Down Payment Constraints, Homeownership and Household Spending*

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Abstract

This paper examines how easing down payment constraints affects homeownership and household spending by studying a large-scale UK policy initiative called Help-to-Buy. Exploiting geographical variation in exposure to the program we document a significant increase in home purchases as a result of HTB, especially benefiting young buyers. The impact on house prices was subdued, except in the London area. Regions more exposed to the program experienced a relative increase in durable consumption. Government programs that ease down payment constraints can thus boost homeownership of young buyers as well as household spending.

JEL classification: E21; G21; R21; R28

Keywords: down payment constraints; mortgage market; homeownership; household spending

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1 Introduction

Homeownership rates, especially for younger households, are in long-term decline. And this trend has accelerated since the global financial crisis (Figure 1). Weak earnings growth, rising house prices and tighter lending standards make it harder for prospective buyers to qualify for a mortgage. A key issue is the lack of savings for a down payment.[1] Already a barrier in normal times, insufficient savings can become a big constraint when lenders pull low-down payment mortgages from the market, as happened during the global financial crisis (Figure 2) and now during the covid-19 pandemic.[2] This disproportionately affects first-time and young buyers who often rely on low-down payment mortgages to secure a home purchase (Figure 3).

An important question therefore is whether policies that aim to make housing more affordable by easing down payment constraints benefit young and first-time buyers and whether there are spillovers associated with these policies. This paper sheds light on these issues by studying a large-scale UK policy initiative, called Help-to-Buy. Exploiting geographical variation in the exposure to the program and using detailed data on mortgage loans and durable consumption, it shows that the program did not only make it easier for first-time and younger buyers to buy a house, but also led to a surge in consumption. Publicly-funded programs that ease down payment constraints can thus boost both homeownership as well as household spending.

The UK Help-to-Buy (HTB) program was introduced in April 2013, against the backdrop of a frozen market for low-down payment mortgages. The purpose of the program was to make housing more affordable by enabling prospective buyers to purchase a home with only a five percent down payment. The program included two main schemes: the "Equity Loan (EL) Scheme" introduced in April 2013 and the "Mortgage Guarantee (MG) Scheme" introduced in October 2013.[3] Under the EL scheme the government provides home buyers with funds (the equity loan) of up to 20 percent of the cost of the purchase price of a newly built property,[4] while home buyers must provide a down payment of (at least) five percent.[5] Under the MG scheme a qualifying buyer must also pay a five percent down payment. The government provides the lender a guarantee for a further 20 percent of the property price. The MG scheme could be used to purchase both old and new builds. Both schemes were available for first-time buyers and home movers. The MG part of the program was suspended by the end of 2016 but the EL scheme remains in effect.

Studying this particular program is useful for several reasons. First, policy makers in several

[1]Santander recently surveyed over 5000 would be first-time buyers in the UK and this study reveals that the biggest barrier to homeownership is saving enough for a down payment. In addition, several papers show that down payment constraints bind for many young households (see, for example, Linneman and Wachter, 1989; Engelhardt, 1996; Haurin, Hendershott and Wachter, 1996).

[2]See, ft.com/content/88d1274f-e414-4444-9bc7-d7c97c5cfb26

[3]The program consists of two other schemes but these were much smaller in magnitude.

[4]This value increased to 40 percent in the Greater London area in February 2016.

[5]Benetton et al. (2019) show that for the majority of EL loans the down payment is 5 percent.

countries are thinking of ways to make housing more affordable for younger buyers. HTB is one of the biggest government interventions in the UK housing market and its two main schemes are representative of programs implemented in other countries as well.[6] Understanding the effectiveness of these programs, and highlighting potential frictions, can provide valuable insights about their usefulness. Second, while a vast literature exists that studies various interactions between house prices and consumption, very few papers have studied how improved access to homeownership affects consumption. HTB allows us to shed new light on this issue.

Assessing the impact of government programs on the economy is challenging because it is difficult to construct a meaningful counterfactual scenario. What would have happened to the economy in the absence of the program? We address this issue by exploiting geographical variation in exposure to the program in a similar vein as the identification strategies employed by, for example, Wilson (2012), Mian and Sufi (2012) and Berger, Turner and Zwick (2020). Although HTB was national in scope, it specifically targeted households with limited ability to save for a down payment. These types of households do not randomly spread across the country, but tend to be attracted to specific areas where the local housing supply is more suitable and/or with local amenities that are particularly appealing to these buyers. As these local housing market characteristics tend to change only very slowly, an area's *historical* attractiveness should strongly correlate with the number of *potential* low-down payment home buyers at the time HTB came into effect. We can therefore reasonably assume that the impact of HTB is greater in areas where historically households bought their home with as little down payment as possible.

We measure program exposure by the number of low-down payment mortgages issued relative to all mortgages issued in a district between 2005 and 2007.[7][8] The geographical variation allows us to test for different patterns in homeownership and household spending in high versus low-exposure areas, while controlling for other confounding factors. Districts with few potential low-down payment home buyers serve as a control group because the policy is unlikely to induce many people to buy in these districts.

A key challenge in estimating the effect of HTB using geographical and time variation across UK districts is that location-specific variables might be correlated with our exposure measure. Districts with a high share of potential low-down payment home buyers differ in characteristics that could drive the results we find. For example, high exposure areas tend to have lower house prices and higher unemployment. Our empirical strategy enables us to control for all time-invariant differences between districts. In addition, we control for a multitude of time-varying district-level variables, such as house prices, income levels, unemployment and rental prices.

[6]Examples include mortgage guarantees (e.g. United States, Netherlands, United Kingdom), mortgage interest rate deductions (e.g. United States, India, Sweden, Netherlands), government loans (e.g France, United Kingdom) and home buyer tax credits (e.g. United States).

[7]Even though we refer to the UK throughout the paper, we focus our analysis on England, Scotland and Wales only as very few of our data sources include information on Northern Ireland.

[8]Throughout this study the term district refers to Local Authority District (LAD). England, Scotland and Wales comprise of 379 districts.

Furthermore, we exploit heterogeneity across home buyers in the likelihood they face binding down payment constraints. This analysis allows us to include district-time fixed effects and thus to effectively control for all (un)observable time-varying differences between high and low exposure districts. Finally, we provide evidence of parallel pre-policy trends and the start of a clear divergence of trends in high versus low exposure areas when the policy came into full effect which persisted throughout the whole HTB period.

Our paper unfolds in three parts. We begin by using detailed administrative mortgage data to examine whether HTB generated an increase in the purchase of low-down payment mortgages and which buyers benefited most from the program. We focus on the period 2010 to 2016 which captures the period when both schemes were active. Furthermore, limiting our sample to these years ensures that our findings are not affected by the global financial crisis or by the increase in uncertainty as a result of Brexit. Our mortgage data capture the universe of regulated mortgages issued in the UK and include information about the loan value, down payment and property price. Importantly, the data include detailed information about the location of the property, the age of the borrower and whether the mortgage holder is a first-time buyer or home mover.

We document a significant increase in low-down payment mortgages relative to mortgages with larger down payments in areas with a high exposure to HTB. This increase corresponds exactly with the timing of the program. These findings suggest that our HTB exposure measure performs well in explaining the actual take-up of the program. We show that this differential effect remains when controlling for time-varying and time-invariant district-level controls. In addition, we find no evidence of differential pre-trends in low and high exposure areas. In other words, HTB produced the intended effect of improving access to low-down payment mortgages.

Did the program make low-down payment mortgages more accessible to buyers that more likely have limited savings? Indeed, we find that the increase in the share of low-down payment mortgages was particularly pronounced for first-time and younger buyers, i.e. those households that are more likely liquidity constrained. Our estimates suggest that during the program period a younger buyer in a high exposure area (75th percentile exposure) is around 60 percent more likely to access a low-down payment mortgage than a young buyer in a low exposure area (25th percentile exposure). Our estimates are similar for first-time buyers. These results are robust to excluding the London area and remain when controlling for district-time fixed effects.

The demonstrated increase in the availability of low-down payment mortgages can impact demand for housing via an extensive margin, a timing, or an intensive margin effect. The first two of these effects will have a positive impact on home purchases and the transition into homeownership, while the latter would only result in a switch from high to low-down payment mortgages. In the second part of the paper, we provide an assessment of the extent to which HTB translated into a rise in home purchases and so homeownership.

We document a significant increase in home purchases in high exposure relative to low exposure districts. During the policy period, we estimate that approximately 320,000 additional homes were purchased due to HTB that would not have been purchased otherwise. This implies that HTB increased home sales by 18 percent during the policy period. The increase was the result of both households moving homes as well as households transitioning into homeownership, with the latter accounting for 80 percent of the increase. Younger households (both first-time buyers as well as home movers) were responsible for 92 percent of the increase. This evidence suggests that HTB indeed enabled previously down payment constrained buyers to purchase a home.

In addition, we find that districts more exposed to the program experienced only a slight increase in house prices, except in the London area where the impact on house prices was more pronounced. These findings are consistent with Carozzi, Hilber and Yu (2020) who show that responsiveness in housing supply, which is weak in London, critically determined whether house prices reacted to the EL scheme.

In the final part of the paper, we explore to what extent a loosening of down payment constraints affects household spending. From a theoretical point of view, the impact of policies aimed at making homeownership more affordable via a reduction in down payment constraints is *a priori* unclear. On the one hand, if the down payment is a binding liquidity constrained then the purchase of a house should free up disposable income with a positive effect on consumption (Engelhardt, 1996). Furthermore, homeowners tend to invest more in their home compared to renters and this could generate an increase in housing-related household spending, especially when prospective home buyers put money aside (on top of their down payment) to invest in their future home. On the other hand, while moving houses is shown to be positively linked to moving-related expenditures, this is in some cases offset by lower consumption in other categories (Best and Kleven, 2017). In addition, households that become more indebted due to their mortgage might lower their consumption to service their debt and to save more in order to lower future debt levels. A systematic look at the impact of HTB using detailed consumption data can help understand any positive or negative spillover effects of these kind of programs on household spending.[9]

We exploit district level data on car sales over the period 2010 to 2016 to examine the impact of HTB on durable consumption. We employ the same difference-in-differences strategy, which enables us to control for many (time-varying) district-level covariates that could be correlated with the demand for cars. We find that more exposed areas experienced a relative increase in car sales after HTB came into effect. We do not find evidence of differential pre-trends in high and low-exposure areas.

[9] Another channel through which a loosing of down payment constraints can affect consumption is through its impact on house prices. Higher housing values can positively affect consumption through a wealth channel, home extraction channel or reduction in borrowing constraints. As we are interested in the direct relationship between the purchase of a home by down payment constraint households and consumption, we abstract from this channel but control for it by including house prices at the district level in our analysis.

While several drivers can explain these findings, they are consistent with the idea that aspiring home buyers for whom down payment constraints bind hold their consumption low in the years prior to purchasing a home in order to save for a down payment. Once they have bought the house, their disposable income increases again allowing them to consume more. A recent survey by Santander indeed shows that almost half of aspiring home owners in the UK cut back on unnecessary spending and socializing in order to save enough for a down payment. Overall the evidence presented indicates that government programs that make housing more affordable by easing down payment constraints not only make it easier for first-time and younger buyers to buy a house, but boost household spending as well.

We want to caution against over-interpretation of our findings. While we document an increase in durable consumption in areas more exposed to HTB, this does not mean that household spending remains permanently higher in these areas. It is very well possible that the increase in durable consumption that we document reflects a temporary catch-up on consumption that will be reversed later on. Unfortunately, the uncertainty induced by Brexit makes it difficult to test how household spending behaved in the medium term. Furthermore, higher levels of mortgage debt can lead to instability as indebted households that are faced with an economic or financial shock are more likely cut their spending (e.g., Dynan, 2012; Mian, Rao and Sufi, 2013; Baker, 2018 and Kovacs, Rostom and Bunn, 2018). Regions where homeownership increased as a result of the program might therefore be more susceptible to a decline in household spending during the Covid-19 crisis. Furthermore, HTB was introduced when the economy was doing well. The impact of a similar program introduced at the height of a crisis might be different.

The remainder of the paper is structured as follows. The next section provides a review of the related literature. Section 3 discusses the policy background. Section 4 describes the data and Section 5 introduces the empirical strategy. Section 6 reports the results on the effects of HTB on the mortgage market, Section 7 on the housing market and Section 8 on household spending. Section 9 concludes.

2 Review of the Literature

Our paper contributes to the emerging literature on policy responses to stimulate homeownership of marginal buyers. Berger, Turner and Zwick (2020) evaluate a US tax credit policy exclusively targeted at first-time buyers: the First-Time Homebuyer Credit. Besides an increase in total sales volumes, they document a marked increase in the transition to homeownership and a positive impact on house prices. Mabille (2020) develops a business cycle model with regionally binding credit constraints that allows him to evaluate several stimulus policies. He shows that housing stimulus policies targeted at marginal buyers can have important heterogeneous regional effects. While not specifically focusing on marginal buyers, Best and Kleven (2017) study the effect of fiscal stimulus through a tax holiday on housing sales in the UK.

They find a positive effect on home sales that only reverses partially post-policy and document a temporary increase in moving-related household spending.

We complement these papers in several ways. First, instead of evaluating a fiscal stimulus program designed to support housing markets during the Great Recession, we study a policy introduced when the UK housing market was stable and that was specifically aimed at making housing more accessible to buyers with difficulties saving for a down payment. Second, while the program targeted marginal buyers there were no restrictions as to who could use the program (par from buy-to-let and second home buyers). This feature, combined with our detailed mortgage data, allows us to examine who ultimately benefits from such a program. Third, by exploiting geographical variation in program exposure we distinguish important local market effects. Fourth, focusing on a key durable consumption item, the purchase of a car, we show that a program that lowers down payment constraints can also have a positive effect on household spending, beyond moving-related expenses.

Our evidence sheds novel light on the impact of down payment constraints on marginal buyers. In a seminal housing model Stein (1995) shows that down payment constraints can explain the positive correlation between house prices and demand for housing. Ortalo-Magne and Rady (2006) explicitly incorporate first-time buyers in their life-cycle model of the housing market and show that any factor that impacts the ability of potential first-time buyers to afford a down payment can have a big impact on the housing market. Fuster and Zafar (2016, forthcoming) elicit from a specifically targeted survey that a reduction in down payment has a much larger effect on households' willingness to purchase a house than a decline in mortgage rates. This suggests that many households face difficulties saving for their down payment, especially in areas with high home prices. In line with these studies, a tightening of loan-to-value (LTV) regulation is found to negatively affect transition into homeownership by liquidity constrained borrowers (Bekkum et al., 2019) and to induce the purchase of lower quality homes in lower socioeconomic neighborhoods (Tzur-Ilan, 2020). Our work shows that a government intervention that reduces down payment constraints can positively impact homeownership of young buyers and has spillover effects via household consumption but with important regional differences. As such it also adds to the literature that shows that national policies affecting the mortgage market can have very diverse regional consequences (see, for example, Hurst et al., 2016; Beraja et al., 2019).

Our analysis of HTB spillover effects to household spending links our paper to the broad literature that studies the relationship between the housing market and consumption. A large body of research exists that studies the propensity for households to fund current consumption out of housing wealth. This literature highlights several effects of housing values on consumption: the traditional wealth effect (see, for example, Benjamin, Chinloy and Jud, 2004; Bostic, Gabriel and Painter, 2009; Case, Quigley and Shiller, 2012) and a home equity extraction effect (see, for example, Mian and Sufi, 2009; Mian and Sufi, 2011; Best et al., 2020). In addition, Campbell and Cocco (2007) show that house price growth can affect consumption through a relaxation of borrowing constraints. A related literature shows that households with mortgage debt tend to have larger consumption responses to tax changes (Cloyne and Surico, 2017) and monetary policy shocks (DiMaggio et al., 2017) with much stronger effects for younger homeowners (Wong, 2016).[10]

To the best of our knowledge, only Engelhardt (1996) explicitly studies the impact of down payment constraints on consumption. He finds that households in the US experienced periods of increased food consumption after a home purchase. Distinct from his study, we exploit geographical variation in a government program that was specifically targeted to reduce down payment constraints. This allows us to better control for factors that can both drive the transition into homeownership and consumption.

Finally, our results compliment other studies on the impact of HTB, which tend to focus exclusively on the EL scheme. These papers show that the EL scheme had a positive impact on the purchase of new properties (Finlay, Williams and Whitehead, 2016; Szumilo and Vanino, forthcoming), with households buying more expensive properties, not reducing mortgage debt or house price risk exposure (Benetton et al., 2019). Carozzi, Hilber and Yu (2020) show that the EL scheme induced an increase in house prices but only in areas with unresponsive housing supply. Finally, Benetton, Bracke and Garbarino (2018) exploit the EL scheme to show that lenders use down payment size to price unobservable borrower risk.

3 Policy Background

3.1 Down Payment as Binding Borrowing Constraint

Before turning to the details of the Help-to-Buy (HTB) Program, it is insightful to illustrate the dominance of the down payment constraint in determining the maximum mortgage that a household can access. The maximum loan size L depends on two different borrowing constraints: the down payment constraint and the income constraint. For the down payment constraint, the household's down payment D determines the possible loan size L via the loan-to-value (LTV) requirement, denoted by θ_{LTV}. The maximum loan size for a given LTV requirement is $\theta_{LTV} \times$ House price. For the income constraint, the household's income Y determines the possible loan size L via the loan-to-income (LTI) requirement, denoted by θ_{LTI}. The maximum possible loan size for a given LTI requirement is $\theta_{LTI} \times Y$.[11] Taking these constraints together,

[10]Another strand of the literature has examined the response of household spending to fiscal stimulus in the form of tax refunds (Shapiro and Slemrod, 1995), rebates (Shapiro and Slemrod, 2003; Johnson, Parker and Souleles, 2006; Agarwal, Liu and Souleles, 2007; Parker et al., 2013), or other transfer programs (Hsieh, 2003; Mian and Sufi, 2012; Agarwal and Qian, 2014).

[11]An additional requirement is the payment-to-income (PTI) ratio which depends on household income and the loan interest rate. The PTI ratio is calculated by dividing total recurring monthly debt by monthly gross

the maximum house price a household can afford is given by:

$$\text{Max. house price} = \min\left(\theta_{LTI} \times Y + D, \frac{D}{1-\theta_{LTV}}\right) \tag{1}$$

Figure 4 shows the impact of a loosening of the LTV and LTI constraints on the maximum affordable house price for a household with $Y = £44,000$ and $D = £9,000$.[12] In the top panel we keep θ_{LTI} fixed at 4.5 and allow θ_{LTV} to vary between 75% and 95%. Figure 4 clearly shows that for this hypothetical household the binding constraint is the LTV. This household would be able to borrow $£198,000$ when $\theta_{LTI} = 4.5$. However, with a down payment of $£9,000$ the maximum affordable house when $\theta_{LTV} = 75\%$ is only $£36,000$. When θ_{LTV} increases to 90% the household can afford a house worth $£90,000$, a sharp increase. This increase is even more pronounced when θ_{LTV} increases to 95%; the household can now afford a house worth $£180,000$, representing again a doubling of the maximum house price. As the lower panel of Figure 4 shows, a loosing of the LTI constraint does not have any impact on housing affordability for this household. If we keep $\theta_{LTV} = 95\%$ and let θ_{LTI} vary between 4.5 and 6, the maximum house price under the LTI constraint rises from $£207,000$ to $£273,000$, but the LTV remains the binding constraint.

These figures thus indicate that relative small changes in the LTV can potentially generate large behavioral responses among liquidity constrained households. For households that have a hard time saving for their down payment, an increase in the LTV from 90% to 95% can make a big difference in housing affordability, keeping all else constant. This leverage effect is much smaller for changes in the LTI.[13] A government policy that facilitates the purchase of high-LTV/low-down payment mortgages can thus potentially have a large impact on the housing market, primarily driven by liquidity constrained households. Making housing more affordable for these households was the stated intention of Help-to-Buy.

A relaxation of the down payment constraint can theoretically have three effects on demand in the housing market. First, households that previously preferred to rent as owning a property in their desired location was not feasible, might now switch to buying (extensive margin). Second, households might pull forward their home purchase, as they can now use their existing down payment to purchase a property that was previously too expensive (timing effect). Third, households might use their existing down payment to purchase a more expensive home (intensive margin). In the first two cases, HTB would have a positive impact on home purchases and the

income. In the UK, lenders typically request a PTI smaller than 36%, with no more than 28% of that debt going towards mortgage debt servicing. For simplicity we abstract from the PTI constraint in this section.

[12] These values represent the median household income and the median down payment for home buyers with a low-down payment mortgage in the period 2005 to 2007.

[13] Not surprisingly, over 90 percent of mortgages signed between 2005 and 2007 with a LTV of 95% or higher had a LTI of less than 4.5 (the current regulatory LTI constraint). For wealthier households or households living in areas where house prices on average are very high, the LTI is more often the binding constraint. Indeed, the vast majority of mortgages with a LTI of 4.5 or more are low LTV mortgages, indicating that these borrowers are not constrained by their down payment.

transition into homeownership. In the third case, it would only result in a switch from low to high LTV mortgages, but it would not affect the transition into homeownership. Note that the second and third effect relate to both first-time buyers as well as home movers, while the first effect only relates to first-time buyers.

3.2 The Help-to-Buy Program

The Help-to-Buy (HTB) Program was first announced in March 2013 by George Osborne - the Chancellor of the Exchequer at that time - as part of the UK's 2013 budget. The program was described by some commentators as "the biggest government intervention in the housing market since the 'Right to Buy scheme' of the 1980s."[14]

The key feature of HTB was that it allowed borrowers to buy a home with only a five percent down payment. At the time the program was introduced, the low-down payment segment of the mortgage market was frozen (Figure 2). The explicit objective of the program was to facilitate mortgage market access to borrowers facing significant down payment constraints, with George Osborne explaining in his budget speech that "for anyone who can afford a mortgage but can't afford a big down payment, our [HTB] Mortgage Guarantee will help you buy your own home."[15]

There were two main HTB options. The first was the "Equity Loan" (EL) scheme, which was offered from 1 April 2013 to 31 December 2020. The EL scheme was available for both first-time buyers and home movers (but not for buy-to-let or second home mortgages) and applied to new-build properties with a purchase price of less than £600,000 (£300,000 in Wales). While the borrower(s) required a five percent down payment, the UK Government lent up to 20 percent (40 percent within London from 2016) of the property value via a low-interest "equity loan". A lender provided a mortgage for the remaining amount of up to 75 percent (55 percent in London from 2016) of the property value. The government equity loan component was interest free in the first five years after the property purchase. There were other requirements about the type of qualifying HTB mortgage. For example, the mortgage needed to be a capital repayment mortgage and could not be an interest-only or offset mortgage. Additionally, the LTI of the mortgage needed to be 4.5 or less.

The second main HTB option was the "Mortgage Guarantee" (MG) scheme, which was offered from 1 October 2013 to 31 December 2016. As with the EL scheme, borrowers required a five percent down payment and the scheme was available to first-time buyers and home movers. The UK government provided a guarantee of 20 percent of the property's value to lenders in exchange for a small fee. This meant that MG scheme mortgages effectively had a 75 percent LTV from

[14] Ian Cowie (28 March 2013). "Budget 2013: winners and losers of Osborne's Help to Buy pledge". Link: https://www.telegraph.co.uk/finance/property/buying-selling-moving/9959021/Budget-2013-winners-and-losers-of-Osbornes-Help-to-Buy-pledge.html

[15] The full text of the Chancellor's statement for the 2013 UK budget can be obtained here: https://www.gov.uk/government/speeches/budget-2013-chancellors-statement

a lender's perspective. Unlike the EL scheme, the MG scheme applied to all properties with a purchase price of less than £600,000, rather than new-builds only. Not all lenders provided MG scheme mortgages but most did. Table A.1 in the Appendix presents a summary of the different schemes and their requirements.

The number of completed home purchases under the HTB program from January 2014 to December 2016, when both the EL and MG schemes were on offer, was approximately 200,000. This figure was split almost equally between EL scheme and MG scheme home purchases. HTB mortgages represented around 10 percent of all mortgages (excluding remortgages) over this period and around 18 percent of first-time buyers mortgages. As Figure 5 demonstrates, there is a visible increase in both the number and the share of low-down payment mortgages over the period both EL and MG schemes were offered. The increase started in 2013 but only really took off in 2014 when both programs were active and the public became more aware of the existence of both schemes.

Aggregate patterns are indicative that HTB had an effect. But to properly evaluate the impact of the program on the mortgage market, homeownership and consumption we must form a reasonable estimate for what would have happened if the program had not been implemented (i.e. construct a counterfactual). Our approach is to exploit cross-sectional variation across UK districts in their exposure to HTB based on the presence of *potential* low-down payment home buyers. Areas with few potential low-down payment home buyers serve as the "control group" because buyers in these areas would unlikely make use of the program. The difference between the treated and control areas provides for an estimate of the marginal impact of the program. In Section 5 we describe our research strategy in detail.

4 Data and Summary Statistics

In this section, we describe the data sources and key variables that we use in our analysis, as well as present the corresponding summary statistics. Our data set includes 379 local authority districts (LADs) in the UK for which we have mortgage market data, measures of home sales, household spending data and other macroeconomic data. We refer to LADs as "districts" throughout the text. The data set covers districts in England, Wales and Scotland. We exclude Northern Ireland as this region is not included in several of our main data sources. The districts in our sample cover 97 percent of the UK population and 98 percent of total mortgages issued. We conduct our analysis at the district level because these regions represent naturally integrated economic units similar to the core based statistical areas (CBSAs) in the US.

4.1 Data

To measure the impact of HTB on the housing market and homeownership we use administrative, loan-level mortgage data from the Product Sales Database (PSD). The PSD is a regulatory database collected by the UK Financial Conduct Authority that provides information on all regulated mortgages in the UK from April 2005 onward. These data include information about all mortgage contracts at the point of sale, such as: the date the mortgage was issued, the loan value, the property value, and thus the down payment used, among other information. There is also information about the borrower associated with each loan, such as: borrower type (e.g. first-time buyer or home mover), age, income, and employment status. Finally, the PSD includes information about the lender for each loan and the postcode of the property. We use the November 2018 National Statistics Postcode Lookup data set to map UK postcodes to UK local authority districts.

It is worth discussing some particularities of the UK mortgage market as it has some features that distinguish it from other countries. In particular, UK lenders offer a product menu of quoted interest rates that correspond almost exclusively to "LTV buckets" (see, for example, Best et al., 2020; Robles-Garcia, 2019).[16] The main LTV buckets are: 0-50; >50-60; >60-70; >70-75; >75-80, ..., and >90-95. Mortgages with >95 percent LTV are very rare. An implication of this pricing strategy is that a borrower would be charged the same interest rate with either a 90.1 percent LTV or a 95.0 percent LTV mortgage, because both LTV ratios are in the same pricing bucket. But a borrower would be charged a significantly lower interest rate with a 90.0 percent LTV compared to a 90.1 percent LTV mortgage, because these two LTV ratios are in different pricing buckets. As a result in the UK mortgage market down payments jump in incremental steps of five percent, i.e. from five percent to ten percent with hardly any down payments in between these percentages.

The first outcome variable that we obtain from the PSD is our measure of *"Low-down Payment Mortgages"*. Low-down payment mortgages include all mortgages with a down payment of five percent or less.[17] These include all MG mortgages, but only a subset of the EL mortgages as some households opt for a higher down payment than the five percent minimum that is required to quality for the loan.[18] In order to identify EL mortgages, we match an EL data set collected by the UK Ministry of Housing, Communities and Local Government with the PSD. We merge these data using the approach of Benetton et al. (2019).[19]

A second set of outcome variables that we obtain from the PSD are year-district-level measures

[16] The quoted interest rates and origination fee also reflect the actual cost of the mortgage that a borrower will pay for the product. That is to say that there is no negotiation between a borrower and a lender in the UK (see, e.g. Allen, Clark and Houde, 2014; Benetton, 2018).

[17] These mortgages are otherwise known as 95 LTV mortgages. As explained in the previous paragraph in theory these low-down payment mortgages can have a down payment of up to 9.9 percent, in practice the majority of them have a down payment of 5 percent.

[18] The majority of households put down five percent (see Benetton et al., 2019)

[19] We like to thank the authors for sharing the data and program with us.

of home sales. We construct five measures. Our first measure is the number of *"Home Sales"*, which comprises the total home sales to both first-time buyers and home movers. Our next two measures are the *"First-time Buyer Sales"* and "*Home Mover Sales"*, which comprise the total home sales to first-time buyers and home movers, respectively. Our final two measures are *"Younger Buyer Sales"* and *"Older Buyer Sales"*, which comprise the total home sales to buyers between 20 and 39 years old and to buyers between 40 and 59 years old, respectively. All measures represent flow measures.

To examine the effect of the HTB program on household spending, we use a year-district-level data set on car sales made available by the UK Department for Transport. Our "*Car Sales*" measure is defined as the number of new private car registrations for each year-district combination.

Finally, we collect macroeconomic data at the year-district-level to include as control variables in our analysis. These are important because districts with high HTB exposure may also differ in ways that independently influence the number of low-down payment mortgages and other economic outcomes of interest during the sample period. We include year-end values of district-level average rent, median income, unemployment, average house price and population. The average house price information is taken from the UK Land Registry Price Paid Dataset (PPD). All other control variables, including the migration-related variables used in Section 7.2, are provided by the UK Office of National Statistics (ONS). We adjust all relevant nominal control variables, as well as the nominal PSD variables, to 2016 prices using the Consumer Price Index including owner occupiers housing costs, which is the lead UK inflation index.

4.2 Summary Statistics

Table 1 presents summary statistics for the key variables used in our analysis. Summary statistics are provided for two periods: the "pre-HTB" period (covering 2010 to 2012) and the "HTB" period (covering 2014 to 2016). A few things are worth highlighting.

In the period before HTB, 3 percent of all mortgages required a deposit of only 5 percent. During the years HTB was active this number increased to 18 percent. This can be interpreted as potential *prima facie* evidence that the HTB program had a significant impact on increasing the share of low-down payment mortgages. Furthermore, the share of both first-time buyers and younger buyers was higher in the HTB period compared to the period preceding it.

Similarly, the average number of home sales at the district-time level increased from 1,280 (mortgaged) home sales in the pre-HTB period to 1,660 (mortgaged) home sales in the HTB period, indicating an increase in the overall number of mortgages in the policy period. In addition, the standard deviation grew from 800 to 1080 mortgages, suggesting that the spread also widened. This suggests that the program had a stronger impact in some districts compared to others.

The loan-level control variables do not appear to change much over the two periods. There are some more notable differences in the district-level control variables however. In particular, the mean for the *Unemployment Rate* variable decreases from 7.24 percent in the pre-HTB period to 4.96 percent in the HTB period, while there is an increase for *Average House Prices* from £203,870 in the pre-HTB period to £226,430 in the HTB period. Both are a reflection of the UK economy recovering from the global financial crisis and its aftermath.

5 Empirical Strategy

To assess the effect of Help-to-Buy on homeownership and household spending, we exploit geographical variation in *ex ante* exposure to the program. Our identification strategy has similarities to that of Wilson (2012), Mian and Sufi (2012) and Berger, Turner and Zwick (2020) who exploit geographical variation in exposure to the American Recovery and Reinvestment Act, the Cash for Clunkers program and the First-Time Homebuyer Credit program, respectively. Although HTB was national in scope, exposure to the scheme critically depended on the local housing market. This difference in geographical exposure helps us produce a counterfactual to estimate what would have happened in the absence of the program.

HTB specifically targeted households with limited ability to save for a down payment. These types of households do not randomly spread across the country, but tend to be attracted to specific areas. These are areas where local housing supply is better suited in terms of affordability, housing-type, and certain local amenities, such as pubs and restaurants, schools or parks, that are particularly appealing to these buyers who tend to be relatively young. These local housing market characteristics tend to change only very slowly. We thus expect the impact of HTB to be greater in areas where *historically* households bought their home with as little down payment as possible as this should strongly correlate with the number of *potential* low-down payment home buyers in a given area at the time the HTB program came into effect. Areas with few potential low-down payment home buyers function as the "control group" as buyers in these areas are unlikely to react to the program. The difference between high exposure (treated) and low exposure (control) districts provides then for an estimate of the marginal impact of the program.[20]

[20] This interpretation requires that no spillovers exist between treated and control areas as a result of endogenous moves from low exposure to high exposure areas. If people endogenously move from a low to a high HTB exposure area as result of the program, both high and low exposure areas will be affected. This concern is not relevant for FTBs as they did not own a home before moving, but it could affect our estimate for home movers. Another potential spillover relates to the the presence of real estate chains (linked housing transactions whereby households buying a new house in a high exposure area are simultaneously selling their existing house in a low exposure area or whereby the seller of a property in a high exposure area subsequently buys a property in a low exposure area). Such real estate chains introduce the possibility that the HTB-induced transactions in high-exposure areas trigger additional transactions in low-exposure areas. While, it is difficult to completely rule out endogenous moves taking place, we provide evidence in Section 6 that the majority of people in the UK tend to move within a 20 kilometer radius (i.e. within their own district) and that longer moves tend to be

To measure program exposure we focus on the period when the market for low-down payment mortgages was relatively unconstrained: the years before the financial crisis. We use the loan-level mortgage data and define "*Exposure*" as the number of mortgages with a down payment of five percent or less issued in the district between 2005 and 2007 scaled by the total of number of mortgages issued in the district over that period.[21][22] Figure 6 presents a district-level map of HTB exposure across the UK. Darker areas indicate more exposure to the program. It illustrates that there is significant variation across the whole of the UK. Exposure ranges from 9 percent to 42 percent, with a mean exposure of 23 percent.

We first examine how well our measure performs in capturing the actual take-up of low-down payment mortgages over the period that both the EL and MG schemes were offered. Figure 7 plots the relationship between our *ex ante* HTB exposure measure against the *ex post* number of low-down payment mortgages taken out over the period 2014 to 2016 scaled by the total number of mortgages purchased in the district over that period. It reveals a strong positive correlation. In districts with low HTB exposure the share of low-down payment mortgages is very low (close to zero percent), while in high exposure areas it is much higher (with a maximum of almost 25 percent).

Figure 8 shows that our measure also accurately predicts time variation. It plots both the total number of low-down payment mortgages and the share of low-down payment mortgages in low and high exposure areas over the period 2010-2016. Both the number and share of low-down payment mortgages show similar trends prior to the introduction of HTB, see a small uptick in 2013 and experience a sharp relative increase in high exposure areas when both schemes came into full effect.

A potential concern with our identification strategy is that districts with high exposure to the HTB program also differ importantly in other ways that could independently impact the demand for low-down payment mortgages. If this is the case, our exposure measure could pick up the impact of these variables. Table 2 presents the correlation between our HTB exposure measure and a set of district-level covariates. We observe that exposure to HTB is indeed not random and is positively correlated with the unemployment rate and population and negatively correlated with income levels, rents and house prices. It is important to note that these correlations do not necessarily imply a significant bias of our estimates either upwards or downwards.

Nevertheless, we address this concern in several ways. First, our empirical approach allows us to control for any time-invariant district-level differences that might impact the demand for

related to education and employment reasons. Crucially, we demonstrate that there was no change in inward migration to high exposure districts during the course of the program. We also show that our results hold when we exclude the London Area from our estimates.

[21]PSD starts in 2005. It is therefore not possible to measure exposure going further back in time.

[22]While nowadays mortgages require at least a five percent down payment, before the financial crisis mortgages with lower down payments where also accepted. We include these mortgages in our exposure measure.

low-down payment mortgages. Next, we explicitly include all variables presented in Table 2 as controls in our regressions. We show below that including them hardly impacts our results. In addition, we explicitly test for parallel trends in the period leading up to the program. Finally, our detailed mortgage data allow us to differentiate within districts between households that are more or less likely liquidity constrained, and therefore more likely to benefit from the program. Differentiating between households within a district allows us to control for all variation at the district-time level and removes many confounds from the analysis.

6 The Effect of Help-to-Buy on the Mortgage Market

6.1 General impact

We start with presenting a regression version of Figure 8. This allows us to validate the time dynamics of the HTB program impact on the mortgage market, to test for pre-event trends and to control for other variables that might drive the differential trends that we observe in high versus low exposure areas. To do this, we estimate the following panel regression model:

$$\begin{aligned} \text{Low Down Payment}_{b,l,d,t} = \; & \textstyle\sum_{s \neq 2012} \mathbb{I}_{t=s} \times \text{Exposure}_d \times \beta_s + \boldsymbol{\gamma}\text{District}_{d,t-1} \\ & + \boldsymbol{\mu}\text{Loan}_{b,l,d,t} + \lambda_{lt} + \delta_d + u_{b,l,d,t} \end{aligned} \tag{2}$$

where b indexes a mortgage, l indexes a lender, d indexes a district and t is the year. Low Down Payment$_{b,l,d,t}$ is a dummy variable that is equal to 1 for all mortgages with a down payment of 5 percent (or less), and zero otherwise. Exposure$_d$ is our measure of *ex ante* exposure to the HTB program, as described in Section 5.

We include a large number of control variables. The loan-level information contained in the PSD allow us to control for any shifts in loan-level and borrower characteristics that may reflect changes in demand for mortgages. $\mathbf{Loan}_{b,l,d,t}$ is a vector of loan-level and borrower control variables that includes: the length of the mortgage term, a set of fixed effects for the rate type (for example, if the loan has a fixed or floating rate), a set of fixed effects for the repayment type (for example, if the loan is "capital and interest"), the loan-to-income ratio, the log of the purchased property value, the log of the gross household income, and a set of fixed effects for employment status. $\mathbf{District}_{d,t-1}$ is a vector of time-varying district-level control variables and includes (the log of): average rent, median income, the unemployment rate, population, and average house prices. Our district-level control variables are predetermined and considered at period $t-1$.

Our specification further includes lender-time fixed effects, λ_{lt}, and district fixed effects, δ_d. This allows us to control for all time-invariant differences between districts that might impact the demand for low-down payment mortgages and for unobservable time-varying factors such as changes in economic conditions that impact all districts. We cluster the standard errors both by lender group and by district. The year 2012 is taken to be the base year.

Figure 9 plots the coefficient estimates of $\{\beta_s\}$ along with the confidence intervals with and without time-varying district-level controls. The β estimate for 2013 is positive but (just) insignificant. This is to be expected as 2013 was only partially exposed to the HTB program, as the EL scheme commenced in April 2013 and the MG scheme commenced only in October 2013. The parameter is positive and highly significant for the years 2014 through 2016. In other words, districts with higher HTB exposure experienced a higher incidence of low down payment mortgages for the duration of the program. The estimate for 2015 implies the probability of a mortgage being low-down payment was around 3.9 percentage points higher in a high exposure area compared to a low exposure area. This is a significant increase as the weighted mean proportion of low-down payment mortgages was only 3.5 percent in 2012.

Importantly, in the two years preceding the program, high exposure districts did not show a higher incidence in low-down payment mortgages compared to low exposure districts. In other words, we do not detect any noticeable pre-program trends. The results remain very similar when including district-level control variables (middle panel), reducing concerns that our HTB exposure measure is correlated with other district-level variables. The results are also similar when we exclude the London area (bottom panel), indicating that these patterns are not driven by particularities of the London housing market.

6.2 First-time and Younger Buyers

As mentioned in Section 3.2, HTB had the stated intention to help households who struggle to buy a home due to a lack of savings. In the UK, lenders charge a significant interest rate spread on low-down payment mortgages (see Figure A.1 in the Appendix). These relatively costly interest rate payments suggest that households who select a low-down payment mortgage tend to be liquidity constrained. Two types of buyers most likely fall into this category. First-time buyers who did not yet have the chance to build up home equity. And younger buyers who tend to have lower incomes and also have less time to save for a down payment (see, for example, Linneman and Wachter, 1989; Engelhardt, 1996; Haurin, Hendershott and Wachter, 1996). Note that in the UK many younger buyers tend to be home movers. The reason for this is that tenants rights are limited and notice periods tend to be short, often only a few months. Therefore households that value certainty in their living arrangements will try and get on the property ladder as soon as possible, buying a small starter home with the intention of upscaling in a couple of years time.

To examine the extent to which HTB had a more pronounced impact on these different buyer-types we estimate the following panel regression model:

$$
\begin{aligned}
\text{Low Down Payment}_{b,l,d,t} = \; & \beta_1 \text{Post}_t \times \text{Exposure}_d + \beta_2 \text{Post}_t \times \text{Exposure}_d \times \text{Buyer-type}_b \\
& + \beta_3 \text{Post}_t \times \text{Buyer-type}_b + \beta_4 \text{Exposure}_d \times \text{Buyer-type}_b + \beta_5 \text{Buyer-type}_b \\
& + \gamma \text{District}_{d,t-1} + \boldsymbol{\mu} \text{Loan}_{b,l,d,t} + \lambda_{lt} + \delta_d + u_{b,l,d,t}
\end{aligned} \tag{3}
$$

where b indexes a mortgage, l indexes a lender, d indexes a district and t is the year. Low Down Payment$_{b,l,d,t}$ and Exposure$_d$ are defined in the same way as in Equation 2. Post$_t$ is a dummy variable equal to 1 for the period 2014 to 2016, and zero otherwise. Buyer-type$_b$ is one of the following two variables: a first-time buyer dummy and a younger buyer dummy, which we define as borrowers that are between 20 and 39 years-old. While there is some overlap between these two buyer-types, the correlation between the two dummy variables is not particularly high at 35 percent.

The control variables and fixed effects are the same as those used in Equation 2 and the standard errors are again clustered both by lender group and by district. The model is estimated over the period 2010 to 2016, excluding 2013. We exclude 2013 because this year was only partially exposed to the HTB program, so it is not obvious whether 2013 should be viewed as a program year or not. [23]

The results are presented in Table 3. We first differentiate between first-time buyers and home movers (columns (1) and (2)). The interaction Post$_t$ $\times$ Exposure$_d$ is positive and significant indicating that both types of buyers show a stronger increase in low-down payment mortgages in high exposure areas during the program period. However, the impact of HTB is significantly stronger for first-time buyers as the triple interaction Post$_t \times$Exposure$_d \times$Buyer-type$_b$ is positive and significant as well. When differentiating between younger and older buyers (columns (3) and (4)) we find that both types of buyers benefit from the program. However, the effect on younger buyers is around six times as large as the impact on older buyers, suggesting that younger buyers tend to be especially constrained by their down payment.

The results are very similar when we replace our district and time fixed effects with district-time fixed effects. This allows us to absorb all time-(in)variant differences across districts and to isolate the impact of HTB purely from within-district heterogeneity. The fact that the results are very consistent, reduces concerns that the patterns we document are driven by differential district-trends.

To sum up, we find that the Help-to-Buy program facilitated the purchase of a home with a low-down payment mortgage, which especially benefited younger households and first-time buyers, i.e. those types of buyers that most likely face down payment constraints.

[23] We examined whether our results are robust to including 2013 in either the pre- or the post-HTB period. This did not materially affect our results. Results are available upon request.

7 The Effect of Help-to-Buy on the Housing Market

7.1 Help-to-Buy and Home Sales

In the previous section we established that HTB led to an increase in the incidence of low-down payment mortgages, especially benefiting younger households and first-time buyers. We next provide an assessment of the extent to which this translated into an increase in home sales and transition into homeownership in these areas.

As explained in Section 3.1, an increase in the availability of low-down payment mortgages can theoretically have three effects on the demand houses. First, households that previously preferred to rent, as owning a property in their desired location was not feasible, might switch to buying (extensive margin). Second, households might pull forward their home purchase, as they can now use their existing down payment to purchase a property that was previously too expensive (timing effect). Third, households might use their existing down payment to purchase a more expensive home (intensive margin). In the first two cases, HTB would lead to an increase in home sales. It would also lead to an increase in homeownership if those houses are bought by first-time buyers. In the third case, it would only result in a switch from higher-down payment mortgages to low-down payment mortgages, but it would not affect the number of homes sold nor the transition into homeownership. Note that the second and third effect relate to both first-time buyers as well as home movers, while the first effect only relates to first-time buyers.

We start by examining the impact of HTB on the number of home sales by estimating the following panel regression model:

$$\begin{aligned} \text{Home Sales}_{d,t} = \quad & \beta_1 \text{Post}_t + \beta_2 \text{Post}_t \times \text{Exposure}_d + \beta_3 \text{Exposure}_d \\ & + \gamma \text{District}_{d,t-1} + u_{d,t} \end{aligned} \tag{4}$$

where d indexes a district and t is the year. The dependent variable Home $\text{Sales}_{d,t}$ equals the number of home sales in a given year and district. We remove outliers by dropping the values below the 1st and above the 99th percentile.[24] Post_t is a dummy variable equal to 1 for the period 2014 to 2016, and zero otherwise. Exposure_d is our measure of *ex ante* exposure to the HTB program. $\textbf{District}_{d,t-1}$ is the same vector of time-varying district-level control variables as those described in Section 6.1. In some regression specifications we include district fixed effects, δ_d, and time fixed effects θ_t and drop Post_t and Exposure_d. The baseline model is estimated over the period 2012 to 2016, excluding 2013. Standard errors are clustered at the district level.

The results are presented in Table 4. The first column shows the average effect of Help-to-Buy on home sales. It indicates that after the program came into effect the number of home sales

[24] Our results are robust when we include the outliers.

significantly increased, a reflection that the housing market was recovering from the global financial crisis. When we differentiate between districts according to their HTB exposure we however see that the impact is much stronger in high-exposure districts (column (2)). The magnitude of this effect hardly changes when we control for district and time fixed effects (column (3)) and becomes only slightly smaller when we also include the time-varying district-level control variables (column (4)). Excluding districts in the London area does not have a materially impact (column (5)). Furthermore, the results still hold when we include the year 2013 in the post-period (column (6)) or in the pre-period (column (7)). In line with the fact that 2013 is partly a program year, the coefficient estimates of β_2 become smaller, but they remain highly significant at the one percent level.

The economic significance on the program is large. Figure 10 provides the annual cumulative increase in home sales due to HTB comparing a low exposure district (the 25th percentile of the HTB exposure variable) with a high exposure district (the 75th percentile of the HTB exposure variable). The calculations are based on the estimates in column (4) of Table 4. By the end of 2016, the number of home sales is 50 percent higher in our representative low exposure district, while in our representative high exposure district this number is close to 105 percent. In terms of numbers, our estimates imply that approximately 320,000 additional home sales occurred due to HTB program exposure.

The results in Section 6.2 indicate that first-time and younger buyers were especially likely to buy a home with a low-down payment mortgage as a result of Help-to-Buy. We next examine whether this also lead to a disproportional increase in homes purchased by these buyers in high-exposure areas. This does not necessarily have to be the case if these borrowers disproportionately use HTB to buy a bigger home with the same down payment (i.e. switch between mortgages types) instead of using HTB to transition into homeownership or pull the purchase of their next home forward.

We augment Equation 4 and estimate the following panel regression model:

$$\begin{aligned}\text{Home Sales - Buyer-type}_{d,t} = \quad & \beta_1 \text{Post}_t \times \text{Exposure}_d + \boldsymbol{\gamma}\text{District}_{d,t-1} \\ & + \delta_d + \theta_t + u_{d,t}\end{aligned} \tag{5}$$

where d indexes a district and t is the year. The dependent variable Home Sales - Buyer-type$_{d,t}$ equals the number of home sales to a given buyer-type in a given year and district. Table 5 covers four buyer-types: column (1) considers home sales to first-time buyers; column (2) considers home sales to home movers; and column (3) and (4) consider home sales to younger and to older buyers, respectively. The rest of the model is the same as Equation 4.

The results in Table 5 are very much in line with the results in Table 3. The program led to a relative increase in home sales to both home movers and first-time buyers in more exposed districts. But in terms of numbers the impact was much more pronounced for the first-time buyers. Of the 320,000 additional homes purchased due to HTB exposure, our estimates imply that first-time buyers accounted for approximately 80 percent of the increase. Similarly we find that home sales to younger and older buyers increased more during the program period in more exposed districts, but the effect was again larger for younger buyers who accounted for approximately 92 percent of the increase in homes purchased due to HTB exposure.

7.2 Help-to-Buy and Internal Migration

The positive and significant effect of Help-to-Buy on the number of home sales that we document in the previous section indicates that the program did not just induce households to buy a more expensive home with the same down payment. Such an intensive margin effect would not lead to a relative increase in the number of home sales. Under the assumption that households do not endogenously move between districts, the increase in home buyers can only be explained by a timing or extensive margin effect. While endogenous moves are more likely in the London area, for the rest of the country it is unlikely to explain much of the impact that we find. For example, Lomax (2020) finds that 68 percent of the moves in the UK tend to occur in the same postcode area, which implies that the majority of moves takes place within districts (which typically contain multiple postcodes). Longer-distance moves are mostly for educational or employment reasons rather than housing-related reasons (Thomas, Gillespie and Lomax, 2019).

We can take these arguments one step further, and use our exposure measure to test whether HTB induced longer-distance housing-related internal migration in the UK. To do so, we augment Equation 4 and estimate the following panel regression model:

$$\begin{aligned}\text{Internal Migration Inflows}_{d,t} = \;& \beta_1 \text{Post}_t \times \text{Exposure}_d + \boldsymbol{\gamma}\text{District}_{d,t-1} \\ & + \lambda \text{Migration}_{d,t-1} + \delta_d + \theta_t + u_{d,t}\end{aligned} \tag{6}$$

where d indexes a district and t is the year. The dependent variable Internal Migration Inflows$_{d,t}$ equals the number of persons that move from another UK district to district d in a given year. We remove outliers by dropping the values below the 1st and above the 99th percentile.[25] In addition to the $\mathbf{District}_{d,t-1}$ vector of time-varying district-level control variables described in Section 6.1, we include a $\mathbf{Migration}_{d,t-1}$ vector of time-varying district-level control variables. $\mathbf{Migration}_{d,t-1}$ includes (the log of) predetermined $(t-1)$: job density and net immigration from outside the UK, following Hatton and Tani (2005) who find these to be important determinants of internal migration in the UK.[26] The rest of the model is the same as Equation 4.

The results are presented in Table 6. The first column shows the average effect of Help-to-Buy on internal migration inflows. It indicates that after the program came into effect, there was no

[25] Our results are robust when we include the outliers.

[26] We use job density in place of job vacancy however, as the UK job vacancy series was discontinued in 2012. We also include working age population in our district controls rather than total population, consistent with the migration literature.

change to internal migration inflows in high-exposure districts (column (1)). This result holds when we exclude districts in the London area (column (2)).

When we differentiate between the London area and the rest of the UK (columns (2) and (3)) we see that there is a weakly significant result for the London area only. This makes sense, given that people may make housing related moves within the London area. Long distance moves in other areas do not appear to be induced by housing related reasons such as HTB exposure, which is consistent with the aforementioned literature that finds that longer-distance moves tend to be due to employment or education reasons rather than housing-related reasons. We can therefore reasonably assume that our results, particularly those excluding the London area, are not biased due to HTB-induced endogenous moves. This means that districts with low exposure are unaffected by HTB and can therefore function as a control to provide meaningful estimates of the marginal impact of the program.

7.3 Help-to-Buy and House Prices

In Section 4, we document an increase in home sales as a result of HTB. This increase in demand for housing can lead to a rise in house prices if supply is restricted. To examine whether HTB led to and increase in house prices, we estimate the following panel regression model:

$$\text{House Prices}_{d,t} = \beta_1 \text{Post}_t \times \text{Exposure}_d + \boldsymbol{\gamma}\text{District}_{d,t-1} + \delta_d + \theta_t + u_{d,t} \tag{7}$$

where d indexes a district and t is the year. The outcome variable is House Prices$_{d,t}$, which is defined as annual house price growth at district-level; the remainder of the model is the same as for Equation 4. As London house prices have very different dynamics compared to house prices in the rest of the country we estimate a model for those districts in the London area and all other districts separately.

The results in Table 7 reveal stronger house price growth in high exposure districts compared to low exposure districts over the course of the program. When we differentiate between the London area and the rest of the UK (columns (2) and (3)) we see that the increase was much more pronounced in the London area. A one standard deviation increase in program exposure relates to a 0.7 percentage point increase in house price growth in the rest of the UK, compared to 3 percentage point increase in house price growth in the London area.

Overall we conclude that HTB resulted in only a marginal increase in house prices, except in the London area. These findings are consistent with Felipe Carozzi, Christian Hilber and Xiaolun Yu (2020) who show that responsiveness in housing supply (which is much weaker in the London area) is a critical determinant as to whether house prices reacted to the EL part of HTB.

8 The Effect of Help-to-Buy on Household Spending

Having established that HTB had a positive impact on home sales and transition into homeownership, we examine in this section whether there were any spillover effects of the program via household spending. From a theoretical point of view, the impact on household spending of a policy aimed at making homeownership more affordable via a reduction in down payment constraints is *a priori* unclear. On the one hand, a home purchase should free up disposable income with a positive effect on consumption when the down payment is a binding liquidity constraint. A household that is planning to buy a home but for whom the down payment constraint binds, will lower consumption in the years before buying a house in order to increase savings. Since the down payment is simply a well-defined liquidity constraint, growth in consumption is expected when it no longer binds. In line with this, Engelhardt (1996) documents that households reduce food consumption when they are about to buy a home and increase food consumption back to long-run levels afterwards. Even though he does not differentiate between different types of buyers, this finding provides some evidence that households might indeed become less constrained after a home purchase, leading them to increase consumption.

Buying a home can also have a positive effect on consumption via its impact on housing-related household spending. Homeowners tend to invest more in their home compared to renters and moving house is associated with substantial spending on items such as repairs and improvements, removals, furniture, appliances, and commissions. Indeed, Best and Kleven (2017) study the impact of a stamp-duty holiday and find that house transactions trigger extra spending in moving related-consumption in the year of the move and one year after. The relative increase in consumption after moving is likely particularly high when in the years before the home purchase prospective home buyers put money aside (on top of their down payment) to invest in their future home.

On the other hand, buying a home can have a negative effect on household spending. Households that become more indebted due to their mortgage might lower their consumption to service their debt and to save more out of their current income to lower future debt levels. Furthermore, the increase in moving-related expenditure might crowd-out non-moving related expenditure (Best and Kleven, 2017). A systematic look at the impact of HTB using consumption data can help understand any positive or negative spillover effects of these kind of programs on household spending.

Another channel through which homeownership can affect consumption is through its impact on house prices. Higher housing values can positively affect consumption through a wealth channel, home extraction channel or reduction in borrowing constraints. As we are mainly interested in the relationship between consumption and the transition into homeownership by marginal buyers, we abstract from this channel but control for it by including district-level house prices in our specifications.

In this section, we set out to evaluate how consumption reacted to the increase in homeownership induced by Help-to-Buy. We again exploit regional variation in exposure to the program which provides us with a meaningful counterfactual. We focus on car sales, which represents one of the most significant durable goods that a household can purchase.

8.1 Help-to-Buy and Car Sales

We identify the instances in which households purchase a car by looking at the number of new car registrations at the district-year level. This captures the purchase (both with and without a loan) of all privately owned new cars. Figure 11 plots the number of car sales in both low and high exposure districts. It shows that trends in the two types of districts are very similar in the pre-HTB period. Over the exposure period we see that there is a positive trend in low and high exposure districts, a reflection of the UK economy recovering from the global financial crisis and its aftermath. However the positive trend is stronger in high exposure districts.

We formally examine the impact of the HTB program on car sales by estimating a panel regression model similar to Equation 4:

$$\text{Car Sales}_{d,t} = \beta_1 \text{Post}_t \times \text{Exposure}_d + \boldsymbol{\gamma}\text{District}_{d,t-1} + \delta_d + \theta_t + u_{d,t} \tag{8}$$

where d indexes a district and t is the year. The outcome variable is Car $\text{Sales}_{d,t}$, which equals the number of new private car registrations for a given year and district; the remainder of the model is the same as for Equation 4. We remove outliers by dropping the values below the 1st and above the 99th percentile.[27]

The results in Table 8 show that car sales are significantly higher in high compared to low exposure areas during the period HTB is in effect. The result is present when we include the full set of district and time fixed effects and time-varying district-level macroeconomic variables, including house prices. Importantly the result barely changes when we exclude London area districts from the sample (column (2)) and is insignificant for the London area only. The latter finding might reflect the fact that parking is more difficult in London and many new builds do not allow for parking permits. Our regressions control for house prices so they are not driven by a wealth effect due to higher house prices in high exposure areas.

While several drivers can explain the positive effect of HTB on car sales, they are consistent with the idea that aspiring home buyers for whom down payment constraints bind need to hold their consumption low in the years prior to purchasing a home in order to save for a down payment. Once they have bought the house, their disposable income increases again allowing them to consume more. A recent survey by Santander indeed shows that almost half of aspiring home owners in the UK cut back on unnecessary spending and socializing in order to save enough for

[27] Our results are robust when we include the outliers.

a down payment.[28] Overall the evidence presented indicates that government programs that make housing more affordable by easing down payment constraints not only make it easier for first-time and younger buyers to buy a house, but boost household spending as well.

9 Concluding Remarks

Accessing the mortgage market has become increasingly more difficult in recent years, especially for young and first-time buyers. Many governments have implemented or are considering implementing policies that help prospective buyers on the property ladder. Yet we still know very little about the effectiveness and spillover effects of government schemes that make housing more affordable by loosening down payment constraints. This article evaluates a large-scale policy intervention in the UK, called Help-to-Buy. This program enabled prospective buyers to purchase a home with only five percent down payment at a time when the market for low-down payment mortgages was all but frozen.

The novelty of our analysis lies in part with our empirical strategy, where we exploit geographical variation in exposure to the program. Although HTB was national in scope, exposure to the scheme critically depended on the local housing market. We take advantage of these local differences and construct a measure that captures local exposure to the program, based on the historical attractiveness of an area for low-down payment home buyers. This enables us to more effectively control for the many confounding factors that could also drive the demand for housing. In addition, we do not only examine the impact of the program on the housing market but subsequently examine its impact on wider economic activity via household spending.

Our results reveal a strong impact of HTB on the purchase of low-down payment mortgages, especially benefiting first-time and younger buyers. This translated into an increase in home purchases for these groups of buyers over the course of the program. In other words, the program succeeded in making it easier for marginal buyers to purchase a home in more exposed districts. We document a marginal impact on house prices, except in the London area where prices reacted more strongly presumably due to larger supply constraints.

We then explore to what extent household spending reacted to the program and find evidence of a relative increase in car sales in districts more exposed to HTB. These findings indicate that aspiring home buyers, for whom down payment constraints bind, restrict their consumption the years prior to purchasing a home in order to save for a down payment. Once they have bought the house, their disposable income increases again allowing them to consume more.

[28]Santander recently surveyed over 5000 would be first-time buyers in the UK and their study reveals that the biggest barrier to homeownership is saving enough for a down payment. A large share of aspiring home owners (45 percent) said that they have cut back on unnecessary spending and socializing in order to raise the necessary down payment.

Taken together, our results support the view that policies aimed at making homeownership more affordable through easing of down payment constraints can have a meaningful impact on macroeconomic conditions. This evidence complements the findings of Agarwal et al. (2017) who show that mortgage modification programs, when used with sufficient intensity, lead to an increase of durable spending. They also support the findings DiMaggio et al. (2017) who find that a reduction in mortgage rates can have a meaningful impact on consumption. Our work extends these papers by focusing on policies aimed at prospective home buyers, rather than changes in mortgage payments.

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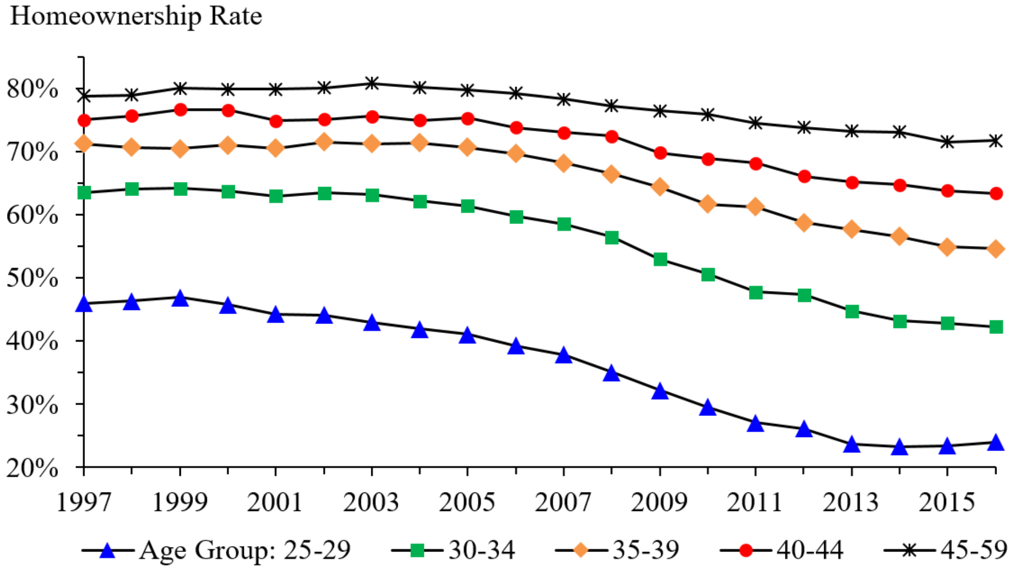
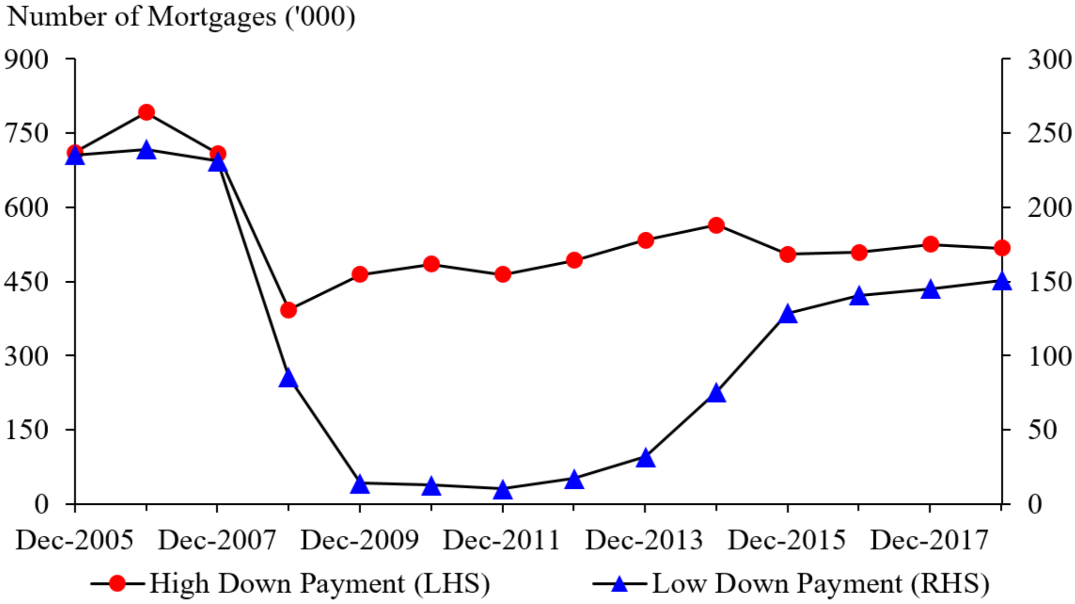
Figure 1: **Homeownership in the UK by Age Group**



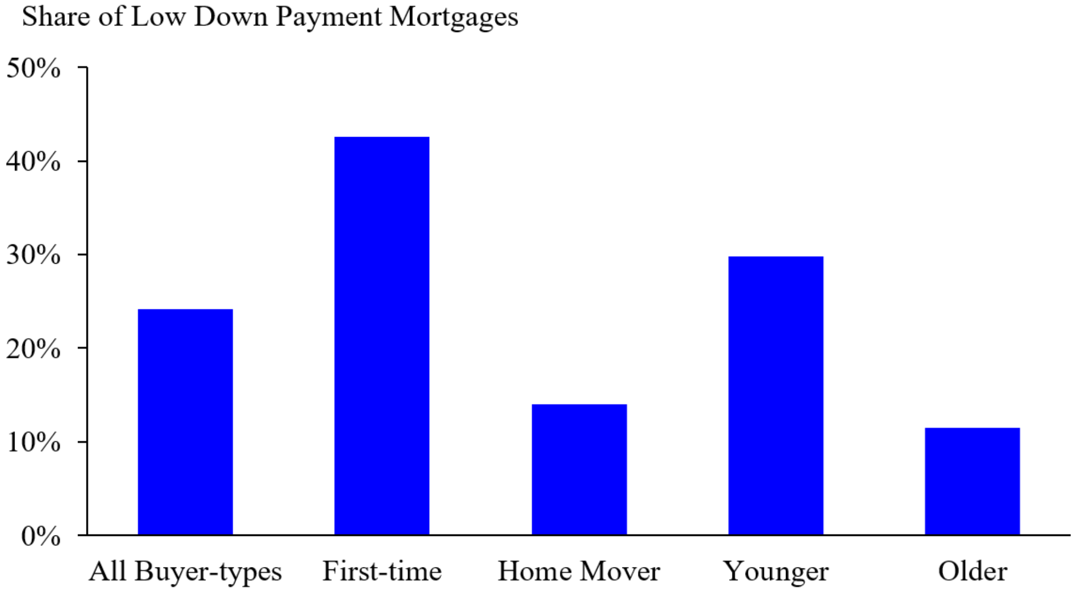
The figure shows homeownership rates for those aged 25 to 59 years, grouped into five specified age bands, over the period from 1997 to 2016. The estimates are taken from the UK Labour Force Survey and calculations similar to those of Cribb, Hood and Hoyle (2018).

Figure 2: **Number of Mortgages by Down Payment Category**



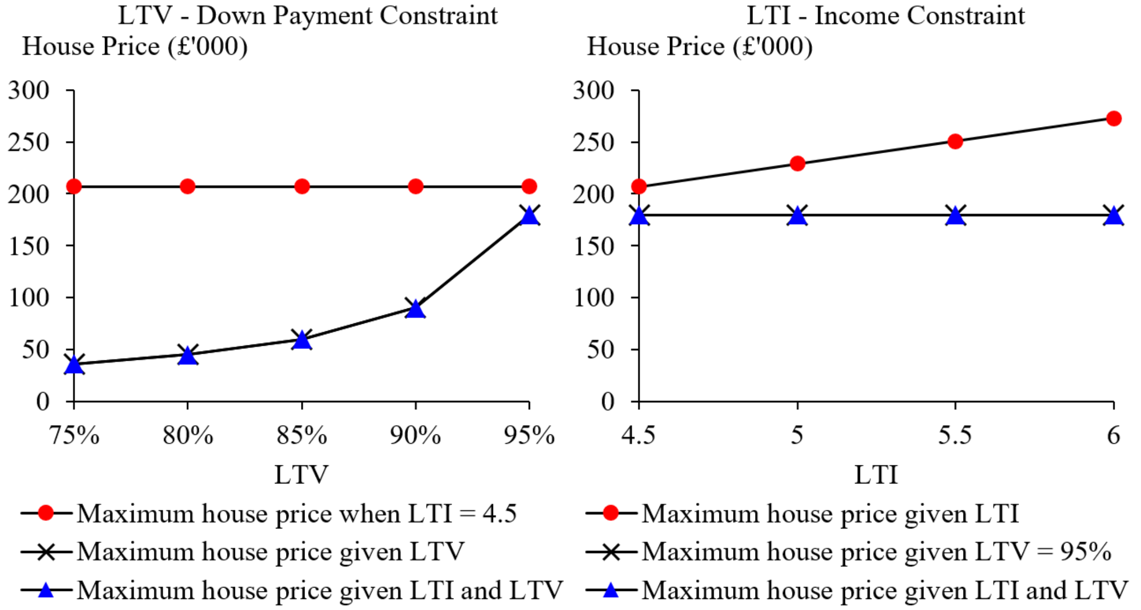
The figure shows the year-end aggregate number of high and low down payment mortgages purchased over the period from 2005 to 2018. Low down payment mortgages include all mortgages with a down payment of 5 percent or less.

Figure 3: **Pre-Crisis Low Down Payment Mortgage Share by Buyer-type**



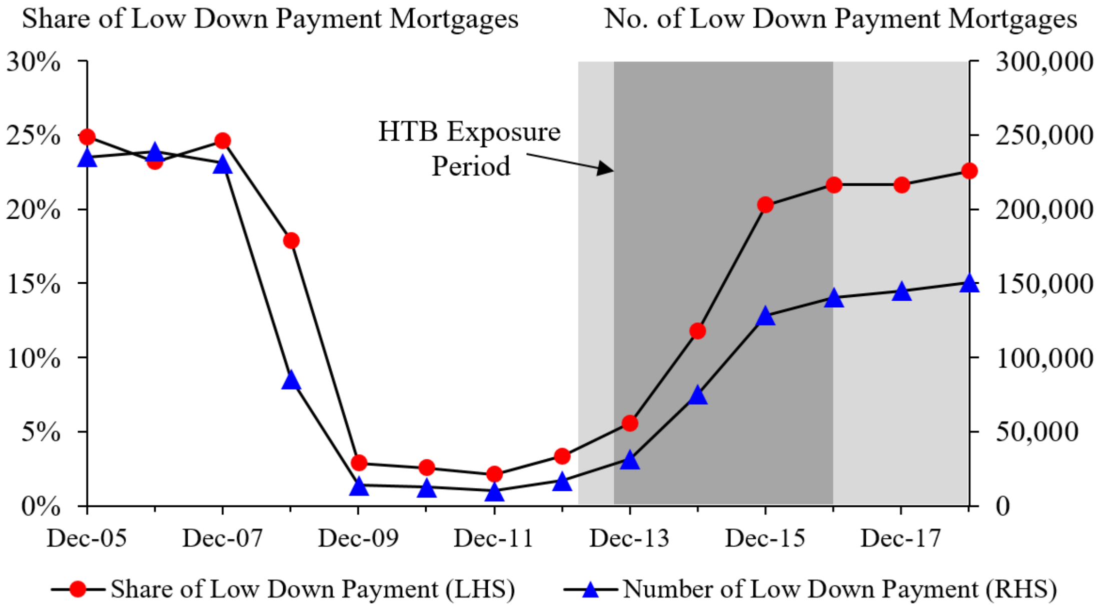
The figure shows the share of low-down payment mortgages (as a proportion of all mortgages) over the period 2005 to 2007 for different types of buyers. Low down payment mortgages include all mortgages with a down payment of 5 percent or less. Younger buyers are 20-39 years-old and older buyers are 40-59 years-old.

Figure 4: **Maximum House Prices for Different Borrowing Constraints**



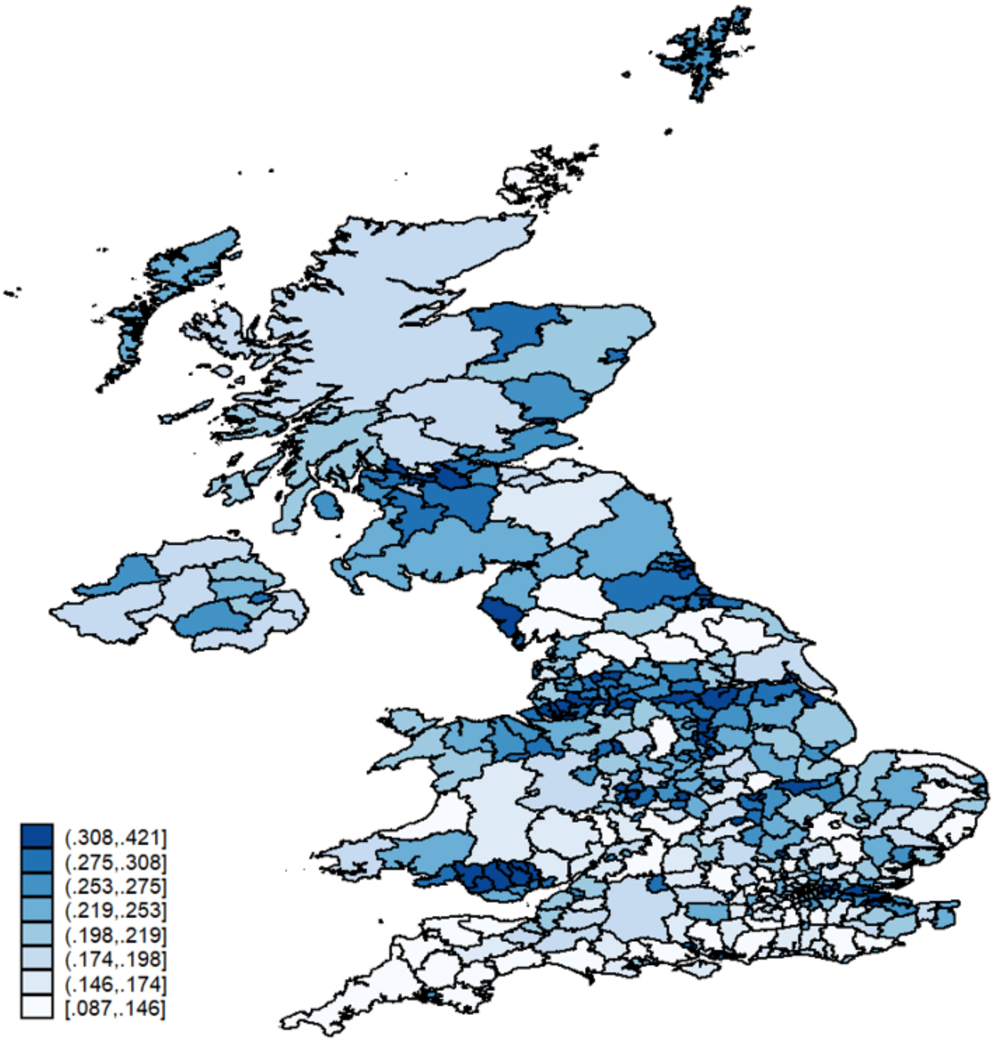
The figure presents the maximum house price a household with an income of £44,000 and a down payment of £9,000 is able to afford under different loan-to-value (LTV) and loan-to-income (LTI) requirements. For the left panel of the figure, the LTI requirement is kept fixed at 4.5 and the LTV is allowed to vary between 75 and 95 percent. For the right panel of the figure, the LTV requirement is kept fixed at 95 percent and the LTI is allowed to vary between 4.5 and 6.

Figure 5: **Number and Share of Low Down Payment Mortgages**



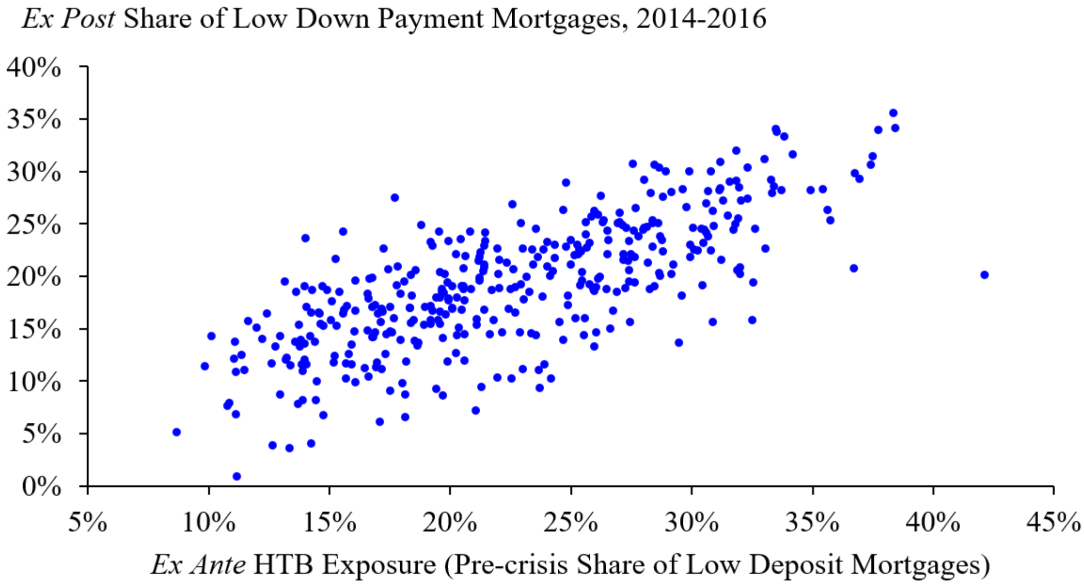
The figure shares the share and number of low down payment mortgages before and during the Help-to-Buy Program exposure period. Low down payment mortgages include all mortgages with a down payment of 5 percent or less. The dark-shaded area indicates the period that both the EL and MG schemes are in effect (October 2013 to December 2016). The light-shaded area indicates the period that only the EL scheme is in effect (April 2013 to present).

Figure 6: **Help-to-Buy Exposure across the United Kingdom**



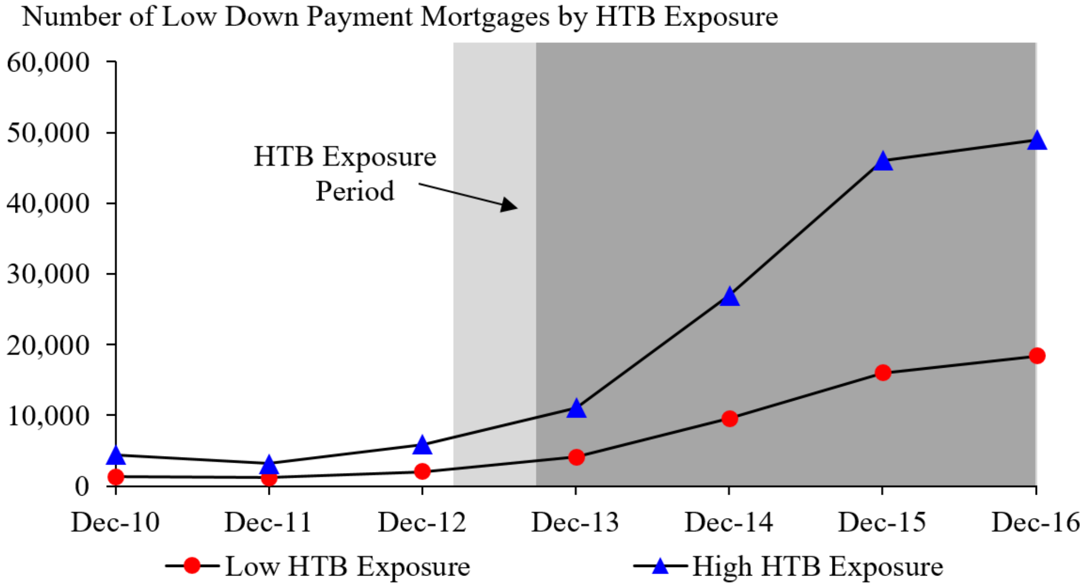
The figure shades local authority districts across the UK by shows Help-to-Buy (HTB) Exposure. HTB Exposure equals the number of low-down payment mortgages in a district in the period 2005-2007 divided by the total number of mortgages in 2005-2007. Districts with a darker shading have a higher exposure to the HTB program.

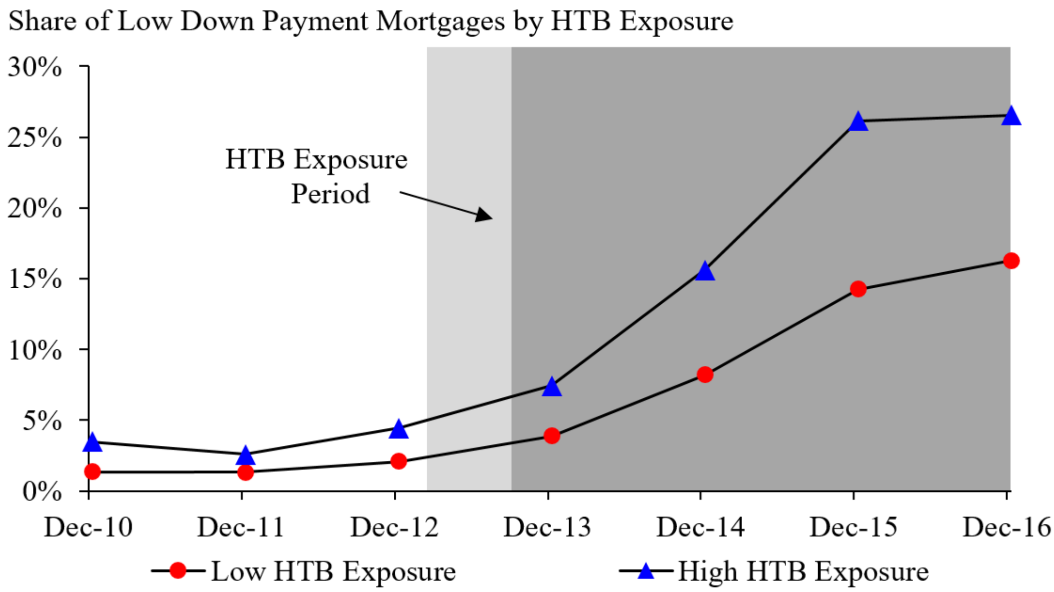
Figure 7: **Help-to-Buy Exposure and Ex Post Low Down Payment Mortgages**



The figure shows the relationship between our measure of Help-to-Buy program exposure and the actual purchase of low-down payment mortgages over the program period from 2014 to 2016 at the district level. The number of low-down payment mortgages is scaled by total number of mortgages purchased in the district over the program period. HTB exposure is defined as the number of low-down payment mortgages in a district in the period 2005-2007 divided by the total number of mortgages in 2005-2007.

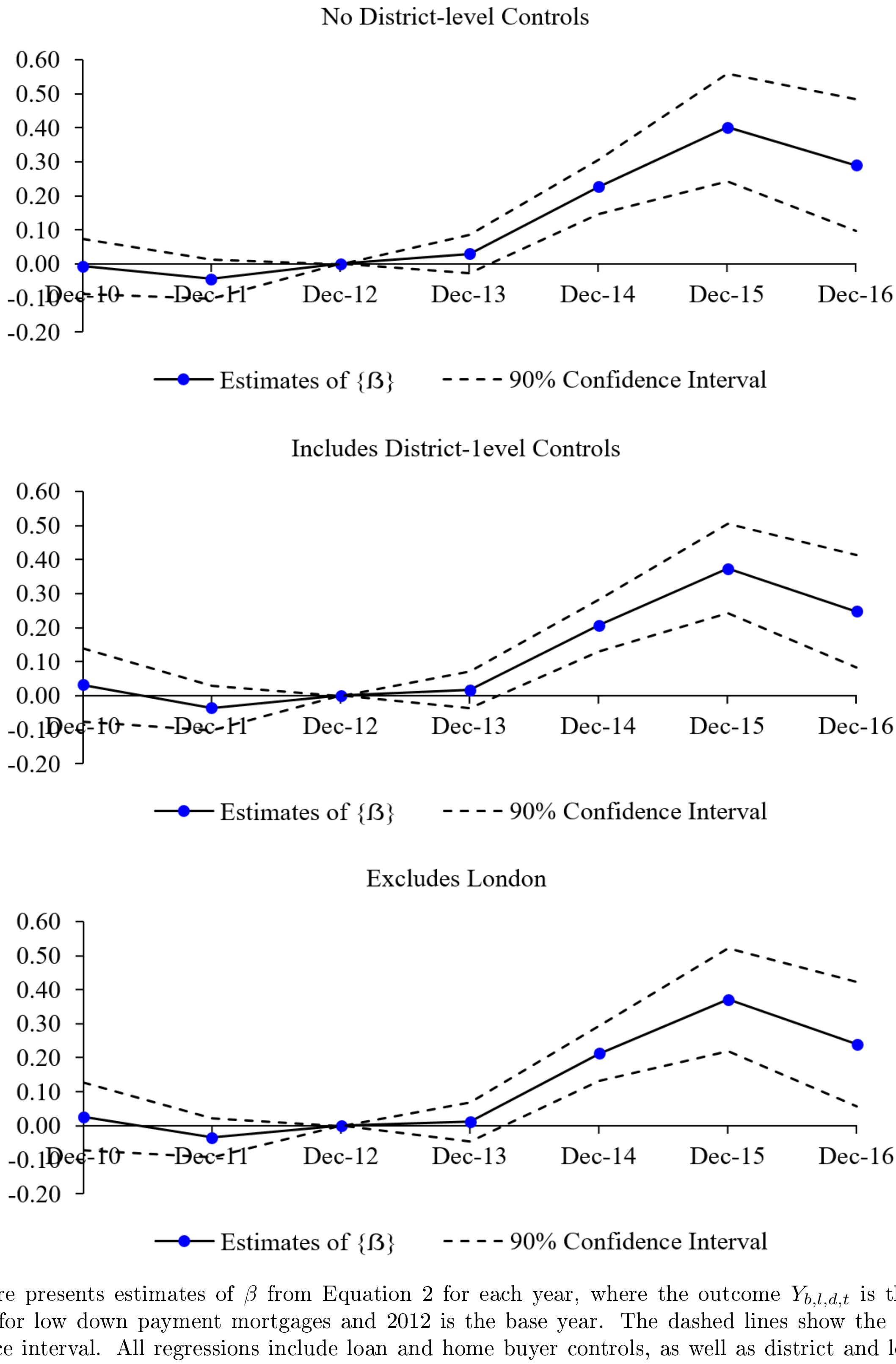
Figure 8: **Evolution of Low Down Payment Mortgages by Help-to-Buy Exposure**





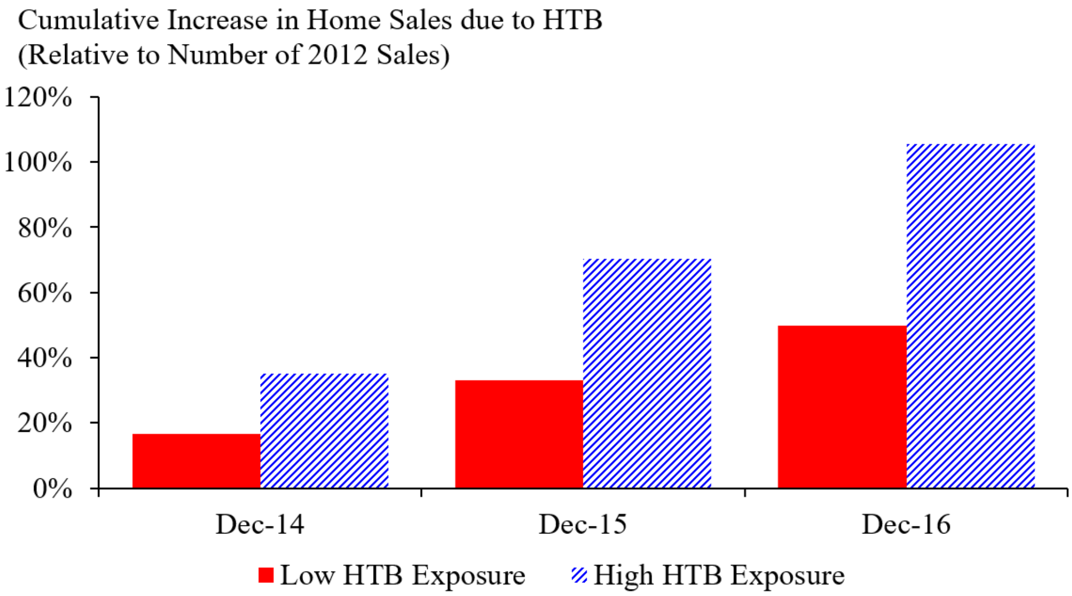
The top panel of the figure shows the aggregate number of low-down payment mortgages over the period from 2005 to 2016 for districts that are grouped according to their HTB exposure. The bottom panel shows the weighted average share of low-down payment mortgages (as a proportion of all mortgages excluding remortgages). Low-down payment mortgages include all mortgages with a down payment of 5 percent or less. HTB exposure is defined as the number of low-down payment mortgages in a district over the period 2005 to 2007 divided by the total number of mortgages in 2005 to 2007. Low HTB exposure includes districts with HTB exposure less than the 25th percentile HTB exposure. High HTB exposure includes districts with HTB exposure greater than the 75th percentile HTB exposure. The dark-shaded area indicates the period that both the EL and MG schemes are in effect (October 2013-December 2016). The light-shaded area indicates the period that only the EL scheme is in effect (April 2013-present).

Figure 9: The Effect of Help-to-Buy on Low Down Payment Mortgage Lending



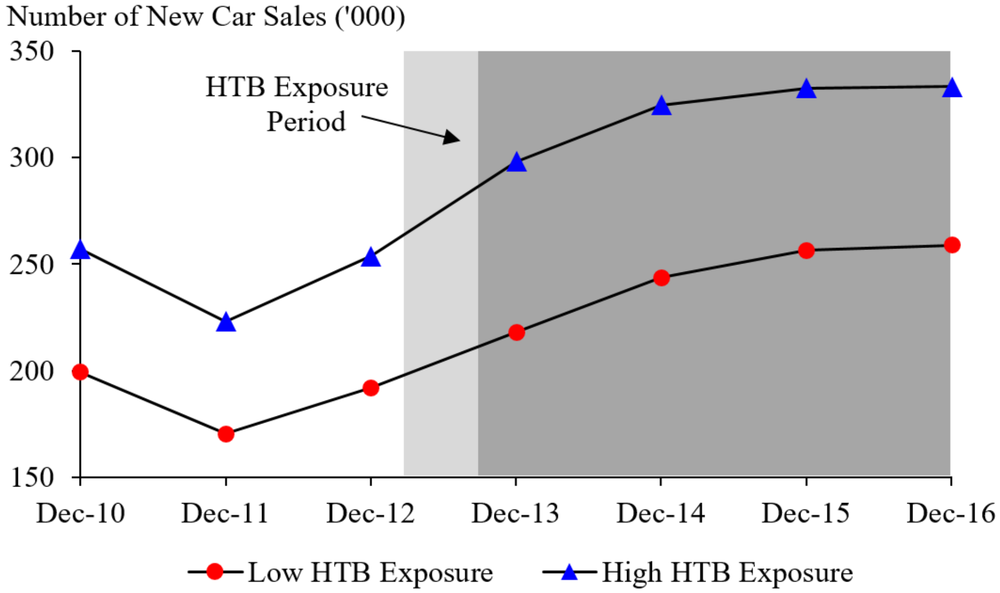
The figure presents estimates of β from Equation 2 for each year, where the outcome $Y_{b,l,d,t}$ is the dummy variable for low down payment mortgages and 2012 is the base year. The dashed lines show the 90 percent confidence interval. All regressions include loan and home buyer controls, as well as district and lender-time fixed effects. The middle panel also includes the time-varying district-level controls. The bottom panel excludes London. Standard errors are clustered at the district and lender level.

Figure 10: **Economic Significance of Help-to-Buy**



The figure is computed using estimates of β_3 from Equation 4. For example in December 2014, the annual increase in home sales due to Help-to-Buy for region i is $(\beta_3 \times \text{HTB Exposure}_i)\,/\text{Home Sales}_{i,2012}$. HTB exposure is defined as the number of low-down payment mortgages in a district over the period 2005 to 2007 divided by the total number of mortgages in 2005 to 2007. Low HTB exposure is the district with the 25th percentile increase in home sales due to HTB exposure. High HTB exposure is the district with the 75th percentile increase in home sales due to HTB exposure.

Figure 11: **Car Sales by Help-to-Buy Exposure**



The figure shows the aggregate number of new private car registrations over the period from 2010 to 2016 for districts that are grouped according to their HTB exposure. HTB exposure is defined as the number of low-down payment mortgages in a district over the period 2005 to 2007 divided by the total number of mortgages in 2005 to 2007. Low HTB exposure includes districts with HTB exposure less than the 25th percentile HTB exposure. High HTB exposure includes districts with HTB exposure greater than the 75th percentile HTB exposure. The dark-shaded area indicates the period that both the EL and MG schemes are in effect (October 2013-December 2016). The light-shaded area indicates the period that only the EL scheme is in effect (April 2013-present).

Table 1: **Summary Statistics**

Variable Name (Unit)	Pre Help-to-Buy Mean	Pre Help-to-Buy Median	Pre Help-to-Buy Std. Dev.	Post Help-to-Buy Mean	Post Help-to-Buy Median	Post Help-to-Buy Std. Dev.
Loan-level Dependent Variable						
Low-Down Payment (0/1)	0.03	0	0.16	0.18	0	0.38
Loan-level Control Variables						
First-time Buyer (0/1)	0.39	0	0.49	0.46	0	0.50
Younger Buyer (0/1)	0.65	1	0.48	0.69	1	0.46
Household Annual Income (£'000)	61.13	45.76	97.53	61.55	47.03	786.28
Employed (0/1)	0.90	1	0.31	0.89	1	0.31
Self-employed (0/1)	0.02	0	0.12	0.01	0	0.12
Property Value (£'000)	264.67	201.78	577.75	272.71	212.50	309.15
Down Payment (£'000)	98.32	53.74	534.01	90.25	47.98	178.94
Loan-to-income Ratio	3.09	3.07	2.27	3.26	3.33	1.37
Maturity (Years)	24.12	25.00	7.27	25.96	25.00	9.63
Rate-type: Fixed (0/1)	0.70	1	0.46	0.92	1	0.27
Rate-type: Floating (0/1)	0.29	0	0.46	0.07	0	0.26
Repayment: Capital (0/1)	0.87	1	0.34	0.97	1	0.16
Repayment: Interest (0/1)	0.11	0	0.31	0.02	0	0.14
District-level Dependent Variables						
Home Sales ('000)	1.28	1.04	0.80	1.66	1.37	1.08
First-time Buyer Sales ('000)	0.49	0.36	0.40	0.77	0.57	0.60
Home Mover Sales ('000)	0.78	0.68	0.45	0.89	0.78	0.53
Younger Buyer Sales ('000)	0.82	0.64	0.58	1.14	0.90	0.81
Older Buyer Sales ('000)	0.45	0.40	0.24	0.52	0.46	0.30
First-time Buyers ('000)	0.72	0.55	0.56	1.18	0.89	0.88
House Price Growth (%)	-1.46	-2.07	4.46	5.53	5.00	3.66
Car Sales ('000)	2.21	1.85	1.43	3.04	2.47	2.00
District-level Control Variables						
Exposure (%)	22.57	21.94	6.63	22.66	22.01	6.62
Unemployment Rate (%)	7.24	6.87	2.39	4.96	4.59	1.77
Median Weekly Income (£)	445.34	428.24	76.63	433.58	419.43	64.33
Average Weekly Rent (£)	92.83	88.45	17.83	102.38	98.05	19.33
Average House Price (£'000)	203.87	186.19	92.55	226.43	193.70	128.95
Population ('000)	161.77	125.99	109.01	167.47	129.92	114.50

The table presents summary statistics for the variables used in our empirical analyses. Summary statistics are reported for both the pre Help-to-Buy (HTB) Program period (from 2010 to 2012) and the post HTB period (from 2014 to 2016). There are 379 districts across the UK included in our sample. In the pre HTB period, there are 1,354,320 loan-level observations and 1,066 district-level observations. In the post HTB period, there are 1,877,724 loan-level observations and 1,133 district-level observations.

Table 2: **Correlation between Help-to-Buy Exposure and District Variables**

	District-level Variables	Coefficient	R^2	N
(1)	ln(Unemployment Rate)$_{d,t-1}$	0.120***	0.447	2,576
		(0.005)		
(2)	ln(Median Weekly Income)$_{d,t-1}$	-0.127***	0.088	2,576
		(0.019)		
(3)	ln(Average Weekly Rent)$_{d,t-1}$	-0.077***	0.046	2,576
		(0.017)		
(4)	ln(Average House Price)$_{d,t-1}$	-0.117***	0.498	2,576
		(0.006)		
(5)	ln(Population)$_{d,t-1}$	0.038***	0.101	2,576
		(0.006)		

Each row in this table presents bivariate regression of Help-to-Buy exposure on the five different district-level variables and a constant. Standard errors are clustered at the district level and are shown in parentheses. ***, **, and * indicate statistical significance at the 1 percent, 5 percent and 10 percent confidence level, respectively.

Table 3: **The Effect of Help-to-Buy on Low Down Payment Mortgage Lending to First-time and Younger Home Buyers**

	Buyer-type			
	First-time		Younger	
	(1)	(2)	(3)	(4)
$\text{Post}_t \times \text{Exposure}_d$	0.0763**		0.0452*	
	(0.031)		(0.027)	
$\text{Post}_t \times \text{Exposure}_d \times \text{Buyer-type}_b$	0.1387**	0.1471**	0.2641***	0.2619***
	(0.067)	(0.067)	(0.061)	(0.058)
$\text{Post}_t \times \text{Buyer-type}_b$	0.1094***	0.1114***	0.0334***	0.0359***
	(0.016)	(0.017)	(0.012)	(0.013)
Control Variables				
$\text{Exposure}_d \times \text{Buyer-type}_b$	Yes	Yes	Yes	Yes
Buyer-type_b	Yes	Yes	Yes	Yes
Home Buyer Characteristics	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes
District Characteristics	Yes	No	Yes	No
Fixed Effects				
Bank×Time	Yes	Yes	Yes	Yes
District	Yes	No	Yes	No
District×Time	No	Yes	No	Yes
Model Statistics				
N	3,232,044	3,232,044	3,232,044	3,232,044
R^2	0.2991	0.3024	0.2883	0.2914

The presents coefficient estimates for Equation 3 for the period 2010 to 2016 (excluding 2013), which show the effect of the Help-to-Buy program on the issuance of low-down payment mortgages across buyer-types. The dependent variable is a dummy variable equal to 1 if the mortgage is a low-down payment mortgage. Post is a dummy variable equal to 1 for the period 2014 to 2016. Exposure equals the number of low-down payment mortgages in a district in the period 2005-2007 divided by the total number of mortgages in 2005-2007. Columns (1) and (2) present estimates where the impact of Exposure is allowed to vary for first-time buyers. Columns (3) and (4) present estimates where the impact of Exposure is allowed to vary for younger buyers (20 to 39 years-old). Standard errors are clustered by lender groups and by district, and are shown in parentheses. ***, **, and * indicate statistical significance at the 1 percent, 5 percent and 10 percent confidence level, respectively.

Table 4: **The Effect of Help-to-Buy on Home Sales**

					Excl. London	2013 post	2013 pre
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post_t	0.3367***	-0.0318					
	(0.020)	(0.063)					
$\text{Post}_t \times \text{Exposure}_d$		1.6194***	1.7441***	1.2864***	1.2458***	0.9787***	1.2032***
		(0.278)	(0.199)	(0.198)	(0.185)	(0.170)	(0.174)
Exposure_d		1.4989***					
		(0.479)					
Control Variables							
District Characteristics	No	No	No	Yes	Yes	Yes	Yes
Fixed Effects							
District	No	No	Yes	Yes	Yes	Yes	Yes
Time	No	No	Yes	Yes	Yes	Yes	Yes
Model Statistics							
N	2,159	2,159	2,159	2,159	1,967	2,529	2,529
R^2	0.0424	0.0820	0.9590	0.9624	0.9656	0.9650	0.9659

The table presents coefficient estimates for Equation 4 for the period 2012 to 2016 (excluding 2013), which show the effect of the Help-to-Buy program on home sales. The dependent variable is the number of home sales purchased with a mortgage. Post is a dummy variable equal to 1 for the period 2014 to 2016. Exposure equals the number of low-down payment mortgages in a district in the period 2005-2007 divided by the total number of mortgages in 2005-2007. Column (5) presents estimates from specification that excludes all London districts. Column (6) presents estimates from specification that includes 2013 in the post-HTB period. Column (7) presents estimates from specification that includes 2013 in the pre-HTB period. Standard errors are clustered at the district level and are shown in parentheses. ***, **, and * indicate statistical significance at the 1 percent, 5 percent and 10 percent confidence level, respectively.

Table 5: **The Effect of Help-to-Buy on Home Sales by Buyer-type**

	Buyer-type			
	First-time	Home Mover	Younger	Older
	(1)	(2)	(3)	(4)
$\text{Post}_t \times \text{Exposure}_d$	0.9983***	0.1837**	1.0769***	0.0867*
	(0.124)	(0.081)	(0.155)	(0.047)
Control Variables				
District Characteristics	Yes	Yes	Yes	Yes
Fixed Effects				
District	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes
Model Statistics				
N	2,054	2,054	2,052	2,054
R^2	0.9467	0.9658	0.9551	0.9569

The table presents coefficient estimates for Equation 5 for the period 2012 to 2016 (excluding 2013), which show the effect of the Help-to-Buy program on home sales across buyer-types. The dependent variable is the number of home sales purchased with a mortgage by the buyer-type. Post is a dummy variable equal to 1 for the period 2014 to 2016. Exposure equals the number of low-down payment mortgages in a district in the period 2005-2007 divided by the total number of mortgages in 2005-2007. Columns (1) to (4) present estimates where the buyer-type is: first-time buyers only, home movers only, younger (20 to 39 years-old) and older (40 to 59 years-old), respectively. Standard errors are clustered at the district level and are shown in parentheses. ***, **, and * indicate statistical significance at the 1 percent, 5 percent and 10 percent confidence level, respectively.

Table 6: **The Effect of Help-to-Buy on Internal Migration**

	All Districts	Excl. London	London Only
	(1)	(2)	(3)
$\text{Post}_t \times \text{Exposure}_d$	0.2993	-0.4973	7.5575*
	(0.466)	(0.419)	(3.885)
Control Variables			
District Characteristics	Yes	Yes	Yes
Migration Controls	Yes	Yes	Yes
Fixed Effects			
District	Yes	Yes	Yes
Time	Yes	Yes	Yes
Model Statistics			
N	1,842	1,664	178
R^2	0.9941	0.9935	0.9746

The table presents coefficient estimates for Equation 6 for the period 2012 to 2016 (excluding 2013), which show the effect of the Help-to-Buy program on internal migration inflows. The dependent variable is district-level internal migration inflows (from all other districts to district d). Post is a dummy variable equal to 1 for the period 2014 to 2016. Exposure equals the number of low-down payment mortgages in a district in the period 2005-2007 divided by the total number of mortgages in 2005-2007. Column (2) presents estimates from specification that excludes all London districts. Column (3) presents estimates from specification that includes only London districts. Standard errors are clustered at the district level and are shown in parentheses. ***, **, and * indicate statistical significance at the 1 percent, 5 percent and 10 percent confidence level, respectively.

Table 7: **The Effect of Help-to-Buy on House Price Growth**

	All Districts	Excl. London	London Only
	(1)	(2)	(3)
$\text{Post}_t \times \text{Exposure}_d$	0.1392***	0.1107***	0.4483***
	(0.020)	(0.018)	(0.099)
Control Variables			
District Characteristics	Yes	Yes	Yes
Fixed Effects			
District	Yes	Yes	Yes
Time	Yes	Yes	Yes
Model Statistics			
N	2,136	1,944	192
R^2	0.8339	0.8550	0.8308

The table presents coefficient estimates for Equation 7 for the period 2012 to 2016 (excluding 2013), which show the effect of the Help-to-Buy program on house price growth. The dependent variable is district-level annual house price growth. Post is a dummy variable equal to 1 for the period 2014 to 2016. Exposure equals the number of low-down payment mortgages in a district in the period 2005-2007 divided by the total number of mortgages in 2005-2007. Column (2) presents estimates from specification that excludes all London districts. Column (3) presents estimates from specification that includes only London districts. Standard errors are clustered at the district level and are shown in parentheses. ***, **, and * indicate statistical significance at the 1 percent, 5 percent and 10 percent confidence level, respectively.

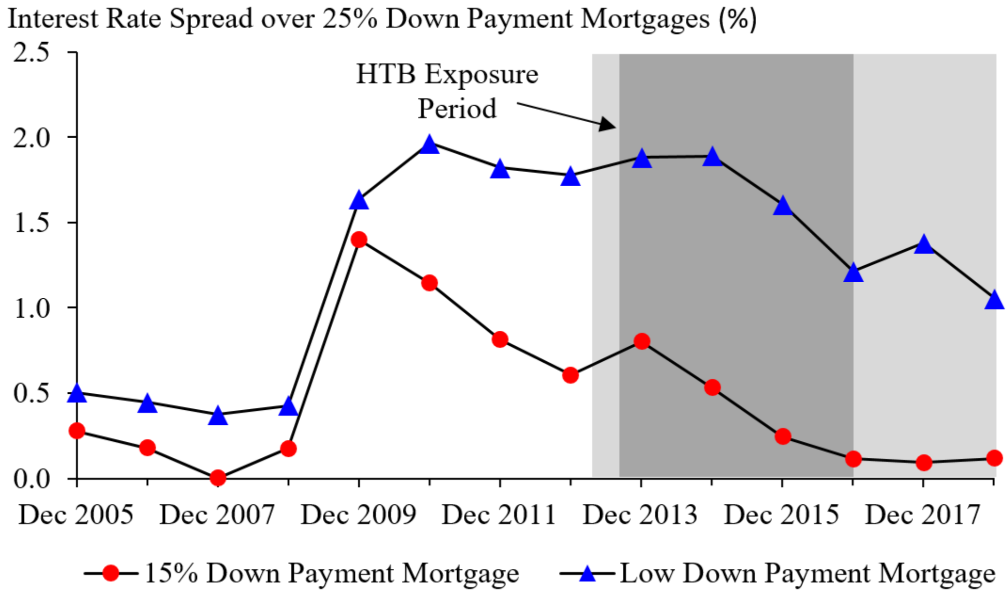
Table 8: **The Effect of Help-to-Buy on Car Sales**

	All Districts	Excl. London	London Only
	(1)	(2)	(3)
$\text{Post}_t \times \text{Exposure}_d$	1.3447***	1.3386***	0.7650
	(0.450)	(0.488)	(1.161)
Control Variables			
District Characteristics	Yes	Yes	Yes
Fixed Effects			
District	Yes	Yes	Yes
Time	Yes	Yes	Yes
Model Statistics			
N	2,165	1,973	192
R^2	0.9487	0.9536	0.9187

The table presents coefficient estimates for Equation 8 for the period 2012 to 2016 (excluding 2013), which show the effect of the Help-to-Buy program on car sales. The dependent variable is the number of private newly registered cars. Post is a dummy variable equal to 1 for the period 2014 to 2016. Exposure equals the number of low-down payment mortgages in a district in the period 2005-2007 divided by the total number of mortgages in 2005-2007. Column (2) presents estimates from specification that excludes all London districts. Column (3) presents estimates from specification that includes only London districts. Standard errors are clustered at the district level and are shown in parentheses. ***, **, and * indicate statistical significance at the 1 percent, 5 percent and 10 percent confidence level, respectively.

Appendix

Figure A.1: Interest Rate Spread for Low Down Payment Mortgages



The figure plots the weighted average interest rate spread (over 25 percent down payment mortgages) for two different mortgage products: first, 15 percent down payment mortgages; and second, low down payment mortgages with a down payment of 5 percent or less.

Table A.1: **The Help-to-Buy Program Requirements**

Requirements	Equity Loan (EL)	Mortgage Guarantee (MG)
Period	Q2 2013 - Q4 2020	Q4 2013 - Q4 2016
Minimum Down Payment	5%	5%
Government Participation	Government equity loan of 20% (40% in London from 2016)	Government guarantees 20% of mortgage made by lender
Qualifying Property	New builds Value < £600k (£300k in Wales)	Any property Value < £600k
Qualifying Borrowers	First-time buyers and home movers	First-time buyers , home movers and remortgagers
Qualifying Loan	LTI ratio < 4.5 Ratio excludes EL component	LTI ratio < 4.5 Ratio includes MG component

The table describes the requirements for the two main Help-to-Buy program schemes: the Equity Loan (EL) scheme and the Mortgage Guarantee (MG) scheme. The requirements apply to the property, loan features and buyer-types.

Table A.2: **Variable Descriptions and Sources**

Variable Name	Variable Description	Data Source
Loan-level Dependent Variable		
Low-Down Payment	Takes the value 1 if down payment 5 percent or less and 0 otherwise	Product Sales Database
Loan-level Variables		
First-time Buyer	Takes the value 1 if first-time buyer and 0 otherwise	Product Sales Database
Younger Buyer	Takes the value 1 if buyer age less than 40 and 0 otherwise	Product Sales Database
Household Annual Income	Total annual household income for borrower(s)	Product Sales Database
Employment-status	Categories: employed; self-employed; other	Product Sales Database
Property Value	Property Value of mortgage	Product Sales Database
Down Payment	Down Payment of mortgage	Product Sales Database
Loan-to-income Ratio	Loan-to-income Ratio of mortgage	Product Sales Database
Maturity	Remaining years until mortgage maturity	Product Sales Database
Rate-type	Categories: fixed; floating; other	Product Sales Database
Repayment	Categories: capital and interest; interest only; other	Product Sales Database
District-level Dependent Variables		
Home Sales	Total number of mortgaged home sales	Product Sales Database
First-time Buyer Sales	Total number of mortgaged first-time buyer sales	Product Sales Database
Home Mover Sales	Total number of mortgaged home mover sales	Product Sales Database
Younger Buyer Sales	Total number of mortgaged home sales for buyer age 20-39 years	Product Sales Database
Older Buyer Sales	Total number of mortgaged home sales for buyer age 40-59 years	Product Sales Database
First-time Buyers	Total number of first-time buyers	Product Sales Database
House Price Change	Log difference in annual average house price	Land Registry House Price Index Data
Car Sales	Total number of new private car registrations	Department for Transport
District-level Control Variables		
Exposure	Share of low down payment mortgages (as a proportion of total) issued between 2005 to 2007	Product Sales Database
Unemployment Rate	Model-based estimates of unemployment rate	Office for National Statistics
Median Weekly Income	Median gross weekly pay for all workers	Office for National Statistics
Average Weekly Rent	Average weekly rent weighted across house-types	Office for National Statistics, Statistics for Wales, Scottish Government Statistics
Average House Price	Average house price for all house transactions in a given year	Land Registry House Price Index Data
Population	Mid-year popultion estimate	Office for National Statistics