Down Payment Constraints, Homeownership and Household Spending

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Abstract

This paper shows that easing down payment constraints positively affects both homeownership and household spending. It studies a large-scale UK policy initiative called Help-to-Buy and exploits geographical variation in exposure to the program. It shows that HTB induced a significant increase in home purchases, especially benefiting young and first-time buyers. Except in the London area, the impact on house prices was subdued. Regions that experienced an increase in home purchases also experienced an increase in durable consumption. This points towards another channel through which homeownership and consumption interact.

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. This trend has accelerated since the global financial crisis, widening preexisting inter-generational housing inequalities (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. 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.[1] This primarily affects first-time and young buyers who often face liquidity constraints and disproportionately rely on low-down payment mortgages to secure a home purchase (Figure 3).[2]

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 exposure to the program and using detailed data on mortgage loans and household spending, it shows that the program not only made it easier for first-time and young buyers to purchase a house, but also led to an increase in durable consumption. This suggests that saving for a down payment can act as a binding liquidity constraint. For such liquidity constrained households purchasing a home frees up discretionary income and as a result their consumption can rise, pointing towards another channel through which home ownership and consumption interact.

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

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

[2] 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).

[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.

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 countries are thinking of ways to address inter-generational housing inequalities by making 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 are 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 very slowly over time, 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.

To measure program exposure we exploit detailed administrative mortgage data that capture the universe of regulated mortgages issued in the UK. These data include, among other things, information about the location of the property, the loan value and property price (and thus the down payment). We define HTB exposure as the number of low-down payment mortgages relative to all mortgages issued in a district between 2005 and 2007, i.e. a period when the market for low-down payment mortgages was relatively unconstrained.[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

[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.

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. We show that our HTB exposure measure performs well in explaining the actual increase in the share and number of low-down payment mortgages over the course of the program.

A key challenge in estimating the effect of HTB on homeownership and household spending 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. 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 two parts. We begin by examining whether HTB generated an increase in home sales and which buyers benefited most from the program. An easing of down payment constraints can impact the 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. We focus on the period 2010 to 2016 which captures the period when both schemes were active. 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.

We document a significant increase in home purchases in high exposure relative to low exposure districts. This increase corresponds exactly with the timing 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. When differentiating between home purchases with different down payments, it is apparent that the increase is entirely driven by home purchases with low-down payments. We estimate that during the policy period approximately 219,000 additional homes were purchased due to HTB that would not have been purchased otherwise. This implies that HTB increased home sales by 10 percent during the policy period. This number reflects both the direct effect of HTB as well as its indirect effect of re-opening the market for low-down payment mortgages outside the two program schemes.[9]

Did the easing of down payment constraints make purchasing a home more accessible to buyers that more likely have limited savings? Indeed, we find that the increase in home purchases was particularly pronounced for first-time and younger buyers, i.e. those households that are more likely to be liquidity constrained. Our estimates indicate that first-time buyers, i.e. households transitioning into homeownership, accounted for 80 percent of the increase in home purchases. 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.

We show that our results are robust to a variety of permutations. We find similar effects when we use an exposure measure which is based on the supply of eligible houses in a district just prior to the start of the program. In addition, our results hold when excluding the London area, indicating that these patterns are not driven by particularities of the London housing market. Finally, we show that our findings cannot be explained by changes in between-district migration patterns during the program period.

When assessing the impact of HTB on house prices, we find that, outside London, districts more exposed to the program experienced only slightly higher house price growth. In the London area 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 second 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, such policies could lead to an increase in household spending. If the down payment is a binding liquidity constraint then the purchase of a house should free up discretionary income, which enables a household to increase its consumption (Engelhardt, 1996). Furthermore, homeowners tend to invest more in their home compared to renters, especially just after moving. This can generate an increase in housing-related household spending (Best and Kleven, 2017). This increase will be especially pronounced if prospective home buyers put money aside (on top of their down payment) to invest in their future home. On the other hand, such policies could also lead to a decline in household spending. An increase in moving-related expenditures might be offset by lower consumption in other categories. 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

[9] Not all banks participated in the HTB schemes because of the cost associated with it. Some instead opted to make low-down payment mortgages available outside the scheme.

spillover effects of these kind of programs on household spending.[10]

To examine the impact of HTB on consumption, we focus on car purchases, a key consumption item that is not housing-related. We exploit district level data on car sales over the period 2010 to 2016 and utilize the same difference-in-differences strategy. 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. These findings are again robust to controlling for district fixed effects and changes in house prices, income levels, unemployment and rental prices at the district level.

More than 85 percent of UK households purchase a new car using some form of unsecured consumer credit, thereby involving a monthly payment plan rather than a large one-off payment. Under the underlying assumption that during the program period car financing terms did not loosen more in high exposure areas, our findings are consistent with the idea that the ability to purchase a home with a low-down payment frees up discretionary income for liquidity constrained households. While other drivers can explain the positive effect of HTB on car sales, they do suggest 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 discretionary income increases allowing them to consume more.[11] This finding indicates the presence of another channel through which homeownership and consumption interact.

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 purchase a home, but boost household spending as well. However, 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 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 (and car finance) 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

[10] 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.

[11] This finding is consistent with a recent survey by Santander which 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 (https://www.santander.co.uk/assets/s3fs-public/documents/santander-first-time-buyer-study.pdf).

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 and provides validation of our exposure measure. Section 6 reports the results on the effects of HTB on the housing market and Section 7 on household spending. Section 8 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).[12]

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

[12] 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).

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 $\theta_{LTI} \times Y$.[13] Taking these constraints together, 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 $D = £9,000$.[14] 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,

[13] 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 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.

[14] 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.

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.[15] 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 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."[16]

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

[15] 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.

[16] 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

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."[17]

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 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

[17] 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

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).[18] The main LTV buckets are: 0-50; >50-60; >60-

[18] 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).

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.[19] 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.[20] 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).[21]

A second set of outcome variables that we obtain from the PSD are year-district-level measures 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 6.4, are

[19] 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.

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

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

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

5.1 Measuring Exposure to Help-to-Buy

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. These differences 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 are 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 very slowly over time. 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 an estimate of the marginal impact of the program.[22]

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.[23][24] Figure 6 presents a district-level map of HTB exposure across the UK. Darker areas indicate more exposure to the program. It illustrates that significant variation exists 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

[22]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 6.4 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 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, i.e. those districts between which endogenous moves are most likely to occur.

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

[24]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.

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 key concern with an identification strategy based on geographical variation in exposure is that districts with high exposure to HTB also differ importantly in other ways that could independently impact the demand for low-down payment mortgages and housing. 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.

5.2 Help-to-Buy and the Mortgage Market

Before turning to our main analysis, we first present a regression version of Figure 8. This allows us to examine whether our HTB exposure measure indeed correlates with a district-level increase in the incidence of low-down payment mortgages when we control for time-varying and time-invariant differences between districts. It also allows us to formally test for any pre-event trends. 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. The dependent variable 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. $\mathbf{Loan}_{b,l,d,t}$ 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 $t-1$. The specification further includes lender-time fixed effects, λ_{lt}, and district fixed effects, δ_d. 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 β_s with and without time-varying district-level controls along with the confidence intervals. The β estimate for 2013 is positive but (just) insignificant. This is not surprising 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. 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 differences between high and low exposure districts prior to the start of the program. The estimates remain very similar when including district-level control variables (bottom panel), reducing concerns that our HTB exposure measure is correlated with other district-level variables.[25] Taken together, this evidence indicates that our HTB exposure measure adequately captures differences in the actual exposure to the program.

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

6.1 Help-to-Buy and Home Sales

We start by examining the impact of HTB on home sales. As explained in Section 3.1, an increase in the availability of low-down payment mortgages can theoretically have three effects on the demand for 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

[25] When excluding the London area the results remain virtually the same, indicating that these patterns are not driven by particularities of the London housing market (results available upon request).

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.

To examine the impact of HTB on the number of home sales, we estimate a panel regression model similar to the model in Equation 2, but now the unit of observation is at the district-time level and not the mortgage-level:

$$\begin{aligned}\text{Home Sales}_{d,t} = \; & \textstyle\sum_{s\neq 2012} \mathbb{I}_{t=s} \times \text{Exposure}_d \times \beta_s + \gamma \text{District}_{d,t-1} \\ & + \theta_t + \delta_d + u_{,d,t}\end{aligned} \tag{3}$$

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.[26] Exposure_d is our measure of *ex ante* exposure to the HTB program. $\mathbf{District}_{d,t-1}$ is the same vector of time-varying district-level control variables as those described in Section 5 and includes (the log of): average rent, median income, the unemployment rate, population, and average house prices. The specification further includes time fixed effects θ_t and district fixed effects δ_d. Standard errors are clustered at the district level. The year 2012 is taken to be the base year. This model provides a series of coefficient estimates of β_s that illustrate the time dynamics of the effect of HTB on home sales, while controlling for time-varying and time-invariant district-level differences that might impact the demand for houses and for unobservable time-varying factors such as changes in economic conditions that impact all districts.

The results are presented in Figure 10. We observe very similar trends in home purchases in the years prior to the program 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. This increase corresponds exactly with the timing of the program. These findings indicate that HTB, by loosening down payment constraints, had a positive impact on the number of home purchases.

The economic significance on the program is large. Figure 11 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 Figure 10. By the end of 2016, the number of home sales is 55 percent higher in our representative low exposure district, while in our representative high exposure district this number is close to 119 percent. Taking the district with the minimum exposure for HTB as the control group, we estimate that approximately 219,000 homes were purchased due to HTB that would not have been purchased otherwise. This implies that HTB increased home sales by 10 percent during the policy period. This number is slightly larger than the approximately 200,000 HTB mortgages issued between the

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

start of the program and the end of 2016.[27]This reflects the fact that HTB also had an indirect effect on home sales by re-opening the market for low-down payment mortgages provided by some banks outside the two program schemes.

To put further rigor to the interpretation of our findings we next allow the impact of HTB to differ across homes purchased with different down payments. As HTB made it easier to purchase a home with only a five percent down payment, the differential increase in home sales in high exposure districts should be driven by homes purchased with a 95 percent LTV. To test this we exploit a distinct feature of the UK mortgage market: discrete interest rate jumps - notches - at various thresholds of the loan-to-value (LTV) ratio. These thresholds are at LTVs of: 60, 70, 75, 80, 85 and 90 percent (with 95 percent being the maximum LTV offered). When the LTV crosses one of these thresholds the interest rate increases on the entire mortgage. This creates very strong incentives to reduce borrowing to a level just below the notch and generates large bunching below the critical LTV thresholds and a missing mass above them (Best et al. (2020)).

We use these LTV thresholds to test whether HTB indeed had a differential impact on homes purchased with a 95 LTV mortgage, compared to home purchased with lower LTV mortgages. We estimate the following panel regression model:

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

where d indexes a district, t is the year and i is the LTV ratio of the mortgage with which the house is purchased. The dependent variable Home $\text{Sales}_{d,t,i}$ equals the number of home sales within an LTV bucket in a given year and district. We remove outliers by dropping the values below the 1st and above the 99th percentile.[28] LTV_i represents the different LTV buckets. 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 5. The regression specifications include district fixed effects, δ_d, time fixed effects θ_t and μ_i LTV bucket fixed effects. The baseline model is estimated over the period 2012 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. Standard errors are clustered at the district level.

The results are presented in Table 3. We start by showing the results using the same dependent variable as used in Equation 3, i,e the number of home sales in a given year and district

[27]Note that under the assumption that the district with the lowest exposure (0.08) is the adequate control group, our estimate captures the impact of HTB on home purchases through the extensive margin and timing effect. The number of actual HTB mortgages also include the intensive margin effect as some of those mortgages will be the result of households decide to use their down payment to purchase a more expensive house. This, however, does not lead to a home purchase that would otherwise not have taken place.

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

without splitting between the different LTV buckets. This provides us with an average effect of HTB over the three program years. In line with our previous findings, we find a positive and highly significant effect. The results remain very similar (albeit a slightly smaller coefficient) when we add time-varying district-level controls (column (2)). In column (3) we measure the number of home sales by LTV bucket, but do not allow $\beta_1$to differ across the different buckets. This captures the average effect of HTB on home purchases with different LTVs. Again, and unsurprisingly, the effect is positive and significant. Next, we allow $\beta_1$to vary over the different LTV buckets. The results show that the increase in home sales in districts more exposed to HTB is entirely driven by homes purchased with a low-down payment with by far the highest impact on homes purchased with only a 5 percent down payment. The presence of a positive, but significant smaller, impact of HTB on mortgages with a down payment of 10 percent, reflects the fact that some mortgages bought under the MG or EL scheme had a somewhat larger down payment than the minimum of five percent (Benetton et al., 2019).

Besides validating that the increase in home sales in high exposure areas is driven by home purchases with a low-down payment, this analysis also allows us to control for all variation at the district-time level by including district-time fixed effects and thus to absorb all time-(in)variant differences across districts. In other words, we isolate the impact of HTB purely from within-district heterogeneity. This removes many confounds from the analysis and significantly reduces the concern that our HTB exposure measure is correlated with any remaining unobservable district-level differences that might also impact the demand for housing. The final column presents the results. They show that they are hardly affected by this change, reducing concerns that the patterns we document are driven by differential district-trends.

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 and have the financial resources available will try and get on the property ladder as soon as possible, i.e. buying a small starter home with the intention of scaling up in a couple of years time.

To examine the extent to which HTB had a more pronounced impact on young and first-time buyers we estimate a panel regression model similar to Equation 4, but instead we differentiate between homes purchased by different types of buyers:

$$\begin{aligned}\text{Home Sales}_{d,t,b} = \;& \beta_1 \text{Post}_t \times \text{Exposure}_d + \beta_2 \text{Post}_t \times \text{Buyer}_b + \beta_3 \text{Exposure}_d \times \text{Buyer}_b \\ & + \gamma \text{District}_{d,t-1} + \delta_d + \theta_t + \kappa_b + u_{d,t,b}\end{aligned} \tag{5}$$

where d indexes a district, t is the year and b is the type of buyer. Buyer_b is one of the following two variables: a first-time buyer dummy and a younger buyer dummy, which we define as buyers 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 rest of the model is the same as Equation 4, except that the LTV bucket fixed effects are replaced by buyer-type fixed effects.

The results are presented in Table 4. We first differentiate between first-time buyers and home movers (columns (1) and (2)). The interaction $\text{Post}_t \times \text{Exposure}_d$ is positive and significant indicating that both types of buyers show a higher increases in home purchases in high exposure areas relative to low exposure areas during the program period. However, the impact of HTB is significantly stronger for first-time buyers as the triple interaction $\text{Post}_t \times \text{Exposure}_d \times \text{Buyer}_b$ 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 four times as large as the impact on older buyers. The results are similar when we replace our district and time fixed effects with district-time fixed effects (columns (2) and (4)), reducing 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. Of the 219,000 additional homes purchased due to HTB exposure, our estimates imply that first-time buyers accounted for approximately 80 percent of the increase. Younger buyers accounted for approximately 92 percent of the increase in homes purchased due to HTB exposure.

6.3 Robustness to Alternative Specifications

We run a number of robustness tests to ensure that our baseline finding, that HTB induced an increase in home purchases, is robust to different permutations of the model. For this we use the same specification as in the Column (2) of Table 3 as our benchmark. We first drop districts in the London area from the sample (Table 5, column (1)). This hardly changes the parameter estimate indicating that our findings are not driven by peculiarities of the London housing market. Next, we test whether the results still hold when we include the year 2013 in the post-period (column (2) or in the pre-period (column (3)). In line with the fact that 2013 is partly a program year, the coefficient estimates of β_1 become smaller, but they remain highly significant at the one percent level. In column (4) we change our specification to a log specification and define the dependent variable Home Sales$_{d,t}$ as the log of the number of home sales in a given year and district. We find again and positive and highly significant parameter for our exposure measure.

In the final two columns we measure program exposure in a different way. We exploit the fact that the MG and EL schemes came with a number of eligibility criteria and construct a measure that captures the supply of *eligible* houses in each district as of December 2012, i.e. just before the policy came into effect. A property is eligible for the HTB program if it has a value less than £600,000. This covers more than 90 per cent of all properties in the UK and so is not a particularly restrictive requirement, except in London. However, home-buyer(s) are eligible for a HTB mortgage only when their loan-to-income (LTI) ratio is less than 4.5. We therefore approximate the share of HTB-eligible properties as being the proportion of properties in a district that have a property value less than the LTI ratio of 4.5 as of December 2012. The LTI is based on the 2012 median household income for each district.[29] We obtain information on all sold properties from the Land Registry Price Paid Dataset (PPD), which covers properties sold in England and Wales.[30] We consider all properties sold in the ten years preceding the announcement of the HTB program, from January 2002 to December 2012. All property prices are updated to December 2012 prices by applying a granular district-level house price index adjustment to the transaction price. We obtain district-level, annual gross median income information from the UK Office of National Statistics (ONS).

This alternative measure of HTB exposure is highly correlated with our original measure, with a correlation of 0.80. This is not surprising as first-time and younger buyers are much more likely to be able to purchase a home in districts where a significant amount of properties do not exceed the 4.5 LTI limit. When we use this alternative measure (column (5)) we again find a positive and highly significant coefficient. As it is impossible to exactly measure each district's exposure to HTB, this gives confidence that our findings are not dependent on one particular way of measuring it.

In the last column, we focus on the EL part of the scheme only. Under this scheme only new builds are eligible. So we adjust the nominator in the exposure measure such that it only includes properties in a district that were sold as new properties between 2002 and 2012 and that have a property value of less than the LTI ratio of 4.5 as of December 2012. The idea is that the share of new builds in a particular district in the past 10 years is a good indicator of how many new properties will come on the market during the HTB program that are eligible

[29]Median household income for a district is estimated for a two-person household and equals two times the median income in the district.

[30]The PPD includes information about the property price, as well as postcode and district information. We also use the granular, district-level, monthly house price indexes from the UK Land Registry.

under the EL scheme. A district where a relatively large amount of new properties come on the market is an area with less supply restrictions. When we use this third exposure measure in the last column, we find again a positive and significant effect. The magnitude of the parameter is much larger as this exposure measure has a mean of 5.6 percent while the one capturing both eligible old and new builds has a mean of 46.4 percent.[31]

6.4 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.[32] In addition to the $\mathbf{District}_{d,t-1}$ vector of time-varying district-level control variables described in Section **??**, 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.[33] The rest of the model is the same as Equation 4.

[31] The mean of our main HTB exposure measure is 22.6 percent (see Table 1).

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

[33] 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.

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 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.

6.5 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.

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

In the previous section we established that HTB had a positive impact on the ability to buy a home (and the ability to transition into home ownership) by liquidity constraint households. In this section we examine the impact of this on 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, such policies could lead to an increase in household spending. If the down payment is a binding liquidity constrained then the purchase of a house should free up discretionary income with a positive effect on consumption. 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 how household spending reacts when down payment constraints are eased.

7.1 Help-to-Buy and Car Sales

We explore to what extent a loosening of down payment constraints affects household spending by studying the impact of HTB on car purchases, a key consumption item that is not housing-related. We again exploit regional variation in exposure to the program which provides us with a meaningful counterfactual. 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 12 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:

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

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. We remove outliers by dropping the values below the 1st and above the 99th percentile.[34] The remainder of the model is the same as for Equation 4. This implies that we also control for changes in house prices at the district level. This is important in this context as 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.

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.

At first sight, it might be puzzling why liquidity constraint households who just purchased a home would have money to spare to purchase a car (the second most expensive consumption item). However, more than 85 percent of UK households purchase a car using some form of unsecured consumer credit, thereby involving a monthly payment plan rather than a large one-off payment. Under the underlying assumption that during the program period car financing

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

terms did not loosen more in high exposure areas, our findings are consistent with the idea that the ability to purchase a home with a low-down payment frees up discretionary income for liquidity constrained households. Instead of saving for a down payment, the money can instead be used to finance a monthly payment plan.

While others drivers can explain the positive effect of HTB on car sales, they do suggest 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 discretionary income increases allowing them to consume more. This finding is consistent with a recent survey by Santander which 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. [35] Our result thus suggests the presence of another channel through which homeownership and consumption interact.

8 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

[35] https://www.santander.co.uk/assets/s3fs-public/documents/santander-first-time-buyer-study.pdf.

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.

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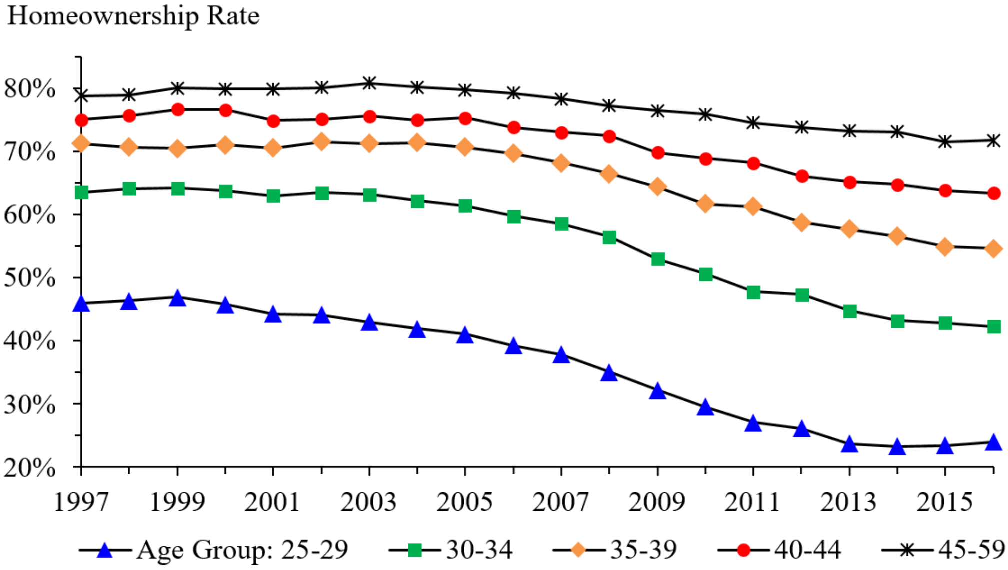
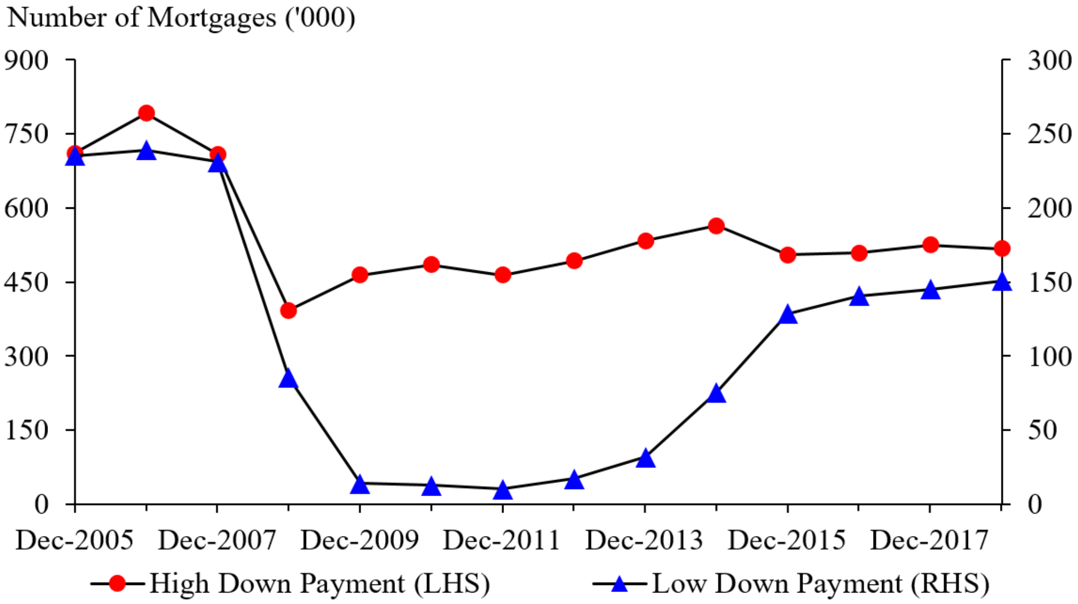
Figure 1: **Homeownership in the UK by Age Group**



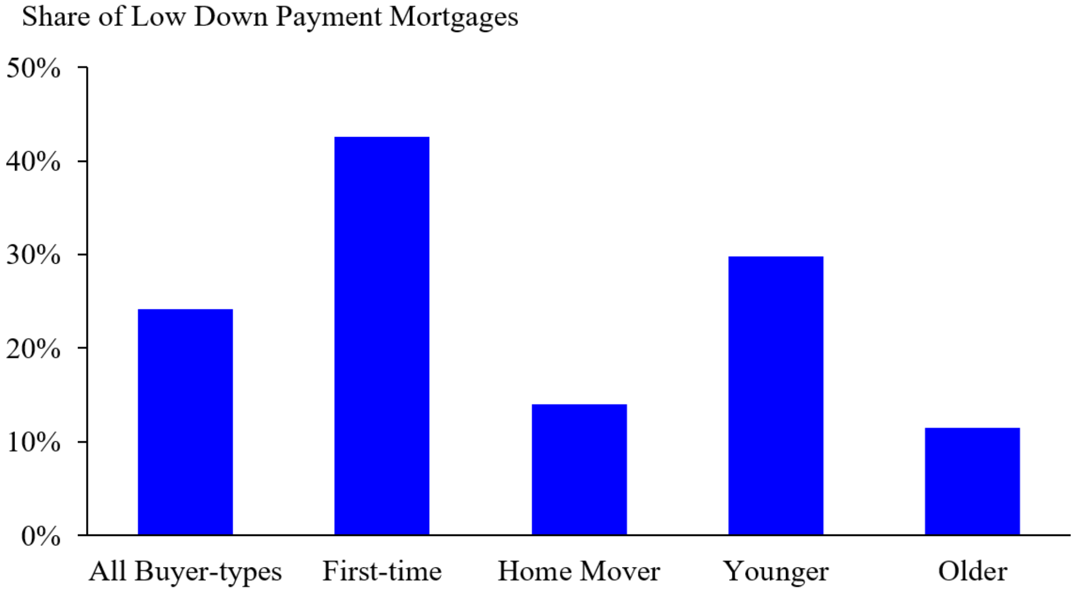
The figure shows homeownership rates for those aged 25 to 59 years, grouped into five specified age bands, over the period from 1997 to 2016. The estimates are taken from the UK Labour Force Survey and calculations similar to those of Cribb, Hood and Hoyle (2018).

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



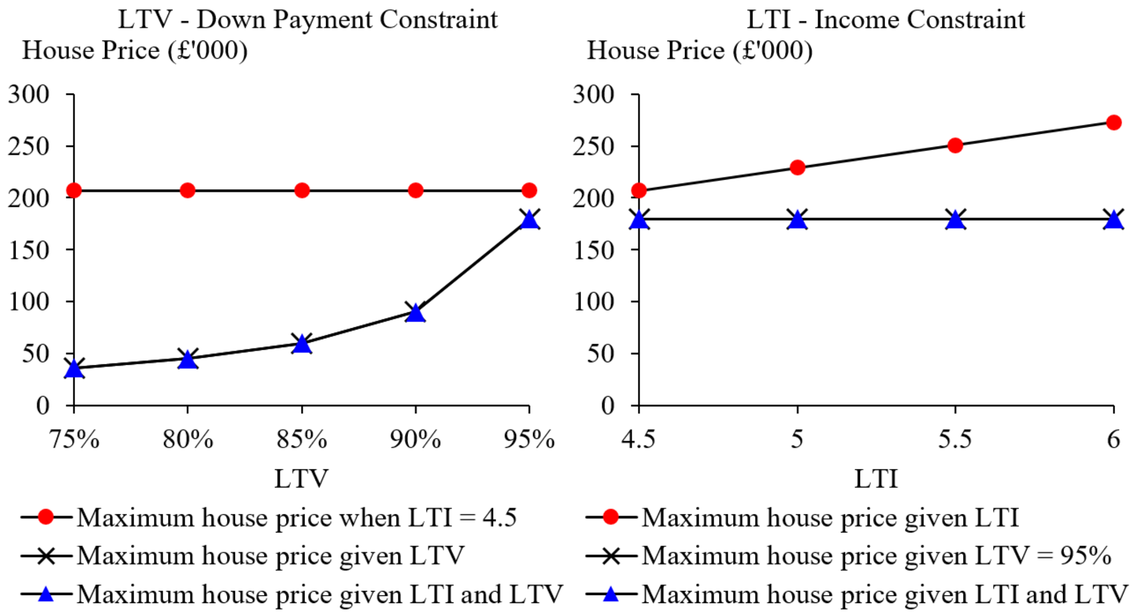
The figure shows the year-end aggregate number of high and low down payment mortgages purchased over the period from 2005 to 2018. Low down payment mortgages include all mortgages with a down payment of 5 percent or less.

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



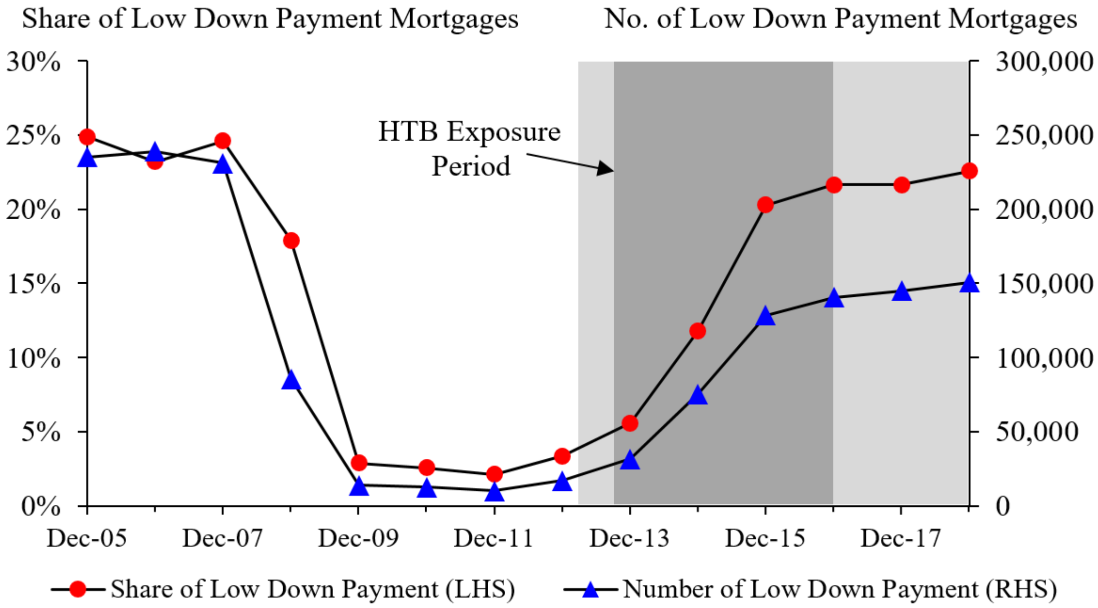
The figure shows the share of low-down payment mortgages (as a proportion of all mortgages) over the period 2005 to 2007 for different types of buyers. Low down payment mortgages include all mortgages with a down payment of 5 percent or less. Younger buyers are 20-39 years-old and older buyers are 40-59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

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



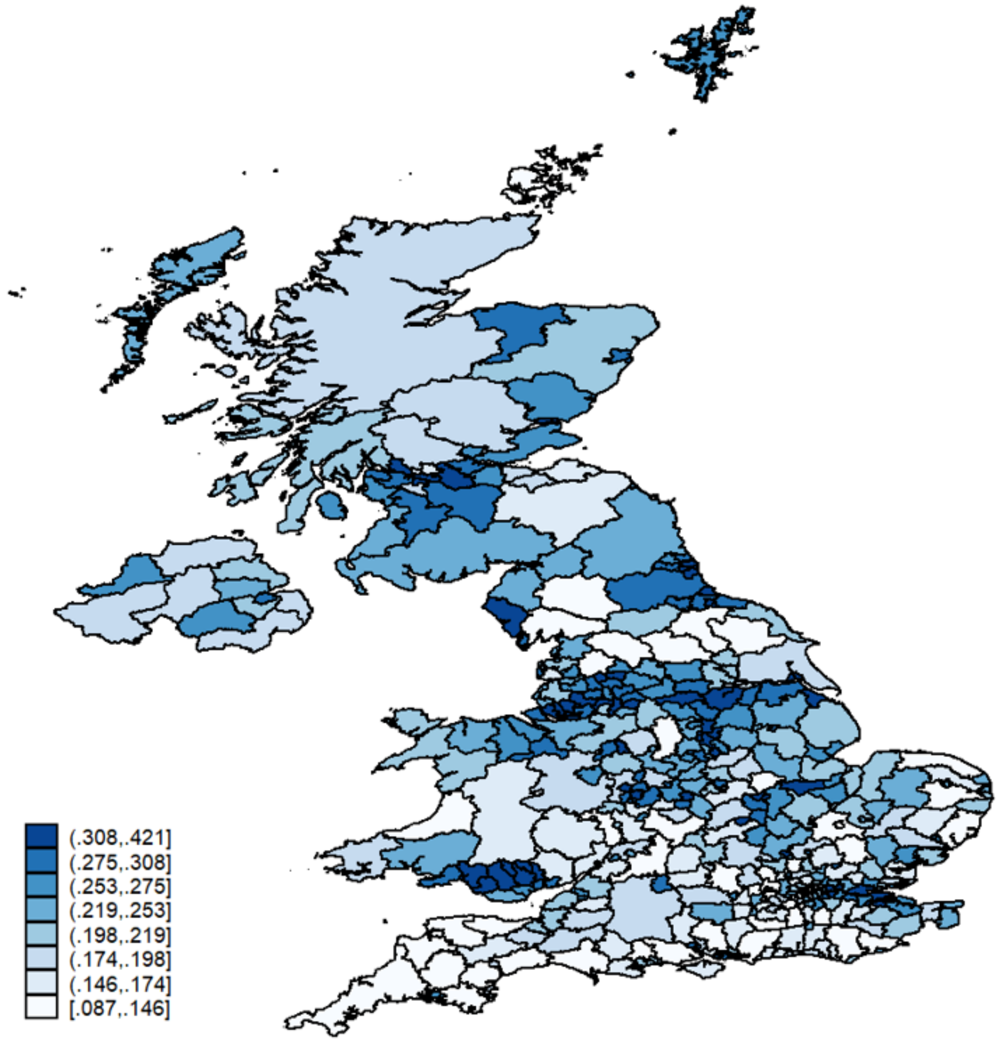
The figure presents the maximum house price a household with an income of £44,000 and a down payment of £9,000 is able to afford under different loan-to-value (LTV) and loan-to-income (LTI) requirements. For the left panel of the figure, the LTI requirement is kept fixed at 4.5 and the LTV is allowed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



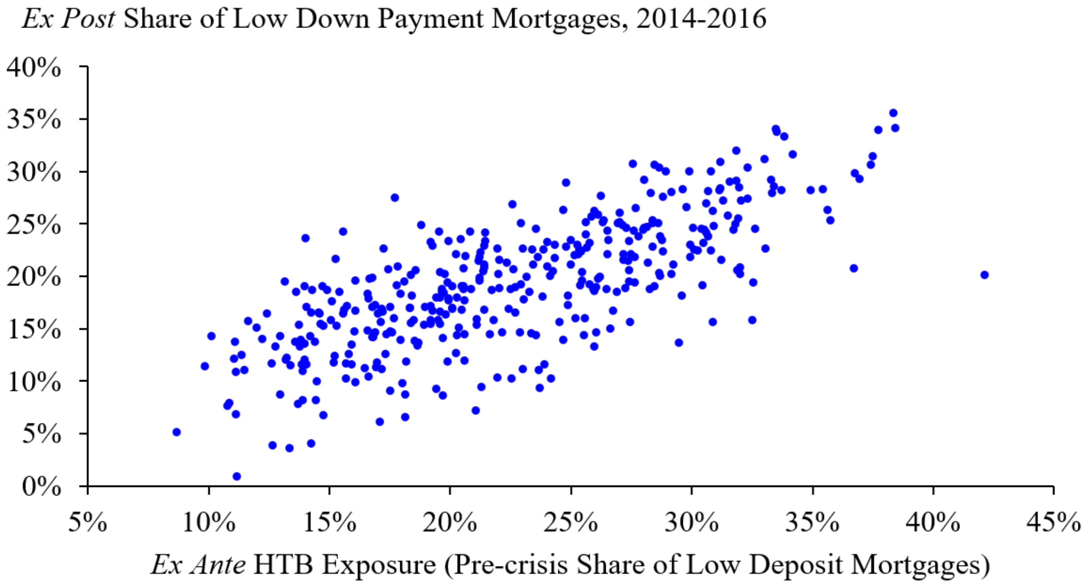
The figure shares the share and number of low down payment mortgages before and during the Help-to-Buy Program exposure period. Low down payment mortgages include all mortgages with a down payment of 5 percent or less. The dark-shaded area indicates the period that both the EL and MG schemes are in effect (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**



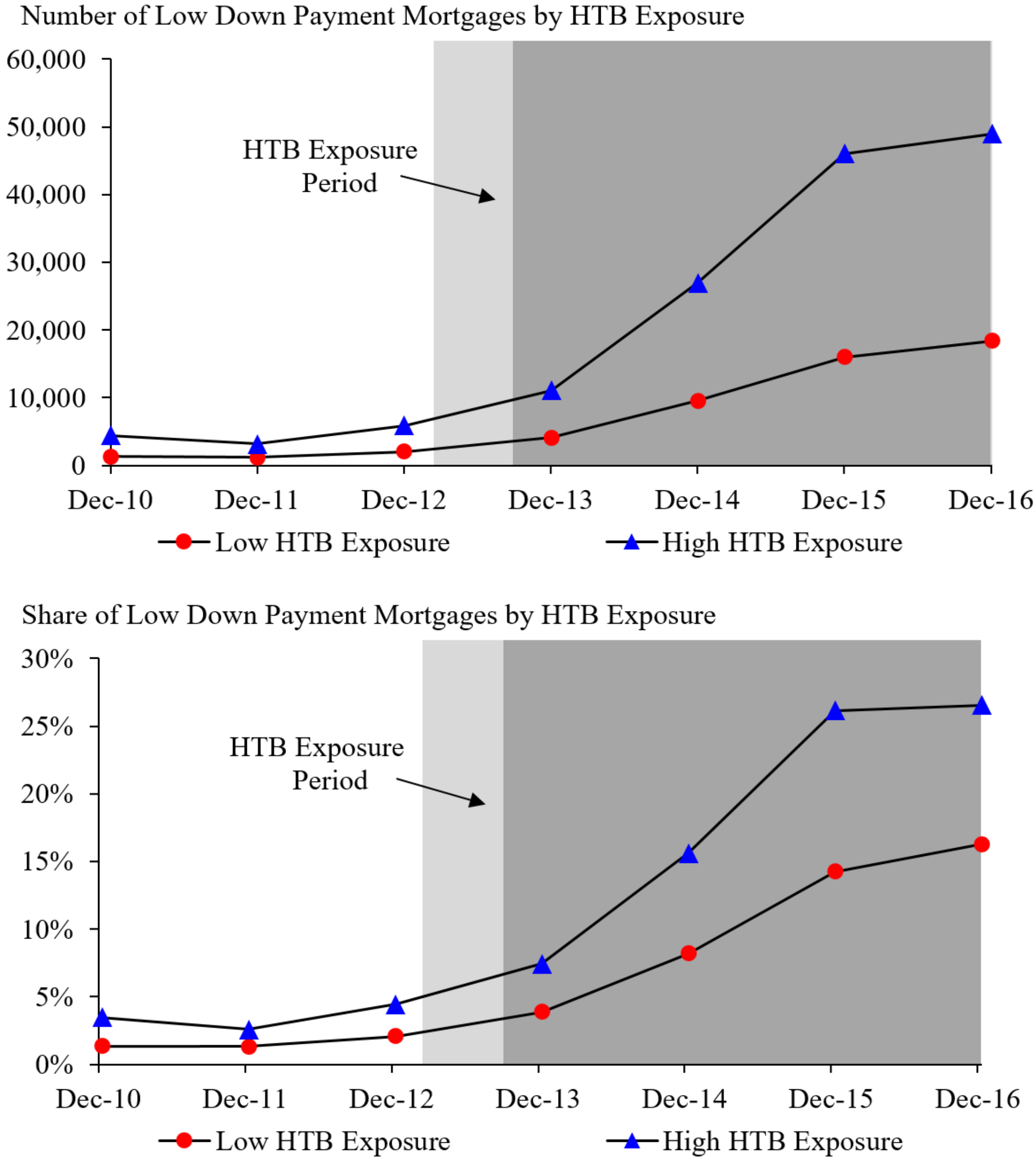
The figure shades local authority districts across the UK by shows Help-to-Buy (HTB) Exposure. HTB Exposure equals the number of low-down payment mortgages in a district in the period 2005-2007 divided by the total number of mortgages in 2005-2007. Districts with a darker shading have a higher exposure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

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



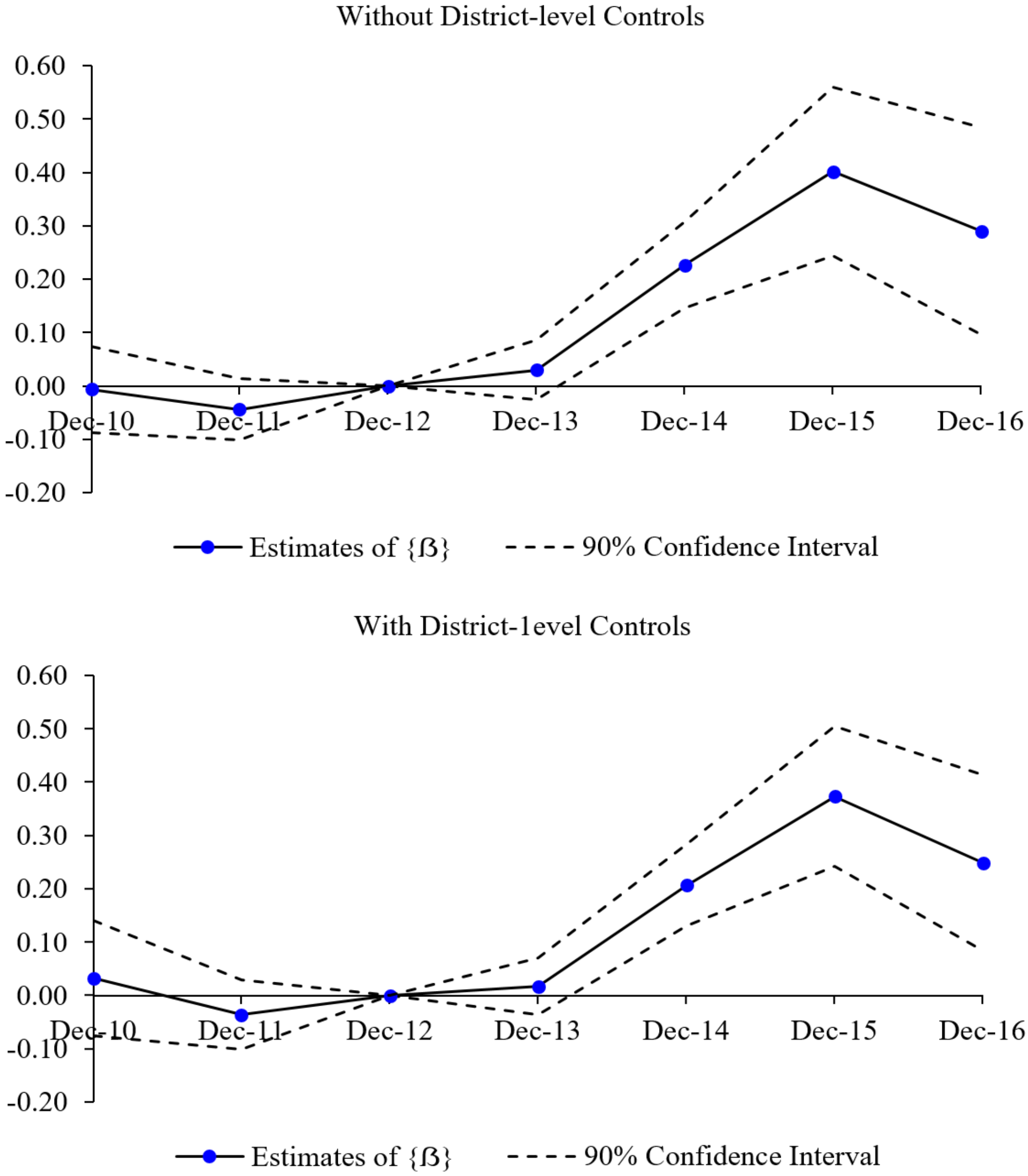
The figure shows the relationship between our measure of Help-to-Buy program exposure and the actual purchase of low-down payment mortgages over the program period from 2014 to 2016 at the district level. The number of low-down payment mortgages is scaled by total number of mortgages purchased in the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



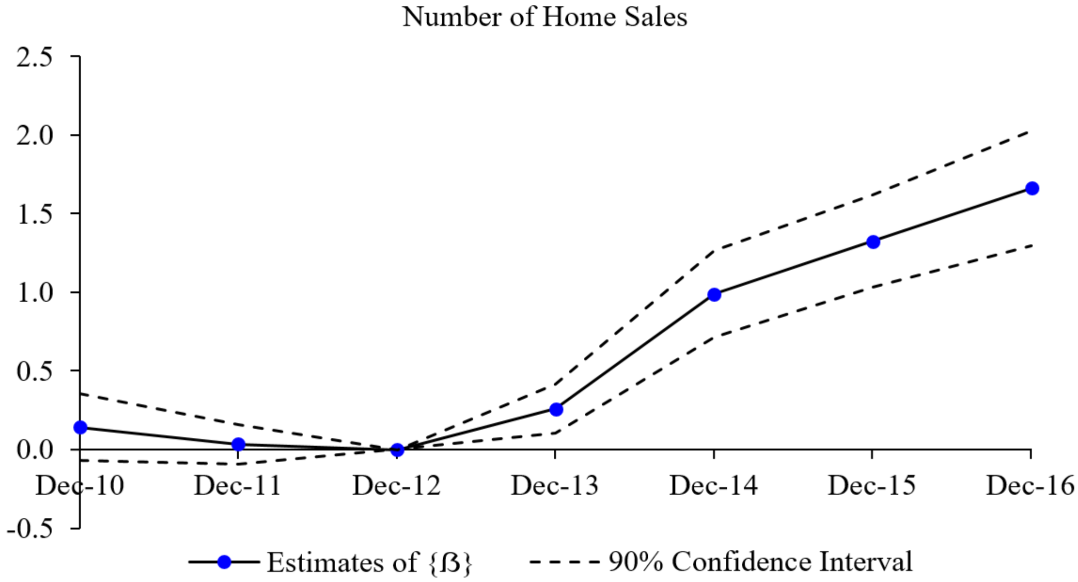
The top panel of the figure shows the aggregate number of low-down payment mortgages over the period from 2005 to 2016 for districts that are grouped according to their HTB exposure. The bottom panel shows the weighted average share of low-down payment mortgages (as a proportion of all mortgages excluding 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



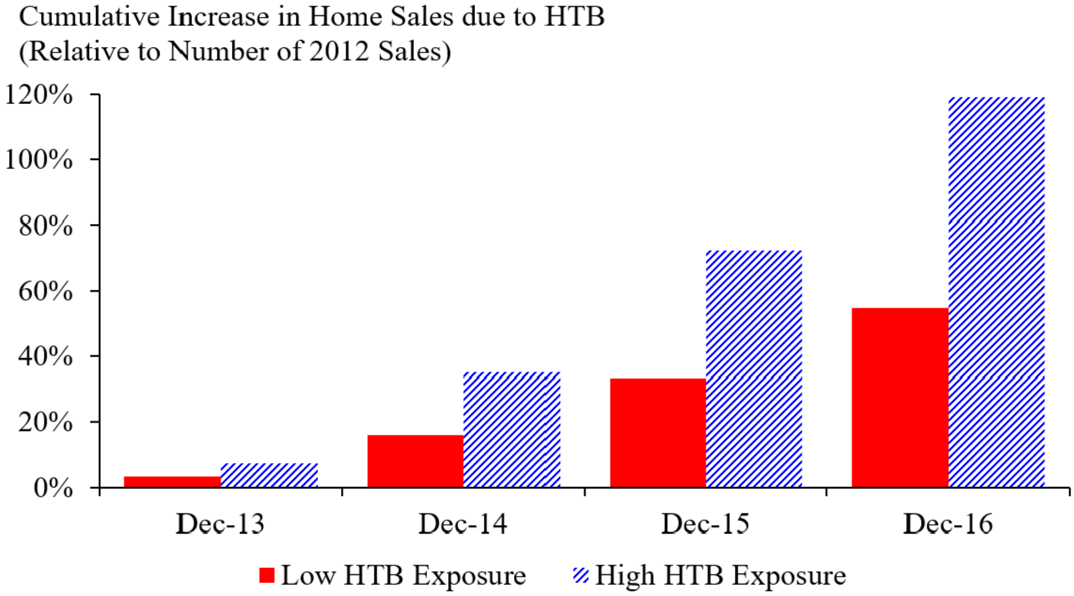
The figure presents estimates of β from Equation 2 for each year, where the outcome $Y_{b,l,d,t}$ is the dummy variable for low down payment mortgages and 2012 is the base year. The dashed lines show the 90 percent confidence interval. All regressions include loan and home buyer controls, as well as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

Figure 10: The Effect of Help-to-Buy on Home Sales



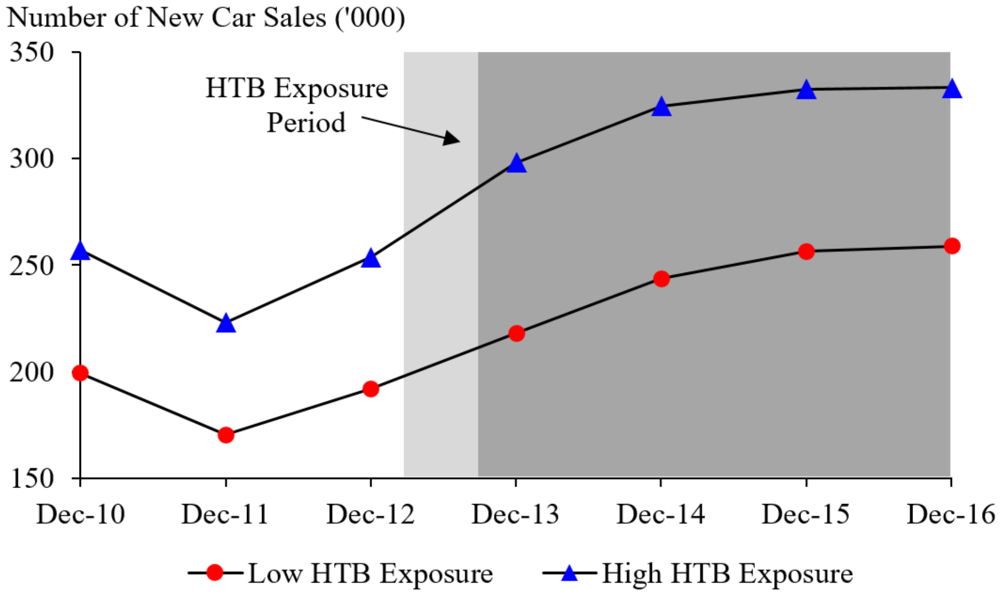
The figure presents estimates of β from Equation 3 for each year, where the outcome variable Home Sales$_{d,t}$ equals the number of home sales in a given year and district and 2012 is the base year. The dashed lines show the 90 percent confidence interval. All regressions include time-varying district-level controls as well as district and time fixed effects. Standard errors are clustered at the district level.

Figure 11: Economic Significance of Help-to-Buy



The figure is computed using estimates of β_3 from Equation 3. For example in December 2013, the annual increase in home sales due to Help-to-Buy for region i is $(\beta_{2013} \times \text{HTB Exposure}_i) / \text{Home Sales}_{i,2012}$. And for December 2016, the cumulative annual increase in home sales due to Help-to-Buy for region i is $[(\beta_{2013} + \beta_{2014} + \beta_{2015} + \beta_{2016}) \times \text{HTB Exposure}_i] / \text{Home Sales}_{i,2012}$. 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 12: 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**

	Pre Help-to-Buy			Post Help-to-Buy		
Variable Name (Unit)	Mean	Median	Std. Dev.	Mean	Median	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)	1.26	1.04	0.72	1.59	1.35	0.87
First-time Buyer Sales ('000)	0.48	0.36	0.35	0.73	0.57	0.47
Home Mover Sales ('000)	0.77	0.68	0.41	0.86	0.77	0.45
Younger Buyer Sales ('000)	0.81	0.64	0.52	1.08	0.89	0.65
Older Buyer Sales ('000)	0.45	0.40	0.22	0.50	0.46	0.25
House Price Growth (%)	-1.48	-2.12	4.47	5.55	5.05	3.67
Car Sales ('000)	2.18	1.85	1.33	2.94	2.45	1.81
District-level Control Variables						
Exposure (%)	22.55	21.94	6.63	22.63	22.01	6.64
Eligible Housing Share Exposure (%)	46.44	46.68	22.84	46.89	47.17	22.82
Eligible New Build Share Exposure (%)	5.56	5.03	3.26	5.56	5.03	3.25
Unemployment Rate (%)	7.23	6.86	2.37	4.94	4.57	1.75
Median Weekly Income (£)	445.72	428.28	76.64	433.75	419.50	64.77
Average Weekly Rent (£)	92.81	88.49	17.90	102.10	98.03	18.76
Average House Price (£'000)	204.62	187.09	92.70	227.21	194.34	129.68
Population ('000)	158.02	125.87	92.40	159.97	128.87	92.77

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 1,057 district-level observations. In the post HTB period, there are 1,877,724 loan-level observations and 1,115 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 Home Sales by LTV**

	Dependent Variable				
	All Home Sales		Home Sales by LTV		
	(1)	(2)	(3)	(4)	(5)
$\text{Post}_t \times \text{Exposure}_d$	1.7402***	1.2848***	0.1641***	-0.0173	
	(0.199)	(0.197)	(0.027)	(0.044)	
$\text{Post}_t \times \text{Exposure}_d \times \text{LTV}_{70}$				-0.0482	-0.0722**
				(0.036)	(0.032)
$\text{Post}_t \times \text{Exposure}_d \times \text{LTV}_{75}$				0.0510	0.0361
				(0.044)	(0.045)
$\text{Post}_t \times \text{Exposure}_d \times \text{LTV}_{80}$				0.0363	0.0226
				(0.040)	(0.038)
$\text{Post}_t \times \text{Exposure}_d \times \text{LTV}_{85}$				-0.0492	-0.0573
				(0.044)	(0.043)
$\text{Post}_t \times \text{Exposure}_d \times \text{LTV}_{90}$				0.3261***	0.3456***
				(0.059)	(0.057)
$\text{Post}_t \times \text{Exposure}_d \times \text{LTV}_{95}$				0.8057***	0.8790***
				(0.094)	(0.088)
Control Variables					
$\text{Post}_t \times \text{LTV}_i$	n.a.	n.a.	No	Yes	No
$\text{Exposure}_d \times \text{LTV}_i$	n.a.	n.a.	No	Yes	No
District Characteristics	No	Yes	No	Yes	No
Fixed Effects					
District	No	No	Yes	Yes	No
Time	No	No	Yes	Yes	No
LTV_i	n.a.	n.a.	Yes	Yes	No
District×Time	No	No	No	No	Yes
$\text{District}\times\text{LTV}_i$	n.a.	n.a.	No	No	Yes
$\text{Time}\times\text{LTV}_i$	n.a.	n.a.	No	No	Yes
Model Statistics					
N	2,172	2,172	15,120	15,120	15,120
R^2	0.9594	0.9628	0.740	0.8322	0.9516

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. 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. In Columns (1) and (2), the dependent variable is the number of home sales purchased with a mortgage in a given district and year. In Columns (3), (4) and (5), the dependent variable is the number of home sales purchased with a mortgage within an LTV bucket (denoted by LTV_i) in a given district and year. 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 4: **The Effect of Help-to-Buy on Home Sales by Buyer-type**

	Buyer-type			
	First-time		Younger	
	(1)	(2)	(3)	(4)
$\text{Post}_t \times \text{Exposure}_d$	0.3810***		0.1889**	
	(0.087)		(0.074)	
$\text{Post}_t \times \text{Exposure}_d \times \text{Buyer-type}_b$	0.5226***	0.6915***	0.8592***	1.0487***
	(0.100)	(0.099)	(0.160)	(0.124)
Control Variables				
$\text{Post}_t \times \text{Buyer-type}_b$	Yes	No	Yes	No
$\text{Exposure}_d \times \text{Buyer-type}_b$	Yes	No	Yes	No
District Characteristics	Yes	No	Yes	No
Fixed Effects				
District	Yes	No	Yes	No
Time	Yes	No	Yes	No
Buyer-type_b	Yes	No	Yes	No
District×Time	No	Yes	No	Yes
$\text{District}\times\text{Buyer-type}_b$	No	Yes	No	Yes
$\text{Time}\times\text{Buyer-type}_b$	No	Yes	No	Yes
Model Statistics				
N	4306	4306	4284	4284
R^2	0.8863	0.9748	0.8398	0.9727

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, where the buyer-type is first-time buyers or home movers in Columns (1) and (2), and the buyer-type is younger (20 to 39 years-old) and older (40 to 59 years-old) in Columns (3) and (4). 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 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: **Robustness to Alternative Specifications**

	Different Samples			*Dep. Variable*	*Exposure Measure*	
	Excl. Lnd	2013 post	2013 pre	ln(Sales)	Elig. Housing	Elig. New-Builds
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Post}_t \times \text{Exposure}_d$	1.2443***	0.9749***	1.2050***	0.4373***	0.3595***	2.1453***
	(0.184)	(0.169)	(0.173)	(0.088)	(0.060)	(0.545)
Control Variables						
District Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
District	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
Model Statistics						
N	1,980	2,545	2,545	2,172	1,920	1,920
R^2	0.9660	0.9653	0.9663	0.9805	0.9613	0.9611

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 in a given district and year. 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 (1) presents estimates from specification that excludes all London districts. Column (2) presents estimates from specification that includes 2013 in the post-HTB period. Column (3) presents estimates from specification that includes 2013 in the pre-HTB period. Column (4) presents estimates from specification where the dependent variable is the *log* of the of the number of home sales. Column (5) presents estimates from a specification where the Exposure measure equals the *ex ante* share of eligible houses in each district. Column (6) presents estimates from a specification where the Exposure measure equals the *ex ante* share of eligible new-builds in each district. 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.

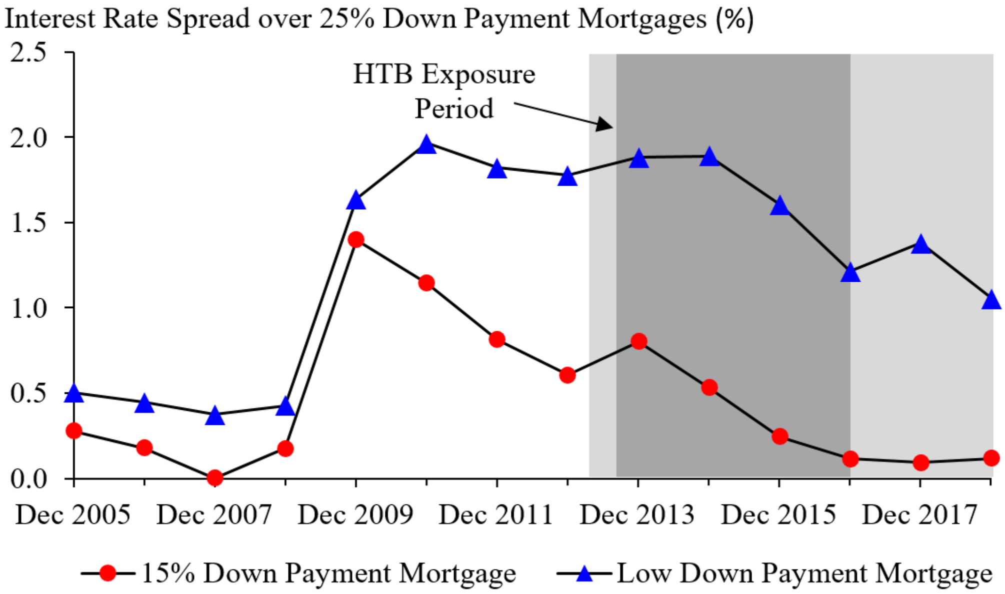
Table 8: **The Effect of Help-to-Buy on Car Sales**

	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
Eligible Housing Share Exposure	Share of Help-to-Buy eligible housing stock as at December 2012	Office for National Statistics, Land Price Paid Data
Eligible New Build Share Exposure	Share of Help-to-Buy eligible new-build housing stock as at December 2012	Office for National Statistics, Land Price Paid Data
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 population estimate	Office for National Statistics