Ethnic minorities' access to mortgages in the UK: The undesirable impact of the Great Financial Crisis

Solomon Y Deku, Alper Kara[1], Kay Smith and Mengxue Xia

Abstract

We examine whether households from ethnic minorities have the same ability to access mortgages in the UK in the period after the Great Financial Crisis (GFC) of 2007-2009. Using a large sample of 20,120 households, we find that Black households are less likely to obtain mortgages in comparison to economically similar White households. Comparing our results to previous studies' findings, we argue that Black households' inability to access mortgages have deteriorated further in the post-GFC period.

JEL classification: D14, J15, G21

Keywords: Mortgage, Ethnic Minorities, Financial Exclusion, UK

1. Introduction

Access to financial services, or *Financial Inclusion*, is widely recognised as an important issue for individuals' economic progress and a basic necessity to lead a normal life (Demirguc-Kunt et al., 2018). However, the empirical evidence shows that individuals face financial exclusion based on their demographic characteristics (Demirgüç-Kunt and Klapper, 2013, Devlin, 2005, Hogarth et al., 2005, Munnell et al., 1996, Simpson and Buckland, 2009). For example, ethnic minorities are particularly vulnerable in accessing credit. A well-established literature documents the persistent financial exclusion of non-White households in the US (Benston and Horsky, 1992, Black et al., 1978, Munnell et al., 1996, Schafer and Ladd, 1981, Tootell, 1996). Recent studies also provide empirical evidence from other developed and developing countries that ethnic minorities are less likely to have access to credit and more likely to experience credit denials (Bowles et al., 2011, Charron-Chénier and Seamster, 2020, Gonzales Martinez et al., 2020, Luan, 2019, Simpson and Buckland, 2009, Stegman and Faris, 2005, Wyly et al., 2009). In the UK, ethnic minorities face inequality in a number of areas in society (Equality and Human Rights Commission, 2016), including financial services (Devlin, 2005, Finney and Kempson, 2009, Kempson and Whyley, 1999). Limited empirical evidence on credit exclusion of ethnic minorities shows that in the UK non-White households are less likely to have consumer credit (Deku et al., 2016), and Black households with low incomes are less likely to have mortgages (Kara and Molyneux, 2017) when compared to White households with similar demographic characteristics.

In this paper, we examine access to mortgages across ethnicities in the UK. We contribute to the literature by providing the first evidence for the post-Great Financial Crisis (GFC) period. A shortcoming

[1] Corresponding Author: Alper Kara, Huddersfield Business School, University of Huddersfield, Huddersfield, HD13DH, UK, Email:a.kara@hud.ac.uk, Tel:+44(0)1484473084. Solomon Y Deku, Nottingham Business School, Nottingham Trent University, UK, Email: solomon.deku@ntu.ac.uk. Kay Smith, Huddersfield Business School, University of Huddersfield, UK, Email: k.smith@hud.ac.uk. Mengxue Xia, IBM Solutions and Services Co., Shenzhen, China, Email: xianx1218@outlook.com.

of the previous UK studies is that the periods analysed do not reflect the full effect of the GFC. For example, the most relevant study for our analysis is Kara and Molyneux (2017), whose sample period spanned 2003-10.

This is relevant because banking business became more challenging after the GFC as banks had to comply with increasing regulation, change business models (such as relying less on securitization), and curb their risk appetite. More stringent rules on mortgage lending were introduced in the UK by the Financial Services Authority (FSA) in 2010 as a consequence of the GFC (FSA, 2010), resulting in lenders making significant changes to mortgage products; maturities got shorter, 100+% loan-to-value (LTV) loans were all but withdrawn, and conditions for interest only mortgages became stricter. These products were particularly important for new borrowers and households with limited savings or no assets. More importantly, several lenders grew more conservative when assessing credit risk by tightening loan-to-income and credit score requirements, thereby creating potential barriers for prospective borrowers (Canhoto and Dibb, 2016). The post-2011 period is of particular importance as the new, and more limiting, revised Basel III regulations started to take effect from this year onwards. Banks adjusted their lending and risk-taking behaviour with the new regulations during this period. These changes would suggest that, from a credit supply perspective, financial exclusion may have increased after the GFC. Therefore, it is imperative to understand whether and how relative financial exclusion of ethnic minorities has changed in the UK after the GFC when new regulations were introduced in 2011.

Existing works focusing on demand side explanations examine households' decision to buy or rent, by accounting for demographic and socio-economic variables. Indeed, it is conceivable that homeownership rates remain low among disadvantaged groups because of the rise in property prices relative to real incomes. According to Cribb and Simpson (2018), average house prices increased by 152% between 1995/96 and 2015/16 in real terms compared to a modest rise of 22% in real incomes of young adults during the same period. André and Girouard (2009) also argue that exclusion may be persistent due to housing transaction costs. Furthermore, low levels of homeownership in disadvantaged households may be because of low intergenerational transfers (wealth and savings). In the UK, these disadvantaged households tend to be concentrated within ethnic minority groups (Khan, 2019). For example, minority household incomes were 22%-35% lower than median incomes of White households as of 2015/16 (Corlett, 2017). Also, the fall in average household incomes was much larger for minority groups compared to White households (Fisher and Nandi, 2015). The low ownership rates in minority groups has commonly been attributed to discrimination, especially among African-Americans in the United States (Ladd, 1998, Ravina, 2008). However, some of these households may also prefer renting to circumvent maintenance costs and other unforeseen costs of homeownership and relocation (Hilber, 2007). The focus of this paper is not to disentangle these potential explanations but to explore the extent to which differences in access to mortgages can be attributed to ethnicity in the post-GFC period.

The next section describes the data and empirical strategy. The results are presented in Section 3 and Section 4 concludes.

2. Data and Methodology

We collect our data from the annual Living Costs and Food Survey (LCFS) conducted by the Office for National Statistics in the UK. LCFS collects information on spending patterns and the cost of living at the household and individual levels. Our data covers 20,120 households surveyed between the periods of 2012 and 2015. The survey captures demographics such as age, employment, education, ethnicity, family relations and information on income, spending, tenure, savings and credit usage.

Following the literature (Kara and Molyneux, 2017, Deku et al., 2016) we utilise Propensity Score Matching (PSM) (Rosenbaum and Rubin, 1983) to examine households' access to mortgages. This counterfactual approach allows us to determine the probability of non-White households being without mortgages had they not been non-white (average treatment effect on the treated – ATT).

PSM is less prone to selection bias as being a non-White household is likely to be endogenous and related to various other observable characteristics. PSM involves matching one or more comparable (in terms of demographics and economic indicators) White household for each non-White household according to its propensity score. This procedure allows us to isolate the impact of ethnicity on access to mortgages. Matching restricts inference to the sample of non-White households (treatment group, denoted $T_i = 1$ for household i) and White households (control group, denoted $T_i = 0$). The treatment group is matched with the control group based on its propensity score which is a function of various determinants (X_i). We then proceed to compare our outcome of interest to determine the impact of ethnicity. Our outcome of interest NM_i, No Mortgage, is equal to 1 if household i does not have a mortgage, 0 if they are renting. Following the literature (Kara and Molynuex, 2016), we exclude households which own their houses outright (mortgage-free) from our analysis because the path to ownership is unknown. This restriction confines our analysis to access to mortgages, rather than homeownership. The propensity score:

$$P(X_i) = Prob(T_i = 1|X_i) \ with \ (0 < P(X_i) < 1) \tag{1}$$

measures the probability $P(X_i)$ of a household reference person (HRP) being non-White, conditional on observed covariates, X_i for each household. T_i is the treatment indicator.

We then compute the ATT as follows:

$$ATT = E(NM_{1i} - NM_{0i}|T_i = 1)$$

NM_{1i} is the potential outcome of having a mortgage and NM_{0i} is the potential outcome of not having one for non-white households. Following Dehejia and Wahba (2002), we use nearest neighbour matching with replacement where each non-white household is matched with 1,4, and 8 closest white households. The treatment variable, *non-White*, a binary variable, takes the value of 1 if a household's head is identified as Asian or Black, and 0 if White. We exclude mixed-race households and households that are not identified as Asian or Black to be able to draw a clearer line between White and non-White households.[2]

The covariates include the following observable characteristics: HRP's *Age* is categorized into six groups by decades. HRP's *Employment* status is categorized as employed, unemployed, retired, unoccupied and sick or injured. *Occupational classification* describes level and/or type of HRP's profession and comprises of: (i) large employer/higher managerial/professional occupations, (ii) lower managerial/professional occupations, (iii) intermediate occupations, (iv) small employers/own-account workers, (v) lower supervisory/technical occupations, (vi) routine/semi-routine, and (vii) others. *Education*, which shows the HRP's highest qualification, is categorized into five levels as: (i) degree/higher education below degree level, (ii) A-levels/ONC National level, (iii) GSCE, (iv) others below degree level/no formal qualifications, and (v) unknown. *Gender* is 1 if the HRP is female, 0 if male. *Marital Status* is categorised as married, cohabitee, and single (including widowed/ divorced/separated). *Household size* is number of people living in a household. *Income* is the total earnings of the household in a week. *Benefits* is the amount of social security benefit the household is receiving. *Income gap* equals to 1 if a household's expenditure exceeds its income, and 0 otherwise. We utilise this variable to gauge whether a household is facing a budget deficit. We also include *Region* (R_i) to account for the geographical location of households. Finally, we use time dummies (*Years* – Y_i to control for the macroeconomic environment.

Table 1 presents the descriptive statistics. For each variable we also show the percentage of mortgagors and renting households within that category. For the whole sample, 68.3% of households surveyed do not have a mortgage. White households constitute 93.9% of the sample in comparison 6.1% of non-White. The proportion of non-White households is larger with the renting group (9.3%) in comparison to the mortgagers (4.6%). The average household weekly income is £705. The mean income of the mortgage group is £808 whereas it is £476 for renting households. The mean HRP age is 53.7 and the average age for the renting group is younger (47.2) than those with a mortgage (56.6).

3. Empirical results

Figure 1 compares the distributions of the propensity score of the treatment and control groups. We observe that the propensity scores of White households are more concentrated around 0.1. In contrast, the propensity scores of non-White households are dispersed. To measure the quality of matching, we plot the distribution of the propensity scores for unmatched and matched samples in Figure 2. We observe that in the unmatched sample the propensity score of White households is skewed to the left, while it fits better with the non-White household after matching. Hence, visual inspection shows that

[2] We exclude households which own their houses outright (mortgage-free) from our analysis because the path to ownership is unknown. We follow previous studies' (i.e. Kara and Molyneux, 2016) approach in excluding the outright homeownership without a mortgage. This restriction confines our analysis to access to mortgages, rather than homeownership; hence, our results present the average effect of ethnicity on access to mortgage.

matches are suitable for the samples. We present results of the propensity score estimations in Table 2, however, due to brevity, we do not comment on these.

In Table 3, we present the main results from PSM analysis. We matched the treatment group with one, four and eight nearest neighbours, respectively. In our design we are more interested in the impact of being non-white (treated group) on access to mortgages, hence we focus on the average treatment on the treated (ATT). This estimand measures the average impact of ethnicity on access to mortgages for a non-white household randomly drawn from the treated sub-population, rather than the entire population (Average Treatment Effect - ATE). We find that for the whole sample (Column 2) the Average Treatment Effect on Treated (ATT) is positive and statistically significant in four and eight matched controls. This suggests that the effect of being a non-White household increases the probability of not having a mortgage. Hence, it is harder for non-White households to obtain a mortgage when compared with White households who have similar economic and demographic characteristics.

Subsequently, we look at results in different sub-samples based on income, employment, age, savings and income gap. Income often represents a household's ability to obtain and pay for a mortgage, and households with different incomes may be treated differently. We run the PSM analysis with lower and higher income groups by dividing the sample based on the median income value. We find that ATTs are not significant in the higher income group but significant (in four and eight matched estimations) in the lower income group. These results show that at higher income levels there is no difference between White and non-White households in the ability to access mortgages. However, in lower income groups non-White households are disadvantaged. Being employed may be another indicator for credibility as having a continuous salary can support mortgage payments. Results (Table 3, Column 4) show a positive and significant ATT, indicating that employed non-White households are less likely to have a mortgage. We also use categorise the HRPs to capture the effect of being a non-White household on the sub-group of households that are at the age of purchasing a house. In the UK the average age of a first-time homeowner is 32 (Ministry of Housing, 2017). Accordingly, we focus on the analysis for HRPsthat are above the age of 31. Results (Column 5) show that non-White households are less likely to have a mortgage also within this sub-group. Next, we look at whether having savings, which may signal more credibility for the lenders when borrowing, makes a difference in accessing mortgages. Results (Column 6) show that a non-White household with savings is less likely to have a mortgage in comparison to a White household with savings. Finally, we find similar results when we look at the sub-group of households that are facing an income gap (Column 7).

So far, we have focused on the comparison between non-White and White households. However, the literature finds that there are differences between Black and Asian households when accessing finance (Deku et al., 2015; Kara and Molyneux, 2017) and it is argued that Black households are more likely to be excluded. Accordingly, we run our analysis separately for Asian and Black households.

Results are presented in Table 4 Column 1 for Asian households, where we match each Asian household to a White household with comparable characteristics and exclude Black households from the sample. In Column 2 we undertake the same exercise by including Black and White households only. Results show that there is a difference between the two groups. Asian households are equally likely to obtain a mortgage when compared to a White household. However, Black households are less likely to have a mortgage when compared to White households.

Having identified that Black households drive our main results, we examine whether these findings vary within the Black household sub-samples. We undertake our analysis for all sub-groups by matching Black and White households. Results are presented in Table 5. We find that all ATTs are positive and significant. Results overwhelmingly show that Black households are less likely to have a mortgage in comparison to White households, even though they have similar credentials. Our results are broadly consistent with Kara and Molynuex (2017). However, we identify two important differences between our results and theirs regarding the Black households' access to mortgages. Firstly, they find that only Black households with low incomes are less likely to have mortgages and Black households in the higher income group are not different from White households. In contrast, our results show that both low- and high-income Black households are less likely to have a mortgage. Secondly, the size of ATTs we report for Black households is consistently larger in comparison to the treatment effects reported in Kara and Molyneux (2017). Hence, we argue that Black households' ability to access mortgages have deteriorated further in the period after the GFC. One plausible explanation of what we observe could be that, as it is often argued, banking business has become more challenging after the GFC as banks had to comply with more regulation and curb their risk appetite, and Black households seem to be affected more from the possible change in bank lending behaviour in the mortgage market in comparison to White households.

To verify our results, we use a doubly robust estimator – the inverse probability weight-regression adjustment (IPWRA) estimator (Imbens and Wooldridge, 2009, Wooldridge, 2010). IPWRA uses weighted regression coefficients to calculate treatment-level predicted outcomes, where the weights are the inverse of predicted probabilities of treatment obtained from the treatment model. Our treatment and outcome models are estimated using probit regressions where the treatment is *non-White* and the outcome is *NM*. The covariates used remain unchanged.

IPWRA is more robust to misspecification as only one of the models – treatment and outcome – need to be correctly specified to obtain consistent estimates. However, this estimator becomes unstable in our smaller subsamples as the propensity scores tend to zero or the weights become significantly large. The results, presented in Table 6, are largely consistent with the results obtained from the matching estimator as the ATT is positive and mostly statistically significant. The potential outcome (P.O.) mean refers to the probability of being without a mortgage, had non-White households been White while the positive ATT refers to the additional probability of non-White households being without mortgages as a result of their ethnicity.

We also test for covariate balance where conditions imposed by mean balance are used as overidentifying conditions (Imai and Ratkovic, 2014). As per Table 6, results suggests that we have balanced groups based on the covariates/independent variables used in the treatment model.

4. Conclusion

It is well documented that ethnic minorities are more likely to face financial exclusion across the world, including developed economies. We examine non-White households' access to mortgages in the UK in the post-GFC period by using a sample of 20,121 observations. We find that Black households are less likely to have mortgages in comparison to demographically and economically comparable White households. We also find that Black households' ability to access mortgage finance deteriorated after the GFC. Thus, Black households are affected more by stringent bank lending practices in the post GFC period.

A limitation of our analysis, due to data unavailability, is that we only observe households' tenure status in reduced form and are not able to detect whether the likelihood of having a mortgage is due to supply or demand-side factors, or due to possible cultural differences between Black and White households. Hence, further research is needed to explain why Black households are less likely to access mortgage finance.

Table 1: Descriptive Statistics

Variables	# obs.	% of	% of the group Renting	Mortgage	Variables	# obs.	% of total	% of the group Renting	Mortgage
All	20,120	100.0%	69.0%	31.0%	*Employment status*				
Tenure					Employed	11,775	58.5%	52.2%	61.4%
Renting	13,742	68.3%	100.0%	0%	Unemployed	523	2.6%	6.1%	1.0%
Mortgage	6,378	31.7%	0%	100.0%	Retired	6,149	30.6%	21.3%	34.7%
Ethnic origin					Unoccupied	808	4.0%	9.6%	1.5%
White	18,901	93.9%	90.7%	95.4%	Sick or injured	865	4.3%	10.8%	1.4%
Non-White	1,219	6.1%	9.3%	4.6%	*Occupational classification*				
Age (mean=53.7)		mean=	47.2	56.6	Higher managerial/employer	2,464	12.2%	6.3%	14.9%
16-24	503	2.5%	7.2%	0.4%	Lower managerial/professional	3,731	18.5%	13.1%	21.0%
25-34	2,439	12.1%	21.8%	7.8%	Intermediate occupations	1,490	7.4%	6.6%	7.8%
35-44	3,435	17.1%	19.8%	15.8%	Small employers/own account	1,320	6.6%	5.8%	6.9%
45-54	4,022	20.0%	17.8%	21.0%	Lower supervisory/technical	1,105	5.5%	6.0%	5.3%
55-64	3,676	18.3%	13.4%	20.5%	Routine and semi-routine	3,013	15.0%	25.2%	10.4%
65+	6,045	30.0%	20.0%	34.6%	Others	6,997	34.8%	37.1%	33.7%

Table 1: Descriptive Statistics (Continued)

Variables	# obs.	% of	% of the group Renting	Mortgage	Variables	# obs.	% of total	% of the group Renting	Mortgage
Educational level					*Income (mean=705.4)*			mean=476	mean=808
Degree/higher education	6,245	31.0%	22.4%	34.9%	0 – 200	2,239	11.1%	22.8%	5.8%
A-levels	2,253	11.2%	11.7%	11.0%	201 – 600	8,253	41.0%	50.6%	36.8%
GSCE	3,127	15.5%	19.8%	13.6%	600+	9,628	47.9%	26.6%	57.4%
Others	2,525	12.5%	15.8%	11.1%	*Region*				
Unknown	5,970	29.7%	30.3%	29.4%	North east	972	4.8%	6.0%	4.3%
Gender					North West Merseyside	2,280	11.3%	11.8%	11.1%
Male	12,233	60.8%	50.7%	65.3%	Yorkshire and the Humber	1,856	9.2%	9.8%	9.0%
Female	7,887	39.2%	49.3%	34.7%	East midlands	1,634	8.1%	8.0%	8.2%
Marital status					West midlands	1,871	9.3%	9.3%	9.3%
Married	11,087	55.1%	34.8%	64.3%	Eastern	1,994	9.9%	8.8%	10.4%
Cohabitee	2,575	12.8%	21.6%	8.8%	London	1,651	8.2%	11.0%	6.9%
Single	6,458	32.1%	43.7%	26.9%	South east	2,802	13.9%	11.7%	14.9%
Household size (mean=1.5)					South west	1,805	9.0%	7.8%	9.5%
1	9,521	47.3%	64.1%	39.8%	Wales	938	4.7%	4.1%	4.9%
2	10,433	51.9%	34.0%	59.9%	Scotland	1,701	8.5%	8.8%	8.3%
3	93	0.5%	1.0%	0.2%	Northern Ireland	616	3.1%	3.1%	3.0%
4	45	0.2%	0.5%	0.1%	*Year*				
5+	28	0.1%	0.4%	0.0%	2012	5,448	27.1%	26.8%	27.2%
Income gap					2013	4,987	24.8%	24.9%	24.8%
No income gap (=0)	15,197	75.5%	68.9%	78.5%	2014	4,956	24.6%	24.2%	24.8%
Income gap (=1)	4,923	24.5%	31.2%	21.5%	2015	4,729	23.5%	24.1%	23.2%

Table 2: Propensity Score Estimations

Variables	Whole Sample	Income below median value	Income above median value	Employed HRP	HRP age above 31	Savings	An income gap
Age (age 35-44 is base)							
16-24	0.007 (0.100)	-0.167 (0.128)	0.105 (0.177)	-0.238* (0.140)	-0.389*** (0.053)	-0.649 (0.450)	0.026 (0.176)
25-34	-0.084* (0.051)	-0.110 (0.080)	-0.090 (0.068)	-0.075 (0.056)	0.002 (0.069)	-0.113 (0.101)	-0.039 (0.110)
45-54	-0.265*** (0.101)	-0.190 (0.130)	-0.324* (0.178)	0.019 (0.141)	0.138** (0.054)	0.480 (0.451)	-0.370** (0.178)
55-64	-0.397*** (0.104)	-0.371*** (0.133)	-0.436** (0.182)	-0.135 (0.145)		0.309 (0.454)	-0.436** (0.183)
65+	-0.949*** (0.093)	-1.054*** (0.130)	-0.937*** (0.144)	-1.124*** (0.135)	-0.962*** (0.094)	-1.004*** (0.199)	-1.172*** (0.200)
Employment status (employed is base)							
Unemployed	-0.080 (0.095)	-0.284** (0.118)	0.375* (0.206)		-0.031 (0.108)	-0.203 (0.297)	-0.243 (0.151)
Sick or injured	-0.277*** (0.097)	-0.427*** (0.119)	0.190 (0.237)		-0.227** (0.102)	-0.414 (0.296)	-0.503*** (0.177)
Retired	-0.414*** (0.094)	-0.496*** (0.125)	-0.373** (0.155)		-0.336*** (0.097)	-0.123 (0.195)	-0.549*** (0.170)
Unoccupied	-0.021 (0.084)	-0.114 (0.103)	-0.109 (0.196)		-0.094 (0.103)	-0.228 (0.249)	0.005 (0.129)
Occupational classification (others is base)							
Higher managerial/employer	-0.269*** (0.083)	-0.452*** (0.157)	-0.321** (0.138)	-0.534*** (0.142)	-0.163* (0.095)	-0.063 (0.190)	-0.396** (0.167)
Lower managerial/professional	-0.340*** (0.077)	-0.232** (0.105)	-0.422*** (0.136)	-0.641*** (0.139)	-0.222** (0.088)	-0.140 (0.186)	-0.446*** (0.140)
Intermediate occupations	-0.267*** (0.086)	-0.339*** (0.119)	-0.272* (0.147)	-0.595*** (0.147)	-0.140 (0.098)	-0.079 (0.199)	-0.499*** (0.169)
Small employers/own account	-0.230*** (0.089)	-0.208* (0.115)	-0.394** (0.158)	-0.599*** (0.150)	-0.089 (0.099)	-0.222 (0.214)	-0.412*** (0.148)
Lower supervisory/technical	-0.332*** (0.095)	-0.143 (0.127)	-0.558*** (0.162)	-0.673*** (0.154)	-0.193* (0.106)	-0.271 (0.216)	-0.255 (0.176)
Routine and semi-routine	-0.273*** (0.074)	-0.290*** (0.090)	-0.373** (0.146)	-0.616*** (0.144)	-0.166* (0.086)	-0.100 (0.193)	-0.455*** (0.130)

Table 2: Propensity Score Estimations (Continued)

Variables	Whole Sample	Income below median value	Income above median value	Employed HRP	HRP age above 31	Savings	An income gap
Educational level (degree/higher education is base)							
A-levels	-0.337***(0.057)	-0.413***(0.089)	-0.274***(0.075)	-0.335***(0.063)	-0.361***(0.064)	-0.252**(0.101)	-0.364***(0.121)
GSCE	-0.533***(0.056)	-0.617***(0.083)	-0.493***(0.081)	-0.570***(0.066)	-0.522***(0.061)	-0.382***(0.105)	-0.456***(0.116)
Others	-0.267***(0.056)	-0.331***(0.081)	-0.229***(0.082)	-0.338***(0.067)	-0.247***(0.061)	-0.175*(0.104)	-0.097 (0.108)
Unknown	-0.127**(0.059)	-0.185**(0.079)	-0.079 (0.096)	-0.124 (0.082)	-0.106*(0.062)	-0.091 (0.132)	0.010 (0.114)
Gender							
Female	-0.102***(0.038)	-0.061 (0.056)	-0.128**(0.053)	-0.160***(0.047)	-0.101**(0.041)	-0.083 (0.073)	-0.119 (0.081)
Marital status (married is base)							
Cohabitee	-0.551***(0.059)	-0.675***(0.089)	-0.510***(0.087)	-0.590***(0.071)	-0.639***(0.072)	-0.403***(0.120)	-0.444***(0.118)
Single	-0.354***(0.051)	-0.597***(0.079)	-0.105 (0.073)	-0.426***(0.065)	-0.461***(0.058)	-0.268***(0.105)	-0.344***(0.101)
Household size	-0.104***(0.039)	-0.071 (0.067)	-0.113**(0.049)	-0.132***(0.046)	-0.218***(0.047)	-0.255***(0.080)	0.053 (0.066)
Income	0.000***(0.000)	-0.001***(0.000)	0.000***(0.000)	-0.001***(0.000)	0.000***(0.000)	0.000***(0.000)	-0.001***(0.000)
Benefit	0.001***(0.000)	0.000 (0.000)	0.001***(0.000)	0.002***(0.000)	0.001***(0.000)	0.001*(0.000)	0.000 (0.000)
Region controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income gap	-0.146***(0.041)	-0.223***(0.055)	-0.199***(0.075)	-0.156***(0.054)	-0.195***(0.045)	-0.134 (0.084)	
Constant	-0.838***(0.161)	-0.579**(0.267)	-0.803***(0.235)	-0.302 (0.216)	-0.788***(0.184)	-1.070***(0.338)	-0.914***(0.316)

Notes: The coefficients of probit models estimating the propensity score are shown below, representing the probability of being a non-White household. ***, ** and * represent that p-value is significant at 1%, 5% and 10% level respectively.

Table 3: Propensity Score Matching – Average Treatment Effect on Treated (ATT) for the Whole Sample

		Households with					
# controls matched	Whole Sample	Income above median value	Income below median value	Employed HRP	HRP age above 31	Savings	An income gap
One	0.031 (0.022)	0.019 (0.033)	0.042 (0.028)	0.349*** (0.092)	0.046* (0.024)	0.077** (0.035)	0.123*** (0.048)
Four	0.049*** (0.018)	0.034 (0.027)	0.060*** (0.023)	0.082*** (0.022)	0.066*** (0.019)	0.070** (0.030)	0.101*** (0.038)
Eight	0.053*** (0.017)	0.033 (0.026)	0.058*** (0.022)	0.080*** (0.021)	0.067*** (0.018)	0.052* (0.029)	0.120*** (0.036)
No. of treated obs.	1,219	610	609	873	1,052	298	284
No. of obs.	20,121	10,060	10,060	11,776	18,097	6,911	4,923

Notes: ***, ** and * represent that p-value is significant at 1%, 5% and 10% level respectively.

Table 4: ATT for Asian and Black Households

# controls matched	Asian households	Black households
One	0.008 (0.025)	0.186*** (0.040)
Four	0.003 (0.020)	0.190*** (0.031)
Eight	0.006 (0.020)	0.198*** (0.029)
No. of treated observations	874	345
No. of observations	19,776	19,247

Notes: ***, ** and * represent that p-value is significant at 1%, 5% and 10% level respectively.

Table 5: ATT for the Black Households within Sub-groups

		Households with					
No. of controls matched	Whole Sample	Income above median value	Income below median value	Employed HRP	HRP age above 31	Savings	An income gap
One	0.186*** (0.040)	0.192*** (0.049)	0.197*** (0.060)	0.238*** (0.049)	0.193*** (0.043)	0.012 (0.081)	0.393*** (0.072)
Four	0.190*** (0.031)	0.182*** (0.036)	0.169*** (0.048)	0.405*** (0.225)	0.223*** (0.034)	0.131** (0.062)	0.318*** (0.054)
Eight	0.198*** (0.029)	0.193*** (0.035)	0.191*** (0.046)	0.202*** (0.037)	0.224*** (0.032)	0.122** (0.060)	0.290*** (0.050)
No. of treated obs.	345	203	142	227	300	86	84
No. of obs.	19,247	8,796	9,593	11,130	17,345	6,249	4,516

***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

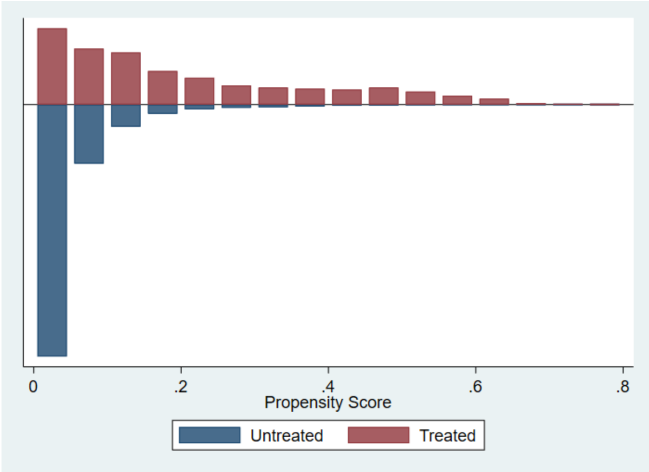

Figure 1: The distributions of the propensity score of the treated group and untreated group.

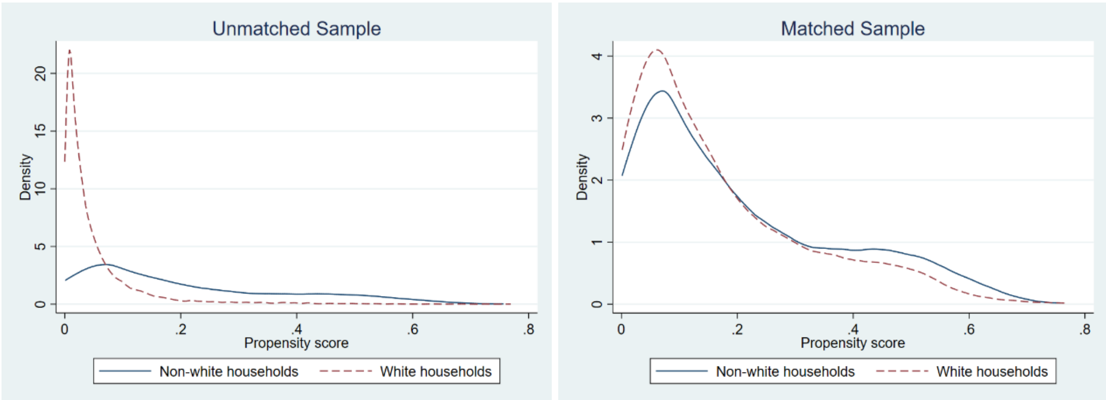

Figure 2: The distribution of the propensity score for before matched and after matched samples

Table 6: Treatment effects estimation using inverse-probability weights with regression adjustment

	Full Sample	Households with				
		Income below median value	Unemployed HRP	HRP age above 31	Savings	An income gap
ATT – non-white (1 vs 0)	0.057*** (0.015)	0.033 (0.022)	0.007 (0.023)	0.060*** (0.016)	0.044* (0.026	0.104*** (0.031)
P.O. mean (non-white = 0)	0.419*** (0.011)	0.604*** (0.018)	0.554*** (0.021)	0.366*** (0.017)	0.229*** (0.015)	0.535*** (0.024)
Overidentification test						
Prob > chi^2	0.139	0.123	0.174	0.151	0.487	0.216
No. of Obs.	20,090	10,019	8,345	18,096	6,911	4,923

***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively

References

André, C. & Girouard, N. 2009. Housing Markets, Business Cycles and Economic Policies. *In:* Arestis, P., Mooslechner, P. & Wagner, K. (eds.) *Housing Market Challenges in Europe and the United States.* London: Palgrave Macmillan UK.

Benston, G. J. & Horsky, D. 1992. The relationship between the demand and supply of home financing and neighborhood characteristics: an empirical study of mortgage redlining. *Journal of Financial Services Research,* 5**,** 235-260.

Black, H., Schweitzer, R. L. & Mandell, L. 1978. Discrimination in mortgage lending. *The American Economic Review,* 68**,** 186-191.

Bowles, P., Ajit, D., Dempsey, K. & Shaw, T. 2011. Urban Aboriginal use of fringe financial institutions: Survey evidence from Prince George, British Columbia. *The Journal of Socio-Economics,* 40**,** 895-902.

Canhoto, A. I. & Dibb, S. 2016. Unpacking the interplay between organisational factors and the economic environment in the creation of consumer vulnerability. *Journal of Marketing Management,* 32**,** 335-356.

Charron-Chénier, R. & Seamster, L. 2020. Racialized Debts: Racial Exclusion From Credit Tools and Information Networks. *Critical Sociology***,** 0896920519894635.

Corlett, A. 2017. Diverse outcomes. Living standards by ethnicity. London: Resolution Foundation.

Cribb, J. & Simpson, P. 2018. Barriers to homeownership for young adults. *IFS Green Budget: October*.

Dehejia, R. H. & Wahba, S. 2002. Propensity score-matching methods for nonexperimental causal studies. *Review of Economics and statistics,* 84**,** 151-161.

Deku, S. Y., Kara, A. & Molyneux, P. 2016. Access to consumer credit in the UK. *The European Journal of Finance,* 22**,** 941-964.

Demirgüç-Kunt, A. & Klapper, L. 2013. Measuring financial inclusion: Explaining variation in use of financial services across and within countries. *Brookings Papers on Economic Activity,* 2013**,** 279-340.

Demirguc-Kunt, A., Klapper, L., Singer, D., Ansar, S. & Hess, J. 2018. *The Global Findex Database 2017: Measuring financial inclusion and the fintech revolution*, The World Bank.

Devlin, J. F. 2005. A detailed study of financial exclusion in the UK. *Journal of Consumer Policy,* 28**,** 75-108.

Equality and Human Rights Commission 2016. Healing a divided Britain: the need for a comprehensive race equality strategy.

Finney, A. & Kempson, E. 2009. *Regression Analysis of the Unbanked: Using the 2006-07 Family Resources Survey*, HM Treasury.

Fisher, P. & Nandi, A. 2015. *Poverty across ethnic groups through recession and austerity*, Joseph Rowntree Foundation York.

Fsa 2010. *Mortgage Market Review: Responsible Lending*, Financial Services Authority.

Gonzales Martinez, R., Aguilera-Lizarazu, G., Rojas-Hosse, A. & Aranda Blanco, P. 2020. The interaction effect of gender and ethnicity in loan approval: A Bayesian estimation with data from a laboratory field experiment. *Review of Development Economics,* 24**,** 726-749.

Hilber, C. The determinants of homeownership across europe: Panel data evidence. 54th Annual North American Meetings of the Regional Science Association International Savannah, 2007.

Hogarth, J. M., Anguelov, C. E. & Lee, J. 2005. Who has a bank account? Exploring changes over time, 1989–2001. *Journal of Family and Economic Issues,* 26**,** 7-30.

Imai, K. & Ratkovic, M. 2014. Covariate balancing propensity score. *Journal of the Royal Statistical Society: Series B: Statistical Methodology***,** 243-263.

Imbens, G. W. & Wooldridge, J. M. 2009. Recent developments in the econometrics of program evaluation. *Journal of economic literature,* 47**,** 5-86.

Kara, A. & Molyneux, P. 2017. Household Access to Mortgages in the UK. *Journal of Financial Services Research,* 52**,** 253-275.

Kempson, E. & Whyley, C. 1999. Understanding and combating financial exclusion. *Insurance Trends,* 21**,** 18-22.

Khan, O. 2019. Economic inequality and racial inequalities in the UK: Current evidence and the possible effects of systemic economic change. Runnymede Trust.

Ladd, H. F. 1998. Evidence on discrimination in mortgage lending. *Journal of Economic Perspectives,* 12**,** 41-62.

Luan, D. X. 2019. Bridging the credit gap for sustainable medicinal plant value chain development in Northwestern Vietnam. *Agricultural Finance Review,* 79**,** 443-466.

Ministry of Housing 2017. *English Housing Survey: Age of first-time buyers*, Financial Services Authority.

Munnell, A. H., Tootell, G. M., Browne, L. E. & Mceneaney, J. 1996. Mortgage lending in Boston: Interpreting HMDA data. *The American Economic Review***,** 25-53.

Ravina, E. 2008. Love & loans: The effect of beauty and personal characteristics in credit markets. *Journal of Finance*.

Rosenbaum, P. R. & Rubin, D. B. 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika,* 70**,** 41-55.

Schafer, R. & Ladd, H. F. 1981. *Discrimination in mortgage lending*, MIT Press.

Simpson, W. & Buckland, J. 2009. Examining evidence of financial and credit exclusion in Canada from 1999 to 2005. *The Journal of Socio-Economics,* 38**,** 966-976.

Stegman, M. A. & Faris, R. 2005. Welfare, work and banking: The use of consumer credit by current and former TANF recipients in Charlotte, North Carolina. *Journal of Urban Affairs,* 27**,** 379-402.

Tootell, G. M. 1996. Redlining in Boston: Do mortgage lenders discriminate against neighborhoods? *The Quarterly Journal of Economics,* 111**,** 1049-1079.

Wooldridge, J. M. 2010. *Econometric analysis of cross section and panel data*, MIT press.

Wyly, E., Moos, M., Hammel, D. & Kabahizi, E. 2009. Cartographies of race and class: mapping the class-monopoly rents of American subprime mortgage capital. *International Journal of Urban and Regional Research,* 33**,** 332-354.