ESSAYS IN PUBLIC AND URBAN ECONOMICS

BY

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DISSERTATION

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ABSTRACT

The first chapter provides evidence on the incidence and distortionary effects of taxes on rental properties, using a unique administrative dataset on housing transactions in Tehran. I exploit a special feature of the tax code in the Tehran rental market where the tax-exemption threshold is based on the property's size (square meters). Large bunching occurs below the tax cutoff, suggesting strong behavioral responses to the kink. I also find higher after-tax rents above the kink. Based on these variations, I develop a structural framework with property taxes and costs of filing to estimate the price elasticities of housing size supply and demand simultaneously. I also examine the question of who bears the property tax burden. I estimate a mid-run (10-year) price elasticity of housing size supply of 1.36, and a price elasticity of housing size demand of -0.17. I find high, but incomplete pass through of the rental tax - implying that most filing costs are borne by renters.

The second chapter provides new evidence on causal impact of air pollution on the housing market. In a co-authored paper, we utilize the dramatic increase in the level of air pollution in Tehran, induced by unprecedented international sanction regimes imposed on Iran because of their nuclear program in 2010. Following some of the sanctions that targeted Iran's import of gasoline, Iran began rapidly to increase its fuel production capacity by converting petrochemical plants to gasoline production refineries. The policy caused substantial increase in the level of air pollution as a result of the domestically produced low-quality gasoline. Using this natural experiment and unique administrative data on Tehran's housing market, we find that a 30 parts-per-billion increase of outdoor concentration of Nitrogen Dioxide leads to approximately a 3 to 6 percent decrease in housing prices. We also find that higher price-rent ratio is associated with lower level of air pollution. Our welfare analysis suggests that air quality deteriorations induced by the 2010 gasoline sanctions are associated with $11 to $16 billion aggregate reduction in housing values in 2011.

To my father who taught me to aim high,

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CHAPTER 1: BEHAVIORAL RESPONSES TO THE TAX KINKS IN THE RENTAL HOUSING MARKET: EVIDENCE FROM IRAN

1.1 Introduction

A large body of literature in public economics estimates structural parameters to measure behavioral responses to taxation. The majority of these studies consider the supply or demand market in isolation, assuming the other market is perfectly elastic. This is more often the case for analysis of the housing market where the relationship between property taxes and housing supply is generally neglected (Lutz 2015). Such an assumption may result in biased estimation of structural parameters because supply and demand responses to taxes are associated with their share of the tax burden, not the full burden. This paper develops a structural model to estimate the price elasticities of housing size supply and demand simultaneously. Based on these estimates, I answer the classic question: "Who bears the property tax burden?"

A central challenge in estimating separate price elasticities of supply and demand is the requirement of observed tax-induced variations in both quantity and price. In the case of the latter, it involves the identification of how changes in taxes are split between producers and consumers, or the "pass through." To point out the essential role of pass through in determining separate elasticities, consider an example of an increase in the taxes on supply that is not fully passed through to be reflected in the price. Since demand responses are correlated with the share of the tax burden that falls on them, estimation of the price elasticity of demand based on full pass through can be downward biased. Pass through hence is a key in determining elasticities, yet it is not straightforward to measure.

This study examines responses to taxation on rental properties, a common policy worldwide, using a special feature of the tax code in Tehran where taxes on owners depend on the size of their property. Specifically, the owner's tax liability becomes positive when the total cumulative size of her rental properties exceeds $150\text{m}^2(\approx 1615\text{ft}^2)$. This policy was implemented in 2001. Moreover, in Tehran, paying rental property taxes requires a specific filing process, different from filing income taxes.[1] Owners with zero rental income tax liability are exempted from filing. Therefore, costs of filing taxes become positive for owners only if the total size of their rental properties surpasses $150m^2$.[2] In this analysis, I use unique administrative dataset that include over 600,000 rental and purchasing transactions in Tehran from 2012 to 2014. Tehran's rental market provides an advantageous setting because the quasi-experimental variation in rental prices around the cutoff allows for quantifying the extent to which the tax burden, including the marginal taxes and filing costs, is passed on to renters.

To model demand and supply responses to a discrete change in the marginal tax rates (a kink) on rental properties of a specific size, which I refer to as the "size kink", I develop a theoretical framework in which taxes are on owners and depend on the size. This framework allows for passing forward some of the tax burden to renters via higher rents. Moreover, it allows for tax-induced changes in the quantity of properties around the size kink. As for the supply responses, I address the hassle costs of complying with taxes by assuming that this size kink adds extra costs for filing taxes in addition to owners' tax liability. Therefore, the total tax liability is made up of two elements: the fixed costs of filing taxes, and the marginal taxes on rental income. On the demand side, renters' responses to taxation can be identified by assuming that renters only observe policy-induced changes in the rental prices above the cutoff. This model predicts that the size kink creates an incentive for both owners and renters to move from above the size kink, and locate at the tax-favored side – or, in other words, to exhibit "bunching behaviors." I show that the amount of bunching, the filing costs, and the policy-induced changes in the rent can characterize price elasticities of housing size supply and demand.

As for the empirical analysis, I apply the structural model to Tehran rental market to identify price elasticities and pass through rates. First, I estimate the discrete increase in the rent-value right above the size kink and the change in rent per square meters further away from the kink to identify filing costs and rent responses. The quasi-experimental design allows for using the average rent of properties below $150\mathrm{m}^2$ as a valid

[1] Wage earners are exempt from filing income taxes.

[2] This contrasts with tax systems in majority of developed countries where taxpayers are required to file taxes even if they do not owe any taxes.

counterfactual for apartments above 150m^2. The results present significantly higher rent (approximately 3.9 percent) right above the size kink in response to the filing costs. The results also show that 1 square meter increase in rent per square meter above the cutoff is associated with 3,700 to 4,300 Rials (roughly $1 in 2015 dollars) increase in rent per square meter. Second, I estimate the excess bunching, defined as the difference between the empirical and counterfactual densities in the small interval below the size kink as in Saez (2010) and Kleven and Waseem (2013). The results indicate large bunching below the cutoff, suggesting strong behavioral responses to the size kink. I find evidence on heterogeneity by age and neighborhoods, with stronger responses for "old apartments" and low rent neighborhoods.

Applying the measures of excess bunching, estimated filling costs, and the rent responses to the model for the entire sample, I find significant price elasticities of housing size supply, ranging from 0.243 to 0.616, and significant but small in magnitudes elasticities of demand, ranging from -0.015 to -0.025. To alleviate the effects of market frictions, I use measure of bunching for the sub sample of newly built properties for which owners are able to take into account tax policy before choosing the size of their properties. While the estimated price elasticities of housing size supply from the representative of the "frictionless" market are roughly 2 to 6 times bigger, elasticities of housing demand are at least 10 times larger, ranging from 0.172 to 0.365. Estimation of the pass-through rate for the frictionless market shows that the majority of the economic incidence of taxation is passed on to renters in the form of higher rents.[3] Overall, the results provide clear evidence of bunching, large frictions, and higher after-tax rent, governed by the size kink, implying that size-based taxation on rental properties is highly regressive and distortionary.

This paper builds on and contributes to a growing body of literature on the distortionary effects of discrete changes in the marginal and proportional taxes. The main contribution of this paper is to develop a framework that incorporates pass through of

[3] In this study tax-incidence is defined as the ratio between the changes in consumer surplus and the changes in producer surplus due to a tax.

taxes costs of filing them to simultaneously estimate price elasticities of housing size demand and supply that the existing literature analyzes in isolation.

A recent literature documents behavioral responses to taxes and transfers using bunching techniques (Saez 2010; Chetty et al 2011; and Kleven et al 2013). A small body of work has also studied sources of frictions, and has pursued different approaches to account for them (Chetty et al 2010; Chetty et al. 2011; Chetty 2012; Kleven et al 2013; Gelber et al 2014). This literature typically concentrates on one side of the market, assuming the other side is perfectly elastic, which implies complete pass through of taxes.[4] This study adds to the existing literature by considering both supply and demand responses simultaneously.[5] This paper also provides quasi-experimental evidence, plausibly hinging on fewer modeling assumptions than elsewhere in the literature, regarding the effects of frictions on the housing market's responses to property taxes.

Another strand of literature to which this paper relates uses transaction taxes to analyze behavioral responses to tax policies in the housing market (Kopczuk et. al 2015; Slemrod et. al 2015; and Best et. al 2016). This paper departs from this literature by focusing on property taxes, which compared to transaction taxes, represent a long-term tax commitment, and thus, arguably reveal long-run behavioral responses. Property taxes are also one the main sources of governments' tax revenue.[6] In addition, this study analyzes the effects of taxes in the rental market, a subject targeted by a variety of urban policies, but one that remains understudied by the literature. My findings of strong evidence of pass through of taxes to renters imply regressive distributional burden. This is different from incidence of transaction taxes (e.g. Besley et al. 2014) where both buyers and sellers are arguably from the same quantile of the income distribution.[7] Lastly, in contrast to the existing literature that focuses on developed countries (e.g., the United States and the United Kingdom), this paper provides evidence of behavioral

[4] Saez et al (2012) mentions that studies on payroll taxes and income-tax reform typically assume the full tax burden is borne by employees.

[5] Several studies have recently examined supply of housing and urban dynamics. See Green et al (2005), Glaeser et al (2006), Epple et al (2010), and Saiz (2010).

[6] In 2012, in the United States, transfer taxes compromise less than 2 percent of the total state tax revenues, while property taxes generated over $480 billion dollars (Census Bureau, Quarterly Sum of State and Local Tax Revenue).

[7] In 2014, in the United States, renters' median income was $33,219, compared to $68,142 for owners (American Community Survey Five-Year Estimates). Accessed 7/4/2016.

responses to taxes in the housing market for an emerging country where raising tax revenue is more of an issue for policy makers.

A few other studies have documented estimates of the costs of filing taxes.[8] Benzarti (2016) suggests that the total burden of filing income taxes in the United States amounts to 1.25 percent of GDP. Kleven et al (2011) model administrative hassle as a policymakers' instrument to screen out individuals with higher opportunity costs. Ramnath and Tong (2016) shows that monetary incentives to file tax returns significantly increase individuals participation in the tax system and increase their welfare in the long run. However, to my knowledge, no literature considers the pass-through burden of filing taxes - in particular, for property taxes. My results suggest that the majority of the burden of complying with rental property taxes is borne by renters.

This paper is also related to an important literature on the incidence of property taxes (Simon, 1943; Mieszkowski 1972; Hamilton 1976; Fullerton et al 2002; Petrucci 2006). Although, a large body of theoretical work attempts to find ways to choose between "old," "benefit," and "new" views, only a very small body of empirical work addresses property taxes' effects on rental housing (Carroll and Yinger, 1994; Muthitacharoen and Zodrow, 2012). To the best of my knowledge, this paper is the first to combine micro administrative data on rental properties with policy-induced quasi-experimental variation to analyze the incidence of property taxes. I find renters bear most of the policy's costs. This result is of relevance because in comparison to owners, renters are normally at the left side of the income distribution.[9]

The paper proceeds as follows. Section 1.2 describes the data sources and overviews the policy. Section 1.3 develops the theoretical framework. Section 1.4 describes the empirical methodology. Section 1.5 presents the results, and Section 1.6 concludes.

1.2 Data and Background

Taxes on rental properties are common around the world, however, tax policy on rental properties in Tehran is unusual because the tax depends on both the size of

[8] Slemrod (1989) and Benzarti(2016).

[9] Median household income in 2014 (in the United States) was $53,482.

properties and their rental income.[10] This policy was implemented in 2001. Figure 1.1 presents the average annual tax paid with respect to size. Taxes are applied to properties located at the right side of the solid line; the taxes depend on the extra rental income, defined as the annual rental income gained from extra square meters above $150m^2$. Based on regulations enforced by the Iranian National Tax Administration (INTA), the policy is progressive, ranging from a low of 15 percent for an extra rental income less than or equal to 30 million Rials (approximately $857 in 2015 USD) to a high of 35 percent for part of an extra income that is over 1,000 million Rials (approximately $28,571 in 2015 USD). Paying rental property taxes requires a specific filing process, different from filing income taxes and owners with zero rental income tax liability are exempted from filing. Table 1.1 shows the percentage of tax that owners pay on their annual rental income for each tax bracket in which they qualify.

The primary data used in this paper are obtained from the Rahbar Informatics Services Company (RISC). Since 2009, the law requires all purchasing and rental transactions to be registered online.[11] Nearly all rental properties in Tehran are owned individually. Therefore, an owner typically leases her rental property through real estate agencies. If the owner and renter reach an agreement, the real estate agent will fill out specific forms online, including information such as rent or price, full address of the unit, size, age, ZIP Code, and date of contract.[12] I also used records on historical real estate listings in Tehran that come from *Iranfile* website, which is the largest real estate portal in Iran.[13] These records contain rich details of each listing, including the number of stories in the building, number of units in each floor, facing direction of the unit, kitchen materials (e.g., steel, wood, MDF, etc.), flooring (e.g. parquet, stone, ceramic, carpet, etc.), building façade materials, years since construction, floor number, number of bedrooms.[14]

[10] Law of direct taxes 53-11 (http://download.tax.gov.ir/GeneralDownloads/DirectTaxLaw.pdf) Accessed 7/24/2016
[11] http://www.iranamlaak.ir/Files/TasvibNameh.aspx
[12] Although personal information of the owner (seller) and tenant (buyer) are recorded, for reasons of confidentiality the provided data do not include this information. See Appendix A for more detail.
[13] www.iranfile.ir
[14] It also has information on number of phone lines, number of parking, storage, and balcony, type of heating/cooling system, and whether the building has elevator, yard, backyard, pool, sauna, and Jacuzzi.

Since owners of two or more rental properties respond to the size kink at $150m^2$ based on the total combined size of all their properties, one potential concern is that the observed distribution of properties does not capture all behavioral responses. The reason is that the multiple-rental-property owners remain unresponsive to the size kink at $150m^2$. However, the aggregate data on homeownership in Tehran shows that only 4 percent of rental properties belong to owners who possess more than one property.[15] Therefore, their impacts on my estimations are negligible.

The raw data include 278,473 rental and 371,904 purchasing observations during the years 2012 – 2014. In the final data, I exclude transactions for which complete information is not available along with all nonresidential and non-apartment transactions.[16] Observations that the district number does not match with the Zip Code, possibly due to data-entering mistakes, are excluded as well. Moreover, to rule out the effects of outliers, I trim observations where the rent and price per square meter are in the least 1 percent and beyond the 99 percent levels. The final sample includes 243,144 rental and 344,774 purchasing observations from 2012 to 2014. Figure 2 shows the distribution of observations across Tehran to examine whether the RISC dataset is representative of the universe of properties in Tehran. As can be seen in Figure 1.2, each panel contains at least 2,800 housing observations for each of the 22 districts, indicating that the data are representative of nearly all neighborhoods.[17]

Another concern is misreporting of size by owners in order to evade taxation. Because owner-occupied units are exempted from taxation, there is no clear incentive for owners to misreport the size when they sell their properties.[18] Therefore, one way to test for misreporting is to check whether the reported sizes match in both rental and purchasing data. In doing so, I merge the two datasets on the basis of 10-digit ZIP Code, district, and floor number. The matched data, composed of the high-quality matches that

[15] Rahbar Informatics Services Company (RISC) has provided this number by summarizing number of different rental transactions in each year for each owner, using owner's unique identification number.

[16] An apartment in this study is defined as a unit that is owned individually, which is very similar to the definition of a condo in the U.S. housing market.

[17] Tehran is divided into 22 different districts.

[18] Misreporting the size of his rental property at the time of sale is a possible but difficult undertaking for an owner. The seller, buyer and real estate agent have to agree. Moreover, the average price of more than $1,000 per-square-meter serves as a disincentive for the seller to report a size that is smaller than the correct one.

result via this method, include 64,677 unique observations. I focus on properties in the proximity of the size kink $(140m^2, 150m^2]$, where the probability of misreporting is expected to be high. The matched data reveal that for over 87 percent of observations the reported size for the rental transaction is exactly the same as for the purchased one. More importantly, for only 4 percent of rental observations in $(140m^2, 150m^2]$ is the reported size for the purchasing transactions over $150m^2$, which suggests that owners do not strategically underreport the size of their rental properties.

Table 2 shows summary statistics for rental transactions. Although median size is well below the cutoff $(150m^2)$, several thousand rental transactions are within $10m^2$ of the size-threshold. The jump in the average rent-value per square meter right above the size-threshold is evident here, as is the dwindling number of observations. Note that, median age of properties is 11 years, which implies the majority of constructions are fairly new in Tehran.

1.3 Theoretical Framework

This section describes a model of behavioral responses to taxation in the rental-housing market; this motivates and underlies the empirical analysis. I first develop a static model with cost of filing to measure the owners' responses to a size kink (i.e. an increase in the marginal tax rates on rental properties at specific size). Second, to calculate price elasticity of housing size demand, I construct a model for renters, who optimize their utility based on housing consumption and rent price. I follow with describing the connection between price elasticities and tax-incidence, and pass-through rates.

1.3.1 Setup

Consider two types of individuals, owners (providers) and renters (tenants). Each owner owns a rental property and chooses how much housing services (square meter) to provide to maximize her profits. Size of an apartment, which denoted by s, represents units of housing services. The gross equilibrium rent per unit of size is denoted by R.[19]

[19] In this study, each unit of size is one square meter.

Therefore, owner of a rental property with size s receives total rent of sR. This analysis allows for heterogeneity on the costs of providing housing services at rent R. Owners provide housing services using composite materials M and land-factor L according to the production function $S(M, L) = kM^{\delta}L^{1-\delta}$, where k is a productivity parameter with a smooth density distribution $g(k)$.[20] Intuitively, the productivity parameter controls for qualitative differences such as age, land characteristics, and location across rental properties. Rewriting all variables on a per-unit of land basis, let $s(m) = km^{\delta}$, where $m = \frac{M}{L}$. The owner's profit per unit of land is then given by:[21]

$$\pi(s) = sR - p_m m - p_l \tag{1.1}$$

where p_m is price per unit of materials factors, and p_l is land factor price. Replacing m with $\left({}^{s}/_{k}\right)^{\frac{1}{\delta}}$ and normalizing p_m to 1, the owner's profit function can be described by:

$$\pi(s) = sR - \left(\frac{s}{k}\right)^{\frac{1}{\delta}} - p_l$$

Suppose that a discrete increase in the marginal tax rate (a kink) is introduced at the size s^*, meaning that owners of rental properties larger than s^* pay taxes on the marginal rental income gained from the extra square meters above the s^*. In response to the size kink, each owner relocates to the new optimal size in the presence of taxes to maximize her profits, but must pay adjustment cost ψ, which for now I assume $\psi = 0$.[22] Moreover, assume that paying taxes adds extra filing costs on owners, denoted by φ. Intuitively, the costs of filing taxes capture the aversion to filing taxes, time costs, record keeping, and tax-preparers' fees. Since the assumption is that owners with zero tax liability do not need to file any taxes, $\varphi = 0$ for properties sized below or equal s^*.

[20] It can be shown that given a smooth tax system, the smooth productivity distribution implies a smooth distribution of properties w.r.t size.

[21] For the sake of simplicity, I just consider one period by assuming that discount rate for rental income $\beta = 0$. Considering a richer model with $\beta \neq 0$ only complicates the analysis, and it does not change the quantitative conclusion.

[22] Think of it as an owner selling his current rental property and buying another property of an optimal size where search costs of selling and buying are negligible. In practice, the adjustment costs are lower for newly built and very old properties. In the case of former, an owner has the opportunity to take into account the effects of tax policy before choosing the optimal size of her rental property. In the case of latter, the opportunity costs of demolishing properties and replacing them with properties smaller than the size kink are arguably lower for owners of old properties.

1.3.2 Elasticity of Housing Supply

A size kink imposes tax liabilities and filing costs to owners, which can be shifted forward to renters (i.e. pass through). Let's consider a pass-through of filing costs φ and tax liability to renters via discrete increase in the total rent for properties sized above s^*, and change in rent per unit of size from R_0 to R_1 for extra size above the cutoff. Hence, profits conditional on size are given by:

$$\begin{cases} \pi(s) = sR_0 - \left(\frac{s}{k}\right)^{\frac{1}{\delta}} - p_l & if\ \ s \leq s^* \\ \pi(s) = [s - s^*]R_1(1-\tau) + s^*R_0 - \left(\frac{s}{k}\right)^{\frac{1}{\delta}} - p_l - (1-\gamma)\varphi & if\ s > s^* \end{cases} \tag{1.2}$$

where R_0 is gross rent per unit of size for properties with $s \leq s^*$, R_1 is gross rent per unit of size for extra size above s^*, φ is the hassle costs of filing taxes, and γ is the portion of the filing costs burden that is passed forward to renters – the pass through rates. Note that for properties larger than s^*, the first term in equation (1.2) arises from after-tax rental income gained from extra square meters above s^*. The last term arises from the net of costs of filing taxes that create a pure discontinuity in profits level at the size kink. Optimizing the profit functions over size yields the following supply functions:

$$\begin{cases} s = k^{\frac{1}{1-\delta}}[R_0\delta]^{\varepsilon_s} & if\ s \leq s^* \\ s = k^{\frac{1}{1-\delta}}[R_1(1-\tau)\delta]^{\varepsilon_s} & if\ s > s^* \end{cases} \tag{1.3}$$

where the elasticity of housing supply in terms of size with respect to the gross rent is given by $\varepsilon_s = \frac{\delta}{1-\delta}$. Figure 1.3 illustrates the implication of this size kink in a production function diagram. Introduction of a size kink creates a discontinuity in the Iso-profit curve at s^* and make it steeper for $s > s^*$.[23] [24] This gap in the Iso-profit curves at s^*

[23] The assumption here is $R_1(1-\tau) \leq R_0$ and $\gamma \leq 1$, implying that the magnitude of pass through is less than or equal the total tax burden. This analysis does not consider the case of over shifting, assuming that owners do not have market power, which is confirmed by data.

[24] To also see why the production functions s = $f(m)$, and Iso-profit curves are tangent at the optimal points, consider maximization of $\pi(s)$ over size for $s \leq s^*$. The first order condition (FOC) yields: $R_0 = [f^{-1}(s)]'$ in which $[f^{-1}(s)]' = {}^{1}/_{f'(m)}$. Therefore, production function's derivative at the optimal size is equal to: ${}^{1}/_{R_0}$. Similarly, right

means owners who would have chosen their rental properties in the range $(s^*, s^* + \Delta s)$ in the absence of the size kink can optimize their profits by providing less housing services and bunch at s^*. Owner LA has the lowest productivity, k_{LA}, among those who choose $s = s^*$. She would provide s^* both in the presence and absence of the size kink. Owner HA has the highest productivity k_{HA} among those who bunch at the s^*. She would provide $s^* + \Delta s$ when there is no size kink. In the presence of the size kink, she is indifferent between supplying s^* and s^I. All owners with productivity parameters in the range $(k_{LA},\ k_{HA})$ will bunch at the cutoff.[25] For the marginal bunching individual, using the FOC condition from equation (1.3), we have $s^I = k_H^{\frac{1}{1-\delta}}[R_1(1-\tau)\delta]^{\frac{\delta}{1-\delta}}$. Replacing it in equation (1.2) yields:

$$\begin{cases} \pi^* = R_0 s^* - \left(\frac{s^*}{k^{HA}}\right)^{1/\delta} - p_l \\ \pi^I = k_{HA}^{\frac{1}{1-\delta}}[R_1(1-\tau)]^{\frac{1}{1-\delta}}\delta^{\frac{\delta}{1-\delta}}[1-\delta] - s^* R_1(1-\tau) - p_l - (1-\gamma)\varphi \end{cases} \tag{1.4}$$

In the absence of the size kink, the marginal buncher would choose an apartment with size $(s^* + \Delta s)$ that implies $k_{HA}^{\frac{1}{1-\delta}} = \frac{s^*+\Delta s}{[\delta R_0]^{\delta/1-\delta}}$. Replacing k_{HA} in equation (4) and from the condition $\pi^* = \pi^I$, the relationship between price elasticity of housing size supply, rent responses, filing costs, and bunching can be written as follows:[26]

$$\begin{aligned} &\frac{1}{\left(1+\frac{\Delta s}{s^*}\right)}\left[\left(1+\frac{\Delta R}{R_0}\right)(1-\tau) \right. \\ &\qquad \left. + \frac{\varphi(1-\gamma)}{s^* R_0}\right] - \frac{1}{1+\varepsilon_s}\left[\left(1+\frac{\Delta R}{R_0}\right)(1-\tau)\right]^{1+\varepsilon_s} \\ &\qquad - \frac{1}{1+\frac{1}{\varepsilon_s}}\left(\frac{1}{\left(1+\frac{\Delta s}{s^*}\right)}\right)^{1+\frac{1}{\varepsilon_s}} = 0 \end{aligned} \tag{1.5}$$

above the cutoff ($s > s^*$), the slope of iso-profit curves are $1/_{R_1(1-\tau)}$ and from the FOC condition we have $R_1(1-\tau) = [f^{-1}(s)]' = 1/_{f'(m)}$.

[25] Note that the above analysis is concentrated on intensive margin responses and cannot identify extensive margin responses. Kleven and Waseem (2013) and Best and Kleven (2015) show that extensive margin responses converges to zero in the vicinity of the cutoff.

[26] Check appendix for the details.

To solve equation (1.5) for ε_s, we need to estimate the size responses Δs, the pass through rate γ, the filing costs φ, the base rent R_0, and the rent responses ΔR. The remaining parameters s^* and τ are directly observable. Size responses Δs can be estimated using total amount of bunching (Saez 2010) - that is number of owners who decide to locate at s^* after the introduction of the size kink:

$$B = \int_{s^*}^{s^*+\Delta s} h(s)\, ds \approx h(s^*)\Delta s \tag{1.6}$$

where $h(s^*)$ is the counterfactual density of s under the assumption of no taxation at s^*. This approximation assumes that $h(s)$ is roughly constant around the bunching interval. Hence, by estimating the amount of bunching B and the counterfactual density $h(s^*)$ at the size-threshold, I can numerically solve for Δs. Section 1.3.4 explains the relationship between price elasticities of housing supply and demand and the pass through rates. Section 1.4.1 describes the empirical methodology for estimating B and $h(s^*)$. Section 1.4.2 describes the identification strategy to estimate rent responses and cots of filing.

1.3.3 Elasticity of Housing Demand

As for the demand model, individuals' preferences only depend on the consumption, which is divided into two groups: consumption of housing and composition of all other goods. Consumption of other goods equals the total income net of rent. Size is used as a proxy for housing consumption. Given all other variables, a larger property provides higher utility for a renter. These individual preferences are represented by a quasi-linear and iso-elastic utility function:

$$U(c,s) = c + \frac{\alpha}{1+\frac{1}{\varepsilon_d}}\left(\frac{s}{\alpha}\right)^{1+\frac{1}{\varepsilon_d}} \tag{1.7}$$

where c is the consumption of market goods, s is the size of the apartment, and α is the housing preferences. The quasi-linearity assumption rules out the income effects, thus, the elasticity of housing size demand ε_d, reflects only the substitution effects in response to rent changes induced by the size kink.[27] Iso-elasticity assumption implies that elasticity of demand is constant. Renters spend their entire income on rent and the composite good, that is to say, $y = sR + c$. Plugging the budget constraint into equation (1.7), we have:

$$U(c,s) = y - sR + \frac{\alpha}{1+\frac{1}{\varepsilon_d}}\left(\frac{s}{\alpha}\right)^{1+\frac{1}{\varepsilon_d}} \tag{1.8}$$

A renter's utility maximization problem with respect to size leads to the following equation:

$$s = \alpha(R)^{\varepsilon_d} \tag{1.9}$$

which demonstrates the negative relationship between gross rent and property size as long as the compensated elasticity is negative.

Although statutory incidence of taxes is on owners, renters bear part of the incidence that is passed into the rent. Let's consider a pass through of the tax burden in the form of discrete increase in the total rent (equals to $\gamma\varphi$) at s^*, and changes in the rent per unit of size from R_0 to R_1 for extra size above s^*. Therefore, her budget constraint for above the cutoff is: $y = s^*R_0 + (s - s^*)R_1 + \gamma\varphi + c$. The discontinuity and nonlinearity in the budget constraint at the right side of the size kink creates incentive for renters to locate at s^* to increase the utility level. Figure 1.4 illustrates the mechanism, assuming heterogeneous housing preferences among individuals. Renter L with the lowest preferences α^L among those who bunch at the tax-cutoff, would choose s^* both in the absence and presence of the size kink. Renter H, the marginal bunching individual with highest preferences α^H, is indifferent between s^I and s^* in the presence of the size kink. Her optimal choice in the absence of the size kink would be $s^* + \Delta s$. All renters with preferences between (α^L, α^H), who would rent properties with size in the range $(s^*, s^* + \Delta s)$, bunch at the size kink. Using the FOC condition from equation (1.8), we have $s^I = \alpha^H(R_1)^{\varepsilon_d}$. Hence, her utility level at s^* and s^I are:

[27] Saez(2010) explains that income effects are negligible when changes in the marginal tax rates are small because income effects depend on the average tax rates.

$$\begin{cases} u^I = y - \alpha^H (R_1)^{1+\varepsilon_d} + s^* \Delta R - \gamma\varphi + \dfrac{\alpha^H}{1+\frac{1}{\varepsilon_d}} (R_1)^{1+\varepsilon_d} = y + s^* \Delta R - \gamma\varphi + \dfrac{\alpha^H}{1+\varepsilon_d} (R_1)^{1+\varepsilon_d} \\ u^* = y - R_0 . s^* + \dfrac{\alpha^H}{1+\frac{1}{\varepsilon_d}} \left(\dfrac{s^*}{\alpha^H}\right)^{1+\frac{1}{\varepsilon_d}} \end{cases} \tag{1.10}$$

In the absence of the size kink, individual H would choose a property with size $(s^* + \Delta s)$, which implies $\alpha^H = {s^* + \Delta s}/{{R_0}^{\varepsilon_d}}$. Replacing α^H in the utility functions and using the condition $u^* = u^I$, the price elasticity of housing demand can be written as an implicit function of size responses, and the change in the average rent:

$$\left(\frac{1}{1+\frac{\Delta s}{s^*}}\right)\left[\left(1+\frac{\Delta R}{R_0}\right) - \frac{\gamma\varphi}{s^* R_0}\right] - \frac{1}{1+\frac{1}{\varepsilon_d}}\left(\frac{1}{1+\frac{\Delta s}{s^*}}\right)^{1+\frac{1}{\varepsilon_d}} - \frac{1}{1+\varepsilon_d}\left(1+\frac{\Delta R}{R_0}\right)^{1+\varepsilon_d} = 0 \tag{1.11}$$

Upon market clearing assumption, the rent response, total volume of bunching, and size response are the same from both supply and demand perspectives. Therefore, using the same measure of rent and size responses from the previous section, we can numerically solve for ε_d.

1.3.4 Pass Through and Incidence

Under perfect competition, the pass through – marginal changes in prices due to a change in taxes - is a function of the relative elasticities of supply and demand (Weyl and Fabinger 2013):

$$\gamma = \frac{dP}{d\tau} = \frac{1}{1 + \left(\frac{\varepsilon_d}{\varepsilon_s}\right)} \tag{1.12}$$

where P is the after-tax price. This equation intuitively means that the greater the price elasticity of one side of the market is, the more the tax burden is borne by the other side.[28]

[28] Note that under imperfect competition, calculation of pass through requires more information about the market structure and demand curvature (Ganapati et al. 2016).

Pass through itself is a key parameter to determine incidence ratio (I), defined as the ratio between the changes in consumer surplus (renters) and the changes in producer surplus (owners). Applying the envelop theorem to the consumers, a decrease in the consumer surplus (renters) due to an increase in a tax is equal to the product of equilibrium quantity Q^*, and γ. Similarly, applying the envelop theorem to producers, the reduction in producer surplus (owners) is equal to Q^* times the change in producers' price $1-\gamma$. Therefore, we have:

$$I = \frac{dCS/d\tau}{dPS/d\tau} = \frac{\gamma}{1-\gamma} \tag{1.13}$$

where CS is the consumer surplus and PS is the producer surplus.[29] Intuitively incidence larger than one means the majority of the tax burden is borne by the demand side of the market. Therefore, under perfect competition, the relative elasticity of supply and demand can fully characterize the pass-through rates and tax incidence.

To numerically solve for ε_s and ε_d, I use an iterative method with an initial guess for the pass through rate γ. This method generate successive approximations to solve equation (1.5) and (1.11), by updating γ using the previous approximations of ε_s and ε_d.

1.4 Empirical Methodology

This section presents the empirical methodology for the identification of excess bunching B, rent responses ΔR, and filing costs φ around the size kink; the parameters required to estimate structural elasticities.

1.4.1 Estimation of Excess Bunching

The difference between the empirical and counterfactual densities around the size kink provides a measure of excess bunching. To recover the counterfactual density, defined as the density of rental properties w.r.t size in the absence of the size kink, I fit a smooth polynomial to the empirical density and exclude the observations around the kink that are affected by the tax policy (Kleven and Waseem 2013). The reason is that in the

[29] These analyses are based on the assumption of infinitesimal changes in tax rates (begin from zero).

presence of the size kink, individuals in the range $(s^*,\ s^* + \Delta s)$ cluster at the left side of the size kink in the range $(\underline{s}, s^*]$.[30] Therefore, apartments are grouped into small size bins (i.e., 1 square meter) and estimate the following regression:

$$N_i = \sum_{j=0}^{p} \beta_j (s_i)^j + \sum_{\upsilon \in V} \vartheta_\upsilon . 1[\frac{s_i}{5} \in N] + \sum_{t=\underline{s}}^{s^*+\Delta s} \theta_j . 1[s_i = t] + \nu_i \qquad (1.14)$$

where N_i is the number of apartments in bin i, s_i is the size-level in bin i, p is the order of the polynomial, and ϑ_υ is a vector of dummy variables that controls for rounding effects. One possible concern is that owners may tend to register the properties' size in round numbers, which can cause spikes at multiples of 5 and 10 in the empirical distribution. Hence, dummy variables are added for multiples of 5 into equation (1.14) to capture the rounding effect. The counterfactual density is the fitted value of the dependent variable from equation (1.14), excluded from the estimated values of dummies in the affected range, that is:

$$\widehat{N}_i = \sum_{j=0}^{p} \hat{\beta}_j (s_i)^j + \sum_{\upsilon \in V} \hat{\vartheta}_\upsilon . 1[\frac{s_i}{5} \in N] \qquad (1.15)$$

As mentioned above, excess bunching is the difference between empirical and counterfactual densities for a range $(\underline{s}, s^*]$, that is: $\hat{B} = \sum_{i=\underline{s}}^{s^*} (N_i - \widehat{N}_i)$.[31] [32] The standard errors for excess bunching are estimated using the bootstrap method.

1.4.2 Estimating Rent Responses and Cost of Filing Taxes

As mentioned in the theoretical section, if owners can pass forward some of the burden of filing costs to renters, the expectation is to observe a discrete increase in total rent right above the size kink. Similarly, an increase marginal tax rates above the cutoff

[30] In practice, excess bunching doesn't occur at one point, instead, it is spread over a tiny band $(s_L, s^*]$. The optimal bunching segment is the one that the difference between the counterfactual and empirical distribution is minimum.

[31] One concern is that this method does not consider the shifting of the observed distributions above $s^* + \Delta s$ to the right of the cutoff. However, Kleven (2016) describes that these effects are negligible in many applications, in particular, if the observed distribution is not steep.

[32] Note that if the number of owners with more than one rental property is significantly high, the estimated bunching underrepresents the true level; in this case my estimation of elasticities will be lower bound. However, in this sample, only 4 percent of properties belong to owners with more than one property.

can be shifted forward to renters in the form of higher rent per square meter for extra size above the cutoff. Figure 1.5 graphically shows how the treatment effect is identified using evidence from data. Comparison between the mean annual rent at the left and right side of the size kink, presented in Panel A, provides clear evidence of a spike in rent payments for properties that are located right above the size kink. The figures provide evidence that a policy-induced spike exists in rent payments at the cut-off, however, to test this hypothesis, I estimate the following regression:

$$\begin{aligned}
&(Rent/m^2)_i = \\
&\alpha + \beta_0 SizeKink_i + \beta_1 SizeKink_i \times (Size_i - 150m^2) + \beta_2 (Size_i - 150m^2) + \\
&\beta_3 Age_i + \beta_4 {Age^2}_i + Zipcode + t + Q + \varepsilon_i
\end{aligned} \qquad (1.16)$$

where $(Rent/m^2)_i$ is the annual real rent per square meter for apartment i. $Size$, Age, and Age^2control for the characteristics of the rental properties. $SizeKink$ is a dummy variable equal to one for properties larger than $150m^2$, zero otherwise. Interaction of *SizeKink* with $(Size - 150)$ captures the change in the slope of rent per square meter above $150m^2$. ZIP Code-level fixed effects are added to control for the neighborhood characteristics. In Iran, the 10-digits ZIP Code locates an address precisely. The first 5 digits of a ZIP Code can properly determine the neighborhood boundaries, which typically contain several blocks.[33] The data cover 2,601 neighborhoods in Tehran. Year fixed-effects t, control for business cycles and macroeconomic variables that may affect the overall rental housing market. Seasonal fixed effects Q, control for seasonal patterns in the rental market.[34]

The main coefficient of interest in equation (1.16) is β_0 that captures the differences of rent value between properties above and below the cutoff due to the pass through of the filing costs. The other coefficient of interest is β_1 that capture the effects of marginal taxes on rent per square meter above the cutoff point. The coefficient of *SizeKink,* β_0, will do a better job in capturing the effects of filing costs around the cutoff because tax liability is very small. On the other hand, as the size gets further away from the cutoff,

[33] A block is defined as the smallest area surrounded by four streets.

[34] The Box-Cox lambda transformation for my specification shows that qualitatively linear transformation is a better choice compared to log-log and log-linear transformations. The transformation parameter is 0.62.

the tax liability becomes larger and β_1 can capture the effects of marginal taxes more precisely. Therefore, we estimate equation (1.16) for different samples: the entire sample, a sample that only include observations around the cutoff, and a sample that exclude the bunching area.

1.5. Results

1.5.1 Graphical Evidence

Figure 1.6 illustrates the distribution of rental properties with respect to size for the entire sample (panel A) and newly built properties (panel B) between March 2012 and September 2014 by bins of $5m^2$. [35] The size kink is denoted by a dashed line, which itself belongs to the tax-zero side of the kink. Two elements are worth noting in these panels. First, there is clear evidence of bunching right below the tax-exemption threshold, followed by a substantial drop in the number of properties above it. Second, sharper bunching at the kink point surfaces in the distribution of newly built properties for which owners have already taken into account the tax policy before choosing the size of their apartments.[36] This is consistent with the optimization friction theory of Kleven and Waseem (2013) that predicts larger responses in frictionless markets compared to the ones observed in the presence of frictions. Sample of newly built properties is a suitable representative of a frictionless market because the adjustment costs of choosing the optimal size are much smaller for owners, who purchase them for leasing. This also implies that more responsive supply leads to stronger bunching at the size kink.[37]

Exploiting the longitudinal feature of the dataset, Figure 1.7 breaks down the full sample of properties into three consecutive years, 2012-2014, to illustrate the dynamics of bunching behaviors.[38] While all three panels show substantial bunching at $150m^2$, the contrast between panel A (year: 2012) and panel C (year: 2014) is still striking, suggesting that behavioral responses are magnified over time. One way of thinking about

[35] Newly built properties are defined as those for which the "year since construction" is zero at the time of transaction.

[36] The reduction in the number of apartments that occurs by moving from the bin $(145\text{m}^2, 150\text{m}^2]$ to the bin $(150\text{m}^2, 155\text{m}^2]$ is 59 percent for panel B, versus 52 percent for panel A.

[37] Appendix Figure A.1 illustrates the distribution of rental properties with respect to size for the entire sample by bins of 3m^2. Appendix Figure A.2 shows the distribution of properties using the matched data described in Section 1.2.

[38] Data are broken down into a three-year period based on Iranian calendar in which the new year starts on March 21st.

this transition is that the stock of existing properties, i.e. properties that were built before the implementation of tax-regulation (2001), decreases through time.[39] The share of existing properties for each year, presented in Table 1.3, demonstrates that sharper bunching is associated with the reduced share of existing stock.

To explicitly verify that the tax policy induces bunching, Figure 1.8 presents the comparison of the density of apartments that were constructed before the tax-regulation and newly built apartments in the owner-occupant market. Sample of newly built properties here is reduced to observations from 2014, which have the furthest time-distance from the tax implementation date.[40] The focus here is on the owner-occupant market that is not subject to the property taxes (as opposed to the rental market). As in the figure, for properties built before the introduction of the regulation, the density smoothly decreases over size and there is no evidence of systematic clustering below the size kink. Moreover, the absence of evident bunching in the density of old properties helps to rule out alternative explanations for bunching at the focal point. In fact, properties in both graphs are similar in all respects except age. In contrast, distribution of newly built properties in 2014 provides clear evidence of bunching at the size kink.

1.5.2 Estimation of Rent Responses and filing costs

I estimate equation (1.16) to measure the rent responses to the tax in Tehran rental market. Under the null hypothesis of no tax policy effects on rent, the coefficients on the dummy variable for size, β_0, and the interaction term, β_1, in equation (1.16) are zero: owners of properties larger than $150m^2$ cannot shift forward the burden of filing costs and marginal taxes to renters through higher rent. On the other hand, as long as supply is not perfectly inelastic, the prediction is that the size kink creates a spike in the rent value right above the tax-cutoff, followed by linear increase in rent per square meter afterward.

Table 1.4 presents the OLS estimates of β_0 and β_1 for various versions of equation (1.16). All specifications include year, seasonal, and 5-digit ZIP Code fixed effects.

[39] Here, I count an apartment as existing if it has been completely constructed before 2004, assuming that those between 2001 and 2003 had already been partly built at the time of the change in the regulation. However, changing the cut-off criteria from 2004 to 2003 or 2002 does not noticeably affect the graphs or results.

[40] Appendix Figure A.3 shows the distribution of newly built apartments for all years 2012 – 2014.

Results for the entire sample, presented in Columns (1) and (2), suggest that introduction of the size kink at $150m^2$ lead to discrete increase in the rent value, and positive change in rent per square meter for each extra square meter above the cutoff. The positive and significant coefficients for β_0 and β_1 imply that some of the tax burden is passed forward to renters. Column (3) and (4) present the results for the sample that removes observations in the range $(140m^2, 160m^2)$. The point estimate of the interaction term in column (4) is larger in magnitude, suggesting that the effects of marginal taxes on rent per square meter tend to enhance further away from the cutoff.

Column (5) and (6) report estimates from specifications that restrict the sample to only include observations within 10 square meters of the cutoff. This restriction plausibly isolates the effects of filing costs on rent.[41] The results in column (5) and (6), which are not significantly different from their counterparts in column (3) and (4), show that the burden of filing taxes is associated with a 140,000(approximately $3.9 in 2015 dollars) Rials increase in rent per square meter.[42] Considering average rent per square meter of 3,600,000 Rials (approximately $100 in 2015 dollars) per square meter below the cutoff, this number can be translated to 3.9 percent increase in rent value right above the cutoff. This is also consistent with findings of Benzarti (2016) and Ramnath and Tong (2017) that show individuals compromise significant amount of money to avoid burden of filing taxes.

1.5.3 Estimation of Excess Bunching

Figure 1.9 presents the results of excess bunching by comparing the empirical and counterfactual distributions of properties with respect to size for different samples. Counterfactual distributions in all panels are estimated based on equation (1.14). Panel A shows the results for the entire sample. Panel B focuses on newly built properties in the rental market where greater bunching is happening arguably due to more elastic supply. Panel C, on the other hand, presents the same graphs in the owner-occupant market by combining purchasing transactions of newly built properties for years 2012 to 2014. Each

[41] This restriction also rules out the alternative explanation that observations with both large size and high rents are driving the results.
[42] Wald test results cannot reject the null hypotheses of restricting the point estimates in column (4) and (6) to be the same.

panel shows the estimation of excess bunching which is defined as the proportion of excess bunching to the counterfactual frequency in the small interval above the kink. [43]

The main findings from these panels are the following. First, excess bunching for all panels is highly significant varying from 1 to 5 times the height of the counterfactual distributions. Second, the estimated parameter is larger for the newly built apartments in both rental and owner-occupant markets, thus supporting the idea that attenuation of frictions leads to stronger responses. Third, the difference in magnitude of excess bunching in panel A and B also suggests that stronger bunching responses are associated with the more elastic supply.

Examining the heterogeneous bunching responses across different type of properties, Figures 1.10 and 1.11 present excess bunching based on property's age and rent-value. Panel A in figure 1.10 includes rental properties that were built at least 5 years before the tax regulation. Panel B presents the same graphs for older rental properties by trimming the dataset further to only include rental properties that were built at least 15 years before the regulation. Figure 1.11 presents excess bunching for high- and low- rent regions. In doing so, the full sample is split into two subsamples, one that include only properties located in postal regions with average rent above the median, and the other one that includes the rest of observations.

There is evidence of heterogeneity by property's age that suggests increasing relationship between age and volume of bunching. This is consistent with the hypothesis that housing deteriorates with age (Brueckner et al 2009). Therefore, older dwellings (with probably lower quality) larger than $150m^2$ can be torn down and replaced with new dwellings with size below $150m^2$ at arguably lower costs. Moreover, Figure 1.11 illustrates that the bunching for apartments in low-rent neighborhoods is strongly larger compared to high rent neighborhoods. This contrast can be interpreted as evidence that owners and renters in low-rent neighborhoods might have higher price elasticities. These figures may suggest that some of the responses are along other margins such as quality.

[43] As a robustness check, I use different orders of polynomials to estimate the counterfactual distributions. The results appear to be insensitive to the order of polynomials.

In section 1.5.5, I compare the housing characteristics of properties at the two side of the cutoff to explore this possibility further.[44]

To rule out alternative explanations for bunching at the focal point, I formally check for the presence of a density discontinuity at the size kink in the owner-occupant market, by performing the McCrary test separately for the distributions of the full sample of newly built properties, and properties built before the regulation (McCrary 2008). The results are consistent with the graphical evidence, suggesting that the log-difference between the frequencies of newly built properties just below and above the size kink are statistically significant, while the null hypothesis that the discontinuity at the size kink is zero cannot be rejected for already built properties.[45] The contrast between these two distributions confirms that the supply of new housing strongly responds to the tax policy. This finding also provides evidence of tax spillovers – i.e. the impact of a tax policy in one market on others – in the housing market.

1.5.4. Estimation of Elasticities and Pass Through

The measures of rent responses, bunching, and costs of filing around the kink point ($150m^2$) allow me to calculate the separate estimation of elasticities of housing size demand and supply using the structural framework introduced in Section 1.2. Table 1.5 presents estimated elasticities for different choices of bunching segments. The table is organized in five columns. Columns (1) and (2) report the price elasticities of housing demand and supply using equation (1.5) and (1.11), respectively. Columns (3) and (4) present estimated elasticities, using the measure of bunching from subsample of newly built properties, the representative of the frictionless market. Column (5) takes the estimated elasticities from column (3) and (4) and embeds them into equation (12) to measure the pass-through rate.

The results for the entire sample show that both elasticities of supply and demand are almost always statistically significant with the expected signs for all specifications,

[44] Saez et al (2012) and Kopczuk et al (2015) argue that tax-induced responses along other margins still indicate the efficiency costs of taxation.
[45] Point estimates of the McCrary tests for distributions in Figure 8 are as follows: Newly built properties: 0.451 (0.039); Built before the regulation: 0.074 (0.045). Optimal bin size and bandwidth as in McCrary(2008).

consistent with the graphical evidence presented earlier.[46] The estimated elasticities of supply for the subsample of newly built properties, the representative of the frictionless market, are 2 to 6 times as large as their counterparts in column (1). This contrast highlights the substantial role of frictions in attenuating the housing supply responses. The estimates of housing demand elasticities, reported in columns (2) and (4), are smaller, but still significant. Results here suggest that the estimation of price elasticity of housing size demand highly depends on the magnitude of bunching responses. Column (5) presents the estimation of the pass-through rates that range between 0.88 and 0.91 across different choice of bunching segments, meaning that the incidence ratio is over one.[47]

1.5.5 Robustness Checks

This section contains additional estimations to ensure that potential biases in the sample or alternative explanations do not drive the results. One alternative explanation is that some of the local response to the size-kink may be due to supply side and demand side adjustment along the quality margin. Although our concentration is on a narrow band around the tax cutoff, it is possible that properties below and above the cutoff are significantly different along housing characteristics other than size. To investigate this possibility, I use records on real estate listings in Tehran for years 2014 to 2016.

Table 1.6 presents the summary statistics for the 875 listings. Column (1) and (2) present the housing characteristics for observations in the size range $(140m^2, 150m^2]$ and $(150m^2, 160m^2]$, respectively. Each row presents the mean value of housing characteristics for both groups. Column (3) presents the results for the mean difference between 2 groups. The t-statistics are in parentheses. Column (4) reports the *p-value*. Note that the average rent per square meter for apartments above the cutoff is 4,894 thousand Rials, which is significantly different from those located below (or equal) the

[46] Although estimated elasticities based on the measure of bunching from the entire sample are small, they are consistent with the literature on behavioral responses to transaction taxes, which finds relatively small elasticities in spite of large housing price responses (e.g. Best and Kleven 2015).

[47] While the results do not seem to be very sensitive to the choice of the bunching segment, increasing the length of the bunching segment lead to inclusion of lower and upper band densities around the size kink that are probably affected by the tax policy (Saez 2010). Therefore, one would expect to see higher elasticities when the length of bunching segments is increased. As a result, the baseline estimations that rely on small bunching segment around the kink are lower-bound estimates.

cutoff. On the other hand, for mostly all key housing characteristics there is no significant difference between the two groups of observations. In fact, the computed Benjamini-Hochberg *p-values* only reject the null hypothesis for one characteristic.[48] Although there is no direct way to fully capture the quality of housing, attributes such as facing direction, kitchen materials, flooring, building façade, and age plausibly reflect the quality of housing. Hence, the results here are reassuring that the base results for the rent responses and costs of filing are not significantly biased by the quality adjustment.

I also run placebo tests to investigate the causality concerns regarding the effect of the tax policy on rent. If my results reflect a treatment effect of the tax kink, then the results should disappear if I falsely assume that my treatment occurs at 10 square meters before or after the actual kink-point. For these tests, I run two additional regressions, one for observations within interval (130m^2, 150m^2) assuming 140m^2 is the size kink, and another one for observations within the interval (150m^2, 170m^2) assuming 160m^2 is the size kink. Results of these regressions, presented in Table A.1 indicate that the coefficients estimates on the falsified kink dummies are insignificant. I do two additional placebo tests for intervals (120m^2, 140m^2) and (160m^2, 180m^2). As in the previous test, results again indicate that falsified dummies are not significant. Therefore, the placebo tests show my baseline results are robust to subsample choices and the size kink has a causal effect on rent values.

1.6 Conclusions

This study has taken advantage of rich micro administrative data on rental properties in Tehran and quasi-experimental variation in marginal taxes to estimate the price elasticities of housing demand and supply simultaneously. Using the estimated elasticities, this paper then examined the pass-through rate of the size kink. My analysis reveals strong evidence of behavioral responses through bunching below the size kink, and a rent spike above it. Using the measure of bunching from newly built properties, for which frictions are less and supply is more elastic, the elasticities of housing supply and demand are at least 10 times larger compared to estimates using the entire sample. The

[48] Although the difference for the number of bedrooms between the two groups is significant, the magnitude is small.

high but incomplete estimation of pass-through rates suggest that owners are able to pass forward the majority of the tax burden in the form of higher rents.

This paper shows the importance of considering the supply responses to uncover structural elasticities of demand. Additional conclusions are reached on elasticities' estimations because the setting accounts for the effects of incomplete pass through in attenuating demand responses. The results from the representation of the "frictionless" market highlight the effects of frictions on attenuating behavioral responses. Moreover, this may be of broader interest in other fields that generally assume completely elastic supply and full pass through. My estimation of incidence ratio above one implies that renters who normally are at the bottom tail of the income distribution are the ones who bear most of the cost of the policy. That is, size-based taxes on rental properties might be highly regressive. Finally, the findings show that rental taxation policy not only distorts the owners' and renters' decisions in the rental market, but also induces large distortionary responses in the owner-occupant market.

In this paper, I provided a framework to estimate separate price elasticities of housing supply and demand using evidence of bunching and incidence. Here, I focus on effects of taxation on locations around the kink-point where agents chiefly react through the intensive margin. It would be interesting to use this evidence to examine the extensive responses to the size kink. I also provided evidence that a size-based tax policy will increase the supply of smaller apartments of a size below the cutoff, which can ultimately lead to higher urban density. Another interesting research question would be to consider the tax-induced variation in urban density to analyze its impacts on labor markets and urban characteristics such as innovation rate, local climate, and energy consumptions.

1.7 Figures and Tables

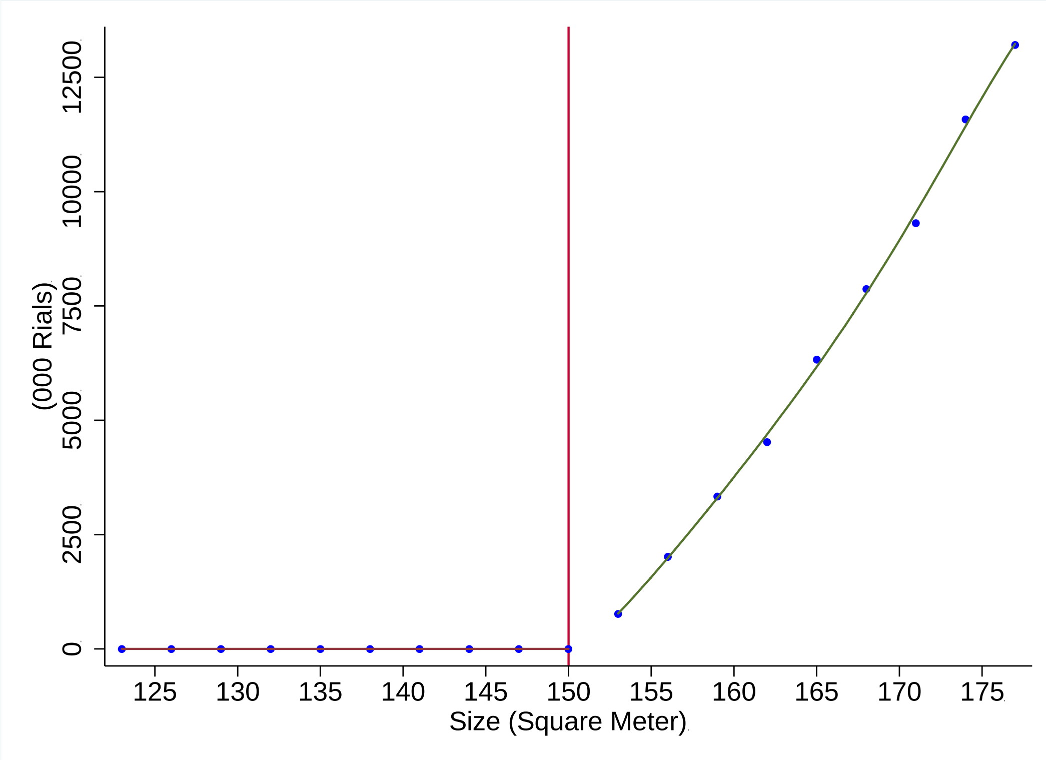
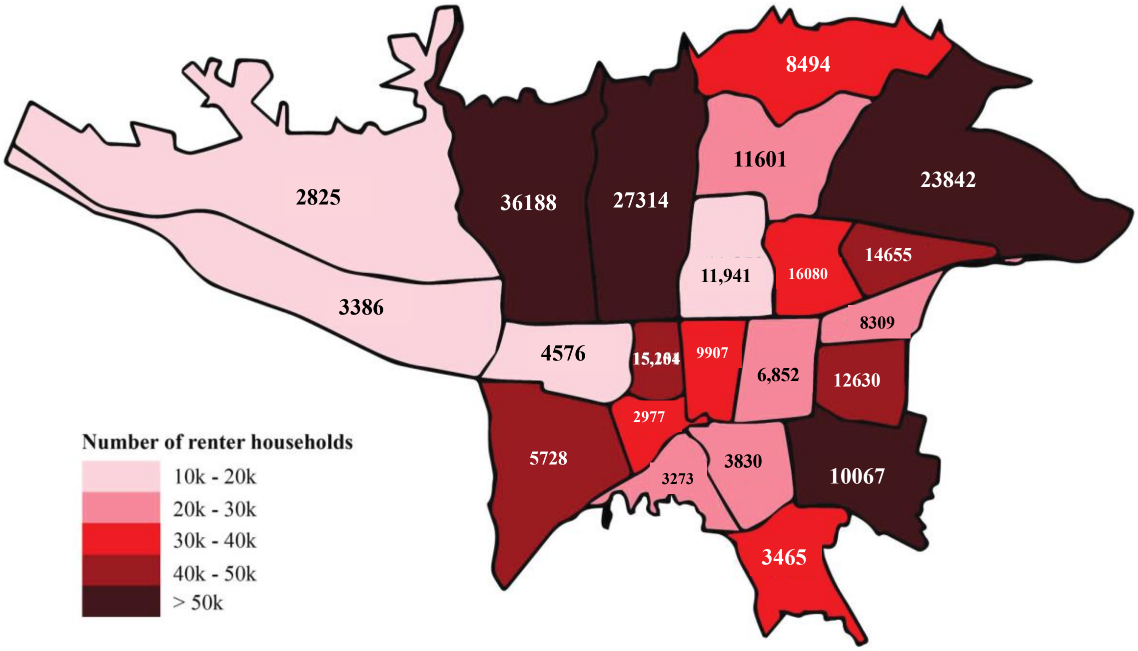


Figure 1.1: Average Annual Tax

Notes: This figure shows the average annual tax liabilities per square meter w.r.t. size for the entire sample. The red line shows the point where taxation begins. Owners of rental properties with total combined size over 150$\boldsymbol{m^2}$ are exposed to the rental income tax. The line itself is in the tax-zero side of the kink. Rent values are deflated to reflect year 2015 prices using the Statistical Centre of Iran Housing Price Index. IRR-USD exchange rate was between 15,000 – 39,000 during the years 2012 - 2014.

Panel A. Rental Market



Panel B. Owner-occupant Market

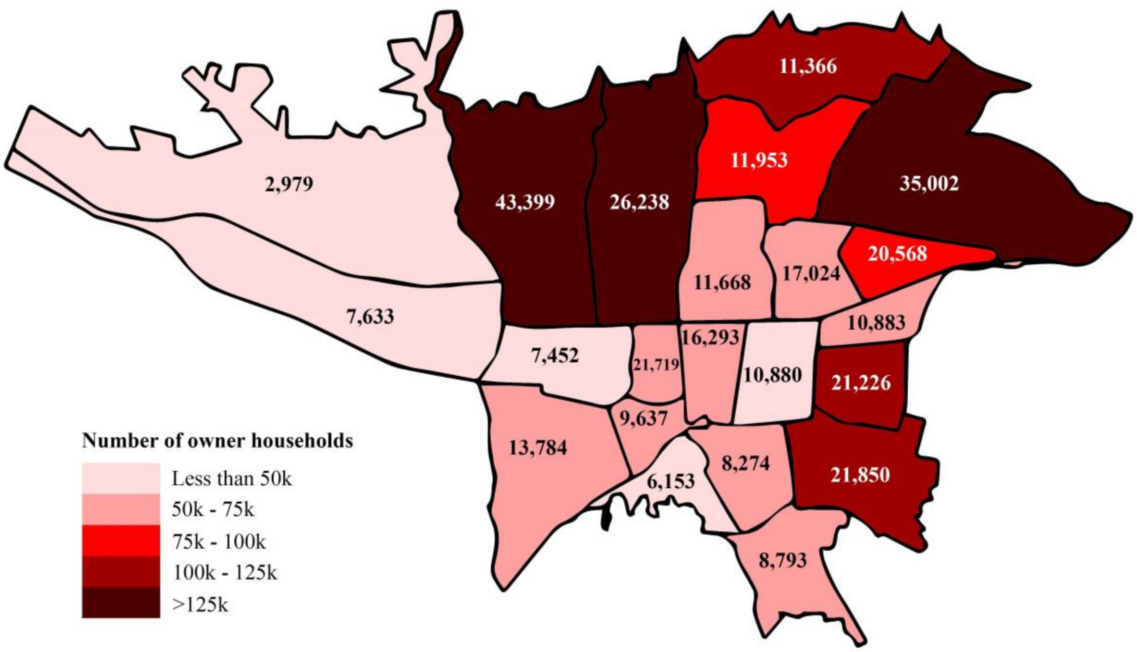


Figure 1.2: Distribution of Observations

Notes: Panel A. shows the number of rental observations in each district for time period March 2012 – September 2014. Panel B. shows the number of purchasing observations in each district for the same time period. Colors in panel A. and B. illustrate the number of actual renter and owner households in each district, respectively.

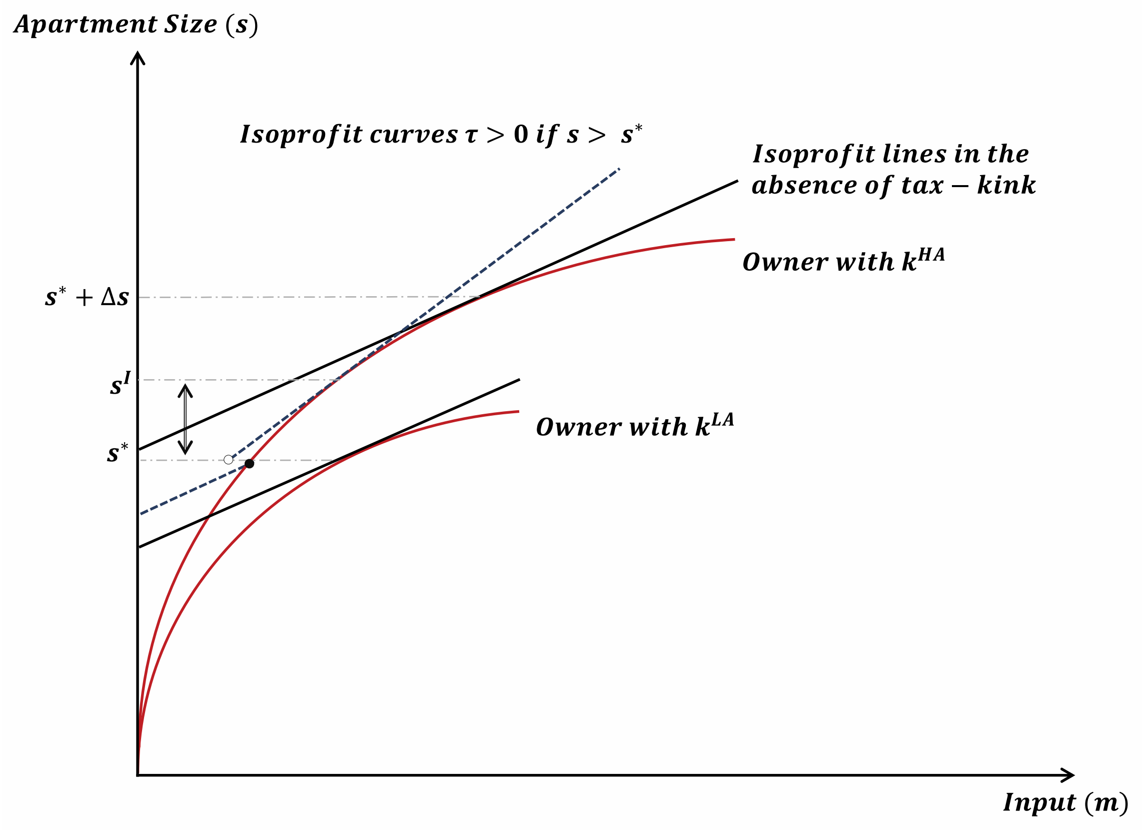


Figure 1.3: Bunching at the Size Kink

Notes: This figure illustrates the impact of a size kink on owners' profits and their decisions on their properties' size. Red curved lines show the production functions. Black solid lines show the Iso-profit curves in the absence of tax. Blue dashed lines show the Iso-profit curves in the presence of the size-kink. Owner *HA* is the marginal bunching individual who would choose a property with size $s^* + \Delta s$ in the absence of size-threshold. In the presence of the size kink, she is indifferent between s^I and s^*. Individual LA, who is not affected by the size kink, chooses a property with size s^* both in the absence and presence of the size kink.

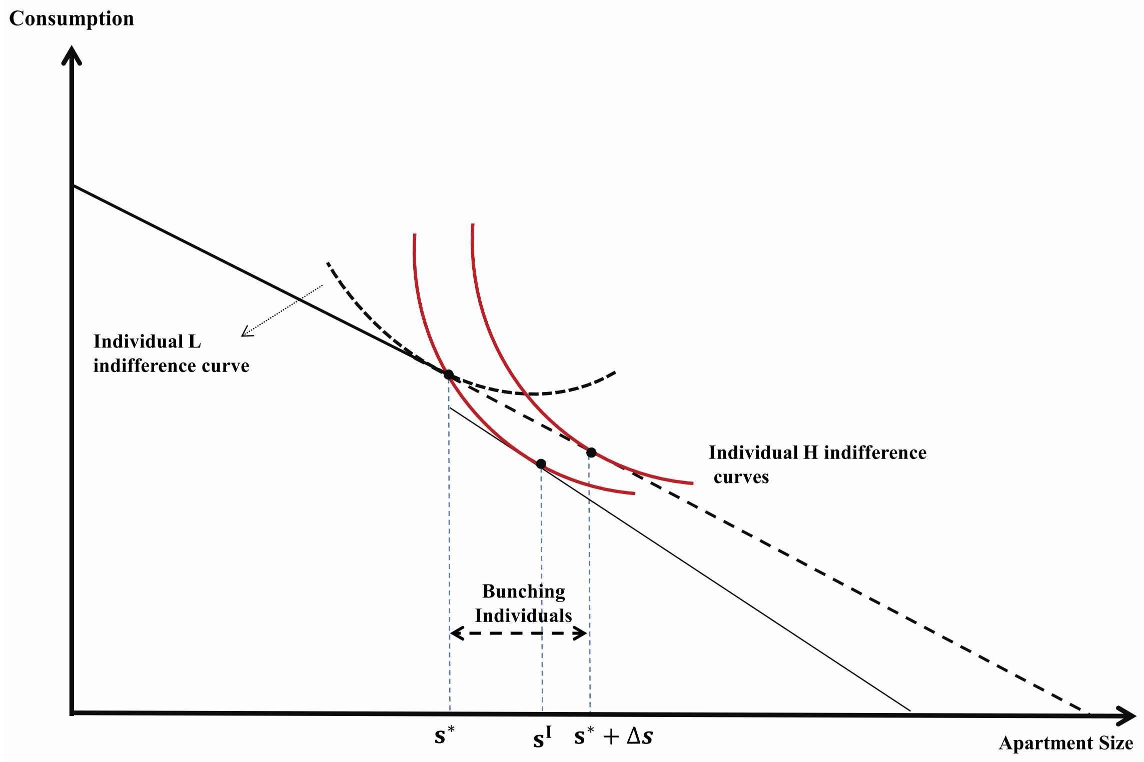


Figure 1.4: Renters' Budget Set Diagram

Notes: This figure illustrates the impact of a size kink on renters' budget sets and their properties choices. Dashed curved line shows renter's L indifference curve. Solid curved lines show renter's H indifference curves.

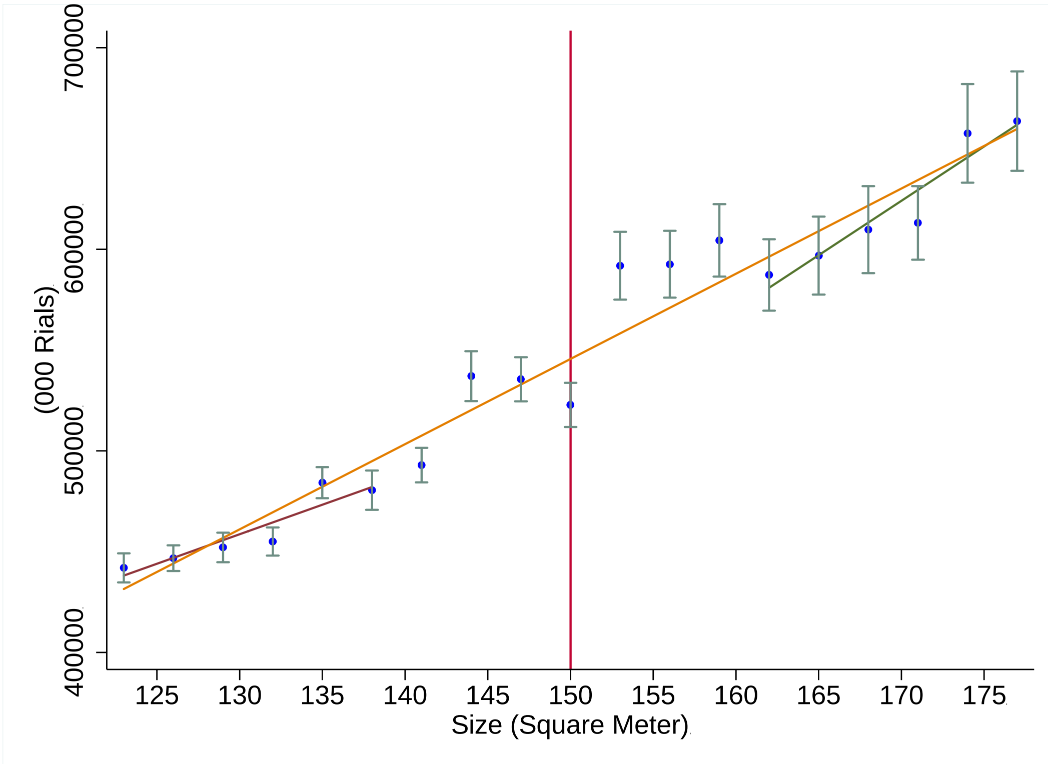
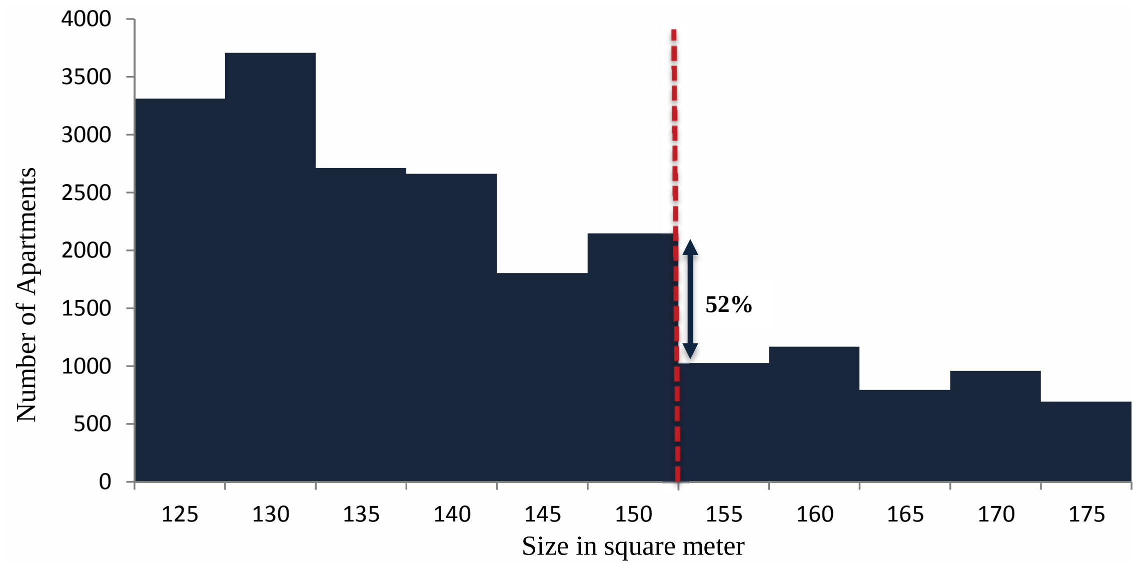


Figure 1.5: Mean Annual Rent around the Kink

Notes: This figure shows the mean annual real rent/$\boldsymbol{m^2}$ and 90% confidence intervals for rental transactions from March 2012 to September 2014. The vertical line shows the point where taxation begins. The line itself is in the tax-zero side of the kink. The red (green) curved line displays the linear fit for properties with size $s \leq \mathbf{150m^2}$ ($\boldsymbol{s} >$ $\mathbf{150\ m^2}$). The inclined line (orange) displays the linear fit. IRR-USD exchange rate was between 15,000 and 39,000 during the years 2012 - 2014.

Panel A. Entire Sample from 2012 – 2014



Panel B. Newly Built Apartments

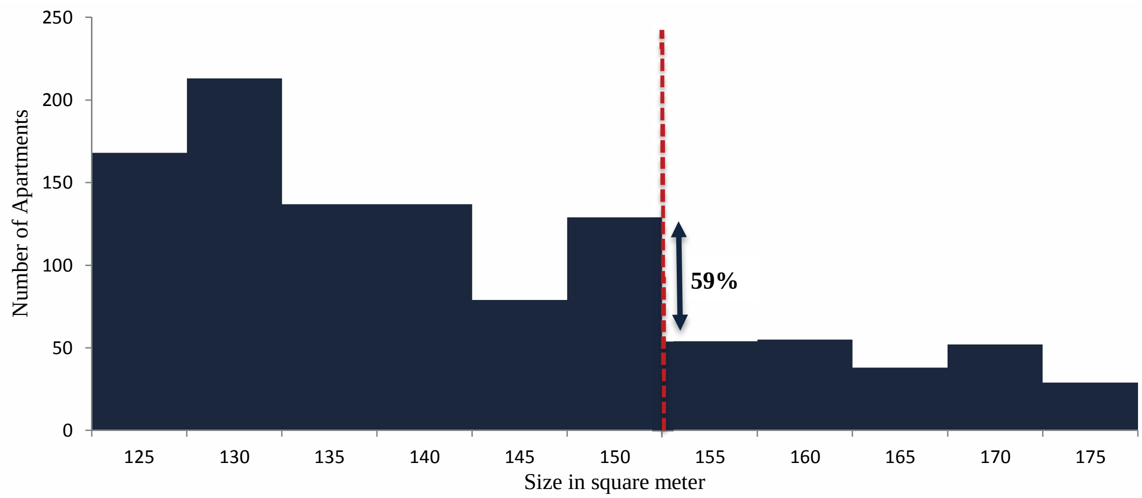
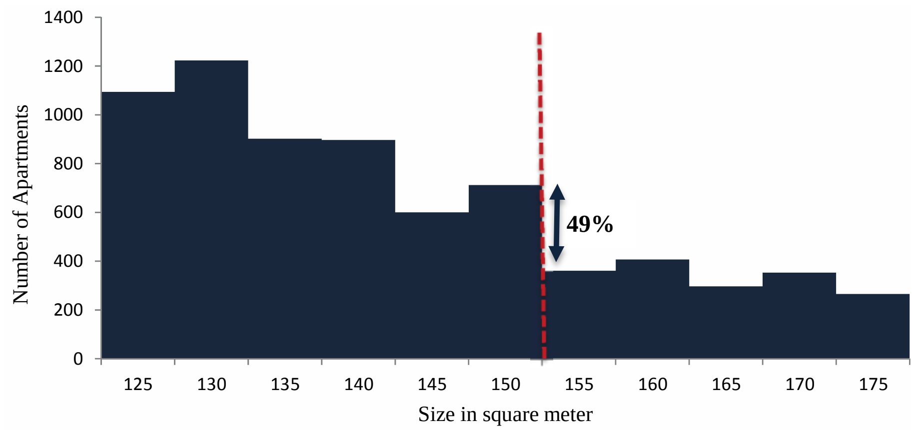


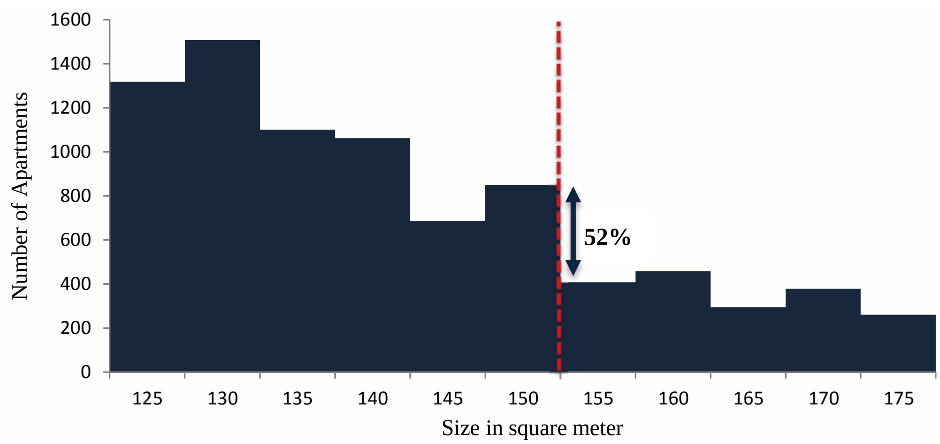
Figure 1.6: Apartments Distribution and the Taxation Point

Notes: This figure displays the histogram of properties' size (by $5m^2$ bins). Panel A. includes all observations from March 2012 to September 2014 for segment $(120m^2, 180m^2)$. Plan B. is reduced to include only newly built apartments. The dashed line shows the starting point of taxation. The line itself belongs to the tax-zero side of the kink. The numbers next to the dashed line are the percentage reduction in the number of apartments that occurs by moving from the bin $(145\text{m}^2, 150\text{m}^2]$ to the bin $(150\text{m}^2, 155\text{m}^2]$.

Panel A. Q2 2012 – Q2 2013



Panel B. Q2 2013 – Q2 2014



Panel C. Q2 2014 – Q3 2014

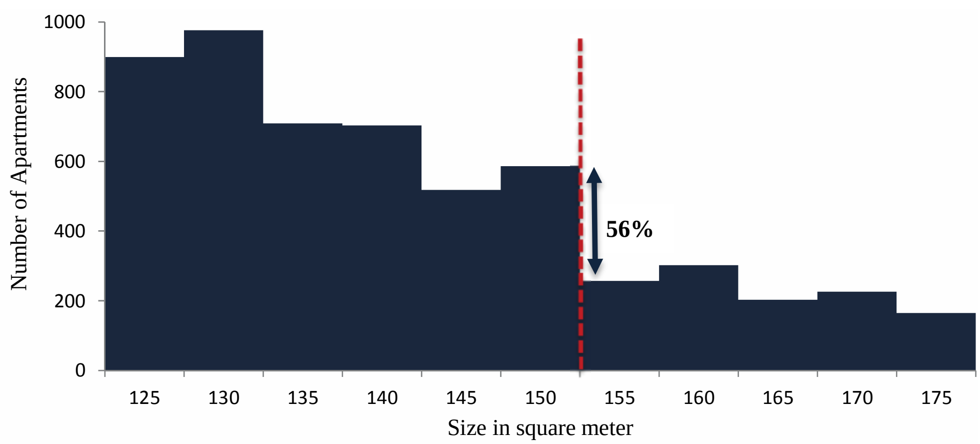


Figure 1.7: Dynamics of Bunching Behaviors

Notes: Figure 1.7 illustrates the histogram of apartments' size for three consecutive years, separately. The solid line shows the starting point of taxation. The line itself belongs to the tax-zero side of the kink. The numbers next to the dashed line are the percentage reduction in the number of apartments that occurs by moving from the bin $(145\text{m}^2, 150\text{m}^2]$ to the bin $(150\text{m}^2, 155\text{m}^2]$.

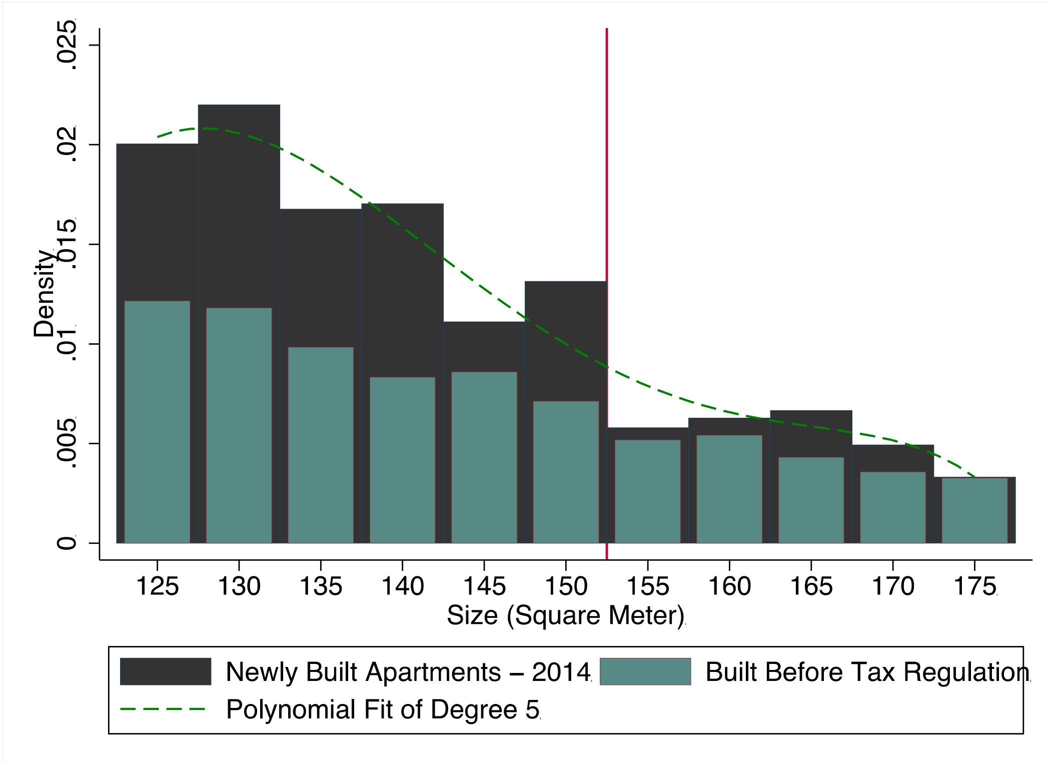
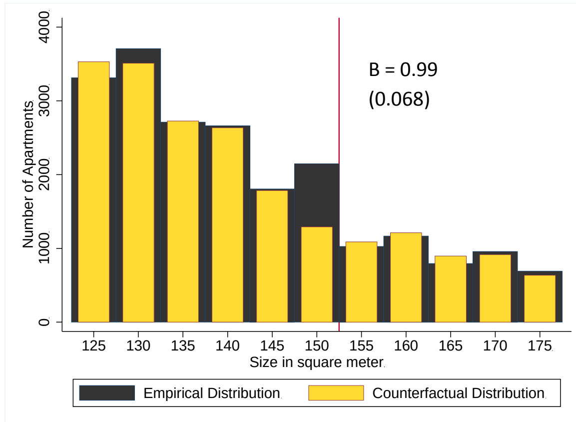


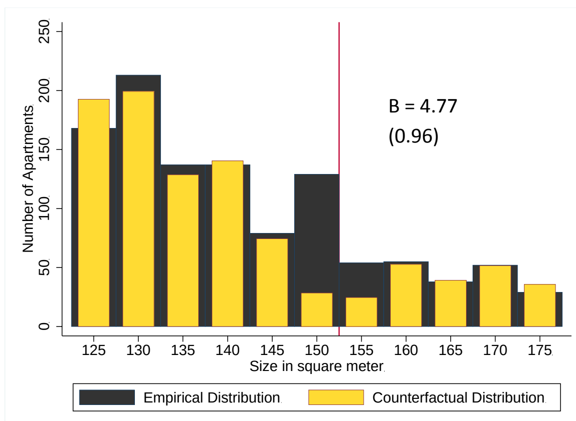
Figure 1.8: Apartments Distribution in the Owning Market

Notes: Figure 1.8 displays the density of newly built and old properties for the owner-occupant market by $5m^2$ bins. The sample of newly built apartments is reduced to include only observations from 2014. The dashed line displays the polynomial fit of degree of five for newly built apartments. The solid line shows the starting point of taxation. The line itself is on the tax-zero side of the kink.

Panel A. Rental Units – Entire Sample



Panel B. Rental Units – Newly Built Apartments



Panel C. Owner-Occupied Units – Newly Built Apartments

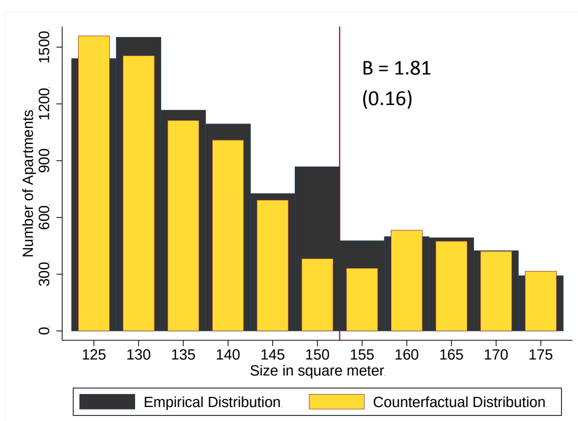
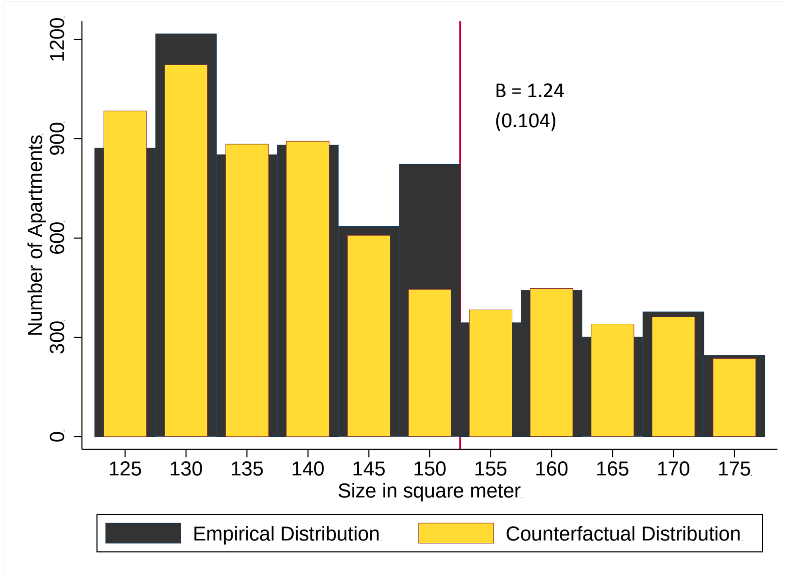


Figure 1.9: Empirical and Counterfactual Distributions around the Size kink

Notes: This figure illustrates the empirical and counterfactual distributions of apartments in Tehran for years 2012 to 2014. The counterfactual distribution is estimated for each panel separately based on equation (1.16), by fitting a fifth-order polynomial to the empirical distribution and excluding the bunching segment. The solid line shows the starting point of taxation. The line itself is on the tax-zero side of the kink. The excess bunching B is the difference between the empirical and counterfactual densities in the small interval below the size kink in proportion to the average counterfactual distribution right above the cutoff. Standard errors are presented in parentheses.

Panel A. Apartments built at least 5 years before the regulation



Panel B. Apartments built at least 15 years before the regulation

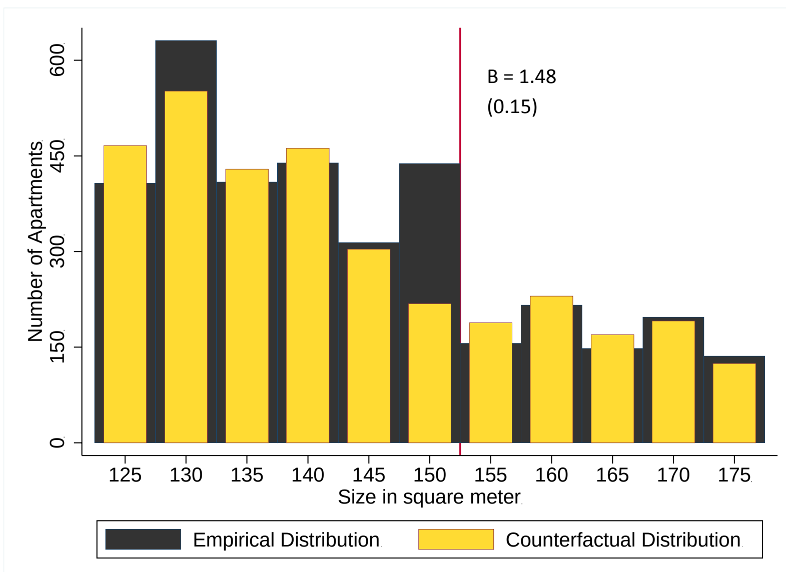
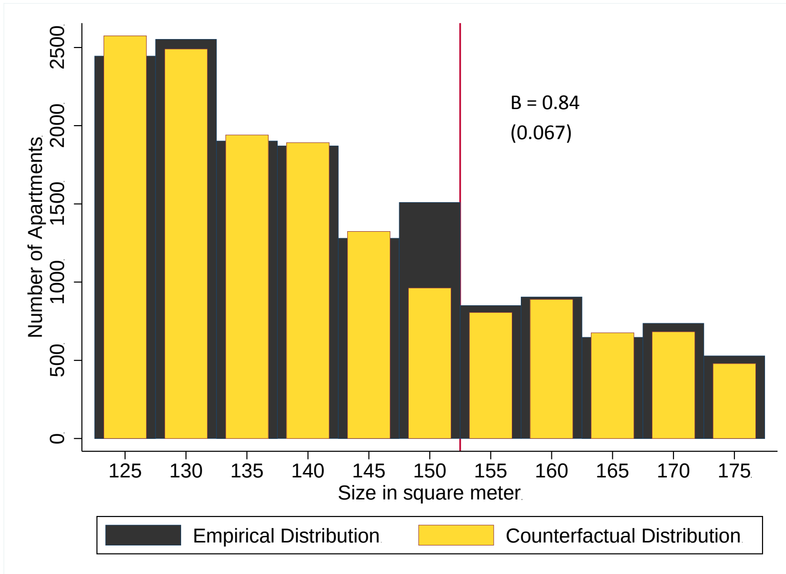


Figure 1.10: Apartment Distributions by Property Age

Notes: This figure illustrates the empirical and counterfactual distributions of apartments in Tehran for years 2012 – 2014. Panel A includes rental apartments that were built at least 5 years before the tax regulation. Panel B presents the same graphs for older rental apartments by trimming the dataset further to only include apartments that were built at least 15 years before the regulation. The counterfactual distribution is estimated for each panel separately based on equation (1.16) by fitting a fifth-order polynomial to the empirical distribution and excluding the bunching segment. The solid line shows the starting point of taxation. The line itself is on the tax-zero side of the kink. The excess bunching B is the difference between the empirical and counterfactual densities in the small interval below the size kink in proportion to the average counterfactual distribution right above the cutoff. Standard errors in parentheses.

Panel A. High-rent Neighborhoods



Panel B. Low-rent Neighborhoods

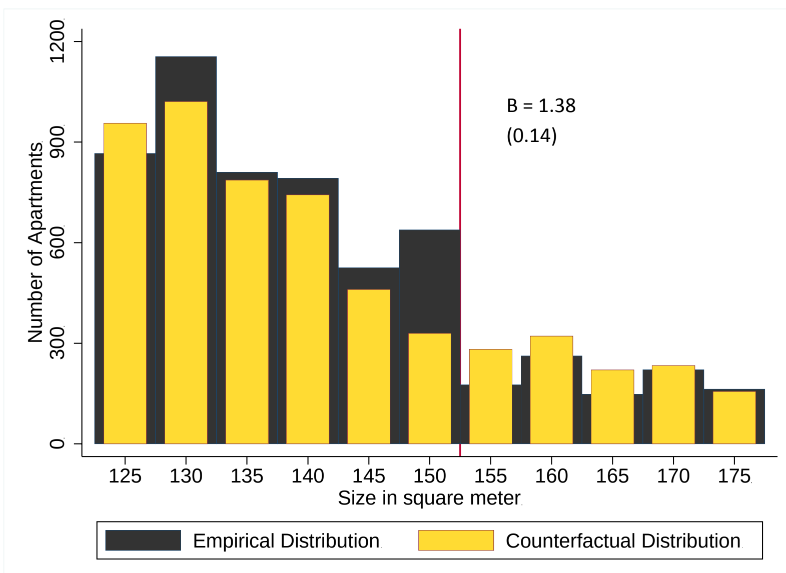


Figure 1.11: Apartment Distributions across Different Neighborhoods

Notes: This figure illustrates the empirical and counterfactual distributions of apartments in Tehran for years 2012 to 2014. Panel A includes only properties that are located in postal regions with average rent above the median, and Panel B includes the rest of observations. The counterfactual distribution is estimated for each panel separately based on equation (1.16) by fitting a fifth-order polynomial to the empirical distribution and excluding the bunching segment. The solid line shows the starting point of taxation. The line itself is on the tax-zero side of the kink. The excess bunching B is the difference between the empirical and counterfactual densities in the small interval below the size kink in proportion to the average counterfactual distribution right above the cutoff. Standard errors are presented in parentheses.

Table 1.1: Rental Income Tax Schedule

Bracket (000 Rials)	Marginal Tax Rate
0 - 30,000	15%
30,000 - 100,000	20%
100,000 - 250,000	25%
250,000 - 1,000,000	30%
Over 1,000,000	35%

Notes: Taxable rental income is shown in thousands of Rials, with the IRR-USD exchange rate varying from 15,000 to 39,000 during these years. For owners of rental properties with combined total size over $150\boldsymbol{m^2}$, each bracket cutoff is associated with a jump in the marginal tax rate.

Table 1.2: Summary Statistics for Rental Transactions

	Number of Observations	Mean Annual Rent/ m^2 (000 Rials)	Mean Age (Year)	Mean Size (m^2)
Entire Sample	243,144	3,046	11	79.4
		(2.69)	(0.02)	(0.07)
In the range ($140 m^2$, $150 m^2$]	3,951	3,635	14.4	146.0
		(25.9)	(0.20)	(0.05)
In the range ($150 m^2$, $160 m^2$)	1,813	3,853	13.7	154.9
		(38.09)	(0.27)	(0.06)

Notes: This Table presents the summary statistics for sample of residential apartments that were rent during the March 2012 to September 2014. Rent values are deflated to reflect year 2015 prices using the Statistical Centre of Iran Housing Price Index. Data is obtained from Rahbar Informatics Service Corporate (RISC). IRR-USD exchange rate was between 15,000 – 39,000 during these years.

Table 1.3: Existing Stock of Housing

Year	#Apts built before 2004	#Apts built after 2004	Share of existing stock (before / (before + after))	Difference (%) in #Apts between bin $150m^2$ and $155m^2$
Q2 2012 - Q2 2013	52,322	25,940	66.9%	49.3%
Q2 2013 - Q2 2014	49,958	49,444	50.3%	51.9%
Q2 2014 - Q3 2014	30,585	34,895	46.7%	56.1%
Total	132,865	110,279	54.6%	52.2%

Notes: This table presents the breakdowns of the number of apartments by year and time of construction. Sharper shrink in the number of apartments above the kink-point is associated with a reduced share of existing stock of housing.

Table 1.4: The Effects of Taxation on Rent

VARIABLES	(1) Rent/m^2 Entire Sample	(2)	(3) Rent/m^2 Excluding (140 m^2- 160 m^2)	(4)	(5) Rent/m^2 (140 m^2- 160 m^2)	(6)
Size > 150 m^2	238.62***	143.66***	293.37***	153.43***	140.09*	125.38
	(26.04)	(29.84)	(29.25)	(35.58)	(81.62)	(86.23)
(Size > 150 m^2) × (Size - 150 m^2)		3.78***		4.30***		5.71
		(0.57)		(0.63)		(17.07)
(Size - 150 m^2)	-3.90***	-4.36***	-4.19***	-4.69***	-17.74**	-19.20**
	(0.19)	(0.21)	(0.20)	(0.21)	(7.21)	(8.74)
Observations	243,144	243,144	237,380	237,380	5,764	5,764
R-squared	0.51	0.51	0.51	0.51	0.54	0.54

Notes: The dependent variable is log of total annual real rent per-square-meter. Regressions are based on equation (1.16) using the entire sample (March 2012 to September 2014). SizeKink is a dummy variable equal to one for properties larger than 150$\boldsymbol{m^2}$. Column 3 includes the interaction of size and size-threshold. All specifications include 5-digit ZIP Code, year, and seasonal fixed effects. Standard errors in all columns are clustered by 5-digit ZIP Code and stars indicate statistical significance level. * = 10 percent level, ** = 5 percent level, *** = 1 percent level.

Table 1.5: Housing Elasticities Estimates

VARIABLES	Measure of bunching from the entire sample: Elasticity of Housing Demand	Measure of bunching from the entire sample: Elasticity of Housing Supply	Measure of bunching from the "frictionless" market (Newly-built apartments): Elasticity of Housing Demand	Measure of bunching from the "frictionless" market (Newly-built apartments): Elasticity of Housing Supply	Measure of bunching from the "frictionless" market (Newly-built apartments): Pass Through Rate $\rho = {}^{1}\!/_{1+\left(\frac{\varepsilon_d}{\varepsilon_s}\right)}$
	(1)	(2)	(3)	(4)	(5)
Bunching Segment (145 m^2- 155 m^2)	-0.015	0.243	-0.172	1.368	0.884
	(0.002)	(0.041)	(0.052)	(0.555)	(0.001)
Bunching Segment (145 m^2- 160 m^2)	-0.017	0.291	-0.211	1.794	0.889
	(0.002)	(0.051)	(0.068)	(0.769)	(0.017)
Bunching Segment (140 m^2- 155 m^2)	-0.024	0.544	-0.302	2.913	0.902
	(0.003)	(0.122)	(0.098)	(1.301)	(0.001)
Bunching Segment (140 m^2- 160 m^2)	-0.025	0.616	-0.365	3.765	0.0907
	(0.003)	(0.174)	(0.113)	(1.579)	(0.001)

Notes: This table presents estimates of elasticities of housing demand and supply using measure of bunching from the entire sample in columns (1) and (2). Columns (3) and (4) present the same estimates using measure of bunching from the market of newly built properties. Column (5) presents the pass-through rates based on column (3) and (4). Each row shows the results for a different choice of bunching segment. Standard errors are presented in parentheses.

Table 1.6: Summary of Housing Characteristics

Variables	(1) (140m^2,150 m^2]	(2) (150m^2 ,160m^2]	(3) Mean difference	(4) P-Value
# of stories in the building	4.79	5.14	0.35	0.145
			(1.46)	
# of units in each floor	2.11	1.96	-0.15	0.260
			(-1.13)	
View	0.228	0.253	0.025	0.391
			(0.86)	
Floor number	2.71	2.79	0.086	0.639
			(0.47)	
# of Bedrooms	2.81	2.90	0.092	0.001
			(3.47)	
Age	12.17	12.25	0.054	0.932
			(0.09)	
Kitchen Materials				
Metal, Half-wooden, High Gloss	0.11	0.08	-0.037	0.082
			(-1.74)	
MDF	0.80	0.85	0.047	0.078
			(1.76)	
High-end	0.081	-0.071	-0.01	0.583
			(-0.55)	
Flooring (1 to 7)				
Carpet	0.40	0.36	-0.035	0.305
			(-1.03)	
Ceramic	0.025	0.036	0.011	0.322
			(0.99)	
Laminate, Mixed				
	0.099	0.105	0.005	0.791
Parquet			(0.27)	
High-end stone	0.422	0.451	0.029	0.389
			(0.86)	
Building Façade Materials				
Stone	0.77	0.76	-0.014	0.627
			(-0.49)	
Roman design	0.038	0.046	0.008	0.547
			(0.60)	
Bricks	0.076	0.092	0.017	0.384
			(0.87)	
Cement	0.036	0.029	-0.005	0.68
			(-0.41)	
Granite	0.031	0.034	0.003	0.792
			(0.26)	
Kenitex	0.025	0.019	-0.006	0.517
			(-0.65)	
Travertine - Composite	0.014	0.012	-0.002	0.796
			(-0.26)	
Parking	0.88	0.88	0.006	0.787
			(0.27)	
Storage	0.87	0.90	0.032	0.156
			(1.42)	
Balcony	0.54	0.51	-0.033	0.355
			(-.092)	
Pool, Sauna, or Jacuzzi	0.1	0.14	0.032	0.141
			(1.47)	
Yard	0.235	0.277	0.043	0.156
			(1.42)	
Elevator	0.547	0.61	0.068	0.047
			(1.99)	
# of Observations	552	323		

Note: Rent is the total rent per square meter. View is a dummy variable equal to one if the unit faces more than one direction. Kitchen Materials, Flooring, Building Façade Materials, Parking, storage, balcony, yard, elevator are dummy variables that get one if the unit has them and zero otherwise. Pool, Sauna, and Jacuzzi is a dummy variable that gets value of one if the unit has a pool, sauna, or Jacuzzi. *t-statistics* in parentheses.

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CHAPTER 2: AIR POLLUTION, HOUSING PRICES, AND COSTS OF SANCTIONS: A NATURAL EXPERIMENT

2.1 Introduction

The association between air quality and housing values has been the subject of economic studies since 1960's. Cross-sectional studies using hedonic price models suggest a negative relationship between air pollution indices and housing prices. However, the estimated cross-sectional hedonic models suffer from a number of econometric problems such as omitted variable bias. Because of such issues, economists question both the validity of the causal inference and the accuracy of estimates of marginal willingness to pay (MWTP) for air quality in traditional hedonic estimations. To address these problems, some studies (e.g. Chay et al 2005; Grainger 2013) suggested Instrumental Variable models using policy regulations as instrumental variables for changes in the level of air pollution.

Chay and Greenstone (2005) results shows that the elasticity of housing values with respect to the level of TSP is larger than what cross sectional studies found and ranges from -0.2 to -0.35. These estimations are based on variations in pollution and housing prices over the course of 10 years from 1970 to 1980. Other studies also utilized IV methods to investigate the long-run association of air pollution and housing values between different regions/counties within a country (e.g. Bayer et al 2009). However, in the long run time horizon, the assumption that the housing supply is inelastic can be problematic. Besides, households and businesses may find enough time to move to regions/counties that have better air quality. All these can lead to biased estimates of individuals' MWTP for the clear air. Finding a policy that induces a fast and heterogeneous increase in the level of air pollutants within a city can provide a framework that addresses these issues.

In this paper, we examine the casual impact of air pollution by exploiting the heterogeneous jump in the level Nitrogen Dioxide within Tehran, induced by unprecedented nuclear sanctions that targeted Iran's import of gasoline. We implement our methodology utilizing this unique natural experiment combined with a rich dataset that includes around one million actual housing transactions both in the owner-occupied market and the rental market over the course of five years. This extensive data set provides the opportunity to compare agents' responses across the two markets in short run where supply is plausibly inelastic. We then examine the impact of air pollution on individuals' expectations of the future housing prices and whether there is any evidence of substitution from owner-occupied market to rental market in highly polluted neighborhoods.

To the best of our knowledge, this study will be the first study that explores the indirect environmental impact of Iranian Nuclear Sanctions. Following the unprecedented Iranian nuclear sanctions and subsequent preemptive actions by the Iranian government, the level of air pollution rapidly increased starting from late 2010 due to the supply of low quality domestically produced gasoline. The heterogeneous nature of this pollution jump within Tehran, which is an important factor in our identification strategy, mostly comes from the wind pattern, urban structure, and the difference in neighborhoods' elevation. Our study addresses the causality issue, exploiting heterogeneous severe increases in the level of pollution in Tehran in the aftermath of sanctions. Since the effects of sanctions were unanticipated, we have no reason to expect households sort based on their preferences for the pollution before the spike. One distinctive feature of this incidence of pollution jump is that it is mainly because of the increase in the level of NO_2 as a prominent combustion-induced air pollutant (as opposed to other papers that mainly focus on pollutants that are mostly induced by industrial activities).

Our research design is based on sharp variation in the pollution indices across 1,700 neighborhoods and comparing housing values within these neighborhoods over time. We employ daily readings of 39 monitors in Tehran to construct daily distance-weighted pollution indices for each neighborhood. For each transaction, we provide pollution indices that reflect the average level of the air pollution in one week, one month, and three months before the transaction date in the respective neighborhood. Our model captures the effects of pollution on housing prices, rents, and price-rent ratio, after adjustment for housing characteristics, time effects, and time-invariant neighborhoods effects.

Our findings demonstrate that 30 parts-per-billion (ppb) increase of outdoor concentration of Nitrogen Dioxide leads to 3.5 to 5.2 percent decrease in housing prices. Compared to Chay and Greenstone (2005), these estimates signify a lower elasticity of housing values with respect to the level of air pollution. Although these results are closer to the findings of most cross-sectional studies, one might consider that this paper's estimates are mainly derived by the housing market responses in a short-time horizon. We find similar adverse effects in the rental market, albeit the estimates are smaller in magnitude. Our welfare analysis indicates a $11 to $16 billion reduction in housing values in 2011 induced by the significant increase in the level of pollution due to gasoline sanctions. Moreover, an increase in the level of air pollution is associated with a decrease in the average price-rent ratio at the neighborhood level. This result suggests that expectations for future prices make agents in the purchasing market more sensitive to the deterioration of the level of air quality when compared to the rental market outcomes.

Our results also reveal that if we restrict purchasing and rental observations to a shorter time-period where supply is more inelastic, the coefficients of interest will be larger. Also, we examine how housing qualities will interact with the impact of the pollution on housing prices. We find evidence on heterogeneity by size, suggesting that the larger the housing unit becomes, the weaker the impact of the air pollution on housing value will be, with the stronger impact in the rental market. Moreover, to mitigate the impact of sellers' (who have currently occupied the housing unit) distaste for the pollution, we run same baseline regressions on newly built housing units where we still find significant and negative coefficients for the pollutions' impact. Merging rental and purchasing data, we find that there is a substitution from the owners-occupant market to the rental market. Based on our estimates, the number of properties that are first sold, and then offered for lease is significantly higher in more polluted neighborhoods. This pattern is consistent with our base results on the negative association between pollution indices and price-rent ratios.

The rest of the paper is organized as follows. Section 2.2 reviews related literature and the history of sanction. Section 2.3 discusses the data. Section 2.4 presents the empirical model, and section 2.5 outlines results and discussion followed by robustness checks. Section 2.6 concludes.

2.2 Literature Review and Background

2.2.1 Literature Review

Ridker and Henning (1967) is one of the first cross-sectional studies in this literature. Their analysis of 167 neighborhoods in St. Louis shows that Sulfation Level index of the air (SO2, SO3, H2S and H2SO4) explains 1.2 percent of the variation of the median property value in that neighborhood. Many other cross-sectional papers based on hedonic price models showed that a decrease in TSP results in an increase in property value. Smith and Huang (1995) provide a meta-analysis of many of those cross-sectional studies. A growing body of literature also uses the housing market to measure values of non-market amenities (e.g. Davis 2004).

Chay and Greenstone (2005) addressed the cross-sectional studies problems namely the causality issue and the heterogeneous taste for clean air by exploiting 1970 Clean Air Act Amendments (CAAA) as an instrumental variable. Grainger (2013) used similar instrumental variable method to compare the impact of the variation in the level of PM10 on rental versus owner-occupied housing values. He found that only half of the increases in the housing value, caused by improvement in the quality of air, are reflected in the form of higher rents. Both studies are based on variations in pollution and housing prices at the county level over the course of 10 years. A growing body of literature also investigates the local impacts of industrial activities with hazardous impacts or toxic pollutants on the housing market (e.g. Davis 2011; Greenstone and Gallagher 2008; Currie, Davis, Greenstone and Walker 2015). Davis (2011) also found that power plants have smaller impacts on local rents than housing values.

A separate but related literature analyzes the relationship between prices and rents in the housing market. Capozza and Seguin (1996) examined how price-rent ratio has predictive power for expected change in future housing prices. Gyourko et al (2013) discussed the correlation between price-rent ratio and future expected prices. They show that a higher price-rent ratio implies that homeowners are willing to accept lower current yield in the form rent to obtain higher expected capital gain in the future.

There is also a body of the literature on the direct impact of sanctions on economic activities of the targeted country. Some articles (mostly not peer review or in the literature of economics) discussed the economic impacts of recent Iranian Nuclear Sanctions. However, to our knowledge, this is the first paper that measures the indirect impact of the mentioned sanctions, especially their environmental impact.

2.2.2 History of Sanctions

Following the development of nuclear program in Iran, a series of international sanctions were imposed on the country's nuclear enrichment program. In 2006, as the International Atomic Energy Agency (IAEA) reported Iran's suspicious activities and non-compliance with its agreements, the first United Nations Security Council Resolution passed in July the same year. The resolution demanded that Iran suspends all of its enrichment related activities. As the dispute continued, a number of other resolutions were passed by the Security Council that mainly targeted Iranian economic activities.[1] The sanctions were not restricted to the Security Council Resolutions. The United States and the European Union imposed several other sanctions against Iran. Consequently, Iran's oil industry, banking sectors, and international trade activities faced the toughest sanctions in the history of the country.

In July 2010, The Comprehensive Iran Sanctions, Accountability, and Divestment Act was passed by U.S. Congress in order to extend the sanctions against Iran. It mainly targeted Iran's import of gasoline.[2] Although Iran was a major producer of oil, the country imported almost 40 percent of its gasoline and 11 percent of its diesel fuel at the time. In that year, as a preemptive action, Iran began rapidly increasing its fuel

[1] Texts of UN resolutions 1696, 1737, 1747, 1803, 1835, 1929, 1984, 2049 are available. After Iran Deal in July 2015 resolution of 2231 has been passed. It aimed to gradually lift UN sanctions against Iran.
[2] Text of the act is available at https://www.treasury.gov/resource-center/sanctions/Documents/hr2194.pdf.

production capacity by converting petrochemical plants to gasoline production refineries in a two-year plan.[3]

2.2.2.1 Sub-Standard Gasoline and Air Pollution

The plan to replace imported gasoline with domestic refineries' produced gasoline resulted in a dramatic shock to the level of air pollution in large cities of Iran, especially the capital city of Tehran, starting from December 2010.[4] The air quality index of NO_2 increased almost 100 percent compared to its previous annual average. Since then, many experts and even government officials blamed the use of low quality gasoline produced by domestic petrochemical refineries as the main cause of air pollution. Later the Iranian oil minister admitted that the main source of the smog is sub-standard gasoline (The Guardian, 2014).

The main reasons that were mentioned as the link between sub-standard gasoline and air pollution are the low octane number, the higher level of Benzene, and the incomplete combustion. It is known that internal combustion engines are one of the main sources of many major pollutant factors like CO, NO_2, and O_3. According to Environmental Protection Agency (EPA), the most prominent source of Nitrogen Dioxide is emissions from cars and other road vehicles.

Daily data on pollution indices obtained from Tehran Air Quality monitors show the rapid increase in levels of both NO_2 and O_3. This favors the argument of those who blame the excessive presence of hydrocarbons like Benzene and imperfect combustion of refineries-produced gasoline as the main reason of post 2010 air pollution.

In this research, we use the rapid increase of the level of Nitrogen Dioxide as an index for air pollution. Nitrogen Dioxide is considered by many international standards as a major air pollution indicator. For instance, the U.S. EPA's National Ambient Air Quality Standard uses NO_2 as an indicator for a group of Nitrogen Oxides (NO_x). It is

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[3] Masoud Mirkazemi Minister of Petroleum at the time announced that the Iran's gasoline production increase action plan will secure the country against eminent sanctions on fuel import and will turn the nation from an importer to an exporter of gasoline.

[4] https://www.theguardian.com/world/2010/dec/09/iran-tehran-pollution-petrol-sanctions.

classified as one of the six common pollutants along with ground-level Ozone, Particulate Matter (e.g. PM2.5 and PM10), Carbon Monoxide, Lead, and Sulphur Dioxide.

2.2.2.2 Nitrogen Dioxide Health Effects

According to the U.S. EPA, high levels of NO_2 have major negative health effects. A short term exposure of more than half an hour brings adverse respiratory effects on children and healthy adults (Chay and Greenstone 2003). Also, it will deteriorate symptoms of those who have respiratory diseases such as Asthma. Increased visits to emergency and hospitals for respiratory issues are connected with increase in the level of this highly reactive gas (Shima and Motarki 2000). Nitrogen oxides also react with ammonia, moisture, and other compounds to form particles that can penetrate into sensitive lung tissues and cause emphysema, bronchitis and premature death.[5] Nitrogen Oxides are also blamed for photochemical processes that lead to the formation of Nitric Acid (Cleveland 1979). Such Acid causes adverse effects on the ecosystem.

The ground-level Ozone that is created by NO_x can also cause shortness of breath, as well as throat and eye irritation. According to some experts, Ozone can be a serious problem for the environment. Plant scientists blame it for 90 percent of the damage to the vegetation in North America. As it can travel long distances, the urban-produced ground-level Ozone can extend its negative effects onto rural and agricultural areas by reduction in crop yields.[6]

Nitrogen Dioxide is a visible gas by absorbing short-wave length blue light. It has a reddish-brown color when warm and is yellowish brown at cold temperatures (Shima and Motarki 2000). Nitrogen Oxides together with Ozone and other photochemical oxidants are key components responsible for the creation of smog. Therefore, not only will a rise in the level of pollutants like NO_2 and O_3 bring negative health effects that are easily identifiable, but it also creates visible smog that makes it easy for individuals to have a negative evaluation of the air quality in the neighborhood. This fact will support the notion that Nitrogen Dioxide is a proper index both for the relevant level of pollution and for individual perception of the air quality.

[5] https://www3.epa.gov/airquality/nitrogenoxides/index.html
[6] Pollution Prevention and Abatement Handbook, WORLD BANK GROUP, 1998, pp 223-225.

2.3 Data

The housing data are obtained from the Rahbar Informatics Services Company (RISC). The air quality data described below come from Tehran Air Quality Control Agency (TAQCA), which provides detailed data on concentrations of 6 major pollutants including nitrogen dioxide over time for a network of monitors. Data on Universal Transverse Mercator (UTM) coordinates of Tehran's neighborhoods and air quality control (AQC) monitors are provided by Iran Post Company. This section describes the data used in this study.

2.3.1 Housing data

Starting from 2009, Iranian law requires all housing transactions including purchasing and rental to be registered online.[7] Typically, an owner sells or leases her property through real estate agencies. If the seller (owner) and buyer (renter) reach an agreement, the real estate agent will complete specific forms online and record needed information. The information recorded in the system includes personal information of the seller (owner) and the buyer (renter), price or rent, full address of the unit, size, age, zip-code, and date of contract. In the address, the floor number of the unit is also available.

The raw data include 348,645 real and 735,436 purchase observations during the years 2009 – 2014, properly covering the 22 different districts of Tehran. In the final data, we remove transactions for which complete information is not available. All nonresidential transactions are also excluded.[8] We also exclude observations where the district number does not match with the zip-code, possibly due to data-entering mistakes. Moreover, to rule out the effects of outliers, the rent and price per square meter are trimmed at the 1 percent and 99 percent levels. The final sample includes 296,613 rental and 690,226 purchase observations from 2009 to 2014.

Table 2.1 illustrates the distribution of data across districts. As shown in the Table, each of the 22 districts contains several thousand rental and purchase observations, indicating that the data are representative of all neighborhoods. Table 2.2 presents

[7] http://www.iranamlaak.ir/Files/TasvibNameh.aspx

[8] An apartment in this study is defined as a unit that is owned individually, which is very similar to the definition of a condo in the US housing market.

summary statistics for both rental and purchasing data. Data cover around 1,700 neighborhoods (i.e. 5-digit zip-codes). Total number of neighborhoods in Tehran is around 2,700 that include non-residential areas such as parks, university campuses, airports, and military zones. We drop zip codes that contain less than 10 residential transactions within 5 years of the data.

Later, to create a measure of price-rent ratio at the 5-digit zip-code level, we calculate daily average rent and price per square meter for each 5-digit zip-code in both rent and purchasing data, respectively, and merge the two data on the basis of 5-digit zip-code, year, month, and day. Keeping high quality matches using this method the matched data include 79,292 unique 5-digit zip-code-day level observations.

2.3.2 Air Quality Data

The air quality data used in this study are provided by TAQCA, which collects hourly observations on concentration of six major pollutant CO, SO_2, O_3, $PM2.5$, $PM10$, and NO_2 using 39 monitors across Tehran. Figure 2.1 shows that the locations of monitors are well spread throughout the city. We employ UTM coordinates for each 5-digit zip-code and 39 air quality monitors to calculate the pollution level for each neighborhood. Note that, In Iran, 10-digit zip-codes locate an address precisely. A 5-digit zip-code typically contains several blocks so that it can properly determine the neighborhood boundaries.[9]

In order to construct the pollution indices, for each 5-digit zip-code, we pick the daily readings of three closest monitors and calculate the inverse distance weighted-average of them.[10] [11] Then we calculate the average of those daily indices for one week, one month, and three months before the time of each transaction. The logarithms of those averages are used as the value of pollution index variable in the model.

[9] A block is defined as the smallest area surrounded by four streets.

[10] The distance-weighted average for each day includes monitors that were active on that day, as some monitors may be added, repaired, or removed the timeframe.

[11] We also construct another Pollution Index using the daily inverse distance-weighted average of all 39 monitors. The results are similar using either version of the Pollution Index.

2.4 Model

Figure 2.2 shows the average level of Nitrogen Dioxide in ppb in Tehran since 2006. This figure demonstrates that before Autumn of 2010, the average level of Nitrogen Dioxide density in the air of Tehran was around 30 ppb. A few months after the announcement of the start of new gasoline production policy, Tehran's air quality monitors show that the level of NO_2 increased almost to 90 ppb and then stabilized around 60 ppb. That is an increase of almost 100 percent in the level of NO_2 Index compared to before 2010.

The mentioned policy shock, caused by sanctions, provides a quasi-natural experiment to study the effect of air pollution on the housing market. First, the impact of this increase in the level of pollution seems to be independent of other factors that may have impact on the housing market. As shown in Figure 2.2, the level of air pollution before the policy is almost stable, and a few months afterwards we observe an evident jump. Therefore, the air quality index of NO_2 does not seem to follow any specific trend or cycle related to macroeconomic factors. Due to sustainability of the increase in pollution along with implementation of new sets of economic sanctions in 2011 and 2012, it is reasonable to assume that individuals consider this increase as a permanent change. Second, we observe a heterogeneous increase in the level of pollution in different neighborhoods. As it was mentioned, our data are from 39 different monitors in different areas of Tehran. Not all neighborhoods and monitors experienced similar increase in the level of pollution. Hence, the expectation is that the exogenous and heterogeneous increase in the level of pollution has affected transaction values differently across neighborhoods. Figure 2.3 shows trends of NO_2 index recorded from two separate monitors with roughly the same latitude.

Figure 2.4 demonstrates the heterogeneity of pollution index across zip codes. This figure graphs the weekly pollution index for two days, one year before and after the time of the pollution spike, December 2010. The figure only includes zip codes that cover sales on both days. As figure 4 illustrates, the pollution index graph for one year before the shock is fairly flat across zip codes with average of 25 ppb. One year after the peak the heterogeneity of pollution index by zip code is evident with some zip code still meet the EPA standards for NO_2 concentration, while for some others the pollution level is more than twice as the standard level. Figure A1 also presents the monthly average of pollution index across zip codes one year before and after the pollution spike peak, December 2010.

In neighborhoods that experience less increase in the level of pollution, the better air quality will be reflected in housing values in the form of higher real price or rent. In fact, in the short run where supply is reasonably inelastic, price adjustment fully captures the demand responses. Marginal willingness to pay for clean air is not necessarily equivalent in the rental market and purchasing market. In the purchasing market, individuals may consider the environmental amenities more than they do in the rental market. One explanation is buyers take into account the long run exposure to pollution. For instance, families may have concerns about the negative long run impact of such low air quality on their children's health.

To formally examine the association between air pollution and housing prices, we fit the following regression model:

$$\begin{aligned}&(Log\ of\ Price\ Per\ Square\ Meter)_{izt} = \\ &\beta_0+\beta_1 Log\ of\ Pollution\ Index_{zt}+\beta_2 Age_{izt}+\beta_3 Size_{izt}+\beta_4 Age_{izt}^2+\beta_5 Size_{izt}^2 + \\ &\beta_6 Age \times Size_i + Floor\ Indicator + Zipcode\ FE + Year\ FE + Season\ FE + \varepsilon\end{aligned} \qquad (2.1)$$

where i is the index of transaction, z represents the 5-digit zip-code, and t indicates the date of transaction. Equation (2.1) controls for seasonal and year fixed effects to account for seasonal patterns and macroeconomic variations that impact the overall housing market. It also includes 5-digit zip-code fixed effects to captures all time-invariant determinants of housing prices in a neighborhood. We also report richer specifications that include district trends to allow for different over-time adjustment of housing prices in each district. There is a separate municipality in each district, which means public investment on infrastructures and local amenities can follow different trend across districts.

To consider the impact of outliers, we utilized logged value of housing prices, rents and pollution indices in our model. We tried other specifications including linear and log-linear model and we got economically and statistically significant results too. However, residuals distribution of the log-log specification look more normal compared to log-linear and linear model. In addition, log-log specification lead to a higher value of R-squared compared to log-linear specification. We also applied Box-Cox lambda transformation to our basic sets of regressions and get small lambda between 0.17-0.25. The null hypothesis of lambda is rejected for all economically sensible transformations of lambda equal to 0, 1 and -1. However, it does not make economic sense to insist on maximizing the log-likelihood score and use the best fitting transformation parameter of 0.17. Qualitatively, the number is closer to zero. Therefore, it seems convincing to use log-log transformation while we also get significant results if we use other forms of specification.

This model follows a difference-in-difference strategy that relies on a comparison of housing transaction prices in less polluted and more polluted neighborhoods. The constructed time-variant pollution index variable captures the heterogeneous variation of pollution across neighborhoods. Therefore, our coefficient of interest in equation (2.1) is β_1. It reflects the impact of different level of pollution across neighborhoods on housing transactions prices. As both the dependent and the explanatory variable are in logarithm form, the β_1 yields the price elasticity of the air pollution.

We also run the same regression in the rental market to compare the difference of the impact in this market versus the purchasing market. In doing so, we use the logarithm of annual real rent per square meter for each transaction as the dependent variable. Moreover, we construct a panel data by merging the rental and purchasing data and run panel regressions with the log of neighborhoods' averages of price-rent ratio as the dependent variable.

2.5 Results

2.5.1 Baseline Results

Table 2.3 presents the baseline results from 8 regressions using equation (2.1). The dependent variable is natural logarithm of real price per-square meter and the parameter of interest is the log of pollution index. These regressions are divided into 4 groups where we use different time periods before the transaction to calculate distance-weighted pollution index for each group. All regressions control for age, size, and floor of the housing unit, along with zip-code, year, and seasonal fixed effects. The even-numbered columns also include district trends. The result of the baseline regression for the purchasing market is based on approximately 650,000 transactions over more than 5 years. Standard errors are adjusted for 1710 clusters based on the notion of 5-digit zip-code. For all regressions in this section, the sample excludes observations within two months before and after the pollution spike (Dec 2010) to better capture the heterogeneity across zip codes. Results including those four months are available in Appendix Table B1 to B3.

As reported in Table 2.3, all coefficients of pollution indices are highly significant and negative. These results demonstrate the elasticity of (negative) 0.035 to 0.052 for house prices with respect to the NO_2 pollutant factor. In other words, 30 units increase in NO_2 pollutant index (almost equal to the average increase in Tehran) will result in 3 to 6 percent decrease in housing values. From Table 3, we observe an increase in the impact as the time duration of pollution index changes from one week in column (1) to 3 months in column (3). The 95 percent confidence intervals for column (1) and (2) do not overlap with the 95 percent confidence interval in column (3). This pattern suggests that agents will demonstrate a higher level of distaste for air pollution if the air quality deterioration is more persistent in a given neighborhood prior to the time of transaction.

Table 2.4 presents results of regressions based on equation (2.1), using the log of real rental prices as the dependent variable. The coefficients' are smaller in magnitude compared to the results for the purchasing market in Table 2.3. One explanation for these different impacts between the purchasing market and the rental market might be due to long-term concerns in buying versus renting a property. In other words, buyers demonstrate larger willingness to pay for the clean air compared to tenants as they probably plan to stay longer in that property. Moreover, one might consider that buying a property is a form of investment. Hence, the expectation of future prices might play an important role in purchasing decision making. Next, we explore this possibility.

In Table 2.5, we construct a panel data using daily average prices and rents in both the purchasing and the rental market for each 5-digit zip-code. The dependent variable is the ratio of daily 5-digit zip-code average price to rent. Similar to previous analyses, the variable of interest is the pollution index here. Following the baseline regression, we control for average age, size, and other features for each zip code. The panel regression also controls for both time and 5-digit zip-code fixed effects.

The estimates from Table 2.5 show that 1 percent increase in the level of air pollution is associated with a 0.019 to 0.028 percent decrease in the price-rent ratio. Controlling for localized trends, presented in even-numbered columns, does not change the results. Our estimates suggest that in more polluted neighborhoods, individuals might expect lower increase in the housing prices over the long run compared to relatively cleaner neighborhoods. This is consistent with the findings of Capozza and Seguin (1996) and Gyourko et al (2013) that show higher price-rent ratio in the housing market is associated with higher expected capital gain. It is worth noting that this result implies that not only pollution affects the current value of housing, but also it negatively affects the expectation of future capital gain.

2.5.2 Alternative Specifications and Robustness Checks

In the short run, housing supply is relatively inelastic, thus, the full welfare effects of pollution are exclusively captured by adjustment in prices (rents). On the other hand, over the long run, some of the welfare effects can be captured by quantity adjustment as supply becomes more elastic. To attenuate the effects of quantity responses, Table 2.6 and 2.7 presents results from equation 1 that restricts purchasing and rental observations to within 20 months of the pollution spike, December 2010.[12] Our estimates for the pollution indices in the short run for both rental and owner-occupied market are larger, but consistent with the base results.[13] Over the shorter period of time with arguably more inelastic supply, house price capitalization explains the full welfare effects so that the point estimates are larger.

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[12] Our data start from March 2009, 20 months before December 2010.

[13] The 95 percent confidence interval for *1 week* and *1 month pollution index* in Table 6 do not overlap those associated with the counterpart estimates in Table 3.

Taking advantage of observable characteristics of properties in our data, we also examine how variation in quality of houses can affect our baseline estimates. The housing characteristics we explore are size and age of properties. Table 2.8 presents the results of this investigation for the owner-occupied market. Regression models are based on the augmented versions of equation 1 that include an additional term for the interaction of the pollution indices with each of the above characteristics. We then estimate another regression model that includes both interaction terms. The paramter estimates associated with *Pollution Index×Property Age* across different specifications are almost all insignificant, indicating that there is no evidence of heterogeneity by property age. On the other hand, we find evidence on heterogeneity by property size. Columns (2), (5), and (8) that include an interaction of *Pollution Index* with *size*, imply that 100 square meter increase in the size of a property reduces the effects of pollution on housing prices by half. A possible explanation for this result is that larger properties are arguably in better quality and have higher level of additions, appliances, and other amenities. These amenities mitigate the adverse effects of air pollution.

Table 2.9 presents respective estimates for the rental market. Similar to estimates in Table 2.8, we only find evidence on heterogeneity with respect to size. Point estimates for the interaction of size and pollution is larger in the rental market. Under the assumption that size is a reasonable proxy for quality of housing, it is possible that at the time of transaction quality of housing is more substitutable with air quality for renters as opposed to buyers. This is to say, renters behave more like short term consumers of housing, while buyers behave more like long-term investors. Moreover, the coefficient estimates of *Pollution Index* in Table 2.9 are significantly smaller than their counterparts in Table 2.8, which coincides with our explanation for the baseline results.

One might expect that in highly polluted neighborhoods sellers with an extreme aversion to air pollution are willing to sell their properties at discount value to move out sooner. In that case the price response to the pollution may be partially driven by sellers distaste for pollution. To alleviate this concern, we rerun the specification 1, focusing only on new constructions. The advantage of this approach is that seller of a new construction is plausibly indifferent to the level of air pollution in the neighborhood of the given property as she probably does not reside there.

Table 2.10 reports the pollution index estimates for subsample of new constructions in the owner-occupied market. Point estimates are smaller in magnitude compared to estimates in Table 2.3, ranging from 0.031 to 0.045. This result suggests that sellers taste for air pollution might have weak influence on our estimates of local responses to the air pollution. However, the 95 percent confidence intervals of estimates for the sample of new constructions overlap those associated with the estimates for the full sample.

Thus far, all the evidence on the effects of air pollution on housing prices and rents use the distance-weighted average for pollution indices. Here we explore an alternative estimation that uses non-distance weighted emissions of Nitrogen Dioxide for the pollution indices. In particular, we construct a one-mile radius circle around each monitor and assign the average of daily readings of Nitrogen Dioxide concentration from a given monitor to the housing transactions that lie within the given circle. Note that if a housing transaction is close to more than one monitor, the pollution index is the average of readings from all close monitors.

Table 2.11 reports the results for the alternative estimations. The regression models are based on equation 1 and include year, seasonal, and 5-digit zip-code fixed effects. The estimates indicate that 100 percent increase in the level of outdoor Nitrogen Dioxide is associated with a 1.8 to 3.1 percent reduction in housing values. Despite the fact that we drop roughly 80 percent of our observations, all estimates are still strongly significant, albeit they are smaller in magnitude than the baseline results. Table B.3 presents the results for half-mile circles to check for the sensitivity of these results to the choice of distance. We find that our results are robust to the choice of distance. Using similar specification for the rental market lead to insignificant coefficients as only 12 to 16 percent of rental observations survive.

2.5.3 Effects of Pollution on Buyers Decision on Property Usage

In this section, we present evidence indicating that the pollution may change the usage of purchased properties from owner occupied to non-owner occupied. In fact, buyers of owner-occupied properties in highly polluted areas can avoid pollution by turning them to rental properties. Moreover, based on our findings of negative correlation between price-rent ratio and the level of pollution, conditional on property's price, the current yield (rent) on housing investment is more likely to be higher in more polluted neighborhoods. Therefore, the prediction is that the number of properties that are first sold, and then offered for lease is significantly higher in more polluted neighborhoods.

To check for the validity of this prediction, we merge the purchased data with the rental data on the basis of 10-digit zip code, floor-level, and district to determine which properties appear in both datasets.[14] Among those, we tag properties that the sales date is before the rent date. There are 55,532 properties for which buyers have decided to offer them to lease, which we refer to as "bought and rent" properties. We formally investigate the impact of air pollution on the probability of the substitution of a property from being owner occupied to rental using the following logit regression:

$$Y_{it} = \beta_0+\beta_1 Log\ of\ Pollution\ Index_{zt}+\beta_2 Age_{izt}+\beta_3 Size_{izt}+\beta_4 Age_{izt}^2+\beta_5 Size_{izt}^2+ \beta_6 Age \times Size_i + Floor\ Indicator + Zipcode\ FE + Year\ FE + Season\ FE + \varepsilon \quad (2.2)$$

where Y_{it} is an indicator equal to one if a property is "bought and rent" and zero otherwise, and t is the date of purchasing transaction. The independent variables are the same as equation (2.1). Table 2.12 reports the results. As predicted, we find that the probability of switching the usage of a property from owner occupied to non-owner occupied is significantly higher in more polluted neighborhoods. One hundred percent increase in the concentration of outdoor Nitrogen Dioxide is associated with approximately 10 percent increase in the odds of renting a purchased property.

2.5.4 Costs of the Sanction

All of our analyses show that air pollution has a causal effect on housing prices and rents in Tehran. Air pollution deterioration in Tehran and its subsequent consequences can be considered as one of the indirect impacts of the sanctions. In this section, we use the results from Table 2.3 to analyze the extent to which the cost of the sanctions that is associated with the adverse effect of pollution on the housing market.

[14] We keep those matched observations that recorded size in purchasing data matches the one in the rental data.

The above hedonic approach leads to estimation of average marginal willingness to pay (MWTP) for 1-unit increase in the pollution index. However, to measure the welfare consequences of sanction-induced non-marginal increase in air pollution, we need to identify the MWTP function (Chay and Greenstone, 2005). Therefore, we calculate the willingness to pay (WTP) for pollution under the assumption of linear and homogeneous preferences, which means constant MWTP.

The National Population and Housing Census (NPHC) data from Iran Statistics Center show that in 2011 about 2.6 million residential units were in Tehran, with a total accumulative size of approximately 228 million square meters. As mentioned before, Tehran's residents experienced an average of 30 units increase of Nitrogen Dixoide index in the year following the implementation of the gasoline sanction (2011), with the capitalization rate of 3.5 to 5.2 percent declines in their property values. Since the nominal price per square meter in 2011 was 20 million Rials ($1,300 in 2011 dollars), means approximate 700 to 1055 thousands Rials ($48 to $72 in 2011 dollars) reduction per square meter of housing.15 These numbers imply that the dramatic increase in air pollution due to sanctions is associated with approximately $11 to $16 billion dollars loss in the owner-occupied market. The cost will be larger if we were to include all other cities, especially large metropolitan regions of Iran.

2.6 Conclusions

This paper exploits a natural experiment to examine the economic value of air quality and infer the indirect costs of sanctions. The exogenous and heterogeneous increase in the level of NO_2 combined with rich individual housing transactions data provide a set-up that mitigates econometrics concerns. One contribution of this research is that with this unique structure we examine agents' responses to the variation in the level of the air quality in both purchasing and rental market within one city in the short run.

We showed that air quality has a considerable impact on housing values. In fact, the dramatic increase in the level of air pollution in Tehran in 2010 is associated with an average of 3.5 to 5.2 percent decrease in housing prices. We also found significant

[15] IRR-USD exchange change rate is approximately 15,000 for 2011.

reduction in rental prices, though the magnitudes were smaller. The panel analysis also reveals that more polluted neighborhoods are associated with lower price-rent ratio, that implies the impact of air pollution on the expectation of future capital gain. This study also provides evidence on marginal substitution between two markets. We find that the increase in the level of air pollution increases the odds of renting a purchased property.

This paper is also the first to use hedonic approach to study one aspect of the indirect and environmental costs of sanctions. Based on a simple cost analysis, this incidence is responsible for the loss of 11 to 16 billion of 2011 dollars in the housing market only in Tehran. As these sorts of sanctions and restrictions are still common throughout the world, our paper can provide a better perspective of total welfare consequences of these policies.

Our finding of different responses from rental and owner-occupant properties might be of interest for future studies that attempt to separate effects of policies on housing consumption and investments. Another extension of this paper is to look at the health impact of sanction-induced increase in air pollution, namely on child birth-weight or mortality of children and the elderly.

2.7 Figures and Tables

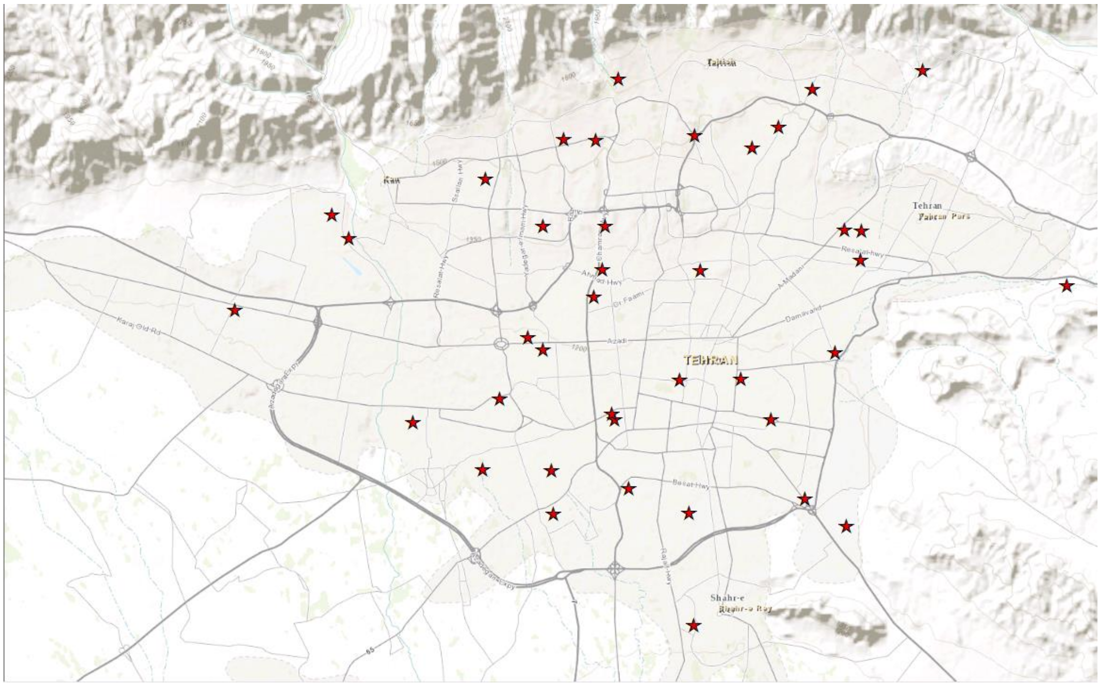

Figure 2.1: Distribution of Monitors across Tehran

Notes: This figure illustrates the location of 39 monitors across Tehran.

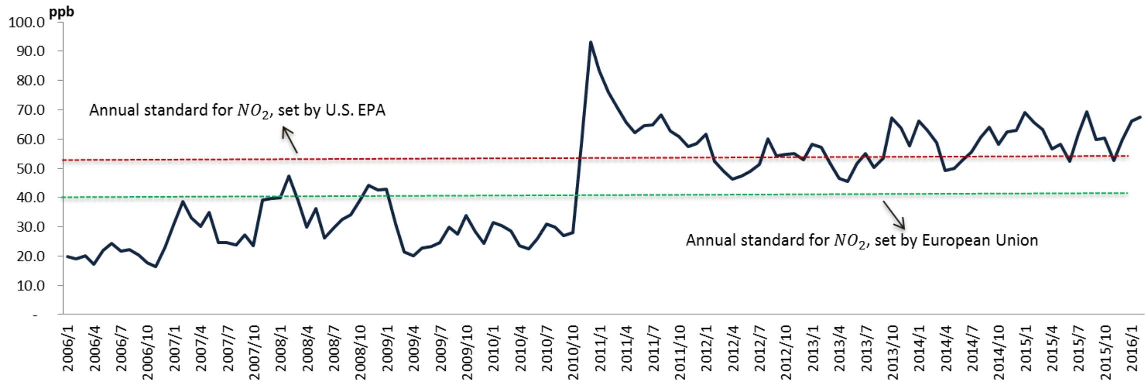

Figure 2.2: Concentration of Nitrogen Dioxide (NO_2) in Tehran

Notes: This figure shows the average quarterly level of NO_2 measured in parts per billion based on daily readings of Tehran Air Quality monitors for years 2006 to 2016. The Comprehensive Iran Sanctions, Accountability, and Divestment Act was passed by U.S. Congress in July 2010 to restrict Iran's import of gasoline. The red dashed line shows the annual standard for NO_2 set by U.S. EPA. The green dashed line shows the annual standard for NO_2 set by the European Union.

Figure 2.3: Concentration of Nitrogen Dioxide across Tehran

Notes: This figure shows the heterogeneous variations in level of Nitrogen Dioxide between two districts in Tehran for years 2009 to 2014. Tehran is divided into 22 municipal regions. District 4, illustrated by the solid line, is located at the west side of Tehran. District 22, illustrated by the dashed line, is located at the east side of Tehran. Both districts are considered to be resided by urban middle class residents.

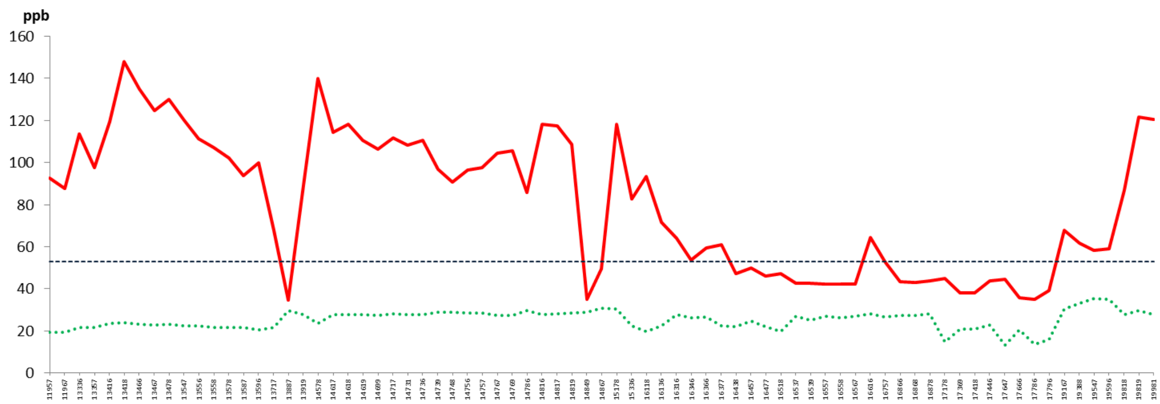

Figure 2.4: The Level of Pollution Index across Neighborhoods

Notes: This figure shows the heterogeneous variations in level of distance-weighted pollution index across zip codes for two days; one year before (12/15/2009) and after (12/15/2011) the peak of the sanction-induced pollution jump. The figure includes zip code that contain sales record for both days. Dashed line shows the annual standard for NO_2 set by U.S. EPA.

Table 2.1: Distribution of Properties across Districts

District	Owner-Occupant Market	Rental-Housing Market
1	24,607	11,591
2	57,938	34,299
3	27,459	14,980
4	73,681	29,136
5	93,777	43,552
6	25,737	15,803
7	37,509	19,522
8	42,408	18,248
9	13,168	5,459
10	40,754	17,782
11	32,217	12,191
12	21,263	8,641
13	24,467	10,470
14	42,618	15,338
15	37,494	11,614
16	14,632	4,660
17	16,931	3,508
18	24,522	6,462
19	9,439	2,704
20	10,747	3,212
21	13,430	4,140
22	5,428	3,301
Total	690,226	296,613

Notes: This table shows the number of housing transactions in each district for years 2009 -2014. Column (2) presents number of purchasing transactions. Column (3) presents number of rental transactions.

Table 2.2: Summary Statistics

Variables	Owner-Occupant Market	Rental-Housing Market
Mean Price per Square Meter (000 Rials)	43,654	
Mean Rent per Square Meter (000 Rials)		3,130
Median Size (Square Meter)	72	71
Median Age (Year)	5	9
Number of Neighborhoods (5-digit zip codes)	1,710	1,699
Total Observations	690,217	296,613

Notes: This Table presents the summary statistics for sample of residential properties transactions for years 2009 to 2014. Rent and price values are deflated to reflect year 2015 prices using the Statistical Centre of Iran Housing Price Index. Each 5-digit zip code in the sample represents one neighborhood.

Table 2.3: The Impact of Air Pollution on Housing Prices

	1 Week		1 Month		3 Months	
	(1)	(2)	(3)	(4)	(5)	(6)
Pollution Index	-0.0349***	-0.0349***	-0.0416***	-0.0416***	-0.0520***	-0.0520***
	(0.00191)	(0.00191)	(0.00219)	(0.00219)	(0.00241)	(0.00240)
Year Fixed Effects	X	X	X	X	X	X
5-Digit Zip-code Fixed Effects	X	X	X	X	X	X
Seasonal Fixed Effects	X	X	X	X	X	X
District Trends		X		X		X
Observations	648,776	648,776	648,606	648,606	647,000	647,000
R-squared	0.619	0.620	0.619	0.620	0.620	0.621

Notes: This table presents the impact of air pollution on housing prices for purchased transactions from years 2009 to 2014. Observations within 2 months after and before the pollution spike (Dec 2010) are excluded. All regressions are based on equation (2.1). The dependent variable is log of real price per-square meter. Pollution index is the daily inverse distance weighted-average of the readings of three closest monitors' measures of $\boldsymbol{NO_2}$ for each zipcode. For columns (1) and (2), the Pollution Index is average of those daily pollution indices for one week before the time of each transaction. For columns (3) and (4), the Pollution Index is average of those daily pollution indices for one month before the time of each transaction. For columns (5) and (6), the Pollution Index is average of those daily pollution indices for three months before the time of each transaction. All specifications include 5-digit zip-code, year, and seasonal fixed effects. The even-numbered columns also include region trend fixed effects. Standard errors in all columns are clustered by 5-digit zip-code and stars indicate statistical significance level. * = 10 percent level, ** = 5 percent level. *** = 1 percent level.

Table 2.4: The Impact of Air Pollution on Rental Prices

	1 Week		1 Month		3 Months	
	(1)	(2)	(3)	(4)	(5)	(6)
Pollution Index	-0.00685**	-0.00676**	-0.00895***	-0.00886***	-0.0136***	-0.0134***
	(0.00271)	(0.00270)	(0.00312)	(0.00311)	(0.00354)	(0.00353)
Year Fixed Effects	X	X	X	X	X	X
5-Digit Zip-code Fixed Effects	X	X	X	X	X	X
Seasonal Fixed Effects	X	X	X	X	X	X
District Trends		X		X		X
Observations	293,605	293,605	293,432	293,432	292,355	292,355
R-squared	0.408	0.411	0.408	0.411	0.408	0.411

Notes: This table presents the impact of air pollution on rental prices for rental transactions from years 2009 to 2014. Observations within 2 months after and before the pollution spike (Dec 2010) are excluded. All regressions are based on equation (2.1). The dependent variable is log of total annual real rent per-square-meter. Pollution index is the daily inverse distance weighted-average of the readings of three closest monitors' measures of NO_2 for each zipcode. For columns (1) and (2), the Pollution Index is average of those daily pollution indices for one week before the time of each transaction. For columns (3) and (4), the Pollution Index is average of those daily pollution indices for one month before the time of each transaction. For columns (5) and (6), the Pollution Index is average of those daily pollution indices for three months before the time of each transaction. All specifications include 5-digit zip-code, year, and seasonal fixed effects. The even-numbered columns also include region trend fixed effects. Standard errors in all columns are clustered by 5-digit zip-code and stars indicate statistical significance level. * = 10 percent level, ** = 5 percent level. *** = 1 percent level.

Table 2.5: The Impact of Air Pollution on Price-Rent Ratio

	1 Week		1 Month		3 Months	
	(1)	(2)	(3)	(4)	(5)	(6)
Pollution Index	-0.0194***	-0.0192***	-0.0235***	-0.0233***	-0.0282***	-0.0282***
	(0.00557)	(0.00556)	(0.00649)	(0.00647)	(0.00732)	(0.00730)
Year Fixed Effects	X	X	X	X	X	X
5-Digit Zip-code Fixed Effects	X	X	X	X	X	X
Seasonal Fixed Effects	X	X	X	X	X	X
District Trends		X		X		X
Observations	78,365	78,365	78,362	78,362	78,329	78,329
R-squared	0.156	0.158	0.156	0.158	0.156	0.158

Notes: This table presents the impact of air pollution on price-rent ratio from years 2009 to 2014. All regressions are based on equation (2.1). Observations within 2 months after and before the pollution spike (Dec 2010) are excluded. The dependent variable is zip code-day average price divided by average rent. Pollution index is the daily inverse distance weighted-average of the readings of three closest monitors' measures of $\boldsymbol{NO_2}$ for each zipcode. For columns (1) and (2), the Pollution Index is average of those daily pollution indices for one week before the time of each transaction. For columns (3) and (4), the Pollution Index is average of those daily pollution indices for one month before the time of each transaction. For columns (5) and (6), the Pollution Index is average of those daily pollution indices for three months before the time of each transaction. All specifications include 5-digit zip-code, year, and seasonal fixed effects. The even-numbered columns also include region trend fixed effects. Standard errors in all columns are clustered by 5-digit zip-code and stars indicate statistical significance level. * = 10 percent level, ** = 5 percent level. *** = 1 percent level.

Table 2.6: The Impact of Air Pollution on Housing Prices within 20 Months of the Pollution Spike

	1 Week		1 Month		3 Months	
	(1)	(2)	(3)	(4)	(5)	(6)
Pollution Index	-0.0477***	-0.0478***	-0.0531***	-0.0531***	-0.0573***	-0.0574***
	(0.00218)	(0.00217)	(0.00240)	(0.00238)	(0.00249)	(0.00247)
Year Fixed Effects	X	X	X	X	X	X
5-Digit Zip-code Fixed Effects	X	X	X	X	X	X
Seasonal Fixed Effects	X	X	X	X	X	X
District Trends		X		X		X
Observations	353,645	353,645	353,475	353,475	351,869	351,869
R-squared	0.653	0.654	0.653	0.654	0.654	0.655

Notes: This table presents the impact of air pollution on housing prices for purchased transactions from years 2009 to 2011. Observations within 2 months after and before the pollution spike (Dec 2010) are excluded. All regressions are based on equation (2.1). The dependent variable is log of real price per-square meter. Pollution index is the daily inverse distance weighted-average of the readings of three closest monitors' measures of $\boldsymbol{NO_2}$ for each zipcode. For columns (1) and (2), the Pollution Index is average of those daily pollution indices for one week before the time of each transaction. For columns (3) and (4), the Pollution Index is average of those daily pollution indices for one month before the time of each transaction. For columns (5) and (6), the Pollution Index is average of those daily pollution indices for three months before the time of each transaction. All specifications include 5-digit zip-code, year, and seasonal fixed effects. The even-numbered columns also include region trend fixed effects. Standard errors in all columns are clustered by 5-digit zip-code and stars indicate statistical significance level. * = 10 percent level, ** = 5 percent level. *** = 1 percent level.

Table 2.7: The Impact of Air Pollution on Rental Prices 20 Months of the Pollution Spike

	1 Week		1 Month		3 Months	
	(1)	(2)	(3)	(4)	(5)	(6)
Pollution Index	-0.0113**	-0.0113**	-0.0167***	-0.0168***	-0.0212***	-0.0212***
	(0.00451)	(0.00449)	(0.00515)	(0.00512)	(0.00571)	(0.00568)
Year Fixed Effects	X	X	X	X	X	X
5-Digit Zip-code Fixed Effects	X	X	X	X	X	X
Seasonal Fixed Effects	X	X	X	X	X	X
District Trends		X		X		X
Observations	96,542	96,542	96,369	96,369	95,292	95,292
R-squared	0.418	0.420	0.419	0.420	0.420	0.421

Notes: This table presents the impact of air pollution on rental prices for rental transactions from years 2009 to 2014. Observations within 2 months after and before the pollution spike (Dec 2010) are excluded. All regressions are based on equation (2.1). The dependent variable is log of total annual real rent per-square-meter. Pollution index is the daily inverse distance weighted-average of the readings of three closest monitors' measures of $\boldsymbol{NO_2}$ for each zipcode. For columns (1) and (2), the Pollution Index is average of those daily pollution indices for one week before the time of each transaction. For columns (3) and (4), the Pollution Index is average of those daily pollution indices for one month before the time of each transaction. For columns (5) and (6), the Pollution Index is average of those daily pollution indices for three months before the time of each transaction. All specifications include 5-digit zip-code, year, and seasonal fixed effects. The even-numbered columns also include region trend fixed effects. Standard errors in all columns are clustered by 5-digit zip-code and stars indicate statistical significance level. * = 10 percent level, ** = 5 percent level. *** = 1 percent level.

Table 2.8: Responses to Air Pollution by Size and Age (Owner-occupied Market)

	1 Week			1 Month			3 Months		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pollution Index	-0.0369***	-0.0717***	-0.0720***	-0.0434***	-0.0814***	-0.0814***	-0.0530***	-0.0915***	-0.0909***
	(0.00217)	(0.00459)	(0.00459)	(0.00248)	(0.00498)	(0.00497)	(0.00273)	(0.00524)	(0.00524)
Pollution Index × Property Age	0.000268*		5.65e-05	0.000241		6.36e-06	0.000133		-0.000108
	(0.000160)		(0.000163)	(0.000166)		(0.000169)	(0.000173)		(0.000176)
Pollution Index × Property Size		0.000467***	0.000466***		0.000506***	0.000506***		0.000500***	0.000503***
		(5.59e-05)	(5.65e-05)		(6.00e-05)	(6.06e-05)		(6.14e-05)	(6.22e-05)
Year Fixed Effects	X	X	X	X	X	X	X	X	X
5-Digit Zip-code Fixed Effects	X	X	X	X	X	X	X	X	X
Seasonal Fixed Effects	X	X	X	X	X	X	X	X	X
Observations	648,776	648,776	648,776	648,606	648,606	648,606	647,000	647,000	647,000
R-squared	0.619	0.619	0.619	0.619	0.620	0.620	0.620	0.620	0.620

Notes: This table presents the impact of air pollution on housing prices for purchased transactions from years 2009 to 2014. Observations within 2 months after and before the pollution spike (Dec 2010) are excluded. Columns 1, 4, 7, and 10 report estimates from a version of equation (2.1) that includes interaction of pollution index and property age. Columns 2, 5, 8, and 11 report estimates from a version of equation (2.1) that includes interaction of pollution index and size. Columns 3, 6, 9, and 12 report estimates from a version of equation (2.1) that includes both interaction terms. The dependent variable is log of real price per-square meter. Pollution index is the daily inverse distance weighted-average of the readings of three closest monitors' measures of $\boldsymbol{NO_2}$ for each zipcode. For columns (1), (2), and (3), the Pollution Index is average of those daily pollution indices for one week before the time of each transaction. For columns (4), (5), and (6), the Pollution Index is average of those daily pollution indices for one month before the time of each transaction. For columns (7), (8), and (9), the Pollution Index is average of those daily pollution indices for three months before the time of each transaction. All specifications include 5-digit zip-code, year, and seasonal fixed effects. Standard errors in all columns are clustered by 5-digit zip-code and stars indicate statistical significance level. * = 10 percent level, ** = 5 percent level. *** = 1 percent level.

Table 2.9: Responses to Air Pollution by Size and Age (Rental Market)

	1 Week			1 Month			3 Months		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pollution Index	-0.00804*	-0.0546***	-0.0534***	-0.0113**	-0.0612***	-0.0606***	-0.0197***	-0.0609***	-0.0633***
	(0.00417)	(0.00663)	(0.00695)	(0.00458)	(0.00717)	(0.00747)	(0.00520)	(0.00786)	(0.00820)
Pollution Index × Property Age	0.000107		-0.000151	0.000211		-7.97e-05	0.000549*		0.000292
	(0.000271)		(0.000276)	(0.000289)		(0.000295)	(0.000320)		(0.000327)
Pollution Index × Property Size		0.000616***	0.000622***		0.000675***	0.000678***		0.000609***	0.000598***
		(7.82e-05)	(7.94e-05)		(8.32e-05)	(8.47e-05)		(8.93e-05)	(9.11e-05)
Year Fixed Effects	X	X	X	X	X	X	X	X	X
5-Digit Zip-code Fixed Effects	X	X	X	X	X	X	X	X	X
Seasonal Fixed Effects	X	X	X	X	X	X	X	X	X
Observations	293,605	293,605	293,605	293,432	293,432	293,432	292,355	292,355	292,355
R-squared	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.409	0.409

Notes: This table presents the impact of air pollution on housing prices for rental transactions from years 2009 to 2014. Observations within 2 months after and before the pollution spike (Dec 2010) are excluded. Columns 1, 4, 7, and 10 report estimates from a version of equation (2.1) that includes interaction of pollution index and property age. Columns 2, 5, 8, and 11 report estimates from a version of equation (2.1) that includes interaction of pollution index and size. Columns 3, 6, 9, and 12 report estimates from a version of equation (2.1) that includes both interaction terms. The dependent variable is log of real price per-square meter. Pollution index is the daily inverse distance weighted-average of the readings of three closest monitors' measures of NO_2 for each zipcode. For columns (1), (2), and (3), the Pollution Index is average of those daily pollution indices for one week before the time of each transaction. For columns (4), (5), and (6), the Pollution Index is average of those daily pollution indices for one month before the time of each transaction. For columns (7), (8), and (9), the Pollution Index is average of those daily pollution indices for three months before the time of each transaction. All specifications include 5-digit zip-code, year, and seasonal fixed effects. Standard errors in all columns are clustered by 5-digit zip-code and stars indicate statistical significance level. * = 10 percent level, ** = 5 percent level. *** = 1 percent level.

Table 2.10: The Impact of Air Pollution on Housing Prices (New Constructions)

	1 Week		1 Month		3 Months	
	(1)	(2)	(3)	(4)	(5)	(6)
Pollution Index	-0.0308***	-0.0307***	-0.0356***	-0.0355***	-0.0452***	-0.0451***
	(0.00364)	(0.00363)	(0.00412)	(0.00412)	(0.00429)	(0.00428)
Year Fixed Effects	X	X	X	X	X	X
5-Digit Zip-code Fixed Effects	X	X	X	X	X	X
Seasonal Fixed Effects	X	X	X	X	X	X
District Trends		X		X		X
Observations	116,051	116,051	116,017	116,017	115,783	115,783
R-squared	0.656	0.656	0.656	0.656	0.656	0.657

Notes: This table presents the impact of air pollution on housing prices for new construction transactions from years 2009 to 2014. Observations within 2 months after and before the pollution spike (Dec 2010) are excluded. All regressions are based on equation (2.1). The dependent variable is log of real price per-square meter. Pollution index is the daily inverse distance weighted-average of the readings of three closest monitors' measures of $\boldsymbol{NO_2}$ for each zipcode. For columns (1) and (2), the Pollution Index is average of those daily pollution indices for one week before the time of each transaction. For columns (3) and (4), the Pollution Index is average of those daily pollution indices for one month before the time of each transaction. For columns (5) and (6), the Pollution Index is average of those daily pollution indices for three months before the time of each transaction. All specifications include 5-digit zip-code, year, and seasonal fixed effects. The even-numbered columns also include region trend fixed effects. Standard errors in all columns are clustered by 5-digit zip-code and stars indicate statistical significance level. * = 10 percent level, ** = 5 percent level. *** = 1 percent level.

Table 2.11: The Impact of Air Pollution on Housing Prices Using Alternative Pollution Index

	1 Week		1 Month		3 Months	
	(1)	(2)	(3)	(4)	(5)	(6)
Pollution Index	-0.0178***	-0.0178***	-0.0231***	-0.0230***	-0.0314***	-0.0313***
	(0.00366)	(0.00366)	(0.00400)	(0.00400)	(0.00400)	(0.00400)
Year Fixed Effects	X	X	X	X	X	X
5-Digit Zip-code Fixed Effects	X	X	X	X	X	X
Seasonal Fixed Effects	X	X	X	X	X	X
District Trends		X		X		X
Observations	130,009	130,009	129,995	129,995	129,836	129,836
R-squared	0.607	0.608	0.607	0.608	0.608	0.608

Notes: This table presents the impact of air pollution on housing prices from years 2009 to 2014 for the sample of purchased properties that are located within 1 mile of at least one monitor. Observations within 2 months after and before the pollution spike (Dec 2010) are also excluded. All regressions are based on equation (2.1). The dependent variable is log of real price per-square meter. For each observation, the pollution index is the daily reading of nitrogen dioxide concentration from a monitor that the housing observation lies within the one mile of the given monitor. If a housing observation is close to more than one monitor, the pollution index is the average of readings from all close monitors. For columns (1) and (2), the Pollution Index is average of those daily pollution indices for one week before the time of each transaction. For columns (3) and (4), the Pollution Index is average of those daily pollution indices for one month before the time of each transaction. For columns (5) and (6), the Pollution Index is average of those daily pollution indices for three months before the time of each transaction. All specifications include 5-digit zip-code, year, and seasonal fixed effects. The even-numbered columns also include region trend fixed effects. Standard errors in all columns are clustered by 5-digit zip-code and stars indicate statistical significance level. * = 10 percent level, ** = 5 percent level. *** = 1 percent level.

Table 2.12: The Impact of Air Pollution on Property Usage

	1 Week	1 Month	3 Months
	(1)	(2)	(3)
Pollution Index	0.0944***	0.125***	0.147***
	(0.0246)	(0.0278)	(0.0302)
Year Fixed Effects	X	X	X
5-Digit Zip-code Fixed Effects	X	X	X
Seasonal Fixed Effects	X	X	X
Observations	648,764	648,594	646,988

Notes: This table presents the impact of air pollution on probability of switching a owner-occupied property to non-owner-occupied property by buyers. The sample covers all purchasing transactions from years 2009 to 2014, excluding observations within 2 months after and before the pollution spike (Dec 2010). All logit regressions are based on equation (2.2). The dependent variable is an indicator equal to one if a purchased property turns to rental property, zero for all other cases. Pollution index is the daily inverse distance weighted-average of the readings of three closest monitors' measures of $\boldsymbol{NO_2}$ for each zip-code. The Pollution Index is average of those daily pollution indices for one week, one month, and three months before the time of each transaction for columns (1), (2), and (3), respectively. All specifications include 5-digit zip-code, seasonal, and region-by-year fixed effects. Standard errors in all columns are clustered by 5-digit zip-code and stars indicate statistical significance level. * = 10 percent level, ** = 5 percent level. *** = 1 percent level.

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APPENDIX A FOR CHAPTER 1

A.1 Proof of equation (1.5) in chapter 1

In the absence of the size kink, Derivation of equation (2) with respect to size for marginal bunching person HA yields:

$$k_H{}^{\frac{1}{1-\delta}} = \frac{s^* + \Delta s}{[\delta R_0(1- \tau_0)]^{\delta/_{1-\delta}}} \tag{20}$$

Since marginal bunching person HA is indifferent between s^* and s^I, so $\pi^*= \pi^I$:

$$\pi^* = R_0 s^* - \left(\frac{s^*}{k_H}\right)^{1/_\delta} - p_l \tag{21}$$

$$\pi^I = R_1[s^I - s^*](1-\tau_1) + s^* R_0 - \left(\frac{s^I}{k_H}\right)^{1/_\delta} - p_l - (1-\gamma)\varphi \tag{22}$$

The first-order condition for π^I yields to $s^I = k_H{}^{\frac{1}{1-\delta}}[R_1(1-\tau_1)\delta]^{\frac{\delta}{1-\delta}}$. Plugging this into (22), we have:

$$\pi^I = k_H{}^{\frac{1}{1-\delta}}[R_1(1-\tau)]^{\frac{1}{1-\delta}}\delta^{\frac{\delta}{1-\delta}} + s^* R_0 - s^* R_1(1-\tau) - k_H{}^{\frac{1}{1-\delta}}[R_1(1-\tau)]^{\frac{1}{1-\delta}}\delta^{\frac{1}{1-\delta}} - p_l - (1-\gamma)\varphi$$

$$= k_H{}^{\frac{1}{1-\delta}}[R_1(1-\tau)]^{\frac{1}{1-\delta}}\delta^{\frac{\delta}{1-\delta}}[1-\delta] + s^* R_0 - s^* R_1(1-\tau) - p_l - (1-\gamma)\varphi$$

Moreover, plugging $k_H{}^{\frac{1}{1-\delta}}$ from equation (20) into (21), we have:

$$\pi^* = R_0 s^* - \frac{(s^*)^{1/_\delta}}{(s^* + \Delta s)^{\frac{1-\delta}{\delta}}}[R_0\delta] - p_l = R_0 s^* \left[1 - \frac{1}{\left(1 + \frac{\Delta s}{s^*}\right)^{\frac{1-\delta}{\delta}}}\delta\right] - p_l$$

Similarly for π^I we will have:

$$\pi^I = \frac{s^* + \Delta s}{[\delta R_0]^{\delta/_{1-\delta}}}[R_1(1-\tau)]^{\frac{1}{1-\delta}}\delta^{\frac{\delta}{1-\delta}}[1-\delta] + s^*R_0 - s^*R_1(1-\tau) - p_l - (1-\gamma)\varphi$$

$$= R_0(s^* + \Delta s)\left[\frac{R_1(1-\tau_1)}{R_0}\right]^{\frac{1}{1-\delta}}[1-\delta] + s^*R_0 - s^*R_1(1-\tau) - p_l - (1-\gamma)\varphi$$

Using the condition that $\pi^* = \pi^I$:

$$R_0(s^* + \Delta s)\left[\frac{R_1(1-\tau)}{R_0}\right]^{\frac{1}{1-\delta}}[1-\delta] + s^*R_0 - s^*R_1(1-\tau) - \cancel{p_l} - \varphi = R_0 s^*\left[1 - \frac{1}{\left(1+\frac{\Delta s}{s^*}\right)^{\frac{1-\delta}{\delta}}}\delta\right] - \cancel{p_l}$$

Therefore:

$$\left(1+\frac{\Delta s}{s^*}\right)\left[\frac{R_1(1-\tau)}{R_0}\right]^{\frac{1}{1-\delta}}[1-\delta] + \left[R_1(1-\tau) - \frac{(1-\gamma)\varphi}{s^*}\right]\frac{1}{R_0} = 1 - \left(1+\frac{\Delta s}{s^*}\right)^{\frac{\delta-1}{\delta}}\delta$$

$$\left[\left(1+\frac{\Delta R}{R_0}\right)(1-\tau) + \frac{(1-\gamma)\varphi}{s^*R_0}\right]\frac{1}{\left(1+\frac{\Delta s}{s^*}\right)} - \left[\left(1+\frac{\Delta R}{R_0}\right)(1-\tau)\right]^{\frac{1}{1-\delta}}[1-\delta] - \left(1+\frac{\Delta s}{s^*}\right)^{\frac{-1}{\delta}}\delta = 0$$

Using $\varepsilon_s = \frac{\delta}{1-\delta}$, we will have:

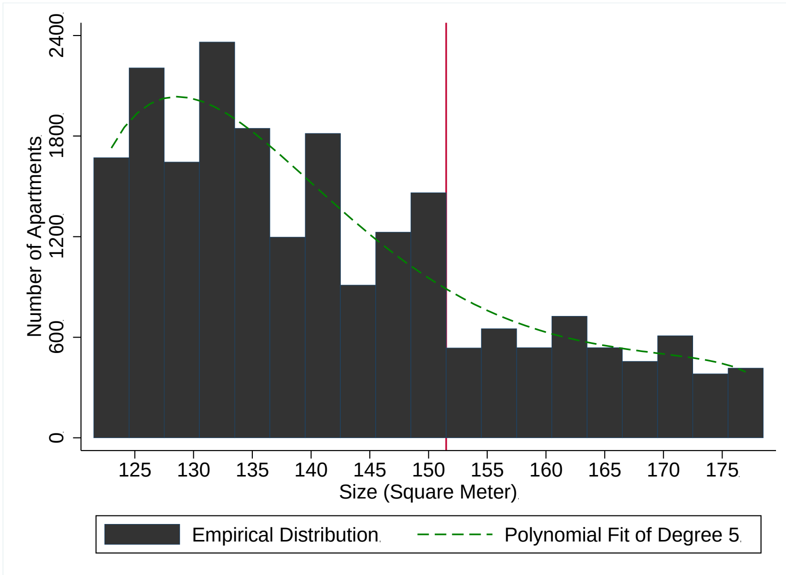
$$\frac{1}{\left(1+\frac{\Delta s}{s^*}\right)}\left[\left(1+\frac{\Delta R}{R_0}\right)(1-\tau) + \frac{(1-\gamma)\varphi}{s^*R_0}\right] - \frac{1}{1+\varepsilon_s}\left[\left(1+\frac{\Delta R}{R_0}\right)\left(1-\frac{\Delta\tau}{1-\tau_0}\right)\right]^{1+\varepsilon_s} - \frac{1}{1+\frac{1}{\varepsilon_s}}\left(\frac{1}{\left(1+\frac{\Delta s}{s^*}\right)}\right)^{1+\frac{1}{\varepsilon_s}} = 0$$

A.2 Details of Rental contracts in Tehran

In Tehran, rent is typically paid in one of the three following forms. One form is called full "Rahn" in which tenant deposits money for the whole period of the lease and will receive the same exact amount of money back at the time of lease expiration. There is a straightforward rule to convert the value of the "Rahn" (deposit) to monthly rent and vice versa. In fact, for each 10,000,000 Rials "Rahn", one can pay 300,000 Rials monthly rent instead.[16] It implies that the interest of the money is 3% a month. Therefore, the interest of 10,000,000 Rials is equal to 300,000 Rials a month, which is the rent here. The Second form is full rent in which the tenant pays a specific amount on a monthly basis and there is no "Rahn" involved. The last form is a combination of the first two in which the tenant pays monthly rent in addition to the initial deposit money. An example can illustrate better how rents can be paid in these three forms. Consider an apartment of $120m^2$ located in downtown Tehran. The landlord can either ask for an upfront deposit of 500 million Rials for a year, the amount that she has to return to the tenant at the end of the year, or instead, she can ask for 15 million Rials monthly rent for 12 months (180 million Rials annually). Alternatively, she can ask for a combination of a "Rahn" (deposit) of 100 million Rials and 12 million Rials of monthly rent. In the empirical analysis, "Rahn"s are converted to rent and total annual rent is used for all estimations.

[16] In 2015, the exchange rate of the U.S. dollar was 34,000 Rials.

Panel A.



Panel B.

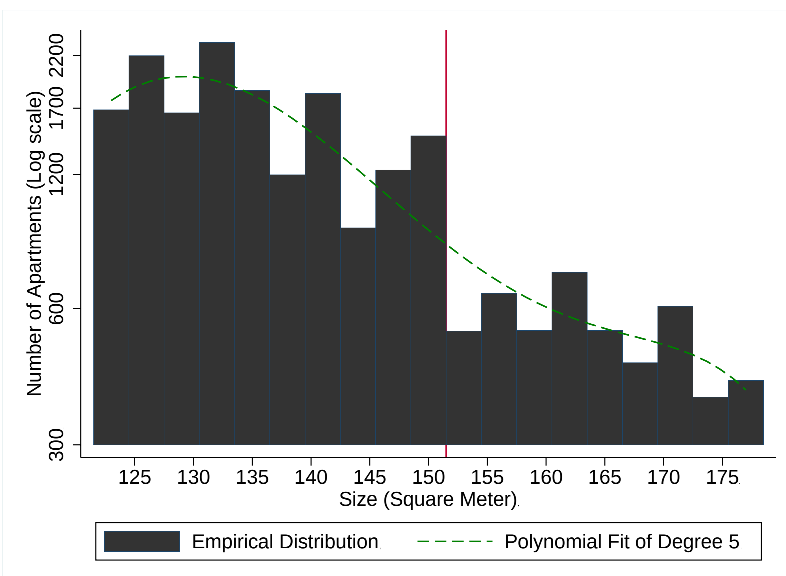


Figure A.1 Apartments Distribution and the Taxation Point (Rental Market)

This figure displays the histogram of apartments size (by $3m^2$ bins). It includes all observations from March 2012- to September 2014 for the segment ($120m^2$, $180m^2$). The solid line shows the starting point of taxation. The solid line itself belongs to the tax-zero side of the kink. Panel B. presents the same histogram using logarithmic scale. The dashed line displays the polynomial fit of degree of five.

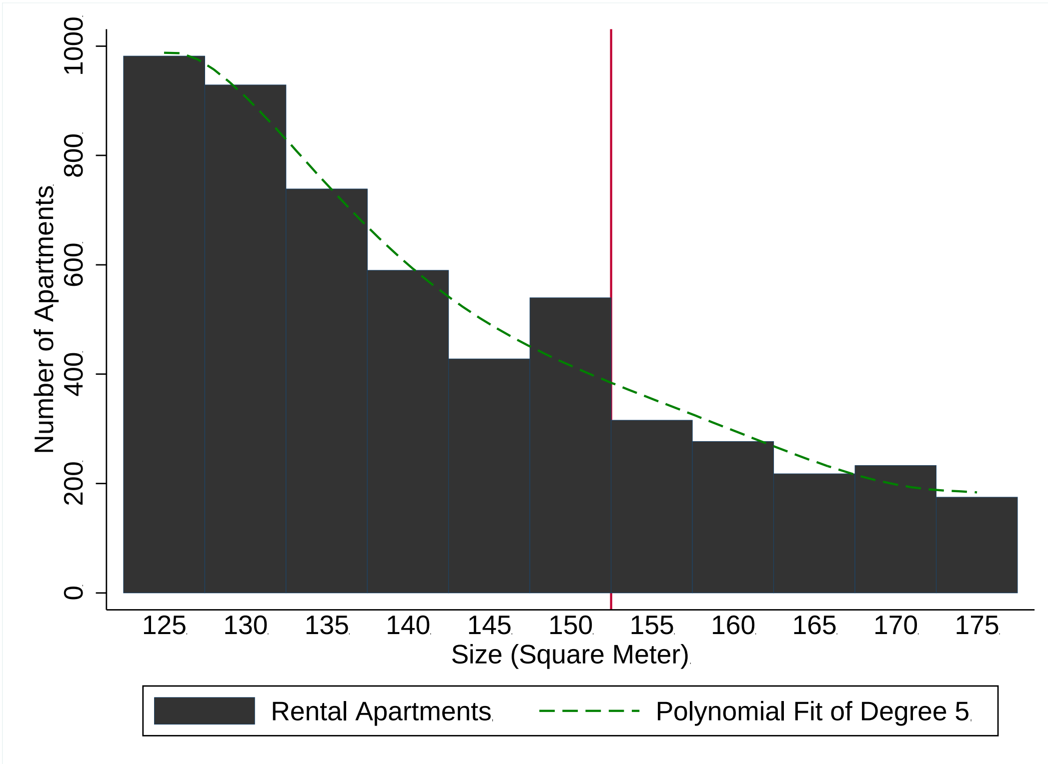


Figure A.2 Apartments Distribution and the Taxation Point (Matched data)

This figure displays the apartments distribution (by $5m^2$ bins) for reduced sample of apartments that have been both sold and rent. It includes all observations from March 2012- September 2014 for segment ($120m^2$, $180m^2$). The solid line shows the starting point of taxation. The solid line itself belongs to the tax-zero side of the kink. The dashed line display the polynomial fit of degree of five.

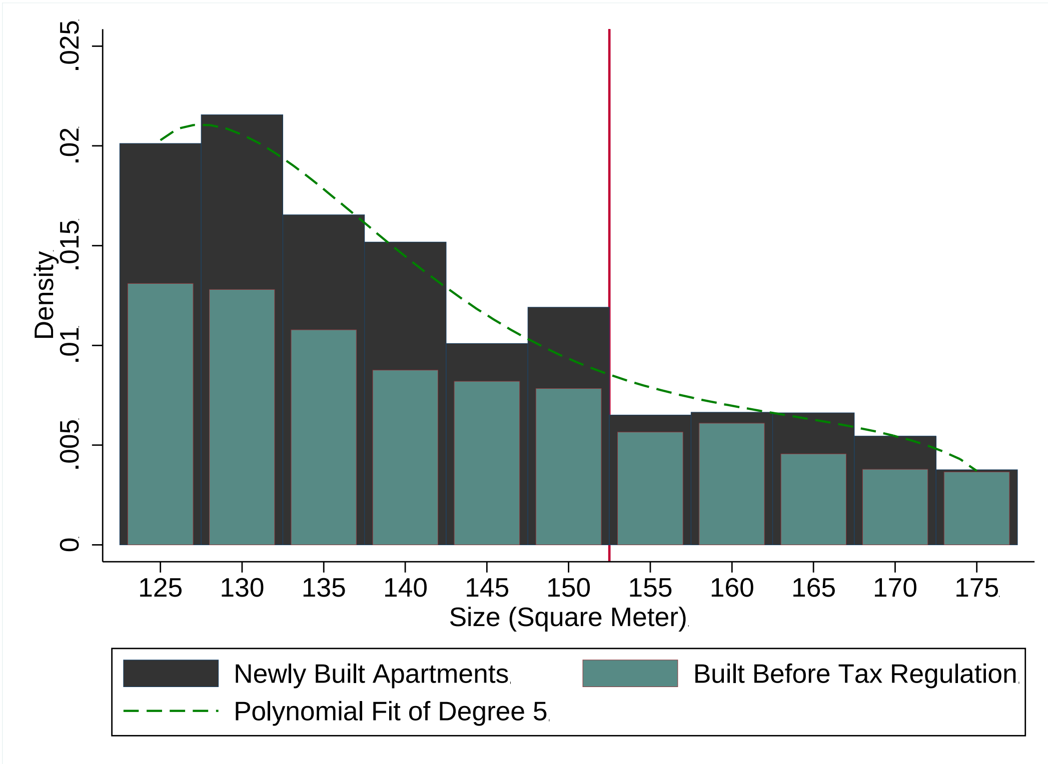


Figure A.3 Apartments Distribution in the Owning Market (Entire Sample)

This figure displays the density of apartments by $5m^2$ bins in the owner-occupant market. The histogram includes all purchasing transactions from March 2012- September 2014. The dashed line displays the polynomial fit of degree of 5 for newly built apartments. The solid line shows the starting point of taxation. The line itself is on the tax-zero side of the kink.

Table A.1: Placebo Tests Using Falsified Dummy Variables

VARIABLES	Rent/m^2 ($120m^2$ - $140m^2$) Cutoff at $130m^2$		Rent/m^2 ($130m^2$ - $150m^2$) Cutoff at $140m^2$		Rent/m^2 ($150m^2$ - $170m^2$) Cutoff at $160m^2$		Rent/m^2 ($160m^2$ - $180m^2$) Cutoff at $170m^2$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Size > Cutoff	69.72	64.67	63.34	44.66	44.30	68.74	124.61	65.72
	(50.40)	(55.23)	(59.23)	(65.34)	(109.49)	(115.74)	(121.52)	(126.78)
(Size > Cutoff) × (Size - Cutoff)		2.53		10.12		-13.70		33.80
		(10.43)		(12.76)		(22.64)		(24.98)
Observations	11,423	11,423	8,500	8,500	3,629	3,629	2,855	2,855
R-squared	0.50	0.50	0.51	0.51	0.56	0.56	0.59	0.59

Notes: The dependent variable is log of annual real rent per square meter in thousands of Rials. Regressions are based on equation (19). SizeKink is a dummy variable equal to one for properties larger than $150\boldsymbol{m^2}$. Kink130, Kink140, Kink160, and Kink170 are falsified dummy variables that get value of one for apartments larger than $130\boldsymbol{m^2}$, $140\boldsymbol{m^2}$, $160\boldsymbol{m^2}$, and $170\boldsymbol{m^2}$, respectively, and zero otherwise. All specifications include 5-digit ZIP Code, year, and seasonal fixed effects. Standard errors in all columns are clustered by 5-digit ZIP Code and stars indicate statistical significance level. * = 10 percent level, ** = 5 percent level, *** = 1 percent level.

APPENDIX B FOR CHAPTER 2

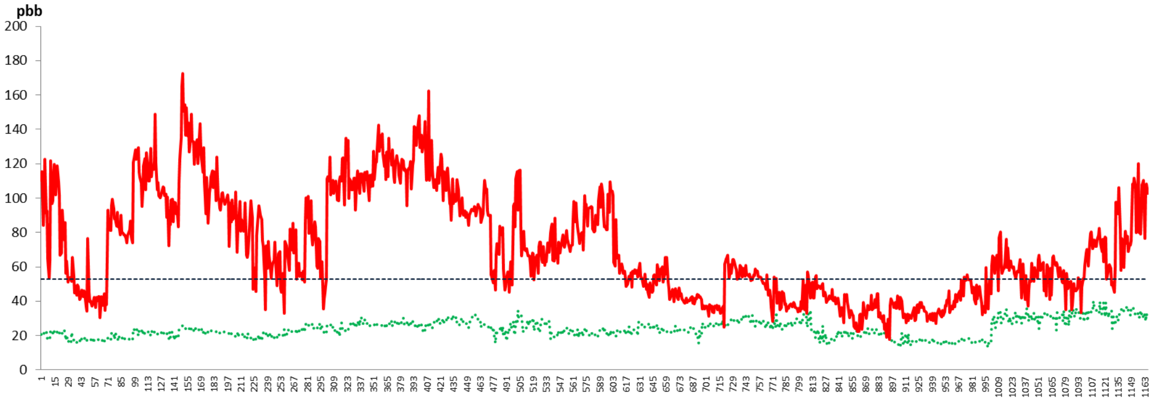


Figure B.1: The Level of One Month Average of Pollution Index across Neighborhoods

Notes: This figure shows the heterogeneous variations in level of distance-weighted pollution index across zip codes for two days; one year before and after the peak of the sanction-induced pollution jump. The figure includes 1166 zip code that contain sales record for both months. Dashed line shows the annual standard for NO_2 set by U.S. EPA.

Table B.1: Baseline Regression Including Months of Increase (Housing Prices)

	1 Week		1 Month		3 Months	
	(1)	(2)	(3)	(4)	(5)	(6)
Pollution Index	-0.0352***	-0.0352***	-0.0426***	-0.0426***	-0.0550***	-0.0550***
	(0.00149)	(0.00149)	(0.00167)	(0.00167)	(0.00194)	(0.00194)
Year Fixed Effects	X	X	X	X	X	X
5-Digit Zip-code Fixed Effects	X	X	X	X	X	X
Seasonal Fixed Effects	X	X	X	X	X	X
District Trends		X		X		X
Observations	690,223	690,223	690,053	690,053	688,447	688,447
R-squared	0.617	0.618	0.617	0.618	0.618	0.619

Notes: This table presents the impact of air pollution on housing prices for purchased transactions from years 2009 to 2014. All regressions are based on equation (2.1). The dependent variable is log of real price per-square meter. Pollution index is the daily inverse distance weighted-average of the readings of three closest monitors' measures of $\boldsymbol{NO_2}$ for each zipcode. For columns (1) and (2), the Pollution Index is average of those daily pollution indices for one week before the time of each transaction. For columns (3) and (4), the Pollution Index is average of those daily pollution indices for one month before the time of each transaction. For columns (5) and (6), the Pollution Index is average of those daily pollution indices for three months before the time of each transaction. All specifications include 5-digit zip-code, year, and seasonal fixed effects. The even-numbered columns also include region trend fixed effects. Standard errors in all columns are clustered by 5-digit zip-code and stars indicate statistical significance level. * = 10 percent level, ** = 5 percent level. *** = 1 percent level.

Table B.2: Baseline Regression Including Months of Increase (Rental Price)

	1 Week		1 Month		3 Months	
	(1)	(2)	(3)	(4)	(5)	(6)
Pollution Index	-0.00201	-0.00198	-0.00326	-0.00322	-0.00725**	-0.00715**
	(0.00255)	(0.00254)	(0.00292)	(0.00291)	(0.00332)	(0.00330)
Year Fixed Effects	X	X	X	X	X	X
5-Digit Zip-code Fixed Effects	X	X	X	X	X	X
Seasonal Fixed Effects	X	X	X	X	X	X
District Trends		X		X		X
Observations	296,612	296,612	296,439	296,439	295,362	295,362
R-squared	0.409	0.411	0.409	0.411	0.409	0.412

Notes: This table presents the impact of air pollution on rental prices for rental transactions from years 2009 to 2014. All regressions are based on equation (2.1). The dependent variable is log of total annual real rent per-square-meter. Pollution index is the daily inverse distance weighted-average of the readings of three closest monitors' measures of $\boldsymbol{NO_2}$ for each zipcode. For columns (1) and (2), the Pollution Index is average of those daily pollution indices for one week before the time of each transaction. For columns (3) and (4), the Pollution Index is average of those daily pollution indices for one month before the time of each transaction. For columns (5) and (6), the Pollution Index is average of those daily pollution indices for three months before the time of each transaction. All specifications include 5-digit zip-code, year, and seasonal fixed effects. The even-numbered columns also include region trend fixed effects. Standard errors in all columns are clustered by 5-digit zip-code and stars indicate statistical significance level. * = 10 percent level, ** = 5 percent level. *** = 1 percent level.

Table B.3: Panel Analysis Including Months of Increase

	1 Week		1 Month		3 Months	
	(1)	(2)	(3)	(4)	(5)	(6)
Pollution Index	-0.0257***	-0.0255***	-0.0308***	-0.0307***	-0.0372***	-0.0372***
	(0.00512)	(0.00511)	(0.00601)	(0.00599)	(0.00687)	(0.00687)
Year Fixed Effects	X	X	X	X	X	X
5-Digit Zip-code Fixed Effects	X	X	X	X	X	X
Seasonal Fixed Effects	X	X	X	X	X	X
District Trends		X		X		X
Observations	79,292	79,292	79,289	79,289	79,256	79,256
R-squared	0.156	0.158	0.156	0.158	0.156	0.158

Notes: This table presents the impact of air pollution on price-rent ratio from years 2009 to 2014. All regressions are based on equation (2.1). The dependent variable is zip code-day average price divided by average rent. Pollution index is the daily inverse distance weighted-average of the readings of three closest monitors' measures of NO_2 for each zipcode. For columns (1) and (2), the Pollution Index is average of those daily pollution indices for one week before the time of each transaction. For columns (3) and (4), the Pollution Index is average of those daily pollution indices for one month before the time of each transaction. For columns (5) and (6), the Pollution Index is average of those daily pollution indices for three month before the time of each transaction. All specifications include 5-digit zip-code, year, and seasonal fixed effects. The even-numbered columns also include region trend fixed effects. Standard errors in all columns are clustered by 5-digit zip-code and stars indicate statistical significance level. * = 10 percent level, ** = 5 percent level. *** = 1 percent level.

Table B.4: The Impact of Air Pollution on Housing Prices Using Alternative Pollution Index (Half Mile)

	1 Week		1 Month		3 Months	
	(1)	(2)	(3)	(4)	(5)	(6)
Pollution Index	-0.0153**	-0.0153**	-0.0241***	-0.0242***	-0.0330***	-0.0332***
	(0.00669)	(0.00670)	(0.00760)	(0.00756)	(0.00782)	(0.00774)
Year Fixed Effects	X	X	X	X	X	X
5-Digit Zip-code Fixed Effects	X	X	X	X	X	X
Seasonal Fixed Effects	X	X	X	X	X	X
District Trends		X		X		X
Observations	34,081	34,081	34,077	34,077	34,031	34,031
R-squared	0.617	0.617	0.617	0.618	0.617	0.618

Notes: This table presents the impact of air pollution on housing prices from years 2009 to 2014 for the sample of purchased properties that are located within half mile of at least one monitor. Observations within 2 months after and before the pollution spike (Dec 2010) are also excluded. All regressions are based on equation (2.1). The dependent variable is log of real price per-square meter. For each observation, the pollution index is the daily reading of nitrogen dioxide concentration from a monitor that the housing observation lies within the one-half mile of the given monitor. If a housing observation is close to more than one monitor, the pollution index is the average of readings from all close monitors. For columns (1) and (2), the Pollution Index is average of those daily pollution indices for one week before the time of each transaction. For columns (3) and (4), the Pollution Index is average of those daily pollution indices for one month before the time of each transaction. For columns (5) and (6), the Pollution Index is average of those daily pollution indices for three months before the time of each transaction. All specifications include 5-digit zip-code, year, and seasonal fixed effects. The even-numbered columns also include region trend fixed effects. Standard errors in all columns are clustered by 5-digit zip-code and stars indicate statistical significance level. * = 10 percent level, ** = 5 percent level. *** = 1 percent level.