Shale Gas Development and Housing Value in the United Kingdom: Impact of the 13th Onshore Licensing, 2008

Esther Lho

Professor Christopher D. Timmins, Faculty Advisor

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Abstract

While shale gas is a prospective energy source, it is known to bring environmental deficits to the drilling neighborhood. Because of such concerns, property values fluctuate upon the possibility of shale gas fracturing. This paper examines the change in housing prices before and after the release of the 13th onshore oil and gas licensing round, which took place in 2008 when shale gas was increasingly being considered as the alternative to ease the United Kingdom's dependency on coal. Results suggest that the 2008 licensing has caused a 3% decrease in housing price growth rate for the licensed areas.

JEL classification: Q5, Q42, Q51

Keywords: shale gas, fracturing, property valuation, housing prices, consumer expectation, hedonic price, United Kingdom

1 Introduction

With cost-reducing technological innovation such as hydraulic fracturing and horizontal drilling, shale gas is becoming an increasingly promising source of energy. With the energy shift suggested by the United States' initiation of the shale energy boom, shale gas has gradually attracted more attention in other countries with shale reserves. The shale gas boom in the U.S. has recently boosted domestic energy companies and the persistent effort has resulted in shale gas exploration becoming more commercially viable. The boom has led some scholars to believe that shale gas will be able to support global energy needs for the next sixty years, especially with the large reserves that are being identified, drawing various countries' interest into their potential wells. While shale gas is receiving a lot of attention as an important energy supply, its exploration has worried many because of its environmental risks. The most prominent concerns include groundwater contamination, surface water contamination, noise, light, air pollution, traffic congestion and road damage (Muehlenbachs, Spiller & Timmins, 2014).

Onshore shale gas production was first proposed in the United Kingdom in 2007, which naturally brought a lot of attention to shale gas fracturing. However, even though test wells were drilled, there has been no commercial drilling in the U.K. One of the U.K.'s shale gas forerunners, Caudrilla faced some setbacks in the process of pursuing a test well and was regulated to a halt due to unstable seismic activity and has also encountered local council's deferment; however, despite such obstacles, shale gas is still considered a prominent energy strategy in the U.K. Active drilling has significant economic benefits not only with respect to possible independence from fossil fuel but also for the local communities where the drilling sites are located. The local economic gains include job creation, lower bills and tax revenues. Drilling companies are also willing to provide incentives to the communities by paying approximately 100,000 GBP as a community benefit and sharing one percent of the production revenue.

The purpose of this paper is to identify the impact of shale gas hydraulic fracturing on the housing market in the United Kingdom. Whether property values will be affected by shale gas development remains controversial. There are claims in the media complaining about the drop in housing prices for regions in vicinity of the exploration wells while the articles were dismissed for lack of evidence by the British Department of Energy and Climate Change (DECC). DECC countered the news release, arguing real estate values should not be affected by shale gas operations as it did not by other oil and gas exploration over the past half a century. In order to

provide more insight into the debate, this paper analyzes the change in housing prices in light of the release of the onshore licensing in 2008 by implementing the hedonic demand theory. First, I will match licensed output areas with non-licensed output areas that have the closest resemblance in household and neighborhood attributes. Then, I will measure the difference-in-difference of the mean prices of post-treatment and pre-treatment. I will do the same for the natural log of the mean prices in the hopes that the results will exemplify the effect of shale gas fracturing on the housing market.

The next section discusses current literature that is relevant to the paper, particularly with regards to academic research conducted on property pricing and the impact of shale gas development. The following section describes how the research was conducted and what kind of empirical framework was utilized. Section 4 describes the data followed by the results in Section 5 and conclusion in Section 6.

2 Background

Throughout literature, it is evident that neighborhood environmental quality is an inevitable factor in property valuation. A number of research projects examine how different sources of contamination impact property prices to what magnitude (e.g. Henrik, Jonsson & Ögren, 2010), and other projects conduct experimental research on consumers' willingness-to-pay to avoid risk of environmental damages such as the protection of local watersheds (e.g. Bernstein, Kinnaman & Wu, 2013). Similar research has been done regarding environmental disruption caused by shale gas (Siikamaki & Krupnick, 2014). Siikamaki & Krupnick, 2014 conducts a study targeting the public on stated preference regarding risk related to shale gas in Pennsylvania and Texas. With the presence of environmental disamenities, it is indisputable that home buyers are going to react to the sign.

With respect to academic research on shale gas, shale gas studies in the U.S., particularly about Pennsylvania and Texas, should be noted as the pioneer pieces. With Klaiber and Gopalakrishnan (2012) as one of the first academic projects that investigated the impact of shale gas wells in Pennsylvania, Muehlenbachs, et al., 2014 discusses the hedonic estimates of housing values from shale gas development in Pennsylvania and New York in more depth. The research focuses on quantifying the numerous costs and benefits of shale gas exploration in an area,

including that brought on by the "boom town" phenomenon, where the developmental areas face population increase, employment opportunities, active business activities, increased crime rates, increased housing rental costs and pollution. The paper looks at four major impact categories: adjacency effects, groundwater contamination risk, vicinity effects and macro effects. In sum, the average effect of shale gas development is less than one percent according to the research. It argues that there is a large negative impact on groundwater-dependent homes whereas relatively smaller positive impact on piped-water-dependent homes and goes into more detail with regards the vicinity level as well as the positive externalities of shale gas development on smaller towns This paper is particularly powerful in that it was able to identify housing sales at what stage was most heavily impacted versus the long-term impact of the wells.

The literature concerning environmental problems mainly delves into the negative externalities that human development has had and provides insight on the magnitude of the negative impact. Since shale gas in the United Kingdom has barely had any noticeable externalities or damages, I would like to tailor my analysis to the earlier development stage in the United Kingdom and observe the public perception on the new energy source rather than restricting it to a specific observable concern. Based on some of the implications from Muehlenbachs, et al., 2014, there seems to be possible positive impacts when drilling companies provide partial lease payments. However, payment in the form of community benefit did not have as positive of an impact as the lease payment, which is what exploring companies are currently offering. Thus, I hypothesized that there would be a decrease in housing prices but because it was only a perceived cost, housing prices would not plummet heavily.

I would eventually like to advance this research into an academic inquiry of several rounds of examination in order to successfully diagnose the influence that shale gas has on consumption behavior. Literature on shale gas in the U.K. is scare, which is why I believe that this paper is valuable in that it provides new information to academia and is especially effective because the exploratory progress of shale gas in the U.K. is still at its introductory level and thus, this addition of knowledge could advise on directions for environmental policy regarding granting permission for and imposing regulations on drillers to explore shale gas.

3 Method

3.1 Hedonic Pricing Model

This paper actively utilizes the hedonic pricing model like many other literatures that implements the method in order to measure the value or cost of environmental amenities that are capitalized in the market price (Klaiber & Gopalakrishnan, 2012). Hedonic pricing model hypothesizes that the price of a good is a function of its attributes. Hedonic price refers to the implicit price of the good's attributes and is observable through differentiated products (Rosen, 1974). In other words, if there were two identical regions with respect to all other attributes except for the treatment variable, the difference in price would indicate consumers' willingness-to-pay for the treatment. For this research, we will assume a linear hedonic price function and homogeneous preferences in order to diagnose the simplified effect of the licenses.[1]

In this study, the composite good is a property and the treatment variable is the presence of the 2008 license. Given that $\mathbf{A} = [a_1, \ldots, a_n]$ captures housing attributes and L is a treatment dummy that takes the value 1 if a property is located within a 2008 license area, the hedonic price function for the property is

$$P = P(L, \boldsymbol{A}) \tag{1}$$

Because consumers' willingness-to-pay is optimally equal to the market price of the commodity, consumers' willingness-to-pay and marginal willingness-to-pay can be expressed as

$$WTP = P(L, \boldsymbol{A}) \tag{2}$$

$$MWTP = \frac{\partial P(L, \boldsymbol{A})}{\partial L} \tag{3}$$

This demonstrates that the coefficient that is yielded as the result represents the change in property value depending on the change in licensing status (Andersson, Jonsson & Ögren, 2009).

Moreover, it is important to note that the license attribute is an aspect borne from consumer expectation. Consumers expect the property to change a certain way and alter their decision (i.e. willingness-to-pay) based on this anticipation.

[1] The linear hedonic price function is not realistic in most empirical settings (Bishop & Timmins, 2011). However, the model is utilized in order to provide a simplified representation of the price change situation rather than to precisely replicate reality.

3.2 Nearest-neighbor matching (NNM) estimator

The nearest-neighbor matching estimator was used to identify matches based on treated areas and controlled areas. The teffects nnmatch function applies the NNM estimator for the average treatment effect (ATE) in this study. The function operates based on the binary-treatment potential-outcome model where t=1 is for licensed areas and t=0 is for unlicensed, controlled areas. Let y_1 be the potential outcome when treatment occurs and y_0 be the potential outcome of where the treatment does not occur. The basic mechanism of ATE is to find

$$\tau_1 = E(y_1 - y_0) \quad (4)$$

Because the treatment is binary, y_{1i} and y_{0i} cannot happen together. The NNM estimator uses the different attributes to match the most similar observations that are in different treatment levels (Abadie, Drukker, Herr & Imbens, 2004). The assumption here is that the treatment's effect is localized and that the treatment status is not correlated with other household or neighborhood attributes. In light of the purpose of the study, shale reserves do not impact household composition or socioeconomic characteristics of the residents neither is it the fundamental foundation for the United Kingdom's housing distributions. Therefore, the assumption seems to be reasonable.

The NNM estimator was conducted for two observation variables: the difference between the mean pre-treatment and post-treatment prices and the difference between the change in mean pre-treatment and post-treatment prices. Moreover, the match number was controlled for match = 1, 4, 10, 15 and 20 matches for each observation variable.

3.3 Difference-in-Difference of mean prices

The double-difference nearest neighbor matching is utilized in order to avoid time variation (Muehlenbachs, et al., 2014). For each output area, the average prices for all years before licensing (i.e. transactions from 2003 to 2007) and after licensing (i.e. transactions from 2009 to 2013) were taken. Transactions for 2008 were not included in the analysis. All prices were normalized with the relevant year's housing price index to be in constant pounds. Then the difference between the post price and pre price was taken, which was used as one of the observation variables when conducting the NNM estimator. For instance,

$$A_{diff} = A_{post} - A_{pre} \quad (5)$$

$$B_{diff} = B_{post} - B_{pre} \quad (6)$$

$$P_{diff} = A_{diff} - B_{diff} \quad (7)$$

where: A is the output area that will be licensed in 2008
A_{post} is the mean price of all transactions after 2008 for area A
A_{pre} is the mean price of all transactions before 2008 for area A
B is the control area
B_{post} is the mean price of all transactions after 2008 for area B
B_{pre} is the mean price of all transactions before 2008 for area B

The results from this observation variable represent how the change in prices in a license area is different from that in a non-licensed area.

3.4 Difference-in-Difference of change in mean prices

Likewise, instead of taking the difference between the prices in section 3.3, the natural log for each pre and post prices were taken. Subsequently, the difference between the natural logs was taken and was run in the estimator.

$$A_{diff\_ln} = \ln(A_{post}) - \ln(A_{pre}) \quad (8)$$

$$B_{diff\_ln} = \ln(B_{post}) - \ln(B_{pre}) \quad (9)$$

$$P_{diff\_ln} = A_{diff\_ln} - B_{diff\_ln} \quad (10)$$

This observation variable demonstrates the difference in the growth rate in prices of a licensed area versus that of a non-licensed area.

4 Data

4.1 Housing transaction data

Housing transaction data originated from the Land Registry Price Paid Data at data.gov.uk. The data was originally organized in months, and I restricted them to the period 2003 to 2013 for the purpose of this research. In the process of clean up, transactions that did not have identifiable output areas were deleted. The dataset consisted of 19,728,346 observations, indicating that there were 19,728,346 transactions between 2003 and 2013.

4.2 Household and neighborhood demographic data

Housing attributes were obtained from the United Kingdom census at the Office for National Statistics. All data was collected from the British Census for 2001. The data was collected for 2001 in order to base all attributes and information on the pre-treatment stage. Data for individual attributes were collected and compiled. Housing attributes that were used as control variables include (for full variable list, see Appendix A.2):

Code	Category
UV02	Population Density
UV03	Sex
UV09	Ethnic Group
UV24	Education Qualifications
UV31	National Statistics Socioeconomic Classification
UV34	Industry of Employment
UV50	Approximated Social Grade
UV51	Number of People in Households
UV56	Accommodation Type: Household Spaces
UV57	Number of Rooms
UV63	Tenure Households
UV65	Household Composition
UV68	Household Type

Other attributes, such as ethnic group, gender, education level, employment status, household tenure status, household type, household size and spatial composition, were chosen based on conventional urban literature. Some essential categories such as age and household income were not available on the output area level or had substitutes (Bajari & Kahn, 2005). For instance, household income has been replaced with industry of employment, approximate social grade and socioeconomic classification, which enables estimation of the household's income level. Household composition, the relationship of the people living in the household, took the place of age; although not synonymous, the two categories both pointed towards family shape, which was an important aspect of comparing housing situations between two geographical areas.

There were 175,434 observations in this dataset and 204 variables. While there are categories that are correlated, this is not significant because the attributes are only used for matching purposes and are not part of the coefficient calculation. Also, some variables are automatically eliminated by the program module due to collinearity.

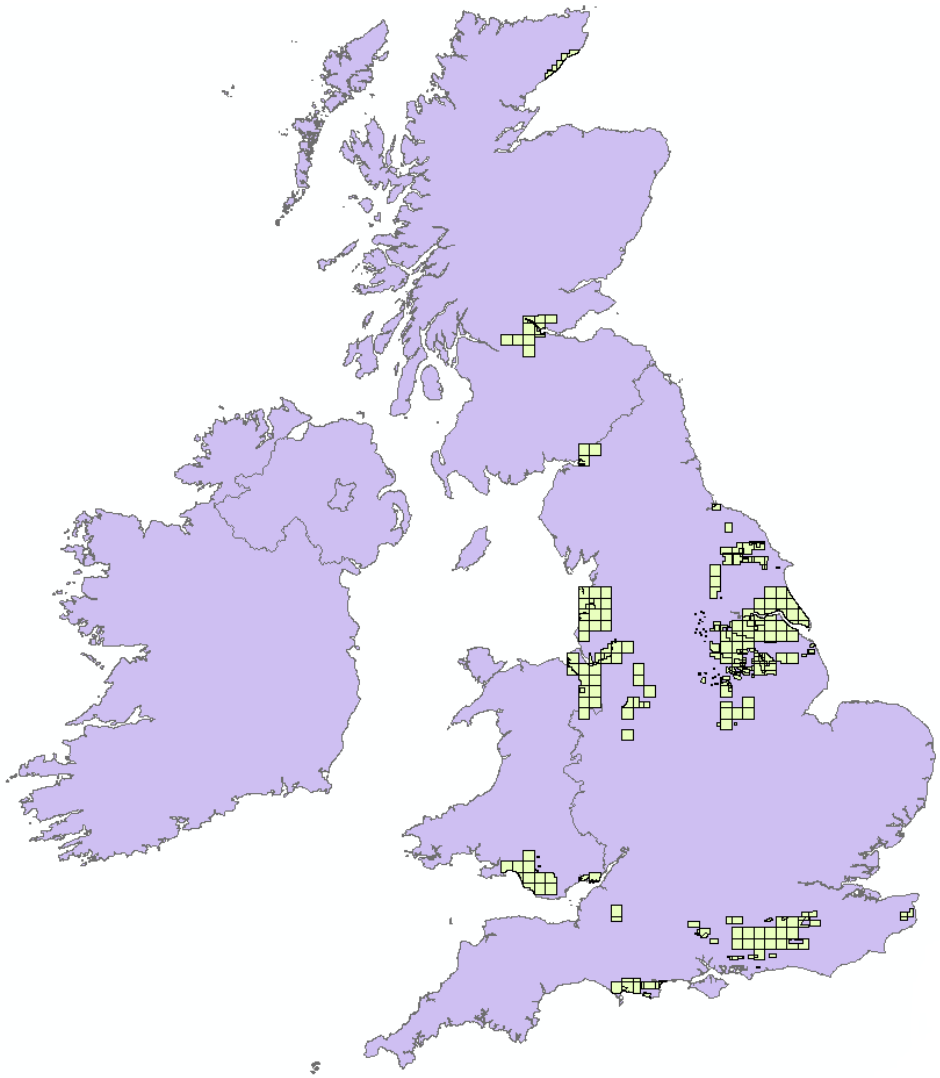
4.3 13th Onshore Oil and Gas Licensing Round

The data on treatment was created through a geographic information system software, ArcGIS, by compiling geographic data accessed from the Office of National Statistics for the output area map and DECC for the license and contour map (see Figure 1).

4.4 Data organization

Output areas were the basic unit of analysis; thus, postcodes were related the output areas during the organization process. Postcode to output area data was accessed through the Office of National Statistics. Transaction prices of each output area were averaged based on their transaction period as aforementioned. The mean price was dependent upon whether it happened pre-treatment (before 2008) or post-treatment (after 2008). Data for mean prices of transactions that happened in 2008 were not used because of the uncertainty of when consumer expectations took place relative to the licensing year. Consequently, there were 173,024 output areas with observations for which the analysis could be conducted on.

Figure 1: Licensed Blocks from 13th Onshore Licensing Round



5 Results

Table 1: Summary Statistics

Match =	1	4	10	15	20	average
DID in P_mean	-6031.663	-6166.181	-6162.12	-6156.979	-6156.863	-6134.7612
DID in ln(P_mean)	-0.0349793	-0.0358497	-0.0360717	-0.0360822	-0.0360922	-0.03581502

Note: The first column demonstrates the results for the geographical difference in difference of mean prices of pre-treatment and post-treatment. The unit for the first column is in pound sterling normalized to 2001. The second column shows the results for the geographical difference in difference of the natural log of mean prices of pre-treatment and post-treatment. The unit for the second column is in decimals and can be represented as a percent increase.

Match = 1 indicates that there were one set of output areas each in different treatment levels that were matched for best similarity among other variables (i.e. housing attributes). According to the first column of Table 1, licensing caused housing prices to decrease by approximately 6,031.66 GBP and the growth rate of housing prices decreased by 3.50% with the presence of the license. Similarly, column 2 show the results when the neighboring matches are set to four matches. Licensing caused housing prices to decrease by approximately 6166.18 GBP and the housing price growth rate to decrease by 3.58%. The same analyses were conducted on ten, fifteen and twenty matches. The average effect of licensing was a 6,162.12 GBP drop and 3.61% reduction in housing price growth rate.

Table 2: Difference between mean of pre- and post-licensed prices

				Match =		20
Treatment-effects estimation				Number of obs =		173024
Estimator: nearest-neighbor matching				Matches requested =		20
Outcome model: matching				min =		20
Distance metric: Mahalanobis				max =		21
mean_norm_~f	Coef.	Al Robust Std. Err.	z	P>|z|	[95% Conf. Interval]	
ATE						
License_Join (1 vs 0)	-6156.863	409.3174	-15.04	0	-6959.11	-5354.615

Table 3: Difference between natural log of mean pre- and post-licensed prices

				Match =		20
Treatment-effects estimation				Number of obs =		173024
Estimator: nearest-neighbor matching				Matches requested =		20
Outcome model: matching				min =		20
Distance metric: Mahalanobis				max =		21
ln_mean_norm_~f	Coef.	Al Robust Std. Err.	z	P>|z|	[95% Conf. Interval]	
ATE						
License_Join (1 vs 0)	-0.0360922	0.003324	-10.86	0	-0.0426072	-0.0295773

The number of matches used does make a difference. Too few matches makes the data rely on too little information whereas a large number of matches forces NNM estimator to generate statistics from non-similar areas. Because the sample size is large (n = 173,024) relative to the number of matches (max = 20), it is likely that the aforementioned sacrifice in forcing non-similar matches is slim. Although it is not clear what the optimal number of matches is, the results shown above demonstrate that the matching mechanism is effective given the stability of the results despite the number of matches. Moreover, P > |z| for all ten results approximate to zero, implying that all the results are significant and that there is a difference between the difference between licensed areas and the non-licensed controlled areas. This implies that home buyers value the environmental well-being of their house and neighborhood more than the potential economic perks such as the community benefit provided in the form of initial bulk payment as well as a possible revenue stream given active utilization of the well. Home buyers expect disamenities caused by environmental development to be of greater loss than the financial payment and the conceivable boom.

6 Conclusion

In this paper, I aimed to study the consequences that the 13th round of onshore oil and gas licensing would bring to the public's reaction with respect to their purchasing behavior in the housing market. I examined the change in housing prices and the change in the growth rate of housing prices before and after the licensing period and found the difference between these differences. Through this study, I was able to find out that housing prices dropped by approximately 6,134.76 GBP and the growth rate of housing prices dropped by approximately 3.58% on average due to the release of the licensing. This is particularly significant considering that the effects of shale gas exploration have not yet taken place and the results were solely a reaction founded on consumers' expectation. As the United Kingdom is on its launching stage of shale gas exploitation, it would be eminent to consider these valuations in the public policy debate.

There are several limitations to this research. First, conducting a difference-in-differences analysis assumes that the locations that have been matched will trend in the same manner if it

were not licensed. In other words, the assumption is that the change in the non-licensed area is identical to that of the licensed area if it were not treated. While the consistency of the results provides some evidence that the matches are well-paired, this is uncertain and is theoretically difficult to replicate.

Moreover, there are several ambiguities in the assumptions. The hypothesis assumes that everybody in the U.K. is well aware of the licensing status and updates of their regions. Although there are articles that show that licensing rounds have been covered in the media such as the news[2], it is uncertain as to how prevalent the knowledge of permits is. On the other hand, it is also possible for people to refrain from purchasing property before the permit is granted if they are aware that a geographical block is being offered in the coming licensing round. For this limitation, it would be helpful to recognize the most popular source of information the local people use and conduct research through that route in order to ensure that people are acting with the knowledge of shale gas development in the area.

Additionally, because the U.K. started gaining interest in 2007 and the idea of shale gas fracturing was viable, this analysis considers all blocks that received the 13th licensing to be interested in testing shale gas. This can be reasonable since the study is measuring consumer expectations; home buyers would be aware of the possibility of fracturing and act accordingly. However, it would have been helpful to know whether there were different routes that the public was gathering shale gas news. By being aware of this route, it would have been possible to acknowledge whether some areas are being mentioned more often than others with respect to company's interest in drilling. Consequently, the locations that were mentioned more often could have experienced a harsher outcome.

For future research, it would be beneficial to examine sources that are more public friendly. For instance, using media coverage as the treatment could be a powerful component because news media is a more accessible source of information and everyday knowledge for the public. For such study, it would be valuable to have a treatment variable that gives variance in degree among the output areas by using factors such as the frequency of coverage or the number of distributor publishing the content. A case study on a relatively active area such as Lancashire

[2] For example, news article regarding recent permission to drill for shale gas. "Fracking firm gains permits to drill for gas in Lancashire," *Lancashire Telegraph*, 8 February 2015. http://www.lancashiretelegraph.co.uk/news/11778913.Fracking_firm_gains_permits_to_drill_for_gas_in_Lancashire/

would be beneficial in order to examine whether the results are applicable to empirical cases. Furthermore, the continuation on the current research topic on licensing would be interesting with the 14th licensing round, which is anticipated to be finalized in 2015.

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http://data.gov.uk/dataset/land-registry-monthly-price-paid-data

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License and contour map - *DECC*
https://www.gov.uk/oil-and-gas-onshore-maps-and-gis-shapefiles

Output Area map – *Office of National Statistics*
http://data.gov.uk/dataset/output-areas-ew-2001-boundaries-full-clipped

Postcode to Output Area, "Postcodes (Enumeration) (2011) to output areas (2011) to lower layer super output areas (2011) to middle layer super output areas (2011) to local authority districts (2011) E+W Lookup" - *Office of National Statistics*
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Appendix A.1

Nearest-neighbor matching estimator results

Table 4: Difference between mean pre- and post-licensed prices

				Match =		1
Treatment-effects estimation				Number of obs =		173024
Estimator: nearest-neighbor matching				Matches requested =		1
Outcome model: matching				min =		1
Distance metric: Mahalanobis				max =		2
mean_norm_~f	Coef.	Al Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
ATE License_Join (1 vs 0)	-6031.663	487.5214	-12.37	0	-6987.188	-5076.139

Table 5: Difference between natural log of mean pre- and post-licensed prices

				Match =		1
Treatment-effects estimation				Number of obs =		173024
Estimator: nearest-neighbor matching				Matches requested =		1
Outcome model: matching				min =		1
Distance metric: Mahalanobis				max =		2
mean_norm_~f	Coef.	Al Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
ATE License_Join (1 vs 0)	-0.0349793	0.0037786	-9.26	0	-0.0423852	-0.0275734

Table 6: Difference between mean of pre- and post-licensed prices

				Match =		4
Treatment-effects estimation				Number of obs =		173024
Estimator: nearest-neighbor matching				Matches requested =		4
Outcome model: matching				min =		4
Distance metric: Mahalanobis				max =		4
mean_norm_~f	Coef.	Al Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
ATE License_Join (1 vs 0)	-6166.181	452.7	-13.62	0	-7053.456	-5278.905

Table 7: Difference between natural log of mean pre- and post-licensed prices

				Match =		4
Treatment-effects estimation				Number of obs =		173024
Estimator: nearest-neighbor matching				Matches requested =		4
Outcome model: matching				min =		4
Distance metric: Mahalanobis				max =		4
ln_mean_norm_~f	Coef.	Al Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
ATE						
License_Join						
(1 vs 0)	-0.0358497	0.0035835	-10	0	-0.0428732	-0.0288262

Table 8: Difference between mean of pre- and post-licensed prices

				Match =		10
Treatment-effects estimation				Number of obs =		173024
Estimator: nearest-neighbor matching				Matches requested =		10
Outcome model: matching				min =		10
Distance metric: Mahalanobis				max =		11
mean_norm_~f	Coef.	Al Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
ATE						
License_Join						
(1 vs 0)	-6162.12	430.3544	-14.32	0	-7005.599	-5318.64

Table 9: Difference between natural log of mean pre- and post-licensed prices

				Match =		10
Treatment-effects estimation				Number of obs =		173024
Estimator: nearest-neighbor matching				Matches requested =		10
Outcome model: matching				min =		10
Distance metric: Mahalanobis				max =		11
ln_mean_norm_~f	Coef.	Al Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
ATE						
License_Join						
(1 vs 0)	-0.0360717	0.0034496	-10.46	0	-0.0428328	-0.0293107

Table 10: Difference between mean of pre- and post-licensed prices

				Match =		15
Treatment-effects estimation				Number of obs =		173024
Estimator: nearest-neighbor matching				Matches requested =		15
Outcome model: matching				min =		15
Distance metric: Mahalanobis				max =		16
mean_norm_~f	Coef.	Al Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
ATE						
License_Join (1 vs 0)	-6156.979	418.1061	-14.73	0	-6976.452	-5337.506

Table 11: Difference between natural log of mean pre- and post-licensed prices

				Match =		15
Treatment-effects estimation				Number of obs =		173024
Estimator: nearest-neighbor matching				Matches requested =		15
Outcome model: matching				min =		15
Distance metric: Mahalanobis				max =		16
ln_mean_norm_~f	Coef.	Al Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
ATE						
License_Join (1 vs 0)	-0.0360822	0.0033777	-10.68	0	-0.0427025	-0.0294619

Appendix A.2

Table 12: Housing Attributes Variable List

Code	Category	Variable List	
UV02	Population Density	All People	
		Area (Hectares)	
		Density (Number of Persons per Hectare)	
UV03	Sex	All People	
		Males	
		Females	
UV09	Ethnic Group	All People	
		White	White: British
			White: Irish
			White: Other White
		Mixed	Mixed: White and Black Caribbean
			Mixed: White and Black African
			Mixed: White and Asian
			Mixed: Other Mixed
		Asian or Asian British	Asian or Asian British: Indian
			Asian or Asian British: Pakistani
			Asian or Asian British: Bangladeshi
			Asian or Asian British: Other Asian
		Black or Black British	Black or Black British: Caribbean
			Black or Black British: African
			Black or Black British: Other Black
		Chinese or Other Ethnic	Chinese or Other Ethnic Group: Chinese

		Group	Chinese or Other Ethnic Group: Other Ethnic Group	
UV24	Education Qualifications	All People		
		No qualifications		
		Level 1 qualifications		
		Level 2 qualifications		
		Level 3 qualifications		
		Level 4 / 5 qualifications		
		Other qualifications: Level unknown		
UV31	National Statistics Socioeconomic Classification	All People		
		1. Higher managerial and professional occupations	1.1 Large employers and higher managerial occupations	L1 Employers in large organisations
				L2 Higher managerial
			1.2 Higher professional occupations	L3.1 Higher professionals (traditional) - employees
				L3.2 Higher professionals (new) - employees
				L3.3 Higher professionals (traditional) - self-employed
				L3.4 Higher professionals (new) - self-employed
		2. Lower managerial and professional occupations	L4.1 Lower professionals and higher technical (traditional) - employees	
			L4.2 Lower professionals and higher technical (new) - employees	
			L4.3 Lower professionals and higher technical (traditional) - self-employed	
			L4.4 Lower professional and higher technical (new) - self employed	
			L5 Lower managerial	
			L6 Higher supervisory	
		3. Intermediate occupations	L7.1 Intermediate clerical and administrative	
			L7.2 Intermediate sales and service	
			L7.3 Intermediate technical and auxiliary	
			L7.4 Intermediate engineering	
		4. Small employers and own account workers	L8.1 Employers in small organisations (non-professional)	
			L8.2 Employers in small organisations (agriculture)	

			L9.1 Own account workers (non-professional)
			L9.2 Own account workers (agriculture)
		5. Lower supervisory and technical occupations	L10 Lower supervisory
			L11.1 Lower technical craft
			L11.2 Lower technical process operative
		6. Semi-routine occupations	L12.1 Semi-routine sales
			L12.2 Semi-routine service
			L12.3 Semi-routine technical
			L12.4 Semi-routine operative
			L12.5 Semi-routine agriculture
			L12.6 Semi-routine clerical
			L12.7 Semi-routine childcare
		7. Routine occupations	L13.1 Routine sales and service
			L13.2 Routine production
			L13.3 Routine technical
			L13.4 Routine operative
			L13.5 Routine agricultural
		8. Never worked and long-term unemployed	L14.1 Never worked
			L14.2 Long-term unemployed
		Not Classified	L15 Full-time students
			L17 Not classifiable for other reasons
UV34	Industry of Employment	All People	
		A. Agriculture, hunting and forestry	
		B. Fishing	
		C. Mining and quarrying	
		D. Manufacturing	
		E. Electricity, gas and water supply	

		F. Construction
		G. Wholesale and retail trade, repairs
		H. Hotels and restaurants
		I. Transport, storage and communications
		J. Financial intermediation
		K. Real estate, renting and business activities
		L. Public administration and defence, social security
		M. Education
		N. Health and social work
		O. Other community, social and personal service activities
		P. Private households with employed persons
		Q. Extra-territorial organisations and bodies
UV50	Approximated Social Grade	All People Aged 16 and over in Households
		AB: Higher and intermediate managerial / administrative / professional
		C1: Supervisory, clerical, junior managerial / administrative / professional
		C2: Skilled manual workers
		D: Semi-skilled and unskilled manual workers
		E: On state benefit, unemployed, lowest grade workers
UV51	Number of People in Households	All Occupied Household Spaces
		1 person living in Household
		2 people living in Household
		3 people living in Household
		4 people living in Household
		5 people living in Household
		6 people living in Household
		7 people living in Household
		8 or more people living in Household

UV56	Accommodation Type: Household Spaces	All Household Spaces		
		In an Unshared Dwelling	House or Bungalow	Detached
				Semi-detached
				Terraced (including end-terrace)
			Flat, Maisonette or Apartment	In a Purpose-Built Block of Flats
				Part of a Converted or Shared House
				In a Commercial Building
			Caravan or Other Mobile or Temporary Structure	
		In a Shared Dwelling		
UV57	Number of Rooms	All Occupied Household Spaces		
		1 room		
		2 rooms		
		3 rooms		
		4 rooms		
		5 rooms		
		6 rooms		
		7 rooms		
		8 or more rooms		
UV63	Tenure Households	All Households		
		Owned	Owns outright	
			Owns with a mortgage or loan	
			Shared ownership	
		Social rented	Rented from Council (Local Authority)	
			Other social rented	
		Private rented	Private landlord or letting agency	
			Employer of a household member	
			Relative or friend of a household member	

			Other	
		Living rent free		
UV65	Household Composition	All Households		
		One person	Pensioner	
			Other	
		One family and no others	All pensioners	
			Married couple households	No children
				With one dependent child
				With two or more dependent children
				All children non-dependent
			Cohabiting couple family households	No children
				With one dependent child
				With two or more dependent children
				All children non-dependent
			Lone parent households	With one dependent child
				With two or more dependent children
				All children non-dependent
		Other households	With one dependent child	
			With two or more dependent children	
			All student	
			All pensioner	
			Other	
UV68	Household Type	All Households		
		Married couple household with dependent child(ren)		
		Married couple household with no dependent child(ren)		
		Cohabiting couple household with dependent child(ren)		
		Cohabiting couple household with no dependent child(ren)		

		Lone parent household with dependent child(ren)
		Lone parent household with no dependent child(ren)
		One person household
		Multi person household: All student
		Multi person household: All other