Impact of First Time Buyer's Relief on Housing Market of Different Property Types in Greater London Area

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1 Introduction

The Great Recession in 2008 demonstrated how changes to the housing market have not only economic but also social consequences. John Bone and Karen O'Reilly (2010) suggest that the recent trend of viewing the purchase of property as an investment rather than a primary place to live contributes to growing housing unaffordability. This socio-economic issue specifically concerns younger people who do not have substantial savings to enter the housing market. According to Nissa Finney and Albert Sabater (2022), as housing in certain areas of England and Wales becomes less affordable, it causes a generational divide in housing opportunities. Age segregation becomes more prominent, presenting challenges to social mobility. Additionally, John Bone and Karen O'Reilly (2010) mention how a larger number of individuals owning a stable home results in more sustainable communities and benefits the overall well-being of many families. According to Nikodem Szumilo (2018), accessible home ownership would not necessarily change wages but might potentially have positive implications for increased economic activity.

McKee et al. (2016) use qualitative analysis to discuss how different political narratives in England, Wales, Scotland and Northern Ireland lead to differences in the housing policies of local authorities. On November 22, 2017, the UK government announced a new policy, the First Time Buyers' (FTB) Relief, which exempted first-time buyers from paying a Stamp Duty Land Tax (SDLT) on an acquired house with a value of less than 300 thousand pounds and removed property tax from house purchases valued less than 500 thousand. This policy targeted the lower end of the housing market and should have increased affordability for many young individuals who were trying to get onto the property ladder (Bolster, 2011).

This study answers the research question about the effects of the First Time Buyers' (FTB) Relief policy on housing prices across diverse property categories within the Greater London region. Addressing this research topic holds substantial economic significance, offering insights into various economic fields including housing affordability, demand-supply dynamics, and potential findings for key stakeholders such as homeowners, real estate developers, and policymakers. The implementation of tax relief measures faces challenges, as their impact depends on several factors such as the elasticity of demand and supply, substitution effects, wealth distribution, consumer expectations, and the fiscal implications on government budgets.

Housing is a necessity, as people require a place to live, and demand for most necessities is inelastic. When the government removes the tax burden, the quantity demanded increases, as individuals pay less. Economic theory predicts that any intervention that intends to decrease dead-weight loss in the market with inelastic demand should not have a substantial effect on quantity but might largely increase the price, especially in the short run. The long-term effect of the policy depends on the elasticity of supply. The supply of housing might increase because higher prices encourage individuals to sell their property and motivate firms to build more housing units. However, the surge in supply happens to a lesser extent in densely populated areas, where the land for new construction projects is scarce. In the long run, housing prices might fall, depending on the increase in supply. As the UK government's policy targets the lower end of the market, the price and quantity changes should happen within the property market for types and areas that are generally less expensive. Therefore, the FTB Relief policy type requires clear evaluation because the intended increase in affordability might have been counteracted by price increases due to post-policy market shifts.

In her work, Anna Bolster(2011) uses difference-in-difference and time-series regression analysis to evaluate the FTB Relief that was temporarily introduced in 2011 but abolished later by HM of Revenue & Customs (p. 27). She concludes that the policy did not make housing more affordable and there was no significant change in transactions, whereas the tax relief was mostly substituted by the surge in prices. Similarly, Shopov, Howell and Claridge(2023) apply the Difference-in-Difference Fixed Effect technique to Financial Conduct

Authority data, using HM Land Registry transactions. They evaluated the FTB Relief implemented in 2017 but they concluded that in the £125,001 to £300,000 band the relief resulted in an 11% increase in transactions over and above the volume of FTB transactions that would have taken place in the absence of the policy.

According to Bryant (2012), FTB Relief does not offer the same benefit to individuals in different regions. For example, compared to other parts of the country, fewer people could use the tax break for purchases of property in London because the average value of housing is much higher, even though the threshold for London was slightly bigger. The author also mentions how the effect of the policy is minimized because many first-time buyers are not aware of the legal costs and transaction fees that come with the purchase of a new home. This paper conducts further research into the effects of the 2017 policy on prices and investigates whether the housing market was affected disproportionally depending on the type of property and location.

This research paper attempts to evaluate how the FTB Relief influenced market prices and what difference it made for various types of housing. To monitor the policy effect, this exploration is limited to property transactions between March 2015 and March 2020, as the COVID-19 pandemic disrupted the economy overall. This research focuses on the Greater London area, the most populated English county with the most expensive housing in the region that accounts for almost 13% of all property transactions in England and Wales.

This paper adds to existing scholarly discourse on the topic of housing policy evaluation, as it estimates the benefits of the policy, comparing its short-term and long-term effects on the price of different housing types. Additionally, the results of this research help understand how the qualification requirements of the tax relief created unique market dynamics, where some sectors of the market were affected more than others.

In section Data, this paper provides a detailed overview of the data used for the analysis. In section Summary Statistics, explores initial insights, describing the data set through visualizations. This paper also presents the key findings of the paper in Results, where it conducts regression and difference-in-differences analyses, also discussing their implications.

2 Data

2.1 Property Transactions

This analysis uses the data provided by HM Land Registry, the non-ministerial department that monitors and documents every housing transaction in England and Wales and has an open database for all purchases since 1995 (HM Land Registry Open Data, 2023). The data set used in this research includes information on each documented property transaction about price, date of transfer, postcode, age of building, tenure, address, city, borough, county and record status (HM Land Registry Open Data, 2023). It includes all transactions from March 2015 to March 2020 within Greater London.

All address variables indicate the location of the sold property. Property Type specifies if it was a flat, detached, semi-detached, or terraced house. Tenure can be freehold or leasehold, a trait common in the housing market of common law countries.

However, this data set considered mainly the demand side of purchases, ignoring the supply side. There was also no information on the area, where each house was situated. Therefore, getting more information on differences between each borough helped understand why some property markets were affected by the FTB Relief more than others, why more houses are purchased in certain places and also why some houses are on average more expensive.

2.2 Number of Green Spaces

Many economists and experts on property discuss how having green spaces in the area adds a 'park premium' to the average price of the house, making it more expensive (Harper, 2019). Several green spaces near the house could have affected to what extent there was a change in demand for housing in certain boroughs after the FTB Relief implementation. The data set about urban green spaces added a lot of additional information to this research and it was not available for download as a file, therefore it was web-scraped. This additional data set helped analyse how the number of green spaces correlates with the average housing price and number of purchases in each borough, as more families and young parents are trying to purchase a house or a flat near parks or gardens.

The data on parks was provided by the register of Historic England and its National

Heritage List about listed parks and gardens in Greater London (Registered Parks & Gardens — Historic England, n.d.). The scraped data set had the number of green spaces for each borough and was merged with the original data set on the level of an individual house. The resulting data included all purchase transactions with a price of the house, its features, conditions of purchase, location and, additionally, the number of parks in the area during the time of a transaction.

2.3 Affordable Housing Supply

Another data set used for this paper consisted of information about affordable housing supply in Greater London. It contained information on total affordable housing completions by financial year in each London borough since 1991/92. The data included homes funded through programs managed by the GLA (and formerly by the Homes and Communities Agency), as well as homes funded through other sources and programs. This data set described affordable housing as the sum of social rent, affordable rent, intermediate rent, and low-cost home ownership. Additionally, it defined new affordable homes as housing units provided to specified eligible households whose needs were unmet by the market. The data was sourced from the Homes and Communities Agency and Local Authorities, providing comprehensive insights into the affordable housing landscape in London. Even though these were affordable housing units, landlords and authorities could increase the annual rent by the change to the Consumer Price Index(CPI) plus 1 percentage point with the maximum 'ceiling' of 7% (Wilson, 2022).

After the merge on the level of an individual purchase, the new data still had observations of transactions. Each transaction indicated information about the property, such as age, type, parks in the area and tenure, as well as the number of affordable houses built in the location of purchase within the same year. This integration enabled a thorough examination of how FTB Relief influenced housing market dynamics across various property types, considering both transactional activity from the original HM Land Registry data set and affordable housing completions from the new data set.

Importantly, the inclusion of information about affordable housing allows for a partial observation of the supply side of the housing market. This enables an analysis of to what extent the effect of the FTB Relief policy on the average price of the purchased property could have been influenced by the quantity of affordable housing supplied in that area.

2.4 Population

The Office for National Statistics (2022) provides annually modelled population for each borough based on 2011 and 2021 census. The information on the number of residents was added to the original data set on the level of transaction, where each purchasing transaction included information on how many people lived in the area, and where the house was purchased, during that time.

In the regression section, the average price of the purchase was found based on all available information, grouping all transactions by property type, tenure, age, borough, time of purchase, number of parks in the area, number of residents in the borough and number of affordable houses built during the purchase.

3 Summary Statistics

3.1 Property Types

In the Greater London area, property purchases exhibit a notable level of variability, as indicated by the substantial standard deviation of 843 thousand pounds. Despite this variation, the price of purchased properties stands at £598,128 on average, suggesting a central tendency within the market. However, the presence of extreme outliers, such as properties priced at 160 million pounds, underscores the existence of high-end segments within the market.

Furthermore, the upper quartile value of 642,500 pounds implies that a majority of purchased property fall below this threshold, reflecting a pronounced demand for more affordable housing options. This demand is further evidenced by the prevalence of flats as the most frequently purchased property type within the data set, which also reflects characteristics of the urban housing composition within a highly populated city. Additionally, the higher frequency of purchases for old housing units compared to new ones suggests a preference for established properties.

Following policy implementation, there has been a marginal increase in the number of purchases, indicative of increased demanded quantity. Notably, the peak in property purchases occurred between March 2015 and February 2016, predating the introduction of the UK government's First-Time Buyer Relief. These observations collectively paint a nuanced picture of the Greater London property market, characterized by varying price ranges, demand dynamics, and policy influences.

The majority of property units were valued below 600 thousand pounds, indicative of a robust demand for more affordable housing options within the market. Specifically, there was a notable concentration of houses and flats purchased in the price range of £300 to 400 thousand pounds, underscoring the prevalence of properties within this relatively lower price bracket. The data reflected the targeted approach of the First-Time Buyer's Relief policy, which aimed to facilitate entry into the housing market for first-time buyers by focusing on properties priced below 500 thousand pounds. By implementing a cap on the qualifying property value, the UK government strategically ensured that it could continue to generate tax revenue from higher-priced transactions, thereby contributing to efforts aimed at reducing the

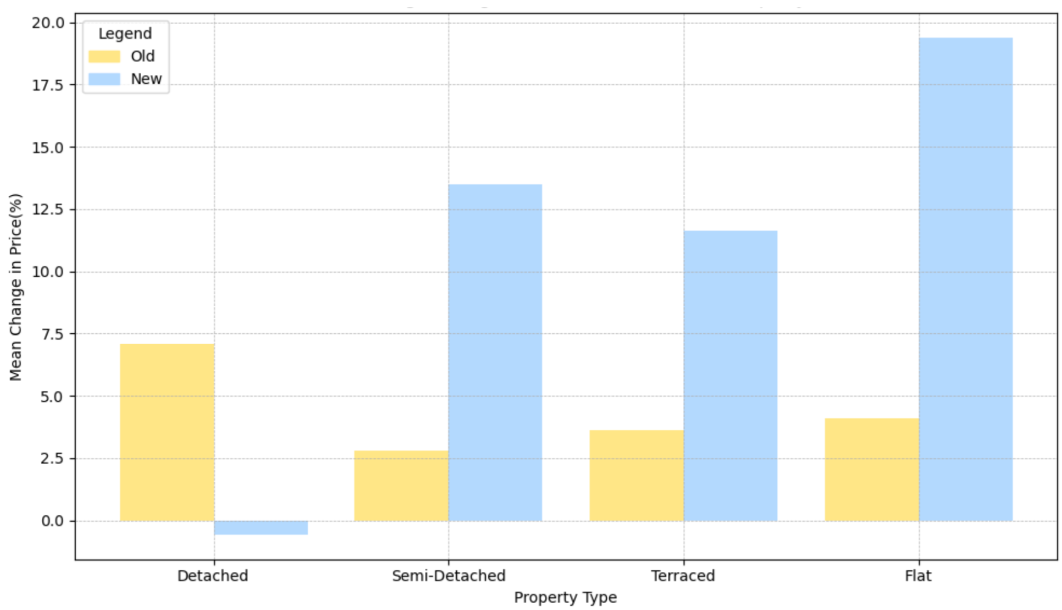

Figure 1: Percentage Change in Price for Old and New Property

national deficit. This policy intervention aligns with broader economic objectives of promoting homeownership among first-time buyers while maintaining fiscal sustainability.

Figure 1 presents a comparative analysis of the growth rates in average property prices for both old and new housing from March 2015 to March 2020. Across all four property types, the data predominantly reflects a positive change in prices for both categories of housing, with new detached houses being the sole exception, demonstrating a marginal decrease in average price over the specified period. Notably, new housing exhibited a notably higher rate of growth in comparison to old housing. New flats emerged as the standout category with the highest rate of growth, reaching an impressive 19 per cent. Among old housing options, detached houses asserted their resilience with a solid 6 per cent price growth. These observed increases align closely with the potential policy effects of the First-Time Buyer's Relief, which specifically targeted the market for more affordable housing options. Flats and terraced houses, typically lower-priced options, demonstrate the highest rates of price growth, further indicating how the policy might have stimulated demand and prices within these segments of the housing market.

According to Figure 2, the average value of flats, semi-detached, or terraced houses tends to be below the 600 thousand pounds mark, with flats exhibiting the lowest average price. The detached property is the most expensive. The volatility observed in detached house

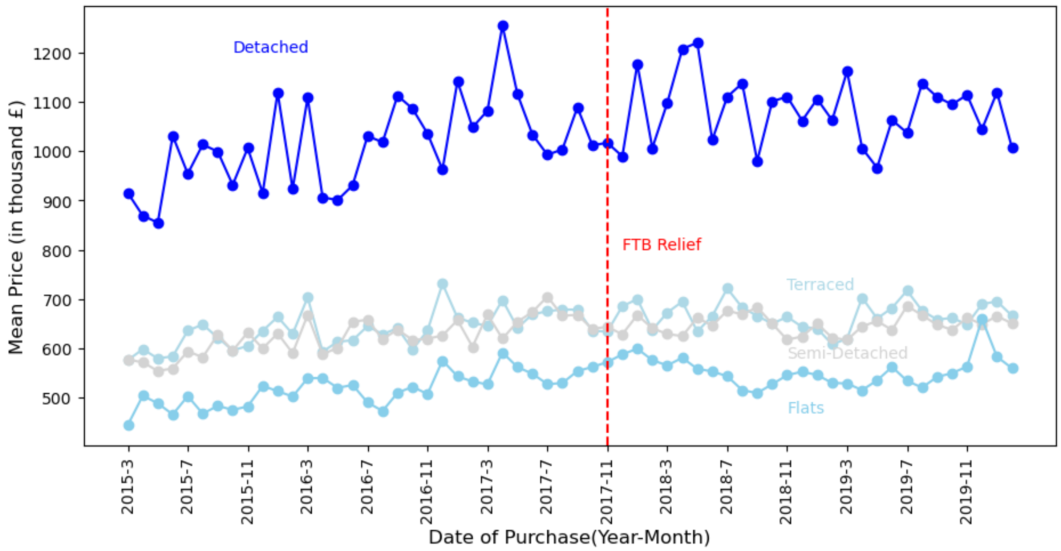

Figure 2: Mean Price over Time

prices can be attributed to seasonal fluctuations, particularly heightened demand during the spring months as families seek to purchase and relocate before the onset of summer (Ngai & Tenreyro, 2014). This surge in demand often triggers competitive bidding wars among prospective buyers, leading to temporary price escalations despite a consistent level of supply. The premium attached to detached houses reflects consumers' heightened willingness to pay for the privacy and autonomy offered by standalone properties, which do not share walls with neighbours.

The implementation of FTB Relief on November 22, 2017, corresponds to a significant short-term price increase of purchased flats and terraced houses that were recently built in the Greater London Area, likely reflecting a surge in demand if there was no significant response by an increase in housing supply in a short-term. These property types were relatively more affordable options in the market and potentially caught new buyers' attention first because they met the eligibility criteria for the tax relief.

Figure 3 illustrates the price difference between detached houses and various property types over three-month intervals. However, this graph takes into account whether the property was constructed recently. Detached properties exhibited minimal price difference post-policy implementation. Therefore, the graph compares the average price of each property type to detached houses. The black line on the graph represents detached property, which indicates no change. The changes in price differences between detached property and other types around

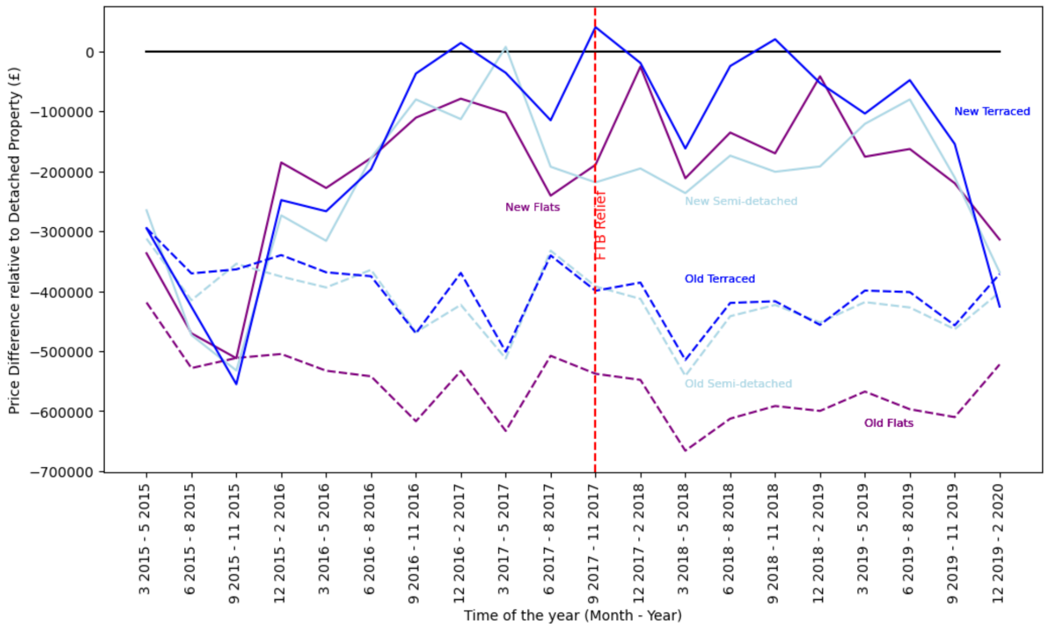

Figure 3: Price Differences over Time

November 2017 reflect the nominal impact of the policy.

The graph section marked by the red line indicating November 22nd, 2017, the day of FTB Relief implementation, reveals significant changes in trends for new terraced houses and new flats, even though they were quite consistent with other types before. These types of property experienced notable price increases compared to detached houses, with new flats almost matching and new terraced houses briefly surpassing detached house prices during that interval. The trend continued for the next three months, but then the market adjusted after the shock. These property types, meeting relief requirements, likely became highly appealing options for first-home purchases, driving demand. However, this surge was relatively brief, indicative of market adjustments coinciding with seasonal patterns, particularly as the 'cold season' started and relocation activity slowed.

The property prices in London also highly depend on location. East London boroughs typically offer more affordable housing options, while districts in the west tend to be more expensive. East London has some of the most low-income districts with high degrees of deprivation (Lawrence, 2022). These pricing disparities remained consistent throughout the five years under study. Areas such as the City of Westminster, Chelsea, and Camden, traditionally exclusive areas with lots of parks, cultural events and restaurants, stood out as the most desirable and priciest locations in London, with average property prices reaching up to 1.5

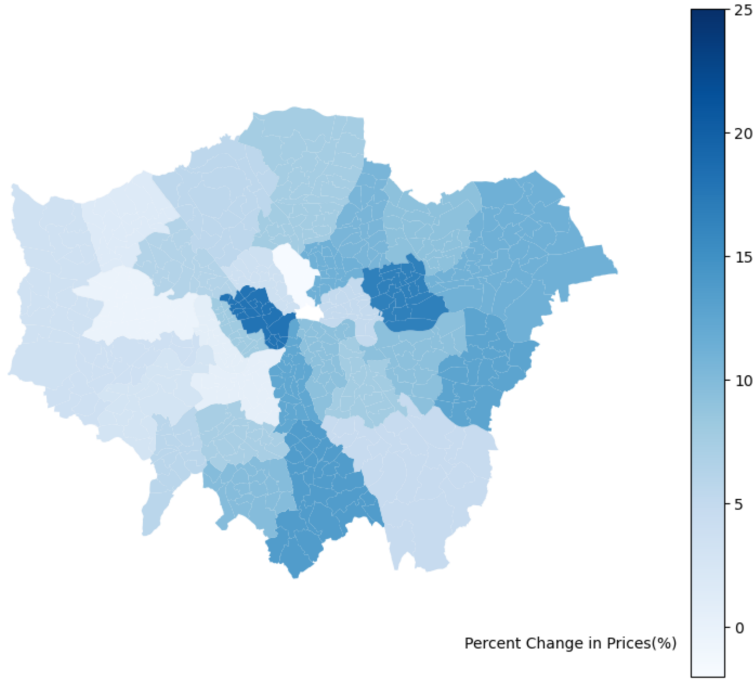

Figure 4: Percent Change in Average Price After the FTB Relief

million (Manton, 2023). As the policy did not target this high-end sector of the market, there should have been no significant price changes observed in these areas. In the east of London, housing tends to be more affordable, presenting potential opportunities for first-time home-buyers under the FTB Relief scheme, which could potentially cause an increase in demand for housing within those districts and therefore in the housing prices.

Figure 4 highlights Hammersmith and Fulham and Newham as the London districts where the value of purchased properties surged by nearly 20 per cent after the policy implementation, but the average price of a property in Hammersmith and Fulham is way above the threshold indicated by the UK Government for first-time buyers to qualify for the tax relief. Although, it is a popular area for young individuals and families (Masey, 2019).

In Newham, however, determining whether this spike can be solely attributed to increased demand resulting from the FTB Relief policy is challenging due to the ongoing gentrification process (Perry, 2016). Many individuals residing in more central London areas opt to relocate to Newham or nearby areas because it offers the most affordable housing while still being close to the city centre. Increased housing demand might have led to price hikes in most boroughs of East London.

Figure 5 illustrates the prevalence of new flat purchases in inner London, reflecting the

Figure 5: Percent Share of New Flats

dense population in these areas. Newham and Tower Hamlets are boroughs with the biggest share of purchased new flats among all purchases in that area even though the number of purchases is similar among all boroughs.

Given that the FTB Relief policy targets lower-priced and smaller properties, flats emerge as a natural preference. Newham and Tower Hamlets are also relatively more affordable, and Newham experienced a significant price spike. All these factors likely indicate that the tax relief affected the Newham property market more than other areas, as it satisfies all requirements of the policy target. More investigation is required to understand the dynamics of the housing market in Tower Hamlets and why the intervention might have not affected it to the same extent.

3.2 Parks

According to Figure 6, boroughs with an an extremely large number of parks were also the same boroughs that experienced minimal price increases after the implementation of first-time buyer policies, yet maintained the highest average prices.

This suggests that homes near parks tend to command a premium, emphasizing the role

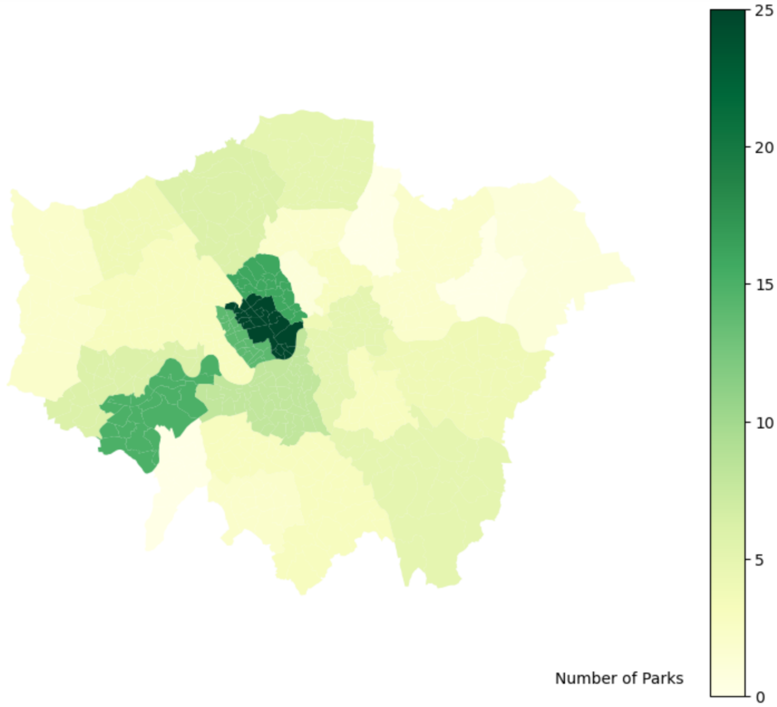

Figure 6: Number of Parks across London Boroughs

of amenities in driving property values. These areas did not experience significant changes in the context of policy interventions such as first-time buyer initiatives, which underscores the relevance of urban features like the proximity of green spaces in shaping housing market dynamics.

Most boroughs exhibit a scarcity of parks, typically numbering between 0 and 9 within their boundaries, with only a few exceptions boasting a higher concentration of green spaces. The biggest share of the cheaper property before and after the policy implementation is located in boroughs that fall within the first category, therefore FTB Relief should affect areas with fewer parks.

Boroughs in Greater London with a higher number of parks generally tend to command higher average property prices, whereas Kensington and Chelsea stands out as a unique case. Despite not having the largest number of parks among boroughs, its remarkable count of 14 parks is noteworthy. Nonetheless, it remains the most expensive in terms of housing, underscoring its exceptional status as London's most luxurious and exclusive property market (Manton, 2023).

This discrepancy highlights the potential interplay between amenities like parks and the

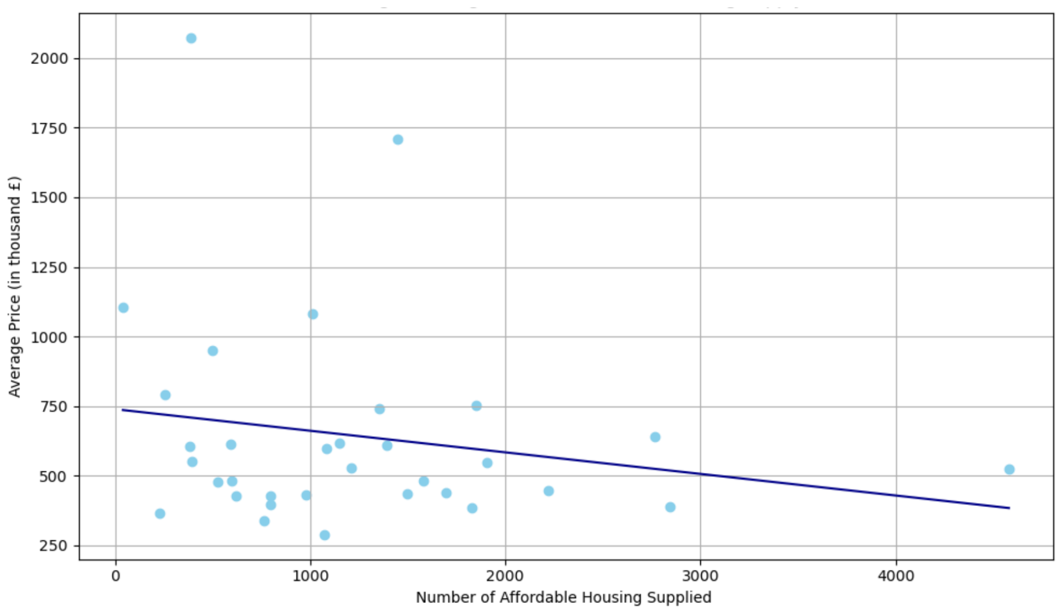

Figure 7: Affordable Housing Supply across London Boroughs

prestigious reputation of certain areas within the city's real estate landscape. This graph indicates again that the property markets with many green spaces tend to have a 'park premium' and did not experience any significant changes after the policy implementation. Areas with more parks tend to not only be more expensive but have less price fluctuations because supply and demand are likely more inelastic, as these are historic areas and it is hard to build new houses there.

3.3 Affordable Housing

Figure 7 includes data points for each borough and highlights a clear negative relationship between the number of affordable housing units supplied in a borough and the average price of houses in that area, which is likely because more affordable housing is supplied in poorer districts. This observation holds significant policy implications, particularly considering that the FTB Relief targets the lower-cost segment of the market. This graph implies that individuals should be drawn to areas with higher availability of affordable housing, as they have lower average prices because it maximizes the benefits of the policy. Ultimately, this underscores how the FTB Relief should have affected not only more affordable areas but also areas with a higher supply of affordable housing, which often tend to be the same.

Tower Hamlets, Newham, and Southwark were significant hubs of affordable housing provision between 2015 and 2020.

From the previous analysis, Tower Hamlets and Newham exhibited similar characteristics, including the highest shares of purchased new flats among all London boroughs and comparable green space amenities. However, while Newham experienced a notable price spike post-policy, Tower Hamlets saw only a minor price adjustment. This difference underscores the larger affordable housing supply in Tower Hamlets, which could potentially counteract increased demand after FTB Relief, moderating price fluctuations. The contrasting outcomes highlight the importance of housing supply elasticity in shaping the economic impacts of policy interventions within urban housing markets.

Greater London also experienced a significant surge in the total supply of affordable housing after the implementation of FTB Relief in November 2017. This notable increase might signify a proactive response to the increased demand and rise in average housing prices caused by the policy intervention. The surge in affordable housing supply can highlight the responsiveness of the market to shifting demand dynamics, potentially reflecting an effort to meet the increased housing needs of first-time buyers incentivized by the policy. This dynamic might illustrate the crucial interplay between supply and demand forces within the housing market, highlighting the adaptability of the market to policy interventions aimed at enhancing housing affordability. Overall, the observed post-policy increase in affordable housing supply likely underscores a strategic approach to address affordability concerns and accommodate the growing demand stimulated by FTB Relief.

4 Results

4.1 Objective Function for OLS Model

The algorithm behind the linear regression model selects the parameters that minimize the mean squared error (MSE) function. Equation (1) is an example of the preferred specification:

$$\begin{aligned}
\frac{1}{N}\sum_{i=1}^{N}\Bigg(&\log(\text{price}_i) - (\beta_0 + \beta_1\text{after}_t + \beta_2\text{after_x_flat_x_new}_t \\
&+ \beta_3\text{after_x_terraced_x_new}_t + \beta_3\text{days}_t + \beta_4(\text{purchases/supplied houses})_{it} \\
&+ \beta_5\text{east_london} + \beta_6\text{east_x_new} + \beta_7\text{flat}_i \\
&+ \beta_8\text{flat_x_new}_i + \beta_9\text{leasehold}_i + \beta_{10}\text{new}_i \\
&+ \beta_{11}\text{num_parks}_i + \beta_{12}\text{population}_{it} + \beta_{13}\text{s_detached}_i \\
&+ \beta_{14}\text{terraced}_i + \beta_{15}\text{terraced_x_new}_i)\Bigg)^2
\end{aligned} \tag{1}$$

It includes the dependent variable ln(price) as well as all independent variables (Xs). The MSE function calculates the average squared difference between predicted and actual prices in the data set used for the model. A lower MSE indicates more accurate predictions, as it signifies less difference between predicted and actual property values.

The values of **F-statistic** above 10 usually imply that the model is overall significant and one will be able to reject the null hypothesis

$$H_0 : \beta_1 = \beta_2 = \beta_3 = \ldots = \beta_k = 0$$

$$H_1 : \text{not all coefficients are } 0$$

Additionally, the significance of each coefficient can be determined through its **p-value**. One, two or three stars should indicate some level of significance for each coefficient, meaning respectively that there is a 5, 1 or 0.1 per cent chance of having that coefficient if the actual coefficient of the model was zero. P-values help evaluate the role of each predictor in a model.

Higher p-values fail to reject the null hypothesis.

$$H_0 : \beta_k = 0$$

$$H_1 : \beta_k \neq 0$$

Finally, **R-squared** indicates the share of variance in the price that can be explained by the independent variables. An increase in R-squared implies a better fit of the model to the data. However, adding more variables naturally increases R-squared, so this paper carefully analyzes all regressions, taking that into account.

4.2 OLS Models

The dependent variable is a log of price. Taking the logarithm makes interpretation easier, especially for property purchases that vary across types, locations, and time. All other variables have linear relationships with price, so scaling for *days* is the only manipulation done. Also, instead of total purchases of property and total affordable housing supply, their ratio is used for easier interpretation and to avoid multicollinearity, as there are tight economic links between supply and demand.

The first regression includes dummy indicators for a type of property, where a detached type is omitted because it is a reference category. They are relevant measures for the price difference, as this research showed that some types of property tend to be more expensive than others, and linear regressions are a good estimate of relationships between dummy variables and price.

In Model 1, the estimation also considers time, population in that area during the time of purchase and demand-to-supply ratio variables, which control for changes over time and market dynamics. They are useful because these variables help predict the values of the purchase at each point in time and take into account demographic shifts and market changes based on supply and demand. The variable *days* measures the number of days that passed since the first purchase in this data set (in March 2015). It is divided by a hundred for easier interpretation.

In Model 2, the analysis looks into prices of different property types, holding time, population, demand-to-supply ratio, and age constant. It includes the dummy variable for new buildings, where the category 'old property' is omitted. It also includes two interaction variables because new flats and terraced houses exhibited different behaviours compared to old housing. These interaction variables help predict the purchase price, considering various effects on the dependent variable depending on the values of other independent variables.

In Model 3, the regression predicts prices of different property types, while holding the type of tenure, market dynamics, time, and population size constant. Tenure is usually an important determinant of price because people prefer housing with more reliable property rights, such as freeholds. Higher demand usually drives prices up and creates disparities in prices of freeholds and leaseholds. Model 4 combines all variables.

The first table shows estimations for the four models below. These four regression models mostly focus on the features of each property, ignoring the amenities that come with location. This helps predict the average purchase price of each property type in Greater London between 2015 and 2020 based on its tenure contract and age, ignoring location within the city. Betas represent coefficients of independent variables. ϵ is an error term that captures all variables that a model does not include, therefore it partially explains the variability of the data set even after controlling for certain features.

(1)

$$\begin{aligned} ln(\widehat{price})_i = \beta_0 + \beta_1 \text{days}_t + \beta_2 \frac{\text{purchases}}{\text{supplied houses}}_{it} \\ + \beta_3 \text{flat}_i + \beta_4 \text{population}_{it} + \beta_5 \text{s\_detached}_i + \beta_6 \text{terraced}_i + \epsilon \end{aligned}$$

(2)

$$\begin{aligned} ln(\widehat{price})_i = \beta_0 + \beta_1 \text{days}_t + \beta_2 \frac{\text{purchases}}{\text{supplied houses}}_{it} + \beta_3 \text{flat}_i \\ + \beta_4 \text{flat\_x\_new}_i + \beta_5 \text{new}_i + \beta_6 \text{population}_{it} + \beta_7 \text{s\_detached}_i \\ + \beta_8 \text{terraced}_i + \beta_9 \text{terraced\_x\_new}_i + \epsilon \end{aligned}$$

(3)

$$\widehat{ln(price)}_i = \beta_0 + \beta_1 \text{days}_t + \beta_2 \frac{\text{purchases}}{\text{supplied houses}}_{it} + \beta_3 \text{flat}_i + \beta_4 \text{leasehold}_i + \beta_5 \text{population}_{it} + \beta_6 \text{s\_detached}_i + \beta_7 \text{terraced}_i + \epsilon$$

(4)

$$\widehat{ln(price)}_i = \beta_0 + \beta_1 \text{days}_t + \beta_2 \frac{\text{purchases}}{\text{supplied houses}}_{it} + \beta_3 \text{flat}_i + \beta_4 \text{flat\_x\_new}_i + \beta_5 \text{leasehold}_i + \beta_6 \text{new}_i + \beta_7 \text{population}_{it} + \beta_8 \text{s\_detached}_i + \beta_9 \text{terraced}_i + \beta_{10} \text{terraced\_x\_new}_i + \epsilon$$

	Dependent variable: ln_price			
	(1)	(2)	(3)	(4)
const	14.130***	14.158***	14.129***	14.157***
	(0.010)	(0.009)	(0.010)	(0.009)
days	0.009***	0.009***	0.009***	0.009***
	(0.000)	(0.000)	(0.000)	(0.000)
demand_supply_ratio	-0.002***	-0.001***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
flat	-0.746***	-0.874***	-0.564***	-0.665***
	(0.005)	(0.006)	(0.008)	(0.008)
flat_x_new		0.362***		0.364***
		(0.015)		(0.015)
leasehold			-0.189***	-0.220***
			(0.007)	(0.007)
new		0.015		0.020
		(0.014)		(0.014)
population	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
s_detached	-0.399***	-0.399***	-0.392***	-0.391***
	(0.006)	(0.006)	(0.006)	(0.006)
terraced	-0.438***	-0.448***	-0.419***	-0.427***
	(0.006)	(0.006)	(0.006)	(0.006)
terraced_x_new		0.129***		0.148***
		(0.018)		(0.018)
Observations	139511	139511	139511	139511
R^2	0.166	0.204	0.171	0.210
Adjusted R^2	0.166	0.204	0.171	0.210
Residual Std. Error	0.560 (df=139504)	0.548 (df=139501)	0.559 (df=139503)	0.545 (df=139500)
F Statistic	4623.798*** (df=6; 139504)	3967.598*** (df=9; 139501)	4100.818*** (df=7; 139503)	3713.621*** (df=10; 139500)
Note:				*p<0.1; **p<0.05; ***p<0.01

All four models are statistically significant, as evidenced by the F-statistic, which remains consistently around 4000, therefore the null hypothesis can be rejected. The inclusion of age and type of tenure in the model leads to a slight increase in the R-squared value. A higher R-squared value indicates that the model performs better in predicting purchase values, as the independent variables explain more variance in the values.

All variable coefficients, except for "new," are statistically significant, with p-values lower than 0.01. Detached houses emerge as the most expensive option, controlling for factors such as age, time, population size, market dynamics, and tenure type. Coefficients on dummy variables for other property types suggest that old terraced, semi-detached houses and flats are, on average, 40 to 65 per cent cheaper compared to old detached houses.

The interaction variable between "new" and "flats" reveals that the premium of new-built properties is relatively higher for flats. Recently constructed flats are, on average, 40 percentage points more expensive than old flats compared to the difference between old and new detached houses, while holding time, population size, market dynamics, and tenure type constant. Terraced houses exhibit similar dynamics, but the average price difference is only 15 percentage points. Osborne (2016) argues, however, that the premium of new builds should have decreased with time due to a larger supply of new housing.

The values of the ratio between total purchases and affordable housing supplied range between 1 and 10. Therefore, an additional purchase per house supplied represents a significant change. However, the coefficient suggests that this increase is associated with only a marginal decrease of 0.02% in prices. The negative sign likely indicates that, on average, more purchases per house supplied within a borough are associated with lower prices because authorities might not supply as much affordable housing when prices are low.

Similarly, the population coefficient is negative, indicating that an increase in the population of a borough by a thousand is associated, on average, with purchases that are 0.02% cheaper. This can suggest that more individuals prefer to reside where housing is more affordable.

In Model 5, the regression includes a dummy variable that indicates whether the purchase is in one of the boroughs located in East London because earlier maps showed that property tends to be more affordable there, as historically that part of the city has mostly attracted the working class (Butler, 2011). The model also has an interaction term between *east_london* and *new* because areas of East London have the highest share of new property purchases.

In Model 6, the regression additionally controls for the number of parks in the area of purchase. Harper (2019) argues that in a highly-populated and busy city, such as London, the proximity of green spaces often adds a premium to the price of a property. Few affordable housing units are located in areas with a large number of parks. Therefore, controlling for them helps to better predict the price of different housing types.

In Model 7, the analysis includes the main variable of interest, which controls for the FTB Relief implementation. The dummy variable *after* indicates whether the purchase occurred before or after that date. The indicator for purchases before the policy is an omitted variable. The effect of the policy is the main focus of this paper and it helps to investigate whether the FTB Relief somehow changed the market dynamics.

Finally, the last model also has two interaction terms - one for *flats*, *new* and *after* as well as a similar term for terraced houses. The key finding of the previous analysis was the immediate price spike for new flats and terraced houses after the policy implementation. Thus, this variable should help better predict the price of the purchase. However, it would mainly consider the long-term effect of the policy, rather than an immediate shock. This is the preferred model as it includes all available variables and provides the most comprehensive estimation of the FTB Relief impact on the housing market. Its estimation has the biggest R-squared, meaning that this model can explain more variability within price values than any previous model.

In the table below, I estimate the following models. These models consider additional factors that might have affected people's decisions but are not directly related to features of the building, such as green spaces near a property, the location of the purchase and whether the purchase happened after the implementation of FTB Relief.

(5)

$$\begin{aligned} ln\widehat{(price)}_i = {} & \beta_0 + \beta_1 \text{days}_t + \beta_2 \frac{\text{purchases}}{\text{supplied houses}}_{it} + \beta_3 \text{east\_london} + \beta_4 \text{east\_x\_new} \\ & + \beta_5 \text{flat}_i + \beta_6 \text{flat\_x\_new}_i + \beta_7 \text{leasehold}_i + \beta_8 \text{new}_i \\ & + \beta_9 \text{population}_{it} + \beta_{10} \text{s\_detached}_i + \beta_{11} \text{terraced}_i + \beta_{12} \text{terraced\_x\_new}_i + \epsilon \end{aligned}$$

(6)

$$ln(\widehat{price})_i = \beta_0 + \beta_1 \text{days}_t + \beta_2 \frac{\text{purchases}}{\text{supplied houses}}_{it} + \beta_3 \text{east\_london} + \beta_4 \text{east\_x\_new}$$
$$+ \beta_5 \text{flat}_i + \beta_6 \text{flat\_x\_new}_i + \beta_7 \text{leasehold}_i + \beta_8 \text{new}_i + \beta_9 \text{num\_parks}_i$$
$$+ \beta_{10} \text{population}_{it} + \beta_{11} \text{s\_detached}_i + \beta_{12} \text{terraced}_i + \beta_{13} \text{terraced\_x\_new}_i + \epsilon$$

(7)

$$\ln(\widehat{\text{price}})_i = \beta_0 + \beta_1 \text{after}_t + \beta_2 \text{days}_t + \beta_3 \frac{\text{purchases}}{\text{supplied houses}}_{it} + \beta_4 \text{east\_london}$$
$$+ \beta_5 \text{east\_x\_new} + \beta_6 \text{flat}_i + \beta_7 \text{flat\_x\_new}_i + \beta_8 \text{leasehold}_i + \beta_9 \text{new}_i$$
$$+ \beta_{10} \text{num\_parks}_i + \beta_{11} \text{population}_{it} + \beta_{12} \text{s\_detached}_i + \beta_{13} \text{terraced}_i$$
$$+ \beta_{14} \text{terraced\_x\_new}_i + \epsilon$$

(8)

$$\ln(\widehat{\text{price}})_i = \beta_0 + \beta_1 \text{after}_t + \beta_2 \text{after\_x\_flat\_x\_new}_t + \beta_3 \text{after\_x\_terraced\_x\_new}_t + \beta_4 \text{days}_t$$
$$+ \beta_5 \frac{\text{purchases}}{\text{supplied houses}}_{it} + \beta_6 \text{east\_london} + \beta_7 \text{east\_x\_new}$$
$$+ \beta_8 \text{flat}_i + \beta_9 \text{flat\_x\_new}_i + \beta_{10} \text{leasehold}_i + \beta_{11} \text{new}_i + \beta_{12} \text{num\_parks}_i$$
$$+ \beta_{13} \text{population}_{it} + \beta_{14} \text{s\_detached}_i + \beta_{15} \text{terraced}_i + \beta_{16} \text{terraced\_x\_new}_i + \epsilon$$

All models are statistically significant but the F-statistic is higher after controlling for the part of the city, the number of parks, and whether the purchase happened after the policy, indicating a lower chance of any coefficient being zero. The null hypothesis can be rejected. The R-squared increases from 0.248 to around 0.43 and stays there for the last three models. This value indicates that around 43 per cent of variance is explained by given independent variables, which is relatively large considering the absence of variables that control for the size of the house, number of bedrooms and many other characteristics.

All coefficients remain statistically significant after controlling for the amount of green spaces in the area. The coefficient of 0.059 implies that having an additional park or garden in an area of purchase is associated with an average price that is almost 6 per cent higher, holding age, type of tenure, type of property, population, location, time and ratio between purchases against supply fixed.

With the same variables and several parks held constant, the property in East London,

	Dependent variable: ln_price			
	(1)	(2)	(3)	(4)
after			-0.057***	-0.076***
			(0.005)	(0.005)
after_x_flat_x_new				0.113***
				(0.007)
after_x_terraced_x_new				0.098***
				(0.018)
const	14.191***	13.799***	13.785***	13.793***
	(0.009)	(0.008)	(0.008)	(0.008)
days	0.009***	0.008***	0.013***	0.013***
	(0.000)	(0.000)	(0.000)	(0.000)
demand_supply_ratio	-0.001***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
east_london	-0.306***	-0.072***	-0.072***	-0.072***
	(0.004)	(0.004)	(0.004)	(0.004)
east_x_new	0.039***	0.022***	0.023***	0.021***
	(0.009)	(0.008)	(0.008)	(0.008)
flat	-0.643***	-0.693***	-0.693***	-0.693***
	(0.008)	(0.007)	(0.007)	(0.007)
flat_x_new	0.359***	0.328***	0.327***	0.277***
	(0.014)	(0.012)	(0.012)	(0.013)
leasehold	-0.219***	-0.244***	-0.244***	-0.244***
	(0.006)	(0.006)	(0.006)	(0.006)
new	0.018	0.032***	0.033***	0.032***
	(0.014)	(0.012)	(0.012)	(0.012)
num_parks		0.059***	0.059***	0.059***
		(0.000)	(0.000)	(0.000)
population	-0.002***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
s_detached	-0.379***	-0.380***	-0.380***	-0.380***
	(0.006)	(0.005)	(0.005)	(0.005)
terraced	-0.399***	-0.445***	-0.445***	-0.445***
	(0.006)	(0.005)	(0.005)	(0.005)
terraced_x_new	0.135***	0.164***	0.164***	0.123***
	(0.017)	(0.015)	(0.015)	(0.017)
Observations	139511	139511	139511	139511
R^2	0.248	0.432	0.432	0.434
Adjusted R^2	0.248	0.432	0.432	0.434
Residual Std. Error	0.532 (df=139498)	0.463 (df=139497)	0.462 (df=139496)	0.462 (df=139494)
F Statistic	3832.950*** (df=12; 139498)	8157.717*** (df=13; 139497)	7591.919*** (df=14; 139496)	6673.796*** (df=16; 139494)

Note: *p<0.1; **p<0.05; ***p<0.01

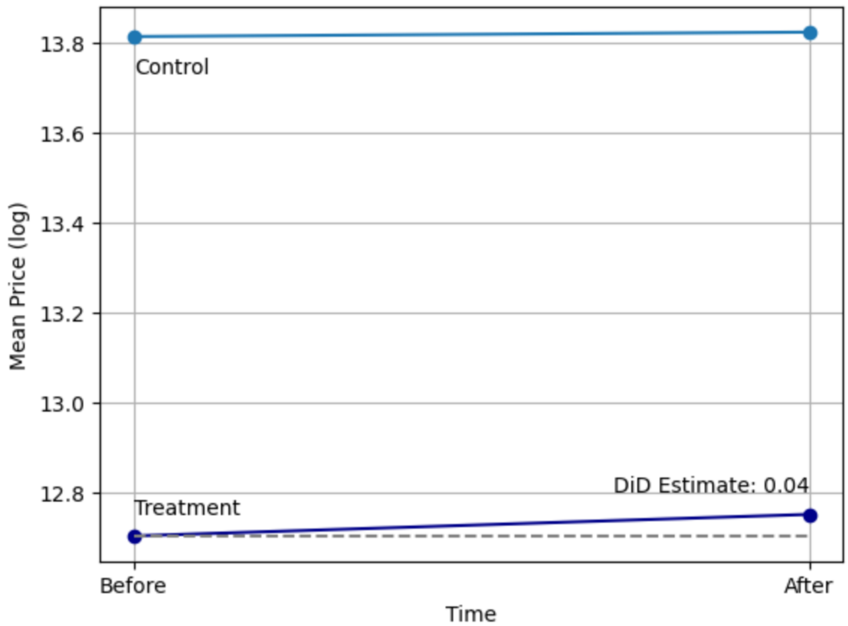

Figure 8: Difference-in-Differences for Prices of Flats

according to the three last models, is associated with an average price that is 7 per cent lower for old properties and 5 per cent lower for new properties compared to West London.

Lastly, the coefficients of *after, after_x_flat_x_new, and after_x_terraced_x_new* provide useful insights into the long-term effects of the FTB Relief. The respective coefficients of -0.076, 0.113 and 0.098 indicate that the average prices of purchases after the policy are associated with a 7 per cent decrease for detached and semi-detached houses, as well as old flats and old terraced houses, holding age, tenure, property type, population, part of the city, day of purchase and demand to supply ratio constant.

The two interaction terms imply that the differences between the average prices of new flats and new terraced houses before and after the policy, compared to old detached houses, are respectively 3.7 and 2.2 percentage points lower after the policy, holding age, tenure, property type, population, part of the city, day of purchase, and demand-to-supply ratio constant.

This increase is statistically significant and likely demonstrates the long-term effect of the policy, as the predicted value of new flats and new terraced houses is slightly higher on average than before.

4.3 Difference-In-Difference

Figure 8 demonstrates the difference-in-differences graph for logged prices of flats. Similar to Shopov, Howell and Claridge (2023), it divides all purchases into two categories, depending on whether a property price was below or above the FTB Relief threshold. Properties that cost more than 650 thousand pounds were a control group, whereas cheaper units were a treated group. The graph showcases the increase in the average prices of flats was 4 per cent higher for transactions that qualified for the tax break.

4.4 Objective Function for Decision Tree

All models in this part use the same variables as the preferred specification, which is described in the OLS Model 8.

The objective function for each region of the regression tree is...

$$\min_{j,s}\left[\sum_{i:x_{i,j}\leq s,x_i\in R1}(ln(price)_i - ln(\hat{price})_{R1})^2 + \sum_{i:x_{i,j}>s,x_i\in R2}(ln(price)_i - ln(\hat{price})_{R2})^2\right]$$

A rectangular region R is defined initially, encompassing all values of X. To create a branch of a tree represented by a smaller rectangular region R_n encompassing a share of values, a feature and location are then selected for splitting, to minimise MSE. This process is repeated iteratively to generate the number of branches that were specified by the depth of the tree.

Then, the tree is pruned, which means selectively removing branches or nodes that do not improve the model's performance. The main purpose of pruning is to avoid overfitting, which usually happens when the model predicts the existing data well but performs badly on a new set of data.

$$\min_{tree\subset T}\sum(\hat{f}(x) - ln(price)^2 + \alpha|\text{terminal nodes in tree}|$$

- **Maximum tree depth** controls the number of levels starting with the root node to the leaf nodes, which determines the complexity of the tree.
- **Minimum leaf size** decides the required minimum number of samples in each node,

influencing how fine or general the region of a new rectangular is after the tree's partitioning.

- α is the regularization parameter. It sometimes balances the trade-off between model complexity and accuracy. Alpha penalizes the complexity of the tree.

The higher maximum depth of the tree makes the model more complex and reduces MSE but it is hard to visualize the model with more levels. An increase in maximum depth also risks overfitting.

Increasing the minimum leaf size motivates more generalized rectangular regions of the data to reduce the chances of overfitting. Setting a larger minimum leaf size might be challenging if the total sample size is small. Also, this approach risks underfitting, as the model would ignore some finer but still valid data trends.

Higher α penalizes the complexity of the tree more aggressively, resulting in simpler and more general models. However, if it is too high, the MSE can be relatively large, indicating a large prediction error.

The minimum leaf size for the model above is 300, which means that each leaf node in the decision tree must contain at least 300 data points. The choice of 300 is feasible, as the total sample size is 20 thousand data points. A maximum tree depth is 3 for easier visualization, whereas α is zero, meaning that the algorithm applies no penalty for the complexity of the tree to minimize MSE.

4.4.1 Regression Tree and Importance Matrix

All decision models include independent variables from the regression model 8 because all coefficients of those variables are statistically significant. Including those Xs leads to the highest R-squared and generates useful insights into the long-term effects of the FTB Relief policy in the UK after the implementation.

The regression decision tree in Figure 9 has three levels, where each split minimizes the MSE. The first feature of the split is the number of parks, meaning that it is the most important variable for the model's predictions. The value is seven because, according to one of the previous graphs, most boroughs have fewer than nine parks, and the split divides the

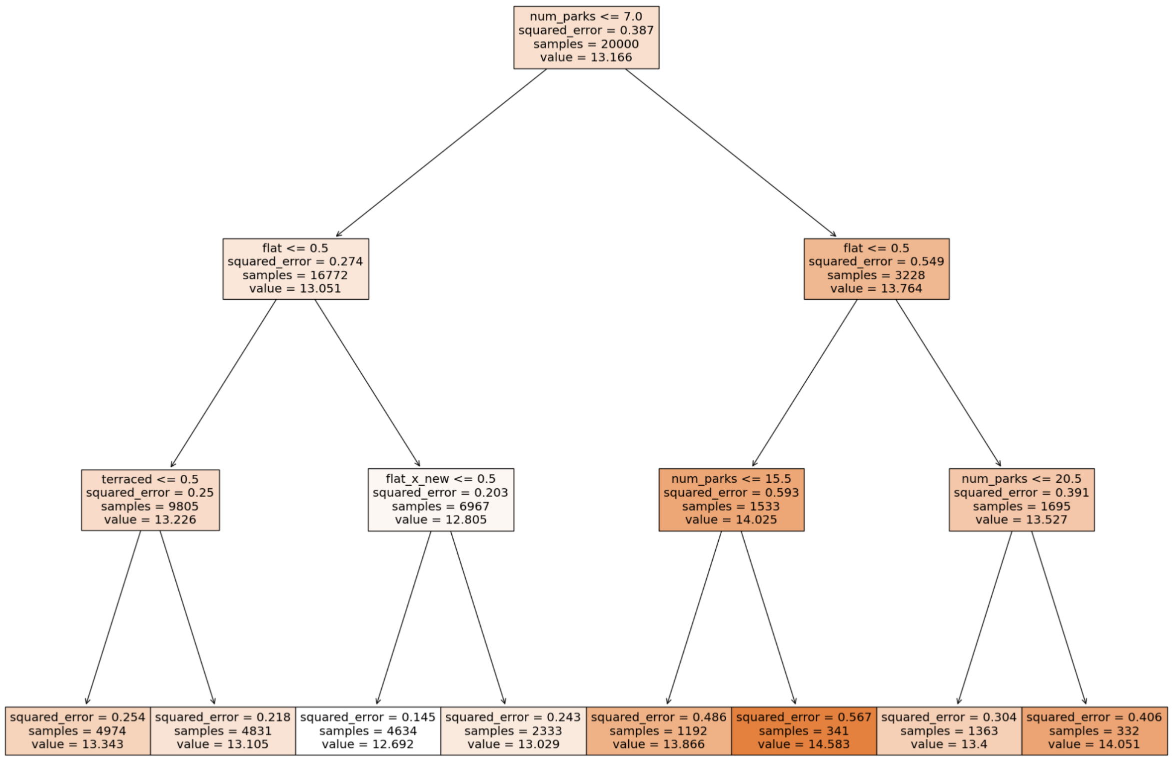

Figure 9: Regression Tree (maximum depth = 3)

sample into sixteen and four thousand data points. The model predicts that a property with more than seven parks in a borough is significantly more expensive. This corresponds to the previous findings, where boroughs with more than ten parks had one of the most expensive average prices for property in London.

The next highly important feature for both splits was whether the property type is a flat, as they are predicted to be the cheapest housing type. The threshold is 0.5 because it is a dummy variable and possible values are only zero and one.

Then, if a property is a flat and the number of parks around is less than seven, the next most important variable is the interaction term between flat and new. It also has a threshold of 0.5 because it is a dummy variable, where potential answers are 'a new flat' or 'not a new flat', represented by one and zero. This choice showcases how new flats exhibit significantly different behaviour compared to old flats or any other housing type.

If the flat is new, the average predicted value is the lowest among all eight subgroups and has also the lowest squared error, indicating the best fit of the model among all eight value subgroups. The potential reason is the concentration of the most purchased new flats in

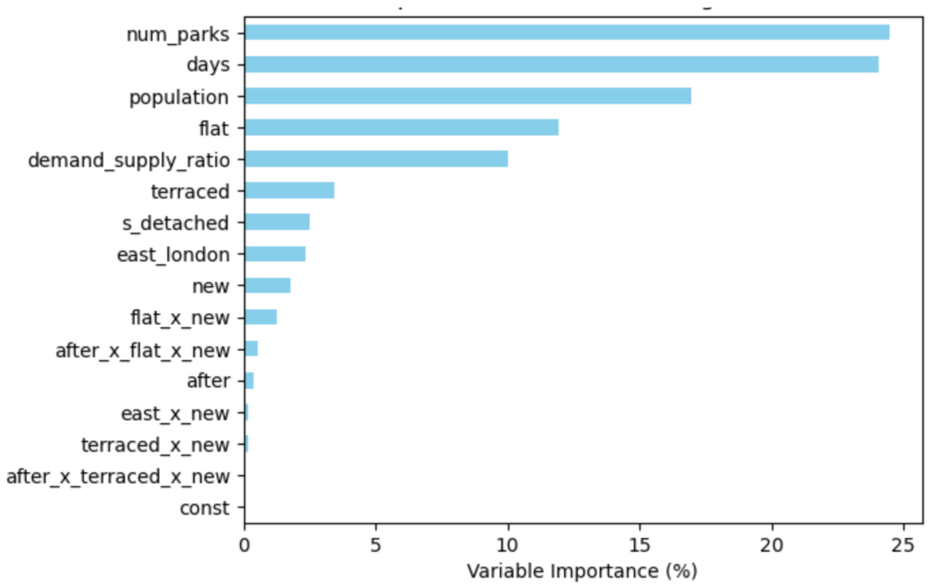

Figure 10: Importance Matrix for Random Forest

certain areas, which lessens price variability. The highest value and error are for the subgroup of non-flats with more than 16 parks in the area. The possible reason is the size of the sample with only 300 values, but it can also indicate higher variance for property prices in the high-end segment of the market, where the difference sometimes can be millions of pounds.

The overall squared error between 0.2 and 0.56 for the dependent variable *ln(price)*, which translates into a difference of a couple of thousand pounds squared, implies that the model predicts actual values quite well but it is not too precise to indicate overfitting.

Overall, according to the Importance Matrix depicted in Figure 10, mostly green spaces, population density, and time of purchase determine how much buyers pay. All other variables had significantly smaller importance share. Whether a property is a flat or not is a more significant predictor of the outcome variable in the model than any other dummy variable for the property type. The most important interaction variables are *flat_x_new* and *after_x_flat_x_new*, signifying weak but present relationships.

4.5 Evaluation

Model	**Mean Squared Error**
Linear	0.219
Regression Tree	0.244
Random Forest	0.025

Table 1: Mean Squared Error for Different Models

Comparing the results from running the OLS regression with those from running a regression tree highlights the strengths and weaknesses of each approach. The difference in MSE for each model indicates that the OLS model is slightly better in predicting price than the regression tree but still not as good as the Random Forest Model.

The OLS regression is a powerful tool for estimating the linear relationship between the price of property and independent variables because it provides coefficients that represent the marginal effect of a change in one variable while holding others constant. All these coefficients are statistically significant and offer economic interpretation, enabling hypothesis testing and informing policy decisions. For instance, while aiming to estimate the impact of the FTB Relief, this paper examines variables such as after, *after_x_flat_x_new*, and *after_x_terraced_x_new*. Even though they are not the most important variables according to the matrix graph, they provide the answer to the research question of this paper. The analysis reveals a significant noteworthy decrease in price percentage differences compared to detached houses, ranging from 2 to 4 percentage points, for newly constructed terraced houses and flats after the policy implementation. The change is economically significant as it translates into a couple thousands of pounds.

In contrast, regression trees offer a different perspective by capturing complex and heterogeneous relationships in the data. They display decision-making processes, showcasing the importance of each variable in predicting house prices. Unlike the OLS regression, where coefficients are estimated for each independent variable, regression trees identify key features and their thresholds during partitioning, focusing on the accuracy of prediction.

For instance, while the OLS model identifies all coefficients as highly statistically significant, it emphasizes the importance of property types in price prediction, with relatively smaller effects for location and time variables. On the other hand, the regression tree estimates the importance of variables differently, with only a dummy for flats being significant, while the presence of parks and the day of purchase play a crucial role in determining prices.

Besides, the highly important variables in the regression trees, such as day of purchase, population and number of parks, had a standard error of 0 in the OLS Model, meaning that their estimates perfectly predicted the true population parameter every time.

Considering the research question, the OLS enabled the analysis to focus on the key variables of interest, whereas the regression tree better displayed the overall picture to help understand the unique market dynamics in Greater London. The regression tree is also a better tool to predict future prices if the UK government implements a similar policy because the MSE value was the lowest among all models.

5 Conclusion and Future Work

The introduction of the First Time Buyers' Relief policy on November 22, 2017, potentially had a significant impact only on housing prices of two property types in the Greater London Area. There was a significant short-term price surge in newly-built flats and terraced houses in the quarter including November 2017, which did not follow the usual trend of price decrease during cold months. These types of property and the price increase correlate with the timing of the policy introduction and tax relief eligibility criteria. The findings of this paper support an economic hypothesis that the introduction of the First Time Buyers' Relief policy in November 2017 significantly impacted affordable housing options in the Greater London Area, particularly affecting newly-built flats and terraced houses.

The OLS models and regression trees suggest that the implementation of the policy had also a significant long-term effect. After the FTB Relief, the difference between average prices of new terraced houses and flats compared to old detached houses in Western London, which is the reference group, decreased by 2 to 4 percentage points, taking the type of tenure, the number of parks, population, and market dynamics into account. Osborne (2016) argued that a higher supply of new housing should decrease the premium of new builds but policy implementation increased demand, which likely counteracted the recent construction.

First-time buyers, usually younger individuals with fewer savings, tend to search for more affordable property options, potentially contributing to increased demand and subsequent price increases of new flats and terraced houses.

The primary constraint of this study lies in the absence of comprehensive official data detailing gentrification processes across each borough. Distinguishing between the price surges attributed to the policy's impact and those stemming from inherent gentrification poses a considerable challenge. Gentrification, occurring organically over time, tends to elevate average property prices, complicating the differentiation process, particularly when considering the broader market dynamics influencing the cityscape (The Guardian, 2016).

While the FTB Relief policy stimulated demand for certain property types, it did not affect all London districts equally. The composition of the housing market in East and West London is very diverse, and certain types of property are historically more concentrated in some areas; for example, central parts of London have more flats, and West London is more attractive to consumers willing to pay higher prices. East London usually offers more affordable housing, as historically it used to be mainly a working-class area (Butler, 2011). The higher increase in property prices in East London can suggest a higher demand for more affordable housing, which corresponds with the hypothesis of the policy that the tax relief should lead to higher demand.

The analysis suggested that property markets with a 'park premium' did not experience significant changes despite FTB Relief implementation, while boroughs with fewer parks experienced greater price fluctuations. This can be explained by the policy target of the lower-priced property market. Also, Tower Hamlets, Newham, and Southwark were significant hubs of affordable housing provision post-FTB Relief, with Tower Hamlets potentially showing minor price adjustments compared to Newham, which has seen an extreme rise in property prices. It likely indicates the relevance of higher housing supply elasticity, as more affordable housing is built annually in Tower Hamlets than in Newham. All boroughs of London had a higher supply of affordable housing post-FTB Relief, which might reflect market responsiveness to increased demand, highlighting the connection between supply and demand in the housing market.

The FTB Relief removed the 2 per cent and 5 per cent property tax from purchases below £300,000 and kept the 5 per cent tax for housing valued between £300,000 and up to £500,000. The long-term effect determined by the regression model indicates that first-time buyers did not significantly benefit from the tax break, as it was offset by the increase in the average price of affordable housing options due to upward shifts in demand.

Further opportunities to improve this research include investigating the number of purchases between March 2015 and March 2020 in Greater London rather than the market price of the property, as it can generate more insights on the number of people that acquired a home and benefited from the scheme (Shopov, 2023). Economists might consider the effect of tax relief on other regions in England and compare results with Greater London to evaluate the spatial efficiency of the policy (McKee et al. 2016). Including the data on gentrification in multiple regression models and decision trees will also improve the reliability of the findings. This further evaluation might help policymakers determine how to efficiently use the resources of the government and what better measures to implement to increase housing affordability or social mobility.

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