Gentrification and its Impact on Disadvantaged Households in London

EC331: Research in Applied Economics

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Abstract

In this paper I attempt to estimate the effect gentrification has on the rate of neighbourhood outmigration for different demographic groups. I take a cross sectional approach to my data analysis using a variety of different sources, including a household survey conducted by the Greater London Authority in 2002, house price data, and demographic statistics from the 1991 and 2001 Census. I find that households in the private rental sector are most likely to move out as a result of gentrification. I also provide moderate evidence that the reasons people are moving out is consistent with notions of displacement. This builds on the previous work by academics such Lance Freeman (2016), Jacob Vigdor (2002) and Rowland Atkinson (2001), and also provides evidence that they may have underestimated the effects of gentrification.

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Chapter 1

Introduction

In June 2017 a fire broke out in Grenfell Tower, a block of social housing apartments in West London. This resulted in a tragic loss of 71 lives, and served as a reminder that low income families are finding it increasingly difficult to find safe, good quality and affordable housing in the UK's capital.

One key aspect of this housing crisis is gentrification. This is the process whereby a traditionally working-class neighbourhood experiences an influx of middle-class residents, which often leads to increased rents for the incumbent residents (Glass, 1964). This paper attempts to examine the effect gentrification has on outmigration (ie. moving to another neighbourhood) for disadvantaged residents in London.

My hypothesis is that disadvantaged households – particularly households in the private rental sector – will face higher rates of outmigration in gentrifying areas compared to their counterparts in non-gentrifying areas, primarily due to increased rent.

This study takes a cross-sectional approach to analysing this hypothesis. The main source of data is from the *Greater London Authority Household Survey, 2002*, which asked 8,158 residents about their housing situation. The key dependent variable is whether respondents report they are likely to move in the next five years. I match this data with neighbourhood house price data and demographic data from the 1991 and 2001 Census, which informs us whether a neighbourhood is gentrifying or not.

Previous studies have taken a similar approach to this (Atkinson, 2001; Vigdor, 2002; Freeman et al., 2016 etc.), but have only found weak evidence of gentrification-induced-outmigration. This paper however finds robust evidence that gentrification leads to outmigration, particularly for households in the private rental sector.

These results are more compelling than previous papers due to the fact that previous studies have tended to use datasets that don't focus on urban populations and aren't intended to record outmigration.

Additionally, there is an endogeneity problem that previous studies do not account for: house price inflation is often associated with an increase in neighbourhood quality. So for every household that moves out due to increased rent, there may be another household that decides to stay put due to the increased neighbourhood quality. I address this by introducing an IV framework to estimate the 'true' effect of house price inflation.

This paper also investigates the reasons given for households moving. This provides moderate evidence that outmigration is consistent with notions of displacement.

Chapter 2

Literature Review

The sociologist Ruth Glass coined the term 'gentrification' in 1964. It was to describe working-class neighbourhoods experiencing an influx of middle-class residents. Originally this was considered an interesting quirk of urban geography but now it has become widespread (Butler and Hamnet, 2009).

One contentious issue is whether gentrification increases outmigration of the incumbent residents. Most papers (Atkinson, 2001; Freeman et al., 2016 etc.) describe this as 'displacement', however I mostly avoid this term because it implies the move is forced. While it may be forced for some households, other households will simply prefer lower rent or will be moving for reasons unrelated to house prices. In Chapter 6 I examine whether the outmigration is indeed due to displacement.

This literature review will examine the evidence for gentrification-induced-outmigration. The empirical evidence for this from previous studies is – at best – mixed.

2.1 Mechanisms

There are a variety of different mechanisms through which gentrification can cause outmigration. Most papers (Atkinson, 2001; Vigdor, 2002; Freeman et al., 2016 etc.) take into account the conventional neoclassical mechanism, whereby increased demand from incoming residents leads to increased house prices and increased rents. This leads to outmigration for incumbent renters, as they prefer cheaper rent. It also leads to outmigration for home owners as they have better outside options for housing, because their current house has increased in value.

Economists have identified additional mechanisms that lead to outmigration.

Freeman and Braconi (2004) observe that in gentrifying areas of cities with rent stabilisation policies, landlords often decrease the quality of their services to their tenants or harass them, because they can only increase rent when tenants move out.

Freeman (2011) and Butcher and Dickens (2016) conduct unstructured interviews with large samples of residents in gentrifying areas. They find that original residents often feel pressure to move out because the new services (eg. expensive shops and cafés) don't cater to their needs.

Chan (2001) uses a dataset of financial information about mortgage holders in the US to investigate residential mobility. She finds that as property prices rise, mortgage holders have increased equity in their property, so are more able to overcome the frictions associated with moving house, for example mortgage down payments, taxes and estate agent fees. Ermisch and Washbrook (2012) find similar results in the UK.

Ferreira et al. (2011) use prospect theory to show that – due to risk preferences – home owner outmigration is more effected by an increase in house prices, than the equivalent decrease in house prices.

2.2 Empirical Studies

Most empirical studies of gentrification and outmigration follow a similar methodology to this paper: gentrifying areas are identified using census/house price data and migration patterns are observed through survey data. Outmigration-rates of disadvantaged households are then compared in gentrifying and non-gentrifying areas.

Atkinson (2001) uses the ONS Longitudinal Study to find high rates of outmigration of working-class people in gentrifying areas of London. However, Atkinson fails to include suitable life cycle controls and his geographical spatial units are only disaggregated to borough level. As such this study is severely limited.

Freeman et al. (2016) provide slightly stronger evidence for displacement. He applies a multivariate model to the British Household Panel Study (BHPS) at the acute geographic unit of Lower Super Output Areas. He finds moderate evidence that low-income households have higher outmigration in gentrifying areas.

However, Vigdor (2002) found that disadvantaged households are *less* likely to experience outmigration in gentrifying areas. This uses data from the American Household Study (AHS) in the Boston area. These results are consistent with studies by McKinnish et al. (2010), Ellen and O'Reagan (2011) and Freeman (2005), who use survey data to find similar results for the rest of the US. Similarly Ding et al. (2016) use a dataset of people's credit ratings and find no evidence of residents with bad credit being disproportionately affected by outmigration.

Freeman et al. (2016) argue that one reason for these counterintuitive results is that gentrification is associated with improved neighbourhood quality, so people are less likely to want to move. I attempt to overcome this endogeneity problem in Chapter 5 through an IV estimation.

Another weakness of these studies is that they use data that wasn't intended to measure urban displacement. Many use national surveys, meaning there are relatively few observations in metropolitan areas. For example, the BHPS used by Freeman et al. (2016) only has approximately 900 households observed in London (iser.essex.ac.uk, 2017). Many studies also fail to use sufficiently small geographical units. Some studies use borough level statistics (Atkinson, 2001; Freeman and Bracconi, 2004), however common sense tells us that you cannot identify gentrification from such large areas.

The data is also limited because many studies use the AHS and similar surveys, which sample housing units rather than families. Displacement is thus observed when a new family moves into a unit. This excludes cases when households are being renovated or demolished, as is often the case with gentrification. This may be a substantial problem, given that for every sample period typically 15% of the units from the previous period are ineligible or otherwise missed the interview (U.S. Census Bureau, 2007).

In contrast, this paper uses a survey of 8,158 households specifically in London. The survey links the observations to the ward level geographical unit, and the purpose of the questions were to assess London's housing situation.

2.3 Quasi-Empirical Studies

Sims (2016) uses public records in LA to identify four areas with clusters of evictions. He then conducts a qualitative analysis of these areas and found that they all experienced phenomena consistent with gentrification, such as increased investment from financial institutions and property intermediaries.

DeVerteuil (2011) identified 81 social service facilities intended for low-income residents in gentrifying areas of London and LA. This included foodbanks and job centres. Through interviewing their employees he found that 21% were displaced and 69% experienced displacement pressure, partly due to the displacement of their clientele.

Chapter 3

Data

3.1 Greater London Authority (GLA) Household Survey, 2002

The GLA Survey conducted 8,158 face-to-face interviews with the head of the household or their partner. It was commissioned by the GLA to inform policy decisions in a wide variety of areas such as housing affordability, poverty and health.

The key dependent variable from this dataset is whether the respondent reports that they are likely to move in the next five years, which I use as a proxy for outmigration. This is not a perfect proxy, as some households will have predicted incorrectly. However, moving house is a big life decision which people have fairly good foresight about.

The survey asks the respondent the reasons they expect to move which I examine in Chapter 6. It also includes useful socio-economic information about the household such as ethnicity, household income and housing tenure.

This survey was based on a random sample of pre-selected addresses, within a non-random sub-sample of wards, which were designed to over represent disadvantaged areas. This selection bias is controlled for through the 'pweights' option in Stata.

The geographical unit in this dataset is wards, which have a population of approximately 10,000. This is a suitable neighbourhood size to examine gentrification and migration patterns. I match the individuals from this dataset with ward-level aggregate statistics from Land Registry data and Census data.

It is not ideal that this dataset is from 2002, as it may be less relevant for today. However 1995 to 2008 was a period of dramatic house price inflation in London, so it is interesting to study in the context of gentrification. Additionally, there are few other surveys focused on housing that have acute geocoded variables available, due to privacy issues.

3.2 HM Land Registry Price Paid Data

HM Land Registry Price Paid Data tracks all residential property sales in England and Wales from 1995 onwards. Cumulative house price inflation by property type (flat, semi-detached, terraced etc.) is calculated in each ward from 1995 to 2001. This house price inflation value is then matched to the ward and house type of each respondent in the survey data (see Appendix B for details).

Due to data constraints the sample period of the house price data (1995 to 2001) does not align to the sample period of the census data (1991 to 2001). This should not significantly affect my results because most house price inflation in the 1990s occurred after 1995 (Nationwide, 2018).

House price inflation should only be treated as an estimated underlying value of the property. Not all home owners necessarily know the price of their property, and not all renters will see their rent going up in proportion to house prices.

3.3 Census Data

From the 1991- and 2001 Census there is data on the proportion of the population in each ward who have an undergraduate degree or equivalent and the proportion of the population who work in professional or managerial jobs. For more details see Appendix C.

3.4 Summary Statistics

Table 1: Neighbourhood descriptive statistics

	All London Wards			***Wards incl. in survey***		
	Mean	Std.Dev.	Obs.	Mean	Std.Dev.	Obs.
Cumulative House Price Inflation (1995 to 2001)	118%	37%	772	119%	34%	448
Proportion with a degree, 1991	18%	10%	773	17%	10%	448
Proportion with a degree, 2001	30%	14%	773	31%	14%	448
Proportion in professional or managerial jobs, 1991	11%	5%	773	11%	5%	448
Proportion in professional or managerial jobs, 2001	34%	11%	773	33%	11%	448

Table 1 illustrates that mean ward-level cumulative house price inflation was 118% from 1995 to 2001 in London. This has a standard deviation of 37%, which gives us suitable ward-level variation to investigate the effects of house price inflation.

Based on census statistics, Table 1 shows that the proportion who have an undergraduate degree or equivalent grew from a ward-level average of 18% in 1991, to 30% in 2001. Similarly, the proportion in professional or managerial jobs grew from 11% to 34%. These statistics are similar to the sub-sample of wards included in the survey.

Table 2: Household descriptive statistics

	Mean	Std.Dev.	Obs
Likely to move in next 5 years	39%	-	8158
Tenure			
Home owner	55%	-	8158
Private Renter	12%	-	8158
Social Renter	31%	-	8158
Other	1.8%	-	8158
Unemployed	12%	-	8158
Undergraduate degree	30%	-	8158
Non-white	31%	-	8158
Marital Status			
Single	58%	-	8158
Married	34%	-	8158
Cohabiting	8%	-	8158
Household Income (£s)	30,676.67	27,033.97	5952
Age	47.28	18.31	8158
Children in Household	0.57	1.00	8158

Table 2 shows that 39% of the 8,158 households interviewed in the GLA survey reported that they were likely to move in the next 5 years. This is a fairly large amount of observations, which is important because this is the key dependent variable in my analysis.

55% of households are home owners, 12% are private sector renters, 31% social renters, and 1.8% are a different form of tenure (eg. squatting or renting from friends/family). The average household income in this period is £30,700 and 31% of households have one or more non-white member of the family.

As Figure 1 shows, the probability of reporting that you are likely to move is higher in wards that experienced above average house price inflation, increasing from 41% to 44% for renters and from 33% to 37% for owner occupied households.

Figure 2 shows that house price inflation was highest in central and east London, in areas around Shoreditch, Canary Wharf and Brixton. This is consistent with local knowledge of the area.

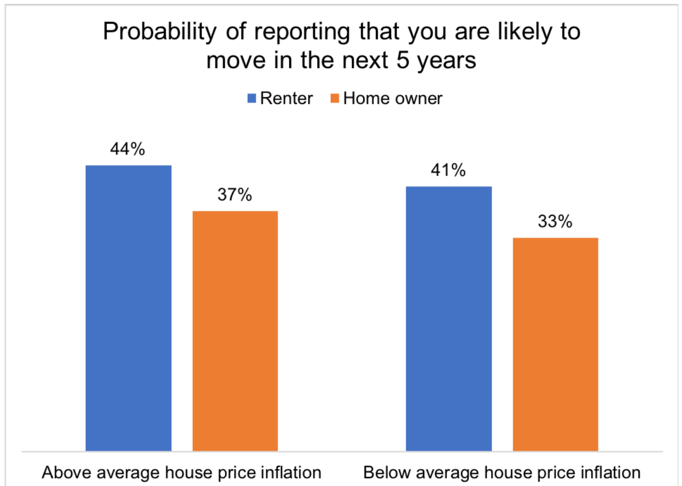

Figure 1: Probability that you report being likely to move

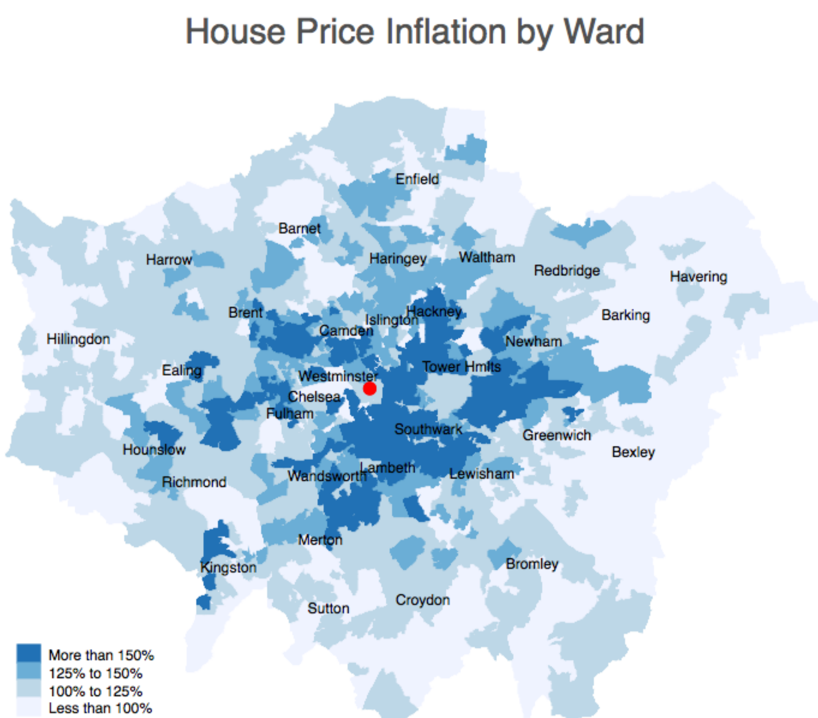

Figure 2: Cumulative house price inflation from 1995 to 2001 by ward

Chapter 4

Model 1: Linear Probability Model

4.1 Theoretical Framework and Empirical Strategy

Initially I use a linear probability model (LPM) to predict the probability of a respondent reporting that their household is likely to move. An LPM is used over a probit as it makes interpreting interactive coefficients simpler.

The key independent variable is ward-level cumulative house price inflation. This serves as a good measure of gentrification because increased house prices are the key mechanism that causes an increase in outmigration.

House price inflation may lead to outmigration for home owners, because they have better outside options if they sell their house. And it may lead to outmigration for private renters because they prefer to pay lower rent. Social renters, however, will not necessarily see their rent increase in line with the market rate, so may not be effected by house price inflation. I have also outlined some behavioural and frictional mechanisms in section 2.1 of the literature review.

Based on these mechanisms, the effect of house price inflation is investigated for different groups through interactive dummy variables.

Given that this study focuses on gentrification, rather than house price inflation more generally, in Columns (2) to (5) my analysis is isolated to neighbourhoods that were disadvantaged at the beginning of the sample period. This is defined as having below median levels of professional/managerial workers in 1991. This was due to the fact that many of the areas that experienced high house price inflation were areas that were already affluent at the start of the sample period, in particular West London neighbourhoods like Richmond, Chelsea and Knightsbridge.

Given that house price inflation is calculated at ward-level and then matched to multiple individual households from the same ward, I use robust-clustered standard errors (clustered by house price inflation). I use this method in all the following models.

Additionally, I control for life cycle variables such as age, children and marital status. When 'low income' is not the interactive term, dummies for household income band are included as controls.

In summary, the specification of the LPM, in the case of Column (3) is:

$$
\begin{aligned}
&\text{Outmigration}_{in} = \\
&\quad (\beta_0 + \beta_1 \text{Inflation}_n + \beta_2 \text{LowInc}_i + \beta_3 \text{Inflation*LowInc}_{in}) \\
&\quad +(\delta_0 + \delta_1 \text{Inflation}_n + \delta_2 \text{LowInc}_i + \delta_3 \text{Inflation*LowInc}_{in}) * \text{Advantaged}_n \\
&\quad +... + \varepsilon_{in}
\end{aligned}
$$

Where 'Outmigration$_{in}$' indicates whether household i in neighbourhood n reported that they were likely to move. 'Advantaged$_n$' indicates whether a ward was advantaged in 1991. In Table 3, only the β_j coefficients are reported.

4.2 Results

Table 3 reports the results of this model. In Column (1) there are no interactive terms and all neighbourhoods are included. The results from this specification indicate that a 10-percentage-point increase in ward-level cumulative house price inflation leads to a 0.56-percentage-point increase in probability of being likely to move (significant to a 0.1% level). This falls to a 0.39-percentage-point increase when effects are isolated to disadvantaged neighbourhoods (significant to a 10% level). While this seems like a small effect, it is important to remember that the average cumulative house price inflation across this period (1995 to 2001) was 118%.

Column (3) and (4) suggest low-income and non-white households are no more likely to be effected by inflation than others.

Column (5) reports the different gentrification effects by household tenure and the predictions of this are graphed in Figure 2. At means, private renters are 22-percentage-points more likely to move than home owners or social renters.

Private renters are also more sensitive to house price inflation. If house price inflation increases by 10-percentage-points, then the probability of moving increases by 1.1-percentage-points (significant to a 5% level) for private renters, compared to only 0.58-percentage-points for home owners (significant to a 10% level) or -0.14-percentage-points for social renters (not significant).

Column 5 has the highest percent correctly predicted, suggesting it has the best functional form of the models in Table 3.

This implies tenure is important in determining a household's sensitivity to gentrification. This is consistent with the mechanisms outlined in the previous section.

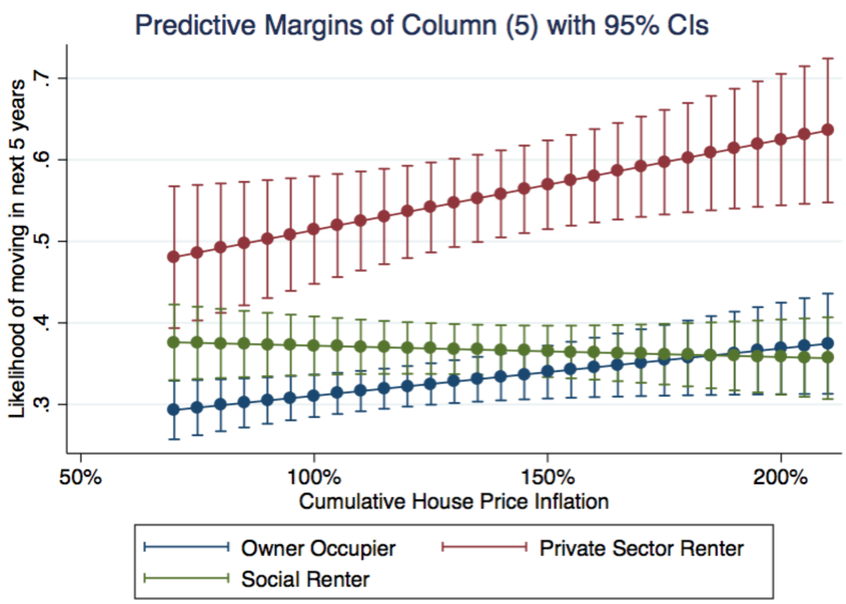

Figure 3: Predictions from Column (5)

Table 3: Predictions from the LPM for reporting that you are likely to move

	(1)	(2)	(3)	(4)	(5)
Inflation	0.0556***	0.0390	0.0483	0.0325	0.0581
	(3.41)	(1.93)	(1.61)	(1.35)	(1.94)
LowInc			-0.0755		
			(-1.23)		
LowInc*Inflation			0.00346		
			(0.07)		
Non-White				-0.0404	
				(-0.89)	
Non-White*Inflation				0.0207	
				(0.66)	
Private Renter					0.150
					(1.86)
Private Renter*Inflation					0.0529
					(0.93)
Social Renter					0.133**
					(2.70)
Social Renter*Inflation					-0.0720*
					(-2.00)
Effects isolated to disadvantaged neighbourhoods	No	Yes	Yes	Yes	Yes
Additional income controls	Yes	Yes	No	Yes	Yes
Percent correctly predicted	66.8%	66.9%	66.8%	66.9%	68.5%
N	8158	8158	8158	8158	8158

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Chapter 5

Model 2: Endogeneity and IV Framework

5.1 Theoretical Framework and Empirical Strategy

If house price inflation is associated with an increase in the quality of a neighbourhood, this may mean that people are less likely to want to move house. Therefore, the house price inflation effect estimated in the previous model and in previous papers may be under estimated. This bias can be overcome through the following IV model.

Consider a model where only incumbent residents observe some aspects of the neighbourhood quality. This unobserved aspect of neighbourhood quality has an upward effect on house prices and downward effect on outmigration. Given that only incumbent residents observe this factor we can treat an influx of new middle-class entrants as a demand-side exogenous shock to house price inflation.

Therefore, we can use a change in education levels as an instrument for house price inflation in an IV context. Change in education levels works well as measure of incoming middle-class entrants because adults rarely change their education levels after the age of 21, so any influx in education levels indicates new entrants to a neighbourhood.

This model is fairly true to life, given that many aspects of neighbourhood quality are only observable to incumbent residents. For example, the local school gaining a new, high quality head-teacher; the council being more efficient in rubbish collection; or an increase in friendliness of neighbours.

Note, that this model does *not* require that incoming residents do not care about neighbourhood quality. It only requires that they care about different aspects of neighbourhood quality than the incumbent residents – aspects of quality which do not affect the outgoing rate of incumbent residents. Some cliché examples of aspects of neighbourhood quality that only 'gentrifiers' care about would be artisan coffee bars or art galleries.

Based on this framework I implement the following IV regression to estimate the 'true' effect of house prices on outmigration:

First Stage:
House Price Inflation$_n = \delta_0 + \delta_1 \Delta$Education Levels$_n + ... + \varepsilon_{1in}$

Strucutral Equation:
Outmigration$_{in} = \beta_0 + \beta_1$House Pri$\hat{c}$e Inflation$_n + ... + \varepsilon_{2in}$

Where ΔEducation Levels$_n$ is percentage-point change in proportion of the population with a degree from 1991 to 2001 by ward.

This may not be the perfect specification, because in reality there will be some aspects of neighbourhood quality that both incumbent and entrant residents care about. However, this would only lead to an under estimate of β_1.

One issue that could lead to β_1 being over estimated, would be if ΔEducation Levels$_n$ and Outmigration$_{in}$ were correlated due to being broad proxies for residential mobility.

In Table 4 I report the results of this IV estimation. Due to complications about introducing interactive variables into an IV estimation, I run the same estimation for different sub-samples of the population indicated by the title of the column.

5.2 Results

In all of the population sub-samples the instrument relevance test is passed, as the F-statistic from ΔEducation Levels$_n$ from the first stage is sufficiently high. This suggests that change in education levels is significant in determining house price inflation. This is in line with the conventional wisdom that house prices increase due to a demand-side shock from middle-class 'gentrifiers'.

In all of the specifications, the 2SLS coefficient on house price inflation (panel A) is greater than if it were estimated by OLS (panel C). This provides evidence that the gentrification effect estimated in the previous section and in previous papers is under estimated.

Looking at all households, Column (1) indicates that a 10-percentage-point increase in house price inflation leads to a 1.27-percentage-point increase in likelihood of moving (compared to a 0.556-percentage-point increase by the OLS estimate).

If we restrict our sample to private sector renters from disadvantaged neighbourhoods, Column (4) indicates that a 10-percentage-point increase in inflation leads to a 3.8-percentage-point increase in likelihood of moving (as opposed to 1.1-percentage-points under OLS). This is only significant to a 10% level, perhaps due to the smaller sample size.

The Wu-Hausman test of exogeneity tests the null hypothesis $H_0 : \beta_{OLS} =$

Table 4: IV estimations for reporting that you are likely to move

	(1)	(2)	(3)	(4)	(5)
Sub-sample:	All wards	Excl. 1991 'advantaged' wards			
	All H.Holds	All H.Holds	Home Owners	Private Renters	Social Renters
Panel A: 2SLS for outmigration					
Inflation	0.127**	0.108*	0.0792	0.380	0.0217
	(2.98)	(2.22)	(1.39)	(1.64)	(0.35)
Panel B: First stage for house price inflation					
Δ Education Levels	2.883***	3.985***	3.939***	3.015*	4.124***
	(12.79)	(8.40)	(10.15)	(2.39)	(7.00)
Panel C: OLS for outmigration					
Inflation	0.0558***	0.0382	0.0567	0.107*	-0.0124
	(3.32)	(1.88)	(1.87)	(2.15)	(-0.46)
N	8158	4629	2250	443	1855
F-stat. of instrument	163.7	70.62	103.1	5.694	49.01
P-Value of Wu-Hausman	0.0790	0.1205	0.6327	0.1531	0.5625

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

β_{2SLS} against the alternative hypothesis $H_1 : \beta_{OLS} \neq \beta_{2SLS}$. Only under the first population sub-sample do I reject this test, therefore I can only provide moderate evidence that a simple linear regression leads to under estimates of the effect of house prices on outmigration.

Given that I only have one instrument for house price inflation, there are no statistical tests for exogeneity of ΔEducation Levels$_n$. This model is therefore based on the assumption that incumbent residents and middle-class entrants care about different aspects of neighbourhood quality (conditional independence assumption) and that change in education levels doesn't effect outmigration directly (exclusion restriction). This argument is outlined in the previous section.

Chapter 6

Model 3: Reasons for outward mobility

6.1 Theoretical Framework and Empirical Strategy

In this Chapter I investigate the given reasons for being likely to move. The GLA Survey asked respondents the main reasons why they expect to move. I define 'direct displacement' occurring if households say they expect to move for reasons such as 'cannot afford rent' or 'to move to cheaper accommodation'.

'Not upwardly mobile' is defined as households that expect to move, but excluding households that give reasons such as 'to move to a better neighbourhood'. The logic behind this variable is that households will prefer to report positive reasons for moving (e.g. 'to move in with romantic partner'), than reporting displacement. Therefore 'not upwardly mobile' can be seen as a broad proxy for displacement.

I also include variables for households who say they expect to move to another borough or leave London. For a full definition of the dependent variables see Appendix F.

I use a simplified LPM to investigate whether each reason for moving is higher in wards with higher house price inflation. I use a simplified model because we have fewer observations of the dependent variable, therefore a more parsimonious model is desirable. The model is:

$$X_{in} = \beta_0 + \beta_1 \text{House Price Inflation}_n + ... + \varepsilon_{in}$$

Where X_{in} is reason for moving, as defined by the title of the Column.

6.2 Results

Column (2) and (4) indicate that direct displacement or displacement out of London is not significantly effected by house price inflation. This may be because there are fewer observations so it is difficult to find significant results. This is an interesting result in itself, as it shows that reported displacement is relatively low in London.

Column (3) and (5) show that a 10-percentage-point increase in house price inflation leads to a 0.46-percentage-point increase in likelihood of a non-upwardly mobile move and a 0.28-percentage-point increase in likelihood of leaving your home borough. This provides some evidence that outmigration is consistent with notions of displacement.

Table 5: LPM predictions for different reasons of moving house

	(1)	(2)	(3)	(4)	(5)
Dependant Variable:	Outmigration	Direct Displacement	Non-Upwardly Mobile	Leave London	Leave Borough
Inflation	0.0887***	0.00501	0.0462**	-0.00510	0.0279***
	(5.14)	(1.15)	(3.13)	(-0.61)	(3.55)
N	8158	8158	8158	8158	8158
Obs. of Dependant Variable	3144	156	1678	671	447

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Chapter 7

Robustness Tests

For all of the models included in this paper, I test the robustness to a variety of specifications including:

- Operationalising the model as a probit or IV-probit, as opposed to an LPM.
- Limiting the analysis to a narrower definition of gentrifying, by isolating the effects to neighbourhoods in the bottom quartile of professional/managerial levels in 1991 (as opposed to the bottom half as used in the models reported above).
- Broadening my analysis to all neighbourhoods and simply looking at the house price inflation effects.

All of the models use robust-clustered standard errors and correct for sample weights. My key findings from model 1 were robust to almost all of these specifications (Appendix D). However the findings from model 2 and 3 were not robust to all of the specifications (Appendix E and F).

Chapter 8

Discussion of Results and Concluding Remarks

Model 1 provides robust evidence that households in the private rental sector face a higher rate of outmigration in gentrifying areas. Model 2 provides some evidence that previous studies have under estimated these effects. Model 3 provides moderate evidence that some of this outmigration is consistent with displacement. These results are in line with people's lived experience, as evidenced by anti-gentrification movements in London and cities across the world (Hancox, 2018).

From a free market perspective this is simply supply and demand: low income households substituting their consumption away from expensive areas is just a form of market clearing. I don't entirely dismiss this argument, however a socially and ethnically diverse neighbourhood could be viewed as a benefit to society as a whole.

Society gains when people from different classes and ethnic groups can grow up as neighbours. One just has to look at the counterfactual, to see that racial tensions and class divisions arise when a city is highly segregated like Paris, where most of the city's poor live in the *banlieue défavorisée*. This can be roughly translated as suburb-slums.

Model 1 and 2 suggest that families living in social housing are less likely to move house as a result of gentrification. This can be seen as a positive result as it shows that government intervention offers some protection against gentrification. However, the proportion of households living in social housing in London has been steadily falling from its peak of 35% in 1985, to 31% at the time of the survey, to only 21% in 2016 (Greater London Authority, 2017). This suggests fewer households have protection against gentrification.

There may be some benefits of gentrification. There is some evidence that residents benefit from better services (Butcher and Dickens, 2016) and lower crime (Papachristos, 2011). Increased house prices also benefit incumbent home owners and model 1 and 2 provide moderate evidence that some home owners take advantage of this by selling their property. Further research is needed to quantify these benefits against the costs to society.

The effects of gentrification reported in this paper and other empirical studies do not show the whole picture. Lived experience shows the effect of gentrification can be damaging both to individuals experiencing displacement and to communities as a whole. As such these results speak to the need for further research into this topic, and for policy makers to assess the availability of affordable housing.

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Appendices

Appendix A: Household Survey

I use the `glahouseholdfile.dta` file. The key variables from this dataset are defined as:

- Outmigration (`movelikely`) - Whether a respondent answers yes to 'Is it likely that you, your household - or some members of your household - will move in the next 5 years ?'
- Home owner (`house_type==1`) - Respondents who own their home outright or own with mortgage.
- Private renter (`house_type==2`) - Whether the respondent pays rent to a private land lord.
- Social renter (`house_type==3`) - Whether the respondent pays their rent to a local authority, council, housing action trust, housing association/co-operative or charitable trust.
- Non-white (`non_white`) - One or more member of the household is reported to be non white.
- Household income (`m2join`) - The total household income from the following sources: Earnings from employment or self-employment; Pension from former employer; State pension; Child benefit; Income support; Other State Benefit; Interest from Savings etc.; Other kinds of regular allowance from outside the household; Other sources of income.
- Low income (`lowinc_quart`) - 0 - not low income; 1 - in the bottom income quartile (income below £10,399); 2 - income not reported.
- Children (`chilren`) - Number of children under 16 who live in the household; and (`child`) - binary variable for presence of at least one child.
- Marital status (`mar_status`) - Marital status of the respondent: 1 - single/divorced; 2 - married; 3 - cohabiting.
- Age (`age age_sqr`) - Age of the respondent and the squared term.

- Probability weights (`wt`) - the given probability that a household was included in the survey due to the sampling bias.

Appendix B: Land Registry Price Paid Data

To generate a house price inflation (`house_infl_2`) variable I followed the following stages:

- Step 1: Download the 1995 and 2001 price paid data (`pp-1995.csv` and `pp-2001.csv`) from data.gov.uk/dataset/land-registry-monthly-price-paid-data.
- Step 2: Using Stata, I match the postcodes from the price paid data to 1991 wards based on a ward-postcode reference dataset generated from the 'match one geography to another' section of geoconvert.ukdataservice.ac.uk/.
- Step 3: Generate the median price paid for a particular house type (Detached, Semi-Detached, Terraced, Flats/Maisonettes and Other) in a particular ward, for both years.
- Step 4: Generate cumulative house price inflation for each house type and ward, based on median house prices, ie:

  $$\frac{\text{Median(House Price}_{2001,w,t}) - \text{Median(House Price}_{1995,w,t})}{\text{Median(House Price}_{1995,w,t})}$$

  where w and t refer to ward and house type respectively. If there is insufficient data to calculate this (eg. no terraced houses were sold in a particular ward), then then house price inflation for the whole ward is used.
- Step 5: Match these values to the wards and house types of each respondent of the survey using Stata. For the summary statistics I use house price inflation for the whole ward.

House price inflation for the whole ward (`house_inflation`) is used for the summary statistics.

Appendix C: Census Data

There were some complications matching the census data to the survey data. The GLA survey uses 1991 wards, and as such it was easy to match the survey data to the 1991 census data (`1991_Census.csv`) from casweb.ukdataservice.ac.uk/. However to match the 2001 census data to the survey data I had to followed the following steps:

- Step 1: Download the 2001 census aggregate statistics by Lower Super Output Area (`2001_Census_toconvert.csv`) from http://casweb.ukdataservice.ac.uk/.
- Step 2: Convert the LSOA aggregate data to 1991 ward level aggregate data using the GeoConvert tool provided by the UK data service, at geoconvert.ukdataservice.ac.uk/. We are able to do this because LSOA are a smaller geographical unit than wards. However, the LSOAs not exactly aligned with 1991 wards, therefore there might be some degree of measurement error from this variable.
- Step 3: Import the `2001_Census_after_GeoConvert.csv` file given by GeoConvert into Stata, and merge this with the survey by ward.

The 1991 census statistics for proportion of people in professional/managerial jobs and proportion of people who have an undergraduate degree are based on a population sub-sample, therefore there may be a small sampling error in this. To find the proportions I calculated: $\frac{\text{All persons with degree (subsamble)}_{Ward}}{\text{Sample Count}_{Ward}}$

Additionally, qualifications classification standards changed slightly across the period. In 1991 I classify 'undergraduate degree or equivalent' as having 'level C' education or higher. This includes some vocational diplomas. In 2001 it is defined as having 'level 4/5' education, which also includes some vocational diplomas.

Key Variables from this dataset include:

- Δ Education Levels (`change_educ`) - percentage point change in proportion of population with undergraduate degree (1991 - 2001).
- (Dis)advantaged neighbourhood (`adv_1991` and `disadv_1991`) - below median proportion of the population with a degree in 1991.

Appendix D: LPM Model and Robustness Checks

The LPM model is calculated through the `reg` command in Stata, and the `[pweights=wt], roubust` and `cluster(house_infl_2)` options. The full list of controls that were not reported in Table 3 is: `age age_sqr i.children i.mar_status (i.m2join)`.

For Column (3), I included an interactive dummy variable for 'income not reported' and inflation, so the default is families who are not low income. I do the same for 'other forms of housing tenure' in Column (5), so the default is home owners.

The percent predicted correctly is based on the 50% prediction boundary.

The marginal effects of house price inflation on outward mobility for different groups are reported in Table 6. Column (1) reports the marginal effects of the standard model as defined in Chapter 4.

Robustness

In order to check the robustness of the model I calculated the same marginal effects for the following variations of the model:

- The probit equivalent of the LPM. This is reported in Column (2). Due to complications estimating the marginal effects of interactive variables in a probit model, I only report the direction of the effect and the associated p-values.
- The same LPM with a narrower definition of 'disadvantaged wards'. This is reported in Column (3). I isolate the effects to wards that were in the bottom quartile of professional and managerial levels in 1991, as opposed the standard model which restricts the effects to the bottom half.
- I do not restrict the effects to 'disadvantaged wards', I purely look at the effect of house price inflation in all wards. This is reported in Column (4).

Table 6: Marginal effects of model 1

	(1) LPM	(2) Probit	(3) Narrow LPM	(4) All Wards LPM
	All Wards			
All Households	0.0556	+ve	-	0.0556
	(0.0007)	(0.0005)	-	(0.0007)
	Effects Isolated to Disadvantaged Wards			*All Wards*
All Households	0.0390	+ve	0.0099	-
	(0.0535)	(0.0455)	(0.6963)	-
Non-Low Income	0.0483	+ve	0.0046	0.0754
	(0.1076)	(0.1147)	(0.9145)	(0.0009)
Low Income	0.0517	+ve	0.0138	0.0528
	(0.1519)	(0.1202)	(0.6369)	(0.0927)
White	0.0325	+ve	-0.0025	0.0505
	(0.1782)	(0.1628)	(0.9245)	(0.0071)
Non-White	0.0532	+ve	0.0226	0.0741
	(0.0497)	(0.0484)	(0.5113)	(0.0028)
Home Owner	0.0581	+ve	0.0153	0.0608
	(0.0531)	(0.0438)	(0.7138)	(0.0055)
Private Renter	0.1110	+ve	0.0588	0.0797
	(0.0285)	(0.0389)	(0.3090)	(0.0440)
Social Renter	-0.0139	-ve	-0.0072	0.0110
	(0.6083)	(0.6507)	(0.8029)	(0.6535)

p-values in parentheses

Consistent with the results in the standard LPM, the marginal effect of house price inflation on outward mobility is not significant for low income households. The standard LPM found that the marginal effect was significant for house holds overall ('all households'), non-white households, and house holds in the private rental sector. This is robust to all specifications apart from the LPM with a narrower definition of 'disadvantaged wards'. This may due to the reduced sample size.

Additionally, I use robust-clustered standard errors in all of the models. Overall my key findings from model 1 are robust.

Appendix E: IV Model and Robustness Checks

The IV estimates from Table 4 are based on the `ivreg2` command in Stata, with the `[pweight=wt], roubust` and `cluster(house_infl_2 change_educ)` options. The F-Statistic of the excluded instrument is found through the `widstat` scalar and the P-Value of the Hausman-Wu test is calculated through the `endog(house_infl_2)` option.

Using the clustered standard errors in an IV setting limits the amount of controls you can include. Therefore I use a paired down set of controls of: `age age_sqr i.child i.lowinc_quart i.mar_status`.

Robustness

In order to test the robustness of the IV model, I test the following variations of the specification:

- Using the same IV model, I restrict my ward samples to 'disadvantaged neighbourhoods' (wards in the bottom 50% of managerial/professional levels) and a narrow definition of 'disadvantaged neighbourhoods' (wards in the bottom 25% of managerial/professional levels). For each of these ward sub-samples, I estimate it for all households, home owners, private renters and social renters. The results from these sub-samples are reported in Table 7.
- In Table 7, I compare the coefficient on house price inflation under the IV estimation, to the same coefficient under OLS.
- Using an IV probit model, I test the same sub-samples. I compare the coefficient on house price inflation from the IV probit model, to the probit model. The results from this are reported in Table 8.

Under almost all of the sub-samples in the IV and IV probit, the F-statistic of the excluded instrument is greater than 10. This suggests change in education levels has a significant effect on house price inflation, therefore the instrument is relevant and robust.

Under most of the specifications the coefficient from the IV is greater than OLS, and the coefficient from the IV probit is greater than the probit. This is in-line with my framework whereby an OLS/probit model would lead to an under estimation of the gentrification effects. However the difference in coefficients is only statistically significant for the 'all households/all neighbourhoods' sample as tested by the Hausman-Wu and Wald test for exogeneity.

Therefore the hypothesis that 'OLS/probit leads to an under estimation of gentrification effects' is not robust to all specifications

Table 7: Robustness checks for IV Model

		β_{2SLS}	β_{OLS}	N	F-Stat. of excl. instrument	P-Value of Hausman-Wu test for exog.
	All Neighbourhoods					
(1)	All Households	0.127**	0.0558***	8158	163.7	0.079
		(2.98)	(3.32)			
(2)	Home Owners	0.116*	0.0668**	4527	206.5	0.2868
		(2.22)	(3.00)			
(3)	Private Renters	0.0234	0.0871*	954	34.44	0.6589
		(0.16)	(2.14)			
(4)	Social Renters	0.0313	0.0134	2526	79.92	0.7594
		(0.51)	(0.55)			
	Disadvantaged Neighbourhoods					
(5)	All Households	0.108*	0.0382	4629	70.62	0.1205
		(2.22)	(1.88)			
(6)	Home Owners	0.0792	0.0567	2250	103.1	0.6327
		(1.39)	(1.87)			
(7)	Private Renters	0.380	0.107*	443	5.694	0.1531
		(1.64)	(2.15)			
(8)	Social Renters	0.0217	-0.0124	1855	49.01	0.5625
		(0.35)	(-0.46)			
	Narrow Disadvantaged					
(9)	All Households	0.0598	0.0128	2389	34.73	0.4467
		(0.86)	(0.51)			
(10)	Home Owners	-0.0138	0.0224	935	48.60	0.291
		(-0.16)	(0.55)			
(11)	Private Renters	0.620*	0.0576	228	13.89	0.0031
		(2.45)	(1.01)			
(12)	Social Renters	0.00778	-0.00687	1192	18.15	0.8529
		(0.09)	(-0.24)			

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix F: 'Reasons' LPM and Robustness Checks

The LPM model is calculated through the `reg` command in Stata, and the `[pweights=wt], roubust` and `cluster(house_infl_2)` options. Because I wish to keep a parsimonious model I use paired down controls of: `i.child i.lowinc_quart i.mar_status`.

The dependent variables from this specification are based on the following reasons for moving:

- Direct displacement (`directdispl`) - 'to move to cheaper accommodation'; 'cannot afford mortgage'; 'cannot afford rent'; 'expect to be evicted'.
- Non-upward mobility (`move_not_up`) - people who expect to move, excluding people who are moving for the following reasons: 'current home is to small'; 'want a garden'; 'better area for schools'; 'better environment'; 'better neighbourhood'; 'area with less pollution'.

Table 8: Robustness checks for IV Probit

		$\beta_{IVProbit}$	β_{Probit}	N	F-Stat. of excl. instrument	P-Value of Wald test for exog.
	All Neighbourhoods					
(1)	All Households	0.381***	0.167***	8158	186.5956	0.0499
		(3.34)	(3.35)			
(2)	Home Owners	0.336*	0.195**	4527	269.9449	0.244
		(2.43)	(3.01)			
(3)	Private Renters	0.0923	0.295*	954	36.3609	0.638
		(0.22)	(2.10)			
(4)	Social Renters	0.115	0.0467	2526	80.2816	0.692
		(0.64)	(0.63)			
	Disadvantaged Neighbourhoods					
(5)	All Households	0.331*	0.115	4629	75.3424	0.0876
		(2.50)	(1.94)			
(6)	Home Owners	0.251	0.171	2250	126.1129	0.556
		(1.56)	(1.93)			
(7)	Private Renters	1.061*	0.318*	443	5.8564	0.199
		(2.01)	(1.98)			
(8)	Social Renters	0.0775	-0.0348	1855	49.4209	0.520
		(0.43)	(-0.43)			
	Narrow Disadvantaged Neighbourhoods					
(9)	All Households	0.182	0.0396	2389	31.5844	0.382
		(1.03)	(0.55)			
(10)	Home Owners	-0.0386	0.0636	935	50.8369	0.589
		(-0.17)	(0.53)			
(11)	Private Renters	1.401***	0.178	228	15.6025	0.00721
		(4.05)	(0.97)			
(12)	Social Renters	0.0325	-0.0178	1192	17.4724	0.814
		(0.14)	(-0.21)			

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

- Leave London (`leavelondon`) - respondents who plan to live outside London when they move.
- Leave Borough (`leaveborough`) - respondents who plan to live outside their current Borough when they move.

Robustness

In order to test the robustness of this model I restrict my analysis to the 'narrow' definition of disadvantaged wards; the broader definition of disadvantaged wards; and all wards. I do this for both an LPM and Probit. I report the coefficients and t statistics in Table 9.

My key finding was that non-upwardly mobile moves and moves out of your home borough are significantly effected by house price inflation. However this is only robust when my analysis is not restricted to disadvantaged boroughs.

Table 9: LPM predictions for different reasons of moving house

Dependant Variable:	(1) Move Likely	(2) Direct Displacement	(3) Non-Upwardly Mobile	(4) Leave London	(5) Leave Borough
Coefficient on Inflation from LPM					
All Neighbourhoods	0.0887***	0.00501	0.0462**	-0.00510	0.0279***
	(5.14)	(1.15)	(3.13)	(-0.61)	(3.55)
Disadvantaged	0.0608**	-0.000169	0.0288	-0.00226	0.0186
	(2.94)	(-0.04)	(1.77)	(-0.23)	(1.90)
Narrow Disadvantaged	0.0250	-0.00248	0.0162	-0.00670	-0.00213
	(0.97)	(-0.62)	(0.88)	(-0.67)	(-0.17)
Coefficient on Inflation from Probit					
All Neighbourhoods	0.240***	0.0963	0.151**	-0.0328	0.232***
	(5.10)	(1.25)	(3.12)	(-0.55)	(4.10)
Disadvantaged	0.165**	-0.00408	0.100	-0.00928	0.141*
	(2.94)	(-0.04)	(1.78)	(-0.13)	(2.17)
Narrow Disadvantaged	0.0685	-0.0637	0.0587	-0.0440	-0.0192
	(0.99)	(-0.55)	(0.88)	(-0.60)	(-0.20)
N	8158	8158	8158	8158	8158
Obs. of Dependant Variable	3144	156	1678	671	447

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$