THE BIZARRE IMPACT OF COVID-19 PANDEMIC ON HOUSING PRICES ON OAHU ISLAND, HI

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**INTRODUCTION**

This paper aims to investigate the multifaceted impacts of the COVID-19 pandemic on the housing market of Oahu Island, Hawaii. Despite recording comparatively lower death rates than other states in the United States, the tourism-dependent economy of Hawaii has not been immune to the adverse consequences of the ongoing crisis. The first positive case in Hawaii was detected on March 6, 2020, when a Grand Princess passenger returned to the island. As the pandemic unfolded, fears and uncertainties gripped society, compelling businesses to suffer, schools to close, and the healthcare system to strain. This study examines how these circumstances have influenced the housing market dynamics on Oahu Island.  
During the progression of the COVID-19 pandemic, an escalation in positive cases prompted the former Mayor of Honolulu to announce stay-at-home orders, effective from March 23, 2020, until April 30, 2020. In an unprecedented move, the Hawaii Tourism Authority requested media outlets to discourage travel to all the islands in Hawaii. Additionally, former Governor David Ige approved a subsequent stay-at-home order spanning from August 27 to September 24, 2020. Notably, Oahu reopened on March 11, 2021. This study aims to assess how households perceive the prevailing housing market conditions amidst the COVID-19 pandemic, and whether these perceptions have exerted a negative, positive, or neutral influence on housing prices. Hawaii, often referred to as a paradise, exhibits a median housing price exceeding one million dollars. Despite a consistently growing demand for housing in Hawaii, the present inquiry scrutinizes whether the pandemic has altered individuals' aspirations of residing in Hawaii and subsequently diminished their enthusiasm for property acquisition on Oahu Island. Paradoxically, an intriguing phenomenon has emerged during the pandemic, as housing prices on Oahu Island experienced a significant upsurge.

The unusual surge in housing prices on Oahu Island can be attributed to a confluence of factors, namely historically low mortgage rates and the perceived safety and desirability of living in Hawaii. The low mortgage rates have incentivized buyers to acquire multiple properties, capitalizing on the reduced costs associated with homeownership. The appeal of Hawaii's relatively safer environment compared to other states has also prompted individuals to seek housing for the sake of health and safety. The low elasticity of housing due to the combination of increased demand and limited supply has further driven up housing prices in Hawaii. Notably, the escalating prices of lumber have played a significant role, with prices nearly tripling since 2020. The amplified demand stemming from home renovation projects, new home constructions, the Honolulu Rail Transit construction, coupled with reduced global production, has contributed to the upward trajectory of housing prices in Hawaii.

This study significantly contributes to the existing literature by conducting the first island-wide analysis encompassing the spatial patterns and heterogeneity of housing price fluctuations in both the single-family housing and condo markets of Hawaii during the COVID-19 pandemic crisis. To the best of our knowledge, no previous studies have specifically examined the impact of the COVID-19 pandemic on an island's housing market. The primary objective of this research is to comprehensively explore the repercussions of the COVID-19 pandemic on housing prices specifically on Oahu Island, Hawaii. By undertaking this investigation, we aim to enhance the understanding of the unique dynamics shaping the housing market amidst the pandemic and provide valuable insights for policymakers, industry professionals, and prospective homebuyers.

**LITERATURE REVIEW**

The studies on the relationship between the COVID-19 pandemic and housing values can be grouped into three categories: studies that find no measurable effects on property values; studies that find all negative impacts on property values; studies that find all positive impacts on property values, and studies that find mixed results from different study areas or different periods during the pandemic.

**Group A: studies that find no measurable effects on property values.**

Zeng and Yi (2022) used the hedonic price model to compile the second-hand housing price index in Wuhan and its neighboring capital cities and then uses the difference-in-difference (DID) model to conduct a comprehensive study on new commercial housing and second-hand housing market. Their results showed that the negative impact of the pandemic on the housing market was mainly reflected in the volume and area of housing transactions, with little impact on housing prices.

**Group B: studies that find all negative impacts on property values.**

Del Giudice et al. (2020) conducted a study in the Campania region of Italy, which revealed a short-term decrease of 4.16% and a mid-term decrease of 6.49% in housing prices between late 2020 and early 2021 because of the global pandemic. Hu et al. (2021) examined five Australian cities and found that for every doubling of newly confirmed COVID-19 cases, housing prices dropped by 0.35% to 1.26% annually. Qian et al. (2021) demonstrated that housing prices are negatively affected in regions with higher infection levels or inadequate healthcare, with a 2.47% reduction observed in Ireland as the pandemic persisted. Allen-Coghlan and McQuinn (2021) also observed an 18-month decline in housing prices in the Irish housing sector due to the COVID-19 pandemic. Francke and Korevaar (2021) noted a temporal increase in housing risk premia in Amsterdam and Paris caused by growing uncertainty and economic disruption from the pandemic, resulting in a reduction in housing prices.

**Group C: studies that find all positive impacts on property values.**

Kadi et al. (2020) conducted a study on the rental housing market in four major Austrian cities, analyzing real estate listings, and identified that property owners reconsidered their usage of units for tourism purposes, subsequently converting them back to the regular rental market due to increasing rental prices. Verma and Husain (2020) assessed the resilience and strength of the Canadian housing market during the pandemic and observed that cities near urban centers experienced an upswing in housing prices. In terms of reported COVID-19 cases, Arcaya et al. (2020) found that housing values increased with rising COVID-19 cases, primarily due to housing displacement pressures caused by the pandemic. Delgado and Katafuchi (2020) studied the relationship between the COVID-19 pandemic and the Japanese housing market during the state of emergency declaration. Their findings revealed a favorable demand for housing during this period. Regarding COVID -19 restrictions, Yang and Zhou (2021) examined the effects of the pandemic on the housing market in China and found a considerable and statistically significant increase in housing prices following the emergence of the pandemic, indicating the need for improved home quarantine measures. Wang (2021) argued that stay-at-home orders and business restrictions have contributed to a surge in housing prices, particularly in properties with better amenities. Yang and Zhou (2022) examined COVID-19's impact on the housing market in the Yangtze River delta region in China by using the average selling price of commercial housing to capture the performance of local housing market. They found out that the COVID-19 has significantly increased housing prices, reflecting the need for families to stay together.

**Group D: studies that find mixed impacts on property values.**

Bricongne, Meunier, and Pouget (2022) analyze a large database and find that the listing prices after the lockdown experienced a continued decline in London but increased in other regions. Yang et.al. (2023) analyze the association between to-metro and by-metro accessibility and house prices in Chengdu, China and find different impacts on low-priced houses and high-priced houses. Cheung et.al. (2021) investigate the COVID-19 epicenter in China and find the house prices fall immediately 4.8% by using hedonic pricing model and 5.0-7.0% by using price gradient model after the breakout. They also find that the house prices in the 62 areas in Wuhan City where the COVID-19 pandemic originated rebounded after the lockdown period, and price gradients were flattened from the epicenter to the urban peripherals. Li and Zhang (2021) conclude that the influence of the COVID-19 pandemic crisis on housing price change varied across space in the U.S. They also conclude that COVID-19 may make Americans more cautious about buying property in densely populated urban downtowns that had higher levels of virus infection.

**DATA and METHODOLOGY**

There are 10 variables associated with housing characteristics and 8 distance variables associated with amenities/disamenities. These distance variables are created using the ‘near’ function of ArcMap. The first step to assess the impact of the HRT on property values is to build a GIS database from the data collected from the Department of Planning and Permitting. Using sales data from the HBR (Honolulu Board of Realtors), more than 23,000 single family housing addresses and 33,000 condo addresses are geocoded. The housing data includes the major physical characteristics of the houses such as the number of bedrooms, bathrooms, square footage, age, etc. Hedonic analysis has been applied to data on heterogeneous goods to estimate shadow prices of bundled characteristics such as housing attributes and public good amenities acquired through the housing market (Ohsfeldt and Smith, 1985). Traditional hedonic estimation has been frequently used for the purpose of making inferences about non-observable values of different attributes like air quality, airport noise, and access to transportation (Espey and Lopez, 2000). There have been many critical views about traditional hedonic models such as information asymmetry, measurement validity of explanatory variables, market limitations, multicollinearity, and price changes. It is thus better to explore additional research designs or to use the hedonic price technique with application to other models.

Assuming P is a vector of house prices associated with a vector of structure variables S and set of location variables N then it follows that their relationship can be represented by the following model:

                                                (1)

where ln(Pi) = natural logarithm of house sale price of property i; Sip = physical attribute p of property i; Niq = location variable q of property i; β0, βp, βq= intercept and coefficients; εi= error. If the neighborhood feature affects house sale prices positively, the first-order relationship of house price with respect to the location variable is:

Shape

Description automatically generated with medium confidence                                                                               (2)

Table 1: Statistic Description of Single-Family Properties

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Variable | Description | Mean | StDev | Min | Max |
| Lnprice | Natural log of single-family housing prices | 11.92 | 0.467 | 11.92 | 16.79 |
| baths | The number of bathrooms | 2.37 | 0.98 | 0 | 17 |
| bedrooms | The number of bedrooms | 3.79 | 21.28 | 0 | 29 |
| Covid | 1 if there are positive covid cases | 0.407 | 0.491 | 0 | 1 |
| covidcases | Number of covid cases in each day | 28152 | 59695 | 0 | 249014 |
| urate | Unemployment rate without the percentage sign | 4.584 | 4.096 | 1.9 | 22.4 |
| age | The age of the house | 39.74 | 34.71 | 0 | 2017 |
| Age2 | The squares of the age of the house | 2784 | 52482 | 0 | 4068289 |
| Parking | The number of parking | 2.90 | 1.50 | 0 | 70 |
| lnsqft | The natural log of the square footage of the house | 7.53 | 0.437 | 5.39 | 10.06 |
| lnrail | The natural log of the distance to the nearest HRT station | 9.82 | 0.892 | 5.88 | 11.61 |
| lngolf | The natural log of the distance to the nearest golf course | 8.11 | 1.33 | 3.15 | 10.81 |
| lnpkschool | The natural log of the distance to the nearest preschool | 7.78 | 0.76 | 3.62 | 10.12 |
| lnprivate | The natural log of the distance to the nearest private school | 8.48 | 0.827 | 4.37 | 10.75 |
| lnpublic | The natural log of the distance to the nearest public school | 7.65 | 0.677 | 3.92 | 10.12 |
| lnhospital | The natural log of the distance to the nearest hospital | 9.44 | 0.885 | 4.44 | 11.14 |
| lnpark | The natural log of the distance to the nearest park | 6.93 | 0.152 | 2.93 | 9.38 |
| lnairport | The natural log of the distance to the nearest airport | 10.14 | 0.731 | 4.27 | 11.46 |
| bad | 1 if the house condition is bad | 0.028 | 0.166 | 0 | 1 |
| fair | 1 if the house condition is fair | 0.062 | 0.242 | 0 | 1 |
| average | 1 if the house condition is average | 0.184 | 0.387 | 0 | 1 |
| aaverage | 1 if the house condition is above average | 0.436 | 0.496 | 0 | 1 |
| excellent | 1 if the house condition is excellent | 0.289 | 0.453 | 0 | 1 |
| Y2016 | 1if the house was sold in the year of 2016 | 0.140 | 0.347 | 0 | 1 |
| Y2017 | 1 if the house was sold in the year of 2017 | 0.150 | 0.357 | 0 | 1 |
| Y2018 | 1 if the house was sold in the year of 2018 | 0.137 | 0.344 | 0 | 1 |
| Y2019 | 1 if the house was sold in the year of 2019 | 0.143 | 0.351 | 0 | 1 |
| Y2020 | 1 if the house was sold in the year of 2020 | 0.145 | 0.352 | 0 | 1 |
| Y2021 | 1 if the house was sold in the year of 2021 | 0.172 | 0.378 | 0 | 1 |
| Y2022 | 1 if the house was sold in the year of 2022 | 0.111 | 0.314 | 0 | 1 |

Table 2: Statistic Description of Condo Properties

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Variable | Description | Mean | StDev | Min | Max |
| Lnprice | Natural log of condo prices | 13.08 | 0.530 | 11.52 | 16.97 |
| baths | The number of bathrooms | 1.497 | 0.558 | 0 | 6 |
| bedrooms | The number of bedrooms | 1.798 | 0.913 | 0 | 8 |
| Covid | 1 if there are positive covid cases | 0.411 | 0.492 | 0 | 1 |
| covidcases | Number of covid cases in each day | 28152 | 59695 | 0 | 249014 |
| 0 | Unemployment rate without the percentage sign | 4.584 | 4.096 | 1.9 | 22.4 |
| age | The age of the house | 39.74 | 34.71 | 0 | 2017 |
| Age2 | The squares of the age of the house | 2784 | 52482 | 0 | 4068289 |
| Parking | The number of parking | 2.90 | 1.50 | 0 | 70 |
| lnsqft | The natural log of the square footage of the house | 7.53 | 0.437 | 5.39 | 10.06 |
| lnrail | The natural log of the distance to the nearest HRT station | 9.82 | 0.892 | 5.88 | 11.61 |
| lngolf | The natural log of the distance to the nearest golf course | 8.11 | 1.33 | 3.15 | 10.81 |
| lnpkschool | The natural log of the distance to the nearest preschool | 7.78 | 0.76 | 3.62 | 10.12 |
| lnprivate | The natural log of the distance to the nearest private school | 8.48 | 0.827 | 4.37 | 10.75 |
| lnpublic | The natural log of the distance to the nearest public school | 7.65 | 0.677 | 3.92 | 10.12 |
| lnhospital | The natural log of the distance to the nearest hospital | 9.44 | 0.885 | 4.44 | 11.14 |
| lnpark | The natural log of the distance to the nearest park | 6.93 | 0.152 | 2.93 | 9.38 |
| lnairport | The natural log of the distance to the nearest airport | 10.14 | 0.731 | 4.27 | 11.46 |
| bad | 1 if the house condition is bad | 0.028 | 0.166 | 0 | 1 |
| fair | 1 if the house condition is fair | 0.062 | 0.242 | 0 | 1 |
| average | 1 if the house condition is average | 0.184 | 0.387 | 0 | 1 |
| aaverage | 1 if the house condition is above average | 0.436 | 0.496 | 0 | 1 |
| excellent | 1 if the house condition is excellent | 0.289 | 0.453 | 0 | 1 |
| Y2016 | 1if the house was sold in the year of 2016 | 0.140 | 0.347 | 0 | 1 |
| Y2017 | 1 if the house was sold in the year of 2017 | 0.150 | 0.357 | 0 | 1 |
| Y2018 | 1 if the house was sold in the year of 2018 | 0.137 | 0.344 | 0 | 1 |
| Y2019 | 1 if the house was sold in the year of 2019 | 0.143 | 0.351 | 0 | 1 |
| Y2020 | 1 if the house was sold in the year of 2020 | 0.145 | 0.352 | 0 | 1 |
| Y2021 | 1 if the house was sold in the year of 2021 | 0.172 | 0.378 | 0 | 1 |
| Y2022 | 1 if the house was sold in the year of 2022 | 0.111 | 0.314 | 0 | 1 |

The hedonic pricing model was first proposed by Lancaster (1966) and later further expanded by Rosen (1974). This model might generate biased results, however, when the relationship between price and housing characteristics is not linear and in the presence of endogeneity. Additionally, the advantage of the hedonic pricing model is only realized in the presence of very reliable and detailed property records. Another issue is spatial dependence, which is derived from Tobler’s first law of geography (1970), “everything is related to everything else, but near things are more related than distant things” an axiom supported by Moran’s I test results indicating that there are strong spatial dependences existing in the house sales data for this study, in other words, there are significant spatial relationships between the houses’ locations and their property values. To address the omitted variable bias, this study uses fixed neighborhood effects model. Fixed effects model assumes that something within the same neighborhood may impact the house prices and those within-neighborhood effects have to be controlled. This model helps remove the effect of unobserved time-invariant or neighborhood-invariant variables from the regression process. The general fixed neighborhood effects model is constructed as follows:



where:

Ln(Pnt)is the housing price for the home located in the *nth* neighborhood in the tth year.

*Snt* is the structural variable for the home located in the *nth* neighborhood in the tth year.

*Lnt* is the location variable for the home located in the *nth* neighborhood in the tth year. is the error term that accounts for the variations between the same neighborhood and the same year.  represents all unobserved factors that vary across neighborhoods but are constant over time while represents all unobserved factors that vary both across the neighborhoods and the years.

 is the constant in the regressions.

To address the spatial dependence problems, this study uses semiparametric model to include geographical coordinates as its nonparametric part. The parametric models always assume strict functional forms, in which the dependent variable is determined by the regressors and unobserved errors are identically and independently distributed (iid). Nonparametric models, on the other hand, impose very few restrictions on the functional form leaving little room for misspecification. However, the precision of estimators which impose only nonparametric restrictions is poor (Powell, 1994) and there is a “curse of dimensionality”. Semiparametric models include the merits of both parametric and purely nonparametric models and is estimated in this study in the form:



where:

β = average coefficient of X.

Xi = a vector of structural and locational variables of for house i.

Zi1 = latitude of house i.

Zi2 = longitude of house i.

λ = error term.

m = purely nonparametric function.

The nonparametric part of the semiparametric model could be explained by the locally weighted regression (LWR) model or LOWESS (locally weighted scatterplot smoothing). It is a purely nonparametric procedure for fitting a regression surface to data through multivariate smoothing: the dependent variable is smoothed as a function of the independent variables in a moving fashion analogous to how a moving average is computed for a time series (Cleveland and Devlin, 1988). Detailed application of this model applying to housing market is found in McMillen and Redfern (2010): The LWR estimator is derived by minimizing the following equation with respect toand:



The kernel function K (*z*) determines the weight that each house sold as an observation in estimating the housing price at target point *X* with *Xi – X* defined as the distance between the target point and the *i*th neighboring house and *h* is a smoothing parameter called the bandwidth. As the distance increases, the weight declines; thus a kernel represents a decreasing function of a distance between two objects. There are various types of kernel functions such as rectangular, triangular, bisquare, tricube or Gaussian, however, the choice of kernel weight function usually has little effect on the results (this study uses the tricube kernel weighting function). The real challenge is the choice of *h* as it determines how rapidly the weights decline with distance.[[1]](#footnote-1) By placing less weight on more distant observations, high values of *h* imply local regressions that produce more smoothing than do smaller bandwidths (McMillen & Redfern, 2010). The choice of optimal bandwidth in this study is based on Silverman’s Rule of Thumb. Silverman (1998) proposes the rule-of-thumb bandwidth as , where is the sample standard deviation, v is the order of the kernel, andis a constant depending on the type of kernel used. Since this study uses the tri-cube kernel, according to Silverman, the constant is 3.15 when the kernel order is 2.

**RESULTS**

**Table 1 Model results with dependent variable: lnprice (N=23,620) for single-family housing market**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | OLS Model | | Fixed Effects Model   (51 groups) | |
| Variables | Coef. | Std. Err. | Coef. | Std. Err. |
| baths | 0.083\*\*\* | 0.003 | 0.068\*\*\* | 0.002 |
| bedrooms | -0.077\*\*\* | 0.002 | -0.049\*\*\* | 0.002 |
| Covid | 0.127\*\*\* | 0.018 | -0.100\*\*\* | 0.014 |
| Covidcases | 4.92e-07\*\*\* | 1.27e-07 | 4.46e-07\*\*\* | 1.01e-07 |
| urate | -0.007\*\*\* | 0.001 | -0.005\*\*\* | 0.001 |
| Age | 0.004\*\*\* | 0.000 | 0.0006\*\*\* | 0.000 |
| Age2 | -1.96e-06\*\*\* | 5.96e-08 | -2.62e-07\*\*\* | 5.16e-08 |
| parking | 0.005\*\*\* | 0.001 | 0.013\*\*\* | 0.001 |
| lnsqft | 0.663\*\*\* | 0.006 | 0.488\*\*\* | 0.017 |
| lnrail | 0.080\*\*\* | 0.003 | 0.073\*\*\* | 0.005 |
| lngolf | -0.006\*\*\* | 0.001 | 0.010\*\*\* | 0.001 |
| lnpkschool | 0.039\*\*\* | 0.003 | 0.026\*\*\* | 0.003 |
| lnprivate | -0.007\*\*\* | 0.003 | -0.039\*\*\* | 0.003 |
| lnpublic | 0.016\*\*\* | 0.003 | 0.026\*\*\* | 0.003 |
| lnhospital | -0.111\*\*\* | 0.003 | -0.009\*\*\* | 0.003 |
| lnpark | -0.026\*\*\* | 0.002 | -0.027\*\*\* | 0.005 |
| lnairport | 0.001\*\*\* | 0.004 | 0.041\*\*\* | 0.004 |
| bad | -0.100\*\*\* | 0.013 | omitted | omitted |
| fair | omitted | omitted | 0.091\*\* | 0.010 |
| average | 0.059\*\*\* | 0.008 | 0.151\*\*\* | 0.009 |
| aaverage | 0.112\*\*\* | 0.008 | 0.200\*\*\* | 0.009 |
| excellent | 0.193\*\*\* | 0.008 | -0.270\*\*\* | 0.009 |
| Y2016 | -0.065\*\*\* | 0.007 | -0.219\*\*\* | 0.022 |
| Y2017 | -0.323\*\*\* | 0.007 | -0.178\*\* | 0.022 |
| Y2018 | omitted | omitted | -0.144\*\*\* | 0.022 |
| Y2019 | -0.006 | 0.007 | -0.148\*\*\* | 0.022 |
| Y2020 | -0.012 | 0.001 | -0.149\*\*\* | 0.019 |
| Y2021 | 0.082\*\*\* | 0.017 | -0.037\*\*\* | 0.016 |
| Y2022 | 0.102\*\*\* | 0.027 | omitted | omitted |
| R-squared | 0.669 | | 0.595 | |

***Notes:*** *\*10% significance, \*\* 5% significance, \*\*\*1% significance*

**Table 2 Model results with dependent variable: lnprice (N=33,597) for condo market**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | OLS Model | | Fixed Effects Model   (53 groups) | |
| Variables | Coef. | Std. Err. | Coef. | Std. Err. |
| baths | 0.131\*\*\* | 0.004 | 0.050\*\*\* | 0.004 |
| bedrooms | -0.159\*\*\* | 0.003 | -0.051\*\*\* | 0.003 |
| Covid | 0.042\*\*\* | 0.016 | 0.041\*\*\* | 0.014 |
| Covidcases | 3.58e-07\*\*\* | 1.02e-07 | 3.26e-07\*\*\* | 0.83e-07 |
| urate | -0.005\*\*\* | 0.001 | -0.004\*\*\* | 0.001 |
| Age | -0.007\*\*\* | 0.000 | -0.009\*\*\* | 0.000 |
| Age2 | 3.84e-06\*\*\* | 8.30e-08 | 4.80e-06\*\*\* | 7.32e-08 |
| parking | -0.011\*\*\* | 0.001 | -0.003\*\*\* | 0.001 |
| lnsqft | 0.945\*\*\* | 0.007 | 0.826\*\*\* | 0.006 |
| lnrail | -0.072\*\*\* | 0.002 | -0.083\*\*\* | 0.003 |
| lngolf | 0.012\*\*\* | 0.001 | -0.007\*\*\* | 0.001 |
| lnpkschool | 0.010\*\*\* | 0.002 | 0.004\*\*\* | 0.002 |
| lnprivate | 0.027\*\*\* | 0.003 | 0.025\*\*\* | 0.003 |
| lnpublic | 0.016\*\*\* | 0.003 | 0.082\*\*\* | 0.003 |
| lnhospital | -0.067\*\*\* | 0.003 | 0.012\*\*\* | 0.003 |
| lnpark | -0.090\*\*\* | 0.002 | -0.065\*\*\* | 0.002 |
| lnairport | 0.095\*\*\* | 0.003 | 0.142\*\*\* | 0.004 |
| bad | -0.096\*\*\* | 0.026 | -0.109\*\*\* | 0.022 |
| fair | omitted | omitted | omitted | omitted |
| average | 0.110\*\*\* | 0.011 | 0.090\*\*\* | 0.009 |
| aaverage | 0.178\*\*\* | 0.010 | 0.151\*\*\* | 0.009 |
| excellent | 0.283\*\*\* | 0.011 | 0.225\*\*\* | 0.009 |
| Y2016 | -0.266\*\*\* | 0.016 | -0.272\*\*\* | 0.014 |
| Y2017 | -0.210\*\*\* | 0.016 | -0.216\*\* | 0.014 |
| Y2018 | -0.168\*\*\* | 0.016 | -0.168\*\*\* | 0.014 |
| Y2019 | -0.163\*\*\* | 0.016 | -0.162\*\*\* | 0.014 |
| Y2020 | -0.169\*\*\* | 0.011 | -0.167\*\*\* | 0.009 |
| Y2021 | -0.101\*\*\* | 0.006 | -0.106\*\*\* | 0.005 |
| Y2022 | omitted | omitted | omitted | omitted |
| R-squared | 0.722 | | 0.595 | |

**CONCLUSIONS**

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1. The tricube kernel is structured as D(t) =(1-|t|3)3*I*(|t|≤1) and 0 otherwise. [↑](#footnote-ref-1)