous hedonic studies, only a few have tried to address this problem. Wallander (2008) looks at the price premium on washing machines with the Energy Star label and uses a hedonic analysis based on regression discontinuity design to reduce bias caused by omitted variables. Under standards set by the US Department of Energy, a washing machine is certified with the Energy Star label if its modified energy factor (MEF) exceeds 1.72. Wallander uses the discontinuity at the threshold MEF level to measure the price effect of the label. A washing machine with a MEF level just above the threshold is likely to be very similar to one just below the threshold MEF level. However, the former will be labeled, while the latter will not. Comparing the price outcomes of the certified and uncertified groups, he finds that the price effect of the Energy Star label is not statistically different from zero.

Table 2 lists previous literature that investigates the existence of price premiums on environmental labeling. The majority of the previous work focuses on US eco-labels and all but Wallander (2008) find evidence of price premiums for eco-labels. My study contributes to this literature in two respects. First, while most previous work studies US labels, I focus on Korean eco-labels. Second, the current study attempts to address the unobserved heterogeneity problems. The issue often has been ignored in hedonic studies of eco-labeling, and most studies concluded that they had found evidence of price premiums on eco-labels. By contrast, I use difference-in-difference and fixed-effects estimation to identify the pure price effect of the label and find that a price premium does not exist.

2.3. Data

Information on the Energy Efficiency Grade Label certification status of televisions is available on the official website of KEMC. Since the beginning of the energy efficiency labeling program in July 2012, approximately 290 television models have been approved by this labeling program (KEMC, 2012). Data on the status of the Eco-label is available on the official website of KEITI, which is the organization in charge of the Eco-label, together with the Ministry of Environment (KEITI, 2012). This certification status is updated every month, but the status of the Eco-label did not change during the period under study. Price data come from the online shopping mall of Himart, Korea's largest electronic appliances retail market.[2] In order to observe price changes resulting from the Energy Efficiency Grade Label, price data were collected before and after July, 2012. I have the data for 129 television models.[3] Out of 129 models, 115 models received an energy efficiency grade label and 14 models did not. Out of 115 models that did receive certification, 111 models received Level 1,

[2]I understand the concern over using a single online retailer for analysis. However, Himart was the largest of electronic appliance retailers, constituting 34.9 percent of market share in 2011 (Park, 2012) and having grown to constitute more than 50 percent of market (Kang, 2016). Additionally, an increasing number of people are shopping online for electronic appliances due to the availability of smart devices (Alba et al., 1997). Srinivasan and Blomquist (2009) uses a single internet-based grocery store, Peapod.com to find that people place substantial, postiive price premium on eco-labeled paper towels.

[3]I have the price data for 164 models in June 2012 and 160 models in August 2012. I selected 129 models whose price data were available for both periods. I follow the assumption that in an efficient market, prices fully reflect all publicly available information and market prices react instantaneously to new information (Belkaoui, 1976).

three models received Level 2, and one model received Level 3. Because the level of energy efficiency hardly varies among the products in the sample, this analysis does not consider how the price effect varies by energy efficiency level and, therefore, the Energy Efficiency Grade Label is represented by a dummy variable.

Table 3 provides summary statistics for the 129 televisions models used in the analysis. Nearly 90 percent of the models were certified with the Energy Efficiency Grade Label as of August 2012. By contrast, approximately 40 percent of the products were certified with the Eco-label as of June, and the status remained the same throughout the two months. The screen size of the televisions ranges from 22 inches to 65 inches. 3D and LED screen televisions seem to be the majority of current television models. About half of the models have "smart" functions[4]. There are approximately the same number of stand-up and wall models. Nearly 90 percent of the models have LED screens. Samsung and LG models constitute almost 90 percent of the models. Table 3 also contains separate statistics for models with and without the Energy Efficiency Grade Label. Models with the energy label are superior to models without the label in almost every dimension. Labeled products have higher price and larger screen size, are more likely to perform 3D and "smart" functions, and are more likely to be LED-screen models. The superior qualities of the televisions may be endogenous to the status of certification.

2.4. Models and Results

Consider the following log-price equation:

$$lnprice_i = \alpha + \beta * energylabel_i + \gamma * ecolabel_i + \delta' Z_i + \nu_i + \epsilon_i, \tag{1}$$

[4] "Smart" function refers to the device's ability to connect to networks via wireless protocols.

where $lnprice_i$ is the log of the price of model i in August, α is a constant term, $energylabel_i$ is a dummy variable which has value 1 if the model was certified with the Energy Efficiency Grade Label in August and 0 if not, and $ecolabel_i$ is a dummy variable for the Eco-label. Based on the assumption that people value environmental externalities, as found in previous literature[5], I expect the two variables to have positive coefficients. Z_i is a vector of explanatory variables that include other important attributes of televisions that possibly influence the price. The variables that are controlled for by Z_i are 1) screen size measured in inches, 2) 3D, 3) "smart" function, 4) screen type, which is either PDP, LCD, or LED, and 5) form, which is either stand-up type or wall type. According to Consumer Reports (2012), these are important features of televisions that consumers should consider when making purchasing decisions. Most likely, screen size, "smart" function, and LED screen type have a positive influence on prices. ν_i is a brand-fixed effect and ϵ_i is an error term.

Table 4 shows the econometric results for Equation (1). The first column presents estimates for two labels, the Energy Efficiency Grade Label and the Eco-label. Columns (2) and (3) control for observable characteristics of televisions and brand effects, respectively. Column (4) presents estimates when all the covariates are controlled for. The price effect of the Energy Efficiency Grade Label is positive and statistically significant in all specifications. However, the magnitude of the effect is reduced considerably once television characteristics are included. Controlling for all the variables, but before proceeding to the difference-in-difference analysis below, the estimated price premium for energy-labeled televisions is almost 20 percent. On the other hand, the Eco-label has a tiny price effect and estimates are statistically insignificant in all four specifications. Larger screen size, "smart" function, and LED screens strongly predict higher prices. A 1 percent increase in screen size corresponds to a 2.5 percent increase in price. Models with "smart" functions have higher prices by approximately 20 per-

[5]Eicholtz et al. (2010), Fuerst and McAllister (2011)

cent. Models with a LED screen have higher prices by 41 to 44 percent. Although not as strong, 3D function and LCD screen predict higher prices as well. When controlling for brand effects only, Samsung, LG and Sony models seem to have higher prices in general, but that effect disappears when observable attributes are included in the model.

The difference between the effect of the Energy Efficiency Grade Label and that of the Eco-label is noteworthy. If the estimated 20 percent price premium is a result of the energy label and not biased by any omitted variable, such a difference may arise because people have higher willingness-to-pay for energy-saving models but not for models that help protect the environment in general. Households may value televisions certified by the Energy Efficiency Grade Label because they reduce electricity expenses, but Eco-labeled models may not be as valued because they affect households' private benefits to a smaller degree. Thus, the results agree with economic theory that people free-ride. That is, a public good is under-supplied because the benefits of a public good can be enjoyed without contribution.

The results in Table 4 make it seem that televisions certified by the Energy Efficiency Grade Label have a price premium. In fact, high R-squared values in Columns (2) and (4) suggest that omitted heterogeneity may not be a huge concern in the hedonic analysis. However, it is too soon to conclude that such higher price is a result of the label. The labeled group not only has higher prices, but also has higher quality in all aspects. Hence, one may naturally be suspicious that unobserved heterogeneity among television models is what gives rise to such price differences.

2.4.1. Difference-in-Difference Estimation

For direct estimation of the effect of the energy label and to address the unobserved heterogeneity problem, I carry out a difference-in-difference (DD) estimation. The "treatment" corresponds to the certification by the Energy Efficiency Grade Label on televisions. The treated televisions are the models that are labeled in August, and the control group are those not labeled. Under the assumption that the treatment group and the control group have identical price trends in the absence of treatment, the DD estimate accounts for permanent differences between the two groups.

Consider the following equation:

$$lnprice_{ij} = \alpha + \beta * energylabel_i + \gamma * time_j + \eta * (energylabel_i * time_j) + \delta' Z_i + \nu_i + \epsilon_{ij}, \quad (2)$$

where $lnprice_{ij}$ is the log of the price of model i from time j, $energylabel_i$ in this model is a dummy variable that applies for both June and August and has value 1 if the model received the label in August and 0 if not, and $time_j$ is a dummy variable which has value 1 if the observation is from August and 0 if it is from June. The term $energylabel_i$ captures permanent differences between the models with and without the label that are not captured in vector Z_i. The term $time_j$ controls for a time trend that may have influenced both labeled and unlabeled groups. η is the coefficient of interest and it corresponds to the "treatment" effect of the Energy Efficiency Grade Label. Standard errors in all specifications are clustered by model to mitigate auto-correlation within models.

Table 5 presents the results of the estimation. The DD estimates shown by the coefficient of the interaction term are the same across all specifications and the effect is nearly zero and statistically insignificant, meaning that there is no price effect of the Energy Efficiency Grade Label. On the contrary, the coefficients on $energylabel_i$ are consistently positive and highly statistically significant. Despite high R-squared values in the hedonic regression, addressing the unobserved heterogeneity problem by DD estimation yields a different outcome. While Table 4 suggests an apparent price premium on the energy label, that link disappears in DD estimation[6].

[6]Data with just two points in time is a limitation of the current study. However, because I am using difference-in-difference estimation under a hedonic framework, this may be less problematic. The dependent variable in the estimating equation is price, and market price instantaneously adjusts

Figure 2 is a graphical illustration of the difference-in-difference estimation result. After normalizing prices, I present the data from June ($time = 0$) to August ($time = 1$) in two panels. The left panel is a scatter of prices for models that did not receive energy certification ($energylabel = 0$), and the right panel is a scatter of prices for models that did receive energy certification ($energylabel = 1$). T-test confirms that prices in June are statistically different from prices in August[7], but a similar trend is present in the two panels, which indicates that the price effect of the energy efficiency label is small. Furthermore, prices of certified models were higher from the beginning, which indicates that any price premium observed is the result of inherent characteristics.

2.4.2. Fixed-Effects Estimation

To rule out all time-invariant model heterogeneity as a source of omitted variable bias, I estimate a fixed-effects model.

Consider the following equation:

$$\Delta lnprice_{ij} = \Delta\alpha_i + \Delta\lambda_j + \rho\Delta energylabel_{ij} + \Delta Z'_{ij}\delta + \Delta\epsilon_{ij}, \tag{3}$$

where $lnprice_{ij}$ is the log price of model i and time j, α_i is a vector of unobserved but fixed heterogeneity of television models, and Z_{ij} is a vector of observed covariates. $energylabel_{ij}$ is a dummy variable for the Energy Efficiency Grade Label, which has value 1 if model i is certified with the label in time j. The Δ prefix denotes the change from June to August. Using repeated observations over two time periods, a fixed-effects model, by first-differencing the data, will absorb the unobserved

to fully reflect all publicly available information in the market such as a policy change in this study. (Belkaoui, 1976)

[7]T-test between prices in June and prices in August yielded $t = 5.5011$, which shows that prices have changed during the two-month period.

permanent model effects α_i. The observed model covariates in vector Z_{ij} are all non-time-varying and therefore, once I estimate Equation (3), they are removed from the equation, similary to the unobserved model heterogeneity α_i. ρ is the causal effect of the Energy Efficiency Grade Label on prices. In addition, I estimate Equation (3) with Z_{ij} back in the equation, which allows me to control for trends in prices across observable characteristics and brands.

Table 6 presents the estimation result. Column (1) suggests that the Energy Efficiency Grade Label does not explain television price differences from June to August. Column (2) of Table 6 lists the coefficient values when I estimate Equation (3) with observed covariates Z_{ij} back in the equation. It is noteworthy that prices of televisions with larger screen size decreased, whereas prices of television models of major domestic brands increased. Previous DD estimation failed to capture such different price trends across model characteristics and brands. Nevertheless, even after controlling for price trend differentials, I find no effect of the energy label on the price difference. Combining the results in Tables 5 and 6, it seems that certified models do have higher prices in general, but the observed price difference arises because of permanent product differences between labeled and unlabeled models rather than the Energy Efficiency Grade Label itself.

2.5. Policy Implications

The outcome that a price premium does not exist has important implications. The labeling program may not have been designed correctly and the criteria used to determine energy efficiency may have been set too low. Out of 129 models, 115 models were certified with Energy Efficeincy Grade Label. Almost all models that were certified received Level 1; those that did not received either Level 2 or Level 3. The natural outcome is that too many of the models turn out to be “energy efficient”, and hence consumers are unable to differentiate energy efficiency of the models in a market full of Level 1 television models, which implies that the energy label may not have greatly reduced the information asymmetry problem.

The other false aspect of the labeling program is that manufactuers perfectly anticipated the new label and were aware of requirements for certification. In fact, the standards used for determining level of energy efficiency, which is information in Table 1, were disclosed one year before the start of certification. Having found out the requirements for certification, firms may have strategically reacted to the policy by manufacturing products that just meet Level 1 requirement. Houde (2014) describes this phenomenon as firms offering products that "bunch" at the certification requirement.

Also, the label may fail to capture willingness-to-pay of an average consumer. Grankvist et al. (2004) found that, while individuals with a strong environmental concern were sensitive to information about positive environmental consequences, those with a weaker concern were primarily attuned to labels signaling negative environmental consequences. Credibility of the label may be another problem. Tiesel and Roe (1998) argue that consumers may question the true motivation of the certifying organization and may therefore disregard the information on the label.

As Klein and Leffler (1981) show, the price of a good is an indicator of quality; a price premium could actually stimulate demand in this situation, and its absence may reduce the incentive of manufacturers to produce energy-saving products. This study exemplifies what may happen when a labeling program does not function properly, and cautions against inattentive policy design.

Based on the speculations above, I suggest that the certifying organization introduce more rigorous and up-to-date standards for the Energy Efficiency Grade Label because the current problem may be that the threshold for the label apparently was set too low.[8] Furthermore, the label should signal not only positive environmental performance but also negative environmental performance so that consumers are able to observe environmental quality difference across products. Under such guidelines, the energy label might play a more important role of providing critical and practical information to consumers.

2.6. Concluding Remarks

Using price data on the Korean television market, this paper finds a price differential for Energy Efficiency Grade Label-certified televisions using the traditional hedonic price model. However, the results of difference-in-difference estimation and first-difference estimation with model-fixed effects suggest that the observed price premium is not caused by the label itself, but by the innate quality difference between the labeled and unlabeled groups. My results are consistent with those in Wallander (2008). He finds an apparent price premium on washing machines with the Energy Star label in simple hedonic analysis, but finds that this premium evaporates when he addresses omitted variable bias, in his case by using a regression discontinuity approach.

The finding that a price premium on the energy label does not exist is important. While most of the past hedonic price studies of environmental labeling neglected to address the endogeneity problem, this paper uses difference-in-difference and first-difference estimation to reduce omitted variable bias and finds that prices were generally higher for labeled products because of pre-existing product differences rather than the label itself.

[8]Accounts of improvement in energy labeling program exist. A news article reported on electronic appliances with Level 1 energy efficiency having widely varying degrees of energy efficiency, up to a 40 percent difference in energy cost (Lee, 2012). As of January 2013, the regulation was strengthened so that only a small proportion of models in the market receive Level 1. The Korean labeling agency may have noticed the inefficiency of incorrect labeling standards and reinforced the requirements for certification.

As the study is based on a natural experiment, the treatment is not perfect in that the labeling program lacks variation in terms of levels of energy efficiency. However, the study contributes to the literature because the start of the labeling program provides a timely setting to analyze the price effect of new certification. Moreover, the study emphasizes the importance of setting appropriate standards by showing the mishaps of a poorly structured labeling program.

The result of the study has an important policy implication. If an eco-labeling or energy efficiency labeling system is optimally implemented, a consumer's willingness-to-pay for energy efficiency will be precisely conveyed through higher prices, thereby providing incentives for producers to produce more energy-efficient goods. The current study shows what may happen when the policy is not implemented well. The thresholds used for determining the level of efficiency presumably were set without careful consideration, and, as a consequence, the labels were not able to differentiate products in terms of energy efficiency. As a result, the marginal willingness-to-pay of consumers could not be captured.

Figure 1: Energy Efficiency Grade Label

R	Level
R $\leq$ 130	1
130 $<$ R $\leq$ 165	2
165 $<$ R $\leq$ 205	3
205 $<$ R $\leq$ 260	4
260 $<$ R $\leq$ 440	5

$R = W/\sqrt{m^2}$, where W is energy used and m^2 is area of screen.

Table 1: How Energy Efficeincy Grade Level Is Determined

Table 2: Previous Studies about Price Premium on Eco-Label

Study	Label, Product & Country	Method	Is there a price premium?
Blend and van Ravenswaay (1999)	eco-labeled apples in the US	survey	40% would buy with $.40 premium, purchase probability decreases as premium increases
Sammer and Wustenhagen (2006)	washing machines with EU Energy Label in Switzerland	discrete choice analysis using survey	30 % price premium
Ward et al. (2011)	refrigerators with Energy Star in the US	online survey	Consumers have positive and significant higher willingness-to-pay(WTP) for labeled refrigerators, WTP estimate ranges from $249.82 to $349.30
Bjorner et al. (2004)	toilet paper, paper towels, detergents with Nordic Swan in Denmark	data on actual purchases	Marginal WTP ranges from 13% to 18% of the price.
Roe et al. (2001)	US green electricity	survey and hedonic regression	1% increase in the use of renewable resources corresponds to yearly $6 premium.
Nimon and Beghin (1999)	US eco-labeled apparel	hedonic regression	33.8% premium for organic fiber, no premium for environment-friendly dyes
Srinivasan and Blomquist (2009)	eco-labeled paper towels in the US	hedonic regression	69.9% price premium
Eichholtz et al. (2009)	Energy Star- and LEED (Leadership in Energy and Environmental Design)-certified buildings in the US	hedonic regression	3.5%, 10%, 15.8% to 16.8% premium on rental rate, effective rental rate, and sales price, respectively
Fuerst and McAllister (2011)	Energy Star- and LEED-certified buildings in the US	hedonic regression	3 to 4% rent premium, 28% sales price premium on dual certified, 18% and 25% sales price premium for Energy Star and LEED, respectively
Wallander (2008)	washing machines with Energy Star in the US	hedonic regression based on regression discontinuity design	Price premium does not exist.

Table 3: Summary Statistics,
With and Without the Energy Efficiency Grade Label

Variable	All	With Energy Label (115)	Without Energy Label (14)
Price in June	2.572	2.708	1.448
	(1.718)	(1.756)	(.704)
Price in August	2.504	2.635	1.431
	(1.658)	(1.694)	(.705)
Energy Efficiency Grade Label	.891	1	0
Eco-label	.419	.426	.357
Screen Inches	44.620	44.991	41.571
	(8.360)	(8.403)	(7.451)
3D	.736	.765	.5
"Smart Function"	.566	.617	.143
Stand-up Type	.527	.530	.5
LED Screen	.884	.904	.714
LCD Screen	.062	.035	.286
PDP Screen	.054	.061	0
Samsung	.318	.357	0
LG	.481	.470	.571
Daewoo	.039	.035	.071
Sony	.140	.139	.143
Haier	.023	0	.214

Prices are in Korean won and in millions.
Standard deviations for continuous variables are in parentheses.
Data: www.kemco.or.kr; www.greenproduct.go.kr; www.e-himart.co.kr

Table 4: Hedonic Regressions, Price in August

Independent Variable	Dependent Variable: Log(Price in August)			
	(1)	(2)	(3)	(4)
Energy Efficiency Grade Label	.529***	.169***	.371**	.191***
	(.148)	(.053)	(.143)	(.048)
Eco-label	.006	-.082**	.077	-.063
	(.109)	(.039)	(.118)	(.052)
Screen Inches		2.481***		2.556***
		(.103)		(.115)
3D		.151**		.167***
		(.059)		(.063)
"Smart" Function		.214**		.197***
		(.047)		(.047)
Stand-up Type		.006		-.004
		(.038)		(.039)
LED Screen		.441***		.414***
		(.104)		(.101)
LCD Screen		.217*		.210*
		(.112)		(.117)
Samsung			.657**	-.096
			(.305)	(.202)
LG			.875***	-.132
			(.276)	(.191)
Daewoo			-.352	.030
			(.372)	(.196)
Sony			1.122***	-.033
			(.291)	(.194)
Constant	14.057***	4.401***	13.396***	4.214***
	(.139)	(.409)	(.236)	(.461)
Observations	129	129	129	129
R-squared	0.0648	0.8984	0.2693	0.9020

Notes: Standard errors are robust and in parentheses.
Significance at 0.10, 0.05, and 0.01 levels are indicated by *, **, and ***, respectively.
The variables PDP Screen and Haier (brand) are omitted because of collinearity.
The variable Screen Inches is log-transformed.

Table 5: Difference-in-Difference Estimation Results

Independent Variable	Dependent Variable: Log(Price)				
	(1)	(2)	(3)	(4)	(5)
Energy Efficiency Grade Label*Time	-.008	-.008	-.008	-.008	-.008
	(.009)	(.009)	(.009)	(.009)	(.009)
Energy Efficiency Grade Label	.538***	.167***	.358**	.219***	.199***
	(.148)	(.054)	(.144)	(.047)	(.047)
Time	-.013*	-.013*	-.013*	-.013*	-.013
	(.007)	(.007)	(.007)	(.007)	(007)
Ecolabel					-.056
					(.050)
Screen Inch		2.494***		2.580***	2.602***
		(.105)		(.105)	(109)
3D		.180***		.207***	.183***
		(.055)		(.057)	(.059)
"Smart" Function		.201***		.185***	.194***
		(.044)		(.045)	(.059)
Stand-up Type		.010		-.007	-.006
		(.037)		(.037)	(.037)
LED Screen		.426***		.386***	.404***
		(.089)		(.087)	(.094)
LCD Screen		.203**		.191*	.199*
		(.101)		(.109)	(.110)
Samsung			.738**	-.210	-.135
			(.298)	(.180)	(.193)
LG			.903***	-.219	-.179
			(.277)	(.175)	(.182)
Daewoo			-.354	-.006	.014
			(.373)	(.186)	(.191)
Sony			1.145***	-.087	-.061
			(.299)	(.182)	(.185)
Constant	14.072***	4.337***	13.417***	4.183***	4.902***
	(.134)	(.424)	(.247)	(.428)	(.447)
Observations	258	258	258	258	258
R-squared	0.0645	0.9003	0.2651	0.9080	0.9089

Notes: Standard errors are robust, clustered and are in parentheses.
Significance at 0.10, 0.05, and 0.01 levels are indicated by *, **, and ***, respectively.
The variables PDP Screen and Haier (brand) are omitted because of collinearity.
The variable Screen Inches is log-transformed.

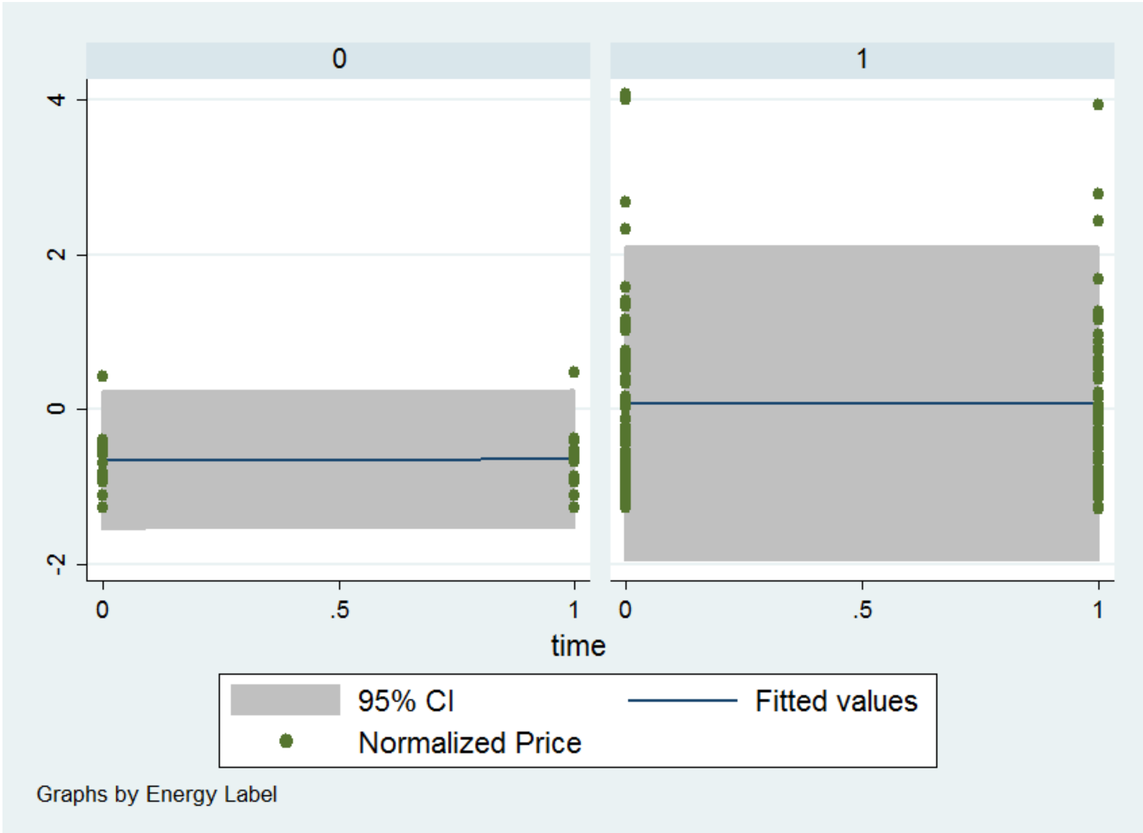

Figure 2: Difference-in-difference Result

Table 6: Fixed-effects Estimation Results

Independent Variable	Dependent Variable: Log(Price in August)-Log(Price in June)	
	(1)	(2)
Energy Efficiency Grade Label	-.008	-.010
	(.009)	(.009)
Eco-label		-.014
		(.010)
Screen Inches		-.090***
		(.028)
3D		-.032
		(.021)
"Smart" Function		.006
		(.008)
Stand-up Type		.004
		(.009)
LED Screen		.020
		(.023)
LCD Screen		.023
		(.016)
Samsung		.079**
		(.036)
LG		.093***
		(.032)
Daewoo		.032
		(.022)
Sony		.057*
		(.033)
Constant	-.012*	.256***
	(.007)	(.096)
Observations	129	129
R-squared	0.0022	0.2326

Notes: Standard errors are robust and are in parentheses.
Significance at 0.10, 0.05, and 0.01 levels are indicated by *, **, and ***, respectively.
The variables PDP Screen and Haier (brand) are omitted because of collinearity.
The variable Screen Inches is log-transformed.

Chapter 3

Housing Prices and Environmental Hazard: The Effects of Industrial Park Openings in Korea

3.1. Introduction

Industrial parks are a salient local disamenity. Although they help boost regional economic growth and local employment, they are a primary source of hazardous chemicals, particulate matter, and toxic substances. The Environmental Protection Agency (2016) reported that industrial activities account for approximately 50% of the pollution in the United States of America. In this respect, environmental and health risks associated with industrial air pollution are severe. Using the publicly available housing transaction data in Korea, I measure the effect of industrial park openings on housing prices.

Many past studies have examined the relationship between housing values and environmental amenities under hedonic framework. Previous studies discuss the housing market impact of environmental hazards such as power plants (Blomquist, 1974; Davis, 2011), waste sites (McCluskey & Rausser, 2003; Ihlanfeldt & Taylor, 2004), incinerators (Kiel & McClain, 1995), and toxic industrial plants (Currie, Davis, Greenstone, & Walker, 2013). A number of studies use U.S. Superfund cleanup (Kohlhase, 1991; Kiel & Zabel, 2001; Gayer, Hamilton, & Viscusi, 2002; Kiel, 2005; Greenstone & Gallagher, 2008) and Clean Air Act (Chay & Greenstone, 2005) to examine the association between environmental quality and housing values.

Table 7 outlines the list of previous literature that uses a hedonic pricing method to analyze association between housing values and local amenities and their findings in chronological order. All studies in the list examined the U.S. housing market.

Most find strong evidence for a decrease in housing price caused by an environmental hazard, with the exception of Greenstone & Gallagher (2008).

Some past hedonic studies examine the price effects of local amenities by comparing locations with environmental hazards to locations without them. Davis (2011) compared housing market outcomes of neighborhoods with power plants to neighborhoods with similar housing and demographic characteristics. Greenstone and Gallagher (2008) examined housing prices of areas surrounding 400 hazardous waste sites chosen for Superfund cleanup to the housing prices of areas surrounding 290 sites that closely missed qualifying for the cleanups. These estimates are potentially biased by unobserved heterogeneity because areas which are subject to an environmental hazard may be inherently different from areas without an environmental hazard. For instance, areas assigned for industrial parks may have housing and demographic characteristics that differ from other regions[9] Thus, the unobserved heterogeneity makes it difficult to identify the housing price effect of environmental risks independently, separate from the effects of other local amenities.

Attempts to mitigate omitted variable bias have been made in several studies. Currie et al. (2015), using a difference-in-difference estimation with plant-by-distance fixed-effects, compared houses located one mile from toxic plants to houses located one-to-two miles from toxic plants. Due to the limitation of data on housing unit charactersistics, they compared the average housing values of the two distance groups. Chay and Greenstone (2005), using an instrumental variable approach, estimated the effect of total suspended particulates on housing values.

My empirical strategy is motivated by that of Currie et al. (2015). I measure the housing effect of an environmental hazard by comparing prices of housing units located in close proximity to industrial parks to prices of housing units located more

[9] Davis (2011) shows that mean demographic and housing characteristics within two miles of a power plant site are significantly different from mean characteristics for the rest of the United States. Mean household income is lower, household size is higher, and household heads are less likely to have completed high school or college.

farther away from parks. Blomquist (1974) and Davis (2011) found that a decrease in housing value occurs within two miles of a source of emissions. Based on this note, I use houses in a two-mile radius from the park as the “near” group and those in a two-to-four-mile radius as the “distant” group. I conduct a sensitivity analysis comparing the effects on one-mile houses and two-mile houses. The underlying assumption is that people living within a four-mile radius will be influenced similarly by the non-environmental factors of the opening of industrial park. For example, they will benefit from the improvement of the transportation system and new employment opportunities to a similar degree. Therefore, the differential housing price effects of these two groups will likely be the result of an environmental hazard.

I contribute to the literature in three primary ways. First, although most hedonic studies estimating the effect of environmental hazards use U.S. data, the current analysis uses Korean data. Many found evidence supporting price effect of environmental hazards in the United States, and one can naturally ask if the behavior of Korean housing market is similar.

Second, using data from multiple transactions within single apartment complex, I use an apartment-complex fixed-effects model to address unobserved heterogeneity.[10] In most past U.S. studies, given that the majority of residential units are houses, it is uncommon to have multiple transactions of the same housing unit in a given period. Only a few used repeated sales data and estimated a fixed-effects model.[11] However, the availability of multiple sales data in the Korean data allows me to estimate an apartment-complex fixed-effects model and address unobserved heterogeneity across apartment complexes.

Third, I compare the housing price effect of the announcement of plans for the

[10] The term “apartment” in Korea is used to denote what is “condominium” in the United States. Apartments in the United States are mostly rental units, but apartments in Korea are owned by households and are subject to rent at one’s own discretion.

[11] Gaeyer et al. (2002) used repeated transaction data for analysis of the housing price effect of reduced cancer risk, and Davis (2004) used repeated house transaction data for analysis of the power plants.

construction of a new industrial park to the effect of the park actually beginning to operate. Most previous studies consider a one-time discrete change in environmental amenities, but I believe housing prices may react from the time of announcement because the information is revealed at the time of announcement. Few past studies examine housing market outcomes of environmental hazards through various phases of information change. Evidence has been found that announcements of toxicity of sites (Kohlhase, 1991; Kiel, 2005) or even rumors of an undesirable facility (Kiel & McClain, 1995) bring significant declines in housing prices. I take advantage of a comprehensive dataset containing dates of announcement and start of operation of industrial parks and compare the housing market impacts of the two different dates.

The results show that when the opening of an industrial park is announced, houses within four miles of industrial parks experience a price premium, but those within a two-mile radius experience a relatively smaller increase in their values. This result indicates that people in general may hold positive expectations about a new industrial park opening because of the benefits it brings, such as improved transportation and job opportunities. However, people do not like to be located in the immediate vicinity of the parks because of perceived environmental risks. Also, the estimation results indicate that the price premium depends on locating farther away from industrial parks. For the houses that are located near multiple industrial park openings, the first opening has a strong impact on housing values, but the subsequent openings do not seem to affect housing prices. When housing values react to the first opening, those that had a greater number of industrial parks prior to 2006 experience greater decline in prices.

Furthermore, the housing price effect of the announcement of an industrial park opening differs from that of actual start of operation. Although housing prices within four miles increase at the time of announcement, by the time parks begin operation, prices do not react any more. On the other hand, the total price effect on the houses in a two-mile radius declines to a negative value by the time parks begin operation. This result suggests that negative effect of locating close to an environmental hazard persists and becomes stronger as the industrial park develops.

Section 2 describes the background of industrial parks in Korea, Section 3 describes the data, Section 4 explains the empirical strategy, Section 5 describes the results, and we conclude in Section 6.

3.2. Background Information

Industrial development was an engine for Korea's economic growth. The first Five-Year Plan of South Korea in 1962 emphasized export-led economic growth through industrial development. As a result, from 1960 to 2010, the average economic growth rate was 7.5%, exports increased by 16,825 times, and GDP per capita increased by 288 times. In 1962, Korea built its first industrial park in Ulsan; by 2015, there were over 1,000 industrial parks nationwide. In the 1,000 industrial parks, there are around 75,000 manufacturing plants with 1,810,000 workers. The area designated for industrial parks is 1.36% of the country and it is two times the area of Seoul. Plants in industrial parks comprise 62% of country's manufacturing, 79% of exports, and 42% of employment. Thus, it is not an exaggeration to claim that industrial parks have played a central role in Korea's economic growth (Kim & Kang, 2013).

Until the 1980s, industrial development centered around large-scale industrial parks in a few particular regions, resulting in regional imbalance. As part of a plan to induce balanced regional growth, the local governments assumed the authority to build industrial parks from the federal government. Since building industrial parks was such a great way to boost a local economy and create jobs in the region, many local governments began to competitively build industrial parks. As a result, Korea has a large number of industrial parks located all around the country.

Industrial parks play an essential role in the manufacturing sector of the Korean economy. Production from industrial parks was 52.2% of all manufacturing in Korea in 2003, and it only grew to 59.2% in 2008 and 68.6% in 2012. In 2012, machinery constituted the largest portion, with 37.5% of manufacturing activity in industrial parks, followed by electricity with 20.6% and chemicals with 9.2%.[12]

Industrial parks are major sources of chemical substances in Korea. As of 2011, 80.7% of chemical substance emissions in Korea were generated from manufacturing facilities in industrial parks (Ministry of Environment, 2011). Each year, industrial parks emit 53 million kilograms of chemical toxicants such as nitrogen oxides and benzene. These toxic pollutants are associated with respiratory irritation, nervous system problems, cancer, and birth defects (Environmental Protection Agency, 2016).

3.3. Measuring Exposure to Environmental Risks

3.3.1. Industrial Parks

The data on industrial parks are managed by Korean Industrial Complex Corporation at industryland.co.kr. The data include detailed information such as the number of employees and the area of the industrial park. Also, given that a single industrial park has multiple manufacturing plants producing different types of goods, the data provide the types of manufacturing in each industrial park. Most importantly, the date of each industrial park's announcement and the month that it started operation are provided. Thus, I am able to compare the housing price effects resulting from information changes. Industrial parks opened at different times, and therefore they form comparison groups for one another.

A total of 1,214 industrial parks are operating as of 2016, of which 477 were announced from 2006 to 2013. Of 477 industrial parks, 146 parks have manufacturing

[12] In 2012, the composition of manufacturing sectors in industrial parks are the following: machinery (37.5%); electricity (20.6%); chemicals (9.2%); transportation (6.8%); steel (5.0%); food and beverage (3.8%); textiles (3.8%); lumber and paper (3.6 %); nonmetal (2.4%); and others (5.4%).

plants in machinery and 141 in electricity, which suggests that the sample used in the analysis closely resembles the overall manufacturing composition of Korea.[13]

3.3.2. Housing Transaction Data

Data on housing transactions is made publicly available by the Ministry of Land, Infrastructure and Transport of Korea (2015). In Korea, 49.6% of households reside in apartments, 37.5% reside in houses, and 3.4% reside in townhouses (Ministry of Land, Infrastructure and Transport of Korea, 2014). Most residential houses are located in remotely rural areas, where the price behavior may be different from that of apartment complexes. Given these facts, I use transactions of apartments only and not residential houses or townhouses. Comprehensive data on street address, transaction price, area, floor, and building age of all units of apartment complexes are available from 2006 to present. The advantage of using a multiple transactions dataset of apartment prices is that I can add apartment-complex fixed-effects in my estimation equation to avoid unobserved heterogeneity.

3.3.3. Measuring Exposure to Environmental Risks

Using the comprehensive dataset that provides precise locations of industrial parks and apartment complexes, I geocode all parks and apartment complexes using Geographic Information System (GIS). The diamond plots in the left-hand panel in Figure 3 illustrate the geographical distribution of industrial parks in the sample. In the right-hand panel in Figure 3, I added the locations of apartment complexes in the sample with circular plots. Then, I created a two-mile ring and a four-mile ring around each industrial park to set the nearby group as the treatment group and the distant group as the control group. Figure 4 is a graphical illustration of this pro-

[13]In my sample, out of 477 industrial parks, the number of industrial parks producing each type of manufacturing is the following: machinery (146), electricity (141), transport (122), chemical (99), food (86), steel (63), nonmetal (46), paper (38), and textile (24).

cess. The rings around the diamond plots represent four-mile radius rings centered around industrial parks. The apartment complexes inside the rings are included in the study's sample. As a result, my analysis considers the prices of apartment units in 13,079 apartment complexes surrounding 285 industrial parks that open from 2006 to 2013. There are apartments that experienced multiple park openings within four miles during the study period. I initially assign the apartment only to the park with the earliest opening and ignor the latter openings, and afterwards, consider how multiple park openings influence housing prices differently.

Table 8 presents the summary statistics for the data. Panel A compares the areas with industrial parks to the rest of Korea. Housing prices and population density are significantly lower, regional GDP per capita is slightly higher, and the amount of harmful emissions is higher in areas with industrial parks. In short, manufacturing parks tend to be located in industrial areas with low housing prices that are not developed for residential purposes. The rest of Korea differs from the areas subject to industrial park siting, and therefore, they are not valid comparison group for this analysis. This underscores the importance of using a property-fixed effects model to address unobserved heterogeneity.

Panel B features the summary statistics for the sample in the study, which include a total of 1,573,273 transactions of apartment units. Means of apartment structural attributes and means of apartment price, GRDP per capita, and hazardous air pollutant emissions are displayed in three columns to show the difference in means when parks are open and not open. In general, housing prices are higher when parks are not open. Regions have higher GRDP per capita when parks open. It may be that manufacturing activity contributes to the economic output of the region, and hence, the output may be higher with parks open. The amount of chemical substance and toxic pollutant emissions in the region is higher when the parks are open, which suggests that there may be an increase in hazardous air pollutants due to industrial parks.

3.4. Empirical Methodology

The hedonic pricing method is largely used to estimate the value of non-market amenities such as environmental quality. Rosen (1974), in his seminal paper, describes that a differentiated good consists of a vector of characteristics. For instance, a house consists of characteristics such as structural attributes and local amenities. In a market with differentiated goods, the price function is determined by the meeting of the value function set by buyers with the offer function set by sellers, and the resulting price function captures the implicit values placed on each characteristic of the good. In other words, houses with higher environmental quality will have higher prices than similar houses with lower environmental quality because people tend to value living in a clean environment. In this regard, the hedonic model predicts that when industrial parks open, due to the risk of environmental damage, the prices of houses nearby will decrease.

To estimate the effect of industrial parks on housing values, I estimate the following fixed-effects model:

$$Y_{it} = \beta_0 + \beta_1 Announce_{it} + \beta_2 Announce_{it} * in2miles_i + \beta_3 PerCapitaGRDP_{it} + \beta_4 X_{it} + \alpha_i + \tau_t + \epsilon_{it}, \quad (4)$$

where Y_{it} denotes the price of apartment complex i in month t. The variable $Announce_{it}$ is an indicator equal to 1 in every month t after the opening of an industrial park nearby apartment complex i is announced and 0 otherwise. The variable $in2miles_i$ is an indicator equal to 1 if apartment complex i is within two miles of the industrial park and 0 otherwise. $PerCapitaGRDP_{it}$ is the GRDP per capita of the district apartment complex i is located in at time t. α_i controls for all time-invariant, unobserved heterogeneity across apartment complexes. The econometric model also includes month-year fixed-effects τ_t to account for trends in housing values over time and apartment structural attributes X_i such as area of apartment unit, floor of the unit, and the age of the apartment. Standard errors are robust and clustered by apartment complexes to correct for autocorrelation. The parameter of interest is β_2 of the interaction term. It captures the differential impact of a park opening on locations within two miles, relative to those two-to-four miles away.

3.5. Results

Columns 1 to 4 in Table 9 feature a comparison of the non-fixed-effects model and the fixed-effects model. Columns 1 and 3 designate houses in a two-mile radius as the treatment group and Columns 2 and 4 designate houses in a one-mile radius as the treated group. Non-fixed effects estimation seems to suggest that all the apartment complexes located within four miles experience a decrease in their values when the nearby park opens. The prices of houses within two miles decrease even more, and the decline is even more severe for houses within one mile. The estimated effect is an almost 20% decline in housing values, or approximately $32,000.

The outcome of the fixed-effects estimation is strikingly different. The prices of apartment complexes located within four miles from the park appreciate by approximately 2.5% to 2.9% at the time of announcement, or approximately $4,000 to $4,600. However, houses located within two miles depreciate by approximately 1.7% (about $2,700) relative to houses located within two-to-four miles when the announcement is made. In total, the opening of industrial parks increases housing values in a two-mile radius only by 1.2%, near $1,900, significant at five percent level. People in general have positive expectations for the opening of the park because of the benefits that it brings such as the development of a local economy and other amenities. However, people are hesitant to live too close because of the perceived environmental risk associated with industrial parks. The negative proximity effect is more severe for houses in a one-mile radius, making the total effect on the one-mile group close to zero.

As for other control variables, all structural attributes of apartment complexes behave as anticipated. Apartments that are larger in size, higher in floor, and are newly built seem to have higher prices.[14] Per capita GRDP negatively impacts housing prices throughout different specifications. The economic output of a region is closely related to the manufacturing activities of the region, and manufacturing facilities tend to locate in industrial areas that have lower population density and lower household income. Hence, the output of a region may negatively affect housing prices.

The estimation results without fixed-effects and the fixed-effects results are vastly different. Both results suggest that the houses in the immediate vicinity experience a relative decrease in their prices because of their proximity to the parks, but the magnitudes differ with and without the apartment-complex fixed-effects. We can infer from this finding that previous literature that has failed to address unobserved heterogeneity may yield an exaggerated effect of environmental hazards.

3.5.1. Announcement Date vs. Start-of-Operation Date

In Columns 5 and 6 of Table 9, I examine whether housing price effects vary as development of industrial parks evolves over time. The estimates indicate that houses located within four miles of parks experience an increase in their values at the time of announcement, but do not experience any additional effect when the parks begin operation. Perhaps, by the time parks begin operation, the positive expectations about parks have already been built into prices, so prices in a four-mile radius do not change anymore. The results for the four-mile houses confirm the hedonic prediction

[14] The coefficient of the term *BuildingAge* is negative and statistically significant in Columns 1 and 2, but the effect is negligible in Columns 3 to 6. That is, once adding an apartment-complex fixed-effect, the age of the building does not affect housing prices. This is due to the fact that apartment complexes do not vary in building age, except for very few cases in which apartment buildings within the same apartment complex were built at different times.

that prices react when news of interest becomes public.

On the other hand, the prices of houses in a two-mile radius decrease by 1.5% relative to houses in two-to-four miles at the time of news, and decrease even more by 4.3% when parks begin operation. That is, a two-mile radius group reacts negatively to the announcement of the park opening, and this relative decline in housing prices becomes stronger by the time parks begin operation, unlike the houses in a four-mile radius. The sum effects of the operation on the two-mile houses and the one-mile houses are -3.1% and -5.4%, respectively. The difference in outcomes between two-mile group and two-to-four-mile group was not anticipated. This result may be caused by people's tendency to react more strongly and for a longer period to negative traits than positive traits (Anderson, 1974; Fiske, 1980). As industrial parks continue to be developed, households may become more aware of risks associated with industrial parks, and therefore the decline in housing values is even greater by the time parks start operation.

The results exhibit strong evidence that prices react from the announcement stage. Furthermore, it is notable that the price behaviors of the nearby group and the distant group differ because of varying exposure to environmental risks.

3.5.2. Premium on Locating Farther Away from the Park

Table 3 uses an indicator variable to assign the location of the housing, whether the house is within two miles or in two-to-four miles from industrial parks. To investigate whether any price premium on locating farther away from parks exists, I estimate the following fixed-effects model:

$$Y_{it} = \beta_0 + \beta_1 Announce_{it} + \beta_2 Announce_{it} * Distance_i + \beta_3 PerCapitaGRDP_{it} + \beta_4 X_{it} + \alpha_i + \tau_t + \epsilon_{it}, \tag{5}$$

where the new term $Distance_i$ denotes distance from apartment complex i to the nearest industrial park. As in my previous estimation, I use the houses in four-mile rings surrounding industrial parks that newly open. In accordance with the hedonic theory, I predict that apartments that are more distant from industrial parks will have higher prices because they face less of an environmental and health threat.

Table 10 exhibits the result of estimating Equation (2). In Table 10, the coefficient of the interaction term is positive and significant at one percent level. That is, when a new industrial park opening is announced, locating 1% farther away from industrial parks leads to 1.1% higher housing values. This result confirms the theoretical prediction that a price premium to locating farther away from the park appears once a new industrial park has been announced.

3.5.3. Houses That Experienced Multiple Industrial Park Openings

Naturally, in my analysis, one apartment complex experiences at least one industrial park opening. As a matter of fact, some apartments have multiple industrial parks that open sequentially during the period from 2006 to 2013. In the previous analysis in Tables 9 and 10, I designated each apartment complex only with the industrial park with the earliest opening and ignored the latter openings. To consider the differential housing price effects of multiple park openings within four miles, I examine the housing price effects of second and third openings.[15]

The result in Columns 1 and 2 of Table 11 suggest that the housing price effect of the first industrial park opening that households encounter is strong. As seen in previous tables, the announcement increases local housing prices, but a smaller price premium is observed for houses in the immediate vicinity. However, when openings of second and third industrial parks are announced, housing prices do not change. This

[15] Out of 13,079 apartment complexes in the sample, 6,126 apartment complexes experienced a second opening, and 2,785 apartment complexes experienced a third opening.

result captures the diminishing marginal utility aspect of environmental hazards. The households react strongly to the first industrial park opening, but latter openings do not affect them because they have already been exposed to the negative externality.

Within the context of multiple industrial park openings, some apartment complexes already had industrial parks within four miles from their locations prior to 2006. I aim to investigate whether the number of industrial parks that existed prior to year 2006 has a varying price effect by estimating the following equation:

$$Y_{it} = \beta_0 + \beta_1 Announce_{it} + \beta_2 Announce_{it} * NumPastParks_i + \beta_3 PerCapitaGRDP_{it} + \beta_4 X_{it} + \alpha_i + \tau_t +$$

where the variable $NumPastParks_i$ is the number of industrial parks that existed within four miles of apartment complex i before 2006.

Column 3 of Table 11 is the estimation result of Equation (3). The announcement effect on local housing values is strong and positive, but the coefficient of the interaction term is negative and statistically significant at one percent significance level. That is, when there is an industrial park opening announcement, housing prices in a four-mile radius increase by 3.6%, but having one more industrial park before that decreases housing prices by 0.6%. Households react positively to the announcement of industrial parks, but households that experienced industrial park developments in the past tend to undervalue another industrial park opening nearby.

3.5.4. Toxicity of Industrial Parks

Industrial parks vary by degree of toxicity. I construct the variable, $HazardProxy_i$ to account for the fact that industrial parks consist of different types of manufacturing plants and they pose varying degrees of environmental and health hazards. When industrial parks are a greater source of hazardous air pollutants, the negative housing price effect may be stronger. Unfortunately, the information on the amount of air pollutants emitted from each industrial park is limited. Therefore, I construct a measure that aims to closely approximate the degree of environmental and health risks.

Korean Industrial Complex Corporation (2016) provides the data on the types of manufacturing plants that each industrial park is equipped with. The Pollutant Release and Transfer Registers (2016) of Korea provides yearly data on the amount of total toxic and cancerous chemical substances released from each type of manufacturing. Combining the two datasets, I calculated a weighted average of hazardous substance emissions for each industrial park. For instance, industrial parks that engage in pollution-intensive industries such as chemicals and plastics have a higher value for $HazardProxy_i$ and those that engage in less pollution-intensive industries such as lumber have a lower value for $HazardProxy_i$.

The estimates in Column 4 of Table 11 suggest that the varying degrees of environmental and health threats of industrial parks do not seem to affect housing prices. This could be the result of two possible reasons. First, people may not pay too much attention to the actual harm that industrial parks cause.[16] They may be more attentive to the presence or non-presence of industrial parks. Second, the constructed hazard measure may have too much measurement error for an effect to be detected. Given that the emission data only provide an absolute amount of air pollutants, it is difficult to assess the relative toxicity of each manufacturing type. This is exacerbated by the fact that the magnitude of air pollutants also depends on the industrial composition of the Korean economy.

[16]Kohlhase(1991), using hedonic regression, finds that households are unlikely to distinguish between the toxicity levels of different sites. Although a price premium for being located farther away from a waste site exists, marginal prices do not depend on toxicity of sites.

3.5.5. Results with Other Controls

I would like to separate out other factors that influence housing prices concurrently with environmental risks. Table 12 reports the estimation results with other controls inserted into the estimation equation. All columns are fixed-effects estimations and include apartment controls. The variable $AreaofPark_i$ is the area of industrial parks given in squared kilometers. As seen in the first column, the parks of greater size decrease nearby housing values when they open. The variable $AirPollutants_{it}$ is the amount of air pollutant emissions in the district where apartment complex i is located in year t. The estimates show that the higher the toxic emissions in the neighborhood, the more housing prices will decrease more when the industrial park opens. This result suggests that areas that already were industrial may be more concerned about another industrial park opening.

3.6. Conclusion

The study examines the impact of industrial park openings on the housing market in Korea under the hedonic framework. The challenge of estimating a hedonic price function is that sitings of local disamenities are not exogenous. For example, waste sites or manufacturing plants with environmental risks tend to be located in urban, industrial areas that inherently differ from other regions. These differences between locations may covary with environmental risk and housing prices. This paper contributes to the literature by using a fixed-effects estimation to address unobserved heterogeneity across housing units. In addition, although most previous literature uses start-of-operation date as treatment, I trace the effect on housing values from the announcement stage. Lastly, this study examines a non-U.S. housing market, which is limited in the hedonic literature.

Once estimating an apartment-complex fixed-effects model, I find that a relatively smaller price premium exists for the houses in close proximity to industrial parks. That is, people in general have positive expectations about a park opening when the announcement is made, but they do not want to be located too close to the park. The comparison between estimation results with and without apartment-complex fixed-effects suggests that the past literature subject to omitted variable bias may yield an exaggerated environmental effect. The results also indicate that the housing price premium on locating farther away from industrial parks appears at the time of announcement. In the case of multiple industrial park openings, the first opening has a strong impact on housing values, but subsequent openings do not seem to influence housing prices, and the houses that had a greater number of industrial parks prior to 2006 experience a greater decline in prices. Finally, the result suggests that the housing price effect appears from the announcement stage and the effects of announcement and operation are different.

Overall, this study demonstrates the importance of mitigating the methodological concern of previous literature and addressing unobserved heterogeneity, using a comprehensive dataset on industrial parks and housing.

Table 7: Previous Hedonic Studies on Environmental Amenity

Study	Environmental Amenity	Is there a price effect?
Blomquist (1974)	Power plants in the United States	Power plant causes a measurable damage over two miles away, costing at least $200,000 to $17 million.
Kohlhase (1991)	Superfund cleanup	Significant discount in the price of homes located close to toxic waste dumps is found only after the sites have been identified and publicized by the EPA.
Kiel and McClain (1995)	incinerators	Some price response to rumors of a facility and strong evidence that prices respond at groudbreaking exist.
Kiel and Zabel (2001)	Superfund cleanup	The benefits from cleaning up waste sites range from $72 million to $122 million.
Gayer et al. (2002)	Superfund cleanup	Willingness-to-pay to avoid cancer risks exists before the EPA releases assessment of waste site and decreases after the release, when perceived risk is lowered.
McCluskey and Rausser (2003)	Waste sites	Houses in close proximity to hazardous waste sites experienced lower housing appreciation rates after the EPA's announcement, but actual cleanup actions are not as important.
Ihlanfeldt and Taylor (2004)	Hazardous waste sites not listed on the National Priority List (NPL)	Properties surrounding waste sites experience non-trivial reductions in property values.
Chay and Greenstone (2005)	Clean Air Act	Elasticity of housing values with respect to particulate concentrations ranges from -0.20 to -0.35.
Kiel (2005)	Superfund cleanup	Announcement of toxicity of waste sites causes house prices to decline.
Greenstone and Gallagher (2008)	Superfund cleanup of hazardous waste sites	Cleanups are associated with economically small and statistically insignificant changes in property values.
Davis (2011)	Power plants openings in the United States	In neighborhoods within two miles of plants, housing prices decrease by 3-7%.
Currie et al. (2015)	Toxic plant openings and closings	Housing prices are about 1.5% lower within one mile of an opening plant and 1.5% higher within one mile of a closing plant.

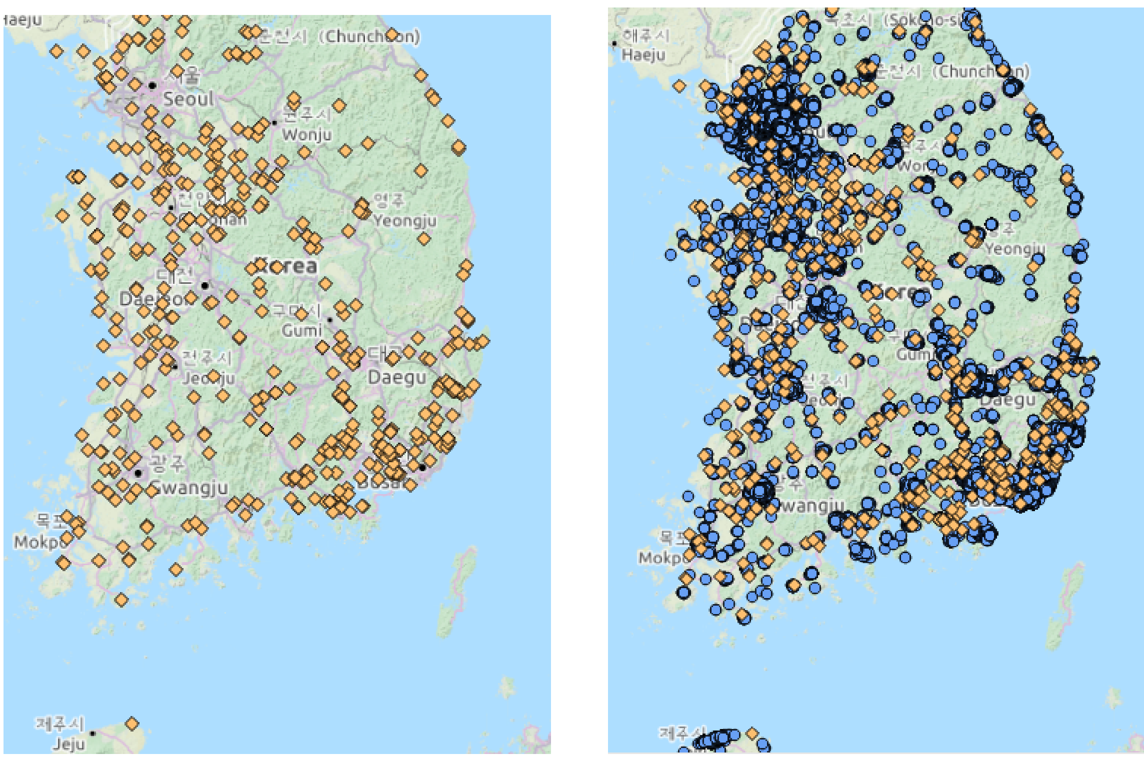

Figure 3: Locations of industrial parks (left) and apartment complexes (right)

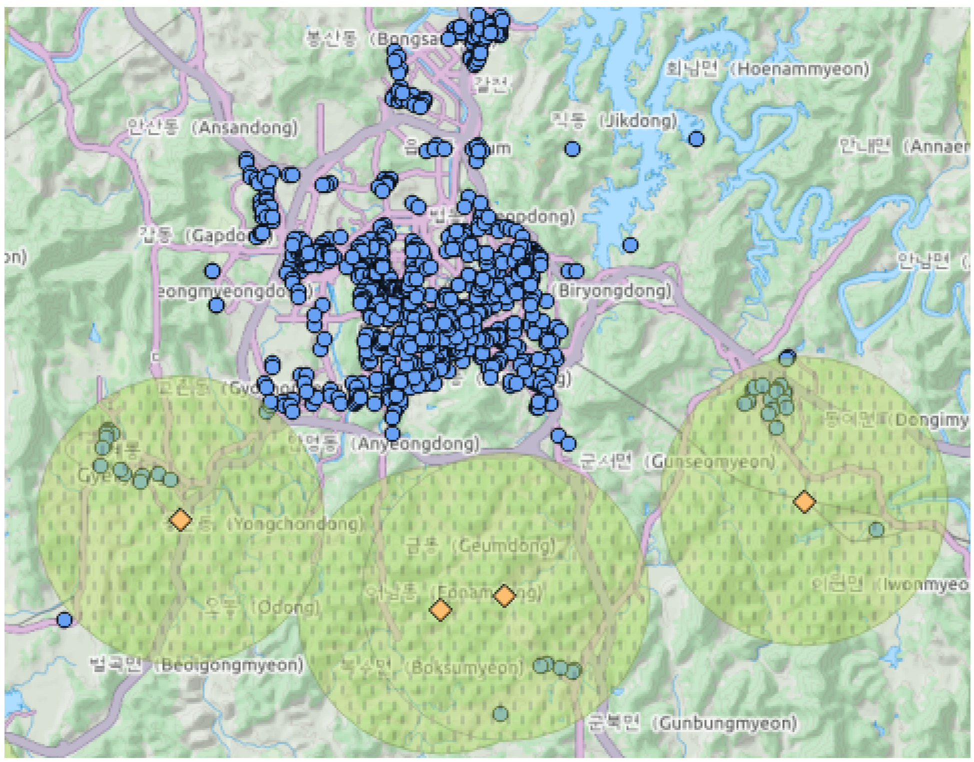

Figure 4: Measuring exposure to environmental risks

Table 8: Summary Statistics

Panel A			
	All of Korea	Areas With Park	Areas Without Park
Housing Price	15710	13540	20812
Population Density	4060	2777	7666
GRDP per Capita	2540	2539	2455
Pollution	271926	286780	177787

Panel B			
	Sample	Open=1	Open=0
Area (m^2)	72.21		
Floor	8.33		
Building Age	16.55		
Apartment Price	16021	15448	16497
GRDP per Capita	2444	2656	2273
Toxic Emission (kg)	320633	347105	297477
N	1573273	699516	873757

Price data are in constant 2010, 10,000 won.

Table 9: The Effect of Industrial Park Openings on Housing Prices

	Dependent Variable: Housing Price					
	(1)	(2)	(3)	(4)	(5)	(6)
Announce	-0.107***	-0.131***	0.029***	0.025***	.028***	.024***
	(0.017)	(0.014)	(0.005)	(0.004)	(0.005)	(0.004)
In 2 Miles	-0.007					
	(0.020)					
In 1 Mile		0.049				
		(0.042)				
Announce*In 2 Miles	-0.100***		-0.017*		-0.015*	
	(0.022)		(0.007)		(0.007)	
Announce*In 1 Mile		-0.187***		-0.029**		-0.028**
		(0.044)		(0.010)		(0.010)
Operate					-0.001	-0.010
					(0.011)	(0.009)
Operate*In 2 Miles					-0.043**	
					(0.014)	
Operate*In 1 Mile						-.0.040**
						(0.016)
GRDP per Capita	-0.099***	-0.094***	-0.296***	-0.293***	-0.296***	-0.292***
	(0.013)	(0.013)	(0.021)	(0.021)	(0.021)	(0.021)
Area	1.291***	1.291***	0.999***	0.999***	0.999***	0.999***
	(0.021)	(0.021)	(0.008)	(0.008)	(0.008)	(0.008)
Floor	0.108***	0.108***	0.046***	0.046***	0.046***	0.046***
	(0.005)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)
Building Age	-0.233***	-0.232***	-0.018	.018	0.018	0.018
	(0.015)	(0.015)	(0.105)	(0.105)	(0.105)	(0.105)
Complex Fixed Effects	no	no	yes	yes	yes	yes
Announce+Announce*In2Miles			0.012*		0.013*	
			(F: 5.10)		(F: 5.08)	
Announce+Announce*In1Mile				-0.004		-0.004
				(F: 0.16)		(F: 0.17)
Announce+Announce*In2Miles+Operate+Operate*In2Miles					-0.031**	
					(F: 6.66)	
Announce+Announce*In1Mile+Operate+Operate*In1Mile						-0.054**
						(F: 10.48)
R^2	0.527	0.526	0.609	0.609	0.609	0.609

$N = 1,573,273$ for all specifications.

Standard errors in parentheses are clustered by apartment complexes.

All columns include month-year fixed-effects.

* ($p < 0.05$), ** ($p < 0.01$), ***($p < 0.001$)

Table 10: Premium on Locating Farther Away From Industrial Parks

	(1)	(2)
	Dependent Variable: Housing Price	
Announce	0.022***	0.014**
	(0.004)	(0.005)
Announce*Distance		0.011**
		(0.004)
GRDP per Capita	-0.293***	-0.294***
	(0.021)	(0.021)
Area	0.999***	0.999***
	(0.008)	(0.008)
Floor	0.046***	0.046***
	(0.001)	(0.001)
Building Age	0017	0.018
	(0.105)	(0.105)
R^2	0.609	0.609

$N = 1,573,273$ for both specifications.
Standard errors in parentheses are clustered by apartment complexes.
Both columns include apartment-complex and month-year fixed-effects.
* $p < 0.05$, ** $p < 0.01$,*** $p < 0.001$

Table 11: Price Effects of Number and Toxicity of Industrial Parks

	Dependent Variable: Housing Price			
	(1)	(2)	(3)	(4)
Announce	0.023***	0.029***	0.036***	0.016*
	(0.004)	(0.005)	(0.006)	(0.007)
2nd Announce	-0.010	-0.003		
	(0.005)	(0.007)		
3rd Announce	-0.009	-0.002		
	(0.010)	(0.022)		
Announce*In 2 Miles		-0.018*		
		(0.007)		
2nd Announce*In 2 Miles		0.008		
		(0.009)		
3rd Announce*In 2 Miles		-0.010		
		(0.025)		
Announce*Num Past Parks			-0.006**	
			(0.002)	
Hazard Proxy*Announce				-0.002
				(0.001)
R^2	0.609	0.609	0.609	0.609

$N = 1,573,273$ for all specifications. Apartment controls are included.
Standard errors in parentheses are clustered by apartment complexes.
All columns include apartment-complex fixed-effects and month-year fixed effects.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: The Effect of Industrial Park Openings on Housing Prices With Other Controls

	Dependent Variable: Housing Price	
	(1)	(2)
Announce	0.119***	0.058***
	(0.019)	(0.011)
Announce*In 2 Miles	-0.016*	-0.015*
	(0.007)	(0.007)
Announce*Area of Park	-0.015***	
	(0.003)	
Announce*Air Pollutants		-0.002**
		(0.001)
GRDP per Capita	-0.297***	-0.311***
	(0.021)	(0.021)
Apartment Controls	yes	yes
N	1,560,369	1,491,293
R^2	0.609	0.608

Standard errors in parentheses and are clustered by apartment complexes.
Both columns include apartment-complex and month-year fixed effects.
* $p < 0.05$, ** $p < 0.01$,*** $p < 0.001$

Chapter 4

The Effect of the Fukshima Nuclear Accident on the Korean Housing Market

4.1. Introduction

Climate scientists express a strong consensus that climate change over the past century is very likely anthropogenic, or due to The Great East Japan Earthquake of magnitude of 9.0 at 2.46 pm on Friday, March 2011 did considerable damage in the region, and the large tsunami it created caused even more. Eleven reactors at four nuclear power plants in the region were operating at the time and all shut down automatically when the quake hit. The reactors proved robust seismically, but vulnerable to the tsunami. The three of the eleven reactors, at Fukushima Daiichi, lost power when the entire site was flooded by the 15-meter tsunami. The three units lost the ability to maintain proper reactor cooling and water circulation functions. The accident was rated 7, the most severe, on the International Nuclear Events Scale due to high radioactive releases. Over 100,000 people were evacuated from their homes, many of whom remain unable to fully return home. (World Nuclear Association, 2017)

There have been no immediate deaths or reported cases of radiation sickness from the accident. However, people who have been exposed to radioactive discharge are susceptible to developing various illnesses. The World Health Organization (WHO) released a report that estimates an increase in risk for specific cancers for certain subsets of the population inside the Fukushima Prefecture. A 2013 WHO report predicts that for populations living in the most affected areas, there is a 70% higher risk of developing thyroid cancer for girls exposed as infants, a 7% higher risk of leukemia in males exposed as infants, a 6% higher risk of breast cancer in females exposed as infants and a 4% higher risk, overall, of developing solid cancers for females (WHO, 2013).

An extensive list of literature examine the direct impact of natural disasters on housing values. Past studies found negative association between natural disasters such as hurricanes (Bin and Polasky, 2013; Bin and Landry, 2013; Daniel et al., 2009; Hallstrom and Smith, 2005; Ortega and Taspirar, 2010), earthquakes (Brookshire et al., 1985; Beron et al., 1997; Naoi et al., 2009), forest fires (Mueller et al., 2009), and pipeline event (Hansen et al., 2006) and housing prices. Most find strong evidence for depreciation of housing values in response to these devastating events.

While many examine the direct impact of hazardous events on housing values, some investigate the indirect impact these events may have on housing prices. Hallstrom and Smith (2005) examine the change in housing prices in the county that nearly missed the hurricane. Abadie and Dermsi (2008) finds strong evidence that a decline in occupant rates in office spaces is observed in Chicago after the 9/11 terrorist attack in New York.

Probably the most in line with the current study are some recent studies that examine the effect of the Fukushima nuclear disaster on risk aversion in unaffected countries. Goebel et al. (2015) find that although Germans are not directly affected by the accident in Japan, their environmental concerns and risk aversion increased due to the Fukushima accident, especially for those groups residing in proximity to nuclear power plants. Huang (2013) describes a similar finding that perceived risk of nuclear plants increased and public acceptance of them decreased significantly in China after the Fukushima nuclear accident.

The study aims to capture the willingness to avoid environmental and health hazards by examining the housing prices near four nuclear plants in Korea. Although these housing units are not directly affected by the Fukushima accident, because of the probability of the accident and the potential threat it causes, households located in Korea may react to the news. Moreover, the proximity of Korea to Japan may exacerbate the tendency to avoid environmental and health risks.

The paper proceeds as the following. Section 2 describes the background facts of nuclear power plants in general and those in South Korea. Section 3 explains the data used in the analysis. Section 4 describes the empirical methodology, and Section 5 shows the estimation results. I conclude in Section 6.

4.2. Background Information

The benefits of nuclear energy clearly exist. First, nuclear energy is known to cause far less greenhouse emissions because it does not discharge substances such as methane and carbon dioxide, which are the primary greenhouse gases. The amount of greenhouse gases are estimated to have decreased by almost half because of the prevalence in the utilization of nuclear power. Second, nuclear power plants produce very inexpensive electricity. The cost of uranium is low and the expenses of operating nuclear plants is relatively low compared to the expenses of building nuclear power plants given that the average life of nuclear reactor ranges from 40 to 60 years. Third is reliability. Compared to the traditional energy, the nuclear energy has persistent energy. It is estimated that with the current rate of uranium consumption, there is enough uranium for another 70 to 80 years. Lastly, nuclear power plants are more efficient that fossil fuels as they have higher energy density compared to other energy sources. (Conserve Energy Future, 2017)

However, there are risks associated with the nuclear power plants. One of the biggest problems is the environmental impact during the process of mining and refining uranium. Also, radioactive waste they create inevitably causes damage to the surrounding environment. Furthermore, radioactive leakage may occur as evidenced first by the Chernobyl accident and the recent Fukushima radioactive disaster. Also, waste disposal matter that come from nuclear plants is another concern. (Conserve Energy Future, 2017) Hence, the two sides are confronting one another with strong claims.

South Korea built its first nuclear power plants in 1962. The country has a small number of generating stations, only four, but each station houses four or more units, and three sites have more reactors planned. Thus, Korea's nuclear power production is slightly more centralized than most nuclear power nations. The total electrical generation capacity of the nuclear power plants of South Korea is 20.5 GWe from 23 reactors. This is 22% of South Korea's total electrical generation capacity, but 29% of total electrical consumption. (World Nuclear News, 2013)

The nuclear plants in South Korea are not without problems. In November 2012, it was discovered that over 5,000 small components used in five reactors at Hanbit Nuclear Power Plant had not been properly certified; eight suppliers had faked 60 warranties for the parts. Reuters reported this as South Korea's worst nuclear crisis, highlighting a lack of transparency on nuclear safety and the dual roles of South Korea's nuclear regulators on supervision and promotion (Reuters, 2012). In 2013, there was a scandal involving the use of counterfeit parts in nuclear plants and faked quality assurance certificates (Reuters, 2013).

Furthermore, anti-nuclear sentiment is growing in South Korea, especially after the Fukushima crisis. This movement consists of environmental groups, religious groups, unions, and professional associations. The groups are demanding for nuclear-free future and feel an enormous sense of crisis after the nuclear disaster in 2011, which demonstrated the destructive power of radiation in the disruption of human lives, environmental pollution, and food contamination. (Womens News Network, 2012)

4.3. Data

4.3.1.Nuclear Plants in Korea

In South Korea, four nuclear power plants with 26 nuclear radiators are located in the coastal regions of the peninsula. The names of the four nuclear power plants are Kori, Wolseong, Hanul, and Hanbit Nuclear Power Plants named after the region they are located. Precise locations of these nuclear power plants are available, which enables me to assign the locations in close proximity to nuclear facilities and those that are relatively farther away.

4.3.2. Housing Transaction Data

Data on housing transactions is made publicly available by the Ministry of Land, Infrastructure and Transport of Korea. In Korea, 49.6% of households reside in apartments, 37.5% reside in houses, and 3.4% reside in townhouses (Ministry of Land, Infrastructure and Transport of Korea, 2014). Most residential houses are located in remotely rural areas, where the price behavior may be different from that of apartment complexes. Given these facts, I use transactions of apartments only and not residential houses or townhouses. Comprehensive data on street address, transaction price, area, floor, and building age of all units of apartment complexes are available from 2006 to present. The advantage of using a multiple transactions dataset of apartment prices is that I can add apartment-complex fixed-effects in my estimation equation to avoid unobserved heterogeneity.

4.3.3.Measuring Exposure to Nuclear Risks

Fukushima nuclear disaster was an unforeseen, powerful event that depicted that uncertain, but massive danger that nuclear power plants cause. I take advantage of this incident to capture the households' willingness to avoid uncertain but disastrous casualty.

Four nuclear power plants are located in four different districts. I pair these four districts that have nuclear power plants with their adjacent neighbor districts located farther away from the plants. Based on the report of emergency plans jointly published by the U.S. Nuclear Regulatory Commission and the U.S. Environmental Protection Agency, the most significant impacts of a nuclear plant accident would be experienced in the area located within an approximately 10-mile radius of the facility (Nuclear Energy Institute, 2016). As all the control districts are located more than 10 miles from nuclear power plants, they make plausible comparison groups. The underlying assumption of this analysis is that because of the geographical proximity, the district with nuclear plant and its pair will be similar in terms of household and local characteristics. Hence, the differential impact these two groups experience will likely be a result of locating in the vicinity of nuclear hazards.

Table 13 presents the summary statistics for the data. Panel A compares the areas with nuclear power plants with the adjacent neighbor areas, and Panel B compares the numbers for the two regions before and after the accident. Housing prices are generally higher in districts with nuclear power plants. This may reflect the tendency of these power plants to attract jobs and local amenities that households appreciate. Also, based on the table, housing prices are higher after the accident than before the accident for both groups of regions. Therefore, it seems to suggest that housing prices actually behaved regardless of the nuclear disaster in Fukushima, Japan.

4.4. Empirical Methodology

The hedonic pricing method is largely used to estimate the value of non-market amenities such as environmental quality. Rosen (1974), in his seminal paper, describes that a differentiated good consists of a vector of characteristics. For instance, a house consists of characteristics such as structural attributes and local amenities. In a market with differentiated goods, the price function is determined by the meeting of the value function set by buyers with the offer function set by sellers, and the resulting price function captures the implicit values placed on each characteristic of the good. In other words, houses with higher environmental quality will have higher prices than similar houses with lower environmental quality because people tend to value living in a clean environment. In this regard, the hedonic model predicts that when industrial parks open, due to the risk of environmental damage, the prices of houses nearby will decrease.

To estimate the effect of Fukushima nuclear accident on Korean housing values, I estimate the following fixed-effects model:

$$Y_{it} = \beta_0 + \beta_1 After_{it} + \beta_2 After_{it} * Nuclear_i + \beta_3 X_{it} + \alpha_i + \tau_t + \epsilon_{it}, \quad (7)$$

where Y_{it} denotes the logged price of apartment complex i in month t. The variable $After_{it}$ is an indicator equal to 1 in every month t after the Fukushima radioactive disaster. The variable $Nuclear_i$ is an indicator equal to 1 if apartment complex i is located in the nuclear district. α_i controls for all time-invariant, unobserved heterogeneity across apartment complexes. The econometric model also includes month-year fixed-effects τ_t to account for trends in housing values over time and apartment structural attributes X_i such as area of apartment unit, floor of the unit, and the age of the apartment. Standard errors are robust and clustered by apartment complexes to correct for autocorrelation. The parameter of interest is β_2 of the interaction term. It captures the differential impact of the nuclear disaster on nuclear possessing districts and their neighbor districts.

4.5. Results

Column 1 of Table 14 shows the estimation results. While apartments in general appreciate in their values after the outbreak of Fukushima nuclear disaster, those units that are located in the nuclear districts depreciate in their values by 16.2%. That is, compared to their neighbors who are not in the immediate vicinity of nuclear power plants, the districts with nuclear plants seem to have behaved strongly and negatively to the news of Fukushima disaster. The net price effect on the housing values in the nuclear districts is approximately negative 9.2%. This amount is approximately $11,644 loss per housing unit and $403 million loss in total. I believe that this differential housing price impact reveals households' perceived risk of environmental and health hazards associated with uncertain nuclear accident. As for other control variables, all structural attributes of apartment complexes behave as anticipated. Apartments that are larger in size, higher in floor, and are newly built seem to have higher prices.

Column 2 of Table 14 shows the same estimation result, but only for the year 2011. I believe that the Fukushima accident was powerful enough for the housing market to react immediately to the news and therefore, the effect can be captured in short term as well. The direction of the impact is similar in the second estimation result. Although apartment complexes are higher in their values after the accident by 2.8 %, those located closer to the facilities experience even greater drop in their values by 5.2 %. The total effect on the apartment complexes nearby nuclear power plants is estimated to be negative 2.4 %.

Combining the Columns 1 and 2, the downward effect on the housing prices due to the Fukushima nuclear disaster is estimated to range from 2.4 % to 9.2 %, which is approximately $3,038 to $11,644 per housing unit. The results indicate that households respond negatively to the nuclear accident. Although the accident does not cause any immediate harm to them, they are hesitant to locate close to nuclear power plants because of they re-evaluate the probability of uncertain, but destructive accident occurring.

The results indicate that housing prices reacted negatively to the news of the Fukushima nuclear disaster. Then, one may ask how long these shocks last in the housing prices. In Column 3, I show how the price effect evolves over a year at two-month intervals. The results confirm that the negative price effect for the nuclear districts is strong right after the accident, but the downward effect cannot be observed two months after the accident. Although the regions in general faced a price increase during that period, there was no separate effect for the districts possessing nuclear power plants. This outcome suggests that the news of the Fukushima nuclear accident had a considerable price effect on the Korean housing market.

4.6. Conclusion

The study examines the impact of the news of Fukushima nuclear accident on the Korean housing market. The results suggest that the values of the houses located in the nuclear-possessing districts decrease following the outbreak of the nuclear disaster in Japan. The finding bears an important policy implication. Korea is in the midst of aggressively expanding nuclear power plants. Proponents of the expansion argue that the benefits exceed the costs because nuclear energy is efficient in terms of cost and energy production. However, it is questionable whether or not they have considered that devastating accidents such as the Fukushima nuclear crisis may happen. The probability of such accident may be low, but the environmental and health outcomes resulting from the accident may be catastrophic.

Table 13: Summary Statistics

Panel A			
	Sample	Nuclear Area	Not Nuclear Area
Apartment Price	10656.87	12656.64	9356.24
Area (m^2)	70.906	76.711	67.130
Floor	7.944	6.805	8.684
Building Age	16.367	15.998	16.607
N	87,951	34,660	53,291

Panel B				
	Nuclear Area		Not Nuclear Area	
	Before	After	Before	After
Apartment Price	11449.9	14641	8331.7	11509.8
Area (m^2)	75.452	78.782	67.566	66.215
Floor	6.844	6.740	8.609	8.842
Building Age	16.589	15.026	16.701	16.409
N	21,533	13,107	36,111	17,180

Price data are in 10,000 won.

Table 14: The Effect of Fukushima Nuclear Accident on Korean Housing Values

	(1)	(2)	(3)
	Dependent Variable: Log-Housing Price		
After Accident	0.070***	0.028***	0.058***
	(0.015)	(0.008)	(0.015)
After Accident*Nuclear	-0.162***	-0.052***	-0.135***
	(0.022)	(0.015)	(0.023)
2 Months After			0.429***
			(0.033)
2 Months After * Nuclear			-0.069
			(0.040)
4 Months After			0.488***
			(0.029)
4 Months After * Nuclear			-0.036
			(0.022)
6 Months After			0.039**
			(0.014)
6 Months After * Nuclear			-0.031*
			(0.016)
8 Months After			0.529***
			(0.029)
8 Months After * Nuclear			-0.117***
			(0.023)
10 Months After			-0.531***
			(0.027)
10 Months After * Nuclear			-0.043*
			(0.021)
1 Year After			0.500***
			(0.030)
1 Year After * Nuclear			-.081***
			(0.017)
Area	0.952***	0.853***	0.952***
	(0.019)	(0.025)	(0.019)
Floor	0.042***	0.047***	0.042***
	(0.002)	(0.003)	(0.002)
Building Age	-1.140*	-1.602***	-1.138*
	(0.478)	(0.397)	(0.479)
year	2006-2013	2011	2006-2013
N	87,951	13,477	87,951
adj. R^2	0.731	0.598	0.733

Standard errors are robust and in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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