The Impact of Vacancy Taxes on Housing Prices: A Synthetic Control Study

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January 13, 2026

Abstract

Importance: Cities in North America are beginning to wield vacancy taxes (a property tax imposed on unoccupied homes) as a tool to reduce rapidly growing home prices. However, these taxes are being implemented with little to no empirical evidence backing their effectiveness.

Objective: To determine whether Washington, D.C.'s 2003-imposed vacancy tax impacted home prices.

Design: A panel data set for the years 1978-2013 was compiled for this analysis. Data was collected on 13 different variables related to the housing market for 31 metropolitan statistical areas, including Washington, D.C. The synthetic control method was applied to create a counterfactual Washington, D.C. using the available variables and donor cities. House price comparisons were then made over time to determine what Washington, D.C.'s average house prices would have been absent their 2003 vacancy tax, as measured by the synthetic control unit. Robustness checks, placebo tests, and time series analyses were subsequently used to validate and investigate the primary results.

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Results: Contrary to expectations, there is a gap following the 2003 treatment that suggests Washington, D.C.'s tax may have increased house prices rather than decreased or limited them. An interrupted time series analysis also shows a statistically significant break in the house price trajectory starting in approximately 2005. However, a placebo in space test casts doubt on any significant results as Washington, D.C.'s outcomes are unremarkable when applying the potential treatment to other U.S. cities.

Conclusions and Relevance: There is no evidence that the 2003 tax reduced house prices. Local governments in North America should be cautious about implementing vacancy taxes if the primary or sole purpose is to reduce or restrict house prices.

1 Introduction

For the 2003 tax year, the city of Washington, District of Columbia ("DC") became the first large city in North America to impose a tax on vacant properties within city limits (a "vacancy tax"). Normally, a vacancy tax is applied to properties that do not have people living in them for most of the tax year. DC follows this model and applies a vacancy tax of \$5.00 per \$100.00 of assessed property value (instead of \$0.85 for residential and a maximum of \$1.89 for commercial) for all properties it deems vacant (City of Washington, D.C., Office of Tax & Revenue, 2022). These vacant properties all fall under Class 3 of properties in the DC Code. Property owners are expected to self-report vacant properties, but DC also regularly audits home occupancies to determine vacancy status (City of Washington, D.C., Office of Tax & Revenue, 2022). Fines are often imposed for property owners that fail to self-report.

Since 2003, other cities including Vancouver, Canada in 2017 (City of Vancouver, 2020) and Oakland, California in 2021 (City of Oakland, 2022) have imposed their own vacancy taxes on city properties that are vacant. While vacancy taxes were initially developed to reduce the prevalence of abandoned and blighted properties, Vancouver uses the same tax to manipulate their housing market. The city highlights that this tax has made more properties available to rent (thereby relieving the housing market by providing renting as a more viable option for residents) (City of Vancouver, 2022). However, Vancouver also uses their vacancy tax to lower house prices by punishing property speculators. Without explicitly stating it, Vancouver's policy approach theorizes that restricted rental supply and non-occupant housing speculation drive up the prices of housing.

Currently, there is only one peer-reviewed study that addresses the impact of vacancy taxes on housing prices. Chen (2001) examined the effects of a hypothetical 1% vacancy tax in Taiwan using simultaneous equations, finding that this tax reduced housing prices by 2.6% to 8.8% in selected study areas. There are, however, limitations to Chen's analysis. Chen's study predicted housing price changes resulting from making renting more viable, but not necessarily to capture the effects of non-occupant property speculation. As well, Chen's estimates using a hypothetical tax do not capture other issues involved in implementing and maintaining a tax, with the most patent omission being tax enforcement (or lack of it).

This paper is the first to determine, using causal inference methods and an applied treatment, whether a vacancy tax could reduce or slow residential property prices. There are several notable strengths to this specific research concept and design. First, this paper explores this relationship through a rigorous application of the synthetic control method and several robustness measures such as placebo tests, interrupted time series, and other time series analyses. Second, to isolate housing price changes, we must control for housing price equilibrium. We do this by controlling for housing demand and supply using carefully picked covariates ranging from per capita income to the subprime credit population percentage. Last, scholars have noted that the trend of non-occupant housing investment in the United States started in the early 2000s as the start of the period's housing bubble (Goldstein, 2018). This means that DC unintentionally implemented their vacancy tax just as non-occupant housing speculation became popular in the United States. Consequently, this paper theorizes that causal modeling should be able to isolate and measure the impacts of non-occupant housing speculation and rental supply. This is possible because of both the timing of the tax and the properties it applies to. If there is any effect of vacancy taxes on housing prices, this research design should capture this.

2 Methodology

The primary method used in this analysis is the synthetic control method as developed by Abadie et al. (2010). Several reasons preclude the possibility of gaining reliable estimates from other methods. Traditional ordinary least squares regression is unsuitable for many political science applications (including urban-level taxation) due to a low number of observations and, consequently, insufficient power (Bonander et al., 2021; Bouttell et al., 2018). Difference-in-differences is a powerful causal inference tool for studies that involve a low number of observations, but this method is fundamentally incompatible with this type of analysis. A difference-in-differences study relies on the assumption of "common trends", which holds that the outcome variable of interest for the treated and control units would have the same trajectory absent the treatment (Stock and Watson, 1988). This assumption does not mean that these units must be identical, but the condition also implies that they must be comparable. If two units are nothing alike, then we cannot reasonably infer that they would have common trends. Here, we cannot safely posit that DC's housing market would be comparable enough to another U.S. city to assume common trends. Housing market trends are dependent upon consumer demand, the credit population distribution, and personal finances, among other considerations. Given the multitude of variables that contribute to the direction of a housing market, it is improbable that one city exists that is compatible on all these factors.

Luckily, the synthetic control method provides a suitable alternative to traditional ordinary least squares regression and difference-in-differences estimation. Rather than relying on one control unit or an unweighted average of control units, we instead find the weighted average of all potential control units that most closely represent the treated unit (Abadie et al., 2010). Assume that we have $J+1$ units in time periods $1, 2, \ldots, T$ and a set of matching covariates denoted as V. Each control unit j is assigned a weight w_j that reflects how much importance it will have in our synthetic control analysis. There are no negative weights and together these weights will sum to 1. Given our matching covariates V, the synthetic control method selects weights that minimize the differences between these variables for the treated unit and synthetic control. We are then left with a combination that provides the best valid counterfactual for the treated unit (denoted as w_j^*). Our synthetic control estimator for the post-treatment period becomes:

$$\hat{\alpha}_{1t} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}$$

where Y_{1t} stands as the treated unit outcome for time period t and the summed term represents the outcome for the synthetic control unit. The α term then represents our "treatment effect". Stata's "synth2" command selects variables based on reducing the mean square prediction error:

$$\text{MSPE} = \frac{1}{T_0} \sum_{t=1}^{T_0} \left(Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt} \right)^2$$

However, the synthetic control method also relies on assumptions to produce causal results. We can only derive a valid result from this estimation if we accept that we have created a valid counterfactual for the treated unit (Bonander et al., 2021). As well, this assumption can be invalidated if there are contemporaneous shocks that impact the treatment and synthetic control in a way that they are differentially affected and cause the outcomes to artificially diverge. Lastly, this assumption would be invalidated if DC's vacancy tax impacted the housing prices of any donor cities.

This paper carefully considers all these potential obstacles and conducts many validation checks including variable comparison tables, outcome graph trajectories, interrupted time series, placebo in space, and autocorrelation graphing.

3 Data

3.1 Treatment Unit and Donors

As previously stated, the treatment in this synthetic control study is the implementation of a vacancy tax. This study classifies a vacancy tax as one that charges property owners a vacancy tax for failing to live or rent that property, subject to reasonable exemptions such as pending litigation or construction.

The Washington-Arlington-Alexandria metropolitan statistical area ("DC Metro") is selected as the treatment unit in this synthetic control study. DC Metro is the ideal choice over Vancouver or Oakland because DC Metro's vacancy tax (i) is much greater (at 4.15% beyond standard property taxes) than either Vancouver (3%) or Oakland ($6,000); (ii) is located in the United States (major North American cities would likely provide poor donor units for Vancouver); and (iii) has been in place since 2003, which provides a lengthy post-treatment period to observe a causal effect.

There are thirty donor unit metropolitan statistical areas in the United States that will create a synthetic DC Metro for our analysis. None of these cities have any form of vacancy tax.

3.2 Variables

This study uses panel data over the course of 35 years (24 years pre-treatment and 10 post-treatment) covering the DC Metro and all 30 donor units. The data collected comes from various sources including the Federal Reserve Bank of St. Louis, the U.S. Census Bureau, the Bureau of Labor Statistics, the United Nations, private corporations (such as Equifax Incorporated), the U.S. Economic Bureau, and the U.S. Federal Housing Finance Agency, among others. Most of the data spans the entire 35-year period, giving the model a substantial amount of data to form a synthetic DC Metro.

The outcome variable of interest is the "All-Transactions Housing Price Index" (the "Housing Index"), as formulated and maintained by the U.S. Federal Housing Finance Agency. The covariates in this analysis are all theoretically related to the value of the Housing Index. In doing so, this study separates the variables into several categories including (i) housing costs; (ii) personal finances; (iii) housing demand and supply considerations; and (iv) urban characteristics. As well, the housing index itself and the first difference of the housing index across all pre-treatment years were used as covariates in the synthetic control analysis to control for short and long-term housing price trends.

Table 1: Variables and Sources

Variable	Source
Housing Costs	
All-Transactions Housing Price Index	U.S. Federal Housing Finance Agency (FRED)
All-Transactions Housing Price Index (First Difference Estimations)	U.S. Federal Housing Finance Agency (FRED)
Average Property Tax (% of Personal Income) (State)	U.S. Census Bureau
Personal Finances	
Log Per Capita Personal Income	U.S. Census Bureau (FRED)
Minimum Wage	U.S. Department of Labor (FRED)
Unemployment Rate	U.S. Bureau of Labor Statistics (FRED)
Housing Demand & Supply	
New Private Housing Units Authorized by Building Permits Per 100,000	U.S. Census Bureau (FRED)
Percent of Equifax Subprime Credit Population (County)	Equifax Inc. (FRED)
Log Allowance for Loan and Lease Loss for Commercial Banks	Federal Financial Institutions
Urban Characteristics	
Economic Conditions Index	FRED
MSA Population	U.S. Census Bureau/United Nations
MSA Population Change	U.S. Census Bureau/United Nations
MSA Population Density (People Per Square Mile)	U.S. Census Bureau/United Nations

Together, the donor units will be matched with DC Metro on the above variables to create a synthetic DC Metro that presents a better counterfactual than could be generated through a single comparator.

4 Results

4.1 Synthetic DC Metro Makeup

As stated above, synthetic DC Metro is constructed from the 30 donor cities and balanced by the 13 covariates specified. If successful, the synthetic control method should be able to provide a better match among covariates than any individual donor unit or the donor pool average. Table 2 below contains the DC Metro, synthetic DC Metro, and donor pool averages for the 13 covariates included in the analysis.

Table 2: Covariate Means of DC Metro, Synthetic DC Metro, and Donor Pool

Variable	DC	Synthetic DC	Donor Pool
All-Transactions Housing Price Index	87.48	88.26	90.51
All-Transactions Housing Index (First Difference)	4.64	4.55	4.35
Property Tax	2.81	5.98	6.02
MSA Population	3,309,760	3,628,000	1,632,000
MSA Population Change	1.66	1.46	1.97
MSA Population Density (People Per Square Mile)	594.85	662.82	411.38
Minimum Wage	4.64	3.91	3.45
Unemployment Rate	3.77	5.16	4.78
Percent of Equifax Subprime Credit Population	39.89	39.36	34.55
Log Per Capita Personal Income	10.12	9.91	9.85
New Private Housing Units Authorized	7,411.07	5,821.26	8,624.33
Economic Conditions Index	2.95	2.30	2.74
Log Allowance for Loan and Lease Loss	12.57	12.56	11.49

Ten variables became closer to the DC Metro average and only three variables moved away from the treatment unit. In addition to the means of more synthetic control unit variables becoming closer to real DC Metro's, we can also see that the magnitudes of these changes are substantial. The house price index, first difference of the house price index, MSA population, MSA population change, MSA population density, and subprime credit population all become very comparable to DC Metro's averages given their previous disparities.

As such, these results demonstrate that the synthetic control method has created a better comparator for real DC Metro than existed in the donor pool.

Table 3 below shows all the donor cities and covariates that contributed to synthetic DC Metro with a non-zero weight. The weights for donor cities were concentrated around four units: Philadelphia, San Diego, Raleigh, and Portland. There was a larger spread of contributing covariates, with 6 of the covariates having a weight greater than 1%, and 3 of the top weighted covariates accounting for approximately 70% synthetic DC Metro's makeup. The diversity of the city and covariate contributors adds reassurance that the synthetic control process has produced a valid counterfactual for real DC Metro.

Table 3: Weights of Donor Cities and Covariates

Cities	**Weight**	**Covariate**	**Weight**
Philadelphia	63.5%	All-Transactions Housing Price Index (First Difference)	32.58%
San Diego	24.1%	Percent of Equifax Subprime Credit Population (County)	30.79%
Raleigh	9.4%	All-Transactions Housing Price Index	12.71%
Portland	3.0%	MSA Population Change	11.05%
		Log Allowance for Loan and Lease Loss	7.92%
		Minimum Wage	4.08%

4.2 The Impact of DC's Vacancy Tax

Figure 1 plots the trajectory of the housing price index of real DC Metro and synthetic DC Metro (as created using Stata's "synth2" package).

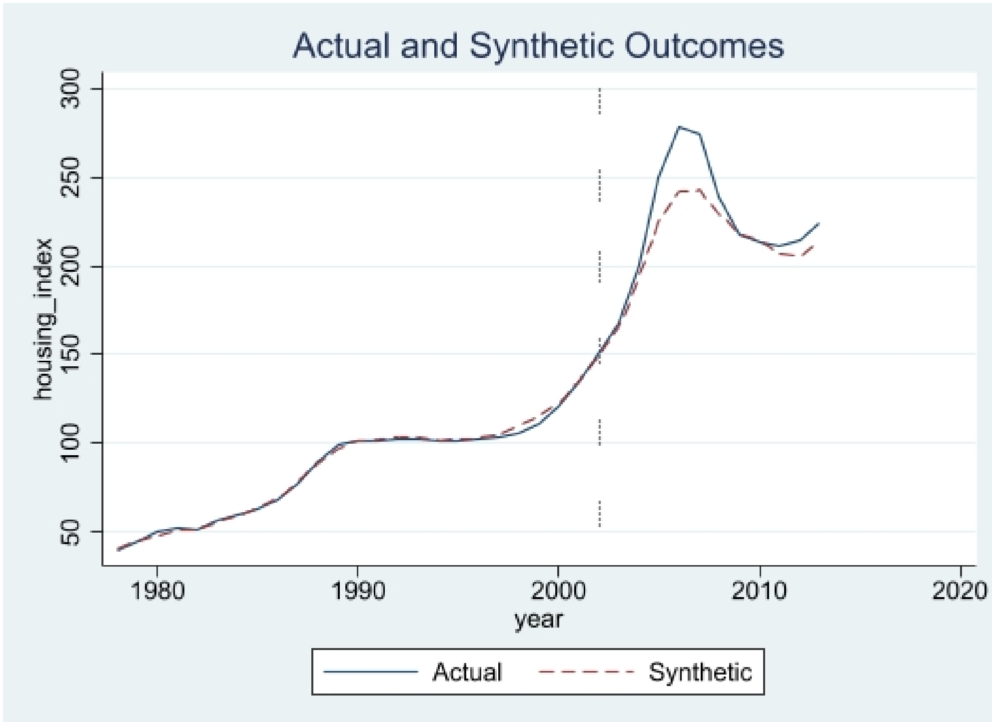

Figure 1: DC Metro and Synthetic DC Metro Housing Index
This figure shows the housing index for Washington D.C. (treated unit) compared to its synthetic control from 1978-2013. The vertical line indicates the implementation of the vacancy tax in 2003.

We now observe that the synthetic control unit has adopted the same plateau of housing prices that DC experiences. Further, the other major trends that were previously visible in real DC Metro, such as the housing growth in the late 1980s and early 2000s are now mimicked by our synthetic unit. The two housing indexes are now close enough that they are almost indistinguishable prior to the treatment period. The reported Root Mean Squared Prediction Error ("RMSPE") for the pre-treatment period is 1.67568, also demonstrating that synthetic DC Metro has provided a valid counterfactual for real DC Metro.

Ultimately, the above shows no indication that DC's vacancy tax had any downward effect on DC Metro's house prices. However, rather than seeing a negative impact of DC's vacancy tax, we instead notice a gap emerging in approximately 2004 or 2005 where real DC Metro's housing index outpaces the synthetic control unit's housing index. It is plausible that this gap is the result of the vacancy tax having been capitalized into housing costs over a short period of time and caused the housing index to increase (Cebula, 2009). However, further tests are required to determine whether this jump is statistically significant or not. This paper later discusses placebo in space, interrupted time series, and autocorrelation trends to explain the emerging gap post-2003.

4.3 Robustness Measures

4.3.1 Leave-One-Out Test

In addition to the comparison of housing index and matching variables, this paper applies a "leave-one-out" robustness check to confirm the validity of our proposed counterfactual. A leave-one-out test involves rerunning the synthetic control analysis while one-by-one leaving out donor units with positive weights towards the synthetic unit. The purpose of the leave-one-out test is to see whether the synthetic unit, absent each donor city weight, substantially matches the trends of the treated unit pre-treatment. The leave-one-out test also checks to see if a less comparative model would provide a larger effect. Figure 2 is a graphical comparison between real DC Metro and synthetic DC Metro using the leave-one-out test.

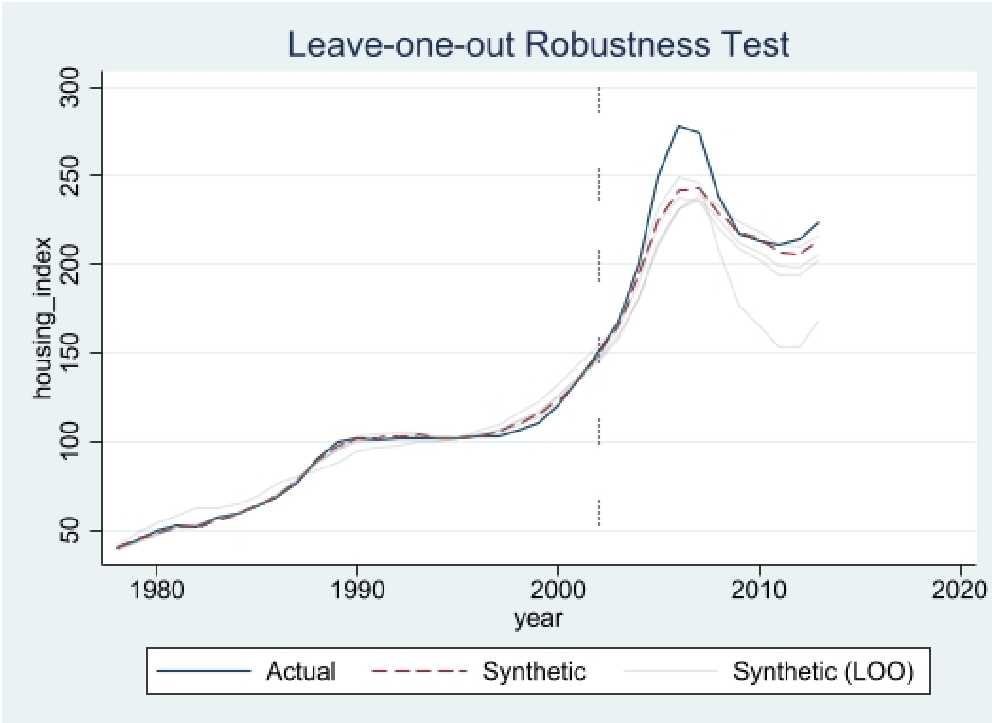

Figure 2: Leave-One-Out Test
Leave-one-out validation results testing the sensitivity of the synthetic control estimates to the exclusion of individual control units.

The leave-one-out test confirms that our synthetic unit is a robust counterfactual to real DC Metro. This conclusion rests on the findings that the housing price trends that DC Metro experiences, such as the consistent increases in the 1980s, the stagnation in the 1990s, and the rapid growth during the early 2000s, are all reflected in each of our synthetic model counterfactuals. This also dispels any worry that Philadelphia's large weight would provide a less robust model. Even without the model's largest donor unit, we still have a valid counterfactual trend for real DC Metro. We also know that real DC Metro's housing index is much higher than all potential synthetic results, which lends argument to the potential that the vacancy tax may have increased average house prices.

4.3.2 Statistical Significance and Randomized Inference: Placebo in Space

This study then utilizes a placebo in space analysis using the pre to post-treatment RMSPE ratios to examine whether the gap post-2003 is statistically significant or not. Essentially, the RMSPE ratio plot attempts to measure the impact of the treatment on DC Metro and other cities as if it had happened there by relying on randomized inference (i.e. the likelihood of a particular effect comparatively to units in the sample) rather than traditional standard errors. The placebo in space tests essentially then plots these RMSPE ratios for comparison, as shown in Figure 3.

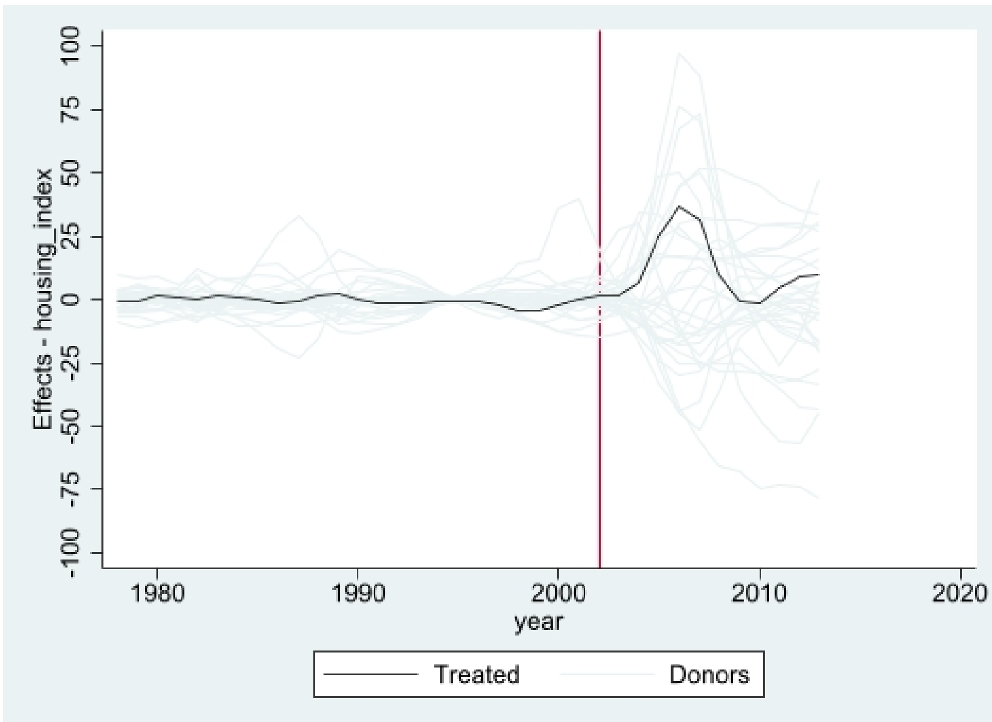

Figure 3: Placebo in Space
This figure displays the RMSPE ratios for all potential donor cities, testing whether Washington D.C.'s post-treatment gap is statistically significant under randomized inference.

The results of the placebo in space analysis again confirms the robustness of synthetic DC Metro's ability to match real DC Metro pre-2003. However, the placebo in space comparison casts doubt on any indication that DC's vacancy tax could have boosted (or reduced) housing prices. While the above chart confirms there is an upward direction in housing prices comparatively to most of the donor units, it is still surpassed by many donor units. Under a randomized inference framework and in place of traditional error estimation, we would expect DC Metro to have either the highest or second highest RMSPE ratio to conclude that DC's vacancy tax had a statistically significant impact (Abadie et al., 2010).

4.4 Time Series Investigation

4.4.1 Interrupted Time Series

An interrupted time series was conducted to assess whether there was a structural break near the point of the 2003 vacancy tax. Interrupted time series is a causal inference method that assesses the time series trajectory both pre- and post-treatment to determine whether there is a statistically significant change in trajectory. This paper utilizes the "itsa" package from Stata, which uses Linden's generalized least squares model (Linden, 2015). The analysis is robust with 44 years of analysis and 30 other time series to compare. Figure 4 shows a plot of the time series analysis.

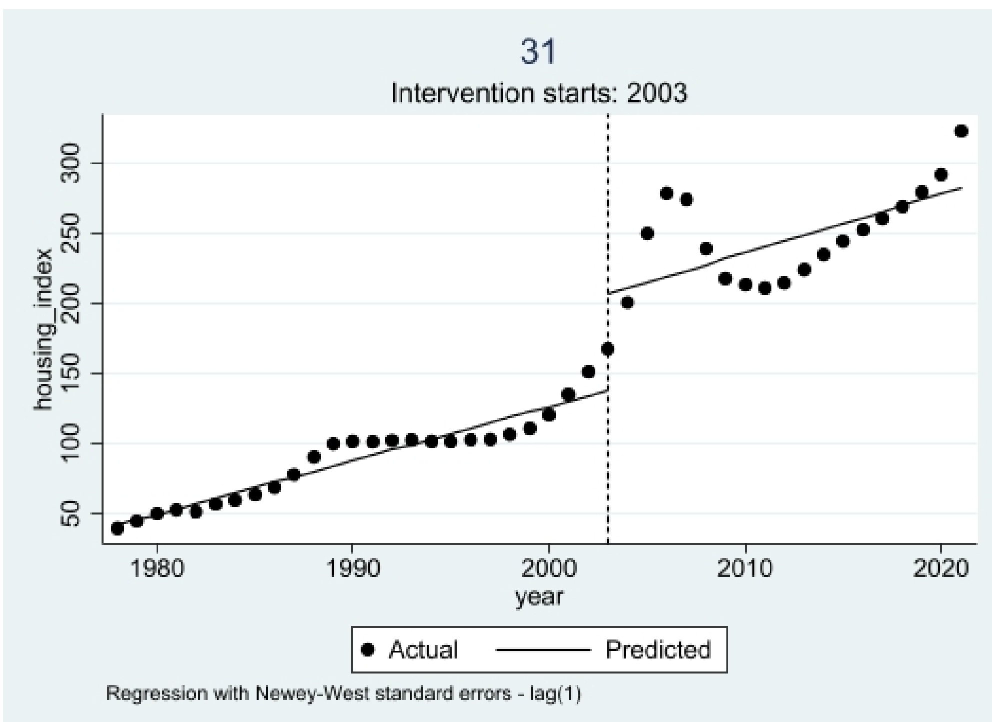

Figure 4: Interrupted Time Series
Results from interrupted time series analysis examining the vacancy tax policy impact. The analysis controls for pre-existing trends and estimates the immediate and gradual effects of the policy intervention.

The above shows that the first and last twenty years of DC's house price index follow dramatically different trends. Interestingly, the slope of each regression lines is similar but there is a notable jump near the treatment period. Further, the interrupted time series analysis reports a structural break in DC's housing market trajectory (p-value = 0.014). These results then confirm that there was a statistically significant increase in the housing market at or around 2003 and somewhat contradict the finding in the placebo in space analysis.

4.4.2 Time Series and Autocorrelation

Absent conclusive evidence that DC's vacancy tax boosted housing prices, it is still crucial to investigate why housing prices in DC Metro increased dramatically comparatively to most cities around 2003. There is substantial proof that many cities across the United States experienced non-occupancy market speculation (Goldstein, 2018; Zelizer, 2010). However, neither DC Metro nor its biggest donor, Philadelphia, were differentially impacted by this trend (Goldstein, 2018). Cities in Florida, Nevada, Arizona, Idaho and Georgia were most impacted by this housing speculation trend. DC Metro did experience non-occupancy housing speculation, but not in a way that would cause a contemporaneous shock that would invalidate the findings of this paper.

On further investigation, the underlying data leads us to believe that housing market trends in DC Metro are primarily a function of relevant economic traits and conditions rather than non-occupancy housing speculation. First, pairwise correlations of the dataset show large correlations between the housing index and most other variables. This reinforces the theory that the housing market is dependent upon a set of factors that include personal finances, urban characteristics, financing, and housing demand/supply. We also see that almost all variables are correlated with time. Together, these findings suggest that housing market trends and their contributing factors all follow and create a housing price trend.

Second, if we accept there is a time trend present that influences the housing market and its contributing factors, it is useful to investigate its form. A Harris-Tzavalis Unit-Root Test (Harris and Tzavalis, 1999) indicates that the panels are stationary and do not contain a unit root, meaning there is only the presence of one-time trend. This unit root test also signals that there may not be a strong competing trend from non-occupancy speculation.

Finally, we observe the autocorrelation specifically present in DC Metro's housing price trends at Figure 5:

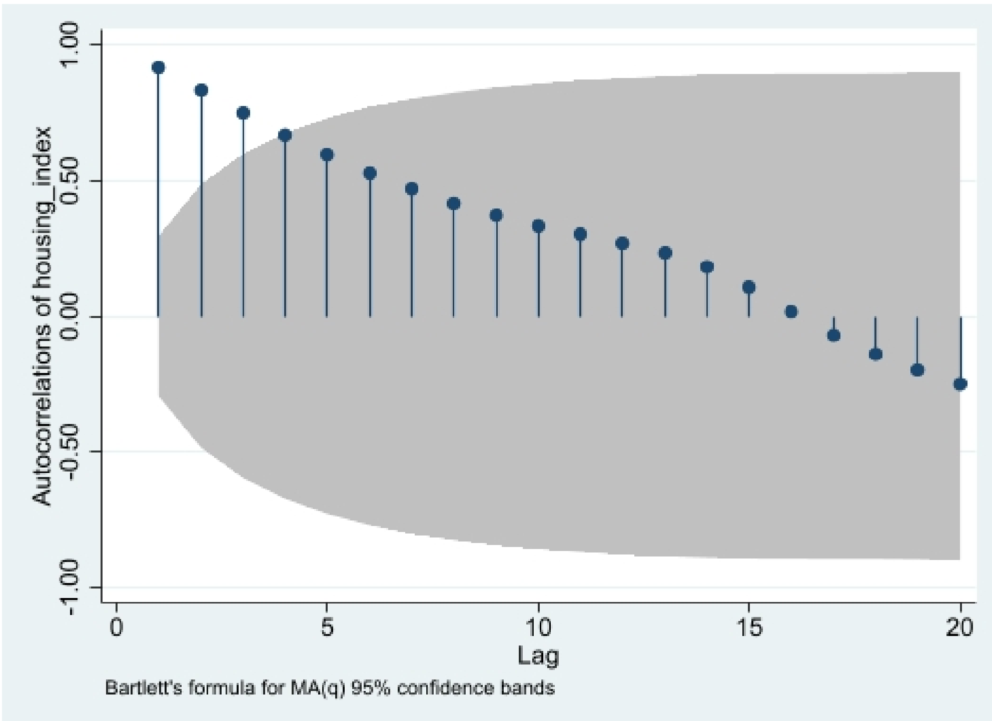

Figure 5: Autocorrelation in DC Metro's Housing Market
Autocorrelation function of model residuals examining the temporal dependence structure in the data and validating model assumptions.

This graph shows that there is autocorrelation present in DC Metro's housing index for at least three years after the impugned period, indicating there are impactful and relevant short-term trends. This test both reaffirms the decision to include the housing index's first difference as a covariate and highlights that DC Metro's housing index is continuously impacted by the prior three years.

Ultimately, the combination of evidence that DC Metro was not differentially impacted by the non-occupancy housing speculation trend, the strong pairwise correlations between house price-relevant variables and time, along with the presence of short-term autocorrelation, all highlight that DC Metro's housing market gains post-2003 are likely a result of the increases/decreases of contributing factors identified in this paper over short-term periods and not that of any vacancy tax.

5 Limitations

There are some important limitations to consider when interpreting the results of this study. First, the external validity of synthetic control studies is always limited (Abadie et al., 2010). The treatment and synthetic control unit are both uniquely tailored to the observations. While this process can still derive a causal inference, we still must acknowledge that the sample here is limited to DC Metro. As such, this study is persuasive, but not conclusive, that vacancy taxes will not reduce or stall house prices elsewhere.

Second, a crucial element of tax effectiveness is enforcement. Studies confirm that tax enforcement increases compliance and therefore larger effects of taxation (Keen and Slemrod, 2017). Theoretically, it is possible that a lack of vacancy tax enforcement in DC could reduce its effectiveness. However, there is no indication that there are historical vacancy tax enforcement issues (City of Washington, D.C., Office of Tax & Revenue, 2022). As well, DC imposes severe fines on property owners that fail to declare and register their properties as vacant (City of Washington, D.C., Office of Tax & Revenue, 2022). As such, while we cannot collect and control tax enforcement data, DC's large fines reduce the likelihood that the vacancy tax is under enforced and by extension less effective.

Third, there are some variables that were not available at the metropolitan statistical area level, such as the property tax data and the subprime credit population. As such, these variables are subject to some level of measurement error. However, because the impugned variables are calculated at a higher level for all donor and treated units, it is likely that the variation between the units at the state/county level are similar to the variation had it been experienced at the metropolitan statistical area level. As such, at the risk of variable omission bias, this model included these covariates as they would more beneficial than detrimental. In any event, only one of the non-zero-weighted contributing variables was measured at a higher level (subprime credit population for county). Counties are much more comparable to metropolitan statistical areas than states, further reducing the potential impacts of measurement error.

Lastly, there is a risk of some omitted variable bias. Efforts were made, for instance, to find and include data concerning school quality and crime rates at the metropolitan statistical area level. While many relevant variables were matched in this analysis, admittedly, crime rates and school quality may impact the housing price index despite not being included in this study.

6 Conclusion

This study utilized the synthetic control method to explore the potential impact of DC's vacancy tax on housing prices. A valid counterfactual to real DC was created using 25 years of pre-treatment data and 13 housing market-related covariates. The viability of this synthetic unit was checked using a leave-one-out test. While the initial results and interrupted time series both indicated that the vacancy tax could have caused upward pressure on housing prices, a placebo in space analysis casts doubt that this gap is significantly different from zero. Finally, unit root tests, pairwise correlations and autocorrelation analyses all indicate that DC's housing market fluctuations and dramatic increases are a result of short-term time trends, economic and financing cycles, and population shifts.

Given the above, we know that DC's vacancy tax did not reduce DC Metro's house prices. It is possible, although unlikely, that the vacancy tax increased house prices. It is more likely that house price trends as a function of other aspects of the housing market increased the

DC Metro housing index more rapidly than other comparable cities.

Cities like Vancouver and Oakland are hoping that their own vacancy taxes will reduce housing prices by deterring non-occupancy house price speculation. However, evidence from this study signals that taxing unoccupied homes may be ineffective in controlling the housing market. This is even more pronounced given the magnitude of DC's vacancy tax and the fact that it was implemented at the beginning of a known period of widespread housing speculation.

Local governments in North America should be cautious about implementing vacancy taxes if the primary or sole purpose is to reduce or restrict house prices. While such policies may serve other legitimate purposes, such as addressing blight or encouraging property utilization, policymakers should not expect significant downward pressure on housing prices as a primary outcome.

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