Facultad de
Ciencias Sociales y Humanísticas

Beyond Average Effects: Distributional Price Effects of an Inclusionary Zoning Program in Auckland

A thesis presented for the degree of

Magíster en Ciencias Económicas

by

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Guayaquil - Ecuador
August 31, 2021

Dedication

To my parents, Marcelo & Rossy, my family and Adriana

for their unconditional love and support.

Marcelo Ortiz Villavicencio

Acknowledgements

Special thanks to Gonzalo Sánchez and Mario Fernández

for their invaluable contributions and comments.

Marcelo Ortiz Villavicencio

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Contents

Abstract

Housing affordability remains a significant social and economic issue in New Zealand and the developed world. Affordability policies such as Inclusionary Zoning (IZ) have been promoted as alternatives to streamline the delivery of land as an intermediate stage to boost the supply of affordable housing. IZ has been applied with relative success in several countries. Nonetheless, research on price effects is relatively scarce and applications of causality approaches remain limited. It is of interest to explore whether voluntary IZ (or rezoning policies in general) may have effects beyond average prices considering the heterogeneity of housing markets. This paper explores if and how a rezoning policy (the Special Housing Areas in Auckland, New Zealand) affects the distribution of prices within designated areas. Our empirical strategy relies on quantile difference-in-difference models to identify distributional effects. We estimate changes-in-changes models to relax functional form assumptions and to incorporate heterogeneity. We use about 175 thousand sales transactions between September 2011 and September 2016 in the Auckland Region. Our findings show that the SHAs program increased housing prices for all distribution segments, ranging from 3% to 7%. That is, the SHAs may have affected market segmentation within the designated areas, and it cannot be concluded that there was a cross-subsidy from more expensive houses toward affordable. Hence, the distributional effects may affect the potential of a voluntary IZ as an affordability policy.

Keywords: Housing Affordability, Inclusionary Zoning, Land Use Regulation ,Counterfactual Distribution, Quantile Difference-in-Difference, Changes-in-Changes

JEL Codes: D04, R21, R31, R58

List of Figures

List of Tables

1 Introduction

Housing affordability remains as one of the most challenging policy issues in New Zealand and other developed countries. The literature is extensive on policy approaches to improve or at least mitigate housing unaffordability. Some demand-side approaches consider forms of subsidies through the use of vouchers to reduce market distortions; progressive homeownership schemes (shared ownership or rent-to-buy); and, home grants to assist households on raising a deposit (Mayo, 1986; Apgar, 1990; Rosenthal et al., 1993; Galster, 1997; Laferrère and Le Blanc, 2004; Priemus et al., 2005; Agiro and Matusitz, 2011; Olsen, 2013; Eriksen and Ross, 2015; Fernandez et al., 2020; Braakmann and McDonald, 2020; Sayag and Zussman, 2020). On the supply-side, policies such as public housing (Lui, 2007; Mohit and Nazyddah, 2011; Yong Hu and Chou, 2015; Li et al., 2019), production cost subsidies for the private sector (Malpezzi and Maclennan, 2001; Malpezzi and Vandell, 2002; Burge, 2011) , and changes on land use planning or zoning have shown differing degrees of success (Calavita and Grimes, 1998; Galster and Lee, 2021).

Inclusionary Zoning (IZ) is a supply-side policy that has received wide attention. IZ refers to local programs that encourage developers to set-aside a percentage (typically between 5% and 20%) of new residential units for low- and middle-income households at affordable prices (Mukhija et al., 2010; Schuetz et al., 2011; Brunick, 2014). IZ has been claimed to improve the social outcomes of competitive housing markets by decreasing housing stress, or by enhancing economic and racial integration (Brunick, 2014; Diagne et al., 2018), as well as to promote not only the delivery of affordable housing supply but also the social integration of otherwise fragmented and sprawled cities without having to resort to tax increases or using public funds (Austin et al., 2014; Morrison and Burgess, 2014; Brunick, 2014; Mukhija et al., 2015; Diagne et al., 2018; Hamilton, 2021).

IZ programs are highly heterogeneous, but they are usually characterized by the target population groups that have access to the program; the criteria or typology of developments that fall under the category of affordable housing; the incentives or cost-offset measures to developers; and, the mandatory or voluntary nature of the program around compliance and enforcement about setting aside the affordable units (Brunick, 2014; Calavita and Mallach, 2010). Under mandatory IZ , developers are subject to legal mandates that bind them to comply with the affordability requirements. Under voluntary IZ, in turn, cost-offset measures are assumed to be equivalent to the foregone revenues of not delivering market-rate units so that developers remain profitable and willing to deliver affordable units. Thus, voluntary IZ relies on the premise that cost-offsets provide sufficient incentive for developers to participate in the arrangement.

Despite its application in several countries, the effects of IZ are yet to be fully understood (Hamilton, 2021). Research suggests that IZ may have contributed to increasing prices and lower rates of development in the Boston area (Schuetz et al., 2011; Means and Stringham, 2012). But it also appears to have increased prices in times of regional price appreciation, or decreased prices during cooler regional markets, but, most interestingly, has not affected new housing development in the Bay Area of San Francisco (Schuetz et al., 2011; Hamilton, 2021). Also, in a set of Californian cities adopting mandatory IZ, they end up with 9% higher prices and 8% percent fewer homes overall (Means and Stringham, 2012). Hence, mandatory IZ has been labelled as a tax on the development of new residential units and a price ceiling on the units that must be set aside at below-market rates (Ellickson, 1981; Brunick, 2004; Schuetz et al., 2011; Brunick, 2014; Mukhija et al., 2015; Dawkins et al., 2017). Furthermore, though mandatory IZ may support mixed-income communities enabling greater social integration (Calavita and Mallach, 2010), it may also influence neighbourhood racial, stigmas, income transition, and alterations to the social web of neighbourhoods (Hughen and Read, 2014; Kontokosta, 2014, 2015; Diagne et al., 2018). In addition, the operation of a mandatory IZ program requires significant investment on monitoring and compliance infrastructure to enforce breaches to the commitment of developers. This may entail non-trivial political risks and challenges that weaken not only the impact but also the structure and fundamentals of the program (Murphy and Rehm, 2013).

Voluntary IZ may bypass some of the political and governance risks of the mandatory IZ. However, it has been proven that voluntary IZ is relatively ineffective on delivering affordable houses precisely because of non-binding rules or insufficient cost-offsetting mechanisms for developers (Stabrowski, 2015; Hamilton, 2021). Even more, an aspect that has not been thoroughly explored is whether the treatment effects of land rezoning as IZ apply uniformly to all segments within the distribution of dwellings prices. As voluntary IZ programs do not impose stringent requirements to developers (relative to mandatory IZ), and legislation about IZ may not be explicit about the sequencing of units to be delivered, there is still an open question about the mix of houses entering the market in IZ areas. Identifying whether heterogeneous effects exist is relevant because, for the purposes of urban planning and infrastructure funding, rezoning as IZ may imply increases in land value, which should be estimated to get better inform taxes, rates or development contributions schemes. Hence, as the purpose of IZ is to boost the supply of affordable housing, it is of interest to focus on any price changes that may have occurred in the lower end of the distribution.

In this context, this paper takes the Special Housing Areas (SHA) program in Auckland (New Zealand's largest city), as a case study of a voluntary IZ and seeks to identify their heterogeneous treatment effects on the prices distribution. We select the SHAs program because it may have affected neighborhoods and potentially raised differences due to the process of densification. That is, in relatively wealthy suburbs, SHAs may have been perceived as disturbances to the social milieu, whereas in less-wealthy areas they may have been perceived as a rehabilitation opportunity. Thus, communities within and around SHA areas may have undergone through changes on their demographic make-up and built environment (Johnson et al., 2019; Terruhn, 2019). At the time of writing this paper, it is not clear whether IZ will be up taken in New Zealand as a mechanism to approach housing unaffordability, it is necessary to develop a comprehensive overview of the spectrum of price changes.

This paper builds on (Fernandez et al., 2019), which estimates an average increase of 5% on prices because of SHAs. However, they do not explore effect of the program on the upper and lower ends of the distribution. In this paper we estimate non-linear difference-in-difference models (Quantile Difference in Difference -QDID, and Changes-in-Changes -CIC) on a dataset of about 175 thousand housing sales transactions in the Auckland region between September 2011 and September 2016. We find that housing prices increase across all percentiles except at the lower end of the price distribution. However, when the outcome variable is the price per square meter, increases across deciles show a U-shaped curve depicting pressures on land becoming scarce for market-rate units.

This paper is structured as follows: Section 2 presents a background of the SHA program in Auckland and the equivalence we draw about it as a voluntary IZ program. Section 3 describes our empirical strategy. Section 4 describes the dataset. Section 5 presents and discusses the results. Section 6 concludes.

2 Background

In the last decade the persistently increasing prices have imposed challenges to the competitiveness of cities or economic hubs as Auckland, as well as worsening equality aspects of population groups (Fernandez, 2019). Just between 2019 and 2021, housing prices increased by 45%, and the average price is above NZ$1 million. Policy efforts have been implemented to boost the competitiveness of the housing and land markets, and to streamline resource consenting process to decrease transactions costs for the construction sector. Major rezoning of land areas have been implemented to promote densification and redevelopment of brownfield areas (Greenaway-McGrevy and Phillips, 2016; Fernandez and Martin, 2020; Greenaway-McGrevy et al., 2020). However, prices have kept soaring. New Zealand ranks as one of the most expensive housing markets relative to income (OECD, 2021). Auckland, home to a third of the country's population, is the fourth most expensive city in the world to buy a home (Bloomberg, 2021) and, has been severely unaffordable in all 16 Annual Demographia International Housing Affordability Survey (Demographia, 2019).

As a mechanism to release land and, consequently, development opportunities to streamline the delivery of (affordable) housing, in October 2013, the Housing Accord and Special Housing Areas Act and Auckland Housing Accord launched the SHA program. For land areas to be designated as SHA, developers had to submit an application to the Auckland Council, which evaluated the proposal and then referred it to the central government for final designation. Then the boundaries of the SHA were set, which could either be part of a whole Census Area Unit (AU[1]) or overlap more than an AU. It was not necessary that parcels inside a SHA to be empty, consequently dwellings may have already existed inside the SHA before designation.

The SHAs were then regarded as a collaborative effort between the central and local governments to facilitate increasing housing supply under a more permissive regulatory environment (McArthur, 2017). The premise of the SHAs program was that national-level legislation was needed to bypass local planning processes that slowed down the delivery of (affordable) housing (Howden-Chapman et al., 2020).

Though the SHAs were not initially considered as a voluntary IZ scheme, their features allow us to construct an equivalence. First, the SHAs entailed that any development with more than 14 dwellings had to allocate at least 10% affordable housing for certain income groups. Second, for a dwelling to be considered as affordable, it had to either be sold for a price no more than 75% of the median house price in the Auckland region, or be sold at a price where the monthly mortgage repayments do not exceed 30% of the median Auckland household income (Auckland Council, 2013). Third, as an incentive to developers, resource consenting processes would be subject to a speedier process that could take about 20 days relative to the conventional process under the Resource Management Act, which could take lengthy consultation processes (about 6 months or more). Hence, the SHAs fit the characteristics of a voluntary IZ program. Though the equivalence may not be perfect, it should be considered that IZ programs worldwide are widely heterogeneous.

[1]Census Area Unit (AU) are defined for population census purposes and to segment areas for public school provision. AU are roughly equivalent to suburbs.

The SHAs were established as an interim measure while the Auckland Unitary Plan (AUP) was being developed. The AUP is the planning rulebook for all of Auckland that replace seven city and district councils regional district plans (Auckland City, Manukau, Waitakere, North Shore, Papakura, Rodney and Franklin) after their amalgamation into the Auckland Council. The AUP sets rules for what, where and how buildings can be built in the city, where its main priorities are to meet economic and housing needs (Fernandez et al., 2020). Then the SHAs became a part of the planning rules and, even though they no longer exist, development would still occur because of the actual rezoning. Nonetheless, the SHAs were superseded by the AUP and some of them were effectively disestablished in November 2016, and the remaining ones were abolished in May 2017. By October 2017, about 30,400 dwelling consents were delivered but only 3157 houses were constructed and only 98 met the affordability criteria (Auckland Council, 2017; Ministry of Business Innovation and Employment, 2017). Hence, though the SHAs may have stimulated housing supply, their impact on the unaffordability crisis was negligible (Murphy, 2016).

3 Empirical Strategy

The application of land areas for designation as SHAs obeys decision rules that are not directly observable. That is, the designation process is not random. Thus, to identify treatment effects, a direct comparison of prices inside and outside the SHAs, or before and after the treatment date is problematic. Any price change may have been caused by any other variable even after controlling for observables.

Also, considering the SHAs as an affordable housing policy, it is of interest to identify whether the effect of the program manifests heterogeneously across the percentiles of the distribution of prices, which may inform implications on low-income households and their chances to become homeowners due to the SHAs program. Consequently, program evaluation should go beyond the Average Treatment of the Treated (ATT) as it may be uninformative to understand the effect of the policy in its entire spectrum. This paper then relies on non-linear DID to estimate the Quantile Treatment Effect on the Treated (QTT) (Athey and Imbens, 2006). The QTT is the difference between the two potential outcome distributions for the treatment units at a particular quantile q. If the SHAs had been randomly assigned, the QTT could be identified directly from the price distributions after treatment from dwellings sold inside any SHA and dwellings sold outside SHAs. That is, at any quantile $q \in (0, 1)$, the QTT is the difference in the q-th quantile in the treatment group versus the control group.

However, the QTT requires the identification of the counterfactual price distribution for the treated in the absence of SHA. Athey and Imbens (2006) describe mechanisms based on the change in the distribution before and after treatment in the control group as an estimate of the change that would have occurred in the treatment group in the absence of treatment.

We follow a quantile approach to evaluate the distributional effects on prices resulting from the implementation of the IZ program. Intuitively we can generalize the well-known specification of a Difference-in-Difference to see in depth how the implementation of this rezoning program impacts on housing prices in the different parts of the distribution as a linear function in the covariates (Koenker and Bassett, 1978). This specification is:

$$Y_{i,t}^{q} = \alpha^{q} + \beta^{q} SHA_{i,t} + \gamma^{q} D_{i,t} + \theta^{q} SHA_{i,t} \times D_{i,t} + \omega^{q} \Lambda_{t} + \psi^{q} \Phi_{i} + \varepsilon_{i,t} \tag{1}$$

Let $t = \{1, ..., T\}$ index time in a monthly basis, and let $i = \{1, ..., n\}$ index the set of dwellings that are sold. The $Y_{i,t}^{q}$ is the logarithm outcome of interest (e.g. Log of Dwelling Price or Log of Price per Square Metre) at q-th quantile; $SHA_{i,t}$ is a dummy variable that equals to one if house i is located inside a SHA and zero otherwise; $D_{i,t}$ is a dummy variable that equals to one if the transaction occurred in the after treatment period[2] and zero otherwise. The treatment effect is captured by θ^{q}, which is different for each q-th quantile. This setup also captures month-by-year fixed effects in Λ_t and AU fixed effects

[2]After treatment period occurs in October 2013 in most cases. However, for New Lynn Area Units occurs in November 2013; for Albany Area Units occurs in May 2014; and for Otahuhu Area Units occurs in June 2014. We adjust the indicator taking into account these considerations.

in Φ_i. Alternative specifications include interactions between legacy districts[3] and quarter-by-year fixed effects and age of housing at the moment of the transaction. In an additional specification we restrict the sample to dwellings located less than 1 km from any SHA, and in another we add leading indicators to ensure the robustness of our specification to the deviations of trends before the program implementation (i.e., anticipatory effects).

Athey and Imbens (2006) present two models, the QDID and the CIC, which are use in this paper to uncover underlying heterogeneous patterns in distributions caused by the implementation of the SHAs program. The following two sections briefly explain the characteristics and differences between the two models.

3.1 Quantile Difference-in-Difference

The standard Difference-in-Difference (DID) model relies on the parallel-trends assumption: in the absence of the SHAs treatment, prices of dwellings inside the SHAs should have moved similarly to prices of dwellings outside SHAs. The QDID extends this assumption and applies DID to each quantile of distribution rather than to the mean. In addition, the QDID relies on a rank preservation assumption: the position of a dwelling in the distribution is the same regardless of the potential outcome distribution. That is, for example, if a dwelling's price is at the quantile 0.5 of the potential price distribution without the SHAs treatment, then it must also be at the quantile 0.5 of the distribution with SHAs. If both hold, the estimated quantile treatment effect is the difference in quantiles across the distribution of prices with SHA and the counterfactual distribution of price in absent of SHA.

The estimated counterfactual distribution of the QDID is calculated in a straightforward manner. We let $F_{Y_{gt}}$ denote the Cumulative Distribution Function (CDF) of the dwelling price, Y, where $g = 1$ for dwellings inside SHA (dwellings outside SHA get $g = 0$), and $t = 1$ indicates the post-policy period (before-treatment period gets $t = 0$). The inverse of the CDF is given by $F^{-1}_{Y_{gt}}$. The counterfactual outcome at quantile q for the post-policy

[3] Legacy districts corresponding to those that amalgamated in 2010 to form the Auckland Council. For an overview, the distribution of housing prices by districts is shown in Figure A.1 in Appendix

treatment group (Dwellings inside SHA) in the absence of treatment is defined as $F^{-1}_{Y^N_{11}}(q)$ and is directly obtained using observed data in the following equation:

$$F^{-1}_{Y^N_{11}}(q) = F^{-1}_{Y_{10}}(q) + [F^{-1}_{Y_{01}}(q) - F^{-1}_{Y_{00}}(q)] \tag{2}$$

Equation 2 indicates that QDID uses the variation in the control group before and after treatment for the estimation of the counterfactual distribution. Notice that a valid quantile difference-in-difference estimate relies on the consistent distribution of unobservables among individuals across groups and time.

3.2 Changes-in-Changes

The CIC model uses the change in the outcome distribution of the control group before and after treatment to recovers the counterfactual distribution of the treated group had not received the treatment. Contrary to the QDID, the CIC, rather than comparing prices across groups and time based on their quantiles, it compares prices between groups based on their outcomes and across time according to their quantile. Thus, the CIC overcomes two drawbacks of the standard DID: (i) Functional form dependence. The parallel-trends assumption is not equivariant to nonlinear transformations (Roth and Sant'Anna, 2020), it is not invariant to the scaling of the outcome variable. (ii) Strong separability assumptions to identify the CDF of the treatment. The CIC estimates the counterfactual distribution of outcomes that would have been experienced by the treatment group in the absence of the treatment and, likewise, for the untreated group in the presence of the treatment.

Let Y_i^N denote the potential outcome for dwelling i if this does not receive the treatment, and let Y_i^I denote the outcome for the same dwelling i if this does receive the treatment. Also, let I_i be an indicator for the treatment. Employing the potential outcome notation in Imbens and Rubin (2015), the observed outcome for dwelling i is:

$$Y_i = Y_i^N \times (1 - I_i) + I_i \times Y_i^I \tag{3}$$

Let $G_i \in \{0, 1\}$ be an indicator of the group (treatment or control) that belongs dwelling i and let $T_i \in \{0, 1\}$ denote an indicator of the time period (before or after the treatment). The standard DID for individual i in the absence of intervention is

$$Y_i^N = \alpha + \beta T_i + \gamma G_i + \varepsilon_i \tag{4}$$

Where ε_i is independent of the group indicator and have the same distribution over time, that is, $\varepsilon_i \perp (G_i, T_i)$. Athey and Imbens (2006) generalize the standard DID model and imposes a structure over equation 4, so the outcome of a dwelling in the absence of intervention satisfy

$$Y_i^N = h_0(U, T) \tag{5}$$

with $h_0(u, t)$ strictly increasing in u for $t \in \{0, 1\}$. U_i represents the unobserved characteristics of dwelling i and equation 5 incorporates the idea that the outcome of an individual with $U_i = u$ will be the same in a given time period, irrespective of the group membership (i.e. $U_i \perp T_i | G_i$) (Imbens and Wooldridge, 2009). Therefore, the average effect of the program for the treated is given by

$$\tau_{CIC} = E[Y_i^I - Y_i^N | G_i = 1, T_i = 1] \tag{6}$$

Assuming that $h_0(u, t)$ is monotone in u and conditionally independent of T_i and U_i, given G_i, Athey and Imbens (2006) show that distribution of Y^N, given $T_i = G_i = 1$ can be identified as:

$$F_{Y_{11}^N}(y) = F_{Y_{01}}(F_{Y_{00}}^{-1}(F_{Y_{10}}(y))) \tag{7}$$

Where $F(\bullet)$ represent the cumulative distribution function of dwelling prices and $F^{-1}(\bullet)$ its inverse for $q \in (0,1)$. Therefore, the counterfactual distribution of prices $F_{Y_{11}^N}(y)$ is directly obtained using observed data.

The estimation of equation 7 is straightforward in absence of covariates. However, under the presence of covariates, Athey and Imbens (2006)suggest parametric estimation assuming a pure linear location shift effect of the covariates. In particular, we first regress a liner model similar to one specified in equation 1 and recover the residuals residuals $\hat{\varepsilon_{i,t}} = Y_{i,t} - \hat{\alpha}^q - \hat{\beta}^q SHA_{i,t} - \hat{\gamma}^q D_{i,t} - \hat{\theta}^q SHA_{i,t} \times D_{i,t} - \hat{\omega}^q \Lambda_t - \hat{\psi}^q \Phi_i$. Then, CIC model is applied using $\hat{\varepsilon_{i,t}}$ as outcome variable.

3.3 Comparison between QDID and CIC methods

A simple graphical exercise shall serve as example in order to introduce our identification strategies intuitively and to distinguish the differences between the two models used[4]. Assume only two groups and two periods (the standard 2x2 setup). For simplicity, we will assume that the 4 distributions are normal, each one with a different mean and variance, respectively.

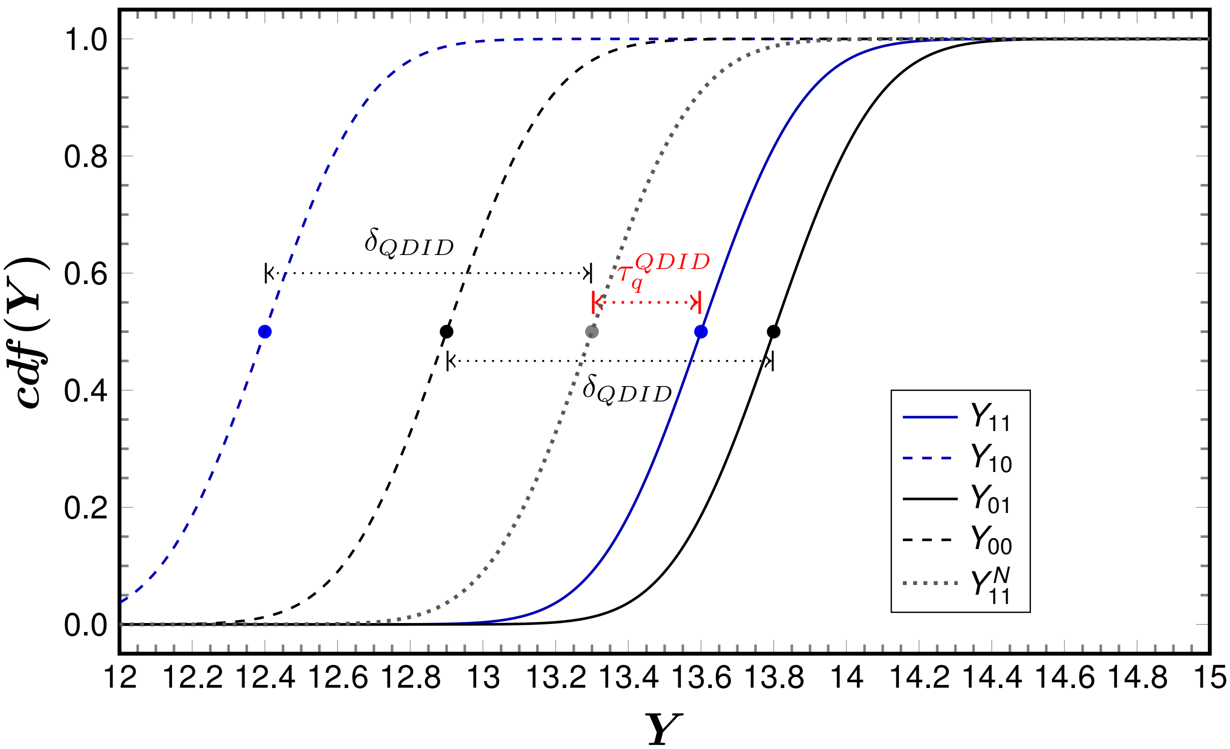
Under the QDID approach and using equation 2, the effect of the SHAs at a given quantile $q \in (0,1)$ in the outcome distribution can be identified by the difference in the actual outcome and the estimated counterfactual:

$$\tau_q^{QDID} = F_{Y_{11}}^{-1}(q) - F_{Y_{11}^N}^{-1}(q) \tag{8}$$

Using simulated data, we construct Figure 1 to describe the mechanism of the QDID. The distributions of the control and treatment groups are represented by the black and blue lines, respectively; the pre-treatment period by dashed lines and the post-treatment period by solid lines. Assume that we want to identify the policy effect at quantile q = 0.5. We

[4]There are other approaches to study the effect on distribution such as RIF-setting by Firpo et al. (2009). For an empirical application, see Havnes and Mogstad (2015)

Figure 1: QDID Mechanics



Note: Illustration of the empirical strategy for QDID model. $Y_{11}, Y_{10}, Y_{01}, Y_{00}$ are simulated outcome distributions for treated and control group in pre- and post-treatment period. See text for details.

compute the difference between the CDFs of the control group before and after program implementation. The shift in outcome over time δ_{QDID} at the q-th quantile of the control group is added to the initial outcome of the treatment group at the same q-th quantile. This sum is the counterfactual estimate for the treatment group. Therefore, the effect of the program at any quantile in the price distribution can be identified by the horizontal difference between the post-treatment inverse CDF value and the counterfactual estimate (τ_q^{QDID} represented by the red horizontal line). To identify quantile effects other than the median, the line representing δ_{QDID} can be moved along the distribution curves.

A caveat with the QDID is its reliance on the consistent distribution of unobservables between individuals across groups and time, which may not hold. Athey and Imbens (2006) address this concern allowing the distribution of unobservables across the treatment and control groups to differ while retaining the assumption that individuals with similar observables and unobservables will be affected by the treatment in the same way. The estimation process of the CIC model relies in those two individuals in the same time period with the same observables and unobservables will have equal outcomes, but if these individuals are in different groups, then their ranking in the distribution may be different.

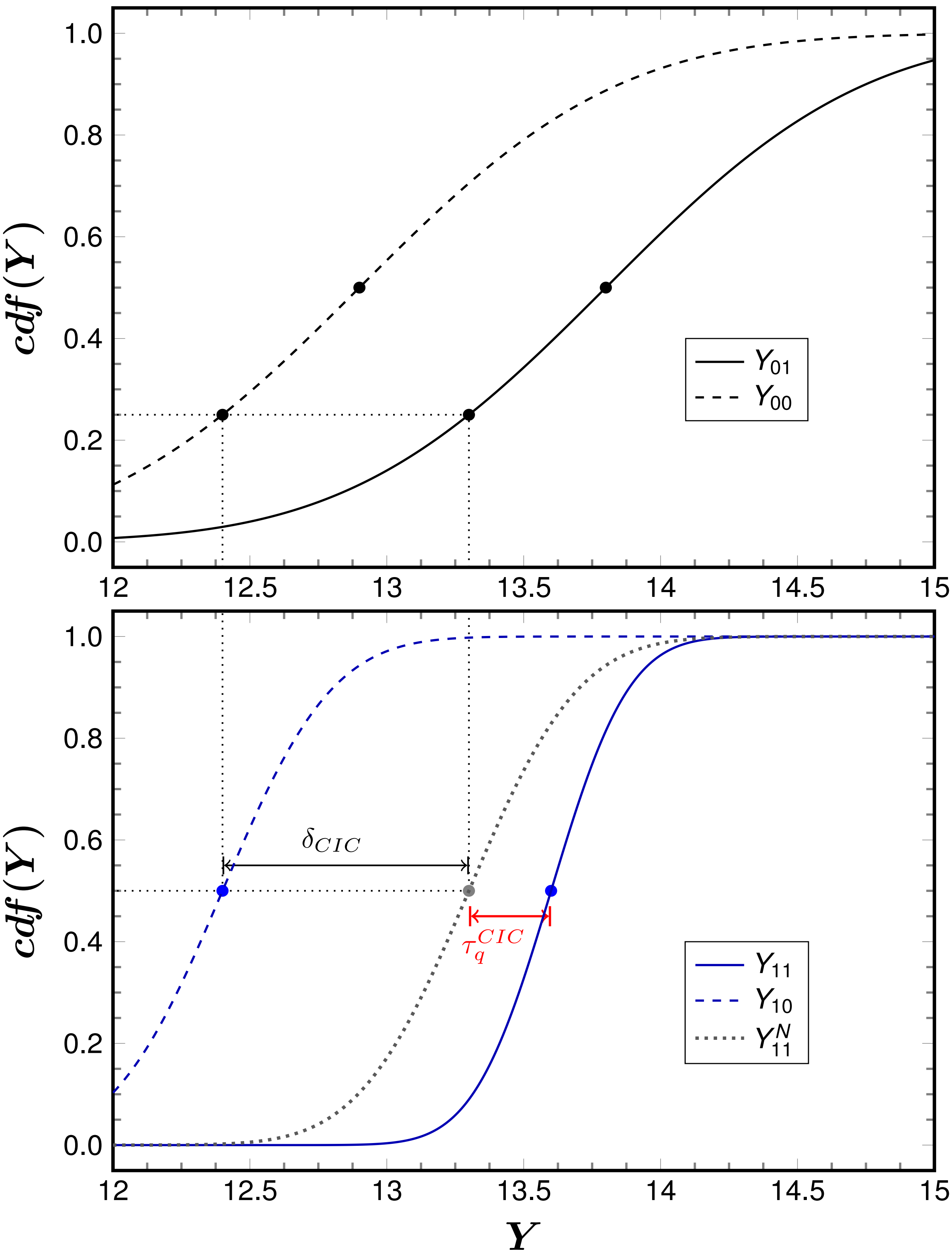
The counterfactual is computed by using the distribution of unobservables of the treatment group in the first period and mapping them into outcomes through the common second period mapping of unobservables (equation 7). The effect of the SHAs on the quantile $q \in (0,1)$ of the distribution is then

$$\tau_q^{CIC} \equiv F^{-1}_{Y_{11}}(q) - F^{-1}_{Y^N_{11}}(q) = F^{-1}_{Y_{11}}(q) - F^{-1}_{Y_{01}}(F_{Y_{00}}(F^{-1}_{Y_{10}}(q))) \tag{9}$$

The mechanism of the CIC estimation is described in Figure 2. We simulate four distributions, which are separated in Panel (a) and (b). Panel (a) corresponds to the control group (black lines) and Panel (b) to the treatment group (blue lines). The pre-treatment period is represented by dashed lines and the post-treatment period by solid lines, and the starting point is the treatment group panel. If we are interested in the quantile treatment effect at the median ($q = 0.5$), we select the median price in the pre-treatment period of the treated group (blue dashed line in Panel b). Unlike the QDID mechanism, where we would search the corresponding outcome at the same quantile, in the CIC the corresponding quantile at the same outcome is searched for (black dashed line in Panel a). Selecting this quantile in the pre-treatment control group, the CIC calculates the shift over time in the control group δ_{CIC} at that same quantile and return to the treatment group panel to add this difference to the initial outcome to get the counterfactual distribution. Finally, the counterfactual quantile outcome is subtracted from the post-treatment outcome in the treatment group to identify the quantile treatment effect τ_q^{CIC}. Athey and Imbens (2006) show that the estimator τ_q^{CIC} has an asymptotically normal distribution and recommend using bootstrapping for inference.

In summary, the QDID assumes that parallel trends hold between treatment and control

Figure 2: CIC Mechanics



Note: Illustration of the empirical strategy for CIC model. $Y_{11}, Y_{10}, Y_{01}, Y_{00}$ are simulated outcome distributions for treated and control group in pre- and post-treatment period. See text for details.

group at the same quantile q, though this may imply potentially different values of the outcome before treatment. The CIC in turn assumes parallel trends holds between treatment and control group with identical outcomes. We use these two approaches as a way of checking that our results are robust under the conditions underlying the two models.

4 Data

Data comes from the Auckland Council Valuation and Rates Base. We use 175,089 housing sales transactions in the Auckland region between September 2011 and September 2016. All transactions are geo-referenced, which allows identifying whether the dwelling sold is located inside or outside a SHA; and, if outside a SHA, the distance to the nearest one (Table 1). The percentage of dwellings sold that were inside a SHA was 3.96% of total sales. Of that percentage, 59.78% were transactions made after the program was launched in September 2013. Throughout the analysis, the selling price of the housing and the price per square meter, both in logarithms, will be the outcome variables.

Table 1: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max	p25	p50	p75
			Panel A: Outside SHA ($N = 168150$)				
Distance to nearest SHA (km)	1.749	3.976	0	80.98	0.423	0.840	1.469
Age at moment of Sale	32.89	25.05	1	167	10	30	48
Log of Dwelling Price	13.34	0.503	10.57	14.85	13.01	13.34	13.65
Log Pricer per Square Metre	8.553	0.402	7.175	9.630	8.287	8.550	8.825
			Panel B: Inside SHA ($N = 6939$)				
Age at moment of Sale	34.49	26.72	1	120	8	38	57
Log of Dwelling Price	13.25	0.472	11.51	14.85	12.93	13.24	13.58
Log Pricer per Square Metre	8.520	0.389	7.177	9.628	8.254	8.520	8.780

Note: Main descriptive statistics for the variables used in this study according to treatment status.

Table 2 is a first approximation to the effects of the SHAs program on the price distribution. Each column estimates the distribution value by quantile for the control and treatment groups in the pre-treatment (i.e., t(0)) and the post-treatment periods (i.e., t(1)). In panel A, the differences in prices are statistically significant and range from NZ$12,000 to NZ$92,000. Panel B shows differences for prices per square meter. These differences become significant around quantile 0.4, ranging from NZ$122.4 to NZ$409.6 per square meter.

Table 2: Price by Treatment Status over quantiles

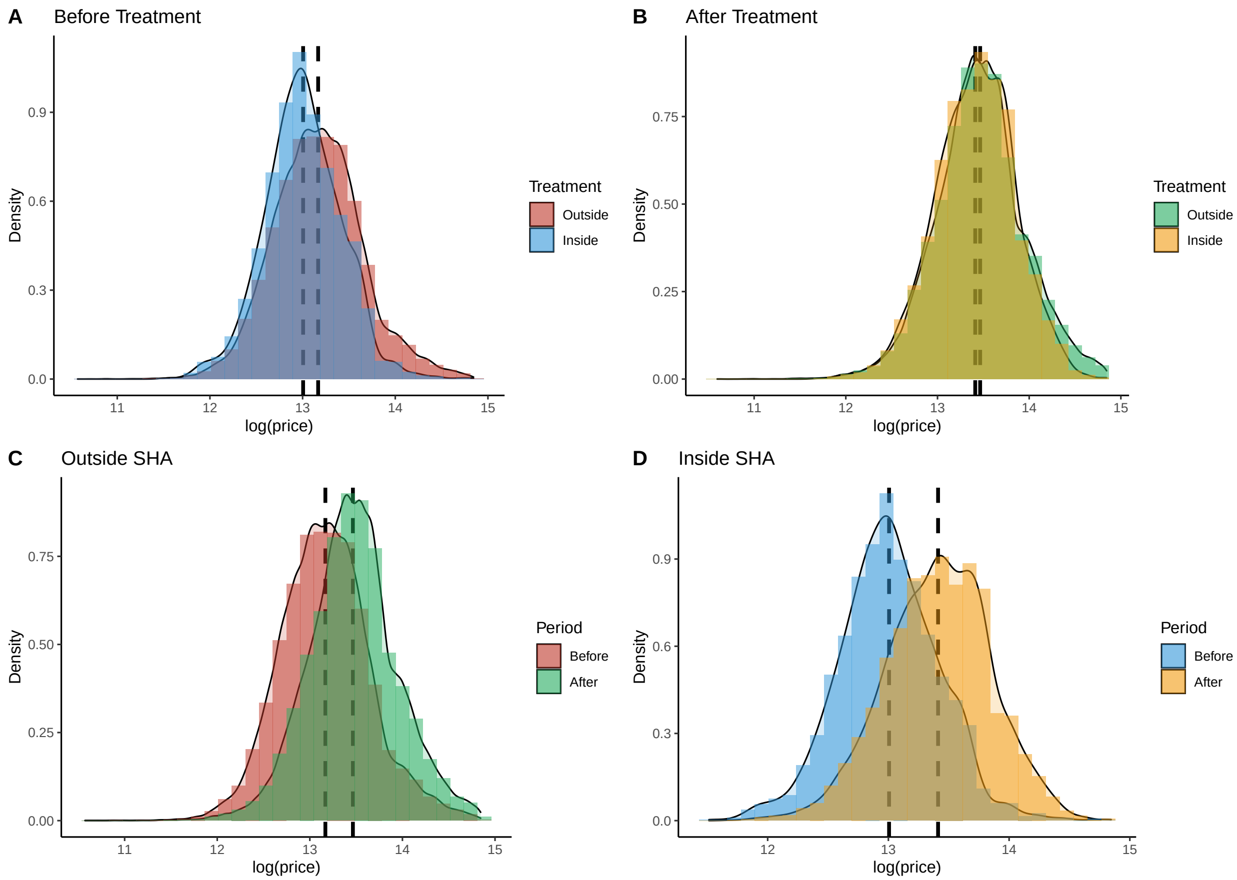
	$q = 0.1$	$q = 0.2$	$q = 0.3$	$q = 0.4$	$q = 0.5$	$q = 0.6$	$q = 0.7$	$q = 0.8$	$q = 0.9$
					Panel A: Dwelling Price (thousands NZ$)				
Diff t(1) - Diff t(0)	12.00*	13.50**	20.00***	36.00***	58.26***	75.50***	91.75***	66.00***	38.00*
	(6.609)	(6.273)	(4.798)	(3.940)	(0.233)	(6.938)	(12.03)	(14.67)	(21.98)
Control t(0)	290	350	405	460	520	582.5	660	759	941
Treated t(0)	270	320	360	400	440	482	545	628	760
Diff t(0)	-20	-30	-45	-60	-80	-100.5	-115	-131	-181
Control t(1)	390	481	560	630	700	780	877.5	1020	1305
Treated t(1)	382	464.5	535	606	678.3	755	854.3	955	1162
Diff t(1)	-8	-16.50	-25	-24	-21.74	-25	-23.25	-65	-143
					Panel B: Price per Square Metre (NZ$)				
Diff t(1) - Diff t(0)	-68.09	-76.09	61.64	122.4**	84.47	168.0***	141.7*	332.5***	409.6***
	(49.30)	(46.49)	(43.45)	(50.91)	(58.88)	(59.26)	(73.42)	(92.50)	(141.8)
Control t(0)	2835	3275	3617	3942	4294	4708	5211	5890	7027
Treated t(0)	2815	3222	3525	3796	4094	4415	4831	5313	6118
Diff t(0)	-20.55	-52.78	-92.43	-145.9	-200.6	-292.9	-379.8	-577.9	-909.6
Control t(1)	3708	4337	4852	5354	5874	6441	7143	8056	9500
Treated t(1)	3619	4208	4821	5331	5758	6316	6905	7810	9000
Diff t(1)	-88.64	-128.9	-30.79	-23.47	-116.1	-124.9	-238.1	-245.4	-500

Note: This table reports a first attempt to identify the effect on the price distribution of SHAs. Each column estimates the distribution value according to each q for the control and treatment group in the pre-treatment (i.e., t(0)) and the post-treatment periods (i.e., t(1)). In panel A, it is observed that the differences in dwelling prices related to the policy range from NZ$12 to NZ$92 thousands. Panel B shows the differences in each quantile q of the distribution for the price per square meter. These differences start to become significant around q = 0.4, ranging from NZ$122.4 to NZ$409.6 per square meter. Bootstrapped standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Figure 3 shows the density of the price distributions using a Gaussian kernel. The two upper graphs show the distribution of prices inside and outside the SHA before treatment and two lower graphs show the distribution of prices inside and outside the SHA after treatment. Prices both inside and outside SHAs are further to the right compared to before treatment.

This suggests a positive effect on prices across the distribution.

Figure 3: Dwelling Price Distribution: Treatment/Control and Before/After



Note: This graph shows the estimation of the density of the logs of dwellings price distribution with a Gaussian kernel. Panels A and B show how the price distribution varies before and after treatment, respectively. Panels C and D show the evolution of prices outside and inside SHA, respectively. Black dashed vertical line in each graph indicates the average of price distribution. The average price before policy outside SHA is 13.2 log units (NZ$ 523K) and the average price inside SHA in the same period is 13 log units (NZ$ 444K). The average price after policy outside SHA is 13.5 log units (NZ$ 704K), and the average price inside SHA in the same period is 13.4 log units (NZ$ 667K).

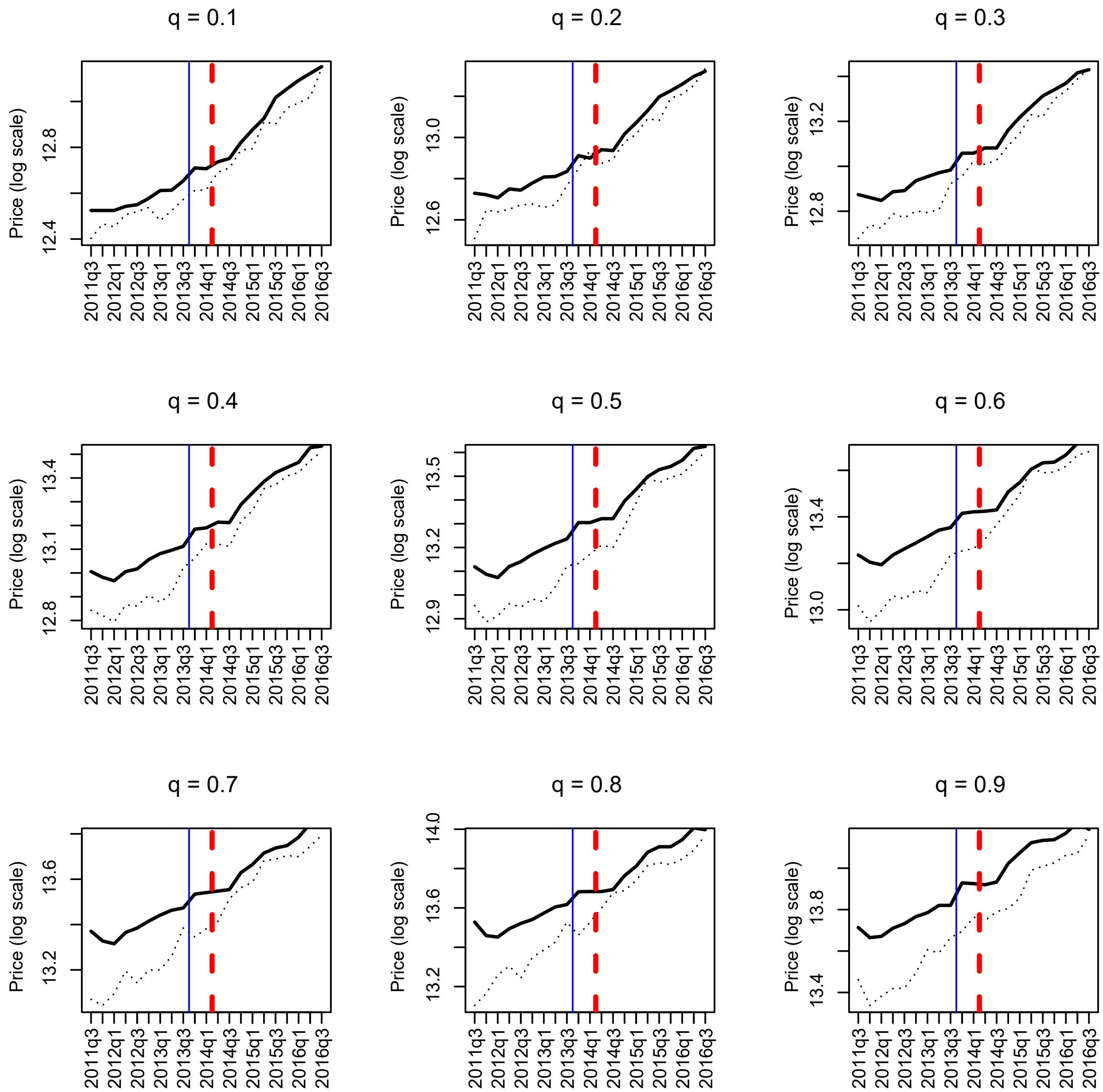
5 Results

5.1 Identification

Our identification strategy involves comparing prices before and after the implementation of the SHAs, for dwelling that were sold inside a SHA (i.e., treatment group) and dwellings that were sold outside SHA (i.e., control group). The QDID requires to verify whether the parallel trends assumptions hold in the pre-treatment period between each pair of quantiles of the treated and control groups. Nonetheless, the CIC relaxes the rank preservation assuming parallel trends between treatment and control units with the same value of the outcome in the pre-treatment period.

Most importantly, endogeneity is a potential concern. The decision for SHAs designation may be correlated with locations with higher market-rate housing prices. Thus, we verify the pre-existing patterns in the price distribution in treatment and control groups. Figure 4 shows the evolution of prices at the median and other selected percentiles. The blue and red vertical line indicate when the first and second SHA groups were implemented in 2013Q3 or 2014Q2, respectively. Note that the prices from dwellings inside SHAs (black dotted line) move parallel to the ones of dwellings outside SHAs (black shaded line) before 2013Q3. Dwelling prices inside the SHAs are below those outside the SHAs. Interestingly, in the post-treatment period, the difference between the two groups narrows down, which would suggest a positive and significant treatment effect on prices. The same graph was plotted in Figure A.2 in Appendix for the Log of Price per Square Meter variable. These results are still similar to those presented in Figure 4. In other words, Prices per Square Meter inside SHAs (outside SHAs) are below (above) over time, but after treatment, the differences between the two groups are narrowing.

Figure 4: Selected quantiles of log of dwelling prices from areas Inside & Outside SHAs



Note: The figure graphs percentiles of the distribution of log of dwelling prices, separately for transactions from treatment (dotted line) and control group (shaded line). Prices inside SHAs (outside SHAs) are below (above) over time, but after treatment, the differences between the two groups are narrowing. The blue and red vertical line indicate when the first and second SHA groups were implemented in 2013Q3 or 2014Q2, respectively.

5.2 Treatment Effects

Table 3 reports the estimation results of the CIC model for quantiles from 0.10 to 0.90. In column (1) we include month-by-year fixed effects and AU fixed effects as covariates and find a positive and significant effects at 99% of confidence for each quantile of the distribution, except when $q = 0.10$, which is significant at 90%. When we introduce time fixed effects per quarter and for each legacy district to control for unobservable equilibrium effects in column (2), the results remain robust, but not in the first decile. In columns (3) and (4) we add the age of dwellings in the moment of sale and restrict the sample of the control group to dwellings within 1 km to the nearest SHA. These results do not vary much with respect to column 2. Nonetheless, to test for anticipatory effects, in columns (5) and (6) we include leading indicators for 3 months and 1 quarter before SHA implementation and results remain robust. Standard errors are computed using Bootstrap.

Table 4 shows results for the QDID model. Following a similar approach to that presented in Table 3, the same specifications were estimated. We find that the pattern with respect to the lower price segment ($q = 0.10$) remains. These results are still similar to those presented in Table 3. In other words, the QTT of the SHA implementation increase in magnitude as you move up to more expensive price segments from $q = 0.2$. Moreover, for the expensive segments ($q > 0.70$) the effects in both models remain positive but are not observed to increase much more with respect to the other price segments. The effect on the first specification ranges from 5.11% to 7.71% using QDID and from 3% to 7.2% using CIC. That is, results depict a positive treatment effect on prices starting on the 20th percentile.

Figure A.3 in the Appendix shows the treatment effects corresponding to column (4) in Tables 3 and 4. For the CIC the effects are lower in absolute value in the lower end of the distribution ($q < 0.4$), the effect $q = 0.9$ is larger than in $q = 0.2$ by a factor of 1.75. Furthermore, the treatment effect for all percentiles is higher when using QDID compared to CIC estimates. This is due to the underlying assumptions behind each model. QDID assumes parallel trends holds between units inside and outside SHAs at the same quantile,

Table 3: Quantile Treatment Effects of SHA on Dwelling Prices using CIC

τ_q^{CIC}	(1)	(2)	(3)	(4)	(5)	(6)
q = 0.1	0.0300*	0.0290	0.0250	0.0170	0.0160	0.00700
	(0.0167)	(0.0205)	(0.0167)	(0.0196)	(0.0179)	(0.0202)
q = 0.2	0.0420***	0.0470***	0.0450***	0.0360***	0.0340***	0.0360**
	(0.0128)	(0.0113)	(0.0137)	(0.0135)	(0.0107)	(0.0168)
q = 0.3	0.0450***	0.0550***	0.0600***	0.0560***	0.0550***	0.0510***
	(0.0129)	(0.0128)	(0.0130)	(0.0120)	(0.0104)	(0.0128)
q = 0.4	0.0480***	0.0530***	0.0590***	0.0550***	0.0550***	0.0550***
	(0.0103)	(0.0108)	(0.0119)	(0.0115)	(0.00977)	(0.0120)
q = 0.5	0.0490***	0.0560***	0.0650***	0.0590***	0.0580***	0.0580***
	(0.0117)	(0.0103)	(0.0105)	(0.0113)	(0.0104)	(0.0108)
q = 0.6	0.0460***	0.0520***	0.0610***	0.0600***	0.0590***	0.0610***
	(0.0110)	(0.0108)	(0.0102)	(0.0101)	(0.00982)	(0.0101)
q = 0.7	0.0540***	0.0630***	0.0560***	0.0510***	0.0500***	0.0500***
	(0.0117)	(0.00975)	(0.0103)	(0.0120)	(0.0101)	(0.0116)
q = 0.8	0.0720***	0.0770***	0.0670***	0.0630***	0.0630***	0.0600***
	(0.0128)	(0.0114)	(0.0119)	(0.0121)	(0.0121)	(0.0128)
q = 0.9	0.0660***	0.0570***	0.0580***	0.0560***	0.0540***	0.0590***
	(0.0117)	(0.0116)	(0.00914)	(0.0127)	(0.0122)	(0.0116)
Observations	175,089	175,089	168,327	100,864	100,864	100,864
AU & Month-by-year FE	YES	YES	YES	YES	YES	YES
Quarter-by-year * District FE	NO	YES	YES	YES	YES	YES
Age	NO	NO	YES	YES	YES	YES
Distance SHA <1km	NO	NO	NO	YES	YES	YES
Monthly lead ind.	NO	NO	NO	NO	YES	NO
Quarterly lead ind.	NO	NO	NO	NO	NO	YES

Note: This table shows the results for the 6 specifications tested using CIC model. τ_q^{CIC} represents the treatment effect for q-th quantile (quantile treatment effect) of the price distribution. The dependent variable for each column is the log of the dwelling price. Bootstrapped Standard Errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Quantile Treatment Effects of SHA on Dwelling Prices using QDID

τ_q^{QDID}	(1)	(2)	(3)	(4)	(5)	(6)
q = 0.1	0.0271	0.0311	0.0303*	0.0244	0.0234	0.0174
	(0.0167)	(0.0196)	(0.0157)	(0.0187)	(0.0166)	(0.0185)
q = 0.2	0.0511***	0.0571***	0.0573***	0.0514***	0.0504***	0.0514***
	(0.0129)	(0.0115)	(0.0136)	(0.0127)	(0.0107)	(0.0161)
q = 0.3	0.0571***	0.0651***	0.0713***	0.0714***	0.0704***	0.0654***
	(0.0128)	(0.0125)	(0.0131)	(0.0111)	(0.0109)	(0.0129)
q = 0.4	0.0621***	0.0641***	0.0713***	0.0704***	0.0694***	0.0704***
	(0.0103)	(0.0109)	(0.0120)	(0.0104)	(0.00930)	(0.0115)
q = 0.5	0.0611***	0.0641***	0.0733***	0.0694***	0.0684***	0.0684***
	(0.0119)	(0.0106)	(0.0109)	(0.0113)	(0.0109)	(0.0112)
q = 0.6	0.0531***	0.0561***	0.0653***	0.0644***	0.0634***	0.0654***
	(0.0114)	(0.0116)	(0.0104)	(0.0105)	(0.00974)	(0.0101)
q = 0.7	0.0611***	0.0661***	0.0583***	0.0514***	0.0504***	0.0504***
	(0.0113)	(0.00949)	(0.00999)	(0.0115)	(0.00965)	(0.0119)
q = 0.8	0.0771***	0.0801***	0.0703***	0.0634***	0.0634***	0.0614***
	(0.0122)	(0.0108)	(0.0117)	(0.0124)	(0.0116)	(0.0132)
q = 0.9	0.0611***	0.0541***	0.0533***	0.0464***	0.0434***	0.0494***
	(0.0126)	(0.0118)	(0.00978)	(0.0124)	(0.0118)	(0.0118)
Observations	175,089	175,089	168,327	100,864	100,864	100,864
AU & Month-by-year FE	YES	YES	YES	YES	YES	YES
Quarter-by-year * District FE	NO	YES	YES	YES	YES	YES
Age	NO	NO	YES	YES	YES	YES
Distance SHA <1km	NO	NO	NO	YES	YES	YES
Monthly lead ind.	NO	NO	NO	NO	YES	NO
Quarterly lead ind.	NO	NO	NO	NO	NO	YES

Note: This table shows the results for the 6 specifications tested using QDID model. τ_q^{QDID} represents the treatment effect for q-th quantile (quantile treatment effect) of the price distribution. The dependent variable for each column is the log of the dwelling price. Bootstrapped Standard Errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Quantile Treatment Effect of SHA on Price per Square Metre using CIC

τ_q^{CIC}	(1)	(2)	(3)	(4)	(5)	(6)
q = 0.1	0.0450***	0.0430***	0.0580***	0.0490***	0.0420***	0.0410***
	(0.0151)	(0.0120)	(0.0137)	(0.0124)	(0.0131)	(0.0139)
q = 0.2	0.0390***	0.0400***	0.0470***	0.0340***	0.0320***	0.0320***
	(0.00887)	(0.00937)	(0.00941)	(0.0103)	(0.0104)	(0.0117)
q = 0.3	0.0230***	0.0250***	0.0410***	0.0300***	0.0280***	0.0280***
	(0.00739)	(0.00739)	(0.00790)	(0.00638)	(0.00698)	(0.00756)
q = 0.4	0.0250***	0.0240***	0.0310***	0.0220***	0.0220***	0.0210***
	(0.00629)	(0.00867)	(0.00756)	(0.00551)	(0.00584)	(0.00724)
q = 0.5	0.0140**	0.0160**	0.0280***	0.0180**	0.0160**	0.0150*
	(0.00709)	(0.00797)	(0.00820)	(0.00770)	(0.00725)	(0.00893)
q = 0.6	0.0200***	0.0200**	0.0220***	0.0150**	0.0120*	0.0120
	(0.00709)	(0.00792)	(0.00797)	(0.00724)	(0.00629)	(0.00789)
q = 0.7	0.0280***	0.0370***	0.0260***	0.0190***	0.0180***	0.0170**
	(0.00763)	(0.00727)	(0.00763)	(0.00737)	(0.00621)	(0.00752)
q = 0.8	0.0400***	0.0460***	0.0340***	0.0300***	0.0290***	0.0290***
	(0.00826)	(0.00849)	(0.00839)	(0.00775)	(0.00814)	(0.00979)
q = 0.9	0.0740***	0.0720***	0.0580***	0.0540***	0.0520***	0.0520***
	(0.0107)	(0.0106)	(0.00957)	(0.00949)	(0.00924)	(0.0102)
Observations	175,089	175,089	168,327	100,864	100,864	100,864
AU & Month-by-year FE	YES	YES	YES	YES	YES	YES
Quarter-by-year * District FE	NO	YES	YES	YES	YES	YES
Age	NO	NO	YES	YES	YES	YES
Distance SHA <1km	NO	NO	NO	YES	YES	YES
Monthly lead ind.	NO	NO	NO	NO	YES	NO
Quarterly lead ind.	NO	NO	NO	NO	NO	YES

Note: This table shows the results for the 6 specifications tested using CIC model. τ_q^{CIC} represents the treatment effect for q-th quantile (quantile treatment effect) of the price distribution. The dependent variable for each column is the log of the price per square meter. Bootstrapped Standard Errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

but potentially different values of the outcome in the before-treatment period may occur. In contrast, the CIC assumes that units with identical outcomes would follow a parallel trend in the absence of treatment.

However, a generalized rise in housing prices may be due to several external factors, including demand for better quality and size homes. To control for possible changes in consumer preferences with respect to house size, we estimate the models now using the Log Price per Square Meter as the outcome variable. Table 5 shows that the CIC treatment effects are positive and significant across all the deciles. Table 6 shows results of the QDID model and, again, it is observed that the effects are higher than the CIC. We select results from column (4) and plot results in Panel D of Figure A.3 in the Appendix. It shows that, for the CIC model, the treatment effect is higher in magnitude value located in both tails of the distribution. That is, price effects are high on the upper and lower quartiles rather than around the median. These results suggest that the policy may have introduced a high bar for houses to be considered as affordable (Criteria A of the SHAs: sales price had to be no more than 75% of the median price in Auckland). That is, those dwellings in the lower quartile suffered a price increase that would match the price ceiling set by the SHAs. On the other hand, the higher treatment effect in the upper end of the distribution may imply developers setting higher prices to compensate for foregone revenues. Nonetheless, this may not be plausible considering the low number of affordable houses delivered. In turn, we argue that the SHAs introduced an additional attribute to market-rate dwellings: prompter delivery times between consenting and construction considering the streamlining of the resource consenting process under the SHAs legislation.

Comparing the results using the log of housing prices and the log of price per square sample shows that for both the affordable segments ($q < 0.20$) and expensive segments ($q > 70$) the effects are inverse with respect to the median of the respective distribution. In other words, using Log of Dwelling Prices for the expensive segments the effects in both models remain positive but are not observed to increase much more with respect to the other price segments, while using Log of Price per Square Meter for the same segment the effects in both models remain positive but are observed to increase much more with respect to price segments around the median. The same pattern is observed for houses in the affordable price segments. These results suggest that the implementation of SHA may have been related to the supply of smaller sized houses. Figure 5 shows how the size of houses inside and outside SHAs has evolved by different size segments. In this figure, $q \in (0, 1)$ represents the different percentiles of the distribution of housing size per square meter. It is observed that the evolution of house size inside SHAs (red line) is more volatile than the evolution of house

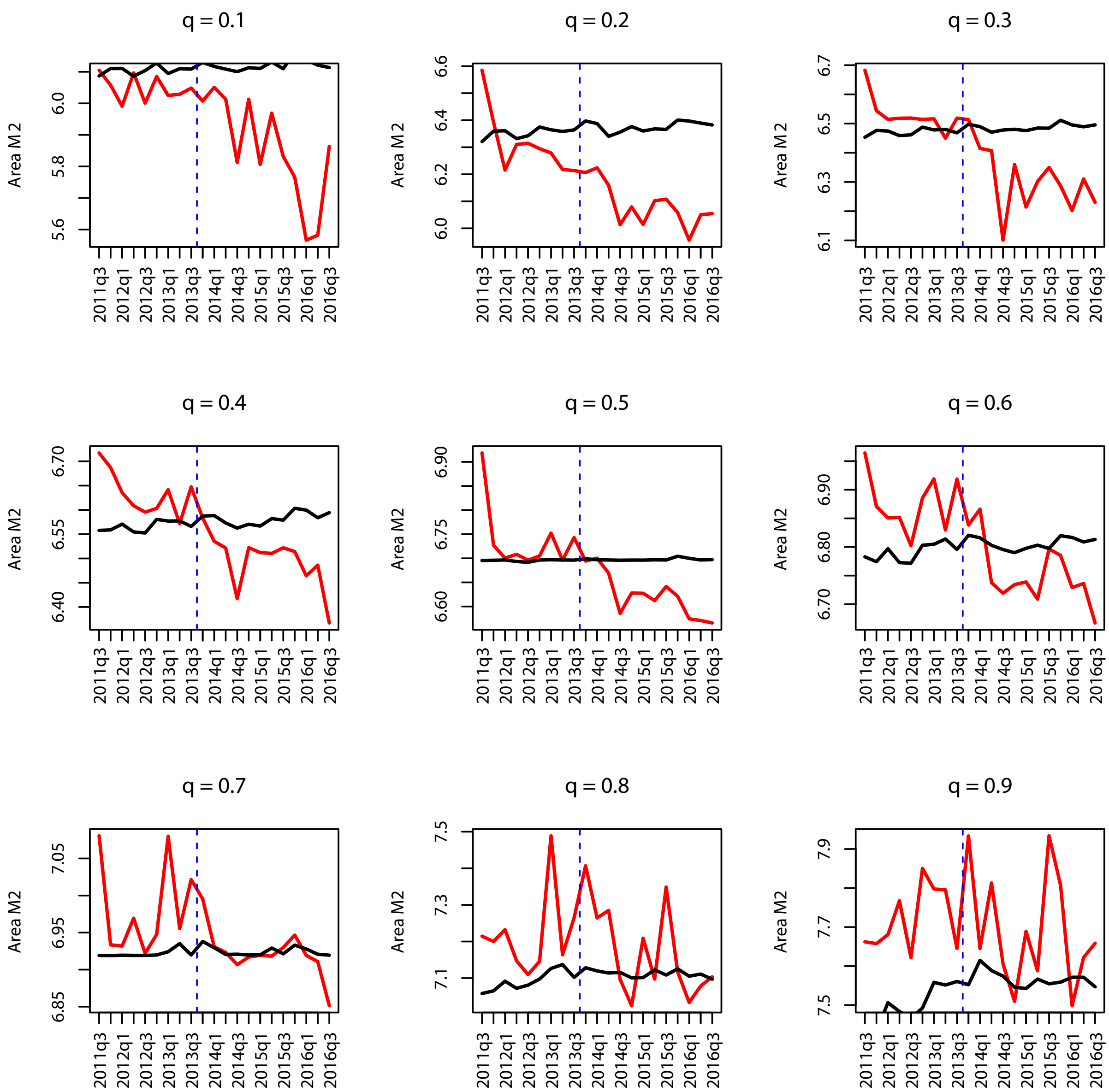
Table 6: Quantile Treatment Effect of SHA on Price per square metre using QDID

τ_q^{QDID}	(1)	(2)	(3)	(4)	(5)	(6)
q = 0.1	0.0310**	0.0291**	0.0472***	0.0395***	0.0344***	0.0304**
	(0.0144)	(0.0115)	(0.0124)	(0.0120)	(0.0126)	(0.0137)
q = 0.2	0.0310***	0.0311***	0.0422***	0.0295***	0.0264***	0.0264**
	(0.00839)	(0.00905)	(0.00891)	(0.00931)	(0.00978)	(0.0109)
q = 0.3	0.0220***	0.0231***	0.0392***	0.0315***	0.0294***	0.0294***
	(0.00707)	(0.00713)	(0.00727)	(0.00573)	(0.00681)	(0.00711)
q = 0.4	0.0290***	0.0281***	0.0352***	0.0285***	0.0284***	0.0274***
	(0.00600)	(0.00817)	(0.00681)	(0.00520)	(0.00563)	(0.00693)
q = 0.5	0.0240***	0.0241***	0.0362***	0.0275***	0.0254***	0.0244***
	(0.00692)	(0.00777)	(0.00751)	(0.00753)	(0.00697)	(0.00840)
q = 0.6	0.0320***	0.0321***	0.0332***	0.0265***	0.0244***	0.0244***
	(0.00695)	(0.00750)	(0.00774)	(0.00737)	(0.00645)	(0.00723)
q = 0.7	0.0410***	0.0491***	0.0382***	0.0305***	0.0294***	0.0284***
	(0.00767)	(0.00711)	(0.00758)	(0.00765)	(0.00654)	(0.00765)
q = 0.8	0.0530***	0.0591***	0.0462***	0.0405***	0.0384***	0.0384***
	(0.00862)	(0.00854)	(0.00835)	(0.00816)	(0.00813)	(0.00982)
q = 0.9	0.0820***	0.0811***	0.0662***	0.0595***	0.0564***	0.0564***
	(0.0110)	(0.0110)	(0.0101)	(0.0102)	(0.00937)	(0.0109)
Observations	175,089	175,089	168,327	100,864	100,864	100,864
AU & Month-by-year FE	YES	YES	YES	YES	YES	YES
Quarter-by-year * District FE	NO	YES	YES	YES	YES	YES
Age	NO	NO	YES	YES	YES	YES
Distance SHA <1km	NO	NO	NO	YES	YES	YES
Monthly lead ind.	NO	NO	NO	NO	YES	NO
Quarterly lead ind.	NO	NO	NO	NO	NO	YES

Note: This table shows the results for the 6 specifications tested using QDID model. τ_q^{QDID} represents the treatment effect for q-th quantile (quantile treatment effect) of the price distribution. The dependent variable for each column is the log of the price per square meter. Bootstrapped Standard Errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

size outside SHAs (black line) in all size segments. In addition, there is a negative trend in house sizes within SHAs and after the implementation of the policy the negative trend is exacerbated.

Figure 5: Evolution of Area in m^2 by size segments



Note: This figure shows quantiles of the distribution of Log of Area in m^2 (size segments), separately for dwellings inside SHAs (black line) and dwellings outside SHAs (red line).

5.3 Robustness Analysis

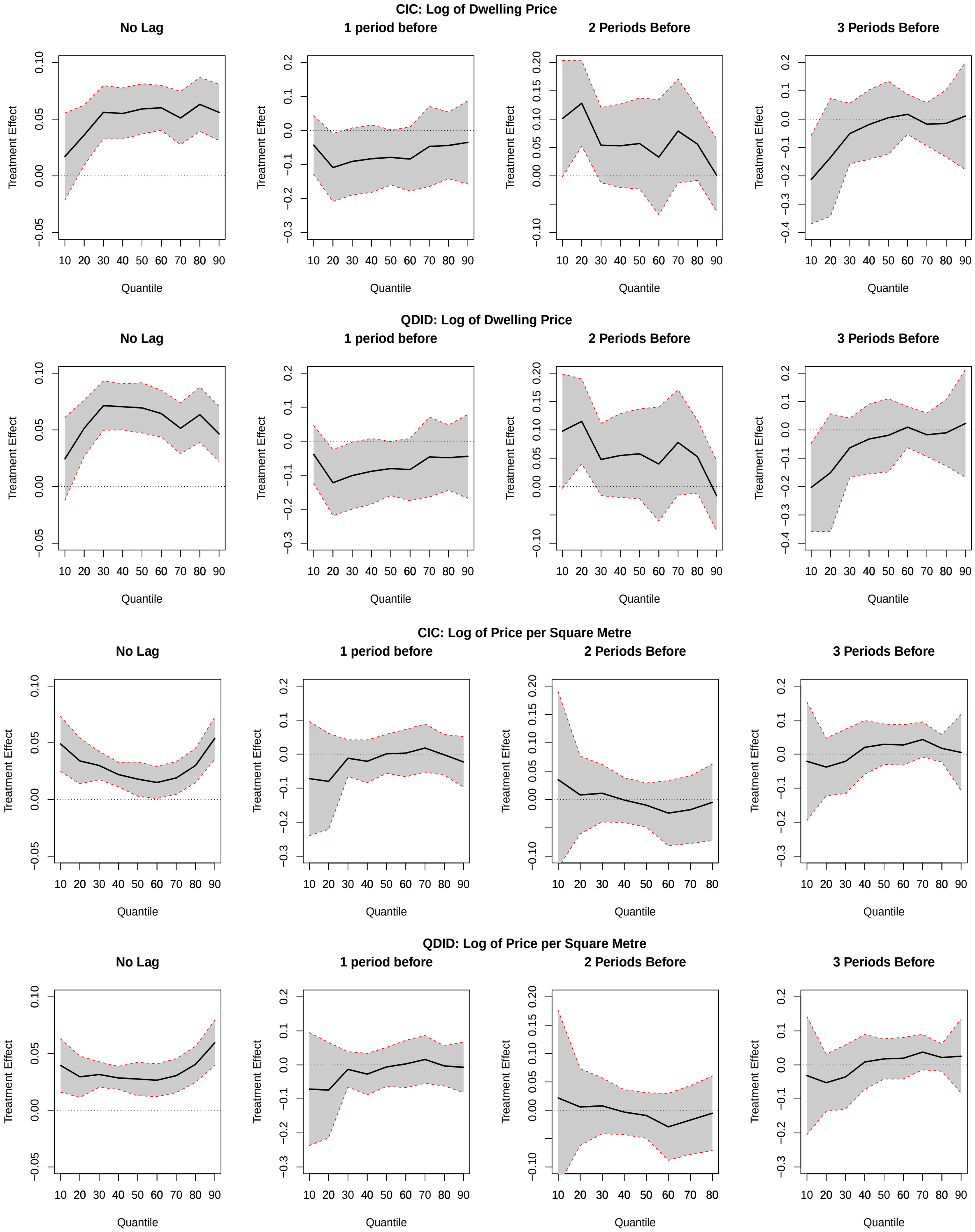
As is the case when we evaluate policies with non-experimental data, we cannot completely avoid selection bias and, thus, this section presents the results of a series of specification checks. These checks are performed for each percentile of the outcome distributions, and not just for the mean. To check robustness with respect to the exact definition of the treatment, we perform a placebo test by changing the date on which the policy was implemented for CIC and QDID specifications. We use one, two and three periods before the treatment to assess the validity of this identification assumption. In our analysis, treatment period occurs in October 2013 in most cases. However, for New Lynn Area Units occurs in November 2013, for Albany Area Units occurs in May 2014, and for Otahuhu Area Units occurs in June 2014. It is expected that by changing the definition of the treatment date, no effect is found along the percentiles of the distribution.

Figure 6 shows statistical insignificance for all quantiles of the distribution, both for log of dwelling price and log of price per square meter as outcome variables. Though some non-zero effects occur these are probably imprecisely estimated. These results support our identification strategy.

6 Discussion

IZ is a policy that encourages developers to set-aside a percentage of new residential units in order to boost the supply of affordable housing for low- and middle-income households. Typically, this kind of programs include: the set-aside percentage for affordable units (between 5% and 20%), the income group of targeted population groups, and the term for housing affordability. Measuring the effects of the IZ is difficult because each program has its own characteristics. Moreover, there is little empirical evidence on the performance of voluntary IZ programs on market outcome variables. Our results attempt to contribute to the causal analysis of this type of policy by making use of a unique dataset of housing transactions in

Figure 6: Robustness Check: CIC & QDID



Note: This figure shows the QTE estimates using the two methodologies and the two outcome variables, but changing the variable of the time of treatment implementation from 1 to 3 periods before the actual period (No Lag).

Auckland.

Housing affordability is a topic of great economic and social interest in developed countries and housing issues have received significant attention. The reason is that, unlike any other type of goods, housing absorbs a significant proportion of a household wealth. Further, home ownership has been linked to building social capital and a sense of community (DiPasquale and Glaeser, 1999), and therefore represents an item of great interest to households.

The Special Housing Areas (SHA) program was created in Auckland under a voluntary IZ scheme, which aimed to increase housing affordability. For its re-structuring or likely replication in other NZ cities, the effects of this policy need to be further evaluated. Using a dataset of around 170 thousand housing sales transactions carried out between 2011 and 2016, we build on the work of Fernandez et al. (2019) and evaluate this policy beyond its average effect, identifying the entire counterfactual price distribution to the policy. Our methodology adds two points to this literature: i) From the empirical point of view, our methodology would be more robust because it deals with possible identification problems using Difference-in-Difference, which have received the most attention in the recent literature, especially those related to the functional form and the assumption of parallel trends. ii) From the public policy point of view, our analysis allows us to address and study possible heterogeneous effects of the policy by analysing whether there was a larger (or smaller) effect on various segments of the price distribution.

Our findings show that the SHA program increased housing prices for all distribution segments, ranging from 3% to 7%. Naturally, these findings are counter-intuitive to the objective of this program. Moreover, our results provide evidence for analyzing whether the program causes an average increase in prices due to homes selling more expensively to subsidize homes selling at an affordable price. In addition, our results suggest that the policy may have had an effect on the size of homes, offering smaller homes in both affordable and expensive segments.

Implications and lessons learnt in this paper are informative to policy makers designing programs that aim to make the Auckland housing market more affordable. Furthermore, the quasi-experimental approach used in this paper may be a benchmark to evaluate similar SHAs/IZ programs in New Zealand or similar countries in a heterogeneous way to direct efforts and resources to segments most in need. Price monitoring especially targeted to low and middle-income segments is critical in an IZ program. Affordability criteria may cause prices to increase in segments that were affordable before the policy implementation to meet the price ceiling set imposed by the criteria defined by the policy. In addition, price increases in more inelastic segments may be the response of developers to offset the costs of providing affordable housing without losing the benefits provided by the policy for new developments like fast-tracking of the resource consenting process. However, to conclude this, it would be necessary to analyze the evolution of regional prices because SHAs/IZ seems to increase prices during times of regional price appreciation, or decrease prices during cooler regional markets (Schuetz et al., 2011; Hamilton, 2021). In the case of Auckland, prices were appreciating during the analysis period. Finally, it is necessary to consider the trade-off between the required percentage of new development and the affordability criteria proposed by the policy.

Moreover, the acceleration of the permitting process, which was one of the benefits of SHAs, allowed developers to offer faster delivery of new construction. It is known that the willingness to pay for a home is composed of a set of features that have properties that increase consumer utility. Therefore, it is to be expected that when an attribute is added that is valued by the consumer there will be an increase in the price of the product (Lancaster, 1966). Consequently, the implementation of SHAs allowed developers to offer houses in less time, which could be valued by consumers, making them willing to pay more.

In the case of the SHAs, the control and enforcement schemes were not clear, which weakened their purpose and mandate. The AHA is not explicit about the voluntary or mandatory nature of the program, and there is no mention of the existence of controls and sanctions in case of noncompliance with the delivery of affordable housing. In fact, from the program's inception, its permanence was not entirely clear to the players. The Housing Accord implemented SHAs as a transitional solution until the operation of the Auckland Unitary Plan in late 2016. Therefore, considering that the implementation of the SHA was in 2013 and that the expected life was around 3 years, this may have generated incentives for developers to wait until the implementation of the new plan and not to offer new developments. Therefore, for the implementation of a rezoning policy, the rules must be clear in order to ensure the best possible performance.

Future research should examine home-buyer behaviour and developer incentives in more detail. However, the results of this paper are informative to housing policy makers and draw the line toward an IZ program evaluation framework.

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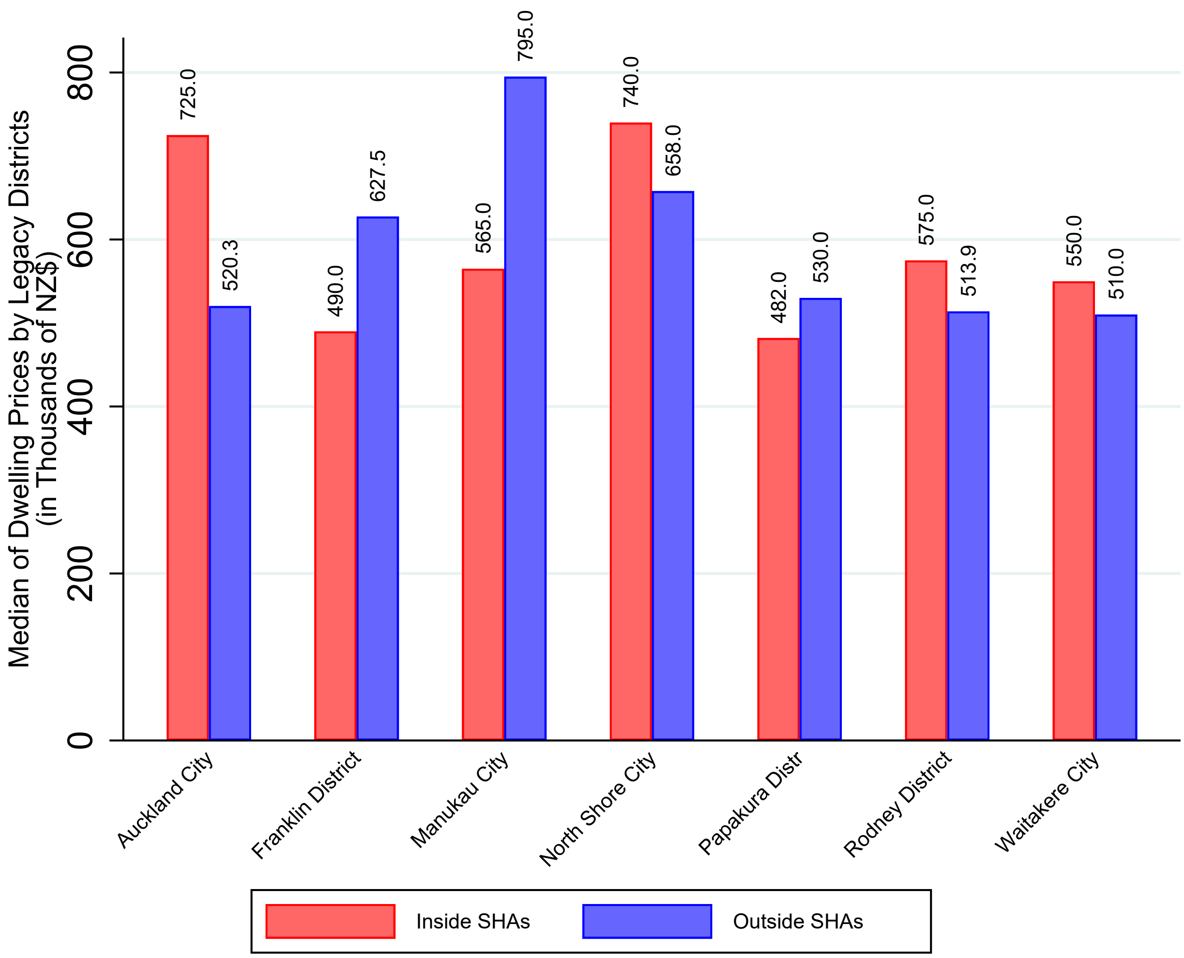
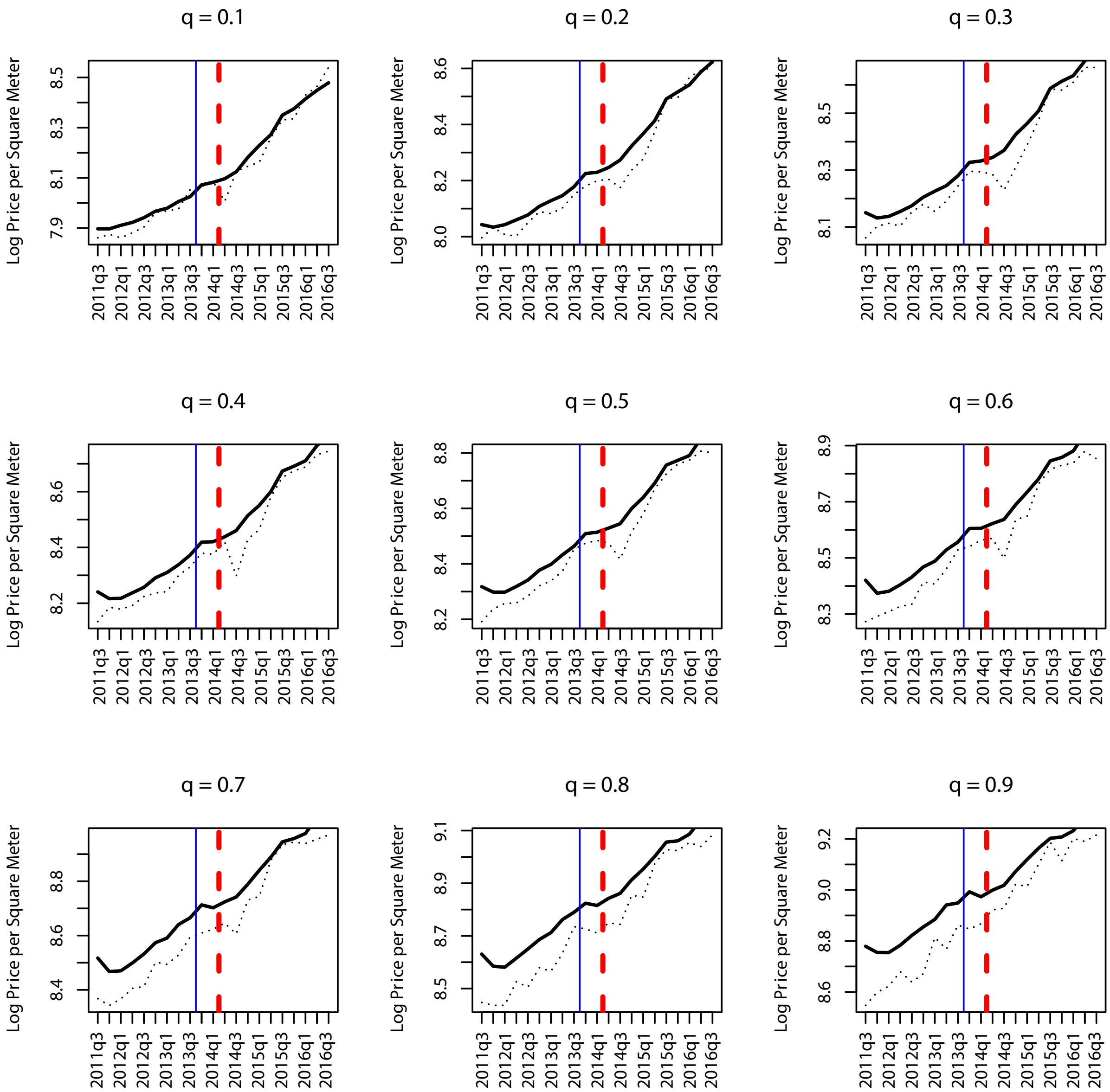
A Appendix

Figure A.1: Dwelling Prices by Legacy Districts



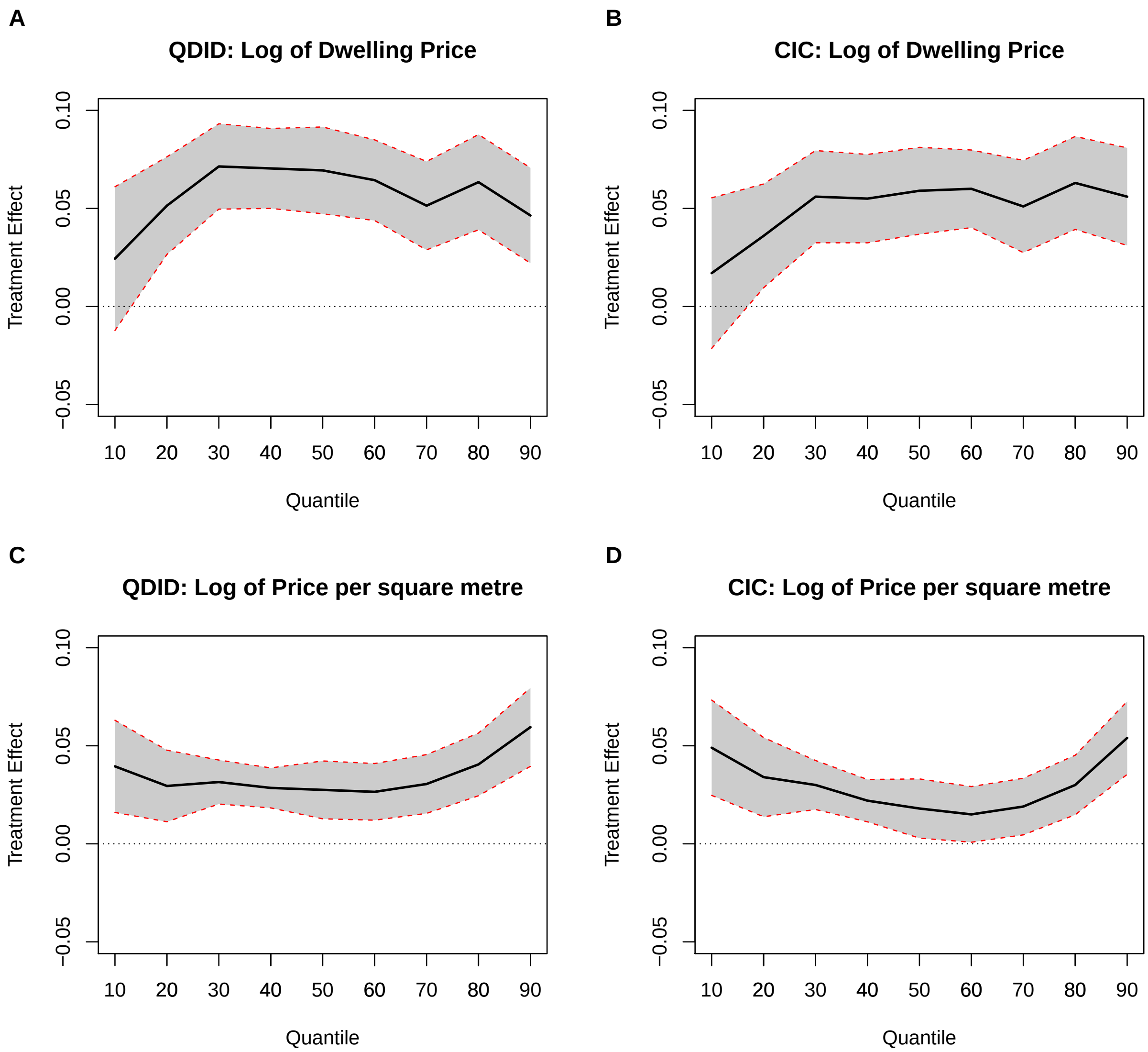
Note: This figure shows the median of dwelling prices inside and outside SHAs for each legacy district. Prices are in thousands of New Zealand Dollars.

Figure A.2: Selected quantiles of Log of Price per Square Meter from areas Inside & Outside SHAs



Note: The figure graphs quantiles of the distribution of Log of Price per Square Meter, separately for transactions from treatment (dotted line) and control group (shaded line). Prices per Square Meter inside SHAs (outside SHAs) are below (above) over time, but after treatment, the differences between the two groups are narrowing. The blue and red vertical line indicate when the first and second SHA groups were implemented in 2013Q3 or 2014Q2, respectively.

Figure A.3: Distributional Effects: CIC & QDID



Note: The figure graphs QTE estimates from QDID and CIC estimator, including a 95% confidence interval based on a non-parametrics boostrap with 100 replications clustered at the AU level. Panels A and B use housing prices as the dependent variable in logs. Panels C and D use price per square meter as the dependent variables in logs.