Help to Spend? The Housing Market and Consumption Response to Relaxing the Down Payment Constraint

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Abstract

We show that relaxing the down payment constraint positively affects household consumption in addition to stimulating housing market activity. For identification, we use the UK Help-to-Buy (HTB) program as a quasi-natural experiment and exploit geographic variation in exposure to the program. We document a significant increase in home purchases, largely driven by first-time and young buyers. More exposed regions also experience a rise in home-related expenditures, non-durable consumption and loan-financed car purchases. Local demand effects appear to partly drive the consumption response. Our findings thus show that interventions in the mortgage market can have important local macroeconomic spillover effects.

JEL classification: E21; G21; R21; R28

Keywords: mortgage market regulation; down payment; housing market; consumption

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1 Introduction

Policymakers have a long history of intervening in the mortgage market. Many countries have introduced macroprudential policies that *limit* mortgage credit access in an effort to reduce household leverage and curb boom-bust cycles.[1][2] At the same time, several countries have acted to *expand* mortgage credit access in an effort to address housing affordability issues and increase homeownership rates.[3] In both cases, these policies influence households' ability to obtain mortgage credit by altering their borrowing constraints. While a growing body of literature provides important insights into the impact of such policies on the housing market, very little is known about how they affect the real economy.[4] Understanding this topic is key as it sheds light on how interventions in the mortgage market affect macroeconomic dynamics and the potential trade-offs policymakers may face.

In this paper, we focus on one particular mortgage market intervention - a relaxation of the down payment constraint - and examine its impact on both the housing market and household consumption. We use the UK Help-to-Buy (HTB) program as a quasi-natural experiment and exploit a rich set of mortgage market, consumption and macroeconomic data. We show that relaxing the down payment constraint stimulated housing market activity and led to a rise in household consumption in more exposed regions. These regions also experienced an increase in non-tradable employment and household income, suggesting that the consumption response was at least partly driven by a rise in local demand. Our findings suggest that interventions in the mortgage market that affect the ability of households to purchase a home can have important local macroeconomic spillover effects.

The purchase of a home typically requires a significant down payment and the minimum down payment requirement - as determined by the loan-to-value (LTV) limit - plays a critical role in mortgage market access. Due to its in-built leverage effect, the down payment requirement has a non-linear impact on housing affordability. In addition, the down payment (and not income) is often the binding constraint for young and first-time

[1] The build up of household leverage during credit booms has been shown to lead to house price busts, lower output growth and higher unemployment (see, e.g., Mian et al., 2017; Reinhart and Rogoff, 2009).

[2] LTV and LTI limits have been introduced in 60 and 42 countries, respectively. In advanced countries LTV limits are the most widely used tool (Alam et al., 2019).

[3] Examples are First-Time Homebuyer Credit (US), Help-to-Buy (UK), Home Ownership Schemes (e.g. Singapore) or targeted stamp duty holidays (e.g. Netherlands, UK).

[4] For an overview of the literature see Section 2.

buyers, who tend to be the drivers of housing market fluctuations (see, e.g., Linneman and Wachter, 1989; Ortalo-Magne and Rady, 2006; Fuster and Zafar, 2021).[5] A mortgage market intervention that lowers the minimum down payment requirement is therefore expected to generate a rise in housing market activity driven by young and first-time buyers.

There are several reasons why loosening the down payment constraint could also affect household consumption. First, it can *directly* impact the consumption of home buyers through a number of different channels. Following the purchase of a new home, households tend to increase home-related expenditures (Best and Kleven, 2017; Benmelech et al., 2017). In addition, (non-home related) consumption may rise if home buyers experience an increase in discretionary income. This happens for example when the mortgage payments of the newly bought house are lower than the combined cost of saving for the down payment and previous rental costs.[6] By contrast, home buyers might lower their consumption in order to pay off mortgage debt if they have an aversion to high leverage (Sodini et al., 2016). Second, it can affect household consumption *indirectly* through local demand effects. A flurry of activity in the housing market, possibly in combination with a rise in construction, can spur regional economic activity which can feed back into consumption. Furthermore, if the rise in housing transactions leads to house price growth, consumption can be stimulated due to its effect on wealth, borrowing constraints and employment.[7]

Ultimately, how relaxing the down payment constraint affects the housing market and household consumption is an empirical question. However, quantifying the effect is not straightforward. One challenge is to find a significant and exogenous shock to the down payment constraint. In addition, a meaningful counterfactual is required in order to assess what would have happened if the intervention had not taken place. Finally, one has to convincingly control for confounding factors that can impact the housing market or household consumption.

The UK provides a unique setting to address these identification challenges. In March 2013, the UK government announced the HTB program. This large-scale mortgage market intervention sought to make housing more affordable for households with a limited

[5] A survey of over 5000 would be first-time buyers in the UK revealed that the biggest barrier to homeownership is saving enough for a down payment (Santander, 2019).

[6] In line with this, Engelhardt (1996) shows that households reduce food consumption in the years prior to buying a home and increase it back to long-run levels afterwards.

[7] See, e.g., Campbell and Cocco, 2007; Mian and Sufi, 2011; Mian et al., 2013; Guren et al. (2020).

ability to save for a down payment. It did so by facilitating home purchases with only a 5 percent down payment. The program was introduced in the aftermath of the global financial crisis and at a time that UK mortgage lenders were unwilling to offer mortgages with less than 10 percent down payment, despite there being no regulatory restrictions to do so.

HTB prompted a significant relaxation of the down payment constraint due to particularities of the UK mortgage market. In the UK, lenders offer notched mortgage interest schedules. That is, mortgage interest rates feature discrete jumps at critical thresholds determined by the down payment (5, 10, 15, ..., and 40 percent). This creates very strong incentives to reduce borrowing to a level just below the notch, and down payments therefore bunch in incremental steps of 5 percentage points (see, e.g., Best et al., 2020; Robles-Garcia, 2019). As Figure 1 shows, HTB was highly effective in relaxing the down payment constraint in the UK mortgage market. While there was no bunching at the 5 percent threshold prior to HTB, significant bunching is evident after the program was introduced. HTB thus initiated a sudden drop in the minimum down payment requirement from 10 to 5 percent. For many buyers, this policy change was key to accessing the mortgage market.

Our research design relies on geographic variation in *ex ante* HTB exposure in a similar vein as the identification strategies of Mian and Sufi (2012) and Berger et al. (2020). We argue that even though HTB was national in scope, and down payment requirements were thus loosened across the UK, parts of the UK were affected differently due to variations in local housing market characteristics. Relaxing the down payment constraint primarily benefits liquidity 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 relaxing the down payment requirement will have a bigger impact in districts where historically many households bought their home with a low-down payment mortgage. Districts with a 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.

Our difference-in-differences design thus compares housing market activity and household consumption in low relative to high exposure areas before and after HTB came into effect. We define HTB exposure as the proportion of households in a district that bought their home with a 5 percent down payment before the financial crisis, a period when the market for low-down payment mortgages was relatively unconstrained.[8] We show that this measure strongly correlates with the actual purchase of low-down payment mortgages after HTB was introduced and also accurately predicts time variation.

We first provide evidence that lowering the minimum down payment requirement to 5 percent led to a rise in housing market activity driven by young and first-time buyers. We estimate that over the period 2013 to 2016, when the two main HTB schemes were active, an additional 217,100 homes were purchased, representing a 9.8 percent increase. This increase was primarily due to a rise in house purchases with a down payment of around 5 percent. First-time buyers accounted for 78 percent of the increase, while younger households (both first-time buyers as well as home movers) were responsible for 91 percent.[9] The magnitude of the effect highlights the critical role of down payment constrained buyers in driving housing market fluctuations (Ortalo-Magne and Rady, 2006).

A potential concern with our identification strategy is the possibility that districts with a larger proportion of low-down payment buyers may also differ in other ways that independently influence home sales during the sample period. To mitigate this concern, we show that our results are robust to the inclusion of district and time fixed effects and various time-varying macroeconomic and housing market controls. Where feasible we include district-by-time fixed effects and isolate the impact of relaxing the down payment constraint purely from within-district heterogeneity. In addition, we provide evidence of parallel pre-event trends in high versus low exposure areas, and we show that the subsequent divergence in trends exactly corresponds with the timing of the program. Furthermore, our findings are robust to excluding the London area, to using different weighting schemes and sample definitions, and to adding explicit controls for contemporaneous policies. Finally, we show that between-district migration patterns cannot explain our findings.

Using district-level data on house prices, we also show that outside London house price growth increased annually by a modest 0.2 percentage points per standard deviation of HTB exposure. In the London area the impact on house prices was larger (2.0 pp) . This is in line with previous findings that housing supply elasticity, which is weaker in London,

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

[9]These numbers reflect 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.

critically determines how strongly house prices react to an increased demand for housing (Favara and Imbs, 2015; Carozzi et al., 2020).

We next focus on consumption and show that relaxing the down payment constraint also spurs local household consumption. This stimulus effect goes beyond the traditional housing wealth and home 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 et al. (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 loosening 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, including house prices.

We document that household consumption increased by 3.8 percent per standard deviation increase in HTB exposure. Once more, we find no evidence of any differential pre-event trends and our results are robust to excluding the London area. In line with the presence of a home purchase channel (Best and Kleven, 2017; Benmelech et al., 2017), the growth in consumption was partly due to a rise in home-related expenditures (5.7 percent per standard deviation). However, we also find that non-durable consumption unrelated to the home rose by 4.0 percent per standard deviation increase in HTB exposure. The increase in non-durable consumption is primarily driven by a rise in consumption by younger households. In aggregate, we estimate that in reaction to a loosening of the down payment constraint, real total household consumption rose by 5.9 percent between 2013 and 2016. All these effects are independent of consumption responses to changes in regional house prices.

Our analysis of car purchases provides further evidence of a consumption stimulus effect unrelated to home-related expenditures or wealth effects. Drawing on administrative data capturing all private new car registrations for the UK, we find that new car purchases increased by 2.4 percent per standard deviation of program exposure. Most of these cars are likely to be loan-financed as in the UK 90 percent of new cars are purchased with some kind of consumer credit (Finance and Leasing Association, 2022).[10] In aggregate, we estimate that relaxing the down payment constraint resulted in an additional 221,081 new car purchases, representing a 5.2 percent increase in new cars purchased.

[10]Evidence from the LCFS supports this assertion.

Our empirical strategy allows us to capture the local general equilibrium consumption response to relaxing the down payment constraint. The effects that we estimate are the sum of a direct consumption effect driven by the new home buyers and an indirect effect due to other households in the same district benefiting from the resulting increase in local demand. In line with the presence of a local demand effect, we show that regions that were more exposed to the policy also experienced a rise in non-tradable employment and household income. We also document a positive, but weak impact on construction.

Overall, we show that relaxing the down payment constraint has a positive impact on household consumption in those areas where housing market activity is stimulated. Our findings thus indicate that a nationwide intervention in the mortgage market can have stimulus effects that go beyond the housing market, but with substantial regional heterogeneity.

The remainder of the paper is structured as follows. The next section provides a review of the related literature. Section 3 discusses the policy background. Section 4 describes the data and Section 5 introduces the empirical strategy and validates 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 builds on a small body of empirical literature that studies the consumption response to government interventions in the mortgage market. This literature has documented that interventions that affect *current* mortgage holders, such as mortgage debt renegotiation and refinancing programs, can have positive stimulus effects (Agarwal et al., 2015; Agarwal et al., 2017).[11] By contrast, we know very little about the impact of interventions that affect *future* mortgage holders. We contribute to this literature in three important ways. First, we focus on a key policy lever that impacts the ability of households to access mortgage credit: the down payment requirement (or LTV limit). Second, we study both survey level consumption data and car sales data which, allows us to paint a comprehensive picture of the consumption response to a relaxation of the down payment constraint. Third, we explore the mechanisms that drive the consumption

[11]Related work has shown that households adjust their consumption in response to lower mortgage payments resulting from a reduction in interest rates and to changes in their ability to access to home equity (Agarwal and Qian, 2014; DiMaggio et al., 2017; Defusco, 2018; Beraja et al., 2019).

effect and uncover important local demand effects. To the best of our knowledge, our paper is the first to provide a comprehensive analysis of how consumption reacts to a policy change affecting new home buyers and the mechanisms that drive it. Consistent with our findings on car sales, Agarwal et al. (2021) find that a stamp duty subsidy for eligible new home buyers in Sydney also increased demand for luxury cars.[12]

Our paper also compliments studies that investigate the reaction of household consumption to developments in the housing market. Much of this literature has focused on the impact of changes in house prices.[13] Another strand has studied how households adjust their consumption behavior after purchasing a home (see, e.g., Engelhardt, 1996; Sodini et al. (2016); Best and Kleven, 2017; Benmelech et al., 2017). We instead explore the consumption response resulting from a mortgage market intervention that made it easier for down payment constraint buyers to purchase a home. We show that the impact on consumption goes beyond the traditional housing wealth and home purchase channels.

Moreover, we add to the literature on the housing market response to interventions in the mortgage market. Studies show that tighter LTV and LTI limits lead to a fall in transaction volumes, a reallocation of mortgage credit from low- to high-income borrowers, and (first-time) buyers being pushed out of hot housing markets (see, e.g., Igan and Kang, 2011; Van Bekkum et al., 2019; Defusco et al., 2020; Carozzi, 2020; Peydro et al., 2020; Tzur-Ilan, 2020; Acharya et al., 2021).[14] By contrast, stimulus policies, such as stamp duty holidays or tax credit policies, temporarily increase sales volumes and when specifically targeted at first-time buyers they also increase homeownership, albeit less so in regions where house prices are high (see, e.g., Best and Kleven, 2017; Berger et al., 2020; Mabille, 2021). We add to this literature by providing a comprehensive assessment of the housing market response to a relaxation of the down payment constraint, documenting a strong, but heterogeneous impact.

Finally, our use of Help-to-Buy as a quasi-natural experiment relates our paper to the literature that studies the impact of HTB, which hitherto has focused exclusively on the

[12] Acharya et al. (2021) provide suggestive survey-based evidence that the introduction of LTV and LTI limits increases savings rates which could potentially translate into lower consumption.

[13] A number of theoretical studies explore various mechanisms through which housing wealth affects consumption (see, e.g., Boar et al., 2017; Berger et al., 2018; Chen et al., 2020; Kaplan et al., 2020). Several empirical studies highlight the effects of housing values on consumption due to a wealth effect (see, e.g., Benjamin et al., 2004; Campbell and Cocco, 2007; Bostic et al., 2009; Attanasio et al., 2011; Case et al., 2005; Mian et al., 2013; Guren et al., 2020) as well as a home equity extraction effect (see, e.g., Hurst and Stafford, 2004; Mian and Sufi, 2011; Cloyne et al., 2019).

[14] In addition, targeted down payment requirements ("mansion taxes") do not seem to affect housing sales, but drive up bidding intensity at the threshold instead (Han et al., 2021)

Equity Loan (EL) scheme of the program. It finds that the EL scheme positively affected the purchase of new properties (Finlay et al., 2016; Szumilo and Vanino, 2018), with households buying more expensive properties instead of reducing mortgage debt or house price risk exposure (Benetton et al., 2021). In addition, it induced an increase in house prices (housing construction) but only in areas with unresponsive (responsive) housing supply (Carozzi et al., 2020). Finally, Benetton et al. (2018) exploit the EL scheme to show that lenders use down payment size to price unobservable borrower risk. Our paper instead focuses on the full HTB program and steps beyond the housing market response to the program by documenting novel spillover effects to the real economy.

3 Institutional Setting

3.1 The Down Payment Constraint

The Help-to-Buy (HTB) Program effectively prompted a significant relaxation of the down payment constraint in the UK. Before describing the program, this section outlines the strong relationship between the down payment constraint and 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 (LTI) 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 minimum down payment requirement from 10 to 5 percent doubles the amount a buyer can borrow for a given down payment. So a household with £10,000 saved for a down payment would be able to buy a house worth only £100,000 with a 10 percent requirement (90% LTV), but one worth £200,000 with a 5 percent requirement (95% LTV).

Importantly, the down payment is the most frequently binding constraint for young and first-time buyers who typically have a hard time saving for their down payment (Linneman and Wachter, 1989; Fuster and Zafar, 2021). For example, over 90 percent of mortgages signed between 2005 and 2007 with a down payment of around 5 percent had a LTI ratio of less than 4.5, currently the maximum LTI for most mortgages in the UK.[15] The average LTI on these mortgages was only 3.4. These statistics have barely changed over time. In 2018, the average LTI on mortgages with a 5 percent down payment was 3.5 and 96 percent of those mortgages had an LTI of less than 4.5.[16] Any change in the down payment constraint thus likely has a significant impact on housing market activity driven by young and first-time buyers.

3.2 Relaxing the Down Payment Constraint via Help-to-Buy

HTB was first announced in March 2013 as part of the UK's budget. The key feature of the program was that it made it easier for households to purchase a home with only a 5 percent down payment. At the time of its introduction, lenders were very reluctant to offer mortgages with less than 10 percent down payment. 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" (Chancellor of the Exchequer, 2013).

Due to peculiarities of the UK mortgage market, HTB triggered a significant relaxation of the down payment constraint. Lenders in the UK offer notched mortgage interest schedules, whereby the mortgage interest rate features discrete jumps at critical thresholds of the down payment (5, 10, 15, ..., and 40 percent). This pricing strategy means that a borrower is charged the same interest rate for a mortgage with either 9.9 or 5.0 percent down payment as both are in the same pricing bucket. By contrast, a borrower is charged a significantly lower interest rate for a mortgage with a 10.0 percent down payment compared to a 9.9 percent down payment as these are in different pricing buckets. This creates very strong incentives to reduce borrowing to a level just below the notch. Mortgage down payments therefore bunch in incremental steps of 5 percentage points with only very few down payments in between these discrete steps (see, e.g., Best et al.,

[15] 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.

[16] Some important regional differences exist however. In areas where house prices on average are very high - for example the London area - the income constraint more frequently binds.

2020; Robles-Garcia, 2019).

Figure 1 illustrates that HTB was highly effective in relaxing the down payment constraint in the UK mortgage market. While there was no bunching at the 5 percent threshold prior to HTB, significant bunching occurred after the program was introduced. HTB lowered the effective minimum down payment requirement from 10 to 5 percent. This policy change was key to accessing the mortgage market for many buyers.

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.[17] 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 5 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 5 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.[18]

The second main HTB option was the "Mortgage Guarantee" (MG) scheme, which was offered from 1 October 2013 to 31 December 2016.[19] As with the EL scheme, borrowers required a 5 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.2 in the Internet Appendix summarizes the two schemes and their requirements.

[17] In April 2021 a new Equity Loan scheme started that is restricted to first-time buyers and includes regional property price caps to ensure the scheme reaches people who need it most.

[18] The EL scheme loosened the income constraint, in addition to the down payment constraint, because the government equity loan was not included in the LTI calculation. This loosening of the income constraint via the EL scheme allowed buyers to purchase a more expensive home (Benetton et al., 2021; Finlay et al., 2016). But Finlay et al. (2016) document that the down payment - and not income - was the critical constraint in determining access to a mortgage and homeownership for the vast majority of potential buyers. In line with this, Table A.1 in our Online Appendix shows little difference in the average income for EL scheme buyers versus MG scheme buyers.

[19] In April 2021, a new mortgage guarantee scheme started along similar lines as the old scheme.

Figure 2 provides a first indication that the program was highly successful in increasing both the number and share of low-down payment mortgages. The increase started in 2013 but really accelerated in 2014 when both programs were active. 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.[20]

We conduct some back-of-the-envelope calculations to measure some of the potential effects on household finances. We estimate that the average household would need to put aside additional savings of £427 per month over 2 years in order to increase a 5 percent down payment up to 10 percent, which is equivalent to 9.5 percent of the pre-tax average household income over the period.[21] Thus, relaxing the down payment constraint can have a significant impact on medium term household finances, which may spillover to household consumption.[22]

Aggregate patterns suggest that HTB had an effect. However, to examine how the housing market and household consumption respond, 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 geographic variation across UK districts in their *ex ante* exposure to HTB based on the presence of *potential* low-down payment home buyers. Areas with few potential low-down payment home buyers can serve as the "control group" because buyers in these areas are unlikely to react to a change in the minimum down payment requirement. The difference between the treated and control areas provides an estimate of the marginal impact of relaxing the down payment constraint from 10 to 5 percent. In Section 5, we describe our research strategy in detail.

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

[21]These calculations for the "average household" use the house purchase price and gross household income of the average HTB buyer in 2016.

[22]This of course comes at the cost of larger monthly mortgage repayments as the household will have borrowed more (i.e. 95 instead of 90 percent of the value of the house). For the average household, this is equivalent to £45 extra per month over the lifetime of the loan. These calculations use the house purchase price, interest rate and mortgage term of the average HTB buyer in 2016.

4 Data and Summary Statistics

In this section, we describe the data sources and key variables that we use in our analysis, as well as present the corresponding summary statistics. Our data set includes 379 local authority districts (LADs) in the UK for which we have mortgage market data, measures of home sales, household spending data and other macroeconomic data. We refer to LADs as "districts" throughout the text. The data set covers districts in England, Wales and Scotland. We exclude Northern Ireland as this region is not included in several of our main data sources. The districts in our sample cover 97 percent of the UK population and 98 percent of total mortgages issued. We conduct our analysis at the district level because these regions most closely represent distinct housing and labor markets. Outside the greater London area they also tend to 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.

We use the PSD to identify all mortgages that are a *"Low-Down Payment Mortgage"*, which covers all mortgages with a down payment of around 5 percent.[23] 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 5 percent minimum that is required to qualify

[23] These mortgages are known as 95 LTV mortgages. 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 vast 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.

for the loan.[24] We identify low-down payment EL mortgages by matching an EL data set collected by the UK Department for Levelling Up, Housing and Communities with the PSD, using the approach of Benetton et al. (2021).[25]

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 homes purchased with a mortgage.[26] Our next measures are the *"First-time Buyer Sales"* and "*Home Mover Sales"*, which comprise the homes purchased with a mortgage by first-time buyers and home movers, respectively. We also calculate *"Younger Buyer Sales"* and *"Older Buyer Sales"*, which comprise the total homes purchased with a mortgage by 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 homes purchased with a mortgage by 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.[27] We winsorize all outcome variables at the 1st and 99th percentile to remove any outliers.[28]

4.2 Household Consumption Data

To examine the effect of relaxing the down payment constraint 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 Expenditures", "Non-durable Consumption"* and *"Durable Expenditures"*. Our home-related expenditures 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

[24]The majority of households put down 5 percent (see Benetton et al., 2021), but around 25 percent provided a down payment of 10 percent or more.

[25]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.

[26]In the UK, the majority of home purchased are financed with a mortgage. For example, in 2012 around 84 percent of total home sales were purchased with a mortgage.

[27]As explained above, mortgages included in *Down Payment 5%* can have a down payment between 9.9 and 5 percent, those in *Down Payment 10%* a down payment between 14.9 and 10 percent etc.

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

semi-durable goods such as clothing, footwear and certain leisure goods. Our durable expenditures measure aggregates spending on motor vehicles, durable personal and durable leisure goods. Both our non-durable consumption and durable expenditures measures exclude any home-related expenditures and so we can create a "*Total Household Consumption*" measure by summing across our three measures. All spending measures are deflated to 2016 values using the Consumer Price Index including owner occupier housing costs (CPIH). We provide a detailed description of these data and spending measures in Section A of the Internet Appendix.

In addition to our household spending measures, we draw on other variables from the LCFS to use as controls. Following 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 novel data set on car sales made available by the UK Department for Transport. To the best of our knowledge this is the first time that this data set has been used in the UK. Our "*Car Sales*" measure is defined as the number of new private car registrations for each year-district combination. The variable is again winsorized at the 1st and 99th percentile. A key advantage of these data is that they comprise the universe of new private car registrations in a given district, and so are free of any measurement issues. In addition, car purchases represent an important durable good. A drawback of these data is that they do not provide information about the buyer beyond the buyer's district.

4.3 Local Demand Effects Data

To examine the effect of the HTB program on local demand, we draw on a number of data sources. Once more, we use the LCFS household survey data to obtain two household income measures: "*Gross Household Income*" and "*Net Household Income*". Our gross household income measure includes labor income as well as non-labor income, such as income from investments. Our net household income measure is similarly defined but is net of paid taxes.

We obtain our employment data from the Business Structure Database (BSD), which is compiled annually based on information taken from the Interdepartmental Business Register (IDBR). It provides details about the geographic location and number of employees for the universe of active firms that are registered for income tax purposes in the UK. We consider four different employment measures: "*Total Employment*", "*Non-tradable Employment*", "*Strictly Non-tradable Employment*" and "*Tradable Employment*". Total employment covers all employees for all firms in a given district and year. We use the approach of Burstein et al. (2020) to obtain our non-tradable and tradable employment measures. Here tradable employment includes firms in goods-producing industries, such as agriculture, mining and manufacturing; non-tradable employment includes firms in service-producing industries. Our strictly non-tradable employment measure includes firms in the retail sector and restaurants, in line with the classification used by Mian and Sufi (2014). We provide a detailed description of these data and industry categories in Section B of the Internet Appendix.

We consider two measures of housing supply and construction: "*Homes Constructed*" and "*Home Starts*". The homes constructed measure follows the approach of Carozzi et al. (2020) and is derived from the UK Land Registry Price Paid Dataset (PPD). It is defined as the number of new build home sales in a given district and year, where this measure is leading by a year to account for delays between the start of a build and the moment the house is actually sold. The home starts measure represents the number of individual dwellings for which building work has commenced in a given district and year, the details of which are provided by the UK Department for Levelling Up, Housing and Communities. Once more, we winsorize all employment and construction-related outcome variables at the 1st and 99th percentile to remove any outliers.

4.4 Control Variables

Finally, we collect various 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 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.

4.5 Summary Statistics

Table 1 presents summary statistics for the key variables used in our analysis, while Table A.3 in the Internet Appendix provides their definitions and sources. Summary statistics are calculated 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 was introduced, 2 percent of all mortgages had a deposit of only 5 percent. During the years HTB was active, and the minimum down payment requirement was reduced to 5 percent, this number increased to 16 percent. This can be interpreted as potential *prima facie* evidence that relaxing the down payment constraint through the HTB program had a significant impact on increasing the number and share of low-down payment mortgages.

The average annual number of homes purchased with a mortgage at the district-time level increased from 1,270 home sales in the pre-HTB period to 1,610 home sales in the HTB period, indicating an increase in the overall number of mortgages after relaxing the down payment constraint. In addition, the standard deviation increased from 800 to 1,050 mortgages, i.e the spread also widened. This suggests that the program had a stronger impact in some districts compared to others. Furthermore, the increase in sales by both first-time and younger buyers is particularly large in the HTB period compared to the period preceding it.

Similarly, most of the additional outcome variables that we consider increased in the HTB period relative to the pre-HTB period. The district average house price growth increased from -1.46 percent to 4.11 percent. Average new car sales increased from 2,210 to 2,950. Average total employment increased from 73,020 to 77,880, with each sub-category for employment increasing in the HTB period too. Average homes constructed and started also increased. The only exception is average weekly real total household consumption which stayed stable.

Finally, there are some more notable differences in the district-level control variables however. In particular, the mean *Unemployment Rate* decreased from 7.24 percent in the pre-HTB period to 5.43 percent in the HTB period, while there was an increase for *Average House Prices* from £203,900 in the pre-HTB period to £219,410 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 impact of lowering the minimum down payment requirement to 5 percent on housing market activity and household consumption, we exploit geographic variation in *ex ante* HTB exposure. Our identification strategy is similar in spirit to that used by Mian and Sufi (2012) who evaluate the effects of the Cash for Clunkers program, by Berger et al. (2020) who evaluate the First-Time Homebuyer Credit program, and by Agarwal et al. (2017) who evaluate the broader consequences of debt relief programs using regional variation. We argue that even though HTB was national in scope, and down payment requirements were thus relaxed across the UK, parts of the UK were more exposed due to variations in local housing market characteristics. These differences in geographic exposure help us produce a counterfactual to estimate what would have happened in the absence of this mortgage market intervention.

Households with a limited ability to save for a down payment will naturally benefit most from the relaxation of the down payment constraint initiated by HTB. These types of households are not randomly spread across the UK and 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 can 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 reducing the minimum down payment requirement to 5 percent via HTB.[29]

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.

[29] This interpretation requires that no spillovers exist between treated and control areas as a result of endogenous moves. We provide evidence that endogenous moves unlikely explain our findings in Section D of the Internet Appendix.

We use the loan-level mortgage data and define "*Exposure*" as the number of mortgages with a down payment of around 5 percent issued in the district between 2005 and 2007 scaled by the total of number of mortgages issued in the district over that period.[30][31] 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 8.7 percent to 42.1 percent, with a mean exposure of 22.6 percent.

We first examine how 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 2013 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 purchased during the HTB period is close to zero percent, while in high exposure areas it is much higher (with a maximum of around 28 percent).

Figure 5 shows that our measure also accurately predicts time variation. It plots both the total number and share of low-down payment mortgages in low and high exposure areas over the period 2010-2016. Both the number and share 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.

Finally, we include a regression version of Figure 5 in our Internet Appendix which allows us to control for various confounding factors. Section C of the Internet Appendix outlines the regression model. Figure A.1 in the Internet Appendix shows that the β parameter estimate accurately captures the timing of the program, becoming significant in the last quarter of 2013 and increasing in magnitude for the years 2014 to 2016. These results suggest that relatively more low-down payment mortgages were obtained in high exposure districts during the program. Figure A.1 also shows no evidence of pre-event trends in the years preceding HTB. Taken together, this evidence indicates that our HTB exposure measure adequately captures differences in exposure to the relaxation of the down payment constraint.

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

[31]That is, we consider all "low-down payment mortgages" as defined in Section 4.1. While nowadays mortgages require at least a 5 percent down payment, before the financial crisis mortgages with lower down payments where also accepted.

5.2 Covariates

Our identification strategy compares outcomes in districts with *many* potential low-down payment home buyers versus districts with *few* potential low-down payment home buyers. Thus, our identifying assumption is that home purchases and household consumption would have a similar evolution across all districts in the counterfactual scenario in which no change to the down payment requirement took place.

A potential concern with this identification strategy is that high exposure districts might differ in ways that could independently impact housing market activity and household consumption. Table 2 presents the correlation between our HTB exposure measure and a set of district-level covariates. It shows that exposure is not random. We observe that exposure to HTB 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 the existence of a significant bias of our estimates either upwards or downwards.

We take careful measures to mitigate concerns regarding alternative explanations. First, we include district-level fixed effects in all specifications to control for any time-invariant differences between districts. Second, we include the time-varying variables shown in Table 2 to control for many potential confounding factors. Additionally, we explicitly test for parallel trends in the pre-event period and examine whether the observed difference in trends coincides with the timing of HTB. Finally, we perform within-district tests exploiting heterogeneity within mortgage and buyer-type which allow us to include district-by-time fixed effects. This approach ensures that we eliminate any differences in time-trends at the district level. We note that our analysis allows for differences in the evolution in house sales and household consumption across districts with higher and lower shares of potential low-down payment buyers that are not due to the relaxation of the down payment constraint, as long as these differences are, controlling for other observables, roughly constant over time during our sample period.

6 The Housing Market Response to Relaxing the Down Payment Constraint

6.1 Home Sales

To examine how the relaxation of the down payment requirement initiated by HTB affected home sales, we start by estimating the following panel regression model:

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

where d indexes a district and t is the year. The dependent variable $Y_{d,t}$ is Home Sales$_{d,t}$, which equals the number of homes purchased with a mortgage in a given year and district. Exposure$_d$ is our measure of *ex ante* exposure to the HTB program. $\mathbf{District}_{d,t-1}$ 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 time fixed effects, θ_t, and district fixed effects, δ_d. We cluster the standard errors by district. We estimate the model over the period 2010 to 2016 and the year 2012 is taken to be the base year. We end the sample period in 2016 as by the end of 2016 the MG scheme was deactivated as the market for low-down payment mortgages had been reestablished.

The model outlined by Equation 1 provides a series of coefficient estimates β_s that illustrate the time dynamics of the effect of HTB on home sales. The specification controls for time-varying and time-invariant district-level differences that might impact the demand for houses, as well as unobservable time-varying factors such as changes in economic conditions that impact all districts.

The results are presented in Figure 6. We observe very similar trends in home purchases in the years prior to the start of HTB. A clear divergence of trends emerges in more exposed areas when the policy came into full effect and the down payment constraint was effectively lowered to 5 percent. This divergence in trends persisted throughout the entire HTB period. The pattern thus corresponds exactly with the timing of the program. These findings indicate that the loosening of the down payment constraint initiated by HTB had a positive impact on the number of homes purchased.

To further explore the validity of this finding, we examine the drivers of this effect. To ease comparison across specifications we estimate a difference-in-differences version of Equation 1 and compare home sales in high versus low exposure areas in the pre-HTB period to the post-HTB period:

$$\begin{aligned} Y_{d,t} = \quad & \beta_1 \text{Pre}_t \times \text{Exposure}_d + \beta_2 \text{Post}_t \times \text{Exposure}_d \\ & + \boldsymbol{\gamma} \text{District}_{d,t-1} + \delta_d + \theta_t + u_{d,t} \end{aligned} \tag{2}$$

where d indexes a district, t is the year. The dependent variable $Y_{d,t}$ is Home $\text{Sales}_{d,t}$, which equals the number of homes purchased with a mortgage in a given year and district. Pre_t is a dummy variable equal to 1 for the period 2010 to 2011, and zero otherwise. Post_t is a dummy variable equal to 1 for the period 2013 to 2016, and zero otherwise. The model is estimated over the period 2010 to 2016, where 2012 is the base year. The other variables and model specifications are the same as in Equation 1.

The results are presented in the first column of Table 3. In line with the results presented in Figure 6, we find a positive and highly significant effect of exposure on home sales in the post-event period. The economic significance is substantial: home sales are 4.4 percent higher per standard deviation of HTB exposure. As a first robustness check, we examine whether these results hold when we exclude the London area. The London housing market has some distinct features compared to those in other parts of the country. For example, international and buy-to-let investors are much more dominant in London. When we exclude London (column 2), we reassuringly see that the estimate for β_2 remains highly significant and similar in value. We also do not find evidence of any pre-event trends in both specifications.

If the observed differential increase in home sales in high exposure districts is a direct consequence of relaxing the down payment constraint, then we should also observe that the vast majority of these home sales are driven by homes purchased with a 5 percent down payment. To test this, we exploit the discrete interest rate jumps that occur at various down payment size thresholds for UK mortgages, as described in Section 3.2. 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).

We replace the dependent variable with Home $\text{Sales}_{d,t,i}$, which equals the number of home purchases within a down payment size category in a given year and district. We then interact the interaction term $\text{Post}_t \times \text{Exposure}_d$ with Down Payment_i, which is a dummy variable for the different down payment buckets. We further expand the model by including down payment bucket fixed effects and the various double interactions. This allows us to examine if the rise in housing market activity is indeed driven by homes purchased with a low-down payment mortgage.

In addition to 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 include district-by-time fixed effects and thus to control for all time-(in)variant differences across districts. In other words, we isolate the impact of relaxing the down payment constraint purely from within-district heterogeneity. This removes many confounding factors 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.

In column 3, we estimate the model but keep β_2 constant across the different buckets. This captures the average effect of relaxing the down payment constraint on home sales with different down payment sizes. Once more, the effect is positive and significant. In column 4 we allow β_2 to vary over the different down payment size categories. The triple interaction term for homes purchased with a 5 percent down payment has by far the largest positive and significant coefficient estimate. These results show that the increase in home sales in more HTB exposed districts is primarily driven by homes purchased with a low-down payment. The triple interaction term for homes purchased with a down payment of 10 percent is also positive and significant, but the estimate is significantly smaller in magnitude relative to the 5 percent down payment term. This likely reflects the fact that some mortgages bought under the MG or EL scheme had a somewhat larger down payment than the minimum of 5 percent (Benetton et al., 2021). Importantly, the results are not particularly affected by including district-by-time fixed effects (column 5), reducing concerns that the patterns we document are driven by differential district-trends.

Our estimates capture the local general equilibrium housing market response to a relaxation of the down payment constraint. The effects that we estimate are the sum of a direct effect of homes purchased by liquidity constrained households who were able to purchase a home with only a 5 percent down payment and an indirect effect of the mortgage market intervention affecting the ability of other households in the same district to purchase a home. For example, an increase in housing market activity can lead to more demand for certain services (e.g. plumbers or contractors) which might induce these service providers to purchase a house as well. The fact that the differential effect is primarily driven by homes purchased with a low-down payment suggests that the direct effect dominates.

6.2 Heterogeneous Effects Across Households

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. UK lenders charge a significant interest rate spread on low-down payment mortgages (see Figure A.2 in the Internet 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 have 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 et al., 1996).

To examine whether relaxing the minimum down payment requirement to 5 percent had a more pronounced impact on young and first-time buyers, we extend Equation 2 and now differentiate between homes purchased by different types of buyers. The dependent variable is replaced with Home $\text{Sales}_{d,t,b}$, which equals the number of home purchases by different buyer types in a given year and district. We first differentiate between first-time buyers and home movers. Second, we differentiate between young and old buyers, where young buyers are buyers that are between 20 and 39 years-old. We now interact the interaction term $\text{Post}_t \times \text{Exposure}_d$ with Buyer_b, which is a dummy variable for either first-time buyers or younger buyers. While there is overlap between these two buyer-types, the correlation between the two dummy variables is not particularly high at 35 percent. The model further includes buyer-type fixed effects and the various double interactions.

The results presented in Table 4 show that the relaxation of the down payment requirement especially benefited younger households and first-time buyers. In columns 1 and 2 we differentiate between first-time buyers and home movers. The coefficient estimate for the interaction term $\text{Post}_t \times \text{Exposure}_d$ is positive and significant, indicating that both types of buyers show higher increases in home purchases in high exposure areas relative to low exposure areas during the HTB period. However, the impact of relaxing the down payment constraint 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 HTB exposure. However, the effect on younger buyers is around eight times as large as the impact on older buyers. The results are similar when we replace our district and time fixed effects with district-by-time fixed effects (columns 2 and 4), reducing concerns that the patterns we document are driven by differential district-trends.

6.3 House Price Growth

In Section 6.1, we document an increase in home sales associated with a relaxation of the down payment constraint. This increase in housing demand can lead to a rise in house prices if supply is restricted. To examine whether this happened, we estimate a similar panel regression model to that outlined by Equation 2, but where the dependent variable $Y_{d,t}$ is now House Prices$_{d,t}$. House Prices$_{d,t}$ is defined as annual house price growth at the district-level, and this outcome variable is winsorized at the 1st and 99th percentile to remove any outliers.

The results are presented in Table 5. Column 1 shows that house price growth increases annually by 0.3 percentage points per standard deviation of HTB exposure. We also estimate the model for districts in the London area and other districts separately, given that London house prices can have different dynamics compared to house prices across the rest of the UK. House price growth increased by 0.2 percentage points per standard deviation outside of London (column 2). In the London area the impact was more pronounced at 2.0 percentage points per standard deviation (column 3). Overall, we conclude that relaxing the down payment constraint resulted in a marginal increase in house prices, except in the London area. These findings are consistent with Carozzi et al. (2020) who show that responsiveness in housing supply, which is much weaker in the London area, is critical in determining any house price reaction to the EL scheme of HTB.

6.4 Economy-Wide Effects

Next we use the estimates presented in Section 6.1 to estimate the aggregate, economy-wide increase in housing sales that can be attributed to the relaxation of the down payment constraint.[32] To do so, we use an approach similar to that of Berger et al. (2020) and Mian and Sufi (2012), where we treat the district with the minimum HTB exposure as the control group.[33] We calculate for each district the additional homes purchased over the period 2013 to 2016, as implied by the estimate of β_2 from Equation 2 (see column 1 of Table 3). This is done by multiplying the coefficient by each district's HTB exposure minus the control district HTB exposure. We then sum the number of

[32]This number does not represent an aggregate general-equilibrium effect as due to our empirical design we cannot capture any economy-wide indirect effects of the intervention.

[33]Our identifying assumption is thus that districts with very low potential low-down payment buyers were not affected by the relaxation of the down payment constraint,

home sales for all districts to get the total aggregate effect in a given year.[34]

We estimate that approximately 217,100 homes were purchased due to the relaxation of the down payment constraint. This implies that lowering the minimum down payment to 5 percent increased home sales by 9.8 percent during the HTB period.[35] This number is slightly larger than the approximately 200,000 HTB mortgages issued between the start of the program and the end of 2016. Two factors can explain this difference. First, during the program years some banks started to provide low-down payment mortgages outside the two program schemes. Second, local demand effects can have stimulated a general demand for housing as well.[36]

Of the 217,100 additional homes purchased, we estimate that first-time buyers accounted for 78 percent of the increase, while younger households (both first-time buyers as well as home movers) were responsible for 91 percent. 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.

6.5 Robustness Exercises

In Section 6.1, we present evidence that our first key finding is robust to the exclusion of the London area and that our findings are robust to the inclusion of district-time fixed effects. This reduces the concern that time-varying, district-specific shocks are correlated with our exposure measure. Furthermore, the absence of pre-event trends suggests that low-exposure areas can serve as a counterfactual for high-exposure areas. And the fact that the timing of the response exactly coincides with the mortgage market intervention further reduces concerns about omitted variables as alternative explanations need to be in line with the precise pattern we document.

Nevertheless, in this section we present results of several additional robustness tests. We use the specification in column 1 of Table 3 as our benchmark. Table A.5 in our Internet

[34]For a given year, this is equivalent to: $\sum_d (\beta_2 \times (\text{ Exposure}_d - \text{Exposure}_{min}))$, where d indexes a district.

[35]As highlighted by Berger et al. (2020), this is a lower-bound estimate. If we treat zero-exposure as the control group and so assume that the minimum HTB exposure group also responds to the program, our estimate becomes 351,200 home purchases, which is equivalent to a 16.8 percent increase.

[36]Furthermore, the number of actual low-down payment mortgages also includes home purchased via an intensive margin effect: households who decide to use the same down payment to now purchase a more expensive house (i.e. switch from a low LTV to high LTV mortgage). Such purchases would not lead to an actual increase in home sales.

Appendix presents the results. The estimates are robust to using a weighted regression (with the parameter becoming slightly larger) and to multi-clustering the standard errors by district and time instead of district only (columns 2 and 3). The year 2013 is only partly a program year so one could argue that it should not be part of the post period. When we drop this year from the sample (column 4) the estimate of β_2, as expected, becomes slightly larger and remains highly significant at the one percent level. Importantly, the parallel trends assumption test yields insignificant coefficients across specifications.

A potential concern is that our findings are confounded by other simultaneous policies designed to impact the housing market. For this to affect our estimates, such policies need to coincide with the timing of our shock. A potentially relevant UK program is the 15%-limit on the proportion of new mortgages with an LTI of 4.5 or higher imposed on lenders, which was introduced in 2014. Peydro et al. (2020) find that this policy induced a contraction in mortgage credit to low-income borrowers in areas more exposed to constrained lenders. If exposure to constrained lenders is correlated with our HTB exposure measure our results could be downward biased. To examine whether this is the case, we adapt the exposure measure of Peydro et al. (2020) to correspond with our district-level analysis, and interact the post dummy with this "LTI-constrained" exposure variable.[37] The results in column 5 show that this does not affect the estimate of β_2 materially. This is not so surprising as most home buyers that purchase their home with a low-down payment mortgage are not constrained by the LTI. In fact, over the period from 2013 to 2016 the average LTI of low-down payment mortgages was 3.4 and 96 per cent of those mortgages had an LTI of less than 4.5.

Our empirical design relies on the fact that no spillovers exist between treated and control areas as a result of endogenous moves. If people move from a low to a high exposure area as result of HTB, 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.[38] While endogenous moves are more likely in the London

[37] Specifically, we first recalculate a similar constrained lender exposure measure to that of Peydro et al. (2020), which is a dummy variable equal to 1 if the lender made 15 percent or more mortgages with an LTI of 4.5 or higher in 2012. We then compute the district-level "LTI-constrained" exposure measure as the proportion of mortgages made by a constrained lender in 2012.

[38] 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 transactions in high-exposure areas induced by relaxing the down payment constraint trigger additional transactions in low-exposure areas.

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 et al., 2019). In Section D of our Internet Appendix, we test this more formally and demonstrate that, except within the London area, there was no change in inward migration to high exposure districts after the policy change. Reassuringly all our results hold when we exclude the London area from our estimates.

7 The Consumption Response to Relaxing the Down Payment Constraint

In this section, we examine whether loosening the down payment constraint has macroeconomic implications that extend beyond the housing market. We are particularly interested in whether the HTB mortgage market intervention affected household consumption. The extant literature provides us with several potential mechanisms through which household consumption can be affected when the down payment constraint is relaxed. They can be divided in two categories: the consumption response of the new home buyers themselves and the consumption response of other households in the same district.

Household consumption of the new home buyers can react in several ways. First, 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 and appliances. As a result, households tend to increase their home-related expenditures following the purchase of a new home (Best and Kleven, 2017; Benmelech et al., 2017). Second, (non-home related) consumption can rise if home buyers experience an increase in discretionary income. This happens when the mortgage payments of the newly bought house are lower than the combined cost of saving for the down payment and rental or mortgage payments. The impact on consumption will be particularly large for liquidity constrained households who have a high propensity to consume out of an income shock (see, e.g., Johnson et al., 2006; Agarwal et al., 2007; Kaplan and Violante, 2014; Misra and Surico, 2014; Baugh et al., 2021). In line with this, Engelhardt (1996) documents that households reduce food consumption when they are about to buy a home and increase it back to long-run levels afterwards. This finding suggests that households might indeed become less constrained after a home purchase, leading them to increase consumption.

While the channels above predict a positive consumption effect, new home buyers might reduce consumption if they have an aversion to high leverage (see, e.g., Caetano et al., 2019). In line with this, Sodini et al. (2016), studying privatizations of municipal apartment 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 and these households did not have to save for a down payment prior to becoming a homeowner. Still, those households able to purchase a home due to the relaxation of the down payment constraint might have a desire to keep consumption low in order to quickly reduce their debt.

In addition to the direct impact of loosening the down payment constraint on the consumption of home buyers, the consumption of other households in the same district can be affected due to local demand effects. A flurry of activity in the housing market, possibly in combination with a rise in construction, can spur regional economic activity that can feed back into consumption, Furthermore, the previously documented increase in house prices in more exposed regions can impact household consumption due to a traditional wealth effect (see, e.g., Benjamin et al., 2004; Bostic et al., 2009; Case et al., 2005), a home equity extraction effect (see, e.g., Mian and Sufi, 2009; Mian and Sufi, 2011; Best et al., 2020) and a relaxation of borrowing constraints (Campbell and Cocco, 2007).

We next empirically examine if and how the relaxation of the down payment constraint initiated by HTB affected household consumption. We focus on two sets of consumption data: household survey data and administrative data on car purchases.

7.1 Household Survey Data and Pseudo Panel Construction

We start by analyzing 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, e.g., Campbell and Cocco, 2007; Cloyne et al., 2020). It has the big advantage that it tracks consumption spending in a variety of categories. These survey data present some well-documented empirical challenges however. 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 et al. (1985) and Deaton (1985). This approach 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 10-year birth year 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 10 regional cohorts that are grouped according to their HTB exposure; districts included in the first (10th) exposure-region are in the first (10th) decile of HTB exposure.

In total, there are 60 region-birth year cohorts and we track how variables associated with these cohorts evolve each year from 2010 to 2016. As described in detail in Section 4.2 we categorize weekly expenditures into three different household spending measures: "*Home-related Expenditures*", "*Non-durable Consumption*", and "*Durable Expenditures*". 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. All told, our LCFS pseudo-panel provides yearly information at the expense of a more granular regional coverage. Section E in our Internet Appendix 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, mortgage payments and rental payments. We take the 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 region-birth year cohort-level for each year. We provide a detailed description of these data and the variable definitions in Section A of the Internet Appendix.

7.2 Household Consumption

To examine how household consumption responds to relaxing the down payment constraint, we estimate the following pseudo-panel regression model:

$$\begin{aligned}\text{Consumption}_{r,c,t} = \; & \beta_1 \text{Pre}_t \times \text{Exposure}_r + \beta_2 \text{Post}_t \times \text{Exposure}_r + \boldsymbol{\gamma} \text{Cohort}_{r,c,t} \\ & + \lambda \text{House Prices}_{r,t-1} + \delta_r + \theta_t + \gamma_c + u_{r,c,t}\end{aligned} \tag{3}$$

where r indexes a exposure-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 expenditures, non-durable consumption or durable expenditures. Exposure_r is our measure of *ex ante* (regional) HTB exposure in exposure-region r, which equals the average exposure across the districts included in each exposure-regions. Pre_t is a dummy variable equal to 1 for the period 2010 to 2011, and zero otherwise. Post_t is a dummy variable equal to 1 for the period 2013 to 2016, and zero otherwise. $\mathbf{Cohort}_{r,c,t}$ is the vector of time-varying cohort-level (that is, the 60 region-birth year group combinations) controls as defined above. We therefore 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 house prices 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 the down payment constraint that is not driven by house price changes. To this end, we include the variable $\text{House Prices}_{r,t-1}$, 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. We cluster the standard errors by region-birth year cohort. The model is estimated over the period 2010 to 2016 and 2012 is the base year.

The results in Table 6 show that more HTB exposed regions not only experienced a relative increase in housing market activity but also a relative increase in household consumption. After the relaxation of the down payment requirement, real total household consumption increased by 3.8 percent per standard deviation in HTB exposure (column 1). Based on the average total household consumption from the LCFS during the exposure period, this is equivalent to an increase in annual consumption of £761, an amount representing 2.5 percent of the average after-tax household income. Reassuringly, we do not detect differential trends in the pre-period. The findings in column 2 show that these results remain excluding the London area, with the coefficient even slightly higher. These effects is independent of consumption responses to changes in regional house prices.

To further understand what drives this increase, 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 et al., 2017), we find that home-related expenditures increased 5.7 percent per standard deviation in HTB exposure (column 2). Interestingly, we find that non-durable consumption unrelated to the home also rose by 4.0 percent per standard deviation in HTB exposure (column 3). Note our measure of non-durable consumption is a broad one that includes some semi-durable consumption and comprises the majority of total consumption (70 percent). We do not find a differential effect for durable expenditures (column 4).

In Section 6.2 we demonstrated that relaxing the down payment constraint especially induced younger households to purchase a home with a low-down payment mortgage. Therefore we next examine whether consumption of younger households also reacted more. To perform our analysis, we extend Equation 3 and include a triple interaction term with $\text{Post}_t \times \text{Exposure}_r$ and Younger_c, which 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. The model further includes the relevant double interactions.

The results are presented in Table 7. Focusing on home-related expenditures (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 high-exposure districts experienced a relative increase in home-related expenditures by both younger and older households. When we focus on consumption unrelated to the home (columns 3 and 4), both the interaction term $\text{Post}_t \times \text{Exposure}_r$ and the triple interaction term $\text{Post}_t \times \text{Exposure}_r \times \text{Younger}_c$ are positive and significant for non-durable consumption. This suggests that in high exposure districts both younger and older households experienced a relative increase in non-durable consumption, but this effect was larger for the young. Both double and triple interactions are insignificant for durable expenditures (columns 5 and 6), in line with the results in Table 6.

Table 7 shows the results are largely unaffected by replacing the region and time fixed effects with region-by-time fixed effects (columns 2, 4 and 6). This significantly reduces concerns that the patterns we document are driven by time-varying regional differences not captured by our control variables. In a further robustness test, we revert back to our original, more granular district-level and conduct a cross-sectional regression analysis where the dependent variable equals the change in average consumption between the three years before HTB and the four years that HTB was active. Reassuringly, the results again show that both home-related and non-durable consumption experience a relative increase in high-exposure districts (see Section E of the Internet Appendix).

7.3 Car Sales

We further explore to what extent relaxing the down payment constraint affected household spending by studying the impact on new car purchases, a key durable consumption good that is not housing-related. 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 all purchases of privately owned new cars.

This novel dataset is available at the granular district-level allowing us to estimate a panel regression model similar to Equation 2. The outcome variable $Y_{d,t}$ is now Car $\text{Sales}_{d,t}$, which equals the number of new private car registrations for a given year and district. As in Equation 2, we include district and time fixed effects, and control for changes in house prices and other macroeconomic and housing market conditions at the district-level.

Consistent with the findings in Section 7.2, we document a relative increase in car sales in high-exposure districts after the down payment constraint was relaxed. The results in Table 8 column 1 show that car sales increase by 2.4 percent per standard deviation of HTB exposure. This result is significant at the 1 percent level. Again, we do not detect any pre-event trends and our result remain when we exclude the London area from our regressions (column 2).

How can we reconcile our (insignificant) results for durable goods consumption in Section 7.2 with our (significant) findings about car sales? First, new car purchases represent only around 18 per cent of durable expenditures and 2 per cent of total household consumption.[39] Second, in the UK around 90 percent of new cars are purchased with some form of unsecured consumer credit Finance and Leasing Association (2022), rendering monthly payments relatively small. It could therefore be the case that relaxing the down payment constraint 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 3, where the outcome variable $\text{Consumption}_{r,c,t}$ is now loan-financed car purchases or outright car purchases. The results in Table 8 (columns 3 to 5) show that loan-financed

[39] These statistics are calculated using the LCFS.

car purchases increased significantly in high compared to low exposure areas during the period HTB was in effect, but there was no significant change in outright car purchases.

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, assuming that car financing terms did not loosen more in high exposure areas during the program period, the results on car sales line up nicely with the results in Section 7.2.

Our findings show that interventions in the mortgage market can have important local macroeconomic spillover effects. Overall the evidence presented indicates that relaxing the down payment constraint not only stimulated housing market activity but also led to rise in household consumption in more exposed regions. Our finding that also non-durable consumption and car sales experienced a relative increase in more affected districts (and we control for house price growth in all specifications), indicates that the impact goes beyond the previously documented home purchase and housing wealth channels.

7.4 Economy-Wide Effects

Similar to the estimates presented in Section 6.1, the estimates presented in Sections 7.2 and 7.3 capture the local general equilibrium consumption response to a relaxation of the down payment constraint. That is, our estimates capture the direct consumption effect of new home buyers as well as an indirect effect from other households in the same district benefiting from the associated increase in local demand. Before examining in more detail the mechanisms behind this effect, we first provide some estimates of the economy-wide increase in consumption that can be directly attributed to the relaxation of the down payment constraint.[40]

First, we calculate the economy-wide effect on household consumption. We take the exposure of the minimum decile exposure-region as the control group and use the various estimates of β_2 from Equation 3 (see Table 6 columns 1, 3 and 4). Under the assumption that the region with the minimum HTB exposure is the legitimate control group, we

[40] Again, this number does not represent an aggregate general-equilibrium effect as due to our empirical design we cannot capture any economy-wide indirect effects of the intervention.

estimate that lowering the down payment requirement to 5 percent increases real total household consumption by 5.9 percent on average. Similarly, we estimate that real non-durable consumption (excluding home-related) and home-related expenditures increase by 6.1 percent and 8.7 percent, respectively. The 5.9 percent increase in total household consumption is equivalent to an annual increase of £1,162, or 3.8 percent of the average after-tax household income, based on the average total household consumption from the LCFS during the exposure period.

Next, we do a similar exercise for car sales, treating the district with the minimum HTB exposure as the control group (as we did in Section 6.4). We calculate for each district the additional cars purchased over the period 2013 to 2016, as implied by the estimate of β_2 in Table 8 column 1. This is done my multiplying the coefficient by each district's HTB exposure minus the control district HTB exposure. We then sum the number of car sales for all districts to get the total aggregate effect. We estimate that approximately 221,081 new cars were purchased due to a relaxation of the down payment constraint that would not have been purchased otherwise. This implies an increase of 5.2 percent.

7.5 Mechanisms

As a final exercise, we explore what factors can explain our consumption findings. Ideally, one would like to determine the relative contribution of the direct consumption effect of new home buyers versus the indirect consumption effect due to an increase in local demand. Testing for the presence of the direct channel requires panel data which capture consumption of households prior to purchasing their home and in the years after the purchase. In addition, given that our identification relies on exploiting geographic variation in exposure to the program, one needs to have enough observations both over time and across regions to provide meaningful estimates. Unfortunately, the LCFS due to its cross-sectional nature does not permit such an analysis. Additionally, our car sales data are anonymous and therefore we cannot match them to our mortgage market data in order to test whether new home buyers were disproportionately responsible for the relative increase in car sales in the high-exposure districts.

However, we are able to explore whether increases in local demand could be (at least partially) behind the increase in consumption that we document. We start by examining the impact on employment. We again estimate a panel regression model similar to Equation 2, but the outcome variable $Y_{d,t}$ is now Employment$_{d,t}$, which equals total number of employees for all firms in a given year and district. The results in Table 9 column 1 indicate a relative increase in total employment in more exposed regions. Again we do not find any evidence of pre-event trends.

If the increase in employment is due to a rise in local demand, this should be driven by an increase in non-tradable employment and not tradable employment. We test these predictions in columns 2 to 4 of Table 9. We use two measures of non-tradable employment. The first one is a broad measure based on the approach of Burstein et al. (2020), and covers employment by all firms in the service-producing industries. The second one is a narrow measure based on the approach of Mian and Sufi (2014), and covers employment only in the retail sector and restaurants. We observe that non-tradable employment experienced a relative increase in high-exposure districts, while we do not detect a differential effect for tradable employment. Overall, the results suggest that the increase in housing market activity generated an increase in local demand.

Next we examine whether there is any relative increase in housing construction in more exposed regions. When more houses are built this can also have a positive impact on local demand. Using the "homes constructed" measure of Carozzi et al. (2020), which captures the number of new homes sold in the next year, we find a weakly significant and positive effect (column 5). However, when we use an alternative "home starts" measure, which captures the number of homes for which building work commenced, the impact is insignificant (column 6). We therefore conclude that an increase in construction does not appear to be the key driver of the consumption response we document.

The insignificant result for home starts (column 6) is *prima facie* surprising. Carozzi et al. (2020) and the media document that homebuilder profits have significantly increased due to HTB.[41] We therefore investigate this result by estimating a panel regression model similar to Equation 2 for the the outcome variable "home starts", but we now include the dummy variables Pre_t and Post_t in the specification by excluding the time fixed effects θ_t. While we do not find a significant effect for the interaction term $\text{Post}_t \times \text{Exposure}_d$, we do find a significant effect for the Post_t dummy variable.[42] That is, home starts significantly increased once HTB was introduced, but they did not increase differentially in high-exposure districts. Instead, home starts increased more in districts with higher rental yields and house prices, as well as in districts with lower unemployment rates. This result appears rational from the perspective of profit-maximizing homebuilders.

[41] See, e.g., Times (2019)

[42] Results are available upon request.

As a final exercise we revert back to the LCFS data and examine whether household income has increased more in higher exposed districts after the down payment constraint was relaxed. Estimating a regression model similar to Equation 3 but using as outcome variable $\text{Income}_{r,c,t}$, which is gross or net (of paid taxes) household income. The results in columns 7 and 8 show that, consistent with our findings for employment, that both gross and net household income experienced a relative increase in high exposure regions. Again, we do not find any evidence of pre-event trends.

To summarize, the findings above suggest that at least part of the consumption response we document was driven by a rise in local demand. The apparent existence of a feedback loop through a rise in local demand can also explain why the consumption response can be quite large.

7.6 Robustness Exercises

In Section 7.2 and Section 7.3 we show that our key findings are robust to the exclusion of the London area for household consumption and new car sales, respectively. We also present evidence in Table 7 that our findings are robust to the inclusion of region-by-time fixed effects, reducing the concern that time-varying, region-specific shocks are correlated with our exposure measure.

The Internet Appendix includes several additional robustness checks for our consumption findings in Tables A.8 and A.9. We document that the household consumption results are robust to weighting the data with the annual probability weights provided for each survey respondent. Similarly, we find that the new car sales results are robust to a weighted regression specification, based on 2012 car sales. Further, our household consumption and new car sales estimates are robust to multi-clustering the standard errors, as well as when we exclude the year 2013 from our estimation.

8 Concluding Remarks

In this paper we examine how a mortgage market intervention aimed at relaxing the down payment constraint affects the housing market, and whether such policies spillover to the real economy. We exploit a large-scale policy intervention in the UK called Help-to-Buy, which prompted a significant relaxation of the minimum down payment requirement from 10 to 5 percent. In other words, the policy effectively lowered the LTV limit.

The intervention proved effective at spurring home sales, driven primarily by young and first-time buyers. House prices reacted as well, but outside the London area only marginally. The housing market stimulus had important feedback effects to the real economy: more exposed regions experienced a rise in home-related expenditures, non-durable consumption and loan-financed car purchases. This appears to be, at least partly, driven by local demand effects as we document a simultaneous increase in non-tradable employment, household income, and, to a lesser extent, construction.

Beyond furthering our understanding of the mechanisms that connect developments in the mortgage market and household consumption, our results are directly relevant to policymakers. Our finding that relaxing the down payment constraint can have positive spillover effects to the real economy is a relevant additional input in the cost-benefit analysis of policymakers deciding on implementing such measures. This benefit goes beyond the positive externalities that homeownership yields (for a review, see Glaeser and Shapiro, 2003).

However, the policy could have additional (long-term) costs as well, which we do not consider. First, due to the intervention more households have high-LTV mortgages. This can make households and the banking system more vulnerable to a sharp economic downturn. Policymakers thus might face an important trade-off: stimulating homeownership and the economy versus protecting households and the banking system against future boom-bust cycles. The rationale behind introducing macroprudential policies aimed at curbing household leverage during credit booms is exactly to prevent costly boom-bust cycles from occurring. While the policy intervention that we examine could potentially increase systemic vulnerabilities, this does not necessarily have to be the case. For example, Berger et al. (2020) show that buyers induced to purchase a home via the First-Time Homebuyer Credit program in the US were not more likely to default than previous or subsequent cohorts of buyers.

Additionally, the consumption-stimulus effect that we document might only be short-term at the expense of more consumption volatility in the long-term. High debt burdens tend to drive aggregate demand down (Mian et al., 2021) and some credit stimulus policies have been shown to increase consumption volatility and to lower average consumption over the cycle (Garber et al., 2021). Therefore, a credit expansion due to a relaxation of the down payment constraint might boost consumption today, but reduce it going forward as households react to higher debt burdens. In our context, it will matter how much of the consumption response we document is driven by indebted households (e.g.

new mortgage holders) and how much it is the result of a general rise in economic activity. While our analysis is not able to fully quantify the relative importance of both effects, our findings that non-tradable employment and household income also rise suggests that the consumption response we document was not solely driven by newly indebted households and might therefore be more long-lived. A full examination of the trade-offs policy makers face is beyond the scope of this paper but presents an exciting avenue for future research.

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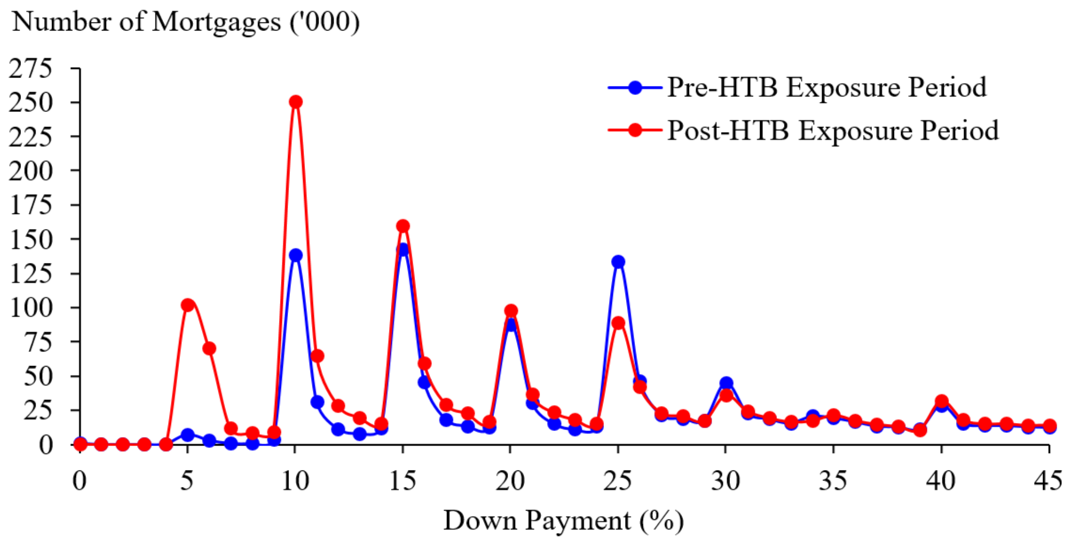
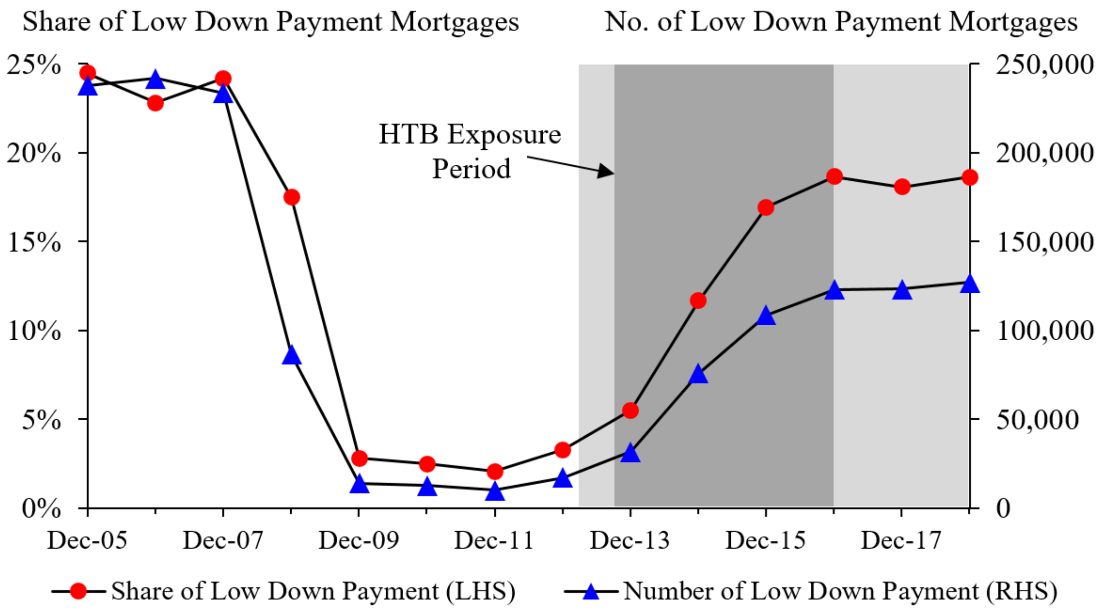
Figure 1: **Down Payment Distribution Among Mortgages**



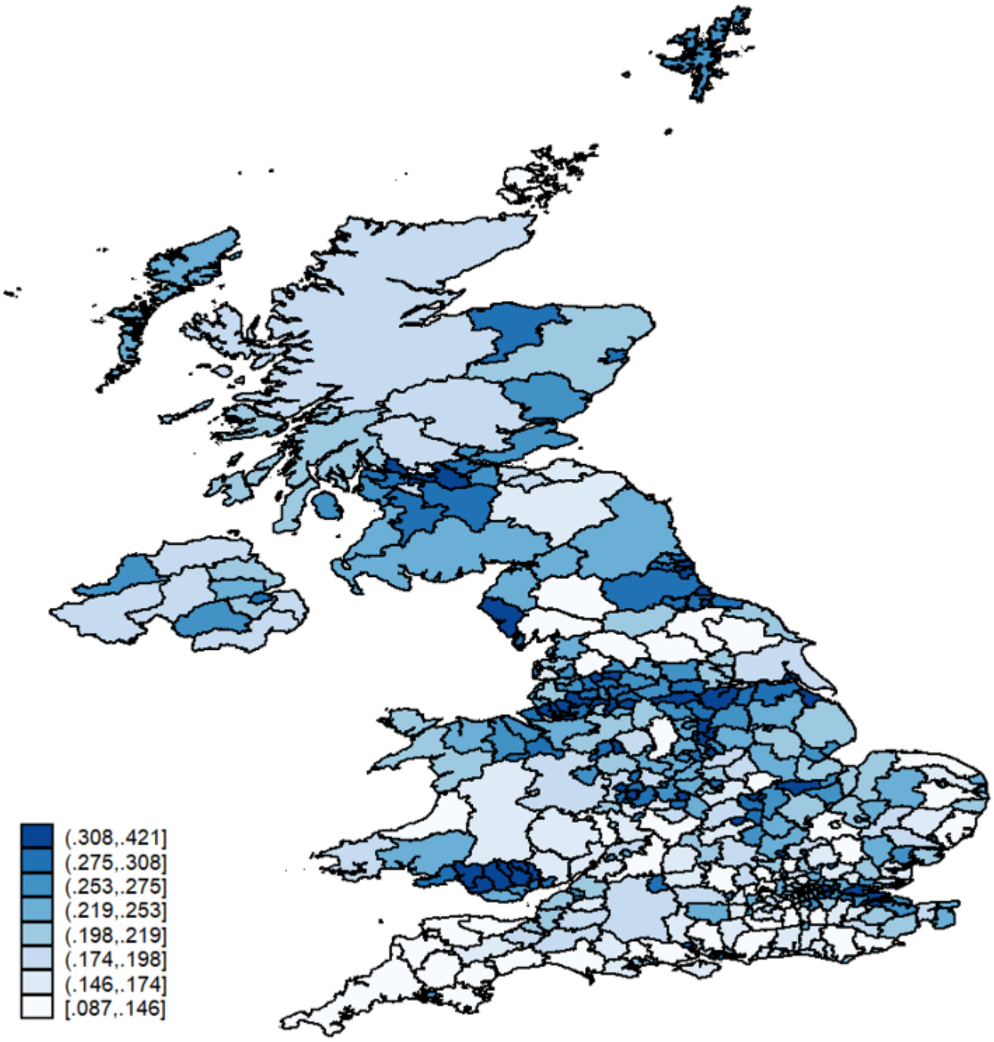
The figure shows the aggregate number of mortgages by down payment size in the pre-HTB and post-HTB exposure periods. The pre-HTB and post-HTB exposure periods cover 2010 to 2012 and 2013 to 2016, respectively.

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



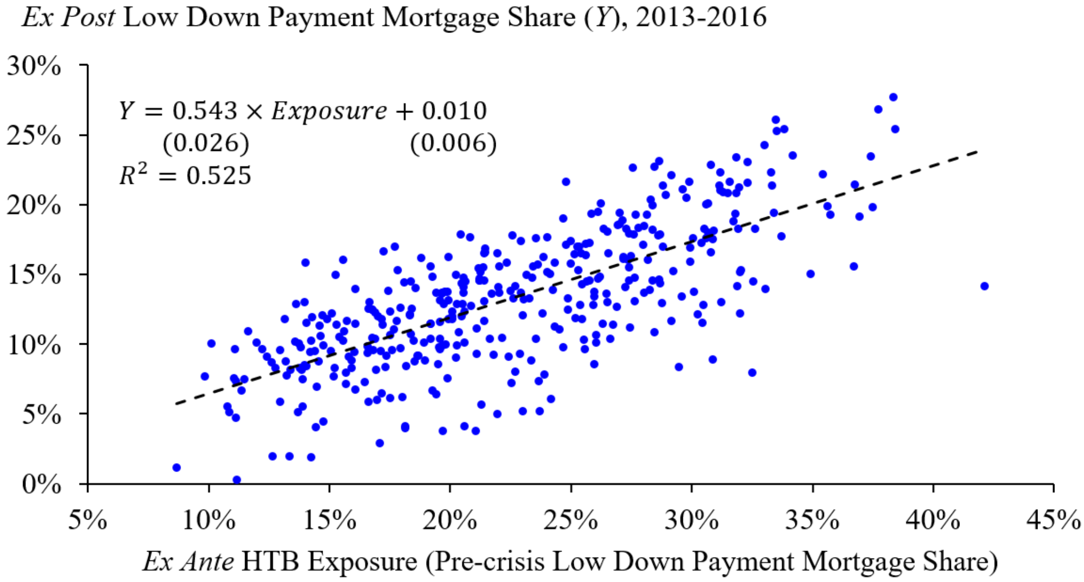
The figure shows the share and number of low-down payment mortgages before and during the HTB exposure period. The dark-shaded area indicates the period that both the EL and MG schemes are in effect (October 2013 to December 2016). The light-shaded area indicates the period that only the EL scheme is 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**



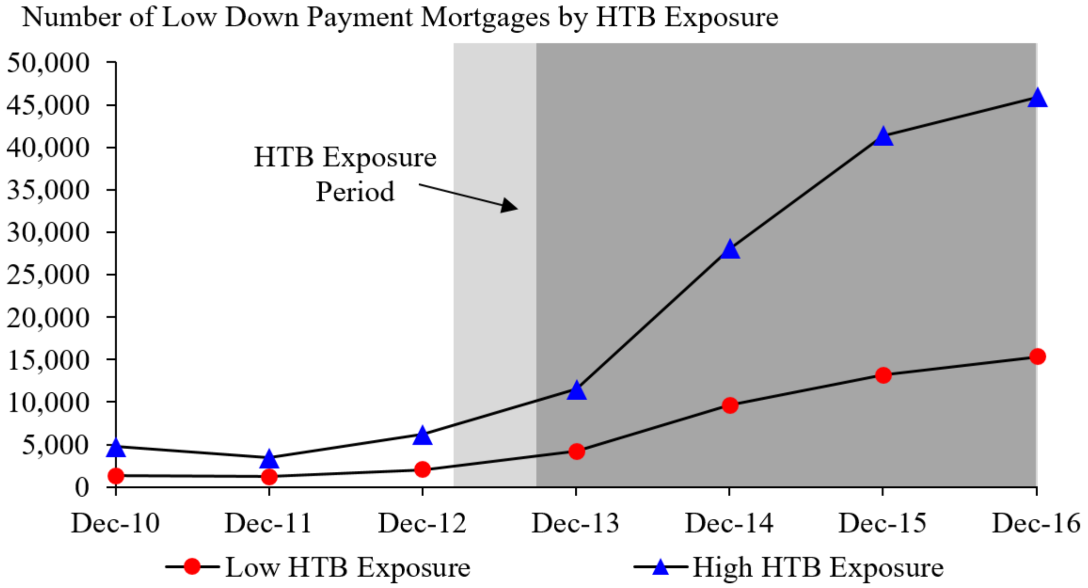
The figure shades local authority districts across the UK by their HTB Exposure. HTB Exposure equals the number of low-down payment mortgages in a district in the period 2005-2007 divided by the total number of mortgages in 2005-2007. Districts with a darker shading have higher exposure.

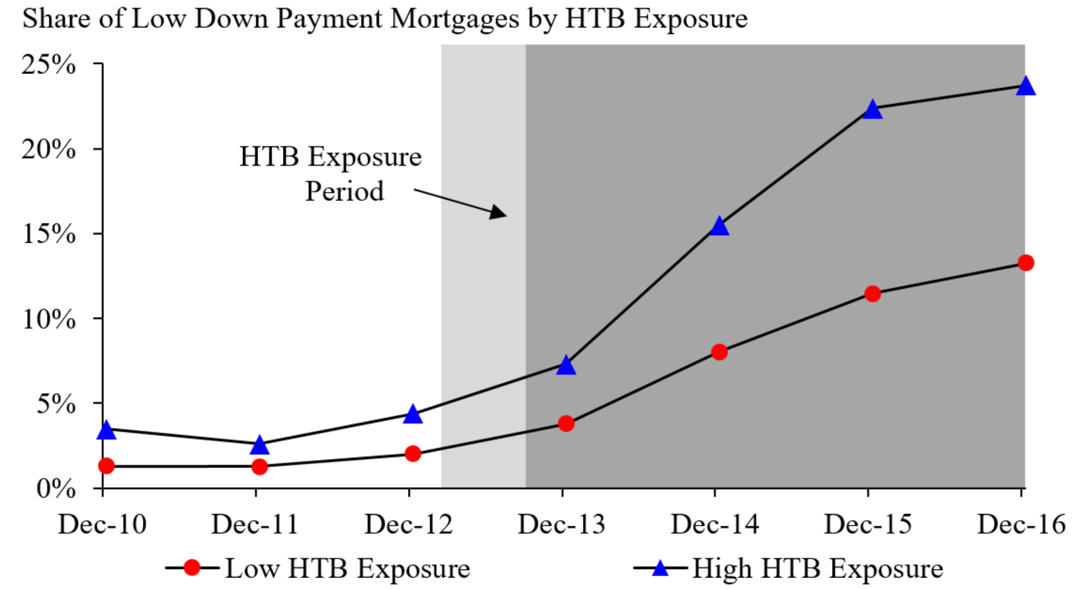
Figure 4: **Help-to-Buy Exposure and Ex Post Low-Down Payment Mortgages**



The figure is a scatter plot, which shows the relationship between our measure of HTB exposure and the actual share of low-down payment mortgages (Y) over the program period (2013 to 2016) at the district level. The dashed line represents the regression of Y on *Exposure*, and we report the corresponding equation and R^2 in the figure. 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.

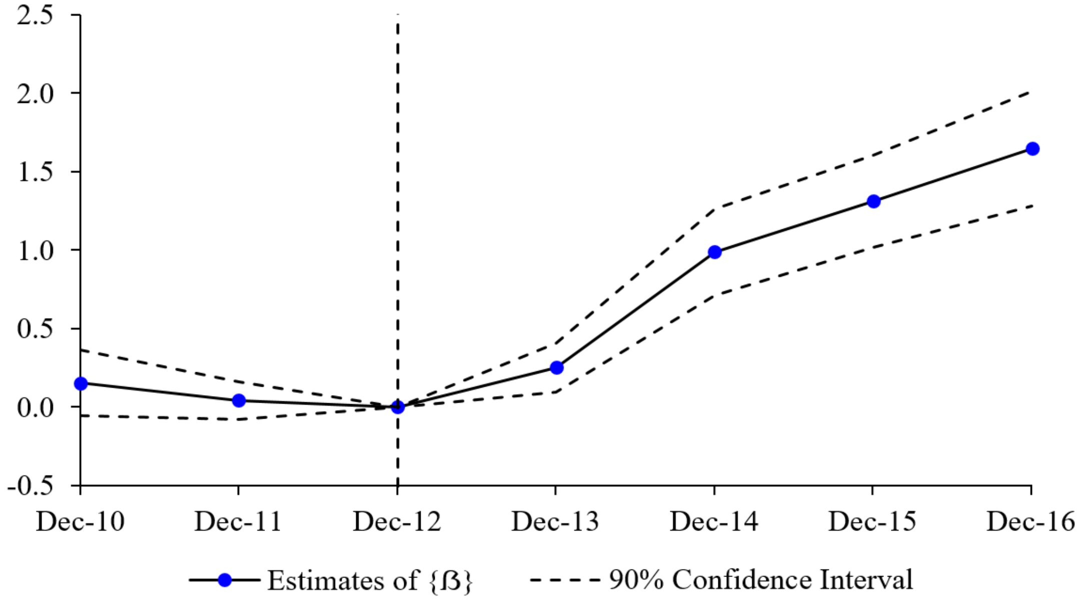
Figure 5: **Evolution Low-Down Payment Mortgages, Low vs High Exposure**





The top panel of the figure shows the aggregate number of low-down payment mortgages over the period 2010 to 2016 for low and high HTB exposure districts. 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 Home Sales



The figure presents estimates of β from Equation 1 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.

Table 1: **Summary Statistics**

	Pre Help-to-Buy			Post Help-to-Buy		
Variable Name (Unit)	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
Panel A: Loan-level Variable						
Low-Down Payment (0/1)	0.02	0	0.16	0.16	0	0.36
Panel B: District-level Variables						
Exposure (%)	22.55	21.94	6.63	22.67	22.01	6.62
Home Sales ('000)	1.27	1.04	0.80	1.61	1.33	1.05
First-time Buyer Sales ('000)	0.49	0.36	0.40	0.74	0.55	0.58
Home Mover Sales ('000)	0.78	0.68	0.45	0.88	0.76	0.52
Younger Buyer Sales ('000)	0.82	0.64	0.58	1.10	0.87	0.79
Older Buyer Sales ('000)	0.45	0.40	0.24	0.51	0.45	0.29
House Price Growth (%)	-1.46	-2.07	4.47	4.11	3.72	4.27
Car Sales ('000)	2.21	1.85	1.43	2.95	2.42	1.95
Total Employment ('000)	73.02	54.27	65.19	77.88	57.64	71.83
Strictly Non-tradable Employment ('000)	11.64	9.30	9.78	12.51	9.69	10.79
Non-tradable Employment ('000)	61.80	43.84	60.29	66.37	47.60	66.82
Tradable Employment ('000)	7.52	6.01	5.62	7.83	6.18	6.03
Homes Constructed ('000)	0.18	0.14	0.16	0.29	0.22	0.25
Home Starts ('000)	0.33	0.25	0.28	0.44	0.34	0.37
Unemployment Rate (%)	7.24	6.86	2.39	5.43	5.03	2.11
Median Weekly Income (£)	445.07	428.04	76.63	432.96	418.55	65.09
Average Weekly Rent (£)	92.92	88.48	18.02	101.26	96.95	19.41
Average House Price (£'000)	203.90	186.46	92.41	219.41	189.09	123.75
Population ('000)	161.40	125.86	108.99	166.87	129.73	113.92
Panel C: Cohort-level Variables						
Total Household Consumption (£, ln)	5.95	5.95	0.22	5.94	5.94	0.22
Home-related Expenditures (£, ln)	3.89	3.91	0.28	3.83	3.85	0.29
Non-durable (excl. Home-related) (£, ln)	5.68	5.70	0.21	5.66	5.65	0.21
Durable (excl. Home-related) (£, ln)	0.98	1.02	0.67	0.97	1.05	0.69
Gross Household Income (£, ln)	6.50	6.55	0.28	6.52	6.55	0.28
Net Household Income (£, ln)	6.35	6.37	0.24	6.37	6.39	0.24

The table presents summary statistics for the key variables used in our empirical analyses. Summary statistics are reported for both the pre HTB period (from 2010 to 2012) and the post HTB period (from 2013 to 2016). There are 379 districts across the UK included in our sample. In the pre HTB period, there are 1,070 district-level observations and 165 cohort-year observations. In the post HTB period, there are 1,510 district-level observations and 235 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)$_{d,t-1}$	0.120***	0.446	2,581
		(0.005)		
(2)	ln(Median Weekly Income)$_{d,t-1}$	-0.127***	0.088	2,581
		(0.019)		
(3)	ln(Average Weekly Rent)$_{d,t-1}$	-0.077***	0.046	2,581
		(0.017)		
(4)	ln(Average House Price)$_{d,t-1}$	-0.117***	0.498	2,581
		(0.006)		
(5)	ln(Population)$_{d,t-1}$	0.038***	0.102	2,581
		(0.006)		

Each row in this table presents bivariate regressions of HTB exposure on the 5 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**

	All Home Sales		Home Sales by Down Payment Size		
	All Districts	Excl. London	All Districts	All Districts	All Districts
	(1)	(2)	(3)	(4)	(5)
$\text{Pre}_t \times \text{Exposure}_d$	0.109	0.051	0.020	0.019	
	(0.089)	(0.077)	(0.015)	(0.015)	
$\text{Post}_t \times \text{Exposure}_d$	1.027***	0.977***	0.172***	-0.020	
	(0.149)	(0.144)	(0.026)	(0.047)	
$\text{Post}_t \times \text{Exposure}_d \times \text{Down Payment}_{25\%}$				-0.141***	-0.147***
				(0.053)	(0.049)
$\text{Post}_t \times \text{Exposure}_d \times \text{Down Payment}_{20\%}$				-0.034	-0.031
				(0.044)	(0.041)
$\text{Post}_t \times \text{Exposure}_d \times \text{Down Payment}_{15\%}$				-0.015	-0.007
				(0.048)	(0.048)
$\text{Post}_t \times \text{Exposure}_d \times \text{Down Payment}_{10\%}$				0.370***	0.392***
				(0.063)	(0.065)
$\text{Post}_t \times \text{Exposure}_d \times \text{Down Payment}_{5\%}$				0.963***	0.991***
				(0.091)	(0.095)
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	Yes	Yes	Yes	Yes	No
Fixed Effects					
District	Yes	Yes	Yes	Yes	No
Time	Yes	Yes	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	2,581	2,581	15,481	15,481	15,481
R^2	0.971	0.974	0.759	0.816	0.959

The table presents coefficient estimates for Equation 2 for the period 2010 to 2016, and shows the effect of HTB on home sales. Pre is a dummy variable equal to 1 for the period 2010 to 2011. Post is a dummy variable equal to 1 for the period 2013 to 2016. The base year is 2012. 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 down payment bucket in a given district and year. All regressions include all districts, except column 2 which excludes all 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 4: **The Effect of Help-to-Buy on Home Sales by Buyer-type**

	Buyer-type			
	First-time		Younger	
	(1)	(2)	(3)	(4)
$\text{Pre}_t \times \text{Exposure}_d$	0.052		0.048	
	(0.043)		(0.042)	
$\text{Post}_t \times \text{Exposure}_d$	0.250***		0.097**	
	(0.063)		(0.046)	
$\text{Post}_t \times \text{Exposure}_d \times \text{Buyer-type}_b$	0.519***	0.576***	0.799***	0.832***
	(0.087)	(0.091)	(0.118)	(0.112)
Control Variables				
$\text{Post}_t \times \text{Buyer-type}_b$	Yes	No	Yes	No
$\text{Exposure}_d \times \text{Buyer-type}_b$	Yes	No	Yes	No
District Characteristics	Yes	No	Yes	No
Fixed Effects				
District	Yes	No	Yes	No
Time	Yes	No	Yes	No
Buyer-type_b	Yes	No	Yes	No
District×Time	No	Yes	No	Yes
$\text{District}\times\text{Buyer-type}_b$	No	Yes	No	Yes
$\text{Time}\times\text{Buyer-type}_b$	No	Yes	No	Yes
Model Statistics				
N	5,162	5,162	5,162	5,162
R^2	0.906	0.981	0.849	0.977

The table presents coefficient estimates for Equation 2 for the period 2010 to 2016, and shows the effect of HTB on home sales across buyer-types. Pre is a dummy variable equal to 1 for the period 2010 to 2011. Post is a dummy variable equal to 1 for the period 2013 to 2016. The base year is 2012. 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 is younger (20 to 39 years-old) and older (40 to 59 years-old) in columns 3 and 4. 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 clustered at the district level and are shown in parentheses. ***, **, and * indicate statistical significance at the 1 percent, 5 percent and 10 percent confidence level, respectively.

Table 5: **The Effect of Help-to-Buy on House Price Growth**

	All Districts	Excl. London	London Only
	(1)	(2)	(3)
$\text{Pre}_t \times \text{Exposure}_d$	-0.014	-0.018	0.023
	(0.020)	(0.021)	(0.076)
$\text{Post}_t \times \text{Exposure}_d$	0.045**	0.035**	0.301***
	(0.018)	(0.017)	(0.069)
Control Variables			
District Characteristics	Yes	Yes	Yes
Fixed Effects			
District	Yes	Yes	Yes
Time	Yes	Yes	Yes
Model Statistics			
N	2,203	2,011	192
R^2	0.847	0.870	0.774

The table presents coefficient estimates for Equation 2 for the period 2010 to 2016, and shows the effect of HTB on house price growth. The dependent variable $Y_{d,t}$ is district-level annual house price growth. Pre is a dummy variable equal to 1 for the period 2010 to 2011. Post is a dummy variable equal to 1 for the period 2013 to 2016. The base year is 2012. 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 6: **The Effect of Help-to-Buy on Household Consumption**

	Total Household Consumption		Home-related	Non-durable	Durable
	All Districts	Excl. London	All Districts	All Districts	All Districts
	(1)	(2)	(3)	(4)	(5)
$\text{Pre}_t \times \text{Exposure}_r$	0.067	0.310	0.745	-0.022	0.620
	(0.259)	(0.236)	(0.428)	(0.235)	(1.177)
$\text{Post}_t \times \text{Exposure}_r$	0.580***	0.609***	0.858**	0.605***	1.049
	(0.175)	(0.168)	(0.344)	(0.177)	(0.933)
Control Variables					
House Prices	Yes	Yes	Yes	Yes	Yes
Cohort Characteristics	Yes	Yes	Yes	Yes	Yes
Fixed Effects					
HTB-Region	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes
Birth Year Group	Yes	Yes	Yes	Yes	Yes
Model Statistics					
N	392	385	392	392	392
R^2	0.826	0.828	0.691	0.823	0.656

The table presents coefficient estimates for Equation 3 for the period 2010 to 2016, and shows the effect of HTB on household consumption. The dependent variable is either real total household consumption, real home-related expenditures, real non-durable consumption or real durable expenditures, where the latter two variables exclude home-related expenditures. Pre is a dummy variable equal to 1 for the period 2010 to 2011. Post is a dummy variable equal to 1 for the period 2013 to 2016. The base year is 2012. Exposure equals the average exposure across the districts assigned to the region, where district-level 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. Regions are grouped according to their HTB exposure, with districts included in the first (10th) exposure region are in the first (10th) decile of HTB exposure distribution. All regressions include all districts, except column 2 which excludes all London districts. Standard errors are clustered at the region-by-birth year cohort 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 Household Consumption of the Young**

	Home-related		Non-durable		Durable	
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Pre}_t \times \text{Exposure}_r$	0.807*		-0.019		0.719	
	(0.407)		(0.231)		(1.182)	
$\text{Post}_t \times \text{Exposure}_r$	0.978***		0.430**		1.492	
	(0.310)		(0.188)		(0.930)	
$\text{Post}_t \times \text{Exposure}_r \times \text{Younger}_c$	-0.378	-0.348	0.495*	0.517*	-1.556	-1.304
	(0.578)	(0.511)	(0.258)	(0.262)	(1.605)	(1.332)
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	392	392	392	392	392	392
R^2	0.700	0.707	0.836	0.834	0.659	0.666

The table presents coefficient estimates for Equation 3 for the period 2010 to 2016, and shows the effect of HTB on household consumption differentiating between younger and older households. The dependent variable is either real home-related expenditures, real non-durable consumption or real durable expenditures, where the latter two variables exclude home-related expenditures. Pre is a dummy variable equal to 1 for the period 2010 to 2011. Post is a dummy variable equal to 1 for the period 2013 to 2016. The base year is 2012. Exposure equals the average exposure across the districts assigned to the region, where district-level 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. Regions are grouped according to their HTB exposure, with districts included in the first (10th) exposure region are in the first (10th) decile of HTB exposure distribution. 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 clustered at the region-by-birth year cohort and are shown in parentheses. ***, **, and * indicate statistical significance at the 1 percent, 5 percent and 10 percent confidence level, respectively.

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

	DfT Data		*Household Survey Data*		
	New Private Car Registrations		Total Car Purchases	Loan-financed Car Purchases	Outright Car Purchases
	All Districts	Excl. London	All Districts	All Districts	All Districts
	(1)	(2)	(3)	(4)	(5)
$\text{Pre}_t \times$ Exposure	-0.405	-0.257	0.280	-0.074	0.402
	(0.293)	(0.307)	(1.170)	(0.717)	(1.016)
$\text{Post}_t \times$ Exposure	1.045***	1.091***	0.001	1.354**	-1.332
	(0.372)	(0.402)	(0.994)	(0.659)	(0.819)
Control Variables					
District/Region Characteristics	Yes	Yes	Yes	Yes	Yes
Fixed Effects					
District/Region	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes
Birth Year Group	n/a	n/a	Yes	Yes	Yes
Model Statistics					
N	2,581	2,357	392	392	392
R^2	0.955	0.958	0.507	0.593	0.169

The table presents coefficient estimates for the period 2010 to 2016, and shows the effect of HTB on car sales. Pre is a dummy variable equal to 1 for the period 2010 to 2011. Post is a dummy variable equal to 1 for the period 2013 to 2016. The base year is 2012. In columns 1 and 2 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 3 to 5, Exposure equals the average exposure across the districts assigned to the region. Columns 1 and 2 present coefficient estimates for Equation 2, where the dependent variable $Y_{d,t}$ is the number of private newly registered cars taken from the Department for Transport data. The control variables and fixed effects are at the district level, as described for Equation 2. Standard errors are clustered at the district level and are shown in parentheses. Columns 2, 3 and 4 present coefficient estimates for Equation 3, where the dependent variable is either total car purchase expenditures, loan-financed car purchase expenditures or outright car purchase expenditures, based on the LCFS data. The control variables and fixed effects are at the HTB-region cohort level, as described for Equation 3. Standard errors are clustered at the region-by-birth year cohort and are shown in parentheses. All regressions include all districts, except column 2 which excludes all London districts. ***, **, 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 Local Demand**

	Employment				Housing Construction		Income	
	Total	Non-tradable	Strictly Non-tradable	Tradable	Homes Constructed	Home Starts	Gross	Net
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Pre}_t \times$ Exposure	-0.940	0.559	0.714	0.559	-0.057	0.383	-0.071	-0.050
	(2.841)	(0.574)	(0.634)	(0.574)	(0.074)	(0.137)	(0.316)	(0.295)
$\text{Post}_t \times$ Exposure	11.225***	10.417***	1.546*	0.431	0.183*	-0.110	0.701***	0.639***
	(3.705)	(3.440)	(0.899)	(0.652)	(0.104)	(0.130)	(0.261)	(0.244)
Control Variables								
District/Region Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects								
District/Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Model Statistics								
N	2,581	2,357	2,581	2,581	2,257	2,257	392	392
R^2	0.996	0.995	0.990	0.986	0.796	0.720	0.853	0.826

The table presents coefficient estimates for Equation 2 for the period 2010 to 2016, and shows the effect of HTB on various variables capturing local demand. Pre is a dummy variable equal to 1 for the period 2010 to 2011. Post is a dummy variable equal to 1 for the period 2013 to 2016. The base year is 2012. In columns 1 to 6 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 7 to 8, Exposure equals the average exposure across the districts assigned to the region. Columns 1 to 6 present coefficient estimates for Equation 2, where the dependent variable $Y_{d,t}$ is either total employment, (strictly) non-tradable employment, tradable employment, homes constructed or home starts. The control variables and fixed effects are at the district level, as described for Equation 2. Standard errors are clustered at the district level and are shown in parentheses. Columns 7 and 8 present coefficient estimates for Equation 3, where the dependent variable is either gross or net income. The control variables and fixed effects are at the HTB-region cohort level, as described for Equation 3. ***, **, and * indicate statistical significance at the 1 percent, 5 percent and 10 percent confidence level, respectively.

Internet Appendix

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 Expenditures, Non-durable Consumption*, *Durable Expenditures* and *Total Household Consumption* as follows:

- *Home-related Expenditure*s: 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 expenditures.
- *Durable Expenditure*s: 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 Expenditures, Non-durable Consumption* and *Durable Expenditures.*

Following Cloyne et al. (2020), housing and rental-related costs are excluded from both non-durable goods and services and durable goods. Home-related expenditures 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 expenditures on durable households goods are excluded from our main measure of durable expenditures.

A.3 Other Cohort Control Variables

- *Proportion of Outright Home Owners*
- *Proportion of Mortgagors*
- *Household Income*: sum of labor- and non-labor household income.
- *Mortgage Payments*: includes both interest payments and capital repayments.
- *Rental Payments*
- *Number of Adults in Household*
- *Number of Children in Household*

A.4 Deflating

We adjust household expenditures, 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 et al. (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 in our main analysis. In show that our results are robust when we do apply the survey household weights.

A.6 Restrictions

We exclude year-region-birth year cohort combinations with 10 or fewer observations. 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 Business Structure Database (BSD)

B.1 Background about the BSD

We obtain our employment data from the Business Structure Database (BSD). The BSD dataset is an annual snapshot taken from the Interdepartmental Business Register (IDBR), which is a live register of data collected by Her Majesty's Revenue and Customs based on tax records. It therefore provides details about the geographic location and number of employees for the universe of active firms that are registered for income tax purposes in the UK. The BSD data reports information for "enterprises" and "local units". An enterprise is defined as the overall business organisation. An enterprise can be made up of one or more local units, such as a shop, branch, or factory. Given our interest in regional employment, and locally non-tradable employment specifically, our regional employment measures are based on the employment at the local unit level.

B.2 Employment Measures

We consider four different employment measures. We broadly define *total employment, non-tradable employment*, *strictly non-tradable employment* and *tradable employment* as follows:

- *Total Employment*: includes all employees for all firms in a given district and year.
  .
- *Non-tradable Employment*: includes firms in service-producing industries, following the approach of Burstein et al. (2020).
- *Strictly Non-tradable Employment*: includes firms in the retail sector and restaurants, following the industry classification #1 approach described in Appendix Table 1 of Mian and Sufi (2014). We map the North American Industrial Classification System (NAICS) codes to the Standard Industrial Classification (SIC-07) codes to create an equivalent measure for UK firms.
- *Tradable Employment*: includes firms in goods-producing industries, such as agriculture, mining and manufacturing, following the approach of Burstein et al. (2020). This definition is almost identical to the definition used by Mian and Sufi (2014).

Table A.4 presents the 4-digit SIC-07 codes and description, along their industry classification used to generate our employment measures. The construction industry (SIC-07 classes 41.10-43.99) is excluded from our tradable and non-tradable employment measures, following Burstein et al. (2020) and Mian and Sufi (2014).

C The Mortgage Market Response to Relaxing the Down Payment Constraint

This section examines whether our HTB exposure measure also correlates with a district-level increase in 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. We estimate the panel regression model:

$$\begin{aligned}\text{Low Down Payment}_{b,l,d,t} = \quad & \textstyle\sum_{s\neq 2012} \mathbb{I}_{t=s} \times \text{Exposure}_d \times \beta_s + \boldsymbol{\gamma}\text{District}_{d,t-1} \\ & +\boldsymbol{\mu}\text{Loan}_{b,l,d,t} + \lambda_{lt} + \delta_d + u_{b,l,d,t}\end{aligned} \tag{4}$$

where b indexes a mortgage, l indexes a lender, d indexes a district and t is a year-quarter. 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, 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. We estimate the model over the period 2010 to 2016 and the first quarter of 2013 is taken to be the base period.

Figure A.1 plots the coefficient estimates of β_s and is discussed in Section 5.1. The estimates as shown in Figure A.1 remain similar without time-varying district controls, reducing the concerns that our HTB exposure measure is correlated with changes in macroeconomic and housing market conditions. Additionally, the results remain almost identical when we exclude London. Results are available upon request.

D Internal Migration

In this section we formally test whether relaxing the down payment constraint induced between-district housing-related internal migration in the UK. To do so, we estimate a similar panel regression model to that outlined by Equation 2:

$$\begin{aligned} Y_{d,t} = \; & \beta_1 \text{Pre}_t \times \text{Exposure}_d + \beta_2 \text{Post}_t \times \text{Exposure}_d \\ & + \boldsymbol{\gamma} \text{District}_{d,t-1} + \delta_d + \theta_t + u_{d,t} \end{aligned} \tag{5}$$

where d indexes a district and t is the year. The dependent variable $Y_{d,t}$ is now Migration $\text{Inflows}_{d,t}$, which equals the number of persons that move from another UK district to district d in a given year scaled by the population in district d. We remove outliers by winsorizing at the 1st and above the 99th percentile. The rest of the model is the same as Equation 2.

The results are presented in Table A.6. The first column shows the average effect of relaxing the down payment constraint on internal migration inflows. It indicates that after HTB came into effect, there was no change to internal migration inflows in high exposure districts (column 1). This result holds when we exclude districts in the London area (column 2).

When we focus on the London area and the rest of the UK separately (columns 2 and 3) we find a significant result for the London area only. This makes sense, given that people may make housing related moves within the London area. Moves in other areas in the UK do not appear to be induced by HTB, 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.

E Alternative Household Survey Panel Construction

E.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 district-level 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 (2010-2012) and the post-HTB period (2013-2016). For each time-district combination, we calculate the average of the logged variables of interest, where "time" is either the pre-HTB or post-HTB period. We exclude time-district combinations with 10 or fewer observations.

E.2 Help-to-Buy and Household Expenditures

We estimating the following cross-sectional regression model:

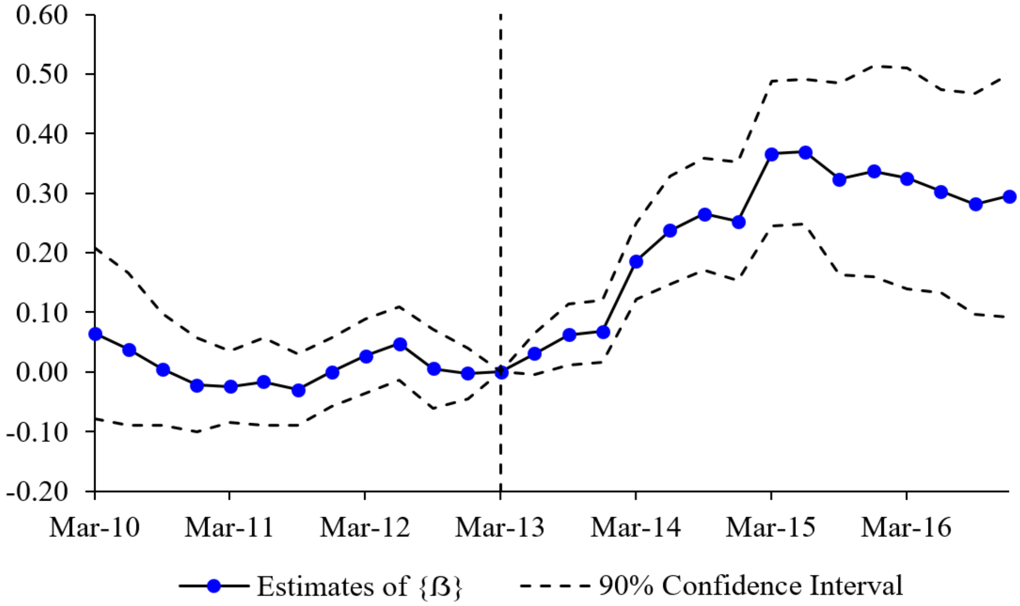
$$\triangle \text{Consumption}_{d,Post} = \beta_1 \text{Exposure}_d + \boldsymbol{\gamma} \triangle \text{Cohort}_{d,Post} + \lambda \triangle \text{House Prices}_{d,Post} + u_d \tag{6}$$

where d indexes a district. The outcome variable $\triangle\text{Consumption}_{d,Post}$ is real total household consumption growth (or home-related expenditures growth, non-durable consumption growth, or durable expenditures growth) for district d, measured as the difference between real total household consumption in the post-HTB period and the pre-HTB period. Exposure_d is our measure of *ex ante* exposure to the HTB program. We also include a vector of district-level controls derived from the LCFS, $\mathbf{Cohort}_{d,t}$, which includes the same controls describe for Equation 3, but measured as pre-post growth rates. $\triangle\text{House Prices}_d$ is the real house price pre-post growth rate.

The results in Table A.7 show that real total household consumption increased more in high exposure regions and this finding is robust to excluding London (columns 1 and 2). In addition, we find that real home-related expenditures and non-durable consumption growth are both higher in high compared to low exposure regions during the HTB-affected period (columns 3 and 4), while durable expenditures do not appear to be affected (column 5). Our regressions control for house prices so they are not driven by a wealth effect due to higher house prices in high exposure regions. All told, the results from this alternative LCFS panel are in line with our findings in Section 7.2.

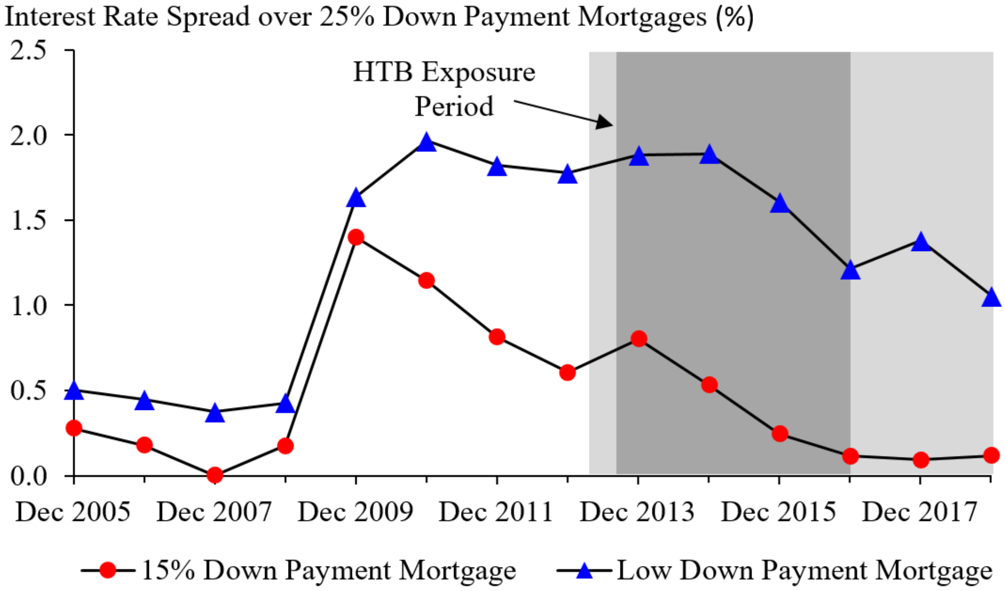
F Additional Figures and Tables

Figure A.1: The Effect of Help-to-Buy on Low-Down Payment Mortgage Lending



The figure presents estimates of β from Equation 4 for each quarter, where the outcome $Y_{b,l,d,t}$ is the dummy variable for low-down payment mortgages and March 2013 is the base period. The dashed lines show the 90 percent confidence interval. All regressions include loan, home buyer and time-varying district-level controls, as well as district and lender-time fixed effects. Standard errors are clustered at the district and lender level.

Figure A.2: Interest Rate Spread for Low-Down Payment Mortgages



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

Table A.1: **Comparison Low- and High-Down Payment First-time Buyers**

	Low-Down Payment (EL)	Low- Down Payment (Non-EL)	High-Down Payment
Age (years)	30.18	30.00	31.51
	(6.35)	(6.09)	(7.55)
Gross Income (£)	48,846.48	47,512.91	47,960.91
	(30,499.97)	(41,821.11)	(181,037.80)
Down Payment (£)	11,678.20	11,969.18	60,448.66
	(5,573.15)	(8,725.13)	(103,894.50)
Property Value (£)	218,565.60	169,001.28	211,571.59
	(91,996.93)	(89,736.74)	(201,678.30)

The table presents the mean and standard deviation (placed below the mean, in brackets) for several key loan and borrower characteristics and for three different first-time buyer-types: low-down payment first-time buyers that purchased with an HTB Equity Loan (EL); low-down payment first-time buyers that purchased with an HTB Mortgage Guarantee (or other low-down payment mortgage); and high-down payment first-time buyers, who did not use HTB. A low-down payment buyer purchases a property with a down payment around 5 percent, and high-down payment buyers includes all other buyers. The statistics are calculated for the post HTB period, from 2013 to 2016. All variables are deflated to 2016 values.

Table A.2: **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 remortgagor
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.3: **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 DLUHC
District-level Variables		
Exposure	Share of low-down payment mortgages (as a proportion of total) issued between 2005 to 2007	Product Sales Database
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 Growth	Log difference in annual average house price	Land Registry House Price Index Data
Car Sales	Total number of private new car registrations	UK Department for Transport
Total Employment	Total number of employees for all firms registered for income tax purposes in the UK	Business Structure Database
Strictly Non-tradable Employment	Total number of employees for all firms in the retail sector and restaurants	Business Structure Database
Non-tradable Employment	Total number of employees for all firms in service-producing industries	Business Structure Database
Tradable Employment	Total number of employees for all firms in goods-producing industries, including agriculture, mining and manufacturing	Business Structure Database
Homes Constructed	Total number of new build home sales	Office for National Statistics, Land Price Paid Data
Home Starts	Total number of individual dwellings for which building work has commenced	UK Department for Levelling UP, Housing and Communities
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

Table A.3: **Variable Descriptions and Sources** *continued*

Variable Name	Variable Description	Data Source
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 Expenditures	Average of log real weekly home-related expenditures 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 expenditures for all households in a given year and cohort	Living Food and Cost Survey
Gross Household Income	Average of log real weekly household income for all households in a given year and cohort	Living Food and Cost Survey
Net Household Income	Average of log real weekly household income net of paid taxes for all households in a given year and cohort	Living Food and Cost Survey

Table A.4: **Industry Definitions for Employment Measures**

SIC-07 Class	SIC-07 Description	Industry Classification
01.11-03.22	Agriculture, forestry and fishing	Tradable
05.10-09.90	Mining and quarrying	Tradable
10.11-33.20	Manufacturing	Tradable
33.13	Repair of electronic and optical equipment	Strictly Non-tradable
33.15	Repair and maintenance of ships and boats	Strictly Non-tradable
45.11-45.19	Sale of motor vehicles	Strictly Non-tradable
45.32	Retail trade of motor vehicle parts and accessories	Strictly Non-tradable
45.40	Sale, maintenance and repair of motorcycles and related parts and accessories	Strictly Non-tradable
47.11-47.99	Retail trade, except of motor vehicles and motorcycles	Strictly Non-tradable
56.10-56.30	Food and beverage service activities	Strictly Non-tradable
35.11-35.30	Electricity, gas, steam and air conditioning supply	Non-tradable
36.00-39.00	Water supply, sewerage, waste management and remediation activities	Non-tradable
45.11-47.99	Wholesale and retail trade; repair of motor vehicles and motorcycles	Non-tradable
49.10-53.20	Transportation and storage	Non-tradable
55.10-56.30	Accommodation and food service activities	Non-tradable
58.10-63.99	Information and communication	Non-tradable
64.11-66.30	Financial and insurance activities	Non-tradable
68.10-68.32	Real estate activities	Non-tradable
69.10-75.00	Professional, scientific and technical activities	Non-tradable
77.11-82.99	Administrative and support service activities	Non-tradable
84.11-84.30	Public administration and defence; compulsory social security	Non-tradable
85.10-85.60	Education	Non-tradable
86.10-88.99	Human health and social work activities	Non-tradable
90.01-93.29	Arts, entertainment and recreation	Non-tradable
94.11-96.09	Other service activities	Non-tradable
97.00-98.20	Activities of households as employers; undifferentiated goods and services producing	Non-tradable
99.00	Activities of extraterritorial organizations and bodies	Non-tradable

Table A.5: **Robustness Exercises for the Effect of Help-to-Buy on Home Sales**

	Benchmark	Weighted by Sales	Multi-clustered S.E.	Excl. 2013	LTI Constraint
	(1)	(2)	(3)	(4)	(5)
$\text{Pre}_t \times \text{Exposure}_d$	0.109	0.205	0.109	0.085	0.125
	(0.086)	(0.133)	(0.068)	(0.087)	(0.086)
$\text{Post}_t \times \text{Exposure}_d$	1.027***	1.128***	1.027***	1.317***	1.153***
	(0.149)	(0.215)	(0.296)	(0.178)	(0.183)
$\text{Post}_t \times \text{LTI-constraint}_d$					-0.231
					(0.167)
Control Variables					
District Characteristics	Yes	Yes	Yes	Yes	Yes
Fixed Effects					
District	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes
Model Statistics					
N	2,581	2,581	2,581	2,203	2,581
R^2	0.971	0.974	0.971	0.968	0.971

The table presents various robustness tests of the baseline result in column 1 of Table 3. The dependent variable in all columns is the number of home sales purchased with a mortgage in a given district and year. Column 1 reproduces the baseline result. Column 2 presents estimates from a specification weighted by 2012 home sales. Column 3 presents estimates from a specification where the standard errors are multi-clustered at the district and time level. Column 4 presents estimates from a specification that excludes 2013. Column 5 presents estimates from a specification that includes the term Post $\times$ LTI constraint, where the "LTI-constraint" measure equals the number of mortgages in a district in the year 2012 made by LTI-constrained banks as defined by Peydro et al. (2020) divided by the total number of mortgages in 2012. Pre is a dummy variable equal to 1 for the period 2010 to 2011. Post is a dummy variable equal to 1 for the period 2013 to 2016. The base year is 2012. 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 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 A.6: **The Effect of Help-to-Buy on Internal Migration**

	All Districts	Excl. London	London Only
	(1)	(2)	(3)
$\text{Pre}_t \times \text{Exposure}_d$	-0.047	0.238	-3.731***
	(0.199)	(0.198)	(1.149)
$\text{Post}_t \times \text{Exposure}_d$	0.203	-0.334	2.084***
	(0.218)	(0.232)	(0.644)
Control Variables			
District Characteristics	Yes	Yes	Yes
Fixed Effects			
District	Yes	Yes	Yes
Time	Yes	Yes	Yes
Model Statistics			
N	2,581	2,357	224
R^2	0.982	0.981	0.977

The table presents coefficient estimates for Equation 5 for the period 2010 to 2016, and shows the effect of HTB on internal migration inflows. The dependent variable is district-level internal migration inflows (from all other districts to district d) scaled by the population in district d. Pre is a dummy variable equal to 1 for the period 2010 to 2011. Post is a dummy variable equal to 1 for the period 2013 to 2016. The base year is 2012. 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 A.7: **An Alternative Synthetic Cohort to Examine the Effect of Help-to-Buy on Household Consumption**

	Total Household Consumption		Home-related	Non-durable	Durable
	All Districts	Excl. London	All Districts	All Districts	All Districts
	(1)	(2)	(3)	(4)	(5)
Exposure_d	0.295*	0.344*	0.522*	0.391**	-0.949
	(0.173)	(0.187)	(0.284)	(0.167)	(0.797)
Control Variables					
House Prices	Yes	Yes	Yes	Yes	Yes
Cohort Characteristics	Yes	Yes	Yes	Yes	Yes
Model Statistics					
N	301	272	301	301	301
R^2	0.425	0.424	0.243	0.444	0.148

The table presents coefficient estimates for Equation 6, and shows the effect of HTB on household expenditures. The dependent variable is either real total household consumption growth, real home-related expenditures growth, real non-durable consumption growth or real durable expenditures growth, in the post-HTB period (2013 to 2016) compared with the pre-HTB period (2010 to 2012). Non-durable consumption and durable expenditures exclude home-related expenditures. All control variables are also growth variables that compare the log change in values between the post-HTB period compared with the pre-HTB period. 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. All regressions include all districts, except column 2 which excludes all London districts. Standard errors are clustered at the region-birth year cohort level and are shown in parentheses. ***, **, and * indicate statistical significance at the 1 percent, 5 percent and 10 percent confidence level, respectively.

Table A.8: **Robustness Exercises for the Effect of Help-to-Buy on Household Consumption**

	Benchmark	Survey Weights	Multi-clustered S.E.	Excl. 2013
	(1)	(2)	(3)	(4)
$\text{Pre}_t \times \text{Exposure}_d$	0.067	0.183	0.067	0.036
	(0.259)	(0.265)	(0.163)	(0.262)
$\text{Post}_t \times \text{Exposure}_d$	0.580***	0.599**	0.580***	0.641***
	(0.175)	(0.185)	(0.124)	(0.206)
Control Variables				
District Characteristics	Yes	Yes	Yes	Yes
Fixed Effects				
District	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes
Model Statistics				
N	392	396	392	335
R^2	0.826	0.809	0.826	0.819

The table presents various robustness tests of the baseline result in column 1 of Table 6. The dependent variable in all columns is real total household consumption. Column 1 reproduces the baseline result. Column 2 presents estimates from specification that uses the annual probability weights provided for each respondent. Column 3 presents estimates from a specification where the standard errors are multi-clustered at the region-birth year cohort and time level. Column 4 presents estimates from a specification that excludes 2013. Pre is a dummy variable equal to 1 for the period 2010 to 2011. Post is a dummy variable equal to 1 for the period 2013 to 2016. The base year is 2012. Exposure equals the average exposure across the districts assigned to the region, where district-level 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. Regions are grouped according to their HTB exposure, with districts included in the first (10th) exposure region are in the first (10th) decile of HTB exposure distribution. Standard errors are clustered at the region-birth year cohort level and are shown in parentheses. ***, **, and * indicate statistical significance at the 1 percent, 5 percent and 10 percent confidence level, respectively.

Table A.9: **Robustness Exercises for the Effect of Help-to-Buy on Car Sales**

	Benchmark	Weighted by Sales	Multi-clustered S.E.	Excl. 2013
	(1)	(2)	(3)	(4)
$\text{Pre}_t \times \text{Exposure}_d$	-0.405	-0.383	-0.405	-0.379
	(0.293)	(0.347)	(0.238)	(0.295)
$\text{Post}_t \times \text{Exposure}_d$	1.045***	1.201*	1.045**	1.051**
	(0.372)	(0.613)	(0.330)	(0.451)
Control Variables				
District Characteristics	Yes	Yes	Yes	Yes
Fixed Effects				
District	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes
Model Statistics				
N	2,581	2,581	2,581	2,203
R^2	0.955	0.613	0.955	0.948

The table presents various robustness tests of the baseline result in column 1 of Table 8. The dependent variable in all columns is the number of private new car registrations in a given district and year. Column 1 reproduces the baseline result. Column 2 presents estimates from specification weighted by 2012 car sales. Column 3 presents estimates from a specification where the standard errors are multi-clustered at the district and time level. Column 4 presents estimates from a specification that excludes 2013. Pre is a dummy variable equal to 1 for the period 2010 to 2011. Post is a dummy variable equal to 1 for the period 2013 to 2016. The base year is 2012. 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 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.