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A Royal Problem: Planning Induced Supply Constraints in London

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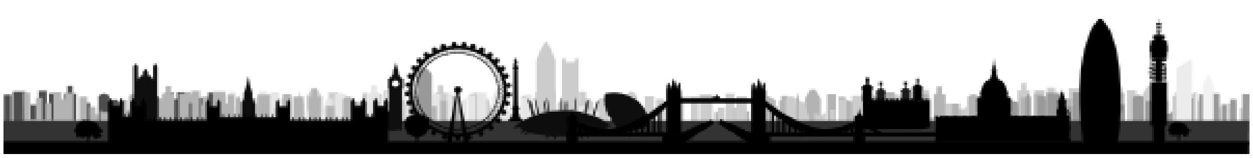
ABSTRACT

We explore the impact of regulatory supply constraints on house price levels following boom and bust periods in London. We hypothesize that when regulatory restrictiveness increases during a boom period, house prices will be higher in the following year compared to house prices in less restricted areas. We also hypothesize that when regulatory restrictiveness increases during a bust period, house prices will be lower in the following year compared to house prices in less restricted areas. We empirically test our hypothesis using a multilevel mixed-effects model with a panel data set of 32 boroughs of London, ranging from 2001 to 2013. Our analysis reveals that our hypothesis holds true. A borough with a strict planning authority will have higher house prices following a boom period and lower house prices following a bust period compared to prices in a borough with a more lenient planning authority.



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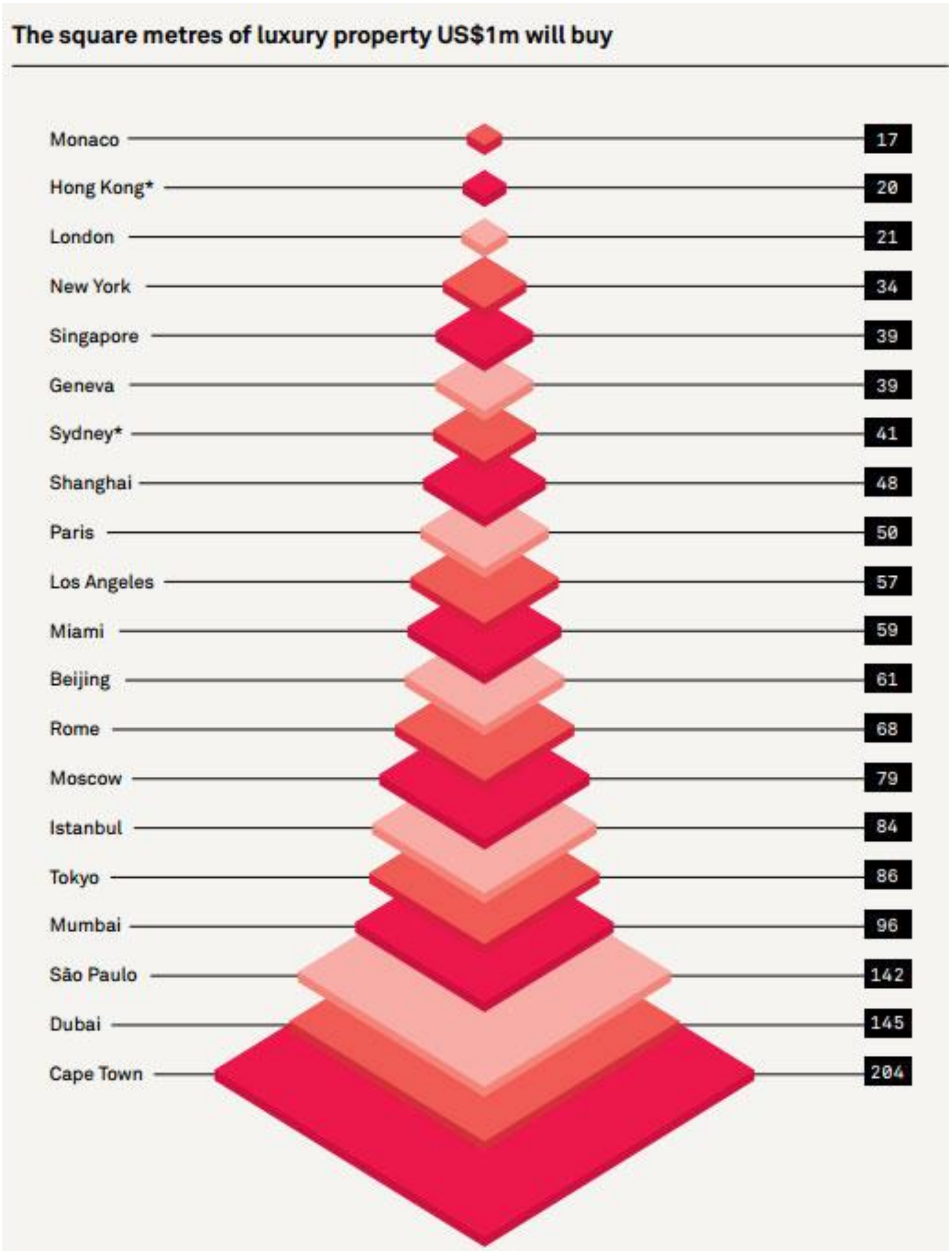
1 INTRODUCTION

London is a vibrant, dynamic, and diverse city with a rich history. Dating back to 43 A.D., London has been able to successfully evolve and sustain itself as a global hub. Though London's urbanization has led to prosperity, challenges inevitably follow. Currently, high and rising house prices pose as a challenge to London and its people.

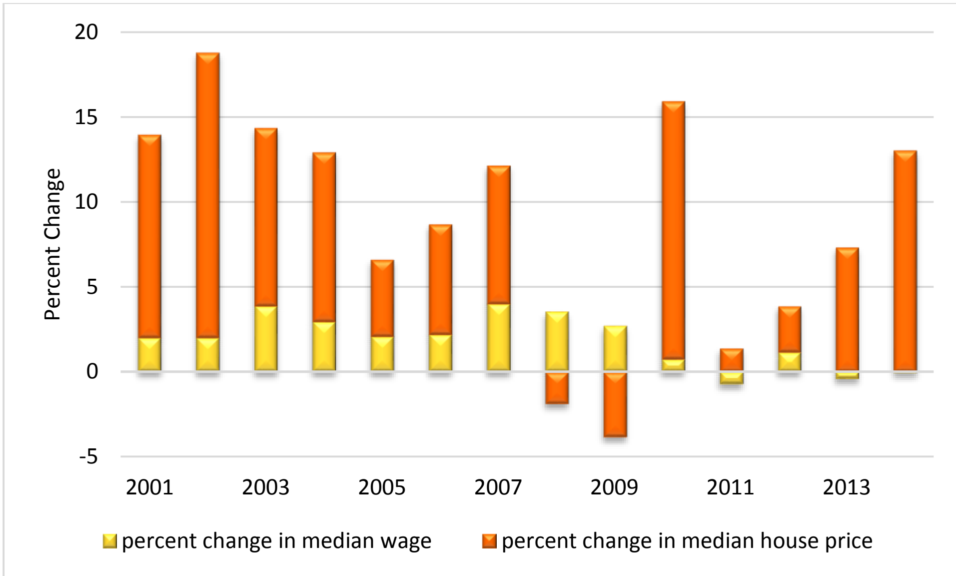
Space is at a premium in the UK's capital. Figure 1 shows that London's residential real estate is the third most expensive in the world. One million US dollars will buy 21 square meters of luxury property in London. This is the result of not building enough housing to accommodate London's growing population. Due to population growth and social changes that have reduced household size, the number of households in London has grown by an estimated 540,000 over the last 20 years (Mayor of London). Housing supply, however, has not been able to grow proportionally. The Office of the Mayor of London estimates that supply has only grown by 430,000 over the same time period (Mayor of London). This gap between housing supply and demand has driven prices up, consequently reducing affordable housing options. In addition, median wages in London have not been able to keep up with the increasing housing prices. This can be seen in Figure 2.

Figure 1: Price Comparison for Major Cities



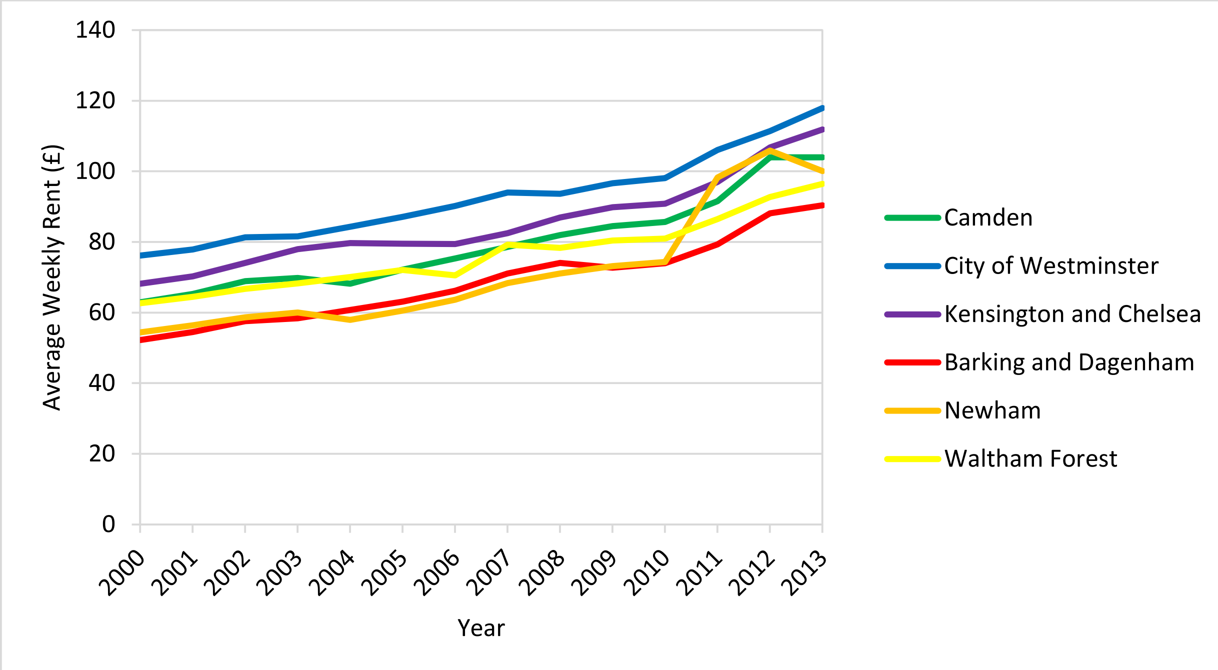
Source: First Post-Wealth Report

Figure 2: Percentage Changes in Median House Prices and Median Weekly Wage in London



Rising real estate prices have multiple implications for housing demand. Those who desire to purchase a home are now less financially able to do so and therefore seek alternative living accommodations. This places further upward pressure on rent prices. Figure 3 illustrates London's rising rent prices over the past 17 years for London's three most expensive boroughs, Camden, City of Westminster, and Kensington and Chelsea, and London's three least expensive boroughs, Barking and Dagenham, Newham, and Waltham and Forest.

Figure 3: London Rent Trends



High house prices place an upward pressure on rental prices, increasing the price of housing for all, both those who purchase a home and those who rent. London's housing affordability, or lack thereof, limits London from reaching its full potential. Edward Glaeser, a well-respected urban economist, states in *Triumph of the City*, "Cities enable the collaboration that makes humanity shine most brightly. Because humans learn so much from other humans, we learn more when there are more people around us. Urban density creates a constant flow of new information that comes from observing others' successes and failures" (245). By encouraging these network effects, a city can in turn benefit by attracting intelligent and creative people who add value. However, unfavorable characteristics, such as exorbitant housing prices, may encourage the people a city could benefit from attracting to look elsewhere. Consequently, high and rising house prices pose a threat to London's future economic growth. For these and many other reasons, further examination of London's housing prices is worthy of exploration.

2 LITERATURE REVIEW

As discussed above, affordable housing prices are critical to the success of a city. However, real estate prices in England, particularly in London and surrounding areas, are considered to be among the highest in the world. In order to develop an effective solution to curtail housing prices and volatility in London, it is imperative to understand the causal drivers. Many economists have already started to lay the groundwork.

Many people believe the housing prices in London are being pushed up by an increase in demand, due to rising incomes, and constrained supply of residential real estate. As people become richer, they often demand larger houses and more outdoor space; however, housing supply is not able to keep up. Cheshire *et al.* state in *Urban Economics and Urban Policy*, "The high price of housing is essentially driven by policy not by natural constraints" (80). Cheshire *et al*, in addition to many other economists, claim land use regulations impact the level and volatility of house prices. The UK planning system, initiated by the Town and Country Planning Act, has the reputation of being inflexible. Hilber and Vermeulen argue, "Historically, it ignored market signals and has failed adequately to cope with changing socio-economic conditions" (1). Since the development of containment policies in 1947, British policy has constrained the housing supply to grow more slowly than demand.[1]

Hilber and Vermeulen develop an empirical model that examines the impact of both regulatory and geographic supply constraints on house price levels in England. Their data set spans 35 years from 1974 to 2008 and includes 353 Local Planning Authorities in England. These locations have, they state, "rich and direct information on regulatory and physical supply

[1] "The act set out to contain urban areas and stop them spilling out into surrounding countryside and preserve amenities of various kinds including separating land uses which might be incompatible (for example industry from residential)" (Cheshire *et al.,* 81).

constraints" (3). Their empirical results show that both regulatory and geographic supply constraints have a strong, positive relationship with real estate prices in the long run.

In addition to housing prices, many economists have investigated house price volatility and how it relates to the elasticity of supply. Cheshire *et al.* argue that, "Since policy intentionally and very firmly restricts the land for housing or any other urban development it is no surprise that the supply of housing has become progressively more inelastic" (83). From the fundamental theory of supply and demand, demand shocks will cause larger price fluctuations in a market with more inelastic supply than in a market with elastic supply.

The English housing market, like all other housing markets, has boom-bust cycles. These cycles, which entail large swings in asset prices, are considered to be a concern for macroeconomic stability. Huang and Tang claim, "Historical experiences in the US and other industrialized countries show that asset price cycles often coincided with, or preceded, booms and busts of business cycles" (1). It is apparent these cycles are significant and require exploration.

In 2008, Glaeser *et al.* develop "a simple model of housing bubbles which predicts that places with more elastic housing supply have fewer and shorter bubbles, with smaller price increases" (1). Using this model and data from 79 metropolitan areas in the US between 1982 and 2006, they find that in places with inelastic supply the average boom lasted for more than four years compared to the average of 1.7 years in elastic areas. In addition, they find that in the housing boom of 1984-1989, real estate prices in real terms increased an average of 23.2 percent in less elastic markets and by a mere five percent in more elastic housing markets. However, their results regarding bust periods are inconclusive. Glaeser *et al.* states, "While the level of mean reversion during the bust is enormous, there is little correlation between price declines during the bust and the degree of elasticity" (37).

To supplement Glaeser *et al.*'s empirical analysis, Huang and Tang develop a model to better define the ambiguous relationship between housing prices and supply constraints during busts. They state, "Because the fall in house prices is the key to the destabilizing impact of a housing price cycle, it is important to understand what contributes to the magnitude of price corrections" (3). In contrast to Glaeser *et al.*'s model which only considered government regulation or "man-made scarcity" as a supply constraint, Huang and Tang's model includes both residential land use regulation and geographic land scarcity as supply constraints. Using a sample consisting of 326 US cities between 2000 and 2009, Huang and Tang's empirical results indicate that the regulatory and geographic supply constraints substantially added to the magnitude of the housing price boom as well as the housing price bust. In addition, their results suggest that both types of supply constraints intensified the responsiveness of real estate prices to an initial demand shock generated from the mortgage market, leading to larger price increases during the boom period and larger price decreases during the subsequent bust.

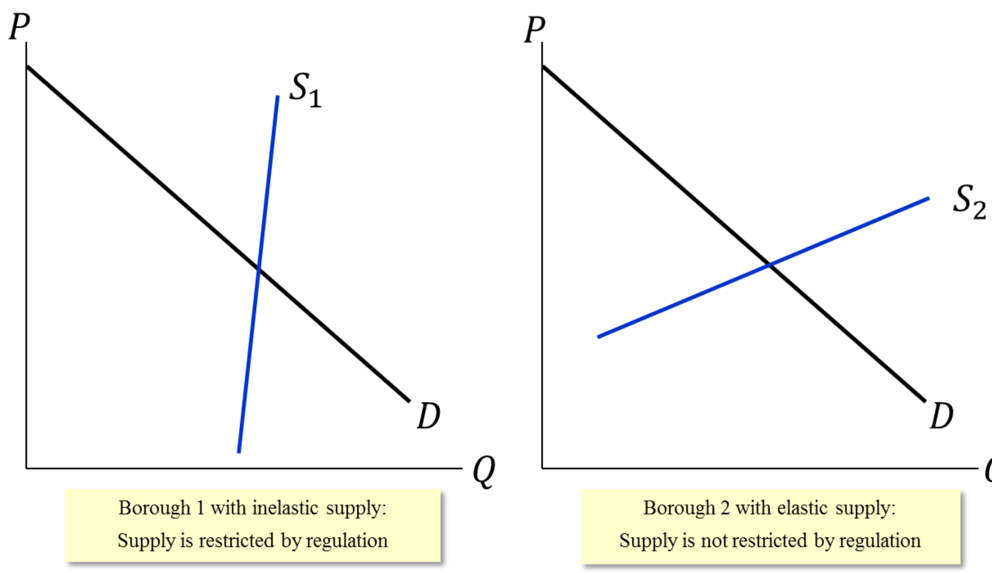
Given what Hilber and Vermeulen's model reveals for England and Huang and Tang's model reveals for the US, we identify a gap in the research for London's housing market specifically. It is common knowledge London's house prices have been on a drastic upswing. From our prior knowledge described above, planning induced supply constraints are contributing factors to these high and rising housing prices. However, from both Glaeser *et al.* and Huang and Tang's research, we know a change in a supply constraint affects housing prices differently during boom periods and bust periods. This leads us to our research question motivating this paper: How do planning induced supply constraints affect price levels following boom periods and bust periods in London? Through the examination of changes in price levels during boom and bust periods, we can better understand and quantify the impact of planning induced supply constraints in London.

3 METHODOLOGY & DATA

3.1 Analytical Framework and Empirical Specification

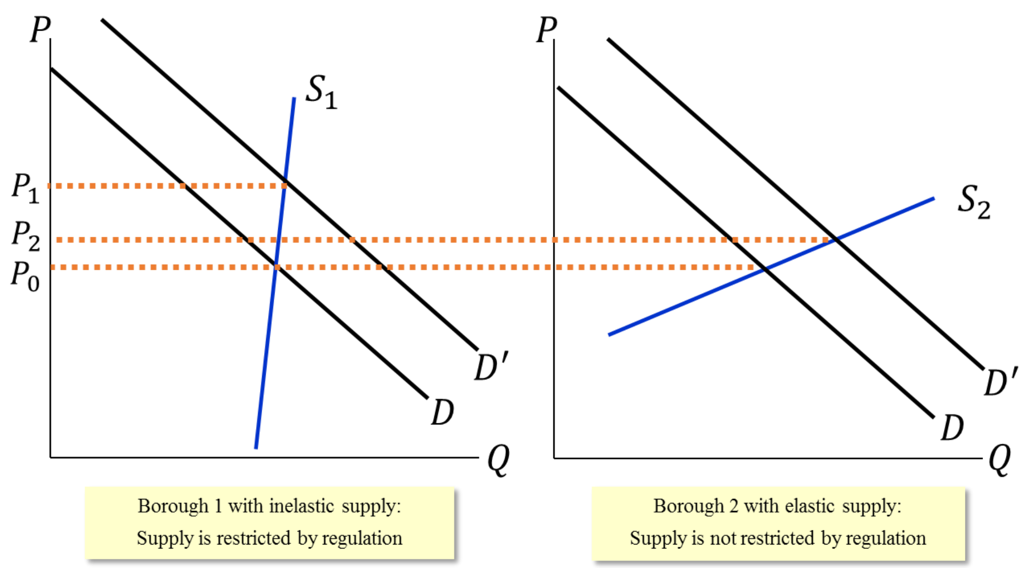
Simple supply and demand diagrams can be used to illustrate how we approach answering our question at hand. Consider two boroughs that are identical in all respects except for the restrictiveness of their planning authorities, as measured by the fraction of applications received for new residential developments that are approved by each authority. In Figure 4, Borough 1 represents a borough with a strict planning authority, meaning the acceptance rate of planning applications submitted is low relative to a more lenient planning authority. Therefore, this translates into an inelastic supply of housing in Borough 1 due to constrained housing development. On the contrary, Borough 2 represents a borough with a lenient planning authority. Housing development is not constrained in Borough 2 and, therefore, the supply of housing is relatively more elastic when compared to Borough 1.

Figure 4: Supply and Demand of Housing Market



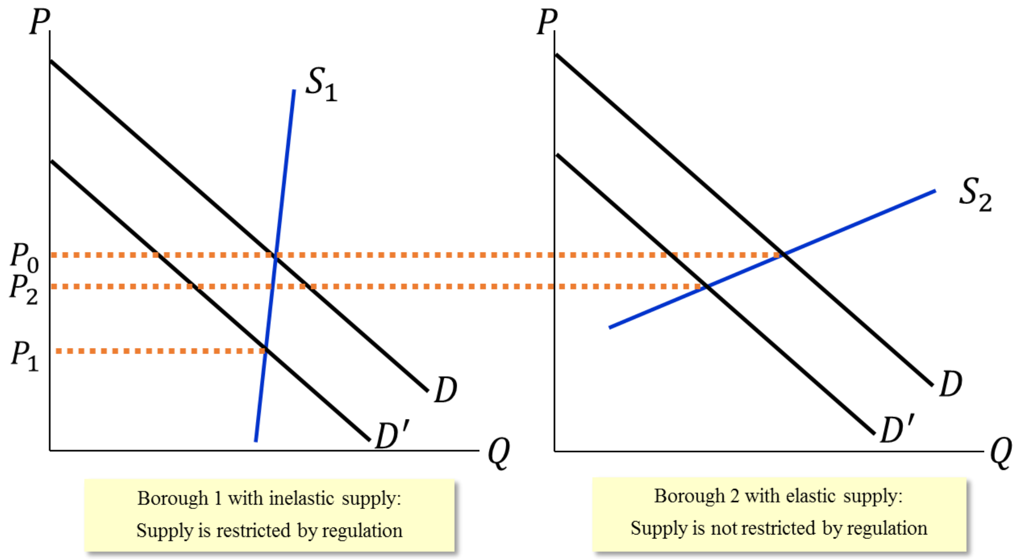
Given an equivalent outward shift of the demand curve for housing in each borough, economic theory tells us prices will be higher in a market with inelastic supply compared to a market with elastic supply. This can be seen in Figure 5. The price increase in Borough 1, from P_0 to P_1, is much larger compared to the price increase in Borough 2, from P_0 to P_2.

Figure 5: Effect of Outward Shift of Demand Curve on Housing Prices



Similarly, given an equivalent inward shift of the demand curve for housing in each borough, economic theory also tells us prices will be lower in a market with inelastic supply compared to a market with elastic supply. This can be seen in Figure 6. The fall in price between P_0 and P_1 is much larger than the fall in price between P_0 and P_2.

Figure 6: Effect of Inward Shift of Demand Curve on Housing Prices



The economic theory laid out in the preceding examples underlies our empirical strategy. Our goal is to identify the effect of supply constraints on price, as measured by planning authority restrictiveness. Our data, as discussed in detail in the next section, are compatible with a "fixed effects" approach. However, we will estimate a multilevel mixed-effects model.[2] "Fixed effects models," as commonly employed in economics, assume that each cross-sectional unit has an effect that is fixed over time without making specific assumptions about the distribution of these "fixed effects" across groups.[3] In a mixed-effects model, the effect of each cross-sectional unit is assumed to be a random number drawn from a normal distribution.

At first glance, the fact that specific distributional assumptions about the cross-sectional-unit-specific intercepts are not made as part of "fixed effects" estimation but are made as part of mixed-effects estimation appears to be a positive feature of the "fixed effects model." However,

[2] Multilevel mixed-effects models are also called hierarchical models.

[3] Note that this does not imply that these "fixed effects," or cross-sectional-unit-specific intercepts, are not random draws from a population characterizable by some specific distribution. It merely implies that these cross-sectional-unit-specific intercepts are not constrained to follow a specific distribution as part of the estimation procedure, whether they are estimated directly in a dummy variable regression fixed effects implementation or calculated post estimation using the estimates obtained from a within transformation fixed effects implementation. For additional details, see Wooldridge (2002, pages 251-252).

this generality allows the estimated effect of each borough to be anything, without regard to any distributional relationship among boroughs.[4] In a mixed-effects model, the effect of each borough is assumed to be drawn from a normal distribution that is centered around a common mean with some variance. The mean and variance that are the most likely to characterize the data generating process that gave rise to the boroughs as observed in the data are estimated as part of the (restricted) maximum likelihood estimation procedure. In this way, the effect of each borough is constrained by each individual borough effect needing to fall within this common normal distribution. This allows the model to better deal with unobserved heterogeneity and has benefits when a cross-sectional unit is missing observations over time.

In order to quantify the relationship between planning induced supply constraints and price levels following boom periods and bust periods, we estimate a multilevel mixed-effects model. Mixed-effects models are unique in the sense that they contain both fixed and random effects. The fixed effects portion of the model is similar to a standard regression's coefficients and is estimated directly. The random effects, however, are not estimated directly. Rather, the random effects are summarized in terms of their estimated variances and covariances. The random effects portion of the model may be included as random intercepts, random coefficients, or both.[5] In addition, a mixed-effects model allows for the inclusion of time-invariant variables.[6]

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[4] In fact, as discussed by Wooldridge (2002, pages 273-274), estimates of cross-sectional-unit-specific intercepts "can contain substantial noise" when the number of time periods is small. Only when the number of time periods is large are these estimates "precise enough to learn something about [their] distribution."

[5] Due to the fact mixed-effects models have more error terms, the model allows for more flexibility in defining the covariance structure. Having the ability to create a model with a more complex covariance structure improves the likelihood of correct specification. Therefore, the model will produce more precise estimates of the standard errors of regression coefficients with more accurate confidence intervals and statistical tests (Ferron *et al.*).

[6] An important limitation of the "fixed effects model" is the inability to include time-invariant variables. In a "fixed effects model," identification is based on changes in the explanatory variables within a cross-sectional unit. Thus, the effect of any variable that does not change over time within a cross-sectional unit cannot be identified without additional assumptions. For example, see Wooldridge (2013, pages 464-462).

Consider the following formal model:

Model 1:

$$\log\left(median\ price_{i,j,t}\right) = \left(\beta_0 + \delta_{0,i}\right) + \beta_1 \cdot boom\ indicator_{t-1}$$
$$+\beta_2 \cdot \left(boom\ indicator_{t-1} \text{ x } percentage\ of\ minor\ applications\ accepted_{i,t-1}\right)$$
$$+\beta_3 \cdot \left(bust\ indicator_{t-1} \text{ x } percentage\ of\ minor\ applications\ accepted_{i,t-1}\right)$$
$$+\beta_4 \cdot year_t + \boldsymbol{X}_{i,t} \cdot \boldsymbol{\beta}_X + \boldsymbol{W}_{i,t-1} \cdot \boldsymbol{\beta}_W + \boldsymbol{Z}_i \cdot \boldsymbol{\beta}_Z + \boldsymbol{K}_j \cdot \boldsymbol{\beta}_K + \boldsymbol{S}_{i,j,t} \cdot \boldsymbol{\beta}_S + \varepsilon_{i,j,t}$$

for borough i, house type j, at time t. $\boldsymbol{X}_{i,t}$ is a vector of time specific control variables, $\boldsymbol{W}_{i,t-1}$ is a vector of lagged control variables, $\boldsymbol{Z}_i$ is a vector of time invariant control variables, $\boldsymbol{K}_j$ is a vector of house type indicator variables, $\boldsymbol{S}_{i,j,t}$ is a vector of interaction variables between house type and total number of sales by type, and finally $\varepsilon_{i,j,t}$ is the idiosyncratic error term. The control variables will be discussed in greater detail in the following section.

In our mixed-effects model, unobserved heterogeneity across boroughs is modeled by inclusion of borough-specific random intercepts, $\delta_{0,i}$, which vary each borough's intercept around the estimated (mean) constant term, β_0. This allows us to account for the clustered structure of our data. For this model we follow conventional methods for estimating linear mixed-effects models by assuming the random component follows a normal distribution and employing restricted maximum likelihood estimation.[7]

The two variables of primary interest contained in the model above are the interaction of the boom indicator and the planning induced supply constraint, and the interaction of the bust indicator and the planning induced supply constraint, where the bust indicator is equal to one minus the boom indicator. Interaction terms allow the effect one explanatory variable has on the *dependent* variable to depend on the value of another explanatory variable. Therefore, the first specified interaction allows us to observe the effect of planning induced supply constraints on

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[7] We assume the idiosyncratic error, $\varepsilon_{i,j,t}$, is independent of $\delta_{0,i}$, and that $\delta_{0,i} \sim N(0, \sigma_\delta^2)$ and $\varepsilon_{i,j,t} \sim N(0, \sigma_\varepsilon^2)$.

house prices following a boom period. Similarly, the second specified interaction term allows us to observe the effect of planning induced supply constraints on house prices following a bust period. In order to obtain the true effect of these interaction terms on the dependent variable, the boom indicator must also be included in our model separately.[8]

In addition, the fixed effects portion of our model includes a simple linear time trend. By including time as an explanatory variable we are able to control for the effects of time in order to more accurately capture the effects of primary interest.[9]

Hypothesis

Our hypotheses for our models, which are based on the economic theory discussed above, are listed in the table below. In a less restrictive environment, meaning when the percentage of applications accepted is high, we predict the average house price will be lower compared to a more restrictive environment following a boom period. We also predict that in a less restrictive environment the average house price will be higher compared to a more restrictive environment following a bust period.

	Less Restrictive Environment	*More Restrictive Environment*
Prices following a Boom Period	-	+
Prices following a Bust Period	+	-

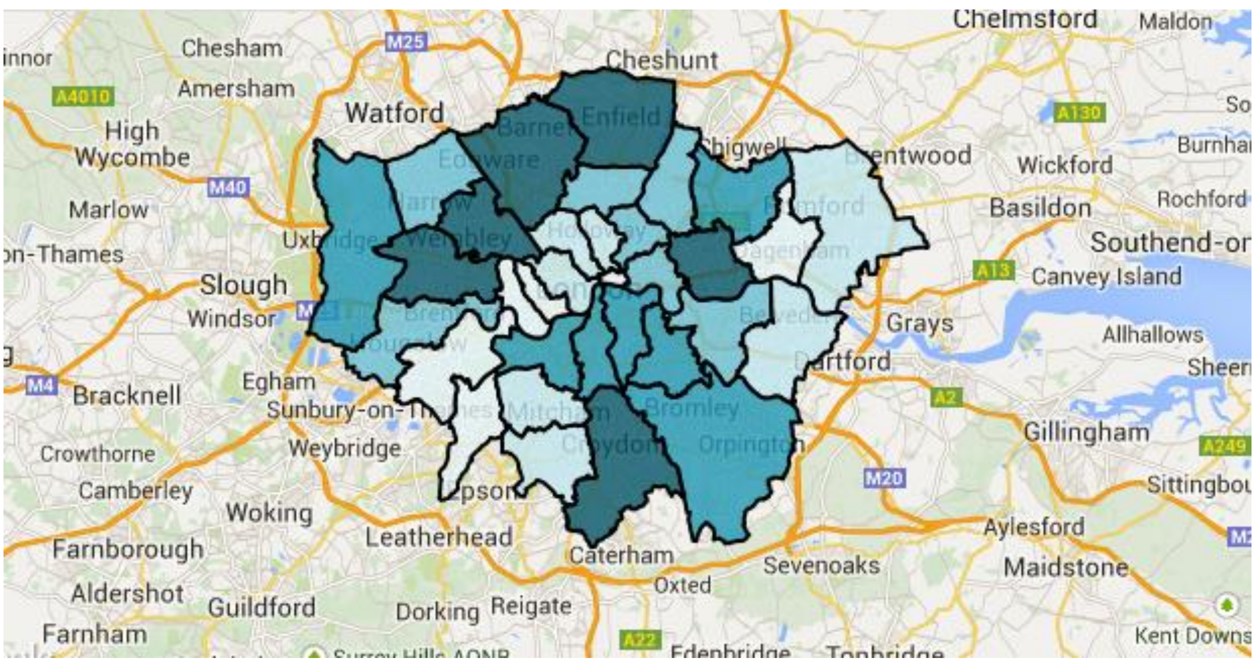
[8] Please note that the interaction terms (boom) x (percentage of applications accepted) and (1-boom) x (percentage of applications accepted) is equivalent to including the percentage of applications accepted and the interaction term (boom) x (percentage of applications accepted).

[9] Through correlogram analysis we were able to determine our model does not require a moving average (MA) or autoregressive (AR) process.

3.2 Data and Descriptive Statistics

Our sample for empirical analysis includes 32 of London's 33 boroughs.[10] These boroughs make up both Inner and Outer London. Figure 7 depicts the geographic borders of each borough. All variables were found for each borough in every year included in the observation period, which begins in 2001 and ends in 2013.[11] The observation period includes 11 price boom periods and two price bust periods, which have been defined based on the overall house market trend.[12] Our specified time period includes two partial booms phases and one full bust phase. These price trends can be seen in Figures 8 and 9 for the three most expensive and three least expensive boroughs.

Figure 7: Map of London Boroughs



Source: Office for National Statistics

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[10] Data collection in London's 33rd borough, the City of London, is not consistent with other boroughs, forcing the omission of this borough. However, this exclusion does not pose a significant concern for our analysis. The total land area and residing population for this borough are significantly smaller compared to the other 32 boroughs, measuring less than half of the next smallest borough along both dimensions. In addition, the City of London is unlike any other borough due to its degree of self-government and relatively limited availability of residential property in comparison with other uses.

[11] Data previous to 2001 is not publically accessible and data post 2013 was not readily available at the time of our data pooling.

[12] Based on observed trends of both London and England's housing market, bust periods have been defined as 2008 and 2009. All other years included in our observation period have been defined as boom periods.

Figure 8: Median House Prices

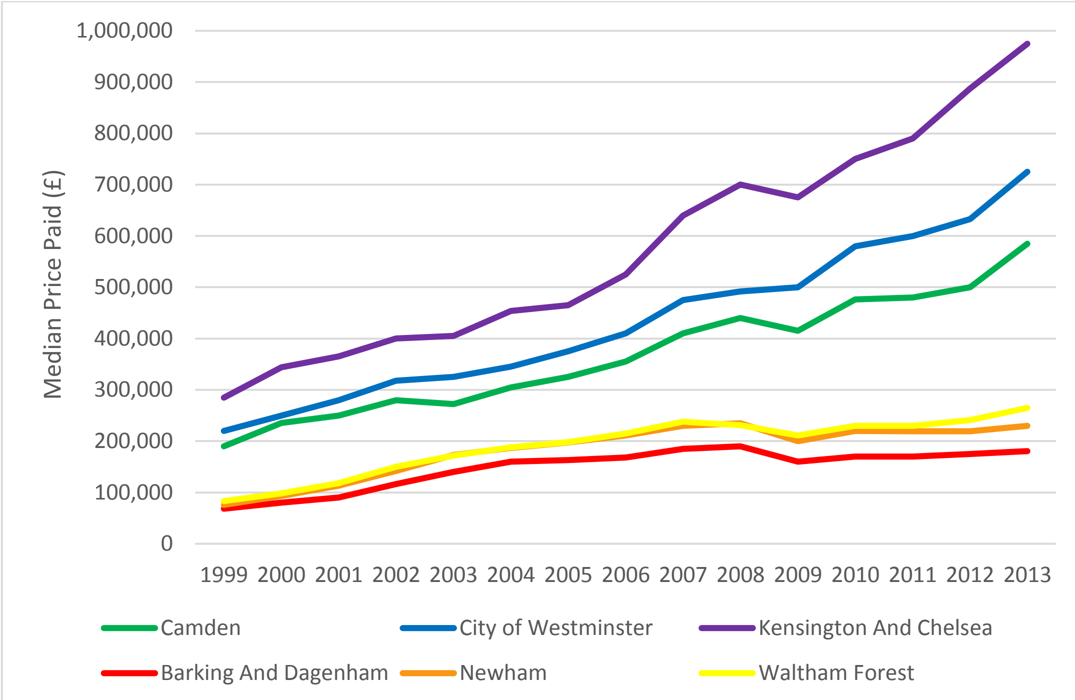
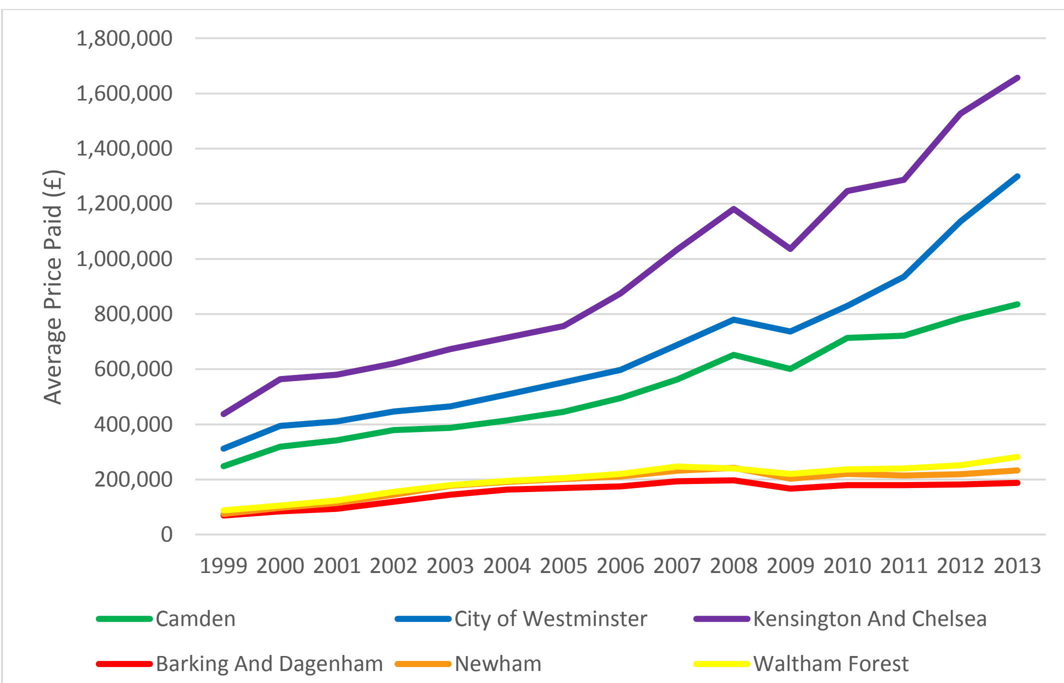


Figure 9: Average House Prices



The dependent variable in our model is the median price of homes by type for a given borough and year. The Land Registry provides these price paid data for four different types of homes: detached, semi-detached, terraced, and flats. Though no clear definition of these house types is provided by the Land Registry, we will rely on common definitions of the various types to better understand the differences. A detached house is defined as a single standing property that does not share any walls with any other adjacent structure. A semi-detached house is defined as a property where one side of the house shares a common wall with a neighboring structure, while the other side of the house is detached. A terraced house is defined as a property that is situated in a long row of houses sharing a common wall on both sides of the house (Property Investment Project). The Land Registry claims the last house type, flats, are difficult to define because there are many types. However, the Building Regulations 2000 define a flat as "a separate and self-contained premises constructed or adapted for use for residential purposes and forming part of a building from some other part of which it is divided horizontally" (Planning Portal).

Trends of these data remain consistent with the overall house market trend and have been on the upswing since the beginning of our observation period, temporarily decreasing around 2008 and 2009. Trends also show that London's three most expensive boroughs have greater price changes compared to price changes in the three least expensive boroughs.[13]

Our measure of regulatory restrictiveness was obtained from the Planning Statistics group at the Department for Communities and Local Government (DCLG). The DCLG provides data on the number of applications submitted and decided for major and minor residential development projects. A major residential project is defined as a project consisting of 10 or more dwellings, and

[13] For certain boroughs, the number of sales for particular types of homes are low partially due to a low stock, which translates into additional noise in these price measures. After taking a natural log transformation of these price paid data, the observed price changes are more symmetric across boroughs and years.

a minor residential project is defined as a project consisting of fewer than 10 dwellings. While Hilber and Vermeulen's model used the percentage of major applications accepted, our model will use the percentage of minor applications accepted. We claim the percentage of minor residential project applications accepted is a better measurement of regulatory restrictiveness because there are other factors that affect submission of major residential applications. Since major residential project applications require a significant amount of both money and time, among other things, to complete, it is reasonable to assume contractors are more likely to not submit an application for major projects if they do not believe it will be accepted. Minor residential project applications on the other hand require less time and money to complete and therefore more people would be willing to submit applications.

The application acceptance rate is included as a lagged variable in our model. We argue a change in the acceptance rate will not affect housing prices until the following year, which is when a housing plan will have had the chance to transition to a development and enter the market.

To keep the following interaction variables contemporaneous, the indicator variable for the state of the housing price cycle will also be lagged. Therefore, this indicator variable will define the state of the housing price cycle from the previous year, which is when the application decisions included in our model have been made.

Our model includes interaction terms between the regulatory supply constraint measurement and the state of the housing price cycle. This allows the effect regulatory supply constraints have on house prices to depend on the state of the housing price cycle. More specifically, the first of the two interaction terms in Model 1 allows us to observe how a change in the percentage of minor residential applications accepted in a *boom* year will affect the average price of all homes for a given borough in the following year. The second of these interaction terms included in this model allows us to observe how a change in the percentage of minor residential applications accepted in a *bust* year will affect the average price of all homes for a given borough in the following year.

In addition, the fixed effects part of our multilevel mixed-effects model includes seven control variables. Controlling for the influence of other variables will allow us to observe a more accurate relationship between regulatory restrictiveness and house prices. The control variables are as follows: population, net migration, number of minor applications submitted, total land area of a borough, distance to the center of London, number of major residential development applications submitted, and number of house sales.

The first control variable included in our model is population. The annual borough population estimates are provided by the Greater London Authority. Including population as a variable in the fixed part of our model partially controls for the size of the market for a given borough.

The second control variable included in our model is net migration. Net migration for a given borough and year was generated by subtracting the number of people flowing out from the number of people flowing in. These data are provided by the Migration Statistics Unit from the Office for National Statistics. This variable serves as a control for the effect of unobservable attractions or deterrents for a given borough on house prices.

The number of minor residential project applications submitted in the previous year will serve as the third independent control variable. These data are provided by the Planning Statistics group at the Department for Communities and Local Government. Incorporating this variable in our model will serve as a control for the planning and development climate in a given borough, as well as an additional control for the attractiveness of living in that borough.

The total area of a borough will serve as the fourth independent control variable. These data are provided by the Greater London Authority. This variable allows us to control for the effect of total area on house prices. It is reasonable to suspect as the area of a borough increases, house prices will be lower because there is more room for expansion of the existing housing stock.

A distance measurement is included as the fifth control variable. The measurements were generated by finding the distance from the center of a given borough to the center of London, which we have defined as the center of the City of London. This variable serves as a control for the effect of central location on house prices. Urban economic theory tells us that as a household moves closer to the center of an urban area, the price will increase to account for the amenities available in the center, in addition to the savings on commuting.

In addition to including the number of minor residential project applications submitted in the previous year, our model also includes the number of major residential project applications submitted in the previous year. These data were also provided by the Planning Statistics group at the Department for Communities and Local Government. This variable allows us to further control for the development climate in a given borough. However, this control adds more weight to the development climate since these development applications require more commitment due to the cost associated with this type of application.[14]

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[14] Planning application fees are based on the total area of a site and the projected number of dwellings. For sites up to and including 2.5 hectares, there is a £385 fee per 0.1 hectare. Applications that have a site larger than 2.5 hectares have a fixed fee of £9,527 and £115 fee per additional 0.1 hectare in excess of 2.5 hectares. Applications that project up to and including 50 new dwellings have a £385 fee per dwelling. For applications that project more than 50 new dwellings have a fixed fee of £19,049 and £115 fee per additional new dwelling in excess of 50. These fees are reported from the 2012 Town and Country Planning Regulations which

The number of house sales by type of home will be the final control variable included in our model. These data are part of the House Price Statistics for Small Areas release, which is produced by the Office for National Statistics. This variable is included in our model to further control for the size of the market since it represents the number of housing transactions in a given borough.

Table 1 provides summary statistics for the variables used in our model. These variables form a panel data set consisting of 32 boroughs for the years 2001 through 2013. The panel data allow us to control for unobservable, time-invariant effects specific to each borough, as well as for overall time trends, by using mixed-effects estimation.

Table 1
Summary Statistics (primary model sample)

	Obs	Mean	Standard Deviation	Min	Max
log(Median Sale Price of Detached Houses)	391	13.28	0.64	11.74	16.01
log(Median Sale Price of Semi- Detached Houses)	391	12.85	0.66	11.64	15.61
log(Median Sale Price of Terraced Houses)	391	12.64	0.58	11.45	14.85
log(Median Sale Price of Flats)	391	12.23	0.39	11.13	13.62
Percentage of Minor Development Applications Accepted	391	57.26	14.49	17.76	94.17
Boom Indicator x Percentage of Minor Development Applications Accepted	391	50.50	24.23	0.00	93.06
Bust Indicator x Percentage of Minor Development Applications Accepted	391	7.57	19.73	0.00	83.85
Number of Major Residential Applications	391	28.05	21.27	0.00	127.00
Number of Minor Residential Applications	391	243.50	152.57	25.00	982.00
Population (in 1,000s)	391	244.31	53.96	146.00	375.80
Total Area (SqKm)	391	49.09	31.12	12.12	150.13
Net Migration (in 1,000s)	391	-2.21	2.29	-10.80	2.05
Distance	391	8.20	3.91	1.29	15.47
Number of Detached Sales	391	173.39	210.36	5.00	1275.00
Number of Semi-Detached Sales	391	624.15	539.38	14.00	2219.00
Number of Terraced Sales	391	1215.61	683.60	194.00	3267.00
Number of Flat Sales	391	2055.58	1110.06	305.00	6320.00

4 EMPIRICAL ANALYSIS

4.1 Estimation Strategy and Results

remain in effect in 2015.Though these fees are associated with only one period in our data set, these rates are provided to show the types of fees associated with these applications.

We report our primary model's results in Table 2.

Table 2

Model 1: Main Results

	Dependent Variable: log(Median Price by Specific Type of House)				
	(1)	(2)	(3)	(4)	(5)
Fixed Effects					
Boom Indicator	0.217***	0.220***	0.218***	0.212***	0.240***
	(3.84)	(3.90)	(3.87)	(3.76)	(4.38)
Boom Indicator x Percentage of Minor Applications Accepted	**-0.00143****	**-0.00148****	**-0.00150****	**-0.00142****	**-0.00149*****
	(-2.41)	(-2.49)	(-2.53)	(-2.39)	(-2.59)
Bust Indicator x Percentage of Minor Applications Accepted	**0.00210****	**0.00211****	**0.00204****	**0.00207****	**0.00220****
	(2.09)	(2.09)	(2.02)	(2.05)	(2.25)
Home Type Indicator: Semi-Detached	-0.426***	-0.426***	-0.426***	-0.426***	-0.342***
	(-29.95)	(-29.95)	(-29.95)	(-29.99)	(-17.38)
Home Type Indicator: Terraced	-0.644***	-0.644***	-0.644***	-0.644***	-0.574***
	(-45.28)	(-45.29)	(-45.29)	(-45.34)	(-23.09)
Home Type Indicator: Flats	-1.056***	-1.056***	-1.056***	-1.056***	-0.875***
	(-74.26)	(-74.27)	(-74.26)	(-74.35)	(-32.75)
Year	0.0640***	0.0626***	0.0638***	0.0644***	0.0614***
	(22.29)	(21.53)	(21.74)	(21.81)	(21.21)
Population (in 1,000s)	-0.00249***	-0.00205**	-0.00248***	-0.00223***	-0.00228***
	(-3.09)	(-2.51)	(-2.99)	(-2.66)	(-2.78)
Net Migration (in 1,000s)	-0.0243***	-0.0239***	-0.0233***	-0.0217***	-0.0229***
	(-4.73)	(-4.65)	(-4.53)	(-4.17)	(-4.56)
Number of Minor Residential Applications	0.000344***	0.000350***	0.000343***	0.000310***	0.000303***
	(6.56)	(6.68)	(6.54)	(5.61)	(5.67)
Total Area of Borough (SqKm)		-0.00583**	0.000358	-0.000166	0.000239
		(-2.38)	(0.10)	(-0.04)	(0.06)
Distance (miles)			-0.0610**	-0.0584**	-0.0610**
			(-2.14)	(-2.03)	(-2.09)
Number of Major Residential Applications				0.000745**	0.000846**
				(1.97)	(2.31)
Detached Indicator x Number of Detached Sales					0.0000966*
					(1.76)
Semi-Detached Indicator x Number of Semi-Detached Sales					-0.000108***
					(-5.09)
Terraced Indicator x Number of Terraced Sales					-0.0000437***
					(-2.72)
Flat Indicator x Number of Flat Sales					-0.0000798***
					(-8.08)
Constant	13.12***	13.31***	13.60***	13.53***	13.53***
	(62.12)	(60.59)	(53.74)	(52.72)	(53.13)
Random Effect					
Variance: Borough Specific Intercept	0.2056606	0.1793952	0.1590960	0.1624608	0.1672646
95% CI: Lower Bound	0.1240333	0.1075419	0.0943182	0.0961506	0.0991316
95% CI: Upper Bound	0.3410076	0.2992567	0.2683634	0.2745018	0.2822248
Variance of Residual	0.0396943	0.0396894	0.0396941	0.0396045	0.0369787
Number of Observations	1576	1576	1576	1576	1576
Number of Boroughs	32	32	32	32	32

Notes: t-statistics in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Columns (1) through (5) provide estimates of primary interest which are the interaction terms boom period x percentage of minor residential applications accepted and bust period x percentage of minor residential applications accepted, where bust period equals one minus boom period. Estimates in Column (1), which includes only three of our control variables, provide evidence corresponding to our hypothesis at the 5 percent significance level. As additional controls are added, the estimates of primary interest remain both consistent with our hypothesis and statistically significant. Details are discussed in the following paragraphs.

Estimates in Column (1) indicate that if the percentage of minor residential applications accepted increases by 1 percentage point during a boom period, when holding all other explanatory variables constant, the median price for each type of home will be, on average, 0.143 percent lower in the following year compared to house prices in an equivalent borough that did not experience the acceptance increase. It is important to keep in mind that this coefficient is the effect of residential application acceptance during a boom period, a period when house prices are rising. The negative coefficient does not imply that house prices decrease in boroughs with higher acceptance rates. Rather, prices do not increase by as much in boroughs with higher acceptance rates, compared to boroughs with lower acceptance rates. This estimate is significant at the 5 percent level.

Estimates in Column (1) also indicate that if the percentage of minor residential applications accepted increases by 1 percentage point during a bust period, when holding all other explanatory variables constant, the median price for each type of home will be, on average, 0.21 percent higher in the following year compared to house prices in an equivalent borough that did not experience the acceptance increase. Just as the negative coefficient discussed in the previous paragraph did not imply that house prices decrease, the positive coefficient presented in this paragraph does not imply that house prices increase in boroughs with higher acceptance rates. Rather, prices do not fall by as much in boroughs with higher acceptance rates, compared to boroughs with lower acceptance rates. This estimate is also significant at the 5 percent level.

Columns (2), (3), and (4) add additional control variables to the specification found in Column (1). Total land area, distance to the center of London, and the number of major applications submitted are added to the specification, respectively.

Column (4) provides estimates for our model when all control variables, except for the number of sales, are included. These estimates indicate that if the percentage of minor residential applications accepted during a boom period increases by 1 percentage point, when holding all other explanatory variables constant, the median price for each type of home will be, on average, 0.142 percent lower in the following year compared to house prices in an equivalent borough that did not experience the acceptance increase. Estimates in Column (4) also indicate that if the percentage of minor residential applications accepted during a bust period increases by 1 percentage point, when holding all other explanatory variables constant, the median price for each type of home will be, on average, 0.207 percent higher in the following year compared to house prices in an equivalent borough that did not experience the acceptance increase. Both estimates remain significant at the 5 percent level.

Estimates in Column (5), which includes number of sales by house type as control variables, indicate that if the percentage of minor residential applications accepted increases by 1 percentage point during a boom period, when holding all other explanatory variables constant, the median price for each type of home will be, on average, 0.149 percent lower in the following year compared to house prices in an equivalent borough that did not experience the acceptance increase.

Estimates in Column (5) also indicate that if the percentage of minor residential applications accepted increases by 1 percentage point during a bust period, when holding all other explanatory variables constant, the median price for each type of home will be, on average, 0.22 percent higher in the following year compared to house prices in an equivalent borough that did not experience the acceptance increase. These coefficients remain essentially unchanged across previous specifications. In addition, the level of significance remains the same, if not improved.

4.2 Robustness Checks

In this section we provide results for several alternative specifications to demonstrate the robustness of the results discussed above. We provide a model (Model 2) that removes the linear time trend from our preferred model (Model 1). Estimates for Model 2 can be found in Table 3.[15] The estimates show that our expected results continue to hold when excluding the time control. However, the level of the effect for the interaction of a boom period and percentage of minor applications accepted on median house prices more than doubles when the time trend is excluded. Also, the level of the effect for the interaction of a bust period and percentage of minor applications accepted on median house prices is marginally larger compared to the estimates with a linear time trend. Though the significance of these estimates improves in Model 2, we provide this model to show that the expected effects on house prices hold true with and without the inclusion of a linear time trend.[16]

[15] A formal equation for Model 2 can be found in the appendix.

[16] Through analysis of our data, we were able to validate that our model does not warrant AR or MA processes. However, Models 2 and 4 encourage the inclusion of a linear time trend making the estimates more robust and unbiased in Model 1, the preferred model.

Table 3

Model 2: Primary Model without Linear Time Trend

	Dependent Variable: log(Median Price by Specific Type of House)				
	(1)	(2)	(3)	(4)	(5)
Fixed Effects					
Boom Indicator	0.295***	0.296***	0.296***	0.295***	0.329***
	(4.70)	(4.71)	(4.71)	(4.68)	(5.40)
Boom Indicator x Percentage of Minor Applications Accepted	**-0.00306*** **	**-0.00310*** **	**-0.00308*** **	**-0.00306*** **	**-0.00302*** **
	(-4.64)	(-4.70)	(-4.66)	(-4.62)	(-4.74)
Bust Indicator x Percentage of Minor Applications Accepted	**0.00271** **	**0.00267** **	**0.00269** **	**0.00271** **	**0.00292*** **
	(2.41)	(2.37)	(2.39)	(2.40)	(2.68)
Home Type Indicator: Semi-Detached	-0.427***	-0.427***	-0.427***	-0.427***	-0.334***
	(-26.87)	(-26.87)	(-26.87)	(-26.87)	(-15.21)
Home Type Indicator: Terraced	-0.644***	-0.644***	-0.644***	-0.645***	-0.562***
	(-40.60)	(-40.59)	(-40.60)	(-40.59)	(-20.28)
Home Type Indicator: Flats	-1.056***	-1.056***	-1.056***	-1.056***	-0.861***
	(-66.54)	(-66.53)	(-66.54)	(-66.53)	(-28.91)
Population (in 1,000s)	0.0135***	0.0135***	0.0135***	0.0136***	0.0126***
	(25.45)	(25.45)	(25.46)	(23.49)	(21.97)
Net Migration (in 1,000s)	-0.0118**	-0.0109*	-0.0112*	-0.0107*	-0.0127**
	(-2.06)	(-1.89)	(-1.94)	(-1.84)	(-2.26)
Number of Minor Residential Applications	0.000609***	0.000609***	0.000610***	0.000599***	0.000575***
	(10.69)	(10.68)	(10.70)	(10.05)	(9.99)
Total Area of Borough (SqKm)		-0.0181***	-0.0248***	-0.0251***	-0.0229***
		(-3.88)	(-3.41)	(-3.41)	(-3.28)
Distance (miles)			0.0688	0.0702	0.0595
			(1.19)	(1.20)	(1.08)
Number of Major Residential Applications				0.000242	0.000375
				(0.57)	(0.92)
Detached Indicator x Number of Detached Sales					0.0000379
					(0.62)
Semi-Detached Indicator x Number of Semi-Detached Sales					-0.000139***
					(-5.88)
Terraced Indicator x Number of Terraced Sales					-0.0000624***
					(-3.49)
Flat Indicator x Number of Flat Sales					-0.0000917***
					(-8.34)
Constant	9.693***	10.60***	10.35***	10.32***	10.52***
	(40.76)	(34.39)	(27.98)	(27.35)	(29.21)
Random Effect					
Variance: Borough Specific Intercept	1.0237110	0.6992752	0.6928703	0.7043979	0.6354198
95% CI: Lower Bound	0.6153264	0.4151390	0.4085817	0.4142287	0.3734061
95% CI: Upper Bound	1.7031360	1.1778850	1.1749650	1.1978320	1.0812850
Variance of Residual	0.0495188	0.0495249	0.0495202	0.0495267	0.0459763
Number of Observations	1576	1576	1576	1576	1576
Number of Boroughs	32	32	32	32	32

Notes: t-statistics in parentheses. *p<0.10, **p<0.05, ***p<0.01.

To show that our results are robust to the measure of housing prices, Models 3 and 4 use the median price of all types of homes[17] as the dependent variable instead of the median price of four different types of homes. This alteration to the dependent variable requires us to omit the vector of house type indicators. In addition, for specification (5) of Model 3 and 4, the number of house sales is for all types of houses instead of each type of house individually, as was included in specification (5) of Models 1 and 2. Models 3 and 4 are otherwise identical to Models 1 and 2.[18]

Estimates for Model 3 are shown in Table 4. The table shows that our results still hold for this new definition of the dependent variable. Estimates in Column (5) indicate that if the percentage of minor residential applications accepted during a boom period increases by 1 percentage point, when holding all other explanatory variables constant, the median price of homes will be, on average, 0.0889 percent lower in the following year compared to house prices in an equivalent borough that did not experience the acceptance increase. This estimate is significant at the 5 percent level. However, the effect of a change in the percentage of minor residential applications accepted during a boom period is slightly smaller on the median price of all homes than on the median price for each type of home. Estimates in Column (5) also indicate that if the percentage of minor residential applications accepted during a bust increases by 1 percentage point, when holding all other explanatory variables constant, the median price of homes will be, on average, 0.163 percent higher in the following year compared to house prices in an equivalent borough that did not experience the acceptance increase. This estimate is significant at the 5 percent level. Similar to the previous interaction, the effect of a change in the percentage of minor

[17] This price paid for housing data is also provided by the Land Registry.
[18] Formal equations for Model 2 and Model 3 can be found in the appendix.

residential applications accepted during a bust period is slightly smaller on the median price of all homes than on the median price for each type of home.

Table 4

Model 3: Alternative Model with Different Dependent Variable

	Dependent Variable: log(Median Price of All House Types)				
	(1)	(2)	(3)	(4)	(5)
Fixed Effects					
Boom Indicator	0.177***	0.178***	0.177***	0.169***	0.132***
	(4.41)	(4.43)	(4.40)	(4.27)	(3.33)
Boom Indicator x Percentage of Minor Applications Accepted	**-0.000920****	**-0.000943****	**-0.000967****	**-0.000881****	**-0.000889****
	(-2.17)	(-2.21)	(-2.27)	(-2.09)	(-2.17)
Bust Indicator x Percentage of Minor Applications Accepted	**0.00199*****	**0.00198*****	**0.00192*****	**0.00194*****	**0.00163****
	(2.78)	(2.76)	(2.68)	(2.74)	(2.36)
Year	0.0611***	0.0607***	0.0616***	0.0624***	0.0661***
	(31.73)	(30.45)	(30.46)	(30.88)	(31.19)
Population (in 1,000s)	-0.00282***	-0.00270***	-0.00300***	-0.00278***	-0.00268***
	(-5.41)	(-4.96)	(-5.39)	(-4.99)	(-4.93)
Net Migration (in 1,000s)	-0.0209***	-0.0208***	-0.0204***	-0.0186***	-0.0173***
	(-5.73)	(-5.68)	(-5.57)	(-5.07)	(-4.82)
Number of Minor Residential Applications	0.000293***	0.000294***	0.000289***	0.000251***	0.000257***
	(7.84)	(7.86)	(7.70)	(6.42)	(6.77)
Total Area of Borough (SqKm)		-0.00108	0.00257	0.00208	0.00137
		(-0.76)	(1.18)	(0.95)	(0.64)
Distance (miles)			-0.0356**	-0.0332**	-0.0304*
			(-2.14)	(-1.99)	(-1.87)
Number of Major Residential Applications				0.000818***	0.000696***
				(3.06)	(2.66)
Number of House Sales					0.0000212***
					(4.72)
Constant	12.40***	12.43***	12.61***	12.55***	12.46***
	(92.43)	(89.39)	(78.15)	(77.38)	(78.28)
Random Effect					
Variance: Borough Specific Intercept	0.0578956	0.0582020	0.0526559	0.0531479	0.0506512
95% CI: Lower Bound	0.0347631	0.0345751	0.0311930	0.0315235	0.0300397
95% CI: Upper Bound	0.0964214	0.0979744	0.0888869	0.0896063	0.0854051
Variance of Residual	0.0051003	0.0051041	0.0050968	0.0049762	0.0047129
Number of Observations	395	395	395	395	395
Number of Boroughs	32	32	32	32	32

Notes: t-statistics in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table 5 provides estimates for Model 4. Model 4 is analogous to Model 2 with the exception of redefining the dependent variable to be the median price of all types of homes. Like Model 2, we exclude the linear time trend to emphasize the robustness of our specified model.

Similar to all specifications of Models 1 and 2, the following estimates show that our expected results hold when excluding the time control. However, the level of the effect for the interaction of a boom period and percentage of minor applications accepted on the median price of all homes more than doubles when the time trend is excluded. This result is consistent with the difference between Models 1 and 2. Also, the level of the effect for the interaction of a bust period and percentage of minor applications accepted on the median price of all homes is marginally larger compared to the estimates with a linear time trend. Again, this result is consistent with the difference between Models 1 and 2 and further emphasizes the robustness of our specified models. Results from Model 4 assert that our selected control variables are indeed sufficient, whether we redefine the dependent variable or not.

Table 5

Model 4: Alternative Model with Different Dependent Variable and No Linear Time Trend

	Dependent Variable: log(Median Price of All House Types)				
	(1)	(2)	(3)	(4)	(5)
Fixed Effects					
Boom Indicator	0.251***	0.253***	0.253***	0.252***	0.291***
	(3.59)	(3.60)	(3.61)	(3.59)	(4.11)
Boom Indicator x Percentage of Minor Applications Accepted	**-0.00254*** **	**-0.00261*** **	**-0.00255*** **	**-0.00254*** **	**-0.00245*** **
	(-3.43)	(-3.52)	(-3.45)	(-3.42)	(-3.31)
Bust Indicator x Percentage of Minor Applications Accepted	**0.00251** **	**0.00244**	**0.00250** **	**0.00251** **	**0.00280** **
	(2.00)	(1.95)	(1.99)	(1.99)	(2.23)
Population (in 1,000s)	0.0119***	0.0118***	0.0119***	0.0119***	0.0106***
	(20.27)	(20.26)	(20.31)	(18.72)	(14.61)
Net Migration (in 1,000s)	-0.00593	-0.00461	-0.00505	-0.00483	-0.00655
	(-0.92)	(-0.72)	(-0.79)	(-0.74)	(-1.01)
Number of Minor Residential Applications	0.000549***	0.000547***	0.000550***	0.000545***	0.000519***
	(8.58)	(8.56)	(8.61)	(8.14)	(7.73)
Total Area of Borough (SqKm)		-0.0127***	-0.0209***	-0.0211***	-0.0183***
		(-3.36)	(-3.67)	(-3.66)	(-3.45)
Distance (miles)			0.0849	0.0855	0.0721
			(1.88)	(1.88)	(1.74)
Number of Major Residential Applications				0.000117	0.000256
				(0.25)	(0.54)
Number of House Sales					0.0000253***
					(-3.30)
Constant	9.283***	9.927***	9.620***	9.602***	9.964***
	(41.95)	(36.67)	(30.59)	(29.82)	(31.45)
Random Effect					
Variance: Borough Specific Intercept	0.6105728	0.4520969	0.4204248	0.4250910	0.3507706
95% CI: Lower Bound	0.3611753	0.2632498	0.2436364	0.2447062	0.1978949
95% CI: Upper Bound	1.0321830	0.7764171	0.7254953	0.7384454	0.6217443
Variance of Residual	0.015613	0.0156266	0.0156137	0.015641	0.0154748
Number of Observations	395	395	395	395	395
Number of Boroughs	32	32	32	32	32

Notes: t-statistics in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Model 5 is the final mixed-effects model we include as a robustness check. Model 5 is analogous to our primary model (Model 1) with the exception of altering a few of the control parameters. Instead of including both population and total area, Model 5 supplements these controls by including population density. The intuition behind changing these parameters addresses potential apprehensiveness of including two similar controls for the size of the market, population and number of sales. Though the correlation estimate between these two variables is low (0.3058), we removed these two controls and replaced them with a similar substitute to reaffirm that our model specification is robust. Results for this model are located in Table 6.

Estimates in Column (3) indicate that if the percentage of minor applications accepted during a boom period increases by 1 percentage point, when holding all other explanatory variables constant, the median price for each type of home will be, on average, 0.156 percent lower in the following year compared to house prices in an equivalent borough that did not experience the acceptance increase. This estimate is significant at the 1 percent level. Estimates in Column (3) also indicate that if the percentage of minor applications accepted during a bust period increases by 1 percentage point, when holding all other explanatory variables constant, the median price for each type of home will be, on average, 0.237 percent higher in the following year compared to house prices in an equivalent borough that did not experience the acceptance increase. This estimate is significant at the 5 percent level. Both estimates are comparable to Model 1's estimates. Results from Model 5 allow us to assert again that our selected control variables are indeed sufficient, whether we redefine the parameters of the controls or not.

Table 6
Model 5: Alternative Model with Different Control Measures

	Dependent Variable: log(Median Price by Specific Type of House)		
	(1)	(2)	(3)
Fixed Effects			
Boom Indicator	0.257***	0.256***	0.244***
	(4.70)	(4.70)	(4.49)
Boom Indicator x Percentage of Minor Applications Accepted	**-0.00168*** **	**-0.00169*** **	**-0.00156*** **
	(-2.93)	(-2.93)	(-2.72)
Bust Indicator x Percentage of Minor Applications Accepted	**0.00238** **	**0.00237** **	**0.00237** **
	(2.44)	(2.44)	(2.44)
Home Type Indicator: Semi-Detached	-0.341***	-0.341***	-0.341***
	(-17.33)	(-17.33)	(-17.40)
Home Type Indicator: Terraced	-0.579***	-0.579***	-0.578***
	(-23.32)	(-23.32)	(-23.35)
Home Type Indicator: Flats	-0.879***	-0.879***	-0.876***
	(-32.94)	(-32.92)	(-32.94)
Detached Indicator x Number of Detached Sales	0.0000815	0.0000815	0.0000810
	(1.49)	(1.49)	(1.48)
Semi-Detached Indicator x Number of Semi-Detached Sales	-0.000115***	-0.000115***	-0.000115***
	(-5.41)	(-5.39)	(-5.40)
Terraced Indicator x Number of Terraced Sales	-0.0000421***	-0.0000421***	-0.0000433***
	(-2.63)	(-2.62)	(-2.71)
Flat Indicator x Number of Flat Sales	-0.0000794***	-0.0000794***	-0.0000806***
	(-8.05)	(-8.05)	(-8.19)
Year	0.0467***	0.0467***	0.0482***
	(23.30)	(21.22)	(21.53)
Population Density (people per hectare)	0.00817***	0.00814***	0.00896***
	(5.70)	(4.39)	(4.80)
Net Migration (in 1,000s)	-0.0279***	-0.0279***	-0.0254***
	(-5.65)	(-5.62)	(-5.07)
Number of Minor Residential Applications	0.000382***	0.000381***	0.000324***
	(7.61)	(7.59)	(6.12)
Distance (miles)		-0.000366	0.00522
		(-0.02)	(0.23)
Number of Major Residential Applications			0.00122***
			(3.35)
Constant	12.05***	12.05***	11.93***
	(96.46)	(42.67)	(41.81)
Random Effect			
Variance: Borough Specific Intercept	0.1464179	0.1497698	0.1525976
95% CI: Lower Bound	0.0881329	0.0894606	0.0912575
95% CI: Upper Bound	0.2432484	0.2507361	0.2551681
Variance of Residual	0.0369373	0.0369451	0.0366861
Number of Observations	1576	1576	1576
Number of Boroughs	32	32	32

Notes: t-statistics in parentheses. *p<0.10, **p<0.05, ***p<0.01.

The four models previously discussed in this section are provided to emphasize our confidence in correctly fitting our multilevel mixed-effects model to the data. However, should the reader be apprehensive about our model's estimation procedure, we provide an alternative model (Model 6) with similar specifications using ordinary least squares (OLS) fixed effects estimation, traditionally a more popular empirical model in economics.

Table 7 presents the findings of our "fixed effects model." This model's estimated effects for the two primary variables of interest on house prices remain both consistent with our hypothesis and statistically significant at the 5 percent level. Further, these estimates and their statistical significance are remarkably similar to those found in Model 1. Comparing the final columns of Tables 2 and 7, we see that the estimated effect of a 1 percentage point increase in minor residential applications accepted on the median price of each type of home is almost identical in each model, -0.160 percent during a boom period and 0.211 percent during a bust period from the "fixed effects model" compared with -0.149 percent during a boom period and 0.220 percent during a bust period from Model 1.

Though these estimates are consistent with those in our primary model, we wish to warn the reader for the reasons discussed in Section 3 that restricted maximum likelihood estimation of the mixed-effects Model 1 remains superior to OLS estimation of the "fixed effects model." A major benefit of the mixed-effects model is highlighted by simple inspection of Tables 2 and 7. Table 7 only includes three specifications, while Table 2 includes five. The reasons for this difference are the measures of borough size and location that are included in Model 1 but that cannot be included in the "fixed effects model." According to well-established urban economic theory, location is an important contributing factor to house prices.[19] This theory is corroborated by the estimates in Columns (3) through (5) of Table 2. Holding the other explanatory variables

[19] In fact, the three golden rules of real estate are "location, location, location."

constant, a one mile increase in a borough's distance from the center of London is predicted to decrease the borough's median house price by around six percent. The inability to include time-invariant explanatory variables is a significant limitation of the "fixed effects" approach to settings with unobserved heterogeneity.

Table 7

Model 5: OLS "Fixed Effects Model"

	Dependent Variable: log(Median Price by Specific Type of House)		
	(1)	(2)	(3)
Fixed Effects			
Boom Indicator	0.218339***	0.2119466***	0.2397704***
	(5.705863)	(5.252786)	(5.350603)
Boom Indicator x Percentage of Minor Applications Accepted	**-0.0016193****	**-0.0015327***	**-0.0015967****
	(-2.164655)	(-2.004056)	(-2.119299)
Bust Indicator x Percentage of Minor Applications Accepted	**0.0019403****	**0.0019791****	**0.0021072****
	(2.589649)	(2.524309)	(2.612969)
Home Type Indicator: Semi-Detached	-0.425755***	-0.4257939***	-0.3422412***
	(-11.23725)	(-11.23684)	(-6.730717)
Home Type Indicator: Terraced	-0.6437092***	-0.6437481***	-0.5760858***
	(-14.1832)	(-14.18311)	(-9.888268)
Home Type Indicator: Flats	-1.055572***	-1.055611***	-0.8732066***
	(-17.79148)	(-17.78862)	(-10.07085)
Year	0.0627546***	0.0631258***	0.0603883***
	(9.729712)	(9.815469)	(10.23309)
Population (in 1,000s)	-0.0020672	-0.0016931	-0.0018411
	(-1.422586)	(-1.20378)	(-1.266999)
Net Migration (in 1,000s)	-0.0243454***	-0.0227393**	-0.0238476**
	(-2.775249)	(-2.514388)	(-2.62007)
Number of Minor Residential Applications	0.0003339***	0.0002981***	0.0002915***
	(4.028193)	(3.581345)	(3.452312)
Number of Major Residential Applications		0.0008167*	0.0009063*
		(1.850964)	(1.973774)
Detached Indicator x Number of Detached Sales			0.0000955
			(.6800293)
Semi-Detached Indicator x Number of Semi-Detached Sales			-0.0001081**
			(-2.145539)
Terraced Indicator x Number of Terraced Sales			-0.0000422
			(-1.571006)
Flat Indicator x Number of Flat Sales			-0.0000807**
			-2.313485
Constant	13.03828***	12.93417***	12.9502***
	(41.64652)	(42.62079)	(40.55315)
Number of Observations	1576	1576	1576
Number of Boroughs	32	32	32

Notes: t-statistics in parentheses. *p<0.10, **p<0.05, ***p<0.01. Standard errors are clustered by borough. All columns are estimated by OLS. Regressions include borough fixed effects.

As a final robustness check, we will assess the fit of our model using deviance analysis. Deviance measures the fit between a model and a given data set, and is calculated by multiplying the log-likelihood by negative two. A model's deviance can then be compared to that of other models, with the smallest deviance indicating best fitness. However, because adding additional independent variables to a model almost always increases the log likelihood and thus decreases the deviance, in order to make an honest comparison of the deviance across model specifications, it is necessary to account for the number of new predictors added to the model. This can be done by simply adding the number of total predictors to the deviance estimate and is known as the adjusted deviance.[20] As additional explanatory variables are added to a model, the adjusted deviance will only decrease, indicating a better fit, if the deviance decreases by more than the number of parameters added to the model. In this way, "adjusted deviance can be used as an adjusted measure that approximately accounts for the increase in fit attained simply by adding predictors to a model" (Gelman and Hill, 525).[21] Additionally, we assess Akaike's Information Criteria (AIC) for each model, which allows us to test out-of-sample predictive power.[22] These fit statistics for our primary model (Model 1) are reported in Table 8.

First consider Columns (1) through (4). Column (1) provides model fit statistics for our primary model when only including house type indicators and a linear time trend. In Column (2), we see that when additional control parameters are included both the adjusted deviance and AIC decrease, which signals improvement in the fit of the model. When our primary variables of interest are added in Column (3), both measures decrease further, indicating additional

[20] Gelman and Hill claim adjusted deviance is analogous to the adjusted R^2 in simple linear regression (525).
[21] "If k predictors are added and the deviance declines by significantly more than k, then we can conclude that the observed improvement in predictive power is statistically significant" (Gelman and Hill, 525).
[22] AIC measures the fit of a model for a given set of data, where AIC = adjusted deviance + number of predictors.

improvement in model fit. To show this improvement is not coincidental, we replace the three primary variables with three random variables that follow a normal distribution with a mean of zero and standard deviation equivalent to that of the specific variable they replace. Column (4) reports the fitness measurements for this specification. We expected the inclusion of our primary variables of interest to improve the fit of the model, but we expect to find no such evidence of improved fit here when the additional variables are nothing but random noise. Indeed, this is what we find; both the adjusted deviance and AIC are larger compared to Column (3)'s values, while the deviance itself is essentially unchanged from Column (2).

Now consider Columns (5) through (7). These specifications follow a progression similar to that just discussed for Columns (2) through (4), except with the inclusion of number of sales by house type. Column (5) provides fitness measurements for our primary model when including number of sales by house type and excluding our three primary variables. Both the adjusted deviance and AIC decrease compared to statistics reported in Column (2), which signals an improvement in the fit of our model when the number of sales by house type is included as a control. When adding our three primary variables of interest in Column (6), we observe an additional decrease in both adjusted deviance and AIC. Again, to show this improvement is not coincidental, we replace the three primary variables with the same randomly generated variables included in Column (4). Interpretation of Column (7)'s deviance statistics remains consistent with Column (4)'s interpretation.[23]

The fitness measurements reported in Table 8 provide statistical support for our decision to include the specified control variables in Model 1 and, most importantly, support the inclusion

[23] Likelihood ratio tests comparing the same models compared using deviance analysis were also conducted with identical conclusions.

of our three primary variables. When adding our primary variables of interest, we are able to improve the fit of our model, which signals the percentage of minor applications accepted during a boom or bust period plays an important role in predicting house prices. This in turn reinforces our argument that there is indeed an effect of planning authority leniency during boom or bust periods on house prices, and that effect not only aligns with what economic theory tells us, but is also statistically significant at the 5 percent level, or better.

Table 8
Model Checking Using Deviance Statistics

	Model Comparison						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Boom Indicator	No	No	**Yes**	No	No	**Yes**	No
Boom Indicator x Percentage of Minor Applications Accepted	No	No	**Yes**	No	No	**Yes**	No
Bust Indicator x Percentage of Minor Applications Accepted	No	No	**Yes**	No	No	**Yes**	No
Home Type Indicator: Semi-Detached	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Home Type Indicator: Terraced	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Home Type Indicator: Flats	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Year	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Population (in 1,000s)	No	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Net Migration (in 1,000s)	No	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Number of Minor Residential Applications	No	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Total Area of Borough (SqKm)	No	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Distance (miles)	No	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Number of Major Residential Applications	No	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Detached Indicator x Number of Detached Sales	No	No	No	No	**Yes**	**Yes**	**Yes**
Semi-Detached Indicator x Number of Semi-Detached Sales	No	No	No	No	**Yes**	**Yes**	**Yes**
Terraced Indicator x Number of Terraced Sales	No	No	No	No	**Yes**	**Yes**	**Yes**
Flat Indicator x Number of Flat Sales	No	No	No	No	**Yes**	**Yes**	**Yes**
Random Variable 1: N(0,0.3479905)	No	No	No	**Yes**	No	No	**Yes**
Random Variable 2: N(0,24.33832)	No	No	No	**Yes**	No	No	**Yes**
Random Variable 3: N(0,19.94635)	No	No	No	**Yes**	No	No	**Yes**
Number of Observations	1576	1576	1576	1576	1576	1576	1576
Number of Parameters	7	13	16	16	17	20	20
Deviance	-336.69	-444.38	-460.43	-444.64	-546.85	-569.47	-547.13
Adjusted Deviance	-329.69	-431.38	-444.43	-428.64	-529.85	-549.47	-527.13
AIC	-322.69	-418.38	-428.43	-412.64	-512.85	-529.47	-507.13

Deviance = -2(log-likelihood) Adjusted Deviance = -2(log-likelihood) + k AIC = -2(log-likelihood) + 2k , where k is the number of parameters
Estimates in this table are compared across models with changing fixed effects parameters and unchanged random effects.
Dependent variable is median price by house type. Log-likelihoods for these estimates were generated under maximum likelihood estimation.
All fit statistics included in this table can be interpreted as “smaller-is-better.”

5 DISCUSSION AND IMPLICATIONS OF RESULTS

Our empirical results are consistent with our hypothesis both following a boom period and bust period. We observe that when regulatory restrictiveness increases during a boom period, meaning housing supply is becoming more inelastic because fewer applications for residential projects are being accepted, resulting in less new development, then house prices will be higher in the following year compared to a less restrictive market holding all else equal. Alternatively, when regulatory restrictiveness decreases, meaning housing supply is becoming more elastic because more applications for residential projects are being accepted, resulting in more new development, then house prices will not rise as rapidly compared to a more restrictive market. This implies, given a price boom, house prices will be lower in areas that have a more lenient planning authority and house prices will be higher in areas that have a stricter planning authority.

Our empirical results also remain consistent with our hypothesis following a price bust. We observe that when regulatory restrictiveness increases during a bust period, meaning housing supply is becoming more inelastic, then house prices will be lower compared to a less restrictive market holding all else equal. Alternatively, given the previous year was a bust, when regulatory restrictiveness decreases, meaning housing supply is becoming more elastic, then house prices will decrease less than under more restrictive regulation. This implies, given the previous period was a bust, house prices will be higher in areas that have a more lenient planning authority and house prices will be lower in areas that have a stricter planning authority.

These results indicate that when a planning authority is stricter by having a low acceptance rate of residential planning applications, then house prices in that area will grow higher during a boom and will fall by more during a bust. Therefore, price changes will be greater compared to areas with less restrictive planning authorities.

Though our hypotheses hold true, there are several opportunities for improvement that warrant further exploration. One is a more detailed examination of the residential project development application process. In the UK, applications for new residential projects are divided into "minor" projects with fewer than ten dwellings and "major" projects with ten or more dwellings. In Section 3 we argued why it is sensible to use the acceptance rate of applications for minor residential projects as the measure of regulatory restrictiveness. However, an examination of alternative measures may deepen our understanding of the effect of supply constraints on housing prices. In addition, a careful consideration of any potential endogeneity in the application and approval process may also prove fruitful.[24]

In future work we would also like to obtain data with more observations across both boroughs and years. This would allow us to examine if the nature of the relationship between planning induced supply constraints and house prices is different in other UK metropolitan areas, and if so, to what extent. Having a richer data set with areas that are geographically separated from the boroughs of London may also allow us to better control for any potential spillover effects. This concern arises due to the close proximity of London's boroughs, which potentially allows nearby boroughs to be substitutes for both housing supply and demand.

In addition, it would be informative to see how policy changes have affected house prices in London. Specifically, what policy changes have created either housing supply or demand shocks, *e.g.,* loan rate or loan acceptance changes? Furthermore, it would be informative to see how foreign investment in London's residential real estate market has affected housing supply and demand. For example, Green and Bentley claim that London Property Partners found that up to 85

[24] For example, if decision makers of a borough's planning authority were to read this paper, how might that affect their future planning decisions?

percent of prime London property purchases in 2012 were made with foreign money and, therefore, the nature of foreign investment is distorting residential development priorities towards more luxury real estate.

6 CONCLUSION

Using data from 32 of London's boroughs, our study empirically examines how planning induced supply constraints affect the median price of houses following a boom period and a bust period between 2001 and 2013. Our analysis reveals that a borough with a strict planning authority will have higher house prices following a boom period and lower house prices following a bust period compared to prices in a borough with a more lenient planning authority. Therefore, house prices in a more restrictive environment with an inelastic housing supply change faster than prices in a less restrictive environment with a more elastic housing supply. As stated previously in this paper, not only are high housing prices of concern, but so too are fast changes in asset prices, both of which can have severe economic consequences. Understanding these partial root causes of the current state of London's residential real estate market is an important step towards ensuring not just the market's success, but also London's success.

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APPENDIX

This appendix includes the regression equations for Models 2, 3, and 4 that were not included in the body of the paper. The equation for Model 1 is also included for ease of comparison. In each equation, $boom\ indicator$ is an indicator variable equal to one in periods of economy-wide rising house prices, $bust\ indicator = 1 - boom\ indicator$, and *percentage of minor applications accepted* is the percentage that are accepted of all applications received for residential development projects affecting fewer than ten dwellings.

Model 1: linear time trend

$$\begin{aligned}\log(median\ price_{i,j,t}) = {} & (\beta_0 + \delta_{0,i}) + \beta_1 \cdot boom\ indicator_{t-1} \\ & +\beta_2 \cdot (boom\ indicator_{t-1}\ \text{x}\ percentage\ of\ minor\ applications\ accepted_{i,t-1}) \\ & +\beta_3 \cdot (bust\ indicator_{t-1}\ \text{x}\ percentage\ of\ minor\ applications\ accepted_{i,t-1}) \\ & +\beta_4 \cdot year_t + \boldsymbol{X}_{i,t} \cdot \boldsymbol{\beta}_X + \boldsymbol{W}_{i,t-1} \cdot \boldsymbol{\beta}_W + \boldsymbol{Z}_i \cdot \boldsymbol{\beta}_Z + \boldsymbol{K}_j \cdot \boldsymbol{\beta}_K + \boldsymbol{S}_{i,j,t} \cdot \boldsymbol{\beta}_S + \varepsilon_{i,j,t}\end{aligned}$$

for borough *i*, house type *j*, at time *t*. $\boldsymbol{X}_{i,t}$ is a vector of time specific control variables, $\boldsymbol{W}_{i,t-1}$ is a vector of lagged control variables, $\boldsymbol{Z}_i$ is a vector of time invariant control variables, $\boldsymbol{K}_j$ is a vector of house type indicator variables, $\boldsymbol{S}_{i,j,t}$ is a vector of interaction variables between house type and total number of sales by type, and finally $\varepsilon_{i,j,t}$ is the idiosyncratic error term.

Model 2: No linear time trend

$$\begin{aligned}\log(median\ price_{i,j,t}) = {} & (\beta_0 + \delta_{0,i}) + \beta_1 \cdot boom\ indicator_{t-1} \\ & +\beta_2 \cdot (boom\ indicator_{t-1}\ \text{x}\ percentage\ of\ minor\ applications\ accepted_{i,t-1}) \\ & +\beta_3 \cdot (bust\ indicator_{t-1}\ \text{x}\ percentage\ of\ minor\ applications\ accepted_{i,t-1}) \\ & +\boldsymbol{X}_{i,t} \cdot \boldsymbol{\beta}_X + \boldsymbol{W}_{i,t-1} \cdot \boldsymbol{\beta}_W + \boldsymbol{Z}_i \cdot \boldsymbol{\beta}_Z + \boldsymbol{K}_j \cdot \boldsymbol{\beta}_K + \boldsymbol{S}_{i,j,t} \cdot \boldsymbol{\beta}_S + \varepsilon_{i,j,t}\end{aligned}$$

for borough *i*, house type *j*, at time *t*. $\boldsymbol{X}_{i,t}$ is a vector of time specific control variables, $\boldsymbol{W}_{i,t-1}$ is a vector of lagged control variables, $\boldsymbol{Z}_i$ is a vector of time invariant control variables, $\boldsymbol{K}_j$ is a vector of house type indicator variables, $\boldsymbol{S}_{i,j,t}$ is a vector of interaction variables between house type and total number of sales by type, and finally $\varepsilon_{i,j,t}$ is the idiosyncratic error term.

Model 3: Linear time trend included

$$\log(median\ price_{i,t}) = (\beta_0 + \delta_{0,i}) + \beta_1 \cdot boom\ indicator_{t-1}$$
$$+\beta_2 \cdot (boom\ indicator_{t-1} \text{ x } percentage\ of\ minor\ applications\ accepted_{i,t-1})$$
$$+\beta_3 \cdot (bust\ indicator_{t-1} \text{ x } percentage\ of\ minor\ applications\ accepted_{i,t-1})$$
$$+\beta_4 \cdot year_t + \boldsymbol{X}_{i,t} \cdot \boldsymbol{\beta}_X + \boldsymbol{W}_{i,t-1} \cdot \boldsymbol{\beta}_W + \boldsymbol{Z}_i \cdot \boldsymbol{\beta}_Z + \varepsilon_{i,t}$$

for borough *i* at time *t*. $\boldsymbol{X}_{i,t}$ is a vector of time specific control variables, $\boldsymbol{W}_{i,t-1}$ is a vector of lagged control variables, $\boldsymbol{Z}_i$ is a vector of time invariant control variables, and finally $\varepsilon_{i,t}$ is the idiosyncratic error term.

Model 4: No linear time trend

$$\log(median\ price_{i,t}) = (\beta_0 + \delta_{0,i}) + \beta_1 \cdot boom\ indicator_{t-1}$$
$$+\beta_2 \cdot (boom\ indicator_{t-1} \text{ x } percentage\ of\ minor\ applications\ accepted_{i,t-1})$$
$$+\beta_3 \cdot (bust\ indicator_{t-1} \text{ x } percentage\ of\ minor\ applications\ accepted_{i,t-1})$$
$$+\boldsymbol{X}_{i,t} \cdot \boldsymbol{\beta}_X + \boldsymbol{W}_{i,t-1} \cdot \boldsymbol{\beta}_W + \boldsymbol{Z}_i \cdot \boldsymbol{\beta}_Z + \varepsilon_{i,t}$$

for borough *i* at time *t*. $\boldsymbol{X}_{i,t}$ is a vector of time specific control variables, $\boldsymbol{W}_{i,t-1}$ is a vector of lagged control variables, $\boldsymbol{Z}_i$ is a vector of time invariant control variables, and finally $\varepsilon_{i,t}$ is the idiosyncratic error term.

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