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Abstract

In 2016, Auckland, New Zealand upzoned approximately three-quarters of its residential land, precipitating a boom in housing construction. In this paper we investigate whether the increase in housing supply has generated a reduction in housing costs. To do so, we adopt a synthetic control method that compares rents in Auckland to a weighted average of rents from other urban areas that exhibit similar rental market outcomes to Auckland prior to the zoning reform. The weighted average, or "synthetic control", provides an estimate of Auckland rents under the counterfactual of no upzoning reform. Six years after the policy was fully implemented, rents for three bedroom dwellings in Auckland are between 22 and 35% less than those of the synthetic control, depending on model specification. Moreover, using the conventional rank permutation method, these decreases are statistically significant at a five percent level. Meanwhile, rents on two bedroom dwellings are between 14 and 22% less than the synthetic control, although these decreases are only significant at a ten percent level in some model specifications. These findings suggest that large-scale zoning reforms in Auckland enhanced affordability of family-sized housing when evaluated by rents.

Keywords: Upzoning, Land Use Regulations, Redevelopment, Housing Costs, Rents, Synthetic Controls.

JEL Classification Codes: R14, R31, R52.

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1 Introduction

Housing has become increasingly expensive in many parts of the world, precipitating an affordability crisis (Wetzstein, 2017; Saiz, 2023). A wide range of economists and urban planners attribute high house costs, at least in part, to restrictive zoning (Gyourko and Molloy, 2015; Been, 2018; Hamilton, 2021). Zoning reform to relax restrictions on housing density is consequently advocated to reduce prices by relaxing regulatory restrictions on housing supply. (Glaeser and Gyourko, 2003; Freeman and Schuetz, 2017).[1] However, up until very recently, few cities have pursued large-scale zoning reforms to enable affordability (Schill, 2005; Freeman and Schuetz, 2017), meaning there little empirical evidence to support the purported effects of zoning reforms.

However, in 2016 the city of Auckland, New Zealand, upzoned approximately three-quarters of its residential land (Greenaway-McGrevy and Jones, 2023), precipitating a construction boom in the city (Greenaway-McGrevy and Phillips, 2023), and affording us six years of data to examine the impact of the reforms on housing costs. In this paper, we assess the impact of the reforms on Auckland's housing costs, adopting a synthetic control approach to specify the counterfactual scenario to the policy change. The synthetic control is constructed from a donor pool comprising 51 commuting zones in New Zealand, and matched to a variety of observed housing market outcomes, including dwellings per capita and the average proportion of household income allocated to housing costs.

Depending on model specification, housing costs for family-sized (i.e., three bedroom) dwellings have decreased by between 22 and 35% relative to the synthetic control six years after the reforms. Housing costs for smaller (two bedroom) dwellings have decreased by 21 to 22% over the same period, depending on model specification. Put differently, the fitted models imply that housing costs for 3 bedroom dwellings in 2022 would be between 28 and 54% higher had Auckland not implemented zoning reforms. Housing costs for 2 bedroom dwellings would be 16 to 28% higher.

To assess the statistical significance of these decreases, we apply the conventional rank permutation test to the ratios of post- to pre- intervention mean square errors (MSEs, Abadie et al. 2010).[2] For three bedroom dwellings, only one of the 51 units in the donor pool has a ratio that exceeds that of Auckland in our baseline model specification. If one were to assign the intervention at random, the probability of obtaining a ratio as large as Auckland's is 0.038 (= 2/52). Under alternative model specifications, Auckland has the largest ratio among all donor units, corresponding to a probability of 0.019 (= 1/52). Thus, the decrease in 3 bedroom rents is statistically significant at the five percent level across various model specifications. For two bedroom dwellings, five of the donor pool units have a larger MSE in our baseline specification, with a corresponding probability of 0.0962 (= 5/52), which would be significant at a ten percent significance level. However, the statistical significance of the decrease varies between models, and is often insignificant, even at the ten percent level. This evidence supports the proposition that upzoning reduced housing costs for larger, family-sized dwellings, but there is less evidence that it decreased housing costs for smaller

[1] "Plexes" refers to duplexes, triplexes, sixplexes, etc.

[2] Abadie et al. (2010) rank root mean squared error, which is a monotonic transformation of MSE.

dwellings.

We use prices on new rental tenancies (hereafter "rents") as our measure of housing costs. We use rents, rather than house prices, for two reasons. First, rents are not directly affected by enhanced redevelopment rights from zoning reform. The effects of upzoning on housing prices is mediated by the land endowment of affected properties. Land prices in desirable locations increase in value (Greenaway-McGrevy, 2023a), reflecting the increased capacity of the land to hold additional floorspace and the right to redevelop the property into capital intensive dwellings. Properties that are relatively land intensive, such as detached single family dwellings on large lots, are likely to appreciate in value. Both (Greenaway-McGrevy et al., 2021) and (Greenaway-McGrevy and Phillips, 2023) show evidence of this occurring in Auckland after the reforms. Rents, on the other hand, are not affected by the enhanced development rights, which accrue to the landowner. Second, rents potentially capture housing costs across a wider socioeconomic demographic, given that low income households are more likely to be tenants.

The differential effects between large and small homes is consistent with LUR changes under the reforms, which relaxed stringent restrictions on floorspace capacity. Prior to the reforms, the vast majority of residential land had an implied maximum floor to area ratio (FAR) restriction identical to that used for detached single family zoning under the reform (Greenaway-McGrevy and Jones, 2023). Minimum lot sizes (MLS) were comparatively low in some targeted locations, but were often paired with restrictive FARs.[3] The combination of stringent floorspace restrictions but comparatively relaxed MLS encourages smaller dwellings in these targeted areas. MLS on existing parcels were abolished under the zoning reforms, and FAR restrictions lifted on three-quarters of residential land.

The finding that large-scale zoning reforms can reduce housing costs is important. While researchers and have advocated for large-scale zoning reform as a means to achieve affordability, studies that focus on localized upzonings typically show muted or no effects on housing supply (Freemark, 2020; Murray and Limb, 2022; Peng, 2023), casting doubt on the ability of zoning reforms to meet intended objectives (Rodríguez-Pose and Storper, 2020). Recently, Stacy et al. (2023) examine over fifty upzonings in various cities in the U.S., finding small effects on housing construction and costs. Results from the present synthetic control approach indicate that the large-scale zoning reform undertaken as part of the Auckland Unitary Plan did enhance housing affordability, at least as measured by rents, suggesting that market-based responses can play a role in redressing unaffordable housing.

The synthetic control method has been applied to evaluate policy in a variety of contexts (see Abadie (2021) for a comprehensive review), and was recently described by Susan Athey and Guido Imbens as "arguably the most important innovation in the policy evaluation literature in the last 15 years" (Athey and Imbens, 2017). We take several steps to ensure that our research design and

[3]For example, zones 3A, 4A, 4B, 6A, 6B and 6C under the former North Shore City Council plan had MLS between $350\text{m}^2$and 450m^2, but also had site coverage ratios and height restrictions that implied a maximum FAR of 0.7. The "Single House" zone under the AUP also has an implied FAR of 0.7, and a MLS on new subdivisions of 600m^2.

implementation is robust to common pathologies. First, we use the longest possible times series on outcomes prior to intervention in order to minimize bias in the synthetic unit (Abadie et al., 2010). Our rental time series spans 1993, when the data begin, to 2022, with the intervention occurring in 2016. Second, our donor pool consists of all commuting zones (except one that was also affected by the same reforms in 2016), meaning that we do not select donors based on subjective judgment, but rather their similarly to Auckland rental market outcomes. Third, our findings are robust to conventional robustness exercises incorporated into study design that are used in the extant literature. Synthetic outcomes for the treated unit are largely unaffected by the "leave one out" robustness check (Abadie et al., 2010), whereby units from the donor pool are iteratively removed from the sample while the procedure is repeated. We also examine how robust our findings are to changes in modeling assumptions. Although the magnitude of implied rent decreases does vary between specifications, in all specifications we find that the decreases in three bedroom dwelling rents are statistically significant.

Nonetheless, there are inherent limitations to the SC method. Donor units will be affected by the policy change if increased housing supply in Auckland affects inter-city migration. We note, however, that in-migration to Auckland from lower housing costs generates attenuation bias in estimates of the casual impact, since it reduces housing demand in other cities and increases it in Auckland, pushing up housing costs in Auckland. More problematic is a population decrease in Auckland from 2020 onwards, widely attributed to COVID-19 and policy responses thereto. Statistics New Zealand estimates that Auckland's population decreased by 1.1% between 2020 and 2022. Although media attention at the time focused mainly on Auckland, the same population estimates show that other cities experienced population decreases, including (but not limited to) Dunedin (1.79%), Wellington (0.14%) and Rotorua (0.4%). (Notably, these cities experienced significant appreciation in rents between 2020 and 2022, despite population decreases.) We address this problem in two ways. First, we end the sample in 2020, when the estimates of Auckland's population peak. Second, we include estimates of population decrease between 2020 and 2022 in the set of predictor variables, and drastically reduce the set of matching variables to those that feasibly predict the exodus, so that the population decrease variable plays a prominent role in constructing the synthetic control for Auckland. Our conclusions remain unchanged under both robustness checks.

The remainder of the paper is organized as follows. The following section provides the institutional details of the policy and backgrounds on Auckland and New Zealand. Section three describes the data. In section four presents the method and results. We first present our baseline empirical specification, before exploring variations of the baseline model. Section five concludes.

2 Institutional Background

Housing costs in New Zealand are among the most expensive in the developed world. Among renters and owner-occupiers with a mortgage, the median proportion of disposable income (i.e. after taxes and transfers) spent on housing costs was 22% in 2021, exceeded only by Australia, Greece and

France among the OECD.[4] Among renting households, the median proportion is 28%. As of the 2018 census, over a third (35.5%) of households are tenants.[5] This figure is higher for Auckland, where more than two-fifths (40.6%) of households rent.

Auckland in the largest city in New Zealand, with a population of 1.57 million in 2018 (source: New Zealand census). In March 2013, the city announced the first version of the Auckland Unitary Plan (AUP), which introduced and applied a standardized set of planning zones across the jurisdiction, including four residential zones intended to encourage medium density housing. After several rounds of reviews and consultation, the plan was operationalized in November 2016. Approximately three-quarters of residential land was upzoned, in the sense that effective FAR restrictions on housing development were relaxed (Greenaway-McGrevy and Jones, 2023).

Although the plan was operationalized in 2016, an agreement between the Auckland Council and the central government allowed developers to build to the rules of the 'Proposed' Auckland Unitary Plan (PAUP), announced in September 2013. This was an inclusionary zoning program that required developers to offer a 10% proportion of affordable housing in exchange for accelerated permitting process and the ability to build to the more relaxed LURs under the PAUP. The program ended once the AUP was implemented. Thus, while the AUP was formally operationalized in 2016, it began to have a small effect from September 2013 onwards. For additional details on the implementation of the plan and the spatial distribution of upzoning, see Greenaway-McGrevy and Jones (2023).

Housing supply quickly responded to the reforms. Figure 1 exhibits annual consents issued per year, decomposed into consents issued in upzoned areas, non-upzoned areas (including business and rural areas). Consents for new dwellings significantly increased year-on-year from 2016 onwards, with all of the new construction occurring on upzoned areas. Note, however that the divergence between upzoned and other areas begins from 2013 onwards, reflecting policy "leakage" as some developers took advantage of the relaxed regulations under the PAUP. The PAUP-SpHA consents were disproportionately located in areas that were upzoned (see Figure 14 in the Appendix, which separately identifies PAUP-SpHA in the data). We use 2016 as the date of the policy intervention in the synthetic control approach, since this the date after which the divergence becomes most evident, although 2012 or 2013 could also feasibly be used as the treatment date.

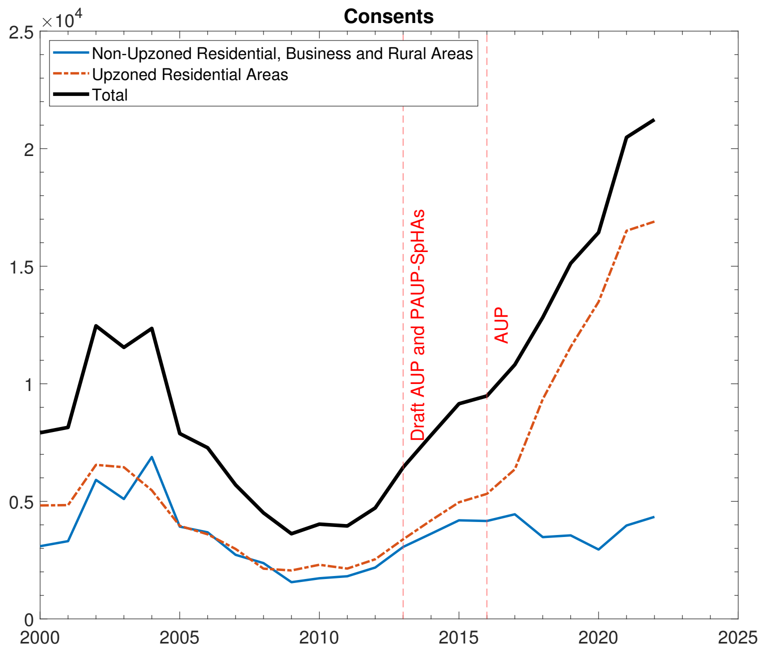
3 Data

Data on new tenancies are compiled by the Ministry of Housing and Urban Development (HUD) on a quarterly basis and are available at the Statistical Area 2 (SA) level. HUD reports the geometric mean rent for dwellings by the number of bedrooms (2, 3, 5 and 5+) and housing types ("Flats" and "Houses"). Because HUD reports the number of new tenancies, we can compute geometric

[4] See Figure 10 here: https://www.msd.govt.nz/documents/about-msd-and-our-work/publications-resources/monitoring/household-income-report/2021/international-comparisons-of-housing-affordability.docx. Data for Auckland is not available.

[5] Source: 2018 census https://www.stats.govt.nz/tools/2018-census-place-summaries/auckland-region#housing

Figure 1: Dwelling Consents in Auckland, 2000 to 2022



Notes: Consents issued per year in different areas of Auckland. The first, "draft", version of the AUP was announced in March 2013, while the "Proposed" AUP (PAUP) was notified in September 2013. Between September 2013 and November 2016, Special Housing Area (SpHA) developments could build to the regulations of the PAUP in exchange for affordable housing provisions. The final version of the AUP became operative in part in November 2016. Source: Greenaway-McGrevy (2023b).

mean rents for aggregations of the quarterly SA data. We aggregate the data into annual frequency for commuting zones.

We use Functional Urban Areas (FUAs) as the geographic units of analysis. These areas are delineated by Statistics New Zealand on the basis of commuting patterns, and are analogous to commuting zones as defined by the OECD.[6] There are 53 FUAs in New Zealand, including Auckland. There is a FUA in the Northern part of the AC jurisdiction that was affected by the reforms (Warkworth). We omit this FUA from the analysis because donor units are assumed untreated in the SC framework (Abadie, 2021). This leaves 51 units in the donor pool. FUAs are agglomerations of SA1s, which is a smaller geographic unit than the SA2s for which rent data are available. We assign an SA2 to a FUA if lies within or overlap the geographic boundary of the FUA.[7]

Rents for each FUA are calculated using data on rental bonds lodged by with central government agencies. Private sector landlords are legally required to lodge bonds at the origination of new tenancy contracts. The data contain information on the location and weekly rent, as well as some limited information on the characteristics of the dwelling, including the number of bedrooms.

Each quarter, the Ministry of Housing and Urban Development (HUD) publishes the geometric mean of weekly rents on new rental contracts and the number of new bonds lodged. These data are available for each statistical area (SAs), and are analogous to census tracts in the US. SAs are a geographic unit used by Statistics New Zealand for the census and cover approximately 2,000–4,000 residents in urban areas and are delineated to reflect communities that interact socially and economically.[8] We construct an annual weighted geometric mean rent for each FUA using a mapping from SAs to FUAs and the number of new bonds as weights.[9]

HUD reports geometric mean rents by the number of bedrooms (2, 3, 4 and 5+) and housing types ("Flats" and "Houses"). In order to account for compositional differences in new rental housing between FUAs and time periods, we construct rents by number of bedrooms. For example, if the proportion of new contracts within a given quarter are for two bedroom dwellings, the average rent across all dwellings is likely to fall in that quarter because two bedroom homes typically rent for less that three or four bedroom homes. By conditioning on the number of bedrooms, we also reduce cross sectional variation due to persistent compositional differences in rental housing between different locations. For example, large metropolitan regions may have a higher proportion of two bedroom dwellings. Due to data sparsity, we do not compute rents for 4 bedroom or 5+ bedroom

[6]See https://www.stats.govt.nz/assets/Methods/Functional-urban-areas-methodology-and-classification.pdf

[7]Thirteen of the SA2s appear in two FUAs that are typically contiguous. In such cases we assign the SA2 to the FUA that accounts for a greater proportion of the SA2's area.

[8]SAs were introduced in 2018, as the previous classification system had not been revised since 1992. The previous statistical geographies no longer reflect current land use and population patterns. The revision was also implemented in order to align the geographic unit standards with international best practice. Population data from the previous census (conducted in 2013) and associated projections were used in the design of the 2018 boundaries. For additional details, see https://www.stats.govt.nz/assets/Uploads/Retirement-of-archive-website-project-files/Methods/Statistical-standard-for-geographic-areas-2018/statistical-standard-for-geographic-areas-2018.pdf [Accessed 1 March 2023]

[9]Missing annual observations are linearly interpolated within each time series.

dwellings.

Figure 2 exhibits the average weekly rent for two- and three- bedroom dwellings in the "main" metropolitan areas of the North Island of New Zealand: Auckland, Hamilton, Tauranga and Wellington.[10] We select these three cities as they are large cities comparatively proximate to Auckland. This comparison is purely for expositional purposes: In the analysis to follow we use the SC method to select controls. We also compare rents in Auckland to population-weighted averages across the 51 other FUAs.

Rents in Auckland trend upward between 2000 and 2018 or so, at which point they flatten out. Meanwhile rents in Hamilton, Tauranga and Wellington continue increase at a substantially faster rate over this period, such that rents in Wellington exceed those in Auckland for both 2- and 3-bedroom homes by the end of the sample, while rents on 3- bedroom homes in Tauranga exceed those in Auckland from 2020 onwards.

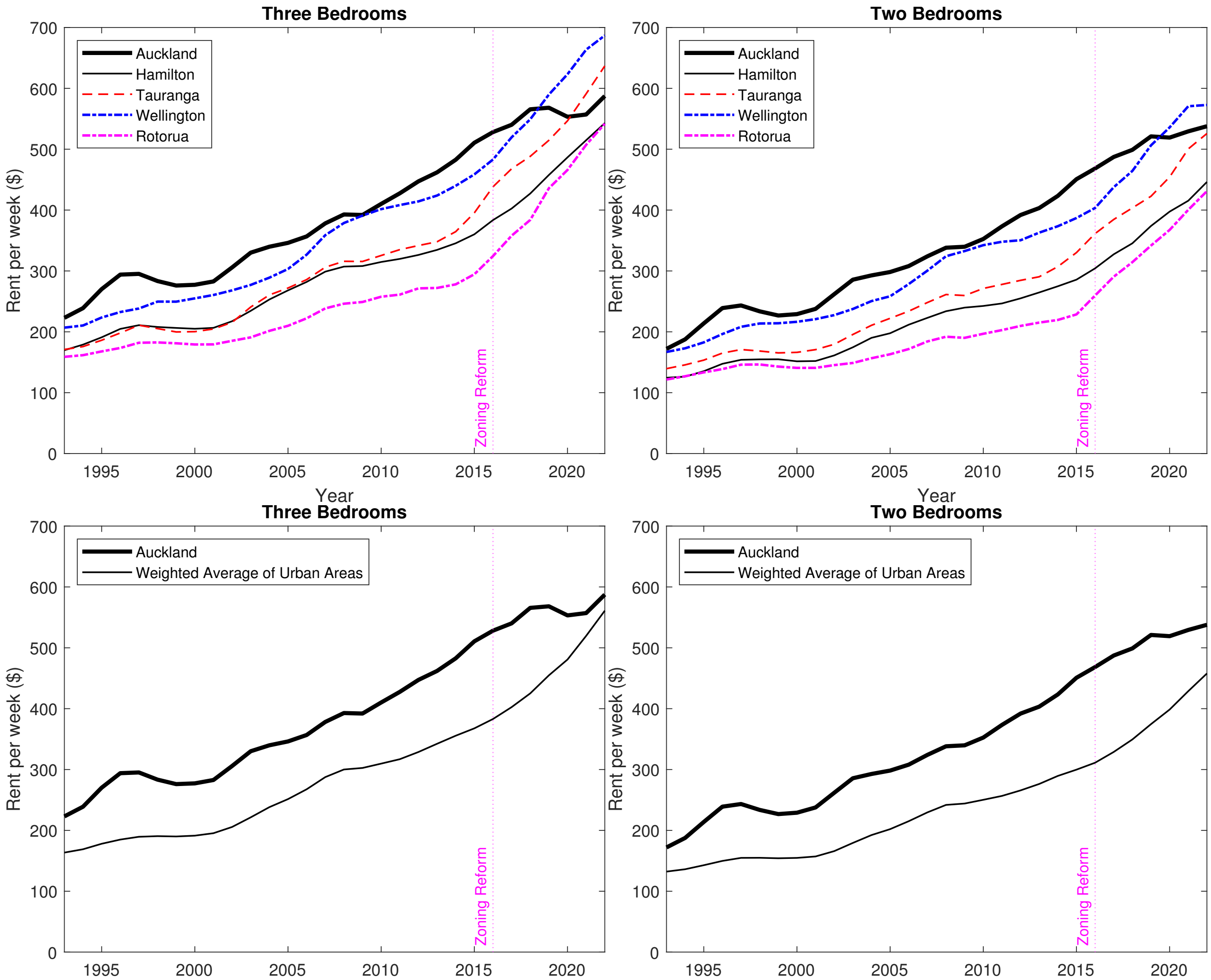
In 2016, the mean rent for a 3 Bedroom in Auckland was \$528.14 per week. By 2022, this has increased in \$587.42 – an increase of 11.2%. In Hamilton, 3 bedroom mean rent increased from \$383.54 to \$542.90, an increase of 41.6%. In Tauranga, 3 bedroom mean rent increased from \$438.70 to \$636.82, an increase of 45.16%. In Wellington, 3 bedroom mean rent increased from \$483.08 to \$686.94, an increase of 42.2%. For 2 Bedroom dwellings, mean rents in Auckland increased by 14.8% over the same period, while those in Hamilton, Tauranga and Wellington increased by 56.2%, 59.3% and 48.0%, respectively. Thus, a rudimentary, subjective analysis that selected a combination of these other large, North Island cities as a counterfactual would imply that the zoning policy reduced three bedroom rents by at least 30%, and 2 bedroom rents by between 33 to 44%. Of course, the synthetic control method is motivated by a more objective selection of units as the relevant counterfactuals.

3.1 Matching Variables

As we demonstrate in more detail in the following section, the SC method selects comparable controls by matching outcomes prior to the policy intervention. These can include the outcome of interest (in our application, rents) as well as other related variables. Here we describe the additional matching variables, all of which are rental or housing market outcomes. First, we include the proportion of renting households within the FUA for the two census years prior to the intervention, 2006 and 2013. Second, we include dwellings per capita to capture demand for housing within the urban area. Dwellings are only available for census years. Dwellings and population by SAs are obtained from Statistics NZ and aggregated up to FUAs. We include data for the previous two censuses, 2006 and 2013. Third, we include the average proportion of household income spent of rental costs, for 2006 and 2013.

[10]Statistics NZ classifies FUAs into "Main", "Large", "Medium" and "Small" metropolitan areas.

Figure 2: Weekly Rents in Metropolitan Areas, 1993–2022



Notes: Geometric mean rents for selected urban areas. Weights based on 2018 census populations.

4 Synthetic Control Method and Results

This section outlines the SC method and applies it to our dataset.

4.1 Synthetic Control Method

This section provides an overview of the SC method. Readers familiar with SC may wish to proceed to the next subsection.

We have time series data on an outcome of interest for $n+1$ units indexed by $i = 1, ..., n+1$, where $i = 1$ corresponds to the unit receiving the policy intervention, and $i = 2, ..., n+1$ indexes the "donor pool", a collection of untreated units that is unaffected by the intervention. Observations on the outcome of interest span $t = 1, ..., T$, where the observations prior to intervention span $t = 1, ..., T_0$ and $T_0 < T - 1$.

$y_{i,t}$ denotes the observed outcome of interest for unit i in period t. A synthetic control is defined as a weighted average of the units in the donor pool. Given a set of weights $w = (w_2, ..., w_{n+1})$, the SC estimator of $y^N_{1,t}$ is$\hat{y}^N_{1,t} = \sum_{i=2}^{n+1} w_i y_{i,t}$. Let $y^N_{i,t}$ be the outcome without intervention for each i, while $y^I_{1,t}$ is the outcome under the intervention for the affected unit in period $t > T_0$. The effect of the intervention is then $y^I_{1,t} - \hat{y}^N_{1,t}$.

Abadie and Gardeazabal (2003) and Abadie et al. (2010) choose $\boldsymbol{w}$ so that the resulting synthetic control best resembles a set of pre-intervention "predictors" for the treated unit. For each i, there is a set of k observed predictors of $y_{i,t}$ contained in the vector $X_i = (x_{1,i}, ..., x_{k,j})$, which can include pre-intervention values of $y_{i,t}$ unaffected by the intervention. The k matrix $\boldsymbol{X}_0 = [X_2 \cdots X_{J+1}]$ collects the values of the predictors for the n untreated units. Abadie and Gardeazabal (2003) and Abadie et al. (2010) select weights $w^* = (w^*_2, ..., w^*_{n+1})$ that minimize

$$\|X_1 - \boldsymbol{X}_0 \boldsymbol{w}\|_{\boldsymbol{v}} = \left(\sum_{h=1}^{k} v_h \left(x_{h,1} - w_2 x_{h,2} - ... - w_{n+1} x_{h,n+1} \right)^2 \right)^{1/2} \tag{1}$$

subject to the restrictions $w_h \in [0,1]$ and $\sum_{h=1}^{k} w_h = 1$, and where $\boldsymbol{v} = (v_1, ..., v_k)$ is a set of nonnegative constants. Following Abadie et al. (2010), we choose $\boldsymbol{v}$ to assign weights to linear combinations of the variables in $\boldsymbol{X}_0$ and X_1 that minimize the mean square error of the synthetic control estimator in the pre-treatment period. Then, the estimated treatment effect for the treated unit at time $t = T_0 \ldots, T$ is $\hat{y}^N_{1,t} = \sum_{i=2}^{n+1} w^*_i y_{i,t}$.

Weights $\boldsymbol{w}$ that minimize (1) can found using standard quadratic programming solvers. To select $\boldsymbol{v}$ in the nested MSE-minimization problem, we use Evolution Strategy with Covariance Matrix Adaptation (CMA-ES), which is a stochastic optimization algorithm for solving difficult optimization problems (Hansen, 2016). It exhibits strong invariance properties (Hansen et al., 2011), is robust to highly non-linear, non-quadratic, non-convex, non-smooth and/or noisy objective problems (Hansen, 2006), and can tackle ill-conditioned optimization problems (Jones, 2021).[11] It

[11]Ill-conditioning refers to when there is a large change in the objective function in response to a small change in arguments. This is possible in the current application because the weights are selected via a quadratic programming

is considered a state of the art evolutionary optimizer (Li et al., 2020).[12]

In our application, we include all pre-treatment realizations of the outcome variable, rents. As discussed in Abadie et al. (2010) and Abadie (2021), increasing the pre-intervention time period T_0 reduces the bias in the synthetic control. In our baseline specification, we include rents between 1993 and 2016. As discussed above, we also include dwellings per capita, the proportion of renting households, and average proportion of household income spent on rent among the matching variables. See section three above for a discussion of the rationale for including these variables.

Conventional SC requires that the predictors of the treated unit must lie within the convex hull of the predictors of the donor pool. The convex hull assumption is necessary for the treated unit's predictors to be approximated by the donor pool's. However, rents in Auckland during the pre-intervention period were generally higher than those of other urban areas, meaning that the conventional convex hull requirement for construction of the synthetic control is unlikely to hold. Following recommendations in Abadie (2021), we subtract the pre-treatment average from each rent time series prior to implementation (Ferman and Pinto, 2021).

4.2 Baseline Specification Results

Table 1 exhibits the selected weights.

The selected donor set for three bedroom homes comprises five urban areas (UAs). Tokoroa receives the largest weight, 0.346. Rents in Tokoroa increased by 110.4% between 2016 and 2022 (see Table 6 in the Appendix). Gore has the next highest weight, at 21.3%. Rents in Gore have increased by 62.5% since 2016. The UA with the third largest weight, Christchurch, is the largest city in the South Island, and has a weight of 0.195. Rents in Christchurch grew by 24.8% over the same period. Whitianga has a weight of 0.146. Rents in Whitianga grew by 60.6% over the same period. Finally, Wānaka receives a weight of 0.099. Rents in Wānaka grew by 37.6% between 2016 and 2022.

Notably the selected donors substantially differ from Auckland in terms of total size, with many smaller towns making up the donor group. Only Christchurch is large enough to be classified as a "major urban area", like Auckland, by Statistics New Zealand. Nonetheless, the synthetic control method is optimized to select donor units that best match the pre-intervention time series of (demeaned) logged rents and predictors in Auckland. In many of our robustness checks to follow, a substantially larger weight is placed on major urban areas in the donor pool.

The donor set for 2 bedroom dwellings includes eight UAs, including Christchurch, Wānaka and Gore, which featured in the 3 bedroom donor set. As illustrated in Table 6 in the Appendix, the remaining five UAs experienced rent increases between 55 and 70% between 2016 and 2022.

problem that sets weights to zero on the majority of donor units.

[12]We adapt the Matlab version of the Synth package provided by Jens Hainmueller (available from https://web.stanford.edu/~jhain/synthpage.html) to incorporate CMA-ES minimization of nested MSE objective function, using the cmaes.m matlab code provided by Nikolaus Hansen (available from http://cma.gforge.inria.fr/cmaes.m) CMA-ES generated significant reductions in the nested MSE objective function. It also improved the MSE of Hainmueller's synth STATA package, though the obtained weights for our baseline models were similar under both approaches.

Table 1: Weights

3 Bedroom		2 Bedroom	
Urban Area	Weight	Urban Area	Weight
Tokoroa	0.346	Christchurch	0.293
Gore	0.213	Te Puke	0.201
Christchurch	0.195	Wānaka	0.162
Whitianga	0.146	Katikati	0.159
Wānaka	0.099	Rotorua	0.132
		Gore	0.024
		Invercargill	0.024
		Kapiti Coast	0.005
Total	1.000		1.000

Table 2: Predictor Variables

	3 Bedroom		2 Bedroom	
Variable	Synthetic Auckland	Auckland	Synthetic Auckland	Auckland
Dwellings per capita, 2013	0.384	0.328	0.370	0.328
Dwellings per capita, 2006	0.370	0.331	0.363	0.331
Proportion of renting households, 2013	0.335	0.388	0.327	0.388
Proportion of renting households, 2006	0.312	0.363	0.302	0.363
Proportion of income spent on rent, 2013	0.207	0.262	0.240	0.262
Proportion of income spent on rent, 2006	0.183	0.244	0.223	0.244

Figure 3 exhibits rents and synthetic rents for Auckland over the 1993 to 2022 period. There is a notable divergence from 2016 onwards, with rents growing much more slowly than synthetic rents.

By the end of the sample, for 3 bedroom dwellings, log rents in Auckland are 0.427 (= 0.927 – 0.500) less than the synthetic control. That equates to a 34.75% decrease in rents relative to the counterfactual. Equivalently, the model implies that rents would be 53.3% higher under the counterfactual of no zoning reform in Auckland. Figure 15 in the Appendix depicts the log rents for the donor units alongside Auckland, showing that two of the three donor units (Rotorua and Whitianga) experienced substantially larger increases in rents after 2016. This is why the differential between Auckland and its synthetic control is so large.

For two bedroom dwellings, log rents are 0.238 (= 0.809 – 0.571) less than the synthetic control by 2022, corresponding to a 21.2% decrease. This is substantially less than that of 3 bedroom dwellings, but is nonetheless non-trivial in magnitude. Equivalently, rents for 2 bedroom dwellings would be 26.9% greater under the counterfactual given by the synthetic control.

Before proceeding, we note that the baseline model yields larger (in magnitude) estimates of the policy effects when compared to alternative specifications explored in our robustness checks.

4.3 Inference

We run placebo interventions on the other donor units to assess whether the decrease relative to the counterfactual is large. Figure 4 plots the difference between the actual outcomes of each donor and its synthetic control. Evidently the decrease in Auckland's prediction error in the greatest among all units over the post-intervention period, indicating that the zoning reform had a substantive negative impact.

Next we depict the MSE in the post intervention period for Auckland and the placebos, $R_i\left(T_0+1,T\right)$, where

$$R_i\left(t_1,t_2\right)=\frac{1}{t_2-t_1}\sum_{t=t_1}^{t_2}\left(Y_{i,t}-\hat{Y}_{i,t}^{N}\right)^2$$

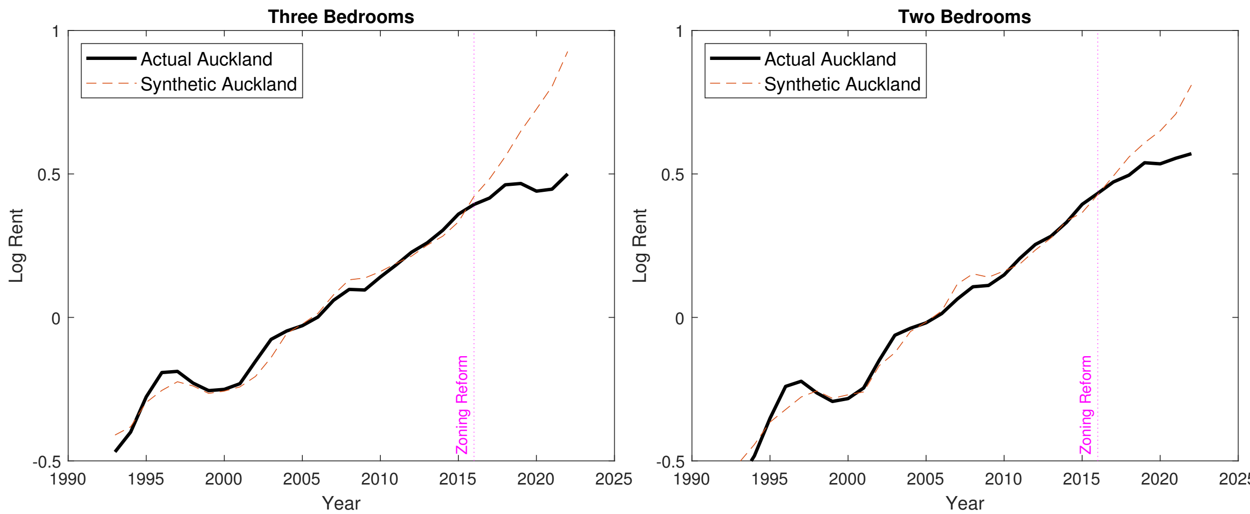
Figure 5 presents a histogram of the MSEs for the 2017 to 2022 period. For three bedroom dwellings, Auckland has the largest MSE.

Figure 4 also shows that the pre-intervention fit of the model is poor compared to many other units. The large post-treatment MSE may be due to poor model fit, rather than the intervention, making it a poor statistic to base inference. Following Abadie et al. (2010), we use the ratio of pre- to post- intervention MSE as a basis for inference,

$$r_i=\frac{R_i\left(T_0+1,T\right)}{R_i\left(1,T_0\right)}$$

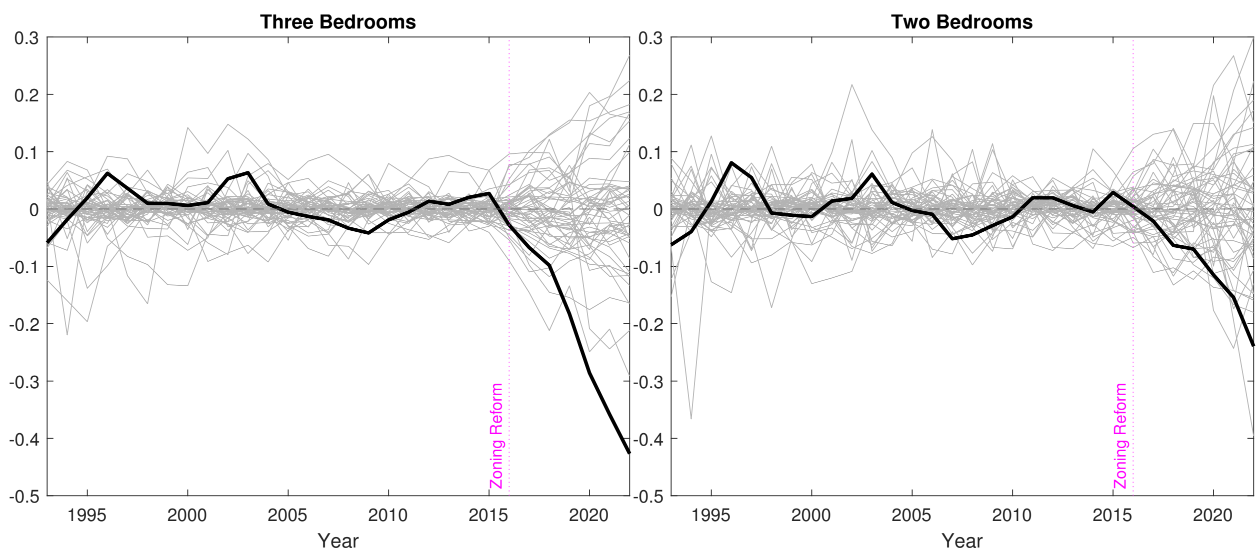
The ratio is constructed for the treated unit and all placebo runs. The rank permutation test is then based on where the ratio for the treated unit ranks among all placebo runs.

Figure 3: Synthetic and actual rents



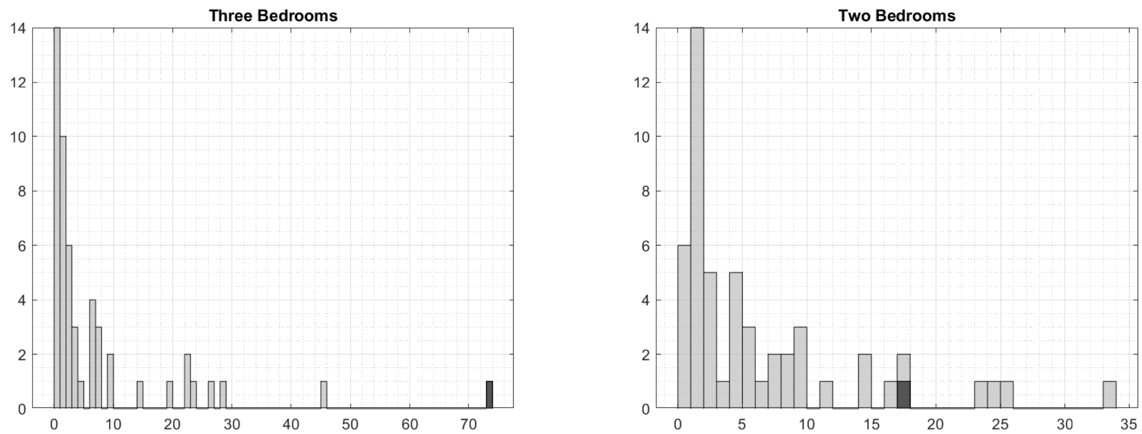
Notes: y-axis is the log normalized rent.

Figure 4: Prediction errors



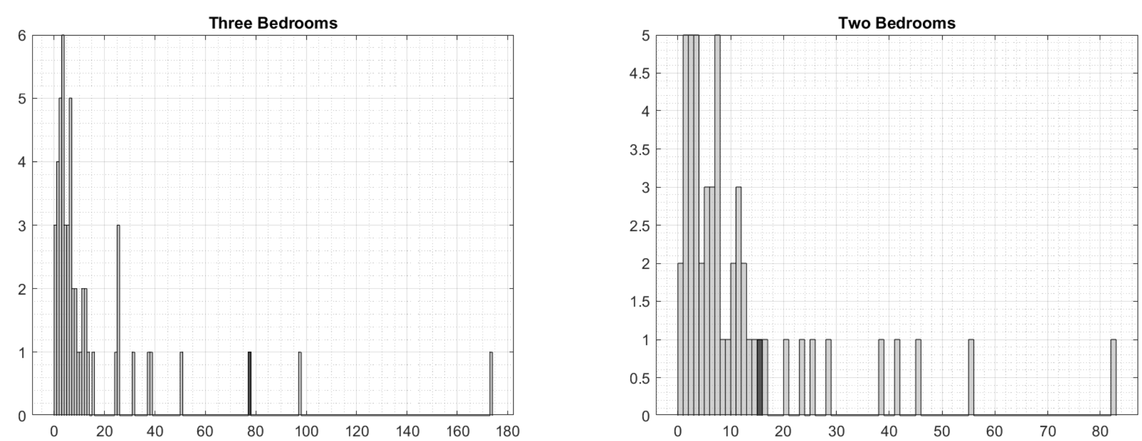
Notes: Difference between actual and synthetic outcomes. Auckland in black. Placebos in grey.

Figure 5: Post-treatment MSE



Notes: Auckland appears in black. MSEs multiplied by 1000.

Figure 6: MSE ratios



Notes: Auckland appears in black.

Figure 6 depicts the histogram of the ratios. Only two UAs have an MSE ratio greater than that of Auckland, meaning that if one were to assign the intervention at random, the probability of obtaining a ratio as large as Auckland's is 0.058 (= 3/52).

One drawback of the ratio is that it does not distinguish between positive and negative deviations from the synthetic unit, whereas many hypotheses posit a directional change from an intervention. For example, the relevant alternative hypothesis in our case is that zoning reforms reduced housing costs. Substantial increases in power can be obtained by testing for reductions relative to the synthetic control, rather than absolute differences (Abadie, 2021). To conduct a one-tailed test, we compute

$$r_i^- = \frac{R_i^-\left(T_0+1, T\right)}{R_i\left(1, T_0\right)}$$

where

$$R_i^-\left(t_1, t_2\right) = \frac{1}{t_2 - t_1} \sum_{t=t_1}^{t_2} \left(\left\lfloor Y_{i,t} - \hat{Y}_{i,t}^N \right\rfloor \right)^2$$

where $\lfloor x \rfloor = 0$ iff $x > 0$ and $\lfloor x \rfloor = x$ otherwise. We refer to this as the "Negative Error MSE ratio", or NE-MSE-R.

Figure 7 depicts the histogram of the ratios. Auckland has the second largest NE-MSE-R, meaning that if one were to assign the intervention at random, the probability of obtaining a ratio as large as Auckland's is 0.038 (= 2/52). For 2 bedroom dwellings, Auckland is ranked fifth, corresponding to 0.096 (= 5/52).

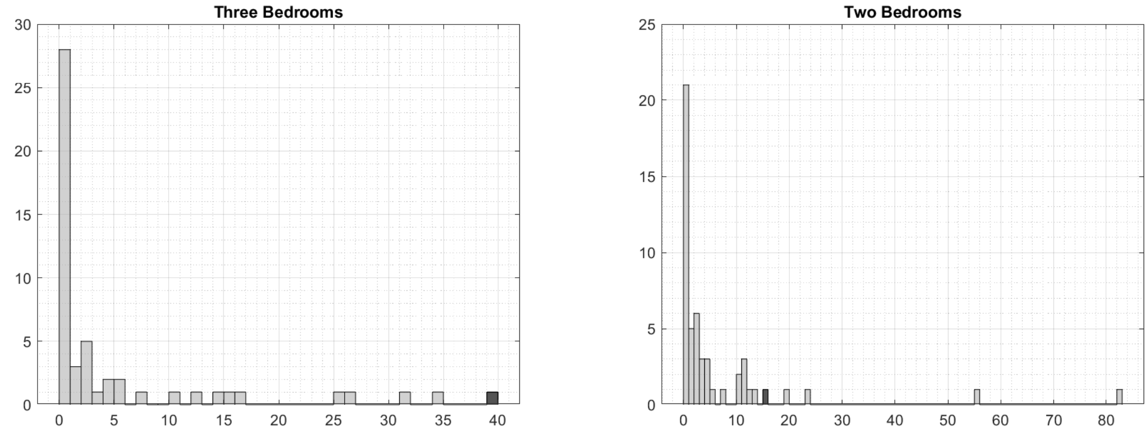
4.4 Robustness Checks

4.4.1 Leave-One-Out

We perform the "leave one out" robustness check (Abadie et al., 2010), whereby units from the donor pool are iteratively removed from the sample while the procedure is repeated. This procedure examines the extent to which the synthetic control may be dependent on any single given donor unit.

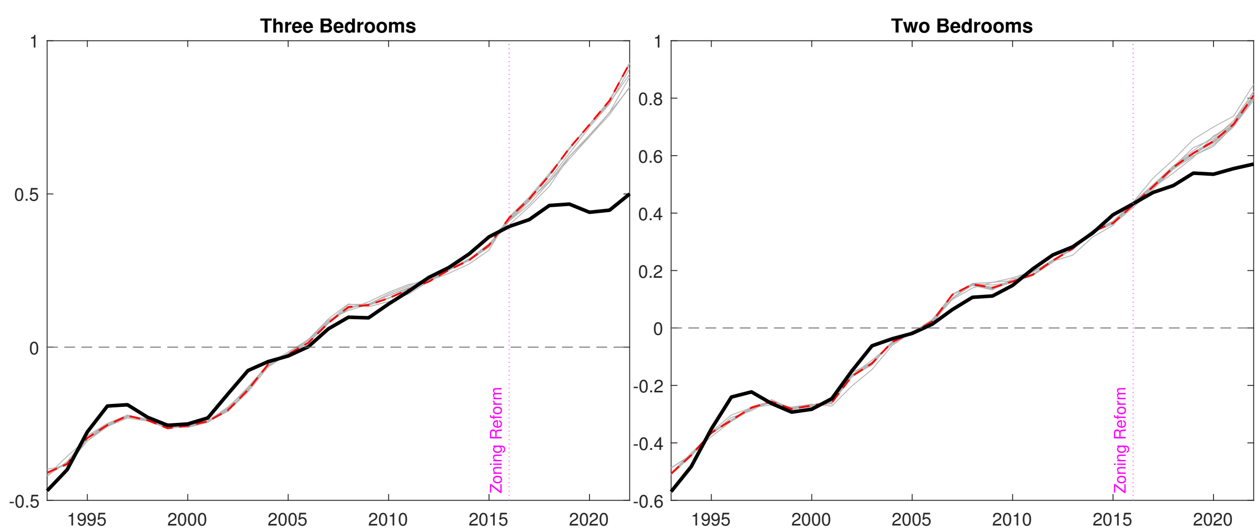
Figure 8 exhibits the full-sample synthetic control (FS-SC red dashed line) alongside the 51 other leave-one-out synthetic controls (LOO-SCs, given by the grey lines). In general, each of the 52 synthetic controls follow a common trend over both the pre- and post- sample period. Moreover, for three bedroom dwellings, Auckland's NE-MSE-ranks either first or second in all 51 LOO replications, indicating that the removal any one donor unit does not have a substantial impact on the synthetic control, and lending strong credibility to our findings based on the full sample. For two bedroom dwellings, Auckland's NE-MSE-ranks is either fourth or fifth in 48 of the LOO replications. It ranks 6th twice, and ninth once.

Figure 7: Negative-error MSE ratios



Notes: Auckland appears in black.

Figure 8: Leave-one-out robustness check



Notes: Leave-one-out replications in grey. The synthetic control for the full sample is the red dashed line.

4.4.2 Normalizing rents to treatment period level

In our baseline specification, we normalize rents by subtracting pre-intervention period averages. The normalized rents therefore reflect growth rates relative to that pre-intervention mean. In this robustness check, we normalize rents by subtracting the rent from the final pre-treatment period, 2016. The normalized rents therefore reflect growth rates relative to the year the policy was implemented, offering greater interpretability of the solution to the objective function.[13]

Table 3 exhibits the selected weights for donor units. For three bedroom dwellings, the weight placed on "major urban areas" (Hamilton and Christchurch) is approximately 59%. For two bedroom dwellings, the weight on Christchurch decreases by five percentage points.

Figure 9 exhibits the prediction errors and histogram of the NE-MSE-Rs. For 3 bedroom dwellings, log rents are 0.329 less than the synthetic control in 2022, which is equivalent to a 28.0% reduction in rents relative to the counterfactual. Auckland has the second largest NE-MSE-R under the rank permutation test (histogram not pictured), which is equivalent to a p-value of 0.038. For 2 bedroom dwellings, log rents are 0.252 less than the synthetic control, equivalent to a 22.3% decrease in rents relative to the counterfactual. Auckland has the fifth largest NE-MSE-R, equivalent to a p-value of 0.096.

4.4.3 Omitting Rental Time Series from the Set of Predictors

By including the full time series of pre-intervention rents in the set of predictors, the selected weights are tilted towards matching Auckland's (normalized) rents in the pre-intervention sample period. In this section we omit the time series of rents from the set of predictors, retaining only rents in 2016 and 2013. We include 2016 as this is the final observation before the AUP becomes fully operational. We include 2013 as (i) this is when the PAUP-SpHA program begins (see section 2 above), and (ii) it matches the timing of the census, when we have observations on the other predictors. Thus each set of variables (rents, dwellings per capita, rental costs as a proportion of income, and proportion of renting households) each have two observations in the donor pool, meaning that the matching algorithm is not tilted towards any one variable by virtue of having more of them. In addition, we do not normalize the rents by subtracting either the pre-intervention mean or the rent in the treatment period. Thus the algorithm for selecting weights is tilted towards matching the level of rents prior to intervention, rather than rent inflation. These changes worsen pre-treatment fit, since weights are not explicitly matching the time series of rent outcomes in the pre-treatment period, but tilt the weights towards better matching the housing market outcomes in the period immediately prior to treatment.

Table 4 exhibits the selected weights for donor units. For three bedroom dwellings, three-quarters of the weight is placed on Wellington, a "major urban area". For two bedroom dwellings, over 90% of the weight is placed on the major urban areas of Wellington and Christchurch.

Figure 10 exhibits the prediction errors. For both three and two- bedroom dwellings, pre-

[13] We only include rents between 1993 and 2015 in the set of the predictors, since all rents are zero by construction in 2016.

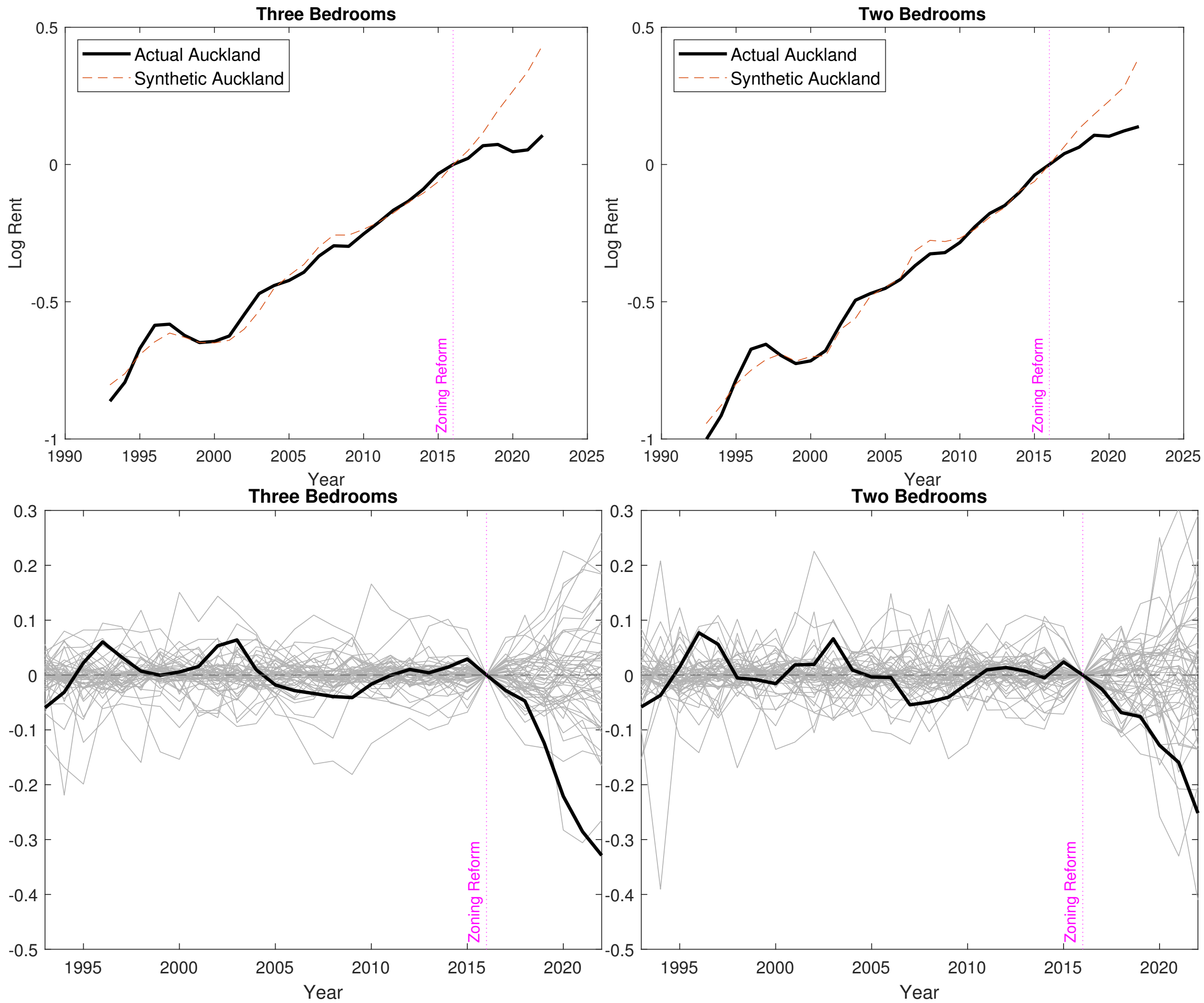
Table 3: Weights, normalizing rents to treatment period level

3 Bedroom		2 Bedroom	
Urban Area	Weight	Urban Area	Weight
Hamilton	0.365	Te Puke	0.327
Tokoroa	0.243	Christchurch	0.239
Christchurch	0.218	Katikati	0.193
Gore	0.082	Wānaka	0.144
Whitianga	0.067	Invercargill	0.055
Wānaka	0.025	Gore	0.043
Total	1.000		1.000

Table 4: Weights, excluding rent time series from predictors

3 Bedroom		2 Bedroom	
Urban Area	Weight	Urban Area	Weight
Wellington	0.746	Wellington	0.682
Queenstown	0.254	Christchurch	0.246
		Queenstown	0.073
Total	1.000		1.000

Figure 9: Synthetic and actual rents, normalizing rents to treatment period level



Notes: Synthetic and actual rents (top) and prediction errors (bottom). Auckland's prediction error is in black. Placebos in grey.

treatment fit is substantially worse, as expected. Notably, the difference between the synthetic and actual rents is not as large as under the baseline specification. For 3 bedroom dwellings, log rents are 0.252 less than the synthetic control, which is equivalent to a 22.3% reduction in rents relative to the counterfactual. Auckland has the second largest NE-MSE-R under the rank permutation test (not pictured), equivalent to a p-value of 0.0385. For 2 bedroom dwellings, log rents are 0.152 less than the synthetic control, equivalent to a 14.1% decrease in rents relative to the counterfactual. Auckland has the eighth largest NE-MSE-R, equivalent to a p-value of 0.154.

4.4.4 Population Decrease after COVID-19

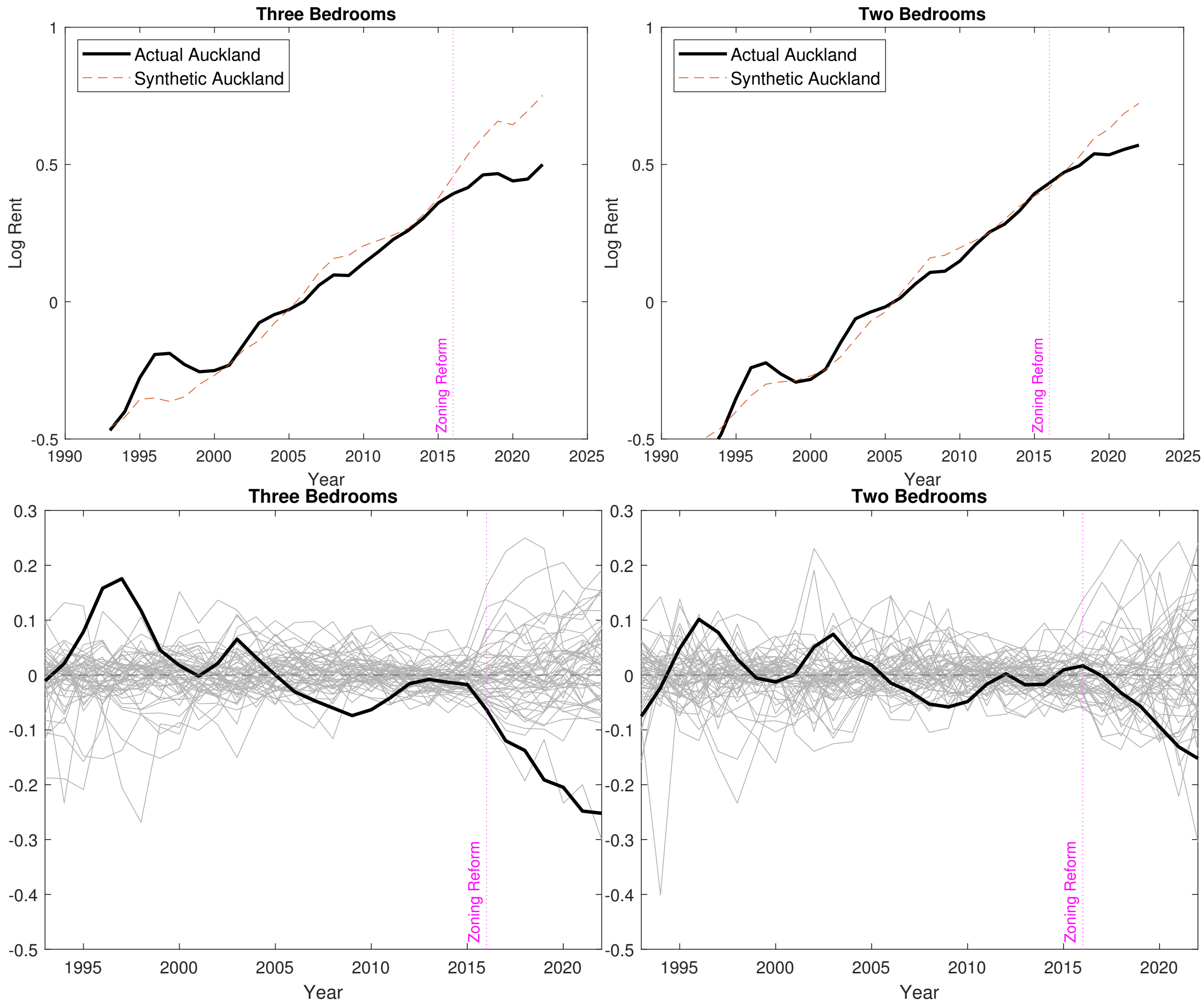
According to Statistics New Zealand estimates, Auckland's population decreased by 1.06% between 2020 and 2022.[14] The ability of the synthetic control to account for the effect of a population decrease on rents in Auckland depends on whether the matching variables select control units that experienced similar decreases. In this regard, Auckland was not unique among urban areas in experiencing a decline. Wellington (-0.14%), Dunedin (-1.79%), Rotorua (-0.40%), Invercargill (-0.66%) and Motueka (-0.65%) also experienced decreases in (estimated) population. Notably, many of these UAs already feature in the selected donor pool for Auckland, suggesting that the set of predictors may span the set of variables that explain the population decline. Figure 11 depicts weekly rents the UAs that experienced population decreases between 2020 and 2022. All except Auckland exhibit substantial appreciation from 2016 onwards, including Dunedin, which is notable for being the UA that experienced a larger population exodus than Auckland. Dunedin's rents on 3 bedroom dwellings increased by 53.4% between 2016 and 2022, while 2 bedroom rents increased by 51.9% (see Table 6). Thus, despite having a larger population exodus than Auckland, Dunedin experienced a substantially larger increase in rents – in fact, the increase was approximately four times as large.

Although Auckland was not the only UA to experience a population decrease, the incidence and responses to COVID-19 may present a unique shock that disproportionately affected Auckland and that proves difficult for the synthetic control to adequately model from 2020 onwards. We modify our empirical strategy in two different ways to address this potential problem. First, we end the sample in 2020, when estimated population in Auckland peaks. Second, we re-specify the set of matching variables to comprise the decrease in population from 2020 to 2022, and a limited number of rental market characteristics. This tilts the synthetic control procedure towards selecting UAs that experienced a decrease in population from 2020 onwards.

Ending the sample in 2020. Because the set of matching variables has not changed, selected weights remain the same as in the baseline specification. Figure 12 exhibits the histogram of the NE-MSE-Rs (note that prediction errors and synthetic units are identical to those given in the baseline sample). For three bedroom dwellings, the Auckland NE-MSE-R ranks second, after

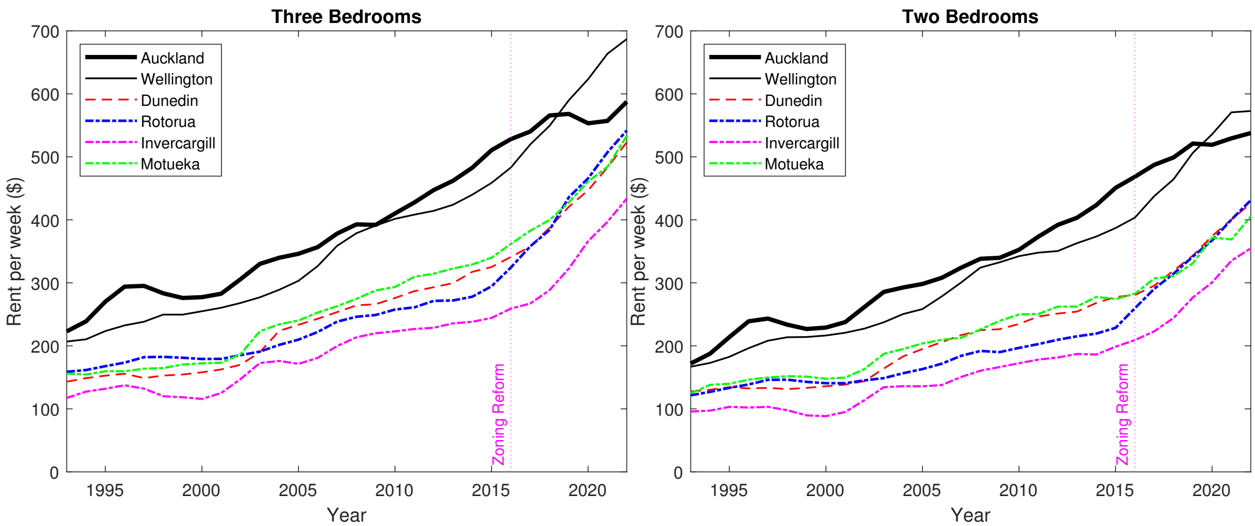
[14] For information on methodology, see https://datainfoplus.stats.govt.nz/item/nz.govt.stats/951e3175-d94d-4d67-9af7-47c0a75f90d9/7. As of May 2023, the subnational population estimates at 30 June 2021 and 2022 are both provisional.

Figure 10: Synthetic and actual rents, excluding rent time series from predictors



Notes: Synthetic and actual rents (top) and prediction errors (bottom). Auckland's prediction error is in black. Placebos in grey.

Figure 11: Weekly Rents in selected Metropolitan Areas, 1993–2022



Notes: Geometric mean rents for urban areas that experienced a decrease in estimated population between 2020 and 2022.

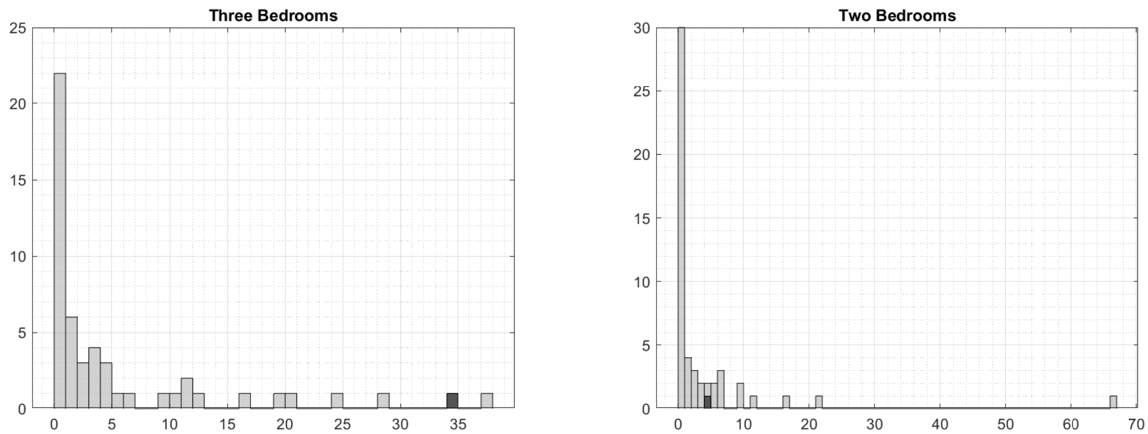
Greymouth, corresponding to a p-value of 0.038 ($= 2/52$). For 2 bedroom dwellings, Auckland ranks fourteenth. We conclude that there remains strong statistical evidence the zoning reform reduced rents on larger, three bedroom dwellings.

Including post 2020 population change as a predictor. We continue to include the rental market outcomes for 2006 and 2013 in our set of predictors, namely, the proportion of renting households, dwellings per capita, and the average proportion of household income spent of rental costs (among renting households). We also include log population change between 2020 and 2022. In addition, we include the proportion of people aged 18 to 22 inclusive, to account for the potential effect of the border closure and international students returning home. Both Auckland and Dunedin, which experienced the largest population decreases, have a large tertiary sector.

Table 5 exhibits the selected weights for donor units. For three bedroom dwellings, nearly 80% of the weights are placed on UAs that experienced a population decrease, namely Rotorua and Wellington. For two bedroom dwellings, over two-thirds of the weights are placed on UAs that experienced a population decline between 2020 and 2022 (Wellington, Dunedin and Rotorua).

For 3 bedroom dwellings, log rents are 0.361 less than the synthetic control, which is equivalent to a 30.3% reduction in rents relative to the counterfactual. Auckland's NE-MSE-R is largest among all UAs. Figure 13 exhibits the synthetic rents and prediction errors. For 2 bedroom dwellings, log rents are 0.218 less than the synthetic control, equivalent to a to a 19.6% decrease in rents relative to the counterfactual. The NE-MSE-R for Auckland is ninth largest among all UAs.

Figure 12: Negative-error MSE ratios, ending the sample in 2020

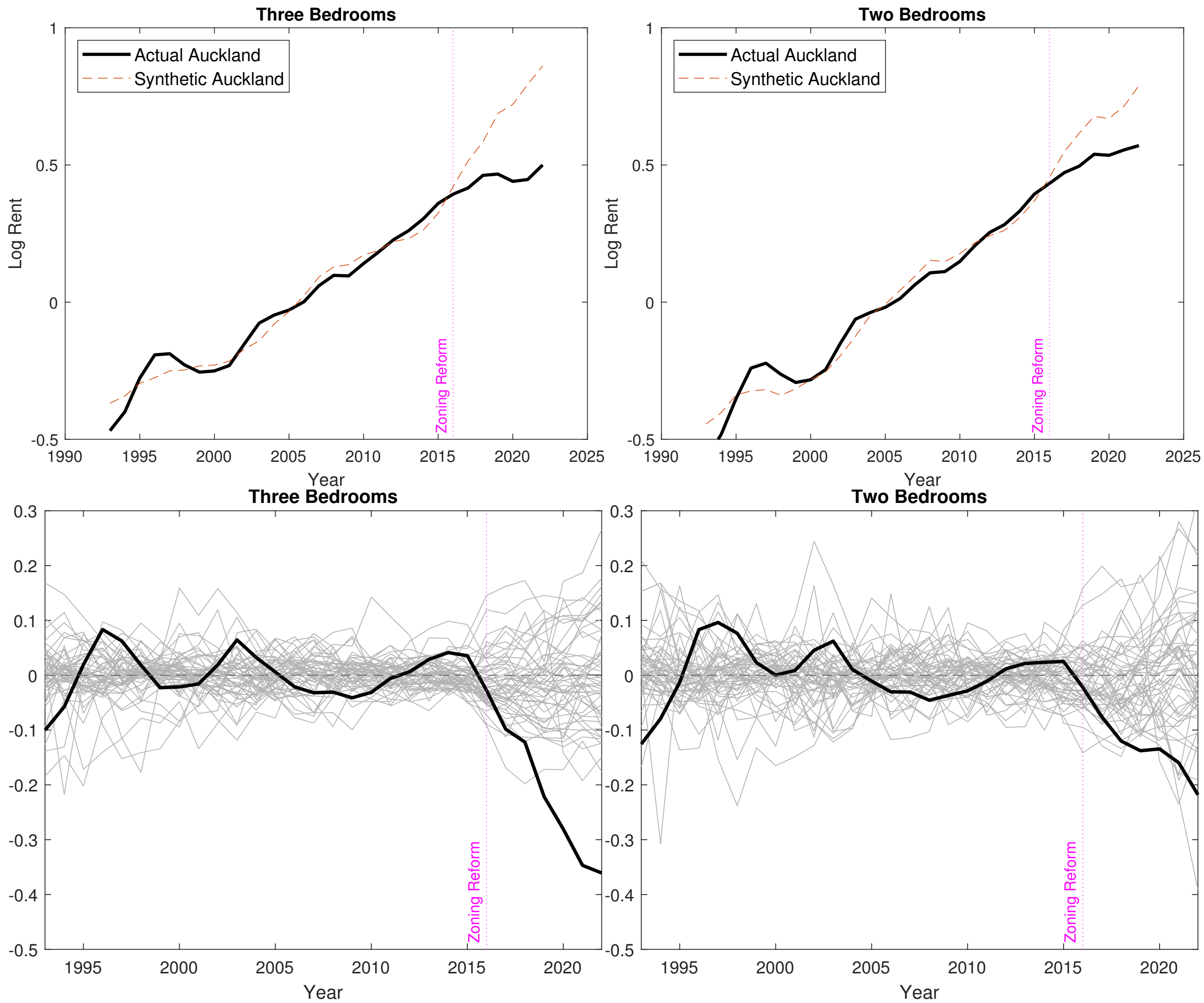


Notes: Prediction errors (top row) and negative error MSE ratios (bottom). Auckland appears in black. Sample period ends in 2020 to mitigate the effects of the incidence and policy responses to COVID-19.

Table 5: Weights, including post 2020 population change

3 Bedroom		2 Bedroom	
Urban Area	Weight	Urban Area	Weight
Rotorua	0.686	Queenstown	0.278
Wellington	0.180	Wellington	0.278
Queenstown	0.115	Rotorua	0.222
Huntly	0.019	Dunedin	0.124
		Motueka	0.098
Total	1.000		1.000

Figure 13: Synthetic and actual rents, including post 2020 population change



Notes: Synthetic and actual rents (top) and prediction errors (bottom). Auckland's prediction error is in black. Placebos in grey. Matching variables include the decrease in UA population between 2020 and 2022 in order to account for a decrease in the estimated population of Auckland immediately after COVID-19.

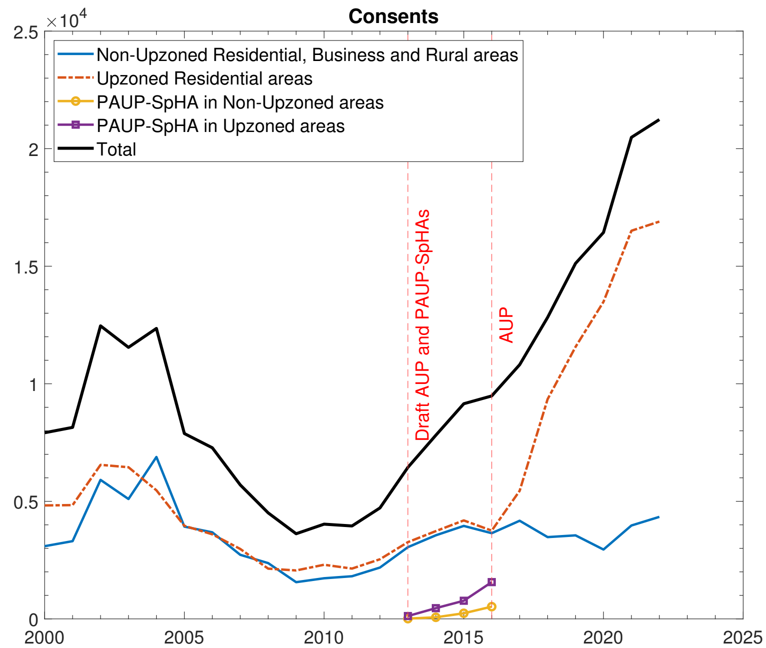
5 Discussion

Housing costs in Auckland remain among the most expensive in the world, as measured by either the proportion of disposable income spent on housing or house prices relative to incomes. The synthetic control approach indicates a 22 to 35% reduction in rents of 3 bedroom dwellings six years on from the policy, relative to the counterfactual of no zoning reform – meaning that rents in Auckland would be even more expensive if the reforms had not been implemented. These reductions are statistically significant (5%, one tailed) using the rank permutation approach. For 2 bedroom dwellings, the synthetic control indicates a 14 to 21% reduction in rents due to the reform, though the statistical significance of this reduction is only marginal in some specifications.

6 Appendix

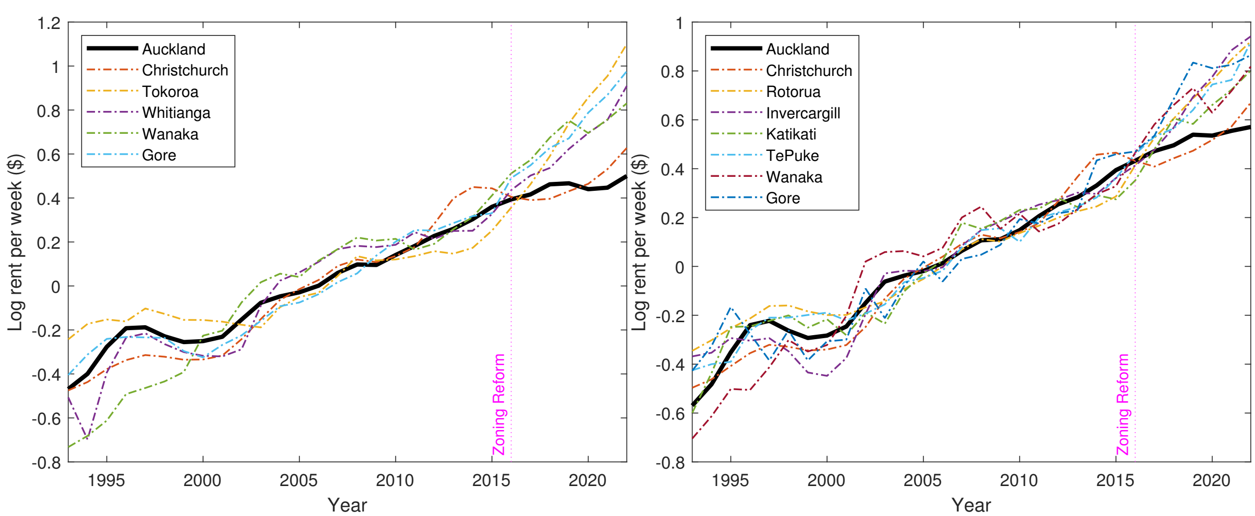
6.1 Additional Tables and Figures

Figure 14: Dwelling Consents in Auckland, 2000 to 2022



Notes: Consents issued per year in different areas of Auckland. The first, "draft", version of the AUP was announced in March 2013, while the "Proposed" AUP (PAUP) was notified in September 2013. Between September 2013 and November 2016, Special Housing Area (SpHA) developments could build to the regulations of the PAUP in exchange for affordable housing provisions. "PAUP-SpHA" denotes permits issued under this program. The final version of the AUP became operative in part in November 2016. Source: Author's calculations.

Figure 15: Rents in Auckland and Donor Units



Notes: 3 Bedroom (left) and 2 Bedroom (right). Rents have been de-meaned using the pre-intervention mean.

Table 6: Percent increase in urban area rents, 2016–2022

	3 Bedroom	2 Bedroom		3 Bedroom	2 Bedroom
Auckland	11.23	14.82	Greymouth	42.95	8.79
Hamilton	41.55	46.65	Ashburton	23.21	16.02
Tauranga	45.30	45.50	Timaru	34.14	43.54
Wellington	42.20	41.93	Oamaru	40.47	40.39
Christchurch	24.83	26.94	Queenstown	13.64	14.33
Dunedin	53.37	51.87	Kaitaia	76.05	73.63
Whangarei	56.76	58.26	Kerikeri	48.29	58.35
Rotorua	67.07	66.03	Whitianga	60.55	58.26
Gisborne	93.97	91.70	Thames	46.53	50.82
Hastings	73.31	75.63	Waihi	52.09	63.37
Napier	68.43	70.77	Huntly	63.34	72.47
New Plymouth	50.70	52.52	Morrinsville	47.99	56.46
Whanganui	97.75	97.24	Matamata	47.53	48.67
Palmerston North	65.90	62.84	Katikati	54.00	56.82
Kapiti Coast	56.89	55.77	Te Puke	48.54	58.07
Nelson	44.18	41.11	Kawerau	103.06	94.84
Invercargill	67.34	69.69	Stratford	86.05	85.72
Cambridge	47.27	49.14	Hawera	76.08	81.00
Te Awamutu	61.19	51.36	Marton	118.02	98.94
Tokoroa	110.37	142.27	Dannevirke	97.94	87.83
Taupo	56.87	62.79	Otaki	74.04	77.62
Whakatane	58.43	47.66	Motueka	47.40	43.34
Feilding	80.58	65.68	Cromwell	44.62	40.24
Levin	92.16	96.04	Alexandra	49.99	43.28
Masterton	77.20	77.45	Wanaka	37.55	42.25
Blenheim	47.55	57.40	Gore	62.49	48.37

Notes: Percent increase in rents between 2016 and 2022 for functional urban areas of New Zealand.

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