BANK OF ENGLAND

Staff Working Paper No. 919

The consumption response to borrowing constraints in the mortgage market

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May 2021

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Abstract

This paper shows that relaxing borrowing constraints positively affects household consumption in addition to stimulating housing market activity. We focus on the UK Help-to-Buy (HTB) program, which provided a sudden relaxation of the down payment constraint by facilitating home purchases with only a 5% down payment. Our research design exploits geographic variation in exposure to HTB and uses administrative data on mortgages and car sales in combination with household survey data. We estimate that the program increased total home purchases by 11%, and the increase was driven almost entirely by first-time and young buyers. Regions that were more exposed to the program experienced a rise in non-durable consumption unrelated to the home and in loan-financed car purchases, in addition to an increase in home-related expenditures. These results are independent of changes in regional house prices. Our findings point to a further link between the housing market and household consumption that does not operate through the home purchase and housing wealth channels.

Key words: Borrowing constraints, consumption, housing market, mortgage market.

JEL classification: E21, G21, R21, R28.

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We are grateful for comments and suggestions from Diana Bonfim (discussant), Matthieu Chavaz, João Cocco, Angus Foulis, Daniel Paravisini, Ricardo Reis, Paolo Surico, participants at the 7th Emerging Scholars in Banking and Finance Conference and the Royal Economic Society Annual Conference, and seminar participants at Villanova WiFI, University of Amsterdam, Bank of England, Humboldt University, King's College London and Amsterdam Business School. We would like to thank the Department for Transport for providing data on regional new car registrations and the Ministry of Housing, Communities and Local Government for providing data on the Help To Buy Equity Loan scheme. This paper was also produced using statistical data from ONS. The use of the ONS statistical data in this paper does not imply the endorsement of the ONS in relation to the interpretation or analysis of the statistical data. This paper uses research data sets which may not exactly reproduce National Statistics aggregates. The views expressed in this paper are those of the authors, and not necessarily those of the Bank of England or its committees.

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ISSN 1749-9135 (on-line)

1 Introduction

To what extent is household consumption affected by borrowing constraints in the mortgage market? This question is key to understanding whether access to mortgage credit has macroeconomic implications that extend beyond the housing market. It is well understood that changes in borrowing constraints affect access to mortgage credit and cause fluctuations in housing transactions, homeownership and house prices (see, e.g., Favara and Imbs, 2015; Acolin et al., 2016; Greenwald and Guren, 2019; Berger, Turner and Zwick, 2020). At the same time, fluctuations in housing market activity have an impact on household consumption. For example, home purchases stimulate demand for goods and services related to the home (Best and Kleven, 2017; Benmelech, Guren and Melzer, 2017), while a rise in house prices spurs consumption through its effect on wealth, borrowing constraints and employment (see, e.g., Campbell and Cocco, 2007; Mian and Sufi, 2011; Mian, Rao and Sufi, 2013; Guren et al., 2020).[1]

How households adjust their consumption when borrowing constraints in the mortgage market change is however far less understood. This paper sheds light on this issue by studying the impact of a relaxation of the down payment constraint. We show that relaxing the down payment constraint positively affects household consumption in addition to stimulating housing market activity. Importantly, the consumption response goes beyond the previously documented home purchase and housing wealth channels. This points to a new link between the housing market and household consumption.

The down payment constraint is one of several borrowing constraints affecting mortgage credit. But due to classic leverage effects, this particular constraint has substantial and nonlinear implications for housing affordability. Changes in down payment requirements especially affect young and first-time buyers as they typically have a hard time saving for their deposit (Linneman and Wachter, 1989; Fuster and Zafar, 2021). More generally, factors that affect the ability of potential first-time buyers to afford the down payment are a powerful driver of housing market fluctuations (Ortalo-Magne and Rady, 2006). A relaxation of the down payment constraint is therefore expected to generate a rise in housing transactions driven by young and first-time buyers.

The resulting effect on household consumption is unclear because various mechanisms can play a role. First, home-related expenditures may increase if more homes are bought, provided that the home purchase channel is potent for down payment constrained buyers. Second, (non-home related) consumption is expected to rise if saving for a down payment acts as a binding liquidity constraint. Liquidity constrained aspiring homebuyers must keep their consumption

[1]Other studies include on the empirical side Case, Quigley and Shiller (2012); Attansio et al. (2009); Attanasio, Leicester, and Wakefield (2011); Carroll, Otsuka, and Slacalek (2011); Cooper (2013); Aladangady (2017); DeFusco (2018); Cloyne et al. (2019); Kaplan, Mitman and Violante (2020*a*) and on the theoretical side Berger et al. (2018); Gorea and Midrigan (2018); Chen, Michaux, and Roussanov (2020); and Kaplan, Mitman and Violante (2020*b*).

low to save for their down payment. After the house is bought, discretionary income rises and consumption can grow again (Engelhardt, 1996). By contrast, if down payment constrained buyers have an aversion to high leverage, purchasing a house might induce them to lower their consumption in order to pay off mortgage debt (Sodini et al., 2016). Finally, in addition to the direct impact on the consumption of the homebuyers, there may be wider regional effects as well. If an increase in housing transactions leads to a rise in house prices (e.g., Favilukis, Ludvigson and Van Nieuwerburgh, 2017) this will stimulate consumption due to wealth effects. Moreover, to the extent that it spurs regional economic activity, a further increase in household consumption can follow.

Given that several interrelated mechanisms are at play, how household consumption responds to a loosening of the down payment constraint is ultimately an empirical question. In order to address this question, we study a large-scale UK government intervention called Help-to-Buy (HTB) first introduced in April 2013. The program intended to make housing more affordable for households with limited ability to save for a down payment by facilitating home purchases with only a five percent down payment. At the time HTB was introduced, the market for low-down payment mortgages was largely frozen (Figure 1). The program thus represented a significant and sudden relaxation of the down payment constraint in the UK mortgage market.

Estimating the impact of government programs on economic outcomes is inherently difficult. A key challenge is to construct a meaningful counterfactual to assess what would have happened in the absence of the program. We tackle this challenge by exploiting geographic variation in exposure to HTB in a similar vein as the identification strategies of Mian and Sufi (2012) and Berger, Turner and Zwick (2020). We argue that even though HTB was national in scope, parts of the UK were differently exposed to the program due to variations in local housing market characteristics. HTB specifically targeted down payment constrained households and these households are not randomly spread across the country. Instead, they tend to be concentrated in specific areas with a more suitable housing supply. As local housing market characteristics typically change very slowly over time one can reasonably assume that the impact of HTB was greater in areas where historically households bought their home with a low-down payment mortgage. Districts with an historically small share of low-down payment home buyers can serve as a control group because HTB unlikely induced many people to buy in these districts. In a standard difference-in-differences setting we can thus compare housing market activity and household consumption in low relative to high exposure areas before and after HTB came into effect, while controlling for a wide range of regional macroeconomic and housing market conditions.

To measure program exposure, we exploit administrative data covering all regulated mortgages issued in the UK.[2] These data include, among other things, information about the property

[2]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.

location, loan value, property price, the down payment and various borrower characteristics. HTB exposure is defined as the proportion of households in a district that bought their home with a five percent down payment before the financial crisis; a period when the market for low-down payment mortgages was relatively unconstrained.[3] We show that our measure of HTB exposure strongly correlates with the actual purchase of low-down payment mortgages during the program period and also accurately predicts time variation.

Our first main result is that relaxing the down payment constraint leads to a rise in housing market activity driven by young and first-time buyers. Over the period 2014 to 2016, when the two main schemes of HTB were active, home purchases increased by 4.5 percent more in parts of the UK that were more exposed to HTB. This increase was almost entirely due to houses purchased with a down payment of only five percent. Importantly, there is no evidence of any differential pre-trends in high versus low exposure areas, and the divergence in trends corresponds exactly with the timing of the program. Furthermore, our findings are robust to the inclusion of time-invariant and time-varying district-level controls, including district-time fixed effects where feasible. In addition, they remain when we exclude the London area from our analysis and when we use an alternative HTB exposure measure. Finally, between-district migration patterns cannot explain our findings.

In aggregate, we estimate that HTB resulted in an additional 220,000 homes being purchased between 2014 and 2016, representing a 10.6 percent increase in homes purchased over the 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 program.[4] Of those additional home purchases, first-time buyers accounted for 78 percent while younger households (both first-time buyers as well as home movers) were responsible for 90 percent. As expected, relaxing the down payment constraint thus especially benefits young and first-time buyers, i.e. those households that tend to have a hard time saving for a down payment. The size of the effect highlights the critical role of down payment constrained (first-time) buyers driving housing market fluctuations (Ortalo-Magne and Rady, 2006).

Using district-level data on house prices, we find that districts that were more exposed to the program experienced modest higher house price growth (1.1 pp). In the London area the impact on house prices was larger (4.6 pp). These findings are consistent with Favara and Imbs (2015) and Carozzi, Hilber and Yu (2020) who find that the elasticity of housing supply, which is weaker in London, critically determines how strongly house prices react to an increased demand for housing.

Our second main result is that relaxing the down payment constraint also spurs household consumption and this stimulus effect goes beyond the traditional housing wealth and home

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

[4]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.

purchase channels. To conduct our analysis, we use household level data from the UK Living Cost and Food Survey (LCFS), which provides detailed expenditure and demographic information in a repeated cross-section format. Using the methodology introduced by Browning, Deaton and Irish (1985) and Deaton (1985), we construct a pseudo-panel based on the birth year of the household head and the district they live in. The richness of the LCFS allows us to examine the impact of a relaxation of the down payment constraint on different types of household consumption, while controlling for changes in (cohort-level) household income, household demographics and regional housing market conditions.

We document a 4.7 percent relative increase in real household consumption in regions that were more exposed to HTB. Once more, we find no evidence of any differential pre-trends in high vs low exposure areas. In line with the presence of a home purchase channel (Best and Kleven, 2017; Benmelech, Guren and Melzer, 2017), the growth in consumption was partly due to a rise in home-related expenditure (6.1 percent). However, we also find that non-durable consumption not related to the home rose by 5.2 percent more in highly exposed regions. The increase is entirely driven by a rise in consumption by younger households, i.e. the same households that drove the increase in house purchases. These effects are independent of consumption responses to changes in regional house prices.

Evidence from car purchases provides further proof of a consumption stimulus effect unrelated to home-expenditures. Drawing on administrative data capturing all private new car registrations for the UK, we find that districts that were more exposed to HTB also experienced a 4.1 percent relative increase in new car purchases. These data do not contain information on how the car is purchased, but they are most likely loan-financed as 90 percent of new cars are purchased with some kind of consumer credit in the UK.[5] Evidence from the LCFS backs this assertion as loan-financed car purchases increased significantly in areas that were more exposed to HTB, but outright car purchases decreased. In aggregate, we estimate that HTB increased new (loan-financed) car purchases by 5.1 percent over the period 2014 to 2016.

Overall we show that relaxing the down payment constraint has a positive impact on household consumption in addition to stimulating housing market activity. Importantly, the effect is not limited to increases in home-related expenditures and goes beyond a rise in household consumption due to house price increases. In other words, the effect we document is distinct from previously documented channels. While it is challenging to specifically quantify the relative importance of the various mechanisms at work, the fact that young households drive the growth in consumption is consistent with the idea that saving for a down payment can act as a binding liquidity constraint. Once the house is bought, discretionary income grows allowing for an increase in consumption. In addition, a rise in regional economic activity as a result of HTB likely contributed to the positive consumption effects as well.

The remainder of the paper is structured as follows. The next section provides a review of the

[5] See: https://www.fla.org.uk/motor-finance/.

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

This paper contributes to the existing literature in several ways. First, it adds to the literature that examines how changes in borrowing constraints affect housing transactions and homeownership. When borrowing constraints tighten, housing transactions and homeownership rates fall as households find it harder to access the mortgage market (see, e.g., Linneman and Wachter, 1989; Acolin et al., 2016; Gete and Reher, 2018).[6] Stimulus policies that ease borrowing constraints, such as stamp duty holidays or tax credit policies, temporarily increase sales volumes (Best and Kleven, 2017) and when specifically targeted at first-time buyers stimulate transition into homeownership as well (Berger, Turner and Zwick, 2020). Among the various borrowing constraints, the down payment constraint is particularly binding for young, first-time buyers and their willingness to purchase a home depends primarily on the down payment needed and less so on the mortgage rate (Fuster and Zafar, 2021). Factors that impact the ability of potential first-time buyers to afford a down payment therefore have a big impact on the housing market (Ortalo-Magne and Rady, 2006). In line with this, when the LTV ratio tightens fewer households transition into homeownership (Bekkum et al., 2019) and buyers are pushed into lower socioeconomic neighborhoods (Tzur-Ilan, 2020).

Consistent with this literature, we show that a stimulus policy directly targeted at relaxing the down payment constraint leads to more houses being purchased by first-time and young buyers, while older buyers hardly react. However, our research design exploiting geographic variation in exposure to HTB enables us to show that relaxing the down payment constraint has broader macroeconomic implications as well. Specifically, it boosts household consumption in those regions where housing market activity increases. This finding complements recent work that shows that national policies affecting the mortgage market can have very diverse regional consequences (see, e.g. Hurst et al., 2016; Beraja et al., 2019; Mabille, 2020).

Our focus on household consumption relates our paper to the broad literature that studies various links between the housing market and household consumption. Most of this literature focuses on the relationship between house prices and consumption. A number of theoretical studies explore various mechanisms through which housing wealth affects consumption (see, e.g., Boar, Gorea and Midrigan, 2017; Berger et al., 2018; Chen, Michaux and Roussanov,

[6] Another body of work studies the links between borrowing constraints, housing prices and economic activity (e.g. Stein, 1995; Favara and Imbs, 2015; Greenwald, 2016; Favilukis, Ludvigson and Van Nieuwerburgh, 2017; Greenwald and Guren, 2019; Kaplan, Mitman and Violante, 2020*b*)

2020; Kaplan, Mitman and Violante, 2020*b*). Several empirical studies highlight the effects of housing values on consumption due to a wealth effect (e.g Benjamin, Chinloy and Jud, 2004; Campbell and Cocco, 2007; Bostic, Gabriel and Painter, 2009; Attanasio, Leicester and Wakefield, 2011; Case, Quigley and Shiller, 2012; Mian, Rao and Sufi, 2013; Guren et al., 2020) as well as a home equity extraction effect (e.g. Hurst and Stafford, 2004; Mian and Sufi, 2011; Cloyne et al., 2019). Another strand shows that home purchases have a positive impact on household consumption due to home-related expenditures (Best and Kleven, 2017; Benmelech, Guren and Melzer, 2017). Focusing more explicitly on the impact of transitioning into homeownership Sodini et al. (2016) document a negative impact on consumption in the first year of homeownership followed by a positive consumption effect in subsequent years, but only for those households who choose to liquify their illiquid housing wealth.[7]

Our paper adds to this literature by documenting a further link between the housing market and household consumption that does not operate through the home purchase and housing wealth channels. In particular, we show that regions that were more exposed to HTB not only experienced a rise in home-related expenditure, but also in loan-financed car purchases and non-durable consumption unrelated to the home, with the latter effect driven by younger households. These effects are independent of consumption responses to changes in regional house prices. We suggest two factors that can explain this. First, an increase in regional economic activity due to the rise in housing market activity. Second, a rise in consumption by new home buyers who had to keep their consumption low prior to purchasing their home in order to save for their down payment. In line with the idea that saving for a down payment can act as a binding liquidity constraint, Engelhardt (1996) finds that US households increase their food consumption after buying a home.[8] Our study further quantifies this finding. Instead of studying changes in consumption of home buyers in general, we focus explicitly on the consumption response to changes in housing market activity driven by down payment constrained buyers. Furthermore, our research design allows us to control for many factors that can both drive the decision to purchase a house as well as household consumption. Additionally, as we study the impact on both home and non-home related consumption, including car purchases, we can shed a more detailed light on the relationship between down payment constraints and household consumption.

Finally, our results complement other studies on the impact of HTB, which tend to focus exclusively on the Equity Loan (EL) scheme of the HTB program. These papers show that

[7]A related literature focuses on mortgage debt. A reduction in mortgage payments can spur consumption by borrowers (Agarwal et al., 2015). Furthermore, households with mortgage debt tend to have larger consumption responses to tax changes (Cloyne and Surico, 2017), monetary policy shocks (DiMaggio et al., 2017) and economic and financial shocks (see, e.g., Dynan, 2012; Mian, Rao and Sufi, 2013; Kovacs, Rostom and Bunn, 2018; Fan and Yavas, forthcoming).

[8]In line with the idea that down payments can act as binding liquidity constraints, Jappelli and Pagano (1994) show that countries with higher down payment requirements have significantly higher aggregate saving rates

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

3 Policy Background

3.1 Down Payment as Binding Borrowing Constraint

The Help-to-Buy (HTB) Program facilitated home purchases with only a five percent down payment and represented a significant and sudden relaxation of the down payment constraint. Before turning to the full details of the program, in this section we highlight the substantial effect that down payment constraints can have on housing affordability.

The down payment constraint is one of several borrowing constraints that limit mortgage access, and it works via the loan-to-value (LTV) requirement. Other constraints include: the income constraint (through the loan-to-income requirement) and the payment constraint (through the payment-to-income requirement), as well as other credit-score related requirements. The most binding constraint will determine the amount a household can borrow.

These different constraints have very different consequences for housing affordability. For example, the income constraint has a linear and proportional impact on potential borrowing. By contrast, the down payment constraint has a non-linear impact due to classic leverage effects. Shifting the LTV requirement from 90% to 95% doubles the amount a buyer can borrow for a given down payment. For example, a household with £10,000 saved for a down payment would be able to buy a house worth only £100,000 with a 90% LTV, but one worth £200,000 with a 95% LTV.

Moreover, for households with limited savings the down payment constraint is most frequently binding. Specifically, our mortgage data on loan size, incomes and deposits indicate that over 90 percent of mortgages signed between 2005 and 2007 with a 95 (or higher) LTV mortgage had a loan-to-value (LTI) ratio of less than 4.5, currently the maximum LTI for most mortgages in the UK.[9] [10]For households living in areas where house prices on average are very high - for example the London area - the income constraint more frequently binds.

[9]In the UK, no more than 15 percent of a lender's new residential mortgages can have LTI ratios at or greater than 4.5.

[10]In 2018 the average LTI on mortgages with a 95% LTV was 3.5 and 95% of those mortgages had an LTI of less than 4.5.

As becomes clear from this discussion, the down payment constraint has substantial and non-linear implications for housing affordability. A government policy that facilitates the purchase of high-LTV/low-down payment mortgages can thus potentially have a large impact on housing market activity, primarily driven by liquidity constrained households. Making housing more affordable for these households was the stated intention of Help-to-Buy.

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."[11]

The key feature of HTB was that it facilitated home purchases 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 1). The explicit objective of the program was to facilitate mortgage market access to borrowers facing significant down payment constraints, with George Osborne explaining in his budget speech that "for anyone who can afford a mortgage but can't afford a big down payment, our [HTB] Mortgage Guarantee will help you buy your own home."[12]

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.[13] 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.[14] As with the EL scheme, borrowers required a five

[11] 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

[12] 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

[13] From April 2021 to March 2023, a new scheme will start that is restricted to first-time buyers and includes regional property price caps to ensure the scheme reaches people who need it most.

[14] In March 2021 the UK government announced a new mortgage guarantee scheme to start in April 2021

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 many 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 first-time buyer and home-mover mortgages over this period and around 18 percent of first-time buyer mortgages.[15] As Figure 2 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 examine how housing market and household consumption respond to a loosening of the down payment constraint we must form a reasonable estimate for what would have happened if the program had not been implemented (i.e. construct a counterfactual). Our approach is to exploit cross-sectional variation across UK districts in their exposure to HTB based on the presence of *potential* low-down payment home buyers. Areas with few potential low-down payment home buyers serve as the "control group" because buyers in these areas would unlikely make use of the program. The difference between the treated and control areas provides for an estimate of the marginal impact of the program. In Section 5 we describe our research strategy in detail.

4 Data and Summary Statistics

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

along similar lines as the old scheme.

[15]When remortgages are included, HTB represented around 6 percent of all mortgages over this period.

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 Mortgages and Home Sales Data

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

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

Using information about the loan and property value we identify all mortgages that are a *"Low-Down Payment Mortgage"*. Low-down payment mortgages include all mortgages with a down payment of around five percent.[17] These include practically all MG mortgages, but only a subset of the EL mortgages as some households opt for a higher down payment than the five

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

[17] These mortgages are otherwise known as 95 LTV mortgages. As explained in the previous paragraph, due to the pricing of these products, they can in theory have a down payment of up to 9.9 percent but in practice the majority of them have a down payment at or close to 5 percent. Our measure of low down payment mortgages includes all mortgages with a down payment less than the 9.9 percent threshold.

percent minimum that is required to qualify for the loan.[18] In order to identify EL mortgages, we match an EL data set collected by the UK Ministry of Housing, Communities and Local Government with the PSD. We merge these data using the approach of Benetton et al. (2019).[19]

Our key outcome variables are year-district-level measures of home sales. We construct several measures. Our main measure is the number of *"Home Sales"*, which comprises the total number of home sales. Our next measures are the *"First-time Buyer Sales"* and "*Home Mover Sales"*, which comprise the home sales to first-time buyers and home movers, respectively. We also calculate *"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. Our final measures are: *"Down Payment 5%"*, *"Down Payment 10%"*, *"Down Payment 15%"*, *"Down Payment 20%"*, *"Down Payment 25%"* and *"Down Payment 30%+"*, which comprise the total home sales to buyers with a down payment size (as a percent of home value) of: 5 percent, 10 percent, 15 percent, 20 percent, 25 percent and 30 percent or more, respectively.[20]

4.2 Household Consumption Data

To examine the effect of the HTB program on household consumption, we draw on two data sources. First, we use household survey data obtained from the Living Costs and Food Survey (LCFS), which contains information on weekly expenditures for all goods and services, as well as household income and demographic variables. We categorize weekly expenditures into three different household spending measures: *"Home-related Expenditure", "Non-durable Consumption"* and *"Durable Expenditure"*. Our home-related expenditure measure includes household services as well as both durable and non-durable household goods. Our non-durable consumption measure is a broad aggregate of spending on non-durable goods and services, which includes some semi-durable goods such as clothing, footwear and certain leisure goods. Our durable expenditure measure aggregates spending on motor vehicles, durable personal and durable leisure goods. Both our non-durable consumption and durable expenditure measures exclude any home-related expenditures and so we can create a "*Total Household Consumption*" measure by summing across home-related expenditures, non-durable consumption and durable expenditures. All spending measures are deflated to 2016 using the Consumer Price Index including owner occupier housing costs (CPIH). We provide a detailed description of these data and the variable definitions in Appendix A.

[18] The majority of households put down five percent (see Benetton et al., 2019), but around 25 percent provided a down payment of 10 percent or more.

[19] We would like to thank the authors for sharing their programs and data with us, with the permission of the UK Ministry of Housing, Communities and Local Government.

[20] As explained above, mortgages included in *Down Payment 5%* can have a down payment between 9.9 and 5 percent and those in *Down Payment 10%* a down payment between 14.9 and 10 percent etc. But as the vast majority of mortgages have a down payment at or very close to the LTV bucket threshold and for ease of exposition we refer to 5 percent, 10 percent etc down payment

In addition to our household spending measures, we draw on other variables from the LCFS to use as controls. Following from Campbell and Cocco (2007), we include: age of household head, household size, the proportion of outright owners, the proportion of mortgagors, household income and mortgage payments. Our household spending measures, as well as income and mortgage payments are deflated to 2016 prices using the Consumer Price Index including owner occupiers housing costs (CPIH), which is a leading UK inflation index.

Second, 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. A key advantage of these data is that they comprise the universe of new private car registrations, and so are free of any measurement issues. A drawback of these data is that they provide information only about new car sales; new car purchases represent an important durable good but are nonetheless only one component of household expenditure.

4.3 Other Variables

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 housing transactions and household consumption 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 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 CPIH.

4.4 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 and the "post-HTB" period (covering the period that both HTB schemes were in effect). A few things are worth highlighting.

In the period before HTB, 2 percent of all mortgages required a deposit of only five percent. During the years HTB was active this number increased to 16 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 1,260 (mortgaged) home sales in the pre-HTB period to 1,590 (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 720 to 870 mortgages, i.e 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 7.23 percent in the pre-HTB period to 4.94 percent in the HTB period, while there is an increase for *Average House Prices* from £204,620 in the pre-HTB period to £227,210 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 the impact of loosening down payment constraints on housing market activity and household consumption, we exploit geographic variation in *ex ante* exposure to HTB. Our identification strategy has similarities to that of Wilson (2012), Mian and Sufi (2012) and Berger, Turner and Zwick (2020) who use geographic variation in exposure to the American Recovery and Reinvestment Act, the Cash for Clunkers program and the First-Time Homebuyer Credit program, respectively. We argue that even though HTB was national in scope, parts of the UK where differently exposed to the program due to variations in local housing market characteristics. These differences in geographic 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. Local housing market characteristics typically change very slowly over time. We can thus expect the impact of HTB to be greater in areas where *historically* households bought their home with a low-down payment mortgage 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 a 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.[21]

[21]This interpretation requires that no spillovers exist between treated and control areas as a result of endo-

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 around 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.[22][23] Figure 3 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 4 plots the relationship between our *ex ante* HTB exposure measure against the *ex post* number of low-down payment mortgages taken out over the period 2014 to 2016 scaled by the total number of mortgages purchased in the district over that period. It reveals a strong positive correlation. In districts with low HTB exposure the share of low-down payment mortgages is very low (close to zero percent), while in high exposure areas it is much higher (with a maximum of almost 25 percent).

Figure 5 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 geographic variation in exposure is that districts with high exposure to HTB also differ importantly in other ways that could

genous 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. 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.

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

[23]That is, we consider all "low down payment mortgages" using our definition in Section 4.1. This variable technically includes all mortgages with a down payment less than 9.9 percent but in practice the majority have a 5 percent down payment due to the pricing of these products. Moreover, we include all mortgages with less than a five percent measure as well. While nowadays mortgages require at least a five percent down payment, before the financial crisis mortgages with lower down payments where also accepted.

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 5. 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:

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

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 around 5 percent (or less), and zero otherwise. Exposure$_d$ is our measure of *ex ante* exposure to the HTB program. $\mathbf{Loan}_{b,l,d,t}$ 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 6 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.[24] Taken together, this evidence indicates that our HTB exposure measure adequately captures differences in the actual exposure to the program.

6 The Housing Market Response to Help-to-Buy

6.1 Home Sales

A relaxation of the down payment constraint can theoretically have three effects on the demand for houses. First, it can lead to home purchases that otherwise would not have taken place (extensive margin effect). Second, households might move 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 effect). In the first two cases, HTB would lead to an increase in home sales (and 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 high- to low-down payment mortgages, rather than an increase in home purchases.

To examine the impact of HTB on the number of home sales, we estimate a panel regression model similar to the model in Equation 1, but now the unit of observation is at the district-time level and not the mortgage-level:

$$\begin{aligned} \text{Home Sales}_{d,t} = \; & \textstyle\sum_{s \neq 2012} \mathbb{I}_{t=s} \times \text{Exposure}_d \times \beta_s + \boldsymbol{\gamma}\text{District}_{d,t-1} \\ & + \theta_t + \delta_d + u_{,d,t} \end{aligned} \tag{2}$$

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.[25] 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 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

[24]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).

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

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 7. 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 8 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 7. By the end of 2016, the cumulative number of home sales (relative to the level of 2012 home sales) is 55 percent higher in our representative low exposure district, while in our representative high exposure district this number is close to 120 percent. Taking the district with the minimum exposure for HTB as the control group, we estimate that approximately 220,000 homes were purchased due to HTB that would not have been purchased otherwise. This implies that HTB increased home sales by 10.6 percent during the policy period. This number is slightly larger than the approximately 200,000 HTB mortgages issued between the start of the program and the end of 2016.[26][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 five percent down payment. To test this we exploit a distinct feature of the UK mortgage market: discrete interest rate jumps - notches - at various down payment size thresholds. These thresholds are at down payments of: 30, 25, 20, 15, 10 and 5 percent (with 5 percent being the minimum down payment size currently offered). When the down payment percentage crosses one of these thresholds the interest rate increases on the entire mortgage. This creates very strong incentives to reduce

[26]The 220,000 additional home estimate is computed using estimates of $\beta_s$from Equation 2. We estimate the home sales due to Help-to-Buy for region i as $(\beta_{2013}+\beta_{2014}+\beta_{2015}+\beta_{2016}) \times (\text{HTB Exposure}_i - \text{HTB Exposure}_{min})$, and sum across all regions to obtain the estimate for total additional home sales due to Help-to-Buy.

[27]Note that under the assumption that the district with the lowest exposure (0.087) 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 deciding to use their down payment to purchase a more expensive house. This, however, does not lead to an actual increase in home sales.

borrowing to a level just below the notch and generates large bunching below the critical down payment thresholds and a missing mass above them (Best et al., 2020).

We use these down payment thresholds to test whether HTB indeed had a differential impact on homes purchased with a low-down payment mortgage, compared to home purchased with higher down payment mortgages. We estimate a difference-in-differences regression model in which we compare home sales in high versus low exposure areas in the pre-HTB period to the post-HTB period:

$$\begin{aligned}\text{Home Sales}_{d,t,i} = \; & \beta_1 \text{Post}_t \times \text{Exposure}_d + \beta_2 \text{Post}_t \times \text{Exposure}_d \times \text{Down Payment}_i \\ & + \beta_3 \text{Post}_t \times \text{Down Payment}_i + \beta_4 \text{Exposure}_d \times \text{Down Payment}_i \\ & + \boldsymbol{\gamma} \text{District}_{d,t-1} + \delta_d + \theta_t + \mu_i + u_{d,t,i}\end{aligned} \quad (3)$$

where d indexes a district, t is the year and i is the down payment size with which the house is purchased. The dependent variable Home $\text{Sales}_{d,t,i}$ equals either the total number of home sales in a given year and district, or the number of home sales within an down payment size category in a given year and district. We remove outliers by dropping the values below the 1st and above the 99th percentile.[28] Down Payment_i represents the different down payment buckets, described in Section 4.1. 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 down payment 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 2, i.e. the total number of home sales in a given year and district without splitting between the different down payment size categories. This specification therefore also excludes the triple interaction and two double interaction terms associated with Down Payment_i as well as the μ_i down payment bucket fixed effects. These results provide 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) of Table 3 we now measure the number of home sales by down payment size buckets, but do not allow $\beta_1$to differ across the different buckets. This captures the average effect of HTB on home purchases with different down payment sizes. Again, and unsurprisingly, the effect is positive and significant. Next, we allow β_1 to vary over the different down payment size categories. The results show that the increase in home sales in districts more exposed to

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

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 not particularly 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 not yet had 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 can be short, sometimes 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 3, but instead we differentiate between homes purchased by different types of buyers:

$$\begin{aligned} \text{Home Sales}_{d,t,b} = \; & \beta_1 \text{Post}_t \times \text{Exposure}_d + \beta_2 \text{Post}_t \times \text{Exposure}_d \times \text{Buyer}_b \\ & + \beta_3 \text{Post}_t \times \text{Buyer}_b + \beta_4 \text{Exposure}_d \times \text{Buyer}_b \\ & + \gamma \text{District}_{d,t-1} + \delta_d + \theta_t + \kappa_b + u_{d,t,b} \end{aligned} \tag{4}$$

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 3, except that the down payment 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. Of the 220,000 additional homes purchased due to HTB that would have not been purchased otherwise, we estimate that first-time buyers accounted for 78 percent of the increase in home purchases, while younger households (both first-time buyers as well as home movers) were responsible for 90 percent of the increase. This evidence suggests that, as expected, relaxing the down payment constraint especially benefits young and first-time buyers, i.e. those households that tend to have a hard time saving for a down payment.

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 specification in 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 $\text{Home Sales}_{d,t}$ 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 house prices are lower and where a significant amount of properties thus 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 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

[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.

eligible old and new builds has a mean of 46.4 percent.[31]

6.4 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 3 and estimate the following panel regression model:

$$\begin{aligned}\text{Internal Migration Inflows}_{d,t} = \;& \beta_1 \text{Post}_t \times \text{Exposure}_d + \boldsymbol{\gamma}\text{District}_{d,t-1} \\ & + \boldsymbol{\lambda}\text{Migration}_{d,t-1} + \delta_d + \theta_t + u_{d,t}\end{aligned} \tag{5}$$

where d indexes a district and t is the year. The dependent variable 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 $\textbf{District}_{d,t-1}$ vector of time-varying district-level control variables described in Section 5.2, we include a $\textbf{Migration}_{d,t-1}$ vector of time-varying district-level control variables. $\textbf{Migration}_{d,t-1}$ 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 3.

The results are presented in Table 6. The first column shows the average effect of HTB 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)).

[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.

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 for 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 House Prices

In Section 6.1, 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:

$$\text{House Prices}_{d,t} = \beta_1 \text{Post}_t \times \text{Exposure}_d + \boldsymbol{\gamma}\text{District}_{d,t-1} + \delta_d + \theta_t + u_{d,t} \tag{6}$$

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 3. 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 1.4 percentage points higher house price growth in high exposure districts compared to low exposure districts due to the program (column (1)). We find that outside of London, districts more exposed to the program experienced a modest 1.1 percentage points higher house price growth (column (2)). In the London area the impact was more pronounced at 4.6 percentage points (column (3)).

Overall we conclude that HTB resulted in only a marginal increase in house prices, except in the London area. These findings are consistent with Carozzi, Hilber and 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 Consumption Response to Help-to-Buy

In the previous section we established that relaxing the down payment constraint has a positive impact on housing market activity, especially among young and first-time buyers, i.e. those buyers that are most likely down payment constrained. In this section, we examine whether this had macroeconomic implications extending beyond the housing market. In particular we are interested in how household consumption changed in regions more exposed to HTB compared to less exposed regions.

The extant literature provides us with several potential mechanisms through which household consumption can be affected when the down payment constraint is relaxed. First, if it leads to an increase in housing transactions, as we show, household consumption is expected to rise through an increase in home-related expenditure. Homeowners tend to invest more in their home compared to renters and moving house is associated with spending on items such as repairs and improvements, removals, furniture, appliances, and commissions. In line with this, Best and Kleven (2017) and Benmelech, Guren and Melzer (2017) document a significant increase in home-related expenditures after households purchase a house. They do not find evidence that recent home buyers increase their non-home spending. However, both papers do not differentiate between different types of buyers. The relationship between buying a home and home-related expenditures might be weaker for the young and first-time buyers that are responsible for the increase in housing market activity in our study. These households tend to have difficulty saving for a down payment, and they might not have enough savings left for relatively large expenditures.

Second, saving for the down payment is a binding liquidity constraint for some households that are planning to purchase a home. These households will need to reduce their consumption in order to accrue a sufficient down payment. If the down payment constraint is relaxed, they no longer need to maintain a high savings rate and can borrow more upfront instead, leading to an increase in their discretionary income.[34] If these households have large propensities to consume out of an income shock, a rise in consumption will follow. This is likely to be the case for these households as liquidity constrained and "wealthy hand-to-mounth" households tend to have large consumption responses to changes in income (Johnson, Parker and Souleles, 2006; Parker et al., 2013; Kaplan and Violante, 2014; Misra and Surico, 2014). 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.[35]

On the other hand, to the extent that households have an aversion to high leverage (e.g. Caetano, Palacios and Patrinos (2019)) they might reduce consumption after a home purchase. In line with this, Sodini et al. (2016), studying privatizations of municipal apartment

[34] The rise in discretionary income is even more pronounced if the cost of renting exceeds mortgage payments plus additional housing costs.

[35] 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.

buildings in Sweden, show that households reduce their consumption immediately after becoming a homeowner. However, the households purchasing a home as a result of HTB are likely somewhat different from the households that become homeowners in Sodini et al. (2016). The privatizations used in their paper were roughly cash-flow neutral because the monthly mortgage payments plus co-op dues post-conversion were about the same as the monthly subsidized rent tenants paid prior to conversion. In addition, these households did not have to save for a down payment prior to becoming a homeowner. By contrast, total housing-related costs may in fact decrease for the typical HTB home buyer to the extent that saving for a down payment on top of paying rent exceeds the cost of mortgage payments.[36] Still, this type of home buyer might have a disproportional aversion to high leverage and a desire to keep consumption low or even reduce it in order to quickly reduce their debt.

Stepping beyond the direct impact on the consumption of home buyers, there may be wider regional effects on household consumption as well. First, an increase in housing market transactions and related changes in household consumption might stimulate regional economic activity which in turn can feed back into household consumption. Second, in Section 6.5 we documented an increase in house prices in regions more exposed to HTB and this can impact household consumption due to a traditional wealth effect (e.g Benjamin, Chinloy and Jud, 2004; Bostic, Gabriel and Painter, 2009; Case, Quigley and Shiller, 2012), a home equity extraction effect (e.g. Mian and Sufi, 2009; Mian and Sufi, 2011; Best et al., 2020) and a relaxation of borrowing constraints (Campbell and Cocco, 2007).

As several interrelated forces are it work it is ultimately an empirical question how household consumption responds to a loosening of the down payment constraint. We address this question by using household survey data and administrative data on car purchases.

7.1 Household Survey Data and Pseudo Panel Construction

To examine the effect of the HTB on household consumption, we start with exploiting survey data obtained from the Living Costs and Food Survey (LCFS). The LCFS is the most comprehensive survey on household spending in the UK and is extensively used in the literature (see, among others, Campbell and Cocco, 2007; Cloyne, Ferreira and Surico, 2020). But these survey data present some well-documented empirical challenges. The first challenge we face is that each annual wave of the LCFS includes only about 5,000 respondents, making it difficult to conduct our analysis at the year-district-level because there are too few observations. The second challenge we face is that each household is observed only once in the LCFS.

We tackle these data limitations by constructing a pseudo-panel from the LCFS using the methodology introduced by Browning, Deaton and Irish (1985) and Deaton (1985). This approach

[36]The same argument holds for households that want to move up the housing ladder if saving for a down payment on top of mortgage payments exceeds the cost of mortgage payments for the new house.

creates "synthetic cohorts" by grouping households with similar fixed characteristics. We group households based on two attributes: the birth year of the household head and their district. We consider six distinct ten-year birth cohorts; the oldest cohort is for individuals born between 1937 and 1946, and the youngest for individuals born between 1987 and 1996. As there are too few observations per district-year unit, we instead consider ten distinct HTB-region cohorts that are grouped according to their HTB program exposure; districts included in the first (tenth) HTB-region are in the first (tenth) decile of exposure to the HTB program.

In total, there are 60 distinct region-birth year cohorts and we track how variables associated with these cohorts evolve each year from 2010 to 2016. We categorize weekly expenditures into three different household spending measures: "*home-related expenditures*", "*non-durable consumption*", and "*durable expenditure*". The latter two measures exclude any home-related expenditures such that the sum of these three spending measures is equal to our measure of "*total household consumption*". For each year-region-birth year combination, we calculate the average of the logged and deflated values for these spending measures We exclude year-region-birth year combinations with ten or fewer observations. All told, our LCFS pseudo-panel provides yearly information and utilizes demographic information at the expense of a more granular regional coverage. Appendix B sets out an alternative LCFS data set that provides granular regional coverage but with a limited time dimension.

In addition to our different household consumption measures, we draw on other variables from the LCFS to create cohort-level controls. These include: age of household head, household size, the proportion of outright owners, the proportion of mortgagors, household income and mortgage payments. We then take the time-cohort-level average of the logged and deflated (where relevant) values for all variables excluding the proportion of outright owners and mortgagors, which are computed at the time-cohort-level. We provide a detailed description of these data and the variable definitions in Appendix A

7.2 Household Consumption

We start our analysis of HTB and household consumption by estimating the following pseudo-panel regression model:

$$\begin{aligned}\text{Consumption}_{r,c,t} = \; & \beta_1 \text{Post}_t \times \text{Exposure}_r + \boldsymbol{\gamma}\text{Cohort}_{r,c,t} \\ & + \lambda \text{House Prices}_{r,t-1} + \delta_r + \theta_t + \gamma_c + u_{r,c,t}\end{aligned} \tag{7}$$

where r indexes a HTB-region cohort, c is the birth year cohort and t is the year. The outcome variable $\text{Consumption}_{r,c,t}$ is real total household consumption, home-related consumption, non-durable consumption or durable expenditure, where the latter two exclude home-related consumption. Exposure_r is our measure of *ex ante* exposure to the HTB program in HTB-region r.[37] $\textbf{Cohort}_{r,c,t}$ is the vector of time-varying cohort-level (that is, the 60 region-birth year group combinations) controls that includes: the proportion of outright owners, the proportion of mortgagors, as well as the log of: age of household head, household size, real net income and real mortgage payments. This way we control for a number of factors that can both impact the decision to purchase a house as well as consumption, such as income shocks or childbirth.

As the relationship between housing values and consumption is well-documented in the literature, we explicitly control for this effect. This allows us to examine the impact of a loosening of down payment constraints that is not driven by house price changes. To this end, we include the variable House $\text{Prices}_{r,t-1}$, which equals the log of the average house price in a given HTB-region considered at period $t-1$. The specification further includes HTB-region cohort fixed effects, δ_d, time fixed effects, θ_t, and birth year group fixed effect, γ_c.

The results in Table 8 show that real total household consumption increased 4.7 percent more in high compared to low exposure areas during the HTB period (column (1)). In other words, regions more exposed to HTB did not only experience an increase in housing market activity but also an increase in household consumption. We do not find evidence of differential pre-trends in household consumption patterns in high versus low exposure areas (see Figure A.2).

To further understand what drives this increase, when we split total household consumption into its sub-components. In line with the presence of a home purchase channel (Best and Kleven, 2017 and Benmelech, Guren and Melzer, 2017) we find that home-related expenditure increased 6.4 percent more (column (2)).While it is not possible to determine whether this channel is more or less potent for down payment constraint buyers compared to other home buyers, it does exist for these types of buyers as well.

Interestingly, when we next focus on non-home-related expenditure (columns (3) and (4)) we find that non-durable consumption not related to the home also rose by 5.2 percent more in highly exposed regions. (column (3)). We do not find a differential effect onn durable expenditure (column (4)). Note that non-durable consumption also includes semi-durable consumption and comprises the vast majority of total consumption (70 percent). Reassuringly we find very similar results if we create a dataset that measures average consumption for each birth-year cohort in the three years before HTB and the three years HTB was active but at the original, more granular, district-level (Appendix B). Importantly, all these effects are independent of consumption responses to changes in regional house prices.

We extend our analysis in Equation 7 to examine whether HTB had a more pronounced impact the consumption of potential liquidity constrained buyers such as younger buyers. In Section 6.2 we demonstrated that HTB especially induced younger households to purchase a home with a low-down payment mortgage. To perform our analysis, we estimate the following pseudo-panel

[37]We take the average exposure across the districts included in the HTB-region, where there are ten HTB-regions categorized into deciles based on their district-level HTB exposure.

regression model:

$$\begin{aligned}\text{Consumption}_{r,c,t} = \ & \beta_1 \text{Post}_t \times \text{Exposure}_r + \beta_2 \text{Post}_t \times \text{Exposure}_r \times \text{Younger}_c \\ & + \beta_3 \text{Post}_t \times \text{Younger}_c + \beta_4 \text{Exposure}_r \times \text{Younger}_c \\ & + \boldsymbol{\gamma} \text{Cohort}_{r,c,t} + \lambda \text{House Prices}_{r,t-1} + \delta_r + \theta_t + \gamma_c + u_{r,c,t}\end{aligned} \tag{8}$$

where r indexes a HTB-region cohort, c is the birth year cohort and t is the year. Younger_c is a dummy variable that equals 1 for the two birth year cohorts that are born between 1977 and 1986 as well as 1987 and 1996, making these households between 20 and 39 years-old in 2016. The rest of the model is the same as Equation 7.

The results are presented in Table 9. When we focus on home-related expenditure (columns (1) and (2)), we see that the interaction term $\text{Post}_t \times \text{Exposure}_r$ is positive and significant, while the interaction term $\text{Post}_t \times \text{Exposure}_r \times \text{Younger}_c$ is insignificant. This indicates that both younger and older households have increased their home-related expenditure as a result of HTB.

When we focus again on consumption not related to the home, (columns (3) and (4)) the interaction $\text{Post}_t \times \text{Exposure}_r$ is now insignificant, while the triple interaction $\text{Post}_t \times \text{Exposure}_r \times \text{Younger}_c$ is positive and significant for non-durable consumption. This suggests that only non-durable consumption for younger households is significantly affected by HTB. Both the double and triple interactions are insignificant for non-home-related durable expenditure (column (5) and (6)), in line with the results in Table 8. The results are robust to replacing our region and time fixed effects with region-time fixed effects (columns (2) and (4) and (6)), reducing concerns that the patterns we document are driven by time-varying regional differences.

Overall the evidence presented indicates that relaxing the down payment constraint has a positive impact on household consumption in addition to stimulating housing market activity. While our empirical strategy cannot isolate the precise mechanism driving the effects, our results highlight that borrowing constraints in the mortgage market can affect household consumption beyond home-related expenditure or wealth effects driven by changes in house prices. As the increase in non-durable consumption is driven by younger households, our findings appear to be consistent with the idea that the ability to purchase a home with a low-down payment frees up discretionary income for liquidity constrained households.[38] Instead of saving for a down payment, these home buyers can use this extra discretionary income to increase their consumption. In addition, a rise in regional economic activity as a result of HTB likely contributed to the positive consumption effects as well.

[38]This interpretation is consistent with recent survey evidence by Santander that 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.

7.3 Car Sales

We further explore to what extent a loosening of down payment constraints affects household spending by studying the impact of HTB on new car purchases, a key durable consumption good that is not housing-related. At first sight, it might seem puzzling as to why liquidity constrained households who just purchased a home would have money to spare to purchase a car (the second most expensive consumption item). However, around 90 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.[39]

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 outright and loan-financed) of all privately owned new cars. We again exploit regional variation in exposure to the program, which provides us with a meaningful counterfactual. Figure 9 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 HTB on car sales by estimating a panel regression model similar to Equation 3:

$$\text{Car Sales}_{d,t} = \beta_1 \text{Post}_t \times \text{Exposure}_d + \gamma \text{District}_{d,t-1} + \delta_d + \theta_t + u_{d,t} \tag{9}$$

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.[40] The remainder of the model is the same as for Equation 3. This implies that we also control for changes in house prices at the district level and other macroeconomic and housing market conditions.

The results in Table 10 show that car sales are 4.1 percent higher in high compared to low exposure areas during the period HTB is in effect. This result is significant at the 1 percent level and reflects a specification that includes the full set of district and time fixed effects and time-varying district-level macroeconomic variables. 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. Once more, our regressions control for house prices so the increase in car sales is not driven by a wealth effect due to higher house prices in high exposure areas. We estimate that HTB increased aggregate new car

[39] See: https://www.fla.org.uk/motor-finance/

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

purchases by 5.1 percent by using the same methodology as in Section 6.1 for aggregate home purchases.

How can we reconcile our (insignificant) results for durable goods consumption in Section 7.2 with our (significant) findings about car sales? New car purchases represent around 18 per cent of durable goods expenditure and 2 per cent of total household consumption.[41] It therefore could be the case that HTB had a positive impact on loan-financed car sales, but does not affect durable goods more broadly that are purchased out of pocket. We use the LCFS to further investigate this hypothesis by estimating the same pseudo-panel regression model in Equation 7, where the outcome variable $\text{Consumption}_{r,c,t}$ is now loan-financed car purchases or outright car purchases. The results in Table 11 show that loan-financed car purchases increased significantly in high compared to low exposure areas during the period HTB is in effect, but outright car purchases *decreased* significantly.

These findings should be interpreted with some caution. In the regressions using data on car registrations we cannot control for factors at the household level that can drive both the decision to purchase a home and to buy a new car, such as childbirth. We can control for these factors when using the LCFS, however the limited LCFS sample sizes mean that very few car purchases are observed in each period for each cohort leading to more noise in the estimates. However, under the underlying assumption that during the program period car financing terms did not loosen more in high exposure areas, the results on car sales line up nicely with the results in Section 7.2. They 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 be used to finance a monthly payment plan. Furthermore, In addition, a rise in regional economic activity as a result of HTB likely contributed to the positive effect on car sales as well.

8 Concluding Remarks

In this paper we studied how housing market activity and household consumption respond to borrowing constraints in the mortgage market, focusing on a relaxation of the down payment constraint. We exploit 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 program thus represented a significant and sudden relaxation of down payment constraints in the UK mortgage market.

Our empirical strategy exploits geographic variation in exposure to the HTB. Although HTB was national in scope, exposure to the scheme critically depended on the local housing market.

[41] These statistics are calculated using the LCFS.

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 or household consumption.

Our results reveal a strong impact of HTB on housing market activity, almost entirely driven by first-time and young buyers. In other words, the program succeeded in making it easier for buyers that tend to have a hard time saving for a down payment to purchase a home in more exposed districts.

We then explore to what extent household consumption reacted to the program. In line with the home purchase channel we document an increase in home-related expenditure in more exposed regions. On top of that we also find a relative increase in non-durable consumption and loan-financed car sales. While it is challenging to specifically quantify the relative importance of the various mechanisms at work, our results highlight that borrowing constraints in the mortgage market can affect household consumption beyond home-related expenditures or wealth effects driven by changes in house prices. The fact that consumption growth is driven by younger households suggests 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 the house is bought, discretionary income increases allowing consumption to grow again. In addition, a rise in regional economic activity as a result of HTB likely contributed to the positive consumption effects as well.

Taken together, our results support the view that policies that ease down payment constraints do not only affect housing market activity but can have a meaningful impact on macroeconomic conditions. Our evidence therefore complements recent work that shows that national policies affecting the mortgage market can have very diverse regional consequences (see, e.g. Hurst et al., 2016; Beraja et al., 2019; Mabille, 2020).

While our paper provides new insights on the impact of relaxing the down payment constraint, some related questions remain unanswered. For example, a potential impact of HTB that we do not consider is that buying a house with a low-down payment could potentially make households and the banking system more vulnerable to sharp house price declines. We also do not measure the impact of HTB on other economic outcomes such as regional employment. A full examination of these issues present exciting avenues for future research.

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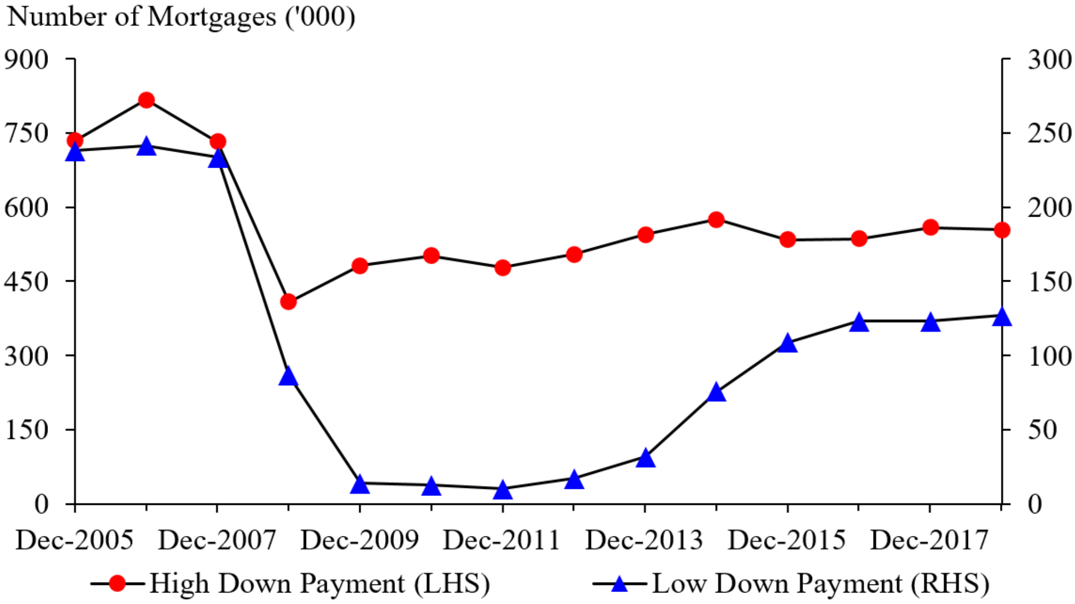
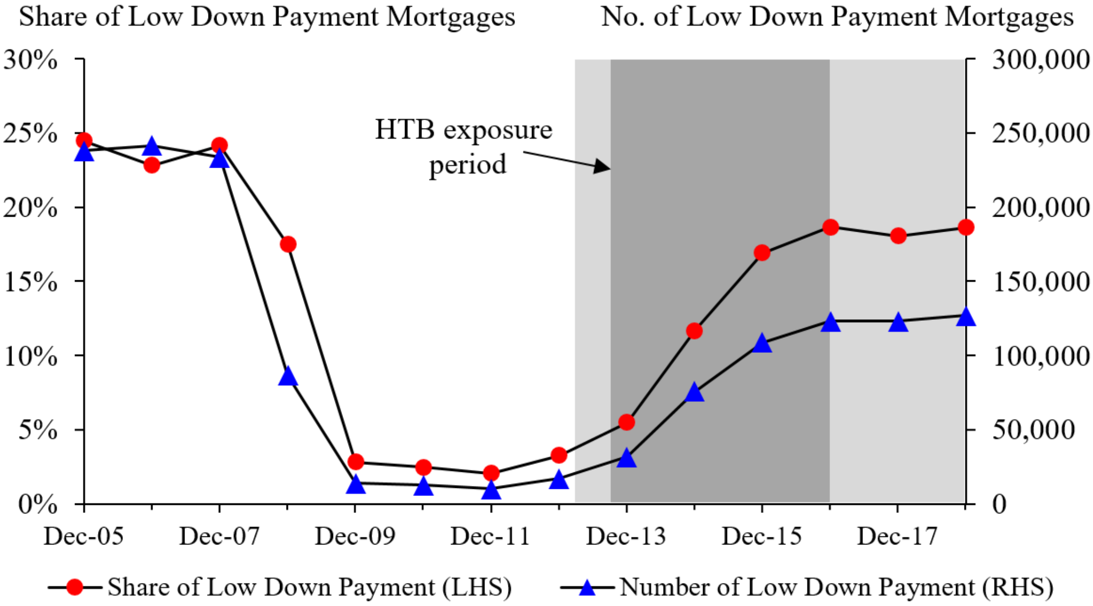
Figure 1: **Number of Mortgages by Down Payment Category**



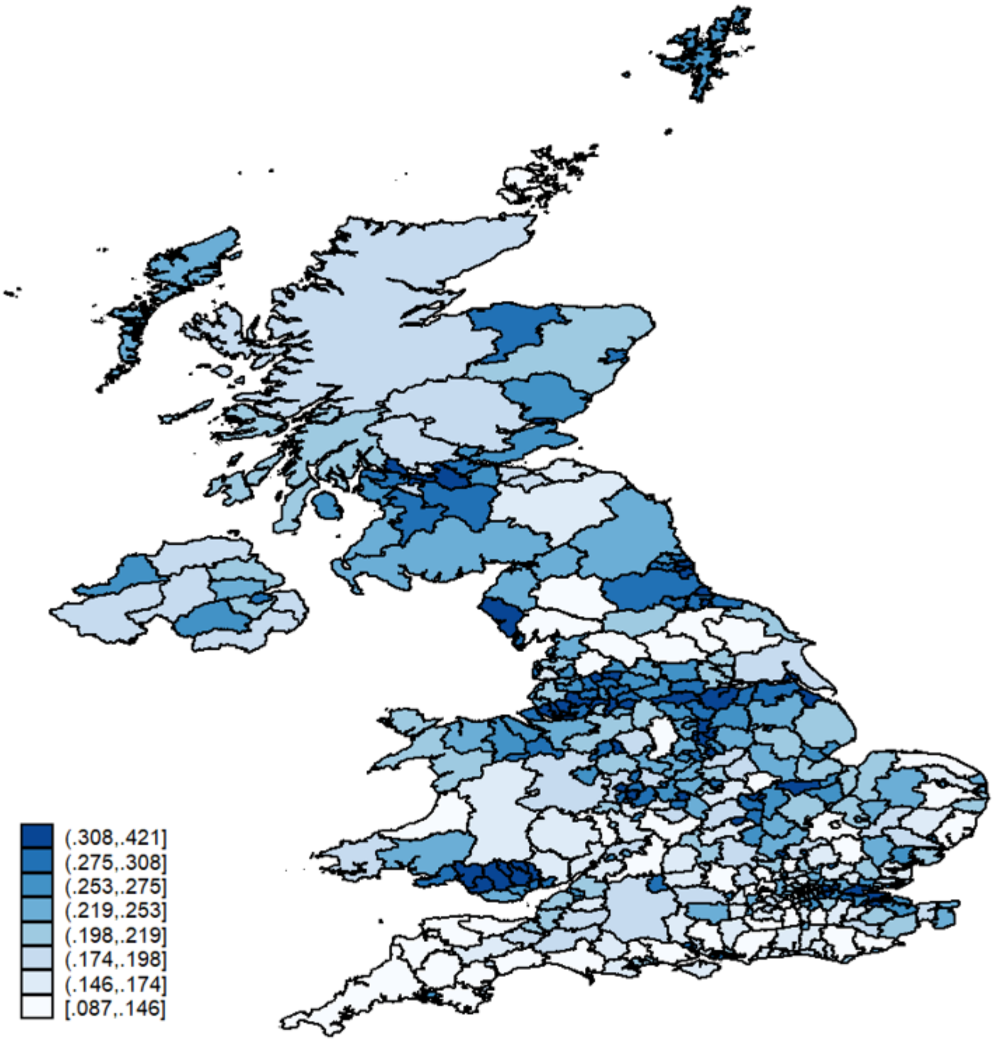
The figure shows the year-end aggregate number of high and low-down payment mortgages purchased over the period from 2005 to 2018. low-down payment mortgages include all mortgages with a down payment of 5 percent or less. We include first-time buyer and home-mover mortgages only in all calculations.

Figure 2: **Number and Share of Low-Down Payment Mortgages**



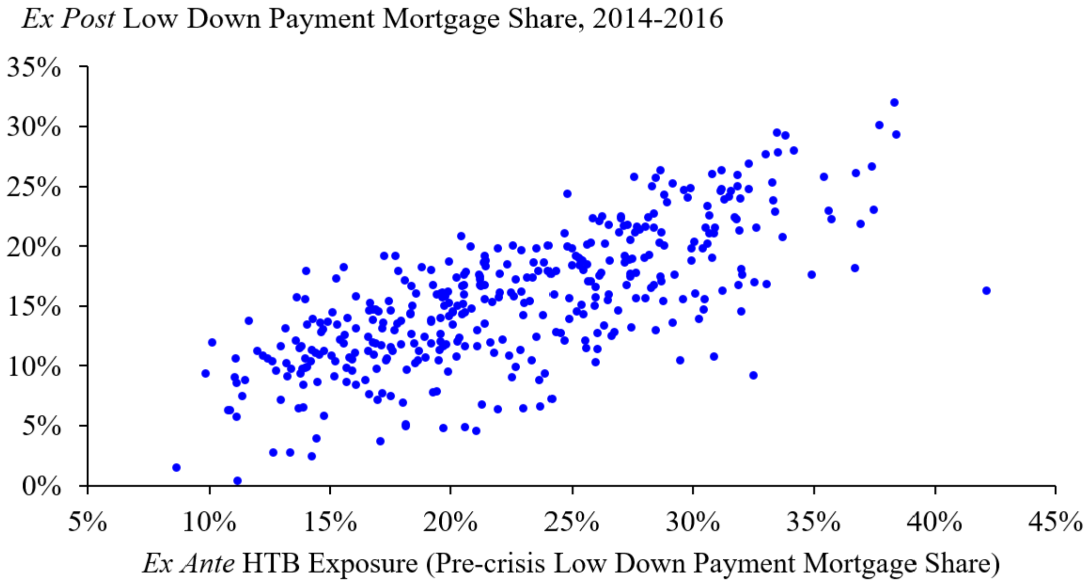
The figure shares the share and number of low-down payment mortgages before and during the Help-to-Buy Program exposure period. Low-down payment mortgages include all mortgages with a down payment of 5 percent or less. The dark-shaded area indicates the period that both the EL and MG schemes are in effect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

Figure 3: **Help-to-Buy Exposure across the United Kingdom**



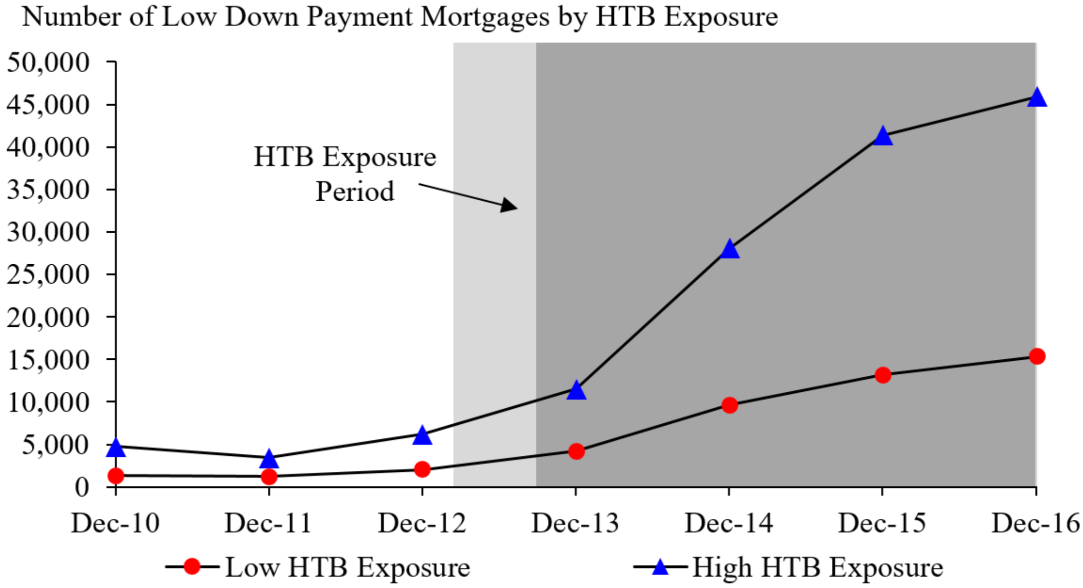
The figure shades local authority districts across the UK by shows Help-to-Buy (HTB) Exposure. HTB Exposure equals the number of low-down payment mortgages in a district in the period 2005-2007 divided by the total number of mortgages in 2005-2007. Districts with a darker shading have a higher exposure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

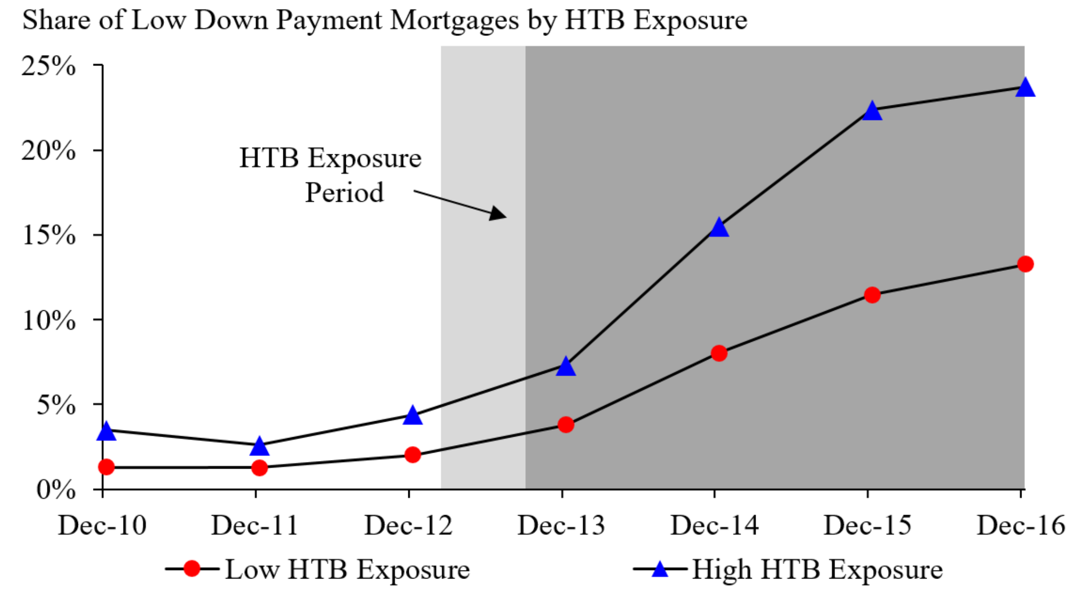
Figure 4: **Help-to-Buy Exposure and Ex Post Low-Down Payment Mortgages**



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. We include first-time buyer and home-mover mortgages only in all calculations.

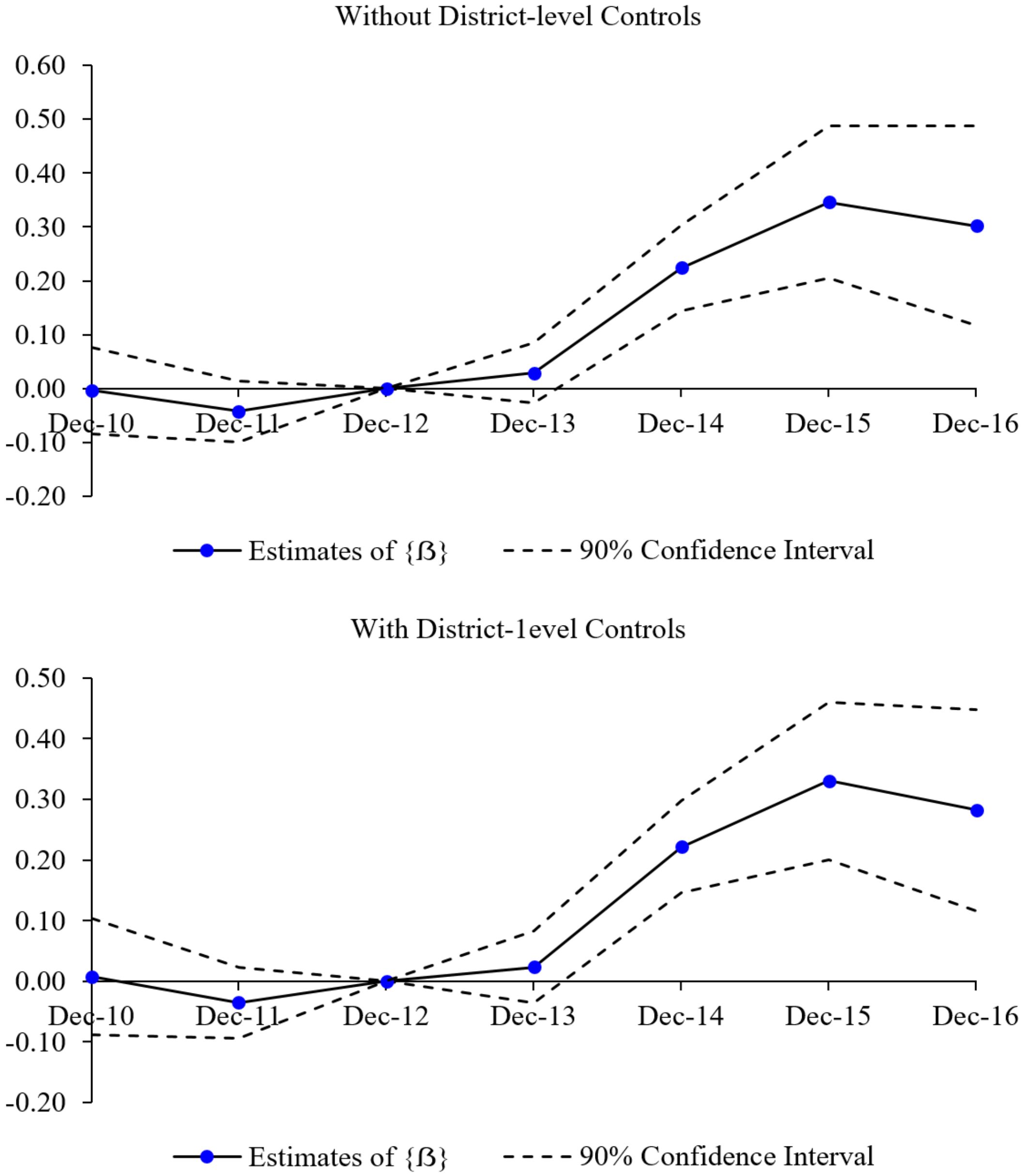
Figure 5: **Evolution of Low-Down Payment Mortgages by Help-to-Buy Exposure**





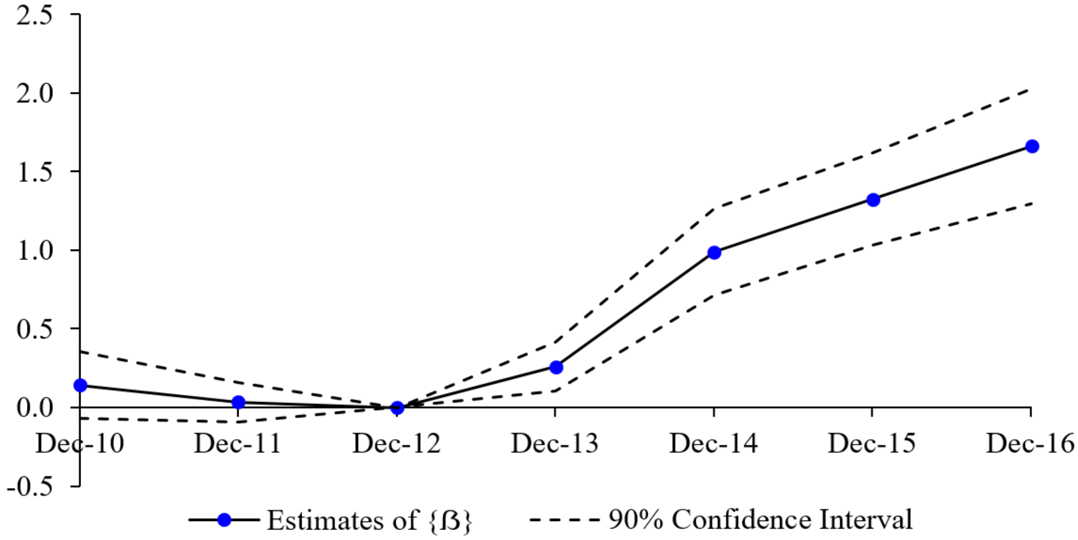
The top panel of the figure shows the aggregate number of low-down payment mortgages over the period from 2005 to 2016 for districts that are grouped according to their HTB exposure. The bottom panel shows the weighted average share of low-down payment mortgages (as a proportion of all mortgages excluding 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). We include first-time buyer and home-mover mortgages only in all calculations.

Figure 6: The Effect of Help-to-Buy on Low-Down Payment Mortgage Lending



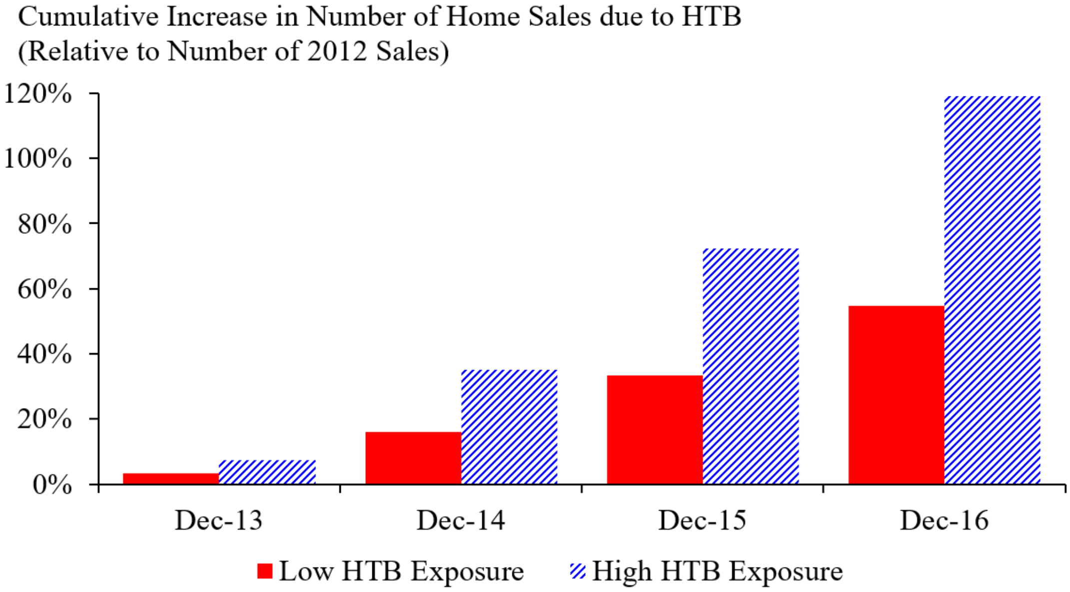
The figure presents estimates of β from Equation 1 for each year, where the outcome $Y_{b,l,d,t}$ is the dummy variable for low-down payment mortgages and 2012 is the base year. The dashed lines show the 90 percent confidence interval. All regressions include loan and home buyer controls, as well as 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 7: The Effect of Help-to-Buy on Home Sales



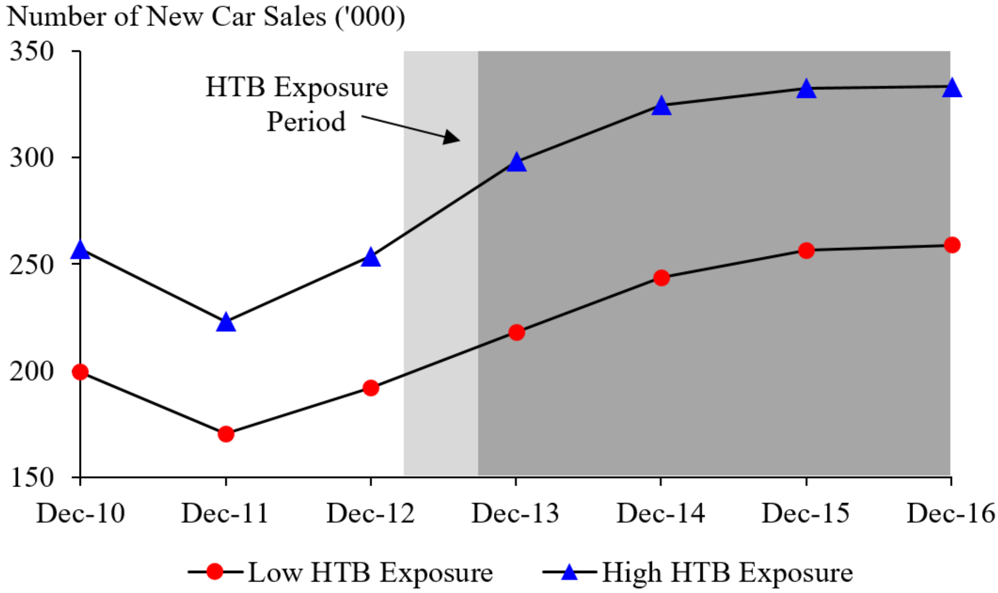
The figure presents estimates of β from Equation 2 for each year, where the outcome variable Home Sales$_{d,t}$ equals the number of home sales in a given year and district and 2012 is the base year. The dashed lines show the 90 percent confidence interval. All regressions include time-varying district-level controls as well as district and time fixed effects. Standard errors are clustered at the district level.

Figure 8: Economic Significance of Help-to-Buy



The figure is computed using estimates of β_s from Equation 2. 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 9: 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 Variables						
Low Down Payment (0/1)	0.02	0	0.16	0.16	0	0.36
First-time Buyer (0/1)	0.38	0	0.49	0.46	0	0.50
Younger Buyer (0/1)	0.63	1	0.48	0.69	1	0.46
Household Annual Income (£'000)	61.14	45.50	102.32	62.17	47.03	1,071.75
Employed (0/1)	0.88	1	0.32	0.88	1	0.32
Self-employed (0/1)	0.03	0	0.16	0.02	0	0.14
Property Value (£'000)	264.71	201.78	574.95	273.61	212.95	314.25
Down Payment Value (£'000)	100.74	54.93	529.02	92.06	48.74	183.29
Loan-to-income Ratio	3.08	3.05	2.30	3.25	3.31	1.45
Maturity (Years)	23.76	25.00	7.59	25.73	25.00	9.83
Rate-type: Fixed (0/1)	0.69	1	0.46	0.92	1	0.27
Rate-type: Floating (0/1)	0.30	0	0.46	0.07	0	0.26
Repayment: Capital (0/1)	0.86	1	0.35	0.97	1	0.17
Repayment: Interest (0/1)	0.11	0	0.32	0.02	0	0.15
District-level 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
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
Cohort-level Variables						
Total Household Consumption (£, ln)	5.95	5.95	0.21	5.95	5.93	0.21
Home-related Expenditure (£, ln)	3.89	3.91	0.28	3.83	3.84	0.28
Non-durable (excl. Home-related) (£, ln)	5.68	5.70	0.21	5.66	5.65	0.20
Durable (excl. Home-related) (£, ln)	0.98	1.24	0.67	1.02	1.08	0.71

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 1,393,570 loan-level observations, 1,057 district-level observations and 165 cohort-year observations. In the post HTB period, there are 1,907,128 loan-level observations, 1,115 district-level observations and 177 cohort-year observations. All variables are deflated to 2016 values.

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

	District-level Variables	Coefficient	R^2	N
(1)	ln(Unemployment Rate)$_{d,t-1}$	0.1204***	0.4443	2,545
		(0.005)		
(2)	ln(Median Weekly Income)$_{d,t-1}$	-0.1290***	0.0905	2,545
		(0.019)		
(3)	ln(Average Weekly Rent)$_{d,t-1}$	-0.0787***	0.0467	2,545
		(0.017)		
(4)	ln(Average House Price)$_{d,t-1}$	-0.1176***	0.5020	2,545
		(0.006)		
(5)	ln(Population)$_{d,t-1}$	0.0403***	0.10106	2,545
		(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 Down Payment Size**

	Dependent Variable				
	All Home Sales		Home Sales by Down Payment Size		
	(1)	(2)	(3)	(4)	(5)
$\text{Post}_t \times \text{Exposure}_d$	1.7402***	1.2848***	0.1889***	-0.0926	
	(0.199)	(0.197)	(0.033)	(0.059)	
$\text{Post}_t \times \text{Exposure}_d \times \text{Down Payment}_{25\%}$				-0.0912	-0.1498**
				(0.063)	(0.060)
$\text{Post}_t \times \text{Exposure}_d \times \text{Down Payment}_{20\%}$				0.0281	-0.0216
				(0.057)	(0.050)
$\text{Post}_t \times \text{Exposure}_d \times \text{Down Payment}_{15\%}$				0.0197	-0.0137
				(0.060)	(0.053)
$\text{Post}_t \times \text{Exposure}_d \times \text{Down Payment}_{10\%}$				0.4431***	0.4296***
				(0.074)	(0.070)
$\text{Post}_t \times \text{Exposure}_d \times \text{Down Payment}_{5\%}$				1.1290***	1.1738***
				(0.120)	(0.116)
Control Variables					
$\text{Post}_t \times \text{Down Payment}_i$	n.a.	n.a.	No	Yes	No
$\text{Exposure}_d \times \text{Down Payment}_i$	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
Down Payment	n.a.	n.a.	Yes	Yes	No
District × Time	No	No	No	No	Yes
District × Down Payment	n.a.	n.a.	No	No	Yes
Time × Down Payment	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 3 for the period 2010 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 to 2007 divided by the total number of mortgages in 2005 to 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)
$Post_t \times Exposure_d$	0.3810***		0.1889**	
	(0.087)		(0.074)	
$Post_t \times Exposure_d \times$ Buyer-type$_b$	0.5226***	0.6915***	0.8592***	1.0487***
	(0.100)	(0.099)	(0.160)	(0.124)
Control Variables				
$Post_t \times$ Buyer-type$_b$	Yes	No	Yes	No
$Exposure_d \times$ 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
District×Buyer-type$_b$	No	Yes	No	Yes
Time×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 4 for the period 2010 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 to 2007 divided by the total number of mortgages in 2005 to 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 3 for the period 2010 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 to 2007 divided by the total number of mortgages in 2005 to 2007. Column (1) presents estimates from specification that excludes all London districts. Column (2) presents estimates from a specification that includes 2013 in the post-HTB period. Column (3) presents estimates from a specification that includes 2013 in the pre-HTB period. Column (4) presents estimates from a 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 5 for the period 2010 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 to 2007 divided by the total number of mortgages in 2005 to 2007. Column (2) presents estimates from a specification that excludes all London districts. Column (3) presents estimates from a 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)
$\text{Post}_t \times \text{Exposure}_d$	0.1396***	0.1110***	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	2,139	1,947	192
R^2	0.8337	0.8546	0.8308

The table presents coefficient estimates for Equation 6 for the period 2010 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 to 2007 divided by the total number of mortgages in 2005 to 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 Household Consumption**

	Total Household Consumption	Home-related Expenditure	Non-durable (excl. Home-related)	Durable (excl. Home-related)
	(1)	(2)	(3)	(4)
$\text{Post}_t \times \text{Exposure}_r$	0.4565**	0.6294*	0.5069**	0.3295
	(0.208)	(0.344)	(0.201)	(0.883)
Control Variables				
House Prices	Yes	Yes	Yes	Yes
Cohort Characteristics	Yes	Yes	Yes	Yes
Fixed Effects				
HTB-Region	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes
Birth Year Group	Yes	Yes	Yes	Yes
Model Statistics				
N	338	338	338	338
R^2	0.8033	0.6956	0.7994	0.6574

The table presents coefficient estimates for Equation 7 for the period 2010 to 2016 (excluding 2013) , which show the effect of the Help-to-Buy program on household consumption. The dependent variable is either real total household consumption, real home-related expenditure, real non-durable consumption or real durable expenditure, where the latter two variables exclude home-related expenditure. 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 region in the period 2005 to 2007 divided by the total number of mortgages in 2005 to 2007. Standard errors are shown in parentheses. ***, **, and * indicate statistical significance at the 1 percent, 5 percent and 10 percent confidence level, respectively.

Table 9: **The Effect of Help-to-Buy on Household Consumption of the Young**

	Home-related		Non-durable		Durable	
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Post}_t \times \text{Exposure}_r$	0.6917*		0.2721		0.7522	
	(0.377)		(0.218)		(0.980)	
$\text{Post}_t \times \text{Exposure}_r \times \text{Younger}_c$	-0.2611	-0.2892	0.7113**	0.7355**	-1.7738	-1.7021
	(0.584)	(0.584)	(0.338)	(0.340)	(1.517)	(1.540)
Control Variables						
$\text{Post}_t \times \text{Younger}_c$	Yes	Yes	Yes	Yes	Yes	Yes
$\text{Exposure}_r \times \text{Younger}_c$	Yes	Yes	Yes	Yes	Yes	Yes
House Prices	Yes	No	Yes	No	Yes	No
Cohort Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
HTB-Region	Yes	No	Yes	No	Yes	No
Time	Yes	No	Yes	No	Yes	No
Birth Year Group	Yes	Yes	Yes	Yes	Yes	Yes
Region×Time	No	Yes	No	Yes	No	Yes
Model Statistics						
N	338	338	338	338	338	338
R^2	0.7042	0.7067	0.8079	0.8073	0.6582	0.6517

The table presents coefficient estimates for Equation 8 for the period 2010 to 2016 (excluding 2013) , which show the effect of the Help-to-Buy program on household expenditure. The dependent variable is either real home-related expenditure, real non-durable consumption or real durable expenditure, where the latter two variables exclude home-related expenditure. 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 region in the period 2005 to 2007 divided by the total number of mortgages in 2005 to 2007. Younger is a dummy variable equal to 1 for the birth year cohorts born in years between 1977 to 1986 and 1987 to 1996. Standard errors are shown in parentheses. ***, **, and * indicate statistical significance at the 1 percent, 5 percent and 10 percent confidence level, respectively.

Table 10: **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 9 for the period 2010 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 to 2007 divided by the total number of mortgages in 2005 to 2007. Column (2) presents estimates from a specification that excludes all London districts. Column (3) presents estimates from a 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 11: **The Effect of Help-to-Buy on Car Sales by Finance-type**

	Total Car Purchases	Loan-financed Car Purchases	Outright Car Purchases
	(1)	(2)	(3)
$\text{Post}_t \times \text{Exposure}_d$	-0.2422	1.3508**	-1.6785**
	(0.897)	(0.640)	(0.740)
Control Variables			
House Prices	Yes	Yes	Yes
Cohort Characteristics	Yes	Yes	Yes
Fixed Effects			
HTB-Region	Yes	Yes	Yes
Time	Yes	Yes	Yes
Birth Year Group	Yes	Yes	Yes
Model Statistics			
N	388	388	388
R^2	0.5089	0.5911	0.1692

The table presents coefficient estimates for Equation 7 for the period 2010 to 2016 (excluding 2013) , which show the effect of the Help-to-Buy program on household expenditure. The dependent variable is either total car purchase expenditure, loan-financed car purchase expenditure or outright car purchase expenditure. 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 region in the period 2005 to 2007 divided by the total number of mortgages in 2005 to 2007. Standard errors are shown in parentheses. ***, **, and * indicate statistical significance at the 1 percent, 5 percent and 10 percent confidence level, respectively.

A Living Costs and Food Survey (LCFS) Data

A.1 Background about the LCFS

We use the Living Costs and Food Survey (LCFS) to obtain our household-level consumption data. Formerly known as the Expenditure and Food Survey (EFS) and the Family Expenditure Survey (FES), the LCFS represents the most comprehensive survey on household spending in the UK. It is conducted by the UK Office of National Statistics, and collects expenditure information from around 5,000 households across the UK throughout each year. Respondents provide a detailed expenditure diary for their household over a two week period. It also gathers information about each respondent's household income and demographic profile. Our study includes survey data from Q1:2010 to Q4:2016.

A.2 Household Consumption

We define *home-related expenditure, non-durable consumption*, *durable expenditure* and *total household consumption* as follows:

- *Home-related Expenditure*: includes household services, non-durable household goods, and durable household goods. This covers spending on furniture and furnishings, bedroom textiles, kitchenware, electric and home appliances, among others.
- *Non-durable Consumption*: includes food, alcohol, tobacco, fuel, light and power, clothing and footwear, personal services, non-durable personal goods, fares, leisure services, non-durable leisure goods, and motoring expenditure.
- *Durable Expenditure*: includes motor vehicles, durable personal goods, durable leisure goods. This covers spending on jewelry, television set purchases, personal computers, audio-visual equipment, among others.
- *Total Household Consumption*: is the sum of our measures for *home-related expenditure, non-durable consumption* and *durable expenditure.*

Following Cloyne, Ferreira and Surico (2020), housing and rental-related costs are excluded from both non-durable goods and services and durable goods. Home-related expenditure on household services and non-durable households goods, which would normally be included in a non-durable consumption measure, are excluded from our main measure of non-durable consumption. Similarly, home-related expenditure on durable households goods are excluded from our main measure of durable expenditure. Our results are robust to alternative measures that adjust our *non-durable consumption* and *durable expenditure* measures to include spending on home-related categories.

A.3 Other Key Variables

- *Household income*: sum of labor- and non-labor household income.
- *Mortgage payments*: includes both interest payments and capital repayments.
- *Household size*: Number of adults and children in household.

A.4 Deflating

We adjust household expenditure, income and mortgage payments for inflation using the UK Consumer Price Index measure including owner occupiers' housing costs (CPIH). The base-year for the deflated variables in 2016.

A.5 Weights

The LCFS includes both annual and quarterly probability weights for each respondent. We follow Dynan, Edelberg and Palumbo (2009) and others, who argue that their use is not suitable when data are organized using demographic selection criteria, and do not use these weights. Are results are robust when we do apply the survey household weights.

A.6 Restrictions

We exclude households that do not report income or report negative net income. We consider households that are private renters, outright owners and owners with a mortgage. That is, we exclude households that are rent-free or in social housing, for example.

B Alternative Household Survey Panel Construction

B.1 Household Survey Data and Panel Construction

We create an alternative panel from the LCFS to tackle the fact that there are too few observations in each wave to conduct our analysis at the year-district-level. This panel provides granular regional coverage at the expense of the time dimension. We pool across several LCFS waves to obtain district-level spending measures for the pre-HTB-period (covering 2010 to 2012) and the post-HTB-period (covering 2014 to 2016). For each time-district combination, we calculate the average of the logged variables of interest, where "time" is either the pre-HTB-period or post-HTB-period. We exclude time-district combinations with ten or fewer observations.

B.2 Help-to-Buy and Household Expenditure

We estimating the following cross-sectional regression model:

$$\triangle\text{Consumption}_{d,Post} = \beta_1\text{Exposure}_d + \boldsymbol{\gamma}\triangle\text{Cohort}_{d,Post} + \lambda\triangle\text{House Prices}_{d,Post} + u_d \tag{10}$$

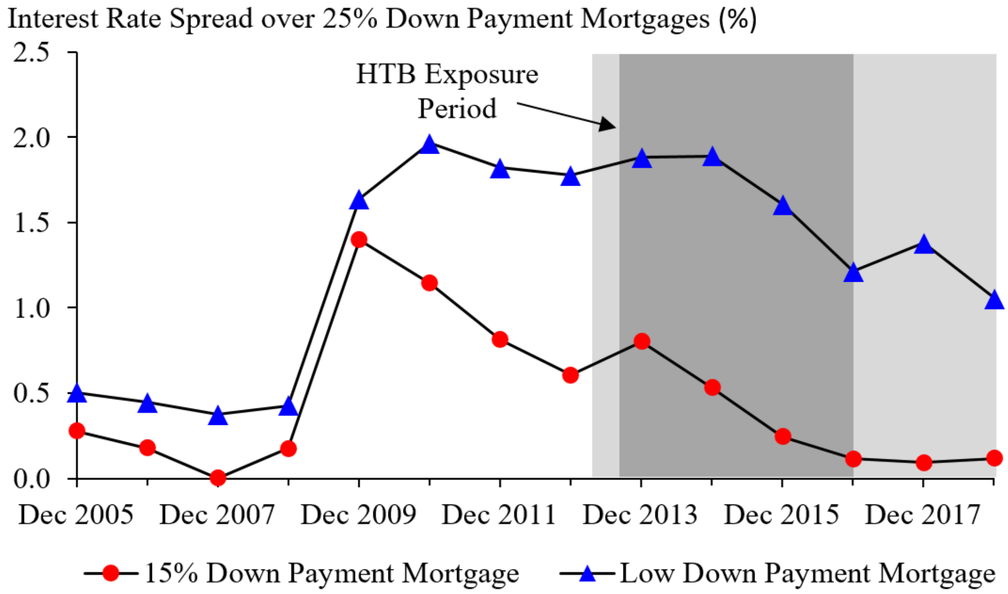
where d indexes a district. The outcome variable $\triangle\text{Consumption}_{d,Post}$ is real total household consumption growth (or home-related expenditure growth, non-durable consumption growth, or durable expenditure growth) for district d, measured as the difference between real total household consumption in the the post-HTB-period (2014 to 2016) and the pre-HTB-period (2010 to 2012).[42]Exposure_d is our measure of *ex ante* exposure to the HTB program. We also include the real growth between the post-HTB-period and the pre-HTB-period for a vector of district-level controls derived from the LCFS, $\mathbf{Cohort}_{d,t}$, which includes the same controls describe for Equation 7. $\triangle\text{House Prices}_d$ is the real house price growth between the post-HTB-period and the pre-HTB-period.

The results in Table A.3 show that real home-related expenditure growth and non-durable consumption growth are both higher in high compared to low exposure areas during the HTB-affected period (columns (2) and (3)). Over the same period, durable expenditure does not appear to be affected by the HTB program (column (4)). Our regressions control for house prices so they are not driven by a wealth effect due to higher house prices in high exposure areas. All told, the results from this alternative LCFS panel complement our findings in Section 7.2.

[42] Our real non-durable consumption (real durable expenditure) measure for district d is calculated as the average of the log of real non-durable consumption (real durable expenditure) for all households in district d pooled over the given period.

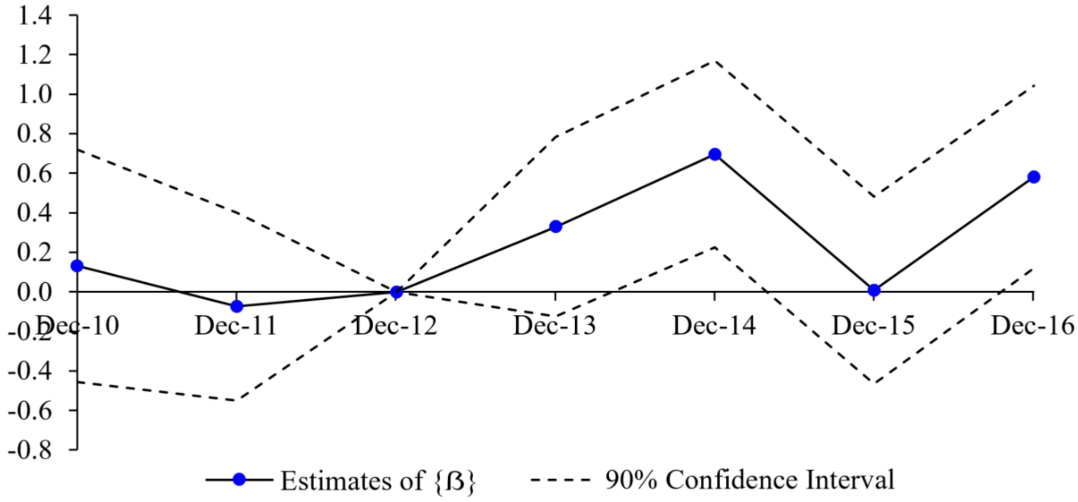
C Additional Figures and Tables

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.

Figure A.2: The Effect of Help-to-Buy on Household Consumption



The figure presents estimates of β from a modified version of Equation 2 for each year. The outcome variable is now $\text{Consumption}_{d,t}$, which equals real total household consumption, as described for Equation 7, in a given year and HTB-region and where 2012 is the base year. The dashed lines show the 90 percent confidence interval. All regressions include time-varying HTB-region-level and time-varying cohort-level controls, as well as HTB-region, cohort and time fixed effects, similar to those described for Equation 7.

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 Variables		
Low Down Payment	Takes the value 1 if down payment 5 percent or less and 0 otherwise	Product Sales Database, UK MHCLG
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 Value	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 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
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
Cohort-level Variables		
Total Household Consumption	Average of log real weekly household consumption for all households in a given year and cohort	Living Food and Cost Survey
Home-related Expenditure	Average of log real weekly home-related expenditure for all households in a given year and cohort	Living Food and Cost Survey
Non-durable (excl. Home-related)	Average of log real weekly non-durable consumption for all households in a given year and cohort	Living Food and Cost Survey
Durable (excl. Home-related)	Average of log real weekly durable expenditure for all households in a given year and cohort	Living Food and Cost Survey

Table A.3: **The Effect of Help-to-Buy on Household Consumption**

	Total Household Consumption	Home-related Expenditure	Non-durable (excl. Home-related)	Durable (excl. Home-related)
	(1)	(2)	(3)	(4)
Exposure_d	0.2313	0.5419*	0.3384*	-1.3789
	(0.193)	(0.293)	(0.185)	(0.885)
Control Variables				
House Prices	Yes	Yes	Yes	Yes
Cohort Characteristics	Yes	Yes	Yes	Yes
Model Statistics				
N	290	290	290	290
R^2	0.3805	0.2402	0.4031	0.1381

The table presents coefficient estimates for Equation 10, which show the effect of the Help-to-Buy program on household expenditure. The dependent variable is either real total household consumption growth, real home-related expenditure growth, real non-durable consumption growth or real durable expenditure growth, in the post-HTB-period (2014 to 2016) compared with the pre-HTB-period (2010 to 2012). Non-durable consumption and durable expenditure exclude home-related expenditure. Exposure equals the number of low-down payment mortgages in a district in the period 2005 to 2007 divided by the total number of mortgages in 2005 to 2007. Standard errors are shown in parentheses. ***, **, and * indicate statistical significance at the 1 percent, 5 percent and 10 percent confidence level, respectively.