The Consumption Response to Borrowing Constraints in the Mortgage Market

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Abstract

We show that easing mortgage-market borrowing constraints stimulates consumption via a local multiplier effect. We document that a sudden relaxation of borrowing constraints, induced by a major UK mortgage-market intervention, positively affects both home purchases and consumption. Two mechanisms generate the observed local multiplier effect. First, there is a 14 percent increase in the volume of new home-buyers, each of whom spend an additional £3,200 on non-durable and home-related items in the year following their home purchase. Second, the rise in home-buyer spending boosts local economic activity, which subsequently brings about a broader increase in consumption. Our findings suggest that the local multiplier effect plays a significant role in explaining the co-movement between housing market activity and consumption.

JEL classification: E21; G21; R21; R28

Keywords: borrowing constraints; consumption; housing market; mortgage market regulation

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1 Introduction

Borrowing constraints are a critical determinant of housing market participation, influencing both who can purchase a home and when (Stein, 1995; Ortalo-Magne and Rady, 2006). At the same time, housing market activity is a key driver of consumption; home purchases often lead to additional spending on renovations and home-related goods (Best and Kleven, 2017; Benmelech et al., 2017), while fluctuations in house prices significantly shape consumption patterns (Campbell and Cocco, 2007; Case et al., 2005; Mian et al., 2013; Guren et al., 2020). Despite extensive research on these individual mechanisms, the connection between them – how borrowing constraints influence consumption via their impact on housing market activity – remains an open question. This paper seeks to fill that gap.

In this paper, we document a local multiplier effect of borrowing constraints, which plays an important role in explaining the co-movement between housing market activity and household consumption. When borrowing constraints in the mortgage market are eased, liquidity constrained households can purchase a home. Every time a home is purchased, new home-buyers spend money on services related to the transaction as well as home-related items and improvements. The local multiplier effect is generated by the increase in demand for local services, which boosts local employment in the non-traded sector.

We address this topic by examining the UK's Help to Buy (HTB) program, a large-scale mortgage market intervention that substantially eased borrowing constraints. Our analysis unfolds in three steps: first, we assess how HTB influenced home sales and house prices; second, we investigate its effects on consumption; and finally, we uncover the mechanisms driving the consumption response. Our findings demonstrate that easing borrowing constraints not only facilitates homeownership but also generates significant consumption spillovers through a local multiplier effect.

Introduced in March 2013, HTB was designed to help borrowers who could afford mortgage payments but struggled to meet high down payment requirements. At the time, most lenders required a minimum down payment of 10 percent, creating significant barriers for households seeking to purchase a home. HTB addressed this by enabling home purchases with only a 5 percent down payment. Figure 1 demonstrates the program's effectiveness: after years of limited availability, the share and volume of low-down payment began increasing rapidly with HTB's introduction and stabilized after 2016, signaling a lasting change in borrowing conditions. By directly addressing the primary borrowing constraint for young and first-time buyers (Linneman and Wachter, 1989; Fuster and

Zafar, 2021), HTB significantly enhanced households ability to purchase a home.

To analyze the program's impact on home sales and household consumption, we exploit geographic variation in *ex ante* HTB exposure (Mian and Sufi (2012), Berger et al. (2020)). Although HTB was implemented nationwide, its effects varied across regions depending on the historical prevalence of low-down payment home buyers. Relaxing the down payment requirement primarily benefits liquidity-constrained households, who are not randomly spread across the country, but concentrated in areas with a more suitable housing supply. Since local housing market characteristics change gradually, it is reasonable to assume that regions with historically higher shares of low-down payment buyers were more affected by HTB.

We measure HTB exposure using administrative mortgage data, defining it as the share of home purchases made with a 5 percent down payment before the global financial crisis, a period when such mortgages were readily available.[1][2] This measure strongly predicts the uptake of low-down-payment mortgages post-HTB and accurately predicts time variation. Using this exposure measure, we employ a difference-in-differences design to compare changes in home sales and household consumption across districts with high and low HTB exposure between 2009 and 2018. Districts with a historically low prevalence of low-down payment buyers serve as a control group, as HTB unlikely influenced home purchases there.

Our identification strategy assumes that, absent the easing of borrowing constraints, home purchases and consumption would have followed similar trends across districts. To address concerns about systematic differences between high and low exposure districts, we include district and region-time fixed effects to account for time-invariant district characteristics and regional economic and housing market cycles. We test for parallel trends in the pre-HTB period and confirm that observed differences align with the program's timing. Where feasible, we include district-time fixed effects to control for time-varying district-level factors. Additionally, we use propensity score matching to balance observable characteristics across districts.

We start with the housing market and estimate that easing borrowing constraints via HTB increased aggregate home purchases by 14.3 percent, adding approximately 536,000

[1]Throughout the paper we use the terms "5 percent" or "low-down payment" mortgages when we refer to mortgages with a down payment of <10%. These mortgages are also known as 95 LTV mortgages. Due to the pricing of mortgage products in the UK, the vast majority of these mortgages have a down payment close to 5 percent (see Section 3).

[2]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.

homes sales over the main stimulus period (2013-2018). Young and first-time buyers were the primary beneficiaries, consistent with the pivotal role of down payment-constrained buyers in shaping housing market fluctuations (Ortalo-Magne and Rady, 2006). Before HTB, home sales followed similar trends in high- and low-exposure districts, but once the policy took full effect, a clear divergence emerged, persisting throughout the policy period. Exploiting within-district heterogeneity, we show that the increase was driven mainly by purchases with a 5 percent down payment, in line with HTB driving the housing response. This finding is robust to excluding London, controlling for confounding policy interventions and using propensity score matching.

Despite the surge in home sales, we find only a modest effect on house prices. While prices increased more in high-exposure areas, outside of London the rise was minimal - only 1.4 pp per standard deviation HTB exposure. The house price increase was more pronounced for the London area, in line with prior research showing that the price response to housing demand depends on supply elasticity, which is far more constrained in London than in other regions (Favara and Imbs, 2015; Carozzi et al., 2020).

Having established that easing borrowing constraints via HTB boosted home sales, we next examine its impact on household consumption. We focus on two sets of consumption data: car sales and household survey data, applying the same difference-in-differences methodology. We document a significant increase in car sales in high exposure regions following HTB's implementation. As in the housing market, trends in high- and low-exposure regions follow a similar trajectory before the policy takes effect, after which a clear and persistent divergence emerges. The results hold when excluding London or using propensity score matching. In aggregate, we estimate that the HTB-induced easing of borrowing constraints resulted in an additional 2,478,900 new car purchases, representing a 16.8 percent increase.[3]

Evidence from the Living Cost and Food Survey (LCFS) provides further support for a consumption response. The richness of the LCFS allows us to examine the impact on different types of consumption, while controlling for changes in (cohort-level) household income and demographics. To account for the repeated cross-section format of the data, we follow Browning et al. (1985) and Deaton (1985) and construct a pseudo-panel based on the birth year of the household head and the district of residence. In aggregate, we estimate that in response to the easing of borrowing constraints, total household consumption rose by 5.7 percent between 2013 and 2018. The increase was driven in

[3]These cars were likely loan-financed as in the UK 90 percent of new cars are purchased with some kind of consumer credit (Finance and Leasing Association, 2022).

part by higher spending on home-related expenditures (10.6 percent) and non-durable consumption unrelated to housing (5.3 percent).

Taken together, these findings show that easing borrowing constraints boosts both home sales and household consumption. The next step is to understand the mechanisms driving this response. We explore three key channels: direct spending by new home-buyers on goods and services, the potential for a local multiplier effect that amplifies consumption through broader economic activity and the role of increased housing construction in shaping these dynamics.

Purchasing a home typically necessitates expenditures on furniture, appliances, and home-related services, suggesting that local consumption should rise as a natural consequence of increased housing transactions (Best and Kleven, 2017; Benmelech et al., 2017). To test this, we construct a novel dataset linking our administrative mortgage data to transaction-level expenditure data from Money Dashboard. This enables us to estimate the consumption response of home-buyers, by comparing their consumption patterns in the 24 months before and after their home purchase using an event-study methodology. To account for treatment heterogeneity, we adopt the imputation approach of Borusyak et al. (2024). Our control group consists "not yet treated" renters who purchase homes outside the event window and "never treated" homeowners. We further control for business cycle fluctuations and household characteristics with district-time and household fixed effects.

We find that home-buyers significantly increase their spending, around the time of purchase, with an average increase of £3,200 in the first year, of which £1,800 occurs within three months of moving. Home-related expenditures show the largest and most sustained rise, remaining elevated for at least 24 months post-purchase. Non-durable consumption also increases, with effects lasting up to 18 months. Durable consumption is unaffected.

These patterns are unlikely to be driven by omitted variables. First, spending levels remain stable until just one month before the purchase, suggesting that the observed increases are directly tied to the transaction itself rather than to external factors. This is especially important in the UK context, where delays of a few months between purchase agreement and final transaction are common. Second, our results hold when we exclude households experiencing major life events, such as childbirth or significant income changes, further reducing the potential for confounding factors. Together, this evidence strongly supports a direct and sustained link between home purchases and increased household consumption.

The scale of the spending increase is substantial: an estimated £1.7 million in the first year alone. This surge in demand may, in turn, stimulate consumption through an indirect channel. As new homebuyers increase their spending, local businesses benefit from higher demand, potentially prompting them to hire more workers, raise wages, or increase supplier orders. These spillover effects could generate additional employment and income gains, amplifying the initial consumption response through a local multiplier effect.

To test whether this mechanism is present, we examine how employment and household income evolve in regions experiencing higher volumes of home sales. Using detailed district-level employment data, we employ the same difference-in-differences methodology but now compare labor market dynamics in high vs low exposure districts before and after the easing of borrowing constraints. We supplement this analysis with data from the LCFS to examine household income dynamics. Our results show that regions with greater HTB exposure also experienced increases in non-tradable employment and household income but not in tradable employment, indicating the presence of a local multiplier effect further driving the consumption response.

Rising construction activity could also contribute to the observed increase in consumption by stimulating local economic activity. However, while construction expanded significantly during the policy period, its growth was not disproportionately concentrated in high-exposure districts. Combined with the modest rise in house prices, this evidence suggests that neither construction activity nor house price dynamics were primary drivers of the consumption response.

Our findings demonstrate that easing borrowing constraints in the mortgage market generates significant economic spillovers. By triggering increased spending by home buyers, home purchases stimulate local economic activity and amplify consumption through a local multiplier effect. These results highlight that mortgage policies not only facilitate access to housing but also serve as a critical lever for influencing broader economic dynamics.

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 and Section 4 describes the data. Section 5 introduces the empirical strategy and Sections 6 and 7 report the results on the effects of HTB on the housing market and consumption, respectively. Section 8 explores the mechanisms driving the consumption response. Section 9 concludes.

2 Review of the Literature

Our study contributes to the literature in four important ways. First, we provide novel evidence of how consumption responds to easing of borrowing constraints in the mortgage market, via it's impact on home sales. Agarwal et al., 2015 and Agarwal et al., 2017 document that interventions that affect *current* mortgage holders, such as mortgage debt renegotiation and refinancing programs, can have positive stimulus effects.[4] Consistent with our findings on car sales, Agarwal et al. (2021) find that a stamp duty subsidy for eligible new home-buyers in Sydney increased the demand for luxury cars. Acharya et al. (2022) provide suggestive survey-based evidence that the introduction of LTV and LTI limits increases savings rates which could potentially translate into lower consumption. We contribute to this literature by examining how consumption reacts to an easing of borrowing constraints affecting new home-buyers (i.e. *future* mortgage holders) and the mechanisms that drive it. Doing so we uncover a novel local multiplier effect driving the consumption response.

Our paper thus compliments studies that investigate the reaction of household spending to developments in the housing market, which has predominantly focused on changes in house prices.[5] 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 driven by a rise in home sales due to an easing of borrowing constraints. We capture a local multiplier effect driving consumption generated by a persistent increase in consumption by the home-buyers themselves and subsequent rise of local economic activity further boosting consumption. As the policy did not materially impact house prices (except in London), the consumption response we document does not seem to be materially driven by wealth effects due to rising house prices.

Moreover, we add to the literature that examines 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

[4]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; Maggio et al., 2017; Defusco, 2018; Beraja et al., 2019).

[5]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).

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., 2022).[6] 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 and consumption response to easing borrowing constraints, documenting that such policies have important economic consequences beyond their impact on the housing market.

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 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 the 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 Help-to-Buy Program

The UK Help-to-Buy (HTB) program, announced in March 2013, significantly eased borrowing constraints in the aftermath of the global financial crisis. The program explicitly aimed to assist borrowers who could afford mortgage payments but struggled to meet high down payment requirements, a primary barrier to homeownership in the UK.[7] At the time, most lenders required a minimum down payment of 10 percent, making it challenging for young and first-time buyers to access the housing market. HTB addressed this

[6] 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).

[7] George Osborne stated this objective explicitly in his budget speech stating 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).

issue by allowing home purchases with as little as a 5 percent down payment, a policy uniquely impactful due to specific characteristics of the UK mortgage market.

In the UK, mortgage interest rates are tied to discrete down payment thresholds (5, 10, 15, ..., and 40 percent). Borrowers with down payments just above these thresholds face higher rates (Appendix Figure 13), creating strong incentives to "bunch" down payments at these levels (see, e.g., Best et al., 2020; Robles-Garcia, 2019). This structure makes low-down payment mortgages disproportionately expensive and only constrained borrowers will opt for them. Figure 2 shows that before HTB, there was no bunching at the 5 percent threshold, reflecting the absence of low-down payment mortgages. After HTB's introduction, significant bunching emerged, demonstrating its success in lowering the effective down payment barrier.

HTB comprised two schemes that shared a 5 percent down payment requirement but differed in design and scope. The Equity Loan (EL) scheme, available from April 2013 to December 2020, targeted first-time buyers and home movers purchasing new-build properties priced under £600,000 (£300,000 in Wales).[8] [9] Borrowers received a government equity loan of up to 20% of the property value (40 percent in London from 2016), while the remaining amount was financed through a lender-provided mortgage. The equity loan was interest-free for the first five years. Mortgages under the scheme were subject to strict criteria, including a maximum loan-to-income (LTI) ratio of 4.5 and a requirement to be capital repayment loans.[10]

The Mortgage Guarantee (MG) scheme, in operation from October 2013 to December 2016, applied to all properties priced below £600,000 and was not restricted to new-builds.[11] [12] The government guaranteed 20 percent of the property's value to lenders, reducing their effective exposure to a 75 percent LTV ratio. This reduced the perceived risk for lenders and encouraged them to issue low-down payment mortgages. Unlike the EL scheme, the MG scheme did not involve direct financial assistance to borrowers and

[8] 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.

[9] Buy-to-let and second home mortgages were excluded from both the EL and MG schemes.

[10] The EL scheme also loosened the income constraint, because the government equity loan was not included in the LTI calculation. This 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 12 in our Online Appendix shows little difference in the average income for EL scheme buyers versus MG scheme buyers.

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

[12] The scheme was also available for refinancing, however due to the high interest rates charged hardly any mortgages for refinancing were taken out under the scheme.

was discontinued in 2016 as the availability of low-down payment mortgages outside the scheme had recovered from its crisis low.[13] Table 13 in the Internet Appendix summarizes the two schemes and their requirements.

At first glance, HTB's impact on the housing market appears substantial. Figure 1 shows that the share and volume of low-down payment mortgages, virtually absent from 2009 to 2012, began rising in 2013 with the program's introduction and stabilized after 2016, suggesting a sustained normalization of access. This pattern is not surprising, as HTB directly addressed the primary borrowing constraint for young and first-time buyers: saving for a down payment (Linneman and Wachter, 1989; Fuster and Zafar, 2021). Moreover, due to its in-built leverage effect, lowering the down payment requirement enhances housing affordability.[14] Consistent with prior research showing that tighter constraints after the global financial crisis reduced transaction volumes and disproportionately excluded first-time buyers (e.g. Van Bekkum et al., 2019; Defusco et al., 2020; Carozzi, 2020), HTB seems to have helped reverse these trends.

While these aggregate patterns suggest that HTB had an significant impact, assessing how the easing of borrowing constraints influenced housing transactions and household consumption requires a comparison to what would have happened without the program. To do so, we construct a counterfactual leveraging geographic variation in exposure to the program across UK districts. The next section describes the data underlying our analysis before we outline our empirical methodology in Section 5.

4 Data

In this section, we describe the various data sources employed throughout the paper, reserving the description of the variables utilized in our analysis for their respective sections.

4.1 Housing Market

To evaluate the effect of easing borrowing constraints on the housing market we examine both the impact on home sales and house prices.

[13] https://www.bankofengland.co.uk/-/media/boe/files/letter/2016/governor-letter-220916.pdf

[14] Lowering the minimum down payment from 10 to 5 percent doubles a buyer's borrowing capacity. For example, with £10,000 saved, a household could afford a £100,000 home at 90 percent LTV but a £200,000 home at 95 percent LTV.

4.1.1 Home Sales

To assess the impact on home sales, we focus on transactions financed with a mortgage.[15] We use administrative mortgage data from the UK Financial Conduct Authority's Product Sales Database (PSD), which covers all regulated mortgages issued since April 2005. This dataset provides detailed information about the mortgage contract, including lender, issuing date, loan and property values, down payment and postcode, as well as borrower characteristics such as type (first-time buyer or home mover), age, income, and employment status. Our analysis excludes refinancing and buy-to-let mortgages.

We identify all homes that are purchased with a *"Low-Down Payment Mortgage*," which are mortgages with a down payment of less then 10 percent. These mortgages are commonly known as 95 LTV mortgages, or 5 percent down payment mortgages, as the vast majority have a down payment close to 5 percent due to the pricing of these products (see Section 3). This category includes practically all MG mortgages, but only a subset of the EL mortgages, as some households choose to make a higher down payment than the minimum 5 percent required for the loan.[16] We identify low-down payment EL mortgages by matching an EL dataset collected by the UK Department for Leveling Up, Housing and Communities with the PSD, following the approach of Benetton et al. (2021).[17]

Furthermore, we distinguish homes purchased with down payment sizes of 10 percent and 15 percent or higher relative to the home value. Specifically, these mortgages have down payments ranging between 14.9% and 10% or 15% and above, respectively. Additionally, we identify homes bought by first-time buyers and home movers, as well as by young buyers (20-39 years old) and older buyers (40-59 years old).

4.1.2 House Prices

To examine how easing borrowing constraints affects house prices, we use transaction-level data on property sales. These data provide detailed information on sale prices across UK districts, allowing us to analyze price dynamics in response to the HTB program.

[15] In the UK, the vast majority of home are bought with a mortgage (84 percent in 2012).

[16] 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.

[17] 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.

4.2 Household Consumption

To examine the effect of easing borrowing constraints on household spending, we draw on three types of data: car sales, household survey data and household transaction-level data.

4.2.1 Car Sales

Car purchases provide a useful lens for assessing the impact of eased mortgage borrowing constraints on household spending. As one of the most significant durable goods, car purchases have been extensively studied in the context of consumption responses to various shocks, particularly in the US (see, e.g., Maggio et al., 2017; Mian and Sufi, 2012). We utilize administrative data on the universe of new private car registrations at the local authority district level from 2009 onward, sourced from the UK Department for Transport. To our knowledge, this is the first study to leverage such granular regional information on new car registrations in the UK.

4.2.2 Household Survey Data

To provide a broader view of the consumption response, we also analyze the Living Costs and Food Survey (LCFS). This is the most comprehensive survey on household spending in the UK and widely used in the literature (see, e.g., Campbell and Cocco, 2007; Cloyne et al., 2020). Conducted annually with approximately 5,000 respondents, the LCFS offers detailed insights into household consumption behavior by tracking expenditures across a wide range of categories.

The survey records weekly expenditures on all goods and services, along with household income and demographic variables. We classify weekly expenditures into three mutually exclusive categories: home-related expenditures, non-durable consumption and durable expenditures. Home-related expenditures include services as well as both durable and non-durable goods. Non-durable consumption covers a broad range of spending on non-durable goods and services, including some semi-durable goods such as clothing, footwear and certain leisure goods. Durable expenditures consists of spending on motor vehicles, durable personal goods and durable leisure goods. The latter two exclude any home-related expenditures, ensuring that total household consumption equals the sum of the three.

For our analysis, we incorporate other variables from the LCFS 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. All spending categories, 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 the leading UK inflation index. A more detailed description of the data and spending categories is provided in Section 10 of the Internet Appendix.

4.2.3 Household Transaction-level Data

To assess the impact of buying a home on household consumption, we use transaction-level data from Money Dashboard (MDB), formerly the largest free online personal budgeting application in the UK. Launched in 2010, MDB provided users with an overview of their financial accounts and transactions by collating information from current, investment and savings accounts and credit cards. The app organized transactions into expenditure categories to help users track their spending. By 2015, MDB had over 100,000 registered users, growing to 500,000 by 2023 before being wound down due to a change in ownership.[18]

The MDB dataset includes transaction-level data for all users, along with the users' postcode of their home address and birth year. Each transaction is tagged with a category (e.g., mortgage payment, wages, online shopping, restaurant, personal loan repayments, credit card finance, cash withdrawal), an indicator whether the transaction is credit or debit, transaction amount, and account type (e.g., current account, credit card) and financial intermediary associated with the account. Where available, merchant details (e.g., Tesco, B&Q, British Gas, Amazon) are also recorded.

To create a monthly panel dataset, we aggregate monthly expenditure at the user level and classify spending using the same three consumption categories as the LCFS: home-related expenditures, non-durable consumption and durable expenditures. This ensures comparability across datasets. Further details on data classification and expenditure tagging are provided in Section 11 of the Internet Appendix.

We merge the MDB information with the PSD mortgage data using postcode, birth year, mortgage payment amount and payment date. This linkage allows us to pinpoint the exact timing of a home purchase and track buyers' consumption response both before

[18]See: https://www.moneydashboard.com/press-coverage

and after a home purchase. Our analysis focuses on a panel of users spanning January 2013 (when the data commence) to December 2018.

4.3 Local Economic Activity Data

To assess the local multiplier effect of easing borrowing constraints, we draw on a variety of data sources. Using the LCFS we obtain a measure of gross household income, which includes both labor and non-labor income (e.g., investment income). For employment data we rely on the Business Structure Database (BSD), an annual dataset compiled from the Interdepartmental Business Register (IDBR). This database covers all UK firms registered for income tax purposes and provides detailed information on their geographic location and number of employees. We create three employment variables: total employment includes all employees in a district-year, non-tradable employment covers service-producing industries and tradable employment covers goods-producing industries such as agriculture, mining, and manufacturing. The tradable and non-tradable employment classifications follow the methodology of Burstein et al. (2020). A detailed description of these data and industry classifications is provided in Section 12 of the Internet Appendix.

To capture construction activity we create a variable home starts, which captures the number of new dwellings for which building work has commenced in a given district-year. This data is sourced from the UK Department for Levelling Up, Housing and Communities.

To provide an overview of our key variables, Table 1 presents summary statistics, while Table 14 in the Internet Appendix details the definitions and data 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).

5 Empirical Methodology

Figure 1 provides compelling initial evidence that HTB had a significant impact on the housing market. However, to estimate the causal impact of the program on home sales and subsequent household spending, we need to construct a counterfactual estimate of what would have happened had the program not been implemented.

Our identification strategy relies on exploiting geographic variation in *ex ante* HTB exposure. This methodology 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.

Relaxing the down payment requirement, the main objective of HTB, primarily benefits liquidity constrained households and these households are not randomly spread across the country. Instead, they tend to be concentrated in areas that have more affordable housing options, specific housing types, and desirable local amenities like pubs, restaurants, schools, and parks – features that are particularly attractive to young buyers. Since local housing market characteristics typically change slowly over time, we can expect HTB to have a greater impact in areas where low-down payment mortgages have *historically* been popular, as this should strongly correlate with the number of *potential* low-down payment buyers 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 easing borrowing constraints via HTB.[19]

We focus on 379 local authority districts (LADs) in England, Wales and Scotland, which cover 97 percent of the UK population and 98 percent of total mortgages issued. Northern Ireland is not included in our analysis due to data limitations. We focus on LADs because, apart from greater London, these areas reflect distinct housing and labor markets, similar to the core-based statistical areas (CBSAs) in the US. To determine the LAD for each mortgage, we use the property's postcode from the PSD and match it using the November 2018 National Statistics Postcode Lookup dataset.

To measure program exposure we focus on the period when the market for low-down payment mortgages was relatively unconstrained: the years before the financial crisis. We use the mortgage data described in Section 4.1 and define "*Exposure*" as the number of low-down payment mortgages issued in the district between 2005 and 2007 scaled

[19]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 13 of the Internet Appendix.

by the total number of mortgages issued in the district over that period.[20][21] 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 HTB period. 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 2018 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, reaching a maximum of around 33 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 (bottom quartile) and high (top quartile) exposure areas from 2009 to 2018. Before HTB's introduction, both measures followed similar trends. From 2013, these trends diverge, with differences becoming more pronounced in 2014 as both schemes took full effect, increasing until 2016 before stabilizing. The modest rise in 2013 reflects the lag between initiating and completing a house purchase, a process often taking several months in the UK. The first mortgages under the MG scheme, which only came into effect late 2013, therefore mostly appear in the 2014 data. All told, Figure 5 indicates that our HTB exposure measure adequately captures differences in exposure to the easing of borrowing constraints.

Using our HTB exposure measure, we employ a difference-in-differences design to compare home sales and household consumption in low- versus high-exposure areas over the period 2009–2018. That is, we examine whether changes in home sales and household consumption after HTB's introduction were larger in high-exposure relative to low-exposure districts. Districts with a historically small share of low-down payment home-buyers can serve as a control group, as HTB unlikely induced many people to buy in these districts.

Our identification strategy relies on the assumption that, absent HTB, home purchases and household consumption would have evolved similarly across districts. A key concern is that high-exposure districts might differ systematically differ in ways that could

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

[21]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.

independently influence home sales and household consumption. To explore this, Table 2 reports the correlation between HTB exposure and a set of district-level covariates. The results indicate that exposure is not random. When including all covariates jointly (column 9), HTB exposure is positively associated with unemployment rates, income levels and rents, while negatively correlated with house prices (all measured in 2009). Variables capturing the impact of the global financial crisis show no significant correlation with HTB exposure.

While these correlations do not necessarily imply a systematic bias in our estimates, we take careful measures to mitigate concerns regarding alternative explanations. All specifications include district and region-time fixed effects to account for (time-invariant) district characteristics and regional economic and housing market cycles.[22] We test for parallel trends in the pre-HTB period and verify that the observed differences align with the program's timing. Where possible, we perform within-district analysis, which allows us to include district-time fixed effects and thus eliminate any time-varying district level differences. Additionally, we assess the robustness of our results using a propensity score technique to balance observable characteristics across districts.

6 The Housing Market Response

6.1 Home Sales

We start by examining how easing borrowing constraints as initiated by HTB affected home sales. To this end we estimate the following panel regression model:

$$Y_{d,t} = \sum_{s \neq 2012} \mathbb{I}_{t=s} \times \text{Exposure}_d \times \beta_s + \delta_d + \theta_k + u_{d,t} \tag{1}$$

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. Summary statistics for these and all other variables are provided in Table 1. The specification further includes district fixed effects, δ_d, and region-time effects, θ_k. We cluster the standard errors by district. We estimate the model over the period 2009 to 2018 and the year 2012 is taken to be the base year.[23] To ensure our results are not driven by outliers, we winsorize the

[22] The regions are categorized at NUTS1 level, comprising a total of 12 regions.

[23] We cannot go further back in time, as 2008 is already "exposed" as high LTV mortgages were still available in the first half of the year.

dependent variable - and all other outcome variables - at the top and bottom percentile, although our results are robust to including outliers.

The model in Equation 1 provides coefficient estimates β_s that capture the time dynamics of the effect of easing borrowing constraints through HTB on home sales. The top panel of Figure 6 shows the results for all districts. In the three years preceding HTB, home sales trends were nearly identical, with insignificant β_s. However, starting in 2013, home sales rose significantly more in more exposed districts, gaining momentum in 2014 when both programs were fully operational. This difference in trends persisted throughout the sample period, stabilizing from 2016 onwards, reflecting the recovery in the market for mortgages with a 5 percent down payment, as highlighted by Mark Carney in a letter to the Treasury.[24] The timing of these changes aligns closely with the timing of the program. The modest rise in 2013 reflects the typically lag of several months to complete a house purchase in the UK. Since the MG scheme was introduced in October 2013, its impact was limited that year and home sales under this program beginning in earnest in 2014.

The economic significance is substantial. Home sales in 2014 are 9.9 percent higher per standard deviation HTB exposure. By 2018, they are 15.0 percent higher per standard deviation HTB exposure. These findings indicate that HTB boosted the number of homes purchased, suggesting that easing borrowing constraints can have a lasting and substantial impact on housing markets, particularly in areas where households face down payment constraints.

To ensure the robustness of our results, we address potential differences between districts with high and low HTB exposure that might explain the different trends from 2013 onwards. First, we re-estimate the model using a subset of districts, where high-exposure (treated) districts are matched with low-exposure (untreated) districts through propensity score matching. Treated districts are defined as those above the median HTB exposure and untreated districts those below the median.

The matching process is based on district-level variables, including the log of the unemployment rate, median income, average rent, and average house price in 2009 (the start of our analysis period), as well as the log changes in these variables from the peak of the housing boom in 2007 to the trough of the bust in 2010. This approach results in 53 treated districts matched with 53 untreated districts. The bottom panel of Figure 6 shows that the matched sample results align closely with those from the full sample, reinforcing the validity of our findings.

[24] https://www.bankofengland.co.uk/-/media/boe/files/letter/2016/governor-letter-220916.pdf

To further validate these findings, we examine whether the rise in home sales was driven by low-down payment mortgages. As discussed in Section 3, HTB primarily reduced borrowing constraints by lowering the minimum down payment requirement from 10 to 5 percent. If the observed increase in home sales in high-exposure districts is directly attributable to the policy change, it should be driven by purchases with a 5 percent down payment. To test this, we leverage the discrete interest rate jumps associated with various down payment thresholds for UK mortgages (Section 3).

We estimate a difference-in-differences version of Equation 1, comparing home sales in high- versus low-exposure districts before and after the HTB implementation, differentiating between homes purchased with different down payment size:

$$\begin{aligned} Y_{d,t,i} = \quad & \beta_1 \text{Pre}_t \times \text{Exposure}_d + \beta_2 \text{Post}_t \times \text{Exposure}_d \\ & + \beta_3 \text{Post}_t \times \text{Exposure}_d \times \text{DP}_i + \delta_d + \theta_k + \mu_i + u_{d,t,i} \end{aligned} \tag{2}$$

where d indexes a district, t is the year and i is the down payment size category. The dependent variable, Home Sales$_{d,t,i}$, equals the number of home sales within a down payment size category in a given year and district. The down payment categories are 5 percent, 10 percent, and 15 percent or more.[25] We then interact the interaction term Post$_t$ $\times$ Exposure$_d$ with DP_i, which is a dummy variable for the different down payment categories. We further expand the model by including down payment category fixed effects and the various double interactions. Pre$_t$ is a dummy variable equal to 1 for the period 2009 to 2011, and zero otherwise. Post$_t$ is a dummy variable equal to 1 for the period 2013 to 2018, and zero otherwise. The other variables and model specifications are the same as in Equation 1.

The results are presented in Table 3. Column 1 presents the model with β_2 held constant across down payment categories, capturing the average effect of easing borrowing constraints via HTB. As expected, the effect is positive and significant, with no differential effect detected in the pre-period.

In column 2, β_2 varies by down payment category. The triple interaction term for 5 percent down payments shows the largest positive and significant coefficient. The term for 10 percent down payments is also positive but smaller, reflecting that some EL mortgages involved somewhat larger down payments than the 5 percent minimum (Benetton et al., 2021). Consistent with HTB driving the observed effects, the interaction term Post$_t$ $\times$ Exposure$_d$ is insignificant, indicating that HTB had no effects on home sales with high

[25] 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.

down payments. These findings highlight that the increase in home sales in high-HTB-exposure districts was primarily driven by purchases with low-down-payments.

Column 3 adds district-by-time fixed effects, thus controlling for all time-(in)variant differences across districts and isolating the impact of HTB purely from within-district heterogeneity. The results remain robust, mitigating concerns that the HTB exposure measure might correlate with unobservable district-level factors influencing housing demand.

To test the robustness further, we exclude Greater London from our analysis in Column 4, as its housing market has some distinctive characteristics, such as a high presence of international and buy-to-let investors. The estimates for β_3 remain significant and even become slightly larger. In column 5, we use the propensity score matched treatment and control districts, and the results closely align with the baseline.

Another potential concern is whether concurrent policies confound our results. One potentially relevant policy is the introduction of a 15 percent limit on new mortgages with a loan-to-income ratio (LTI) of 4.5 or higher in 2014. Peydro et al. (2020) find that this policy reduced mortgage credit for low-income borrowers in areas with constrained lenders. This could bias our results downwards if constrained-lender exposure correlates with HTB exposure and disproportionately affects low-down-payment buyers.

To examine, we adapt the constrained-lender exposure measure of Peydro et al. (2020) to correspond with our district-level analysis, and interact the $\text{Post}_t \times \text{DP}_i$ with the *LTI Exposure* variable.[26] Column 6 shows that this does not materially affect the estimates for β_3, which is unsurprising given that low-down payment buyers are typically not LTI constrained. Between 2013 to 2016, the average LTI of low-down payment mortgages was 3.4, with 96 percent of these mortgages below an LTI of 4.5.

Our empirical design assumes no spillovers between treated and control districts due to endogenous moves. If households moved from low- to high-exposure areas because of HTB, both areas would be affected. This concern is not relevant for first-time buyers, who lack a previous home, but could affect estimates for home movers. Although endogenous moves are more likely in the London area, this factor is unlikely explains much of the observed impact in the rest of the country. Lomax (2020) finds that 68 percent of the UK moves occur within the same postcode area, indicating that most moves take place within districts (which typically contain multiple postcodes). Longer-distance moves are

[26]Specifically, in line with Peydro et al. (2020), we first define constrained lenders as those that issued 15 percent or more of their mortgages with an LTI of 4.5 or higher in 2012. We then compute the district-level *LTI Exposure* measure as the proportion of mortgages issued by these lenders in 2012.

typically driven by education or employment rather than housing reasons (Thomas et al., 2019). In Section 13 of our Internet Appendix, we formally test for migration effects and find no evidence of inward migration to high exposure districts after the policy change.

As a final robustness test, we examine the heterogeneous effects of HTB on buyer groups most likely to face liquidity constraints: first-time buyers and younger buyers (e.g. Linneman and Wachter, 1989; Engelhardt, 1996; Haurin et al., 1996). Using an adapted version of Equation 2, we analyze home purchases by buyer type. The dependent variable is now Home Sales$_{d,t,b}$, representing home purchases by buyer type in a given year and district, and we include an interaction term Post$_t \times$Exposure$_d \times$Buyer$_b$, where Buyer$_b$ is a dummy for first-time or younger buyers (20-39 years old). Results in Table 4 indicate that while HTB increased home purchases across all groups, its impact was significantly stronger for first-time buyers and younger buyers. The results remain robust when replacing district and time fixed effects with district-by-time fixed effect (columns 2 and 5) and when focusing on propensity score-matched districts (columns 3 and 6), confirming that HTB primarily benefited households facing greater down payment constraints.

6.2 Economy-wide Effects

Finally, we use the estimates from Section 6.1 to estimate the aggregate increase in housing sales attributable to HTB.[27] Similar to Berger et al. (2020) and Mian and Sufi (2012), we treat the district with minimum HTB exposure as the control group.[28] For each district, we calculate additional homes purchases over the period 2013 to 2018, 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 the difference between a district's HTB exposure and the control group's exposure. Summing across districts gives the total aggregate effect.[29]

We estimate that approximately 536,000 homes were purchased due to the easing of borrowing constraints, corresponding to a 14.3 percent increase over the HTB period.[30] This is higher than the approximately 316,000 HTB mortgages issued between the start

[27]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.

[28]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,

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

[30]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.

of the program and the end of 2018. Two factors explain this difference. First, some banks offered low-down payment mortgages outside the two program schemes during this period. Second, local demand effects may have stimulated additional demand for housing as well.[31]

Of the 536,000 additional homes purchased, we estimate that first-time buyers accounted for 77 percent, while younger households (both first-time buyers as well as home movers) were responsible for 86 percent. These findings confirm that relaxing the down payment constraint disproportionately benefits young and first-time buyers, who typically face the greatest challenges in saving for a down payment.

6.3 House Price Growth

Given the significant impact of HTB on home sales, it is plausible that the easing of borrowing constraints also exerted upward pressure on house prices. To explore this, we first examine descriptive evidence before turning to more formal estimation. Figure 7 plots the relationship between our HTB exposure measure and average house price growth from 2013 to 2018 across districts. The relationship appears weak, with districts highly exposed to HTB showing no substantial difference in house price growth relative to low-exposure districts.

To formally assess the impact of HTB on house prices, we estimate Equation 2 without mortgage type interaction effects, substituting log house prices as the dependent variable. The model again includes district and region-time fixed effects, with standard errors clustered at the district level and the dependent variable is winzorised at the 1st and 99th percentiles.[32]

Table 5 presents the results, revealing a modest but significant effect of HTB exposure on house prices. Across all districts, house prices increased by 2.34 percent per standard deviation of program exposure. When focusing on districts outside of London the house price increase is very modest, just 1.8 per cent, while it is higher in London districts at 6.9 per cent per standard deviation of exposure (Columns 2 and 3). These findings align with Carozzi et al. (2020) who show that housing supply responsiveness, which is much weaker in London, plays a pivotal role in moderating house price reactions to the

[31] Furthermore, the number of low-down-payment mortgages also reflects an intensive margin effect, where households use the same down payment to purchase a more expensive home - effectively switching from a low-LTV to a high-LTV mortgage. These purchases, do not contribute to an actual increase in the number of home sales.

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

EL scheme of HTB. The result is not materially affected when using propensity score matching (Column 4).

Interestingly, when we control for housing supply elasticity (Columns 5-8) we find that in non-London districts house prices rose more in areas with inelastic housing supply and controlling for this, reduces the impact of HTB even further, to just 0.9 percent. Housing supply elasticity is not significant for London districts, but this likely reflects the fact that there is little variation in this variable for London districts, which all have relatively inelastic housing supply. Overall, our results suggest that while HTB did contribute to modest house price increases, these effects were geographically concentrated and strongly mediated by supply-side constraints.

7 The Consumption Response

Having established that easing borrowing constraints via HTB increased home sale, we now move to examine how household consumption was affected in those regions that experienced a rise in home sales with only a limited impact on house prices. We focus on two sets of consumption data: car sales and household survey data.

7.1 Car Sales

We begin by examining the impact of HTB on new car purchases, a key durable consumption good unrelated to housing. Our identification strategy mirrors that for home sales, comparing car sales in high- and low-exposure districts before and after the easing of borrowing constraints. We adapt Equation 1 and replace the outcome variable with Car Sales$_{d,t}$, which equals the number of new private car registrations per district and year. The model includes district and region-time fixed effects, with standard errors clustered at the district level. The analysis spans 2009 to 2018, with 2012 as the base year. To address potential outliers, the dependent variable is again winsorized at the 1st and 99th percentiles.[33] Summary statistics for the outcome variable are provided in Table 1.

Figure 8 illustrates the time dynamics of the policy's effect on car sales. The top panel shows results for all districts, while the bottom panel focuses on the propensity score matched sample. Prior to HTB, car sales trends were similar across districts. Starting in

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

2013, car sales began to rise more in high-exposure districts, with the differential effect becoming significant in 2014 and remaining so throughout the sample period. This timing aligns with the timing of the policy, with the 2013 insignificance likely reflecting the lag in spillover effects from increased housing activity to broader consumption. Additionally, the modest rise in home sales in 2013 aligns with this delay.[34]

To quantify the aggregate impact, we estimate the total increase in car sales attributable to HTB using the methodology from Section 6.2, treating the district with lowest HTB exposure as the control group.[35] For each district, we calculate additional car purchases from 2013–2018 based on estimates of β_s in Figure 8 and sum these. We estimate an aggregate increase of approximately 2,478,900 new car purchases, or 16.8 percent.

These findings provide the first direct evidence of a consumption effect at the district level, demonstrating that easing borrowing constraints through HTB not only boosted home sales but local consumption as well. This suggests that a targeted housing policy can generate significant spillover effects, amplifying its overall economic impact across the broader economy.

7.2 Household Survey

To further investigate these effects, we now turn to The Living Costs and Food Survey (LCFS), the UK's most comprehensive household spending survey and widely used in the literature (e.g., Campbell and Cocco, 2007; Cloyne et al., 2020). The LCFS tracks consumption across diverse categories and allows us to control for household-level factors, such as childbirth, that influence consumption. However, the LCFS also presents some well-documented empirical challenges: each annual wave includes only around 5,000 respondents, making year-district-level analysis difficult, and households are observed only once.

To address these limitations, we construct a pseudo-panel following the methodology of Browning et al. (1985) and Deaton (1985). This approach creates "synthetic cohorts" by grouping households with similar fixed characteristics. Specifically, we group households by the birth year of the household head (six 10-year cohorts, ranging from 1937–1946 to 1987–1996) and by district. Due to insufficient observations per district-year, we aggregate districts into 10 regional cohorts based on HTB exposure deciles (e.g districts

[34] We find very similar results if we exclude the Greater London districts. Result available upon request.

[35] 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.

in the first decile form the first exposure-region). This results in 60 region-birth year cohorts tracked annually from 2009 to 2018.

As described in Section 4.2, we categorize weekly expenditures into three spending measures: home-related expenditures, non-durable consumption, and durable expenditures, which together sum to total household consumption. For each year-region-birth year cohort, we calculate the average of logged and deflated values for these spending categories. While this pseudo-panel sacrifices district-level granularity, it ensures annual data coverage. For an alternative LCFS dataset offering granular district coverage but limited time dimension, see Section 14 in the Internet Appendix.

We further draw on the LCFS to create cohort-level controls. Following Campbell and Cocco (2007), we include the age of the household head, household size, household income, mortgage and rental payments, and proportions of outright owners and mortgagors. We take the average of the logged and deflated (where relevant) values, except for the proportions of outright owners and mortgagors, which are calculated at the region-birth year cohort level annually. These controls help account for factors like income shocks or childbirth that may independently affect consumption, helping us isolate the effects of HTB.A detailed description of the data and variable definitions can be found in Section 10 of the Internet Appendix. Table 1 presents the summary statistics for outcome and control variables.

We estimate the following pseudo-panel regression model:

$$\text{Consumption}_{r,c,t} = \sum_{s \neq 2012} \mathbb{I}_{t=s} \times \text{Exposure}_r \times \beta_s + \boldsymbol{\gamma} \text{Cohort}_{r,c,t} + \delta_r + \theta_t + \gamma_c + u_{r,c,t} \tag{3}$$

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. Exposure_r is our measure of *ex ante* HTB exposure in exposure-region r. $\mathbf{Cohort}_{r,c,t}$ is the vector of time-varying cohort-level (that is, the 60 region-birth year group combinations) controls. 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 2009 to 2018 and 2012 is the base year. The dependent variable is winsorized at the 1st and 99th percentile.[36]

The results in Figure 9 reveal patterns consistent to those observed for car sales. Following the easing of borrowing constraints, consumption in more exposed regions begins to rise, becoming significant in 2014 and remaining stable thereafter, with the exception of 2015.

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

Reassuringly, we do not detect differential trends in the pre-period. On average, real total household consumption increased by 3.7 percent per standard deviation in HTB exposure during the program years.

Regions with greater HTB exposure thus experienced not only a relative increase in home sales but also a corresponding rise in household consumption. To better understand what drives this consumption response, we decompose total household consumption into its sub-components and estimate the following pseudo-panel regression model:

$$\begin{aligned} \text{Consumption}_{r,c,t} = \quad & \beta_1 \text{Pre}_t \times \text{Exposure}_r + \beta_2 \text{Post}_t \times \text{Exposure}_r + \boldsymbol{\gamma} \text{Cohort}_{r,c,t} \\ & + \lambda \text{House Prices}_{r,t-1} + \delta_r + \theta_t + \gamma_c + u_{r,c,t} \end{aligned} \tag{4}$$

The outcome variable $\text{Consumption}_{r,c,t}$ is real total household consumption, home-related expenditures, non-durable consumption or durable expenditures. Pre_t is a dummy variable equal to 1 for the period 2009 to 2011, and zero otherwise. Post_t is a dummy variable equal to 1 for the period 2013 to 2018, and zero otherwise.

Table 6 begins by confirming the increase in total consumption in high-exposure areas after HTB's introduction (column 1). This result remains robust when excluding London (column 2) and when using propensity scoring (column 3). Columns 4–6 reveal important differences across the three subcomponents of household consumption. Home-related expenditures increased by 5.7 percent per standard deviation in HTB exposure (column 4), consistent with the presence of a home purchase channel (Best and Kleven, 2017; Benmelech et al., 2017). Interestingly, non-durable consumption unrelated to housing, which includes semi-durable goods and accounts for 70% of total consumption, also increased by 4.0 percent (column 5). In contrast, durable expenditures showed no significant change (column 6).

The lack of a significant effect on durable goods at first glance seems inconsistent with the findings for car sales. However, two factors reconcile this discrepancy. First, new car purchases account for only 18 percent of durable expenditures and just 2 percent of total household consumption.[37] Second, in the UK, around 90% of new cars are purchased using unsecured consumer credit Finance and Leasing Association (2022), resulting in relatively small monthly payments. This suggests that while the easing of borrowing constraints and increased home sales boosted loan-financed car purchases, it did not significantly affect broader (non-home-related) durable goods purchases, which are typically paid for out of pocket. Supporting this, a further analysis of loan-financed versus outright car purchases

[37] These statistics are calculated using the LCFS.

from the LCFS using Equation 4) shows a significant rise in loan-financed purchases in high-exposure areas during HTB, but no increase in outright purchases (results available upon request).

To estimate the economy-wide impact, we use the region in the lowest HTB exposure decile as the control group and the β_2 estimates from Table 6 columns 1, 4 and 5. We find that easing borrowing constraints through HTB increased household consumption by 5.7 percent on average. Non-durable consumption and home-related expenditures rose by 5.3 percent and 10.6 percent, respectively. The 5.7 percent increase in total household consumption corresponds to an annual increase of £1,120 or 3.7 percent of the average after-tax household income, based on the average total household consumption from the LCFS during the exposure period.

Taken together, these findings demonstrate that easing borrowing constraints through HTB not only boosts home sales but also generates a substantial rise in consumption. The increase in car sales, home-related expenditures, and non-durable consumption highlights a local spillover effect, where increased home sales stimulate additional local spending. In the next section, we explore the mechanisms behind this spillover effect, focusing on how new homebuyers' spending patterns and broader economic activity interact to shape regional outcomes.

8 Mechanisms Consumption Response

Our findings point to a robust local spillover effect following the easing of mortgage-market borrowing constraints. In this section, we explore potential mechanisms behind this effect. First, we investigate a direct consumption channel, where new home-buyers may increase spending on goods and services, injecting demand into the local economy. Second, we assess the possibility of a local multiplier effect, where this initial spending could stimulate broader economic activity, potentially encouraging firms to expand employment and production, which in turn might amplify consumption. Finally, we consider whether increased housing construction plays a role in these dynamics. By evaluating these channels, we aim to better understand how borrowing constraints influence local economic outcomes.

8.1 Home-Buyer Spending

Home purchases can significantly reshape household spending, particularly in the months immediately following the transaction. Moving to a new property often sparks a surge in home-related expenditures, such as furniture, appliances, or renovations (Best and Kleven, 2017; Benmelech et al., 2017). For instance, Benmelech et al. (2017) document a sharp rise in such spending during the first two months after purchase, which then subsides to pre-purchase levels within six months.

Beyond these temporary shifts, homeownership can also influence broader consumption patterns by altering households' financial constraints. When monthly mortgage payments are lower than prior rent or mortgages costs combined with savings allocated for a down payment, discretionary income rises, enabling higher spending. Such consumption effect is likely stronger among liquidity-constrained households, which have high marginal propensities to consume (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) finds that households often reduce food spending while saving for a down payment but increase it once homeownership is secured, reflecting eased liquidity constraints.

At the same time, some new homeowners may cut back on discretionary spending to manage higher fixed expenses when their mortgage payments surpass previous housing costs. Others may prioritize paying down debt quickly due to aversion to high leverage (Caetano et al., 2019). Thus, whether homeownership ultimately raises or lowers household spending hinges on multiple factors - ranging from changes in monthly costs to individual preferences about debt.

To investigate how households in the UK adjust their consumption after purchasing a home during the HTB period, we leverage transaction-level consumption data matched to mortgage data. This dataset is uniquely suited to identify home purchases and track household spending both before and after the transaction, offering detailed insights into consumption dynamics. These data allow us to precisely analyze how new homeowners adjust their spending over time.

Our sample consists of a monthly panel of current and future homeowners who purchase a home between 2013 and 2018. The dataset includes 122,296 observations for 5,235 homeowners, of whom 3,370 complete a home purchase during this period.[38] Panel B of Table 1 presents summary statistics for the various consumption categories, constructed

[38]We only include new home buyers who have spending data for at least 12 months before and after the home purchase

using the methodology outlined in Appendix 11. On average, total monthly consumption is £1,977, with £246 allocated to home-related expenditures, £1,672 to non-durable goods and services and £16 to durable goods.

Figure 10 offers an initial glimpse into how buying a home may influence household consumption. The figure tracks average household spending in the 24 months before and after a home purchase, revealing two key patterns. First, new home-buyers spend approximately £2,000 more in the three months surrounding their home purchase compared to the pre-purchase average, likely reflecting expenditures on home-related items such as furniture and renovation. Second, post-purchase monthly consumption stabilizes at around £370 higher than pre-purchase levels, suggesting a more sustained shift in spending behavior. While figure 10 provides descriptive evidence and does not establish causality, it strongly hints that the consumption response we document is at least partly driven by the new home buyers.

To estimate the causal impact of a home purchase on household consumption, we conduct an event study using the staggered difference-in-difference estimation approach of Borusyak et al. (2024). The treatment event of interest is a home purchases. Our control group consists "not yet treated" renters who purchase homes outside the event window and "never treated" homeowners. By applying the approach of Borusyak et al. (2024), we can correct for the potential heterogeneous treatment-effects that may arise due to the fact that some control households (e.g. the existing homeowners) may have previously been treated (e.g. when they purchased their home).

We estimate the following model:

$$Y_{d,t,i} = \sum_{h=-24}^{24} \beta_{t+h} D_{i,t+h} + \alpha_i + \theta_k + u_{d,t,i} \tag{5}$$

where d indexes a district, t is the month and i is the household. The dependent variable $Y_{d,t,i}$ is one of our consumption measures (i.e. total consumption, housing-related, non-durables or durables) and captures spending by household i in . $D_{i,t+h}$ is a treatment dummy equal to 1 in the period around a home purchase. The specification further includes household fixed effects α_i and region-by-month fixed effects, θ_k. We estimate the model for home purchases from 2013-2018. Standard errors are clustered at the district level.

For the dependent variable, we use two alternative measures: the level of spending (in pounds per month) and the log of spending (the natural logarithm of 1 + pound spending). These two specifications capture different aspects of the consumption response to a

home purchase. The level specification focuses on absolute changes in spending, naturally giving more weight to households with larger increases in expenditure. The log specification, on the other hand, expresses changes relative to baseline consumption, assigning equal weight to percentage changes across households, regardless of their initial spending levels.

The coefficients of interest β_{t+h} capture the household's incremental spending in each of the 24 months before and after a home purchase, relative to the control group. Household fixed effects account for all time-invariant characteristics of each household, such as baseline preferences or permanent consumption habits, allowing us to focus on changes in spending within each household over time. Region-by-month fixed effects control for regional business cycle fluctuations or other economic shocks.

The top panel of Figure 11 shows a sharp increase in total consumption immediately following a home purchase. Spending rises by an average of £800 in the month of the purchase, £600 in the following month, and £400 in the second month. Thereafter, consumption stabilizes at an additional £150 per month for the remainder of the year. On average, total consumption is £3,200 higher during the first year, with the spending response remaining significantly elevated for just over 12 months. By the 14th month after the purchase, the estimated increase in spending dissipates, returning to pre-purchase levels.

The bottom panel shows that the log of spending displays a similar pattern to the level specification in the months following a home purchase, but the effect persists for longer. In the month of purchase and the following month, spending increases by approximately 30 percent relative to baseline. This effect drops to 23 percent in the second month and 15 percent in the third month. Consumption then stabilizes at around 10 percent above baseline and remains significantly elevated until the 17th month after purchase. The response only becomes statistically insignificant in the 18th month, highlighting the longer-lasting impact on percentage changes in total consumption after a home purchase.

We perform several robustness checks to ensure that our findings are not driven by factors such as income changes or family extensions. The results remain consistent when we add controls for monthly income alongside household fixed effects, addressing concerns that income fluctuations might explain the observed spending patterns. Similarly, excluding households with notable increases in child-related spending during the 24-month window around a home purchase yields similar results, suggesting that the observed spending increases are not influenced by changes in household composition. These checks provide additional confidence that the spending patterns we document are closely tied to the

home purchase.

We now turn to the various consumption categories, with results presented in Figure 12. Consistent with Benmelech et al. (2017) who analyze the impact of home purchases on home-related spending in the US, we find a significant rise in home-related expenditures rise following a home purchase (top panel). On average, these expenditures increase by approximately £2,000 in the first year, with the largest spikes occurring in the month of purchase and the subsequent three months. However, unlike Benmelech et al. (2017), our results indicate that home-related spending remains elevated for at least two years after the purchase, stabilizing at an additional £50 per month. The log specification further reveals that home-related spending increases by 200% around the time of purchase and remains 50% higher than baseline for at least two years. These differences may reflect variations in data sources (survey vs. transaction-level data), differences in the sample period, or behavioral differences between home buyers in the UK and the US.

In addition to the rise in home-related spending, we observe a noticeable increase in non-durable consumption following a home purchase (middle panel). The effect peaks during the month of purchase, with an average increase of £350, and gradually tapers off but remains elevated for at least six months. When measured in logs, the increase is even more pronounced, with non-durable spending rising by 20% in the month of purchase and staying about 10% higher than baseline levels for up to 18 months. In contrast, durable consumption unrelated to the home shows no significant change (bottom panel).

Our results suggest that the consumption response by home-buyers is not solely attributable to expenses directly associated with purchasing a home. Instead, it appears at least partially driven by an increase in discretionary income following the home purchase, which is subsequently spent on non-durable goods and home-related services. If this assumption is correct, we would expect the consumption effect to be stronger among liquidity-constrained households, as they typically have higher marginal propensities to consume (Johnson et al., 2006; Agarwal et al., 2007; Kaplan and Violante, 2014; Misra and Surico, 2014).

To test this hypothesis, we split our sample using three dimensions to identify relatively high vs low liquidity-constrained buyers: households taking low versus high down payment mortgages, first-time buyers versus home-movers, and younger versus older buyers. Table 7 reports the results, focusing on total household consumption. We find no significant differences in absolute consumption levels between constrained and less constrained buyers; if anything, less constrained buyers exhibit slightly larger increases in consumption. However, when we use the log-specification, which accounts for constrained buyers'

likely lower baseline consumption levels, the results indicate a significantly stronger consumption response for households using low down payment mortgages, first-time buyers, and younger buyers. This evidence supports the hypothesis that liquidity constraints amplify the consumption response.

The scale of the spending increase is substantial: an estimated £1.7 million in the first year alone. This raises an important question: does this increased spending by home-buyers stimulate broader economic activity? In the next section, we explore the local multiplier effect, examining how home-buyer spending reverberates through the local economy.

8.2 Economic Activity

We next investigate whether local economic activity responds to the increase in housing market activity and associated home-buyer spending. We examine the response of local employment, local household income, and local housing construction to our measure of HTB exposure.

8.2.1 Employment

We first consider the impact on local employment. A change in local demand should affect local non-tradable employment but not local tradable employment, which depends more on national or global demand. To examine whether this is the case, we estimate a panel regression model similar to Equation 2, but without the triple interaction. The outcome variable $Y_{d,t}$ is now $\text{Employment}_{d,t}$, which equals total number of non-tradable or tradable employees for all firms in a given year and district. The model again includes district and region-by-time fixed effects.

The results in Table 8 indicate a relative increase in non-tradable employment in more exposed districts (column 1). We find similar results for non-tradable employment when we exclude London (column 2) or when we only include the propensity score matched districts (column 3). For tradable employment, there appears to be a possible relative decrease in more exposed regions, which can be explained by potential general equilibrium effects such as local wage adjustments (Mian and Sufi, 2014).

Overall, the results suggest an increase in employment that is consistent with a local multiplier effect where the increase in local demand as new home buyers increase their consumption feeds back into the local economy expanding consumption even further.

8.2.2 Household Income

To further substantiate the presence of increased local activity, we again turn to the LCFS to study how household income responds. We estimate Equation 4 for household income as the dependent variable. Table 8 reports the results in Columns 7-9. We find that household income increased more in high exposure regions, and this finding is robust to when we exclude London or focus on propensity score matched districts only. This increase in local household income is consistent with a local multiplier effect via an increase in local demand.

8.2.3 Construction

Another stated objective of HTB was to encourage additional housing construction. In additional to increasing housing supply, construction activity can positively affect local demand. We therefore estimate Equation 4 for home starts as the dependent variable. Table 9 reports the results. The results in Column 1 indicates that there was an increase housing construction at the time the HTB was active, but Column 2 shows that there was no relative increase in construction in districts more exposed to easing borrowing constraints induced by the program. In fact, there is some evidence of a relative decrease in construction in higher exposure districts.

Instead, Columns 5-8 illustrate that the rise in housing construction that occurred in districts with greater housing supply elasticity. This intuitive result demonstrates that areas more affected by borrowing constraints do not coincide with areas that can easily adjust housing supply. Moreover, housing construction does not appear to be one of the mechanisms contributing to the local multiplier effect of mortgage-market borrowing constraints.

To summarize, the findings above suggest that local demand rose in districts with a rise in housing market activity that induced an increase in economic activity. We do not find evidence that a rise in construction played a significant role. Furthermore, with housing prices only showing a modest increase (see Section 6.3), wealth effects at best played a minor role in the consumption response we document. The apparent existence of a feedback loop through a rise in local demand can also explain why the consumption response can be quite large.

9 Concluding Remarks

In this paper, we examine the role of mortgage-market borrowing constraints in shaping consumption patterns. To do this, we exploit a large-scale policy intervention in the UK called Help-to-Buy, which prompted a sudden and significant relaxation of borrowing constraints. The policy effectively lowered the LTV limit by providing home-buyers with the option to purchase a home with only a 5 percent down payment; prior to the policy, mortgage lenders required a 10 percent down payment.

The intervention proved effective at spurring home sales and household consumption. The observed consumption response is partly driven by a 14 percent increase in the volume of new home-buyers, each of whom spend an additional £3,200 on services, non-durables and home-related items in the year following their home purchase. But the housing market stimulus and new home-buyer spending is also a part of an important local multiplier effect resulting from the easing of borrowing constraints. The rise in home-buyer spending boosts local demand and economic activity–such as non-tradable employment–which subsequently brings about a broader increase in consumption. These local general equilibrium effects are cause an increase in local household income.

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 easing mortgage-market borrowing constraints 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 home-buyer 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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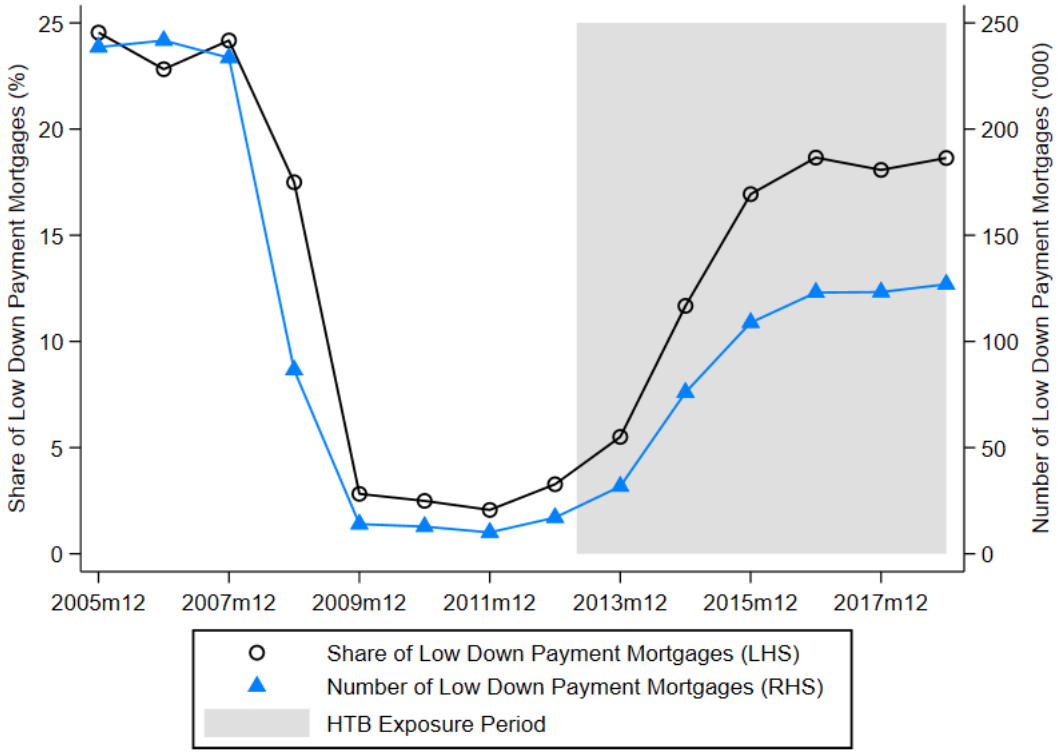
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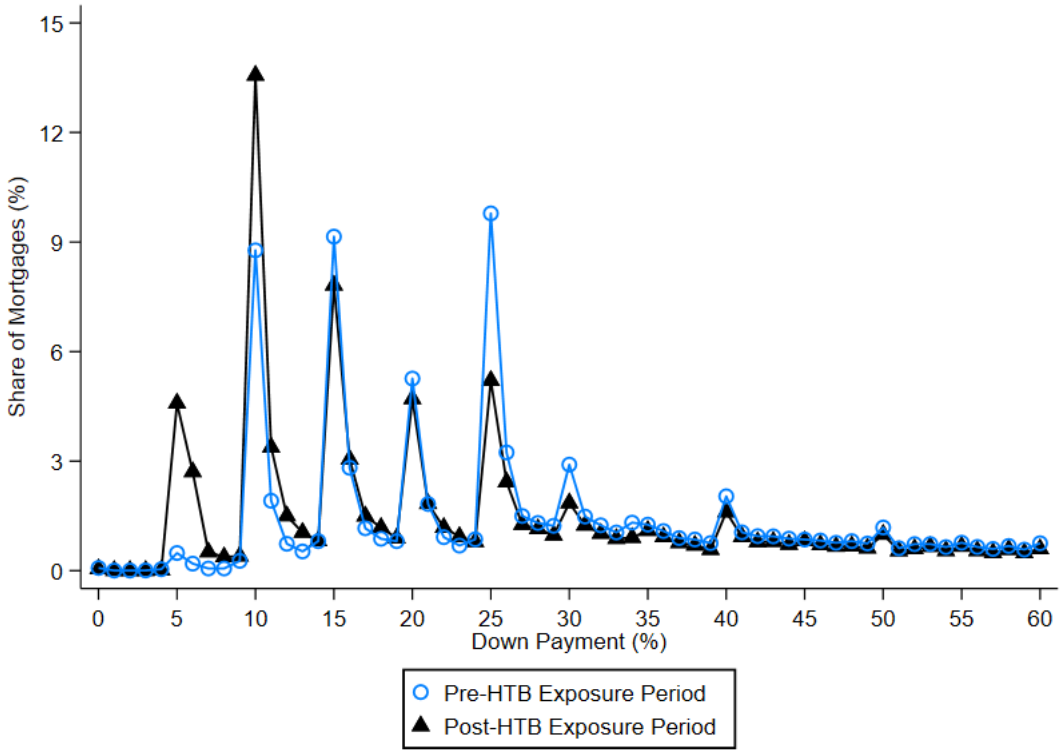
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Figure 1: **Number and Share of Low-Down Payment Mortgages**



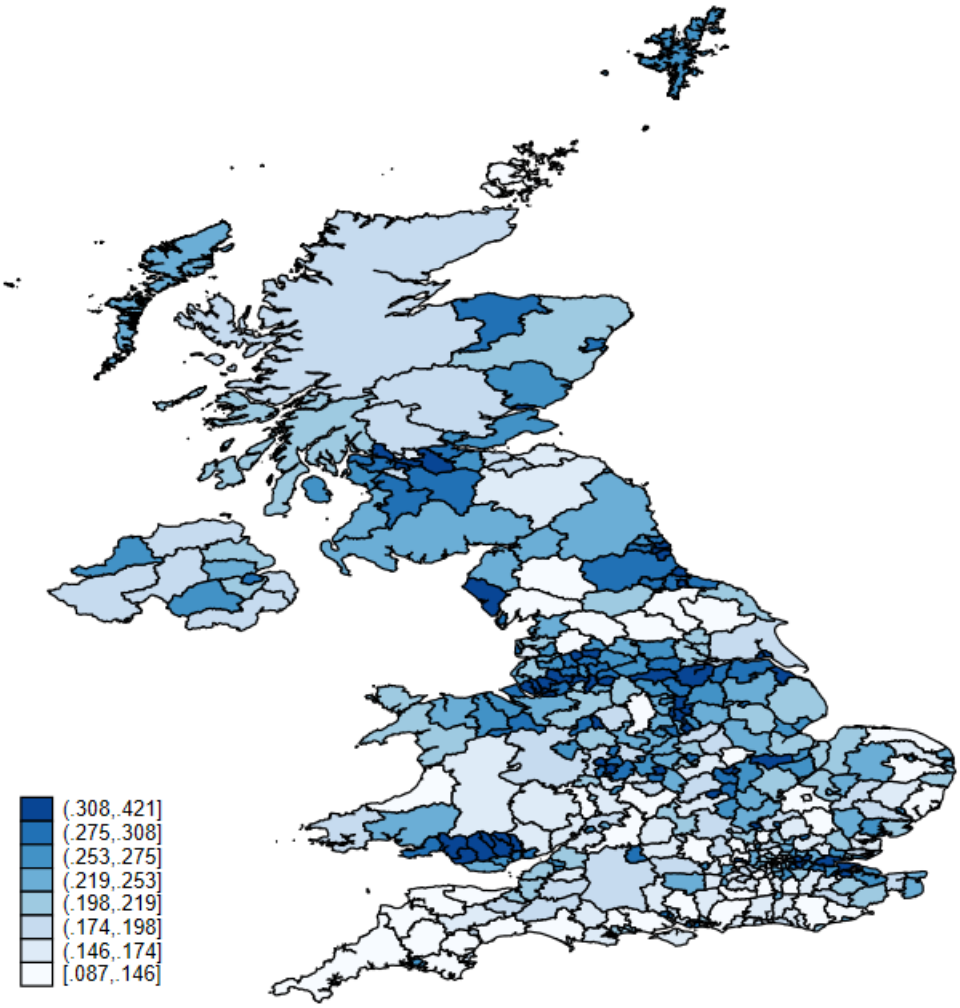
The figure shows the share and number of low-down payment mortgages before and during the HTB exposure period. The shaded area indicates the period that HTB is in effect. Only first-time buyer and home-mover mortgages are included.

Figure 2: **Down Payment Distribution Among Mortgages**



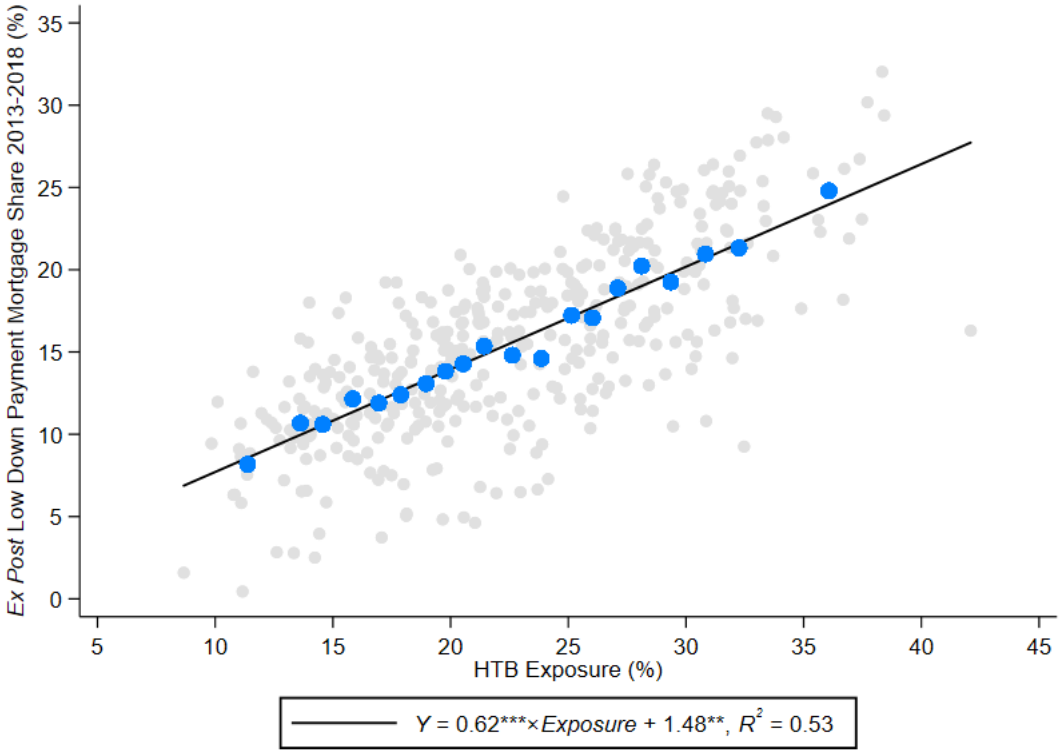
The figure shows the share of mortgages by down payment size in the pre-HTB and post-HTB exposure periods. The pre-HTB and post-HTB exposure periods cover 2009-2012 and 2013-2018, respectively.

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



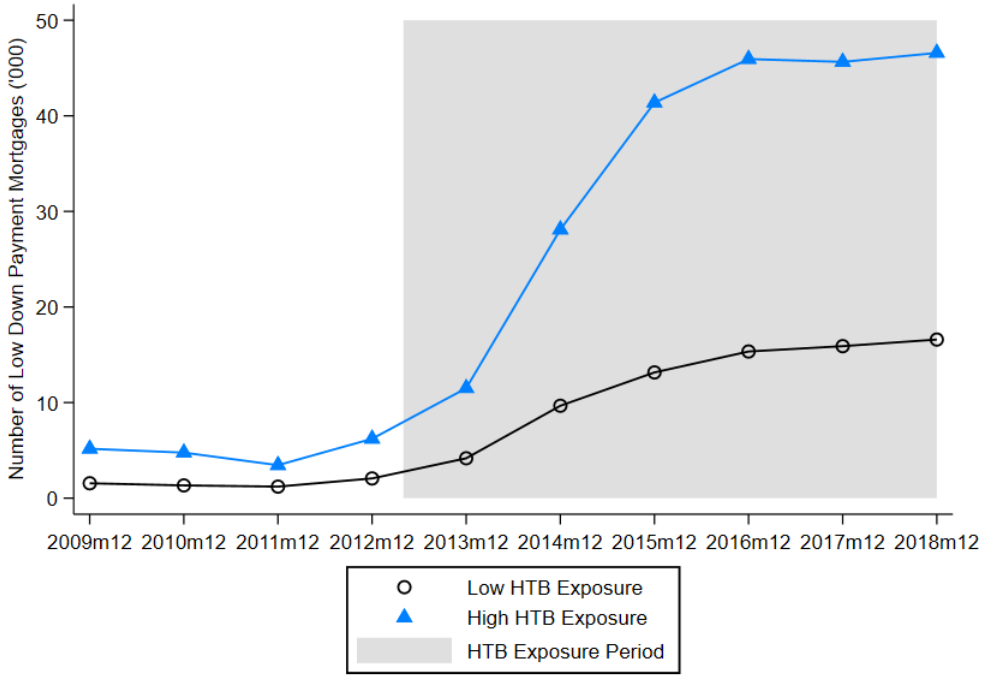
The figure shades local authority districts across the UK by their HTB Exposure. HTB Exposure equals the number of low-down payment mortgages in a district in the period 2005-2007 divided by the total number of mortgages in 2005-2007. Districts with a darker shading have higher exposure.

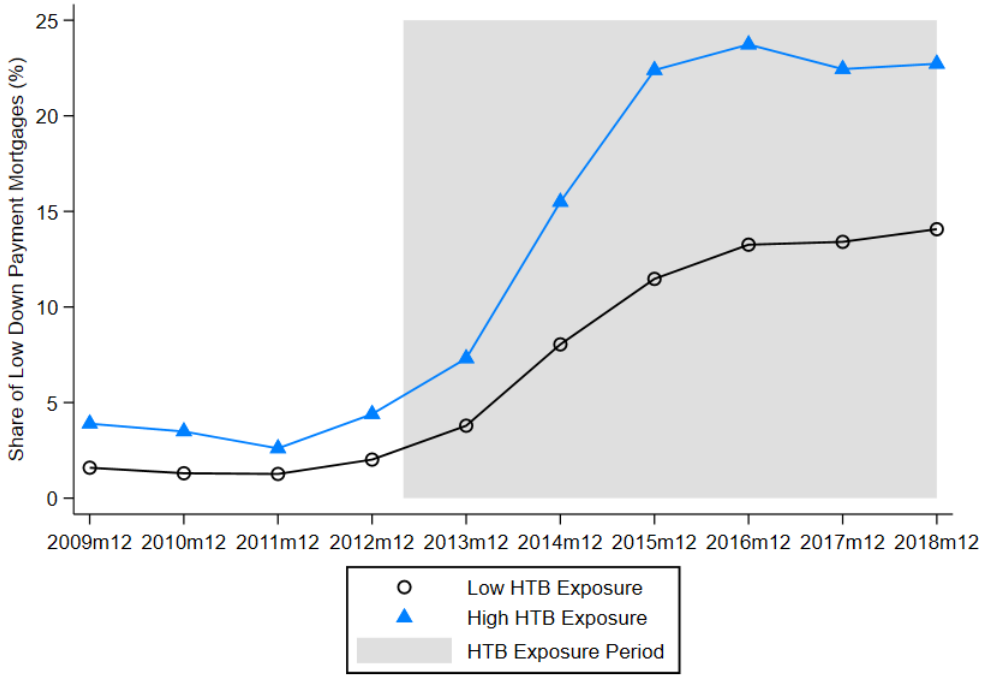
Figure 4: **Help-to-Buy Exposure and Ex Post Low-Down Payment Mortgages**



The figure is a binscatter plot and a scatter plot, which shows the relationship between our measure of HTB exposure (*Exposure*) and the actual share of low-down payment mortgages (Y) over the program period (2013-2018) at the district level. The larger blue dots are the binscatter plot, where *Exposure* is partitioned into 20 equal sized bins and the plot illustrates the average *Exposure* and the average Y within each bin. The smaller gray dots are the scatter plot for *Exposure* and Y observations at the district level, where the dashed line represents the regression of Y on *Exposure*. We also report the corresponding equation and R^2 in the figure. Y is calculated as the number of low-down payment mortgages is scaled by total number of mortgages purchased in the district over the program period. *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. Only first-time buyer and home-mover mortgages are included.

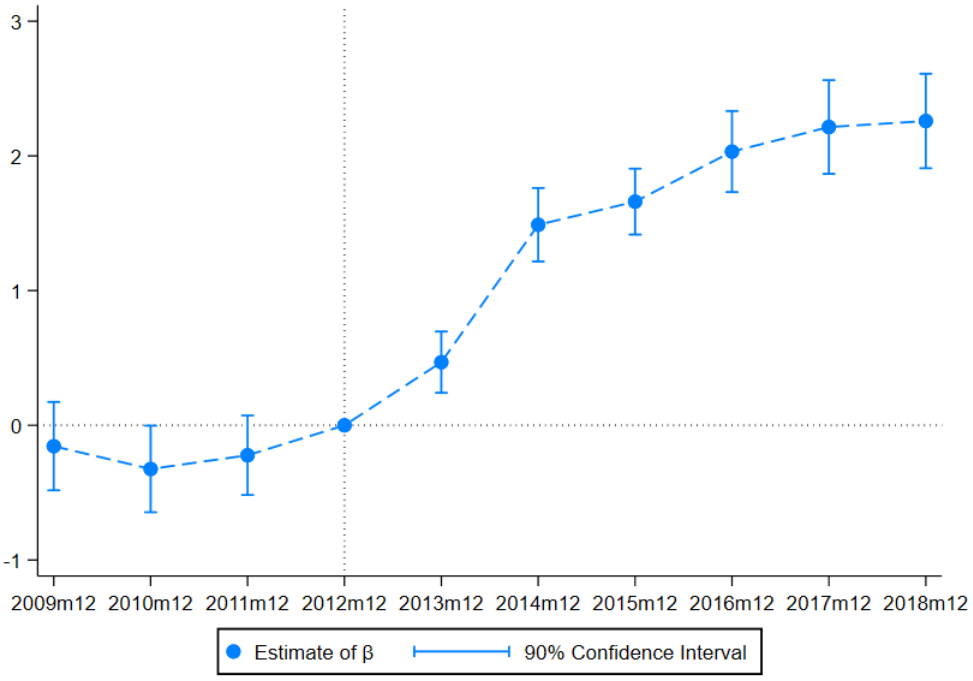
Figure 5: **Evolution Low-Down Payment Mortgages, Low vs High Exposure**

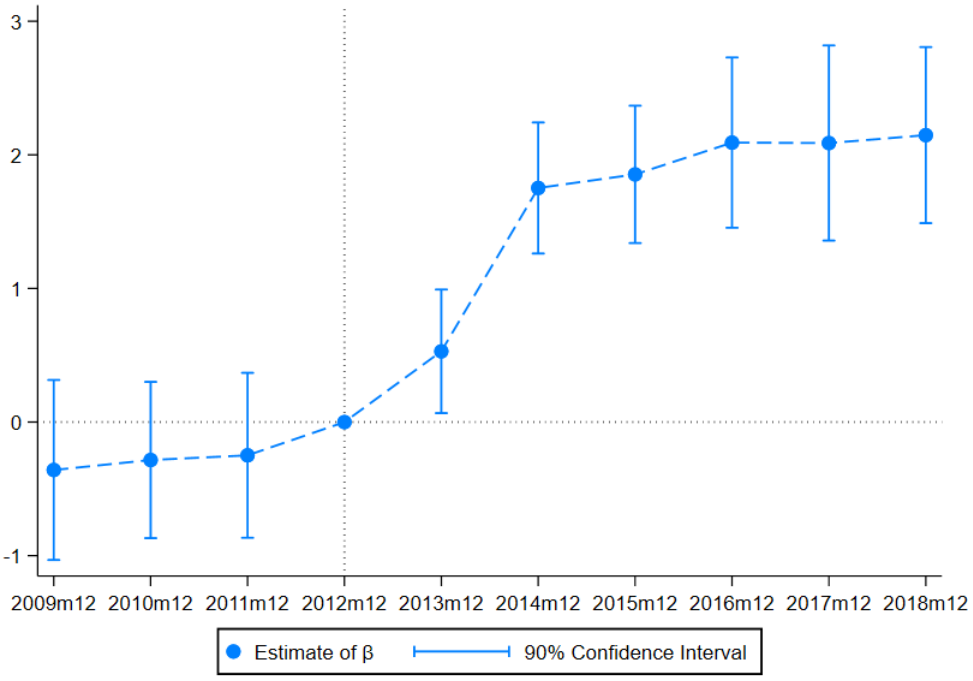




The top panel of the figure shows the aggregate number of low-down payment mortgages for 2009-2018 for low and high HTB exposure districts. The bottom panel shows the weighted average share of low-down payment mortgages (as a proportion of all mortgages). Low-down payment mortgages are mortgages with a down payment of 5 percent or less. HTB exposure is defined as the number of low-down payment mortgages in a district for 2005-2007 divided by the total number of mortgages in 2005-2007. Low (High) HTB exposure includes districts with HTB exposure less (greater) than the 25th (75th) percentile HTB exposure. The shaded area indicates the period that HTB is in effect. Only first-time buyer and home-mover mortgages are included.

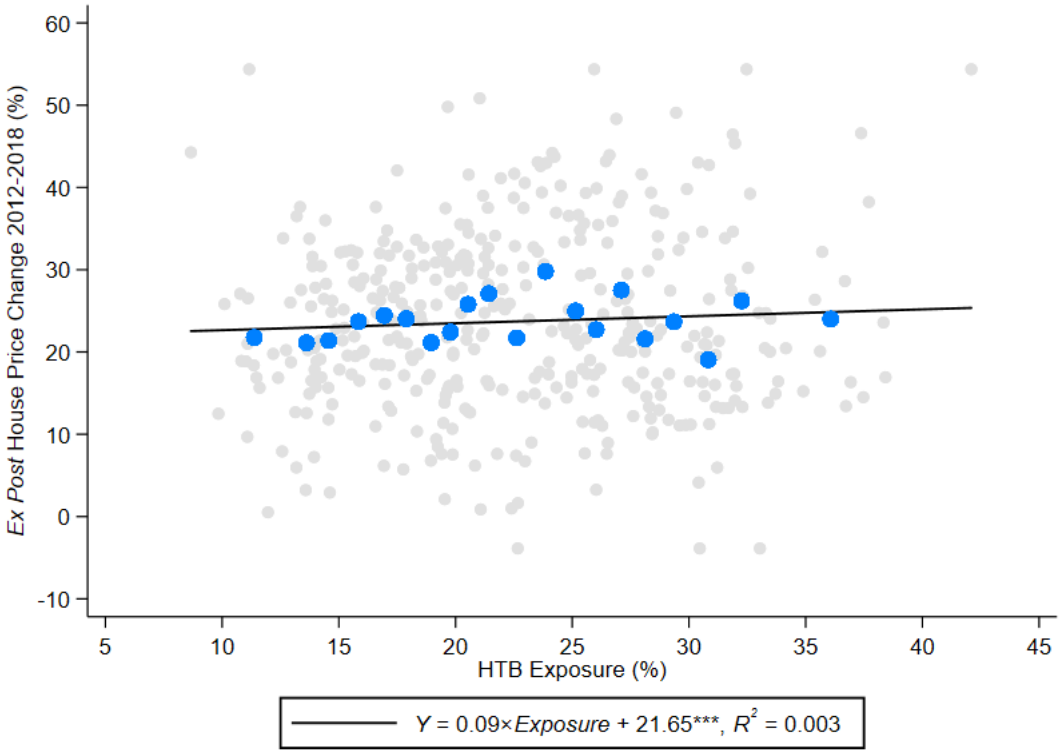
Figure 6: The Effect of Help-to-Buy on Home Sales





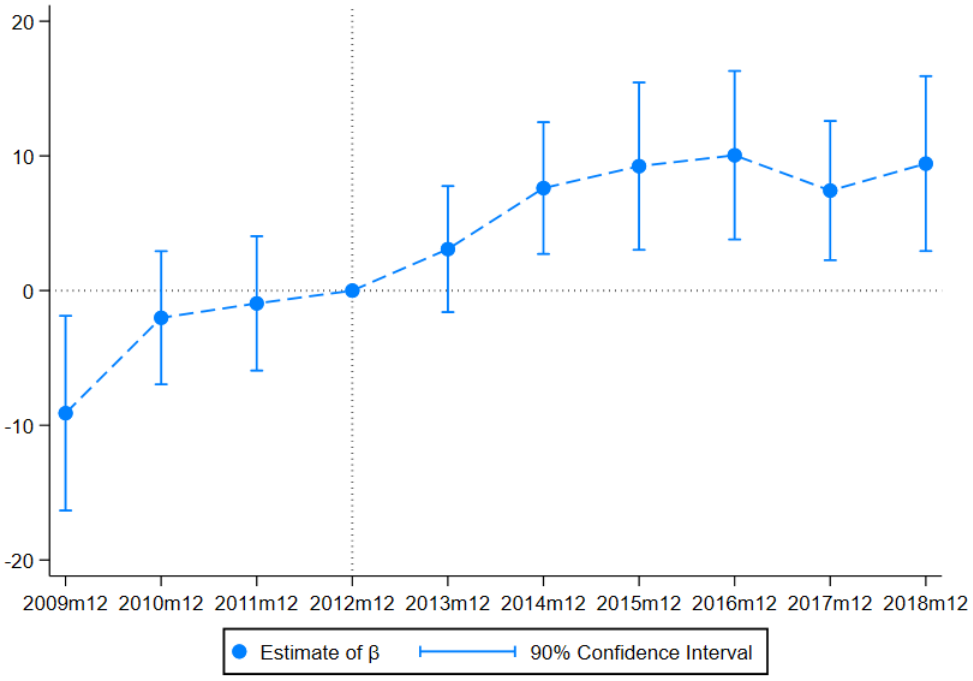
The top panel of the figure presents estimates of β from Equation 1 for each year, where the outcome variable Home Sales$_{d,t}$ equals the number of home sales in a given year and district and 2012 is the base year. The bottom panel presents estimates of β also from Equation 1 for each year, but where the sample is propensity score matched. The error bars show the 90 percent confidence interval. All regressions include district-level fixed effects and region-by-time fixed effects. Standard errors are multi-clustered at the district and time level.

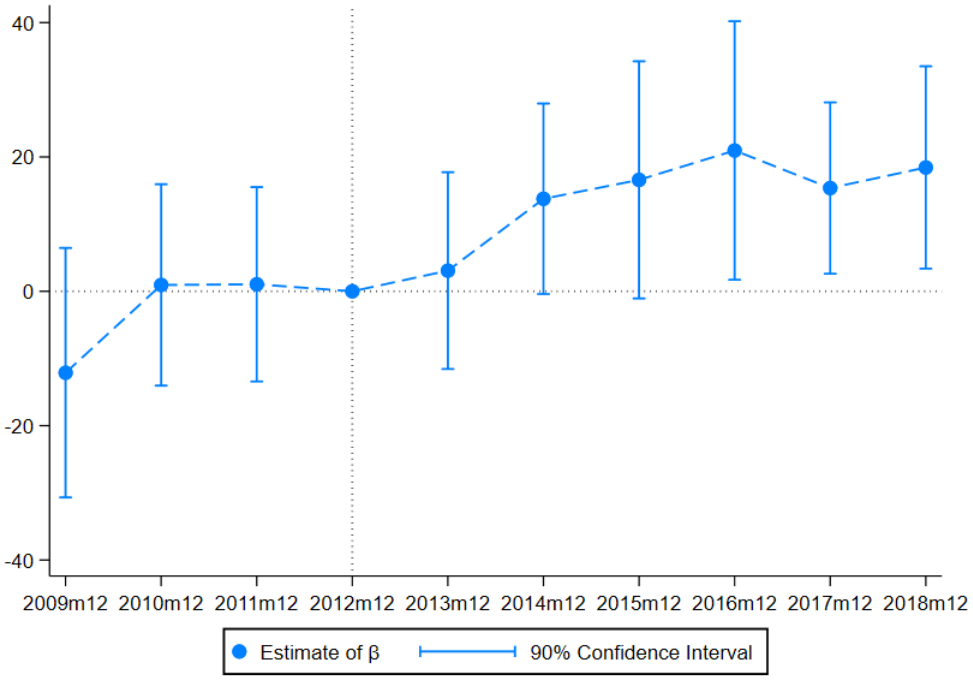
Figure 7: **Help-to-Buy Exposure and Ex Post House Price Change**



The figure is a binscatter plot and a scatter plot, which shows the relationship between our measure of HTB exposure (*Exposure*) and the house price change (Y) over the program period (2013-2018) at the district level. The larger blue dots are the binscatter plot, where *Exposure* is partitioned into 20 equal sized bins and the plot illustrates the average *Exposure* and the average Y within each bin. The smaller gray dots are the scatter plot for *Exposure* and Y observations at the district level, where the dashed line represents the regression of Y on *Exposure*. We also report the corresponding equation and R^2 in the figure. Y is calculated as the average house price change in the district over the program period. *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. Only first-time buyer and home-mover mortgages are included.

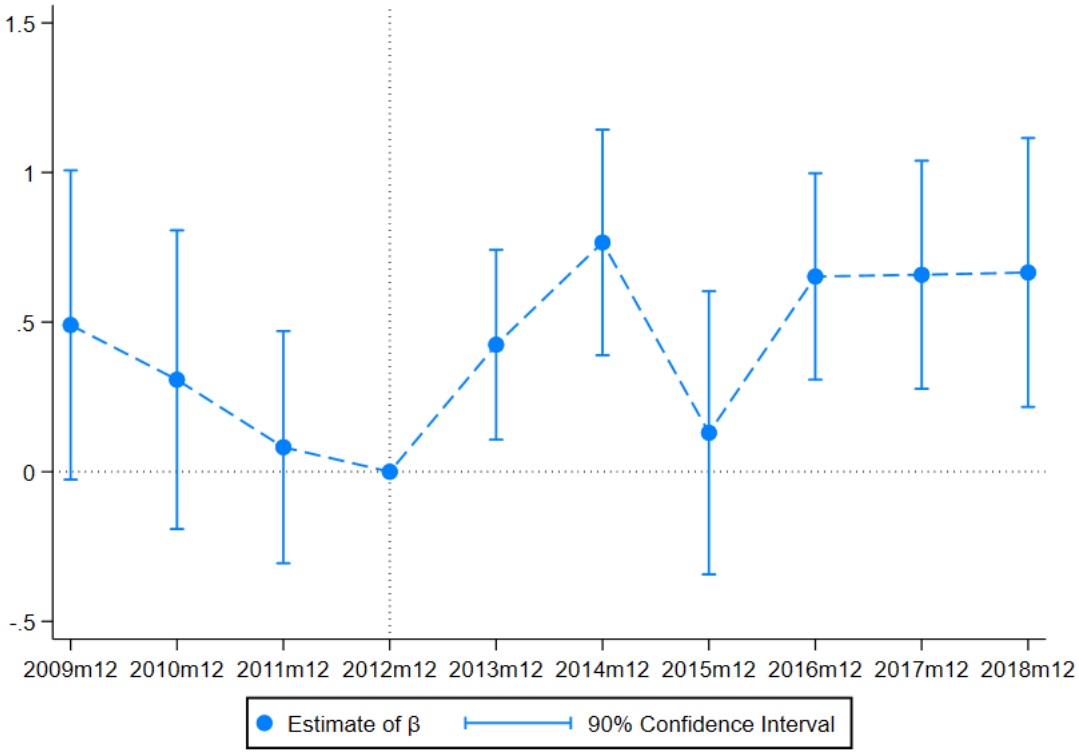
Figure 8: The Effect of Help-to-Buy on Car Sales





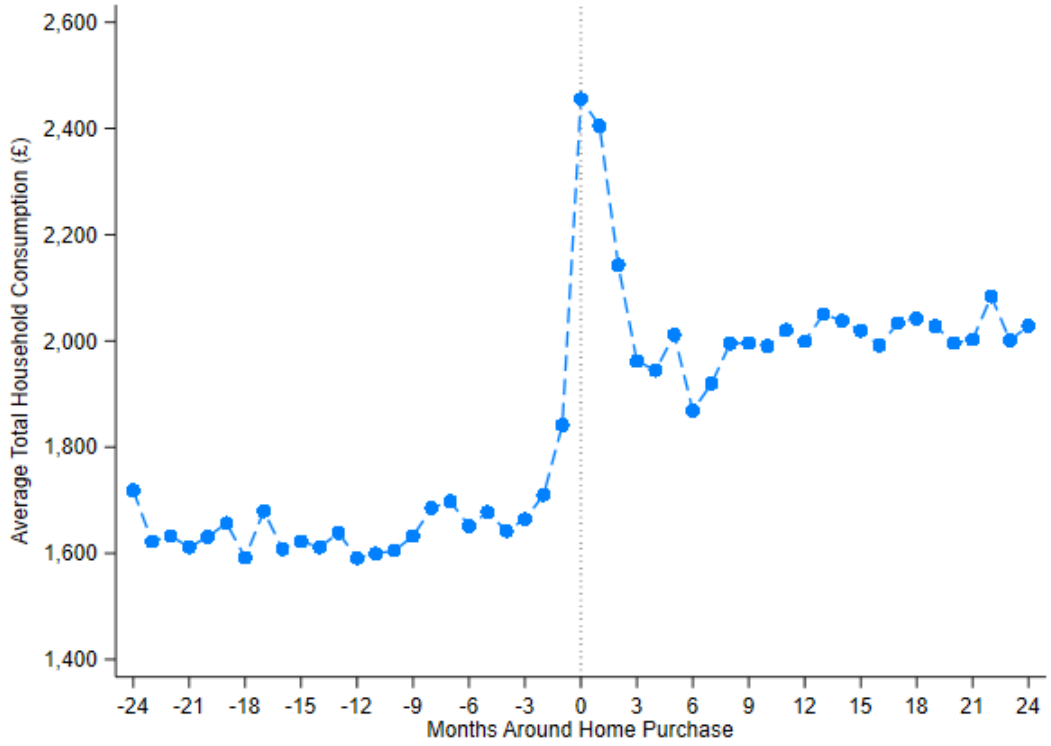
The top panel of the figure presents estimates of β from Equation 1 for each year, where the outcome variable Car Sales$_{d,t}$ equals the number of car sales in a given year and district and 2012 is the base year. The bottom panel presents estimates of β also from Equation 1 for each year, but where the sample is propensity score matched. The error bars show the 90 percent confidence interval. All regressions include district-level fixed effects and region-by-time fixed effects. Standard errors are multi-clustered at the district and time level.

Figure 9: The Effect of Help-to-Buy on Consumption



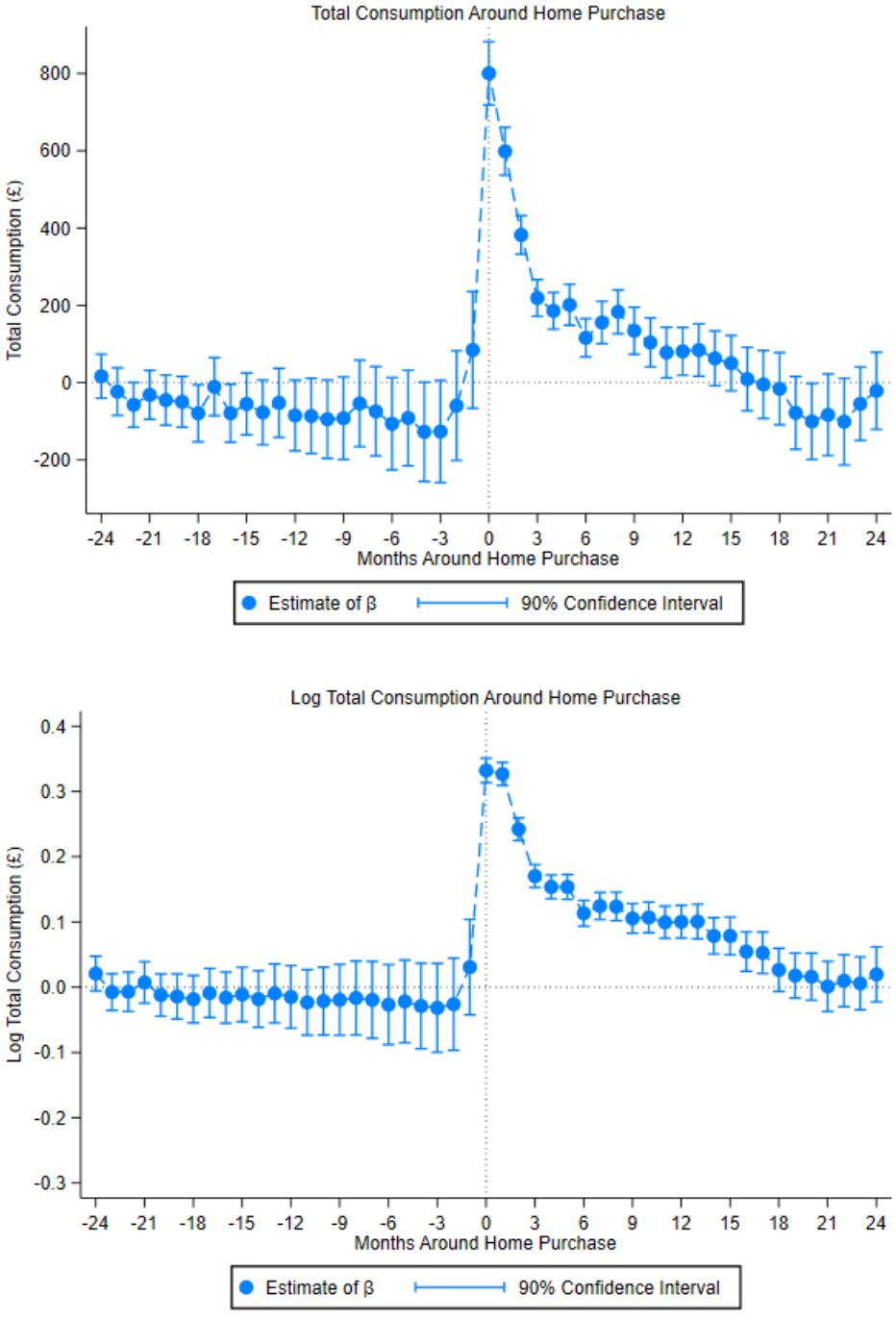
The figure presents estimates of β from Equation 1 for each year, where the outcome variable Car Sales$_{d,t}$ equals the number of car sales in a given year and district and 2012 is the base year. The bottom panel presents estimates of β also from Equation 1 for each year, but where the sample is propensity score matched. The error bars show the 90 percent confidence interval. All regressions include district-level fixed effects and region-by-time fixed effects. Standard errors are multi-clustered at the district and time level.

Figure 10: Household Consumption Before and After a Home Purchase



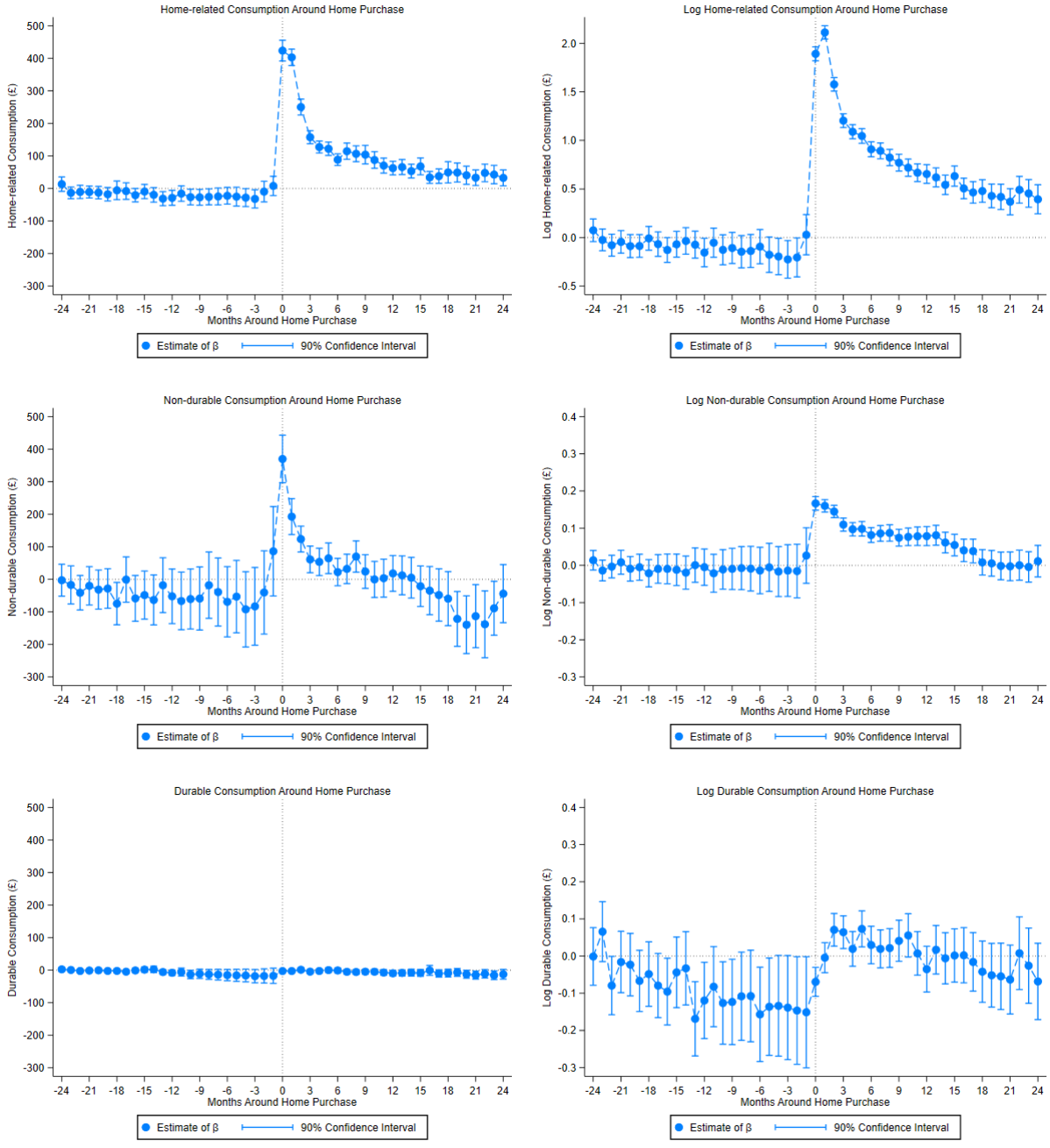
The figure presents the average monthly household consumption for the 24 months before and after a home purchase that occurred during the period 2013 to 2018. The data are deflated to 2016. Households are required to have data for at least the 12 months before and after a home purchase to be included.

Figure 11: The Effect of a Home Purchase on Household Consumption



The figure presents estimates of β from Equation 5 for the 24 months before and after a home purchase that occurred during the period 2013-2018. The top panel is for household consumption in levels and the bottom panel is for household consumption in logs. The error bars show the 90 percent confidence interval. All regressions include district-level fixed effects and region-by-time fixed effects. Standard errors are multi-clustered at the district and time level.

Figure 12: The Effect of a Home Purchase on Household Consumption by Consumption Category



The figure presents estimates of β from Equation 5 for the 24 months before and after a home purchase that occurred during 2013-2018. The top two plots are for home-related consumption, the middle two plots are for non-durable (including services) consumption and the bottom two plots are for durable (excluding home-related) consumption. The left three plots are for consumption in levels and the right three plots are for consumption in logs. The error bars show the 90 percent confidence interval. All regressions include district-level fixed effects and region-by-time fixed effects. Standard errors are multi-clustered at the district and time 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: District-level Variables						
Low-Down Payment (0/1)	0.02	0	0.16	0.16	0	0.36
HTB Exposure (%)	22.62	22.01	6.64	22.62	22.01	6.64
Home Sales ('000)	1.27	1.02	0.82	1.65	1.36	1.08
First-time Buyer Sales ('000)	0.49	0.36	0.39	0.77	0.58	0.6
Home Mover Sales ('000)	0.78	0.67	0.46	0.88	0.76	0.53
Younger Buyer Sales ('000)	0.82	0.64	0.59	1.13	0.9	0.81
Older Buyer Sales ('000)	0.45	0.39	0.25	0.52	0.45	0.3
Car Sales ('000)	4.89	2.92	7.05	6.5	3.72	9.93
Non-tradable Employment ('000)	61.71	43.73	56.09	66.73	48.16	60.96
Tradable Employment ('000)	7.75	6.24	5.68	7.76	6.16	5.81
Home Starts ('000)	0.31	0.24	0.28	0.46	0.35	0.4
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 House Prices (£'000)	230.91	202.62	116.25	278.94	232.07	179.86
Average Weekly Rent (£)	7.2	6.87	2.35	4.93	4.5	1.99
Average House Price (£'000)	449.45	431.54	76.89	435.69	420.58	65.69
Population ('000)	230.91	202.62	116.25	278.94	232.07	179.86
Panel B: Household Variables from Transaction-level Data						
Total Household Consumption (£)	1,630	1,252	1,600	1,977	1,550	1,750
Home-related Expenditures (£)	108	17	411	246	55	740
Non-durable (excl. Home-related) (£)	1,477	1,150	1,465	1,672	1,347	1,428
Durable (excl. Home-related) (£)	15	0	100	16	0	104
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 2009-2012) and the post HTB period (from 2013 to 2018). There are 379 districts across the UK included in our sample. In the pre HTB period, there are 1,516 district-level observations, 42,772 household-level variables from the transaction-level data and 165 cohort-year observations. In the post HTB period, there are 2,274 district-level observations, 55,040 household-level variables from the transaction-level data 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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log of Unemployment Rate, 2009	0.052***								0.028***
	(0.004)								(0.003)
Log of Median Income, 2009		-0.134***							0.161***
		(0.021)							(0.018)
Log of Average Home Price, 2009			-0.141***						-0.209***
			(0.008)						(0.013)
Log of Average Rent, 2009				-0.201***					0.082***
				(0.023)					(0.023)
Log Change in Unemployment Rate, 2007-2010					0.055*				-0.012
					(0.029)				(0.013)
Log Change in Median Income, 2007-2010						-0.011			-0.024
						(0.067)			(0.029)
Log Change in Average Home Price, 2007-2010							-0.553***		0.007
							(0.054)		(0.055)
Log Change in Average Rent, 2007-2010								-0.051	0.011
								(0.093)	(0.040)
N	314	314	314	314	314	314	314	314	314
R^2	0.327	0.103	0.565	0.169	0.008	-0.003	0.234	-0.002	0.810

The table presents coefficient estimates for the regression of HTB exposure on 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 Districts	All Districts	All Districts	Excl. London	Propensity Score	All Districts
	(1)	(2)	(3)	(4)	(5)	(5)
$\text{Pre}_t \times \text{Exposure}_d$	-0.0854	-0.0861				-0.0750
	(0.055)	(0.055)				(0.061)
$\text{Post}_t \times \text{Exposure}_d$	0.5733***	0.0946				0.0689
	(0.042)	(0.160)				(0.175)
$\text{Post}_t \times \text{Exposure}_d \times \text{Down Payment}_{10\%}$		0.5243**	0.5338***	0.7783***	0.4353***	0.4974**
		(0.211)	(0.050)	(0.052)	(0.154)	(0.234)
$\text{Post}_t \times \text{Exposure}_d \times \text{Down Payment}_{5\%}$		0.9070***	0.9397***	1.1719***	1.0675***	0.9957***
		(0.244)	(0.059)	(0.062)	(0.165)	(0.273)
$\text{Pre}_t \times \text{LTI Exposure}_d$						0.0765
						(0.201)
$\text{Post}_t \times \text{LTI Exposure}_d$						-0.1585
						(0.348)
$\text{Post}_t \times \text{LTI Exposure}_d \times \text{Down Payment}_{10\%}$						-0.1048
						(0.410)
$\text{Post}_t \times \text{LTI Exposure}_d \times \text{Down Payment}_{5\%}$						0.2763
						(0.466)
Control Variables						
$\text{Post}_t \times \text{Down Payment}_i$	No	Yes	No	No	No	Yes
$\text{Exposure}_d \times \text{Down Payment}_i$	No	Yes	No	No	No	Yes
$\text{LTI Exposure}_d \times \text{Down Payment}_i$	No	No	No	No	No	Yes
Fixed Effects						
District	Yes	Yes	No	No	No	Yes
Region × Time	Yes	Yes	No	No	No	Yes
Down Payment	Yes	Yes	No	No	No	Yes
District × Time	No	No	Yes	Yes	Yes	No
District × Down Payment	No	No	Yes	Yes	Yes	No
Time × Down Payment	No	No	Yes	Yes	Yes	No
N	11,352	11,352	11,350	10,373	5,099	11,352
R^2	0.7908	0.7954	0.9787	0.9801	0.9793	0.8290

The table presents coefficient estimates for Equation 2 for the period 2009-2018, and shows the effect of HTB on home sales. Pre is a dummy variable equal to 1 for the period 2009-2011. Post is a dummy variable equal to 1 for the period 2013-2018. The base year is 2012. 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. The dependent variable is the number of home sales purchased with a mortgage within a down payment bucket in a given district and year. Column 4 excludes all London districts. Column 5 is for the propensity-score matched sample. Standard errors are multi-clustered at the district and region-by-time 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)	(5)	(6)
$\text{Pre}_t \times \text{Exposure}_d$	-0.119			-0.119		
	(0.075)			(0.073)		
$\text{Post}_t \times \text{Exposure}_d$	0.467***			0.286***		
	(0.085)			(0.090)		
$\text{Post}_t \times \text{Exposure}_d \times \text{Buyer-type}_b$	0.733***	0.733***	1.203***	1.039***	1.039***	1.155***
	(0.118)	(0.052)	(0.126)	(0.169)	(0.060)	(0.146)
Control Variables						
$\text{Post}_t \times \text{Buyer-type}_b$	Yes	No	No	Yes	No	No
$\text{Exposure}_d \times \text{Buyer-type}_b$	Yes	No	No	Yes	No	No
Fixed Effects						
District	Yes	No	No	Yes	No	No
Region × Time	Yes	No	No	Yes	No	No
Buyer-type_b	Yes	No	No	Yes	No	No
District×Time	No	Yes	Yes	No	Yes	Yes
$\text{District} \times \text{Buyer-type}_b$	No	Yes	Yes	No	Yes	Yes
$\text{Time} \times \text{Buyer-type}_b$	No	Yes	Yes	No	Yes	Yes
N	7,580	7,580	3,400	7,580	7,580	3,400
R^2	0.904	0.979	0.978	0.853	0.976	0.975

The table presents coefficient estimates for Equation 2 for the period 2009-2018, and shows the effect of HTB on home sales across buyer-types. Pre is a dummy variable equal to 1 for the period 2009-2011. Post is a dummy variable equal to 1 for the period 2013-2018. 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 2005-2007 divided by the total number of mortgages in 2005-2007. Standard errors are multi-clustered at the district and time 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 Prices**

	All Districts	Excl. London	London only	Propensity Score	All Districts	Excl. London	London only	Propensity Score
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Pre}_t \times$ Exposure	-0.060	-0.081*	0.111	-0.053	-0.022	-0.070	0.058	-0.030
	(0.045)	(0.047)	(0.263)	(0.093)	(0.083)	(0.079)	(0.277)	(0.119)
$\text{Post}_t \times$ Exposure	0.353***	0.268***	1.039***	0.324***	0.342***	0.153**	1.048***	0.142
	(0.045)	(0.044)	(0.236)	(0.079)	(0.083)	(0.073)	(0.241)	(0.112)
$\text{Pre}_t \times$ Elasticity					0.022	0.006	0.094*	0.009
					(0.029)	(0.028)	(0.054)	(0.034)
$\text{Post}_t \times$ Elasticity					-0.041	-0.085***	-0.016	-0.108***
					(0.027)	(0.025)	(0.056)	(0.032)
Fixed Effects								
District	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,790	3,460	330	1,700	3,220	2,890	330	1,680
R^2	0.989	0.987	0.966	0.981	0.988	0.987	0.967	0.982

The table presents coefficient estimates for Equation 1 for the period 2009-2018, and shows the effect of HTB on house prices. Pre is a dummy variable equal to 1 for the period 2009-2011. Post is a dummy variable equal to 1 for the period 2013-2018. The base year is 2012. 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. Elasticity is 1 minus the "Share of Developable Land" measure of Hilber and Vermeulen (2016), where values close to 1 (zero) proxy elastic (inelastic) housing supply. The dependent variable is the log of average house prices in a given district and year. Standard errors are multi-clustered at the district and time 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	Propensity Score	All Districts	All Districts	All Districts
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Pre}_t \times \text{Exposure}_r$	0.2931	0.4230*	0.2662	0.8152*	0.2522	1.4468
	(0.279)	(0.230)	(0.416)	(0.443)	(0.238)	(1.132)
$\text{Post}_t \times \text{Exposure}_r$	0.5589***	0.6305***	0.7650*	1.0493***	0.5213***	1.2789
	(0.137)	(0.114)	(0.137)	(0.386)	(0.142)	(0.794)
Control Variables						
Cohort Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
HTB-Region	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
Birth Year Group	Yes	Yes	Yes	Yes	Yes	Yes
N	555	545	357	555	555	555
R^2	0.8198	0.8265	0.692	0.685	0.8185	0.6292

The table presents coefficient estimates for Equation 4 for the period 2009-2018, and shows the effect of HTB on household consumption. The dependent variable is either total household consumption, home-related expenditures, non-durable and services consumption or durable expenditures, where the latter two variables exclude home-related expenditures. Pre is a dummy variable equal to 1 for the period 2009-2011. Post is a dummy variable equal to 1 for the period 2013-2016. 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 2005-2007 divided by the total number of mortgages in 2005-2007. 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 a Home Purchase on Household Consumption by Buyer-type**

	High Downpayment = 0, Low Downpayment = 1		Home Mover = 0, First-time = 1		Older = 0, Younger = 1	
	Level	Log	Level	Log	Level	Log
	(1)	(2)	(3)	(4)	(5)	(6)
Buyer-type$_b$ = 0	74.0153*	0.0766***	120.1088***	0.0662***	89.9487*	0.0464**
	(41.5657)	(0.0165)	(41.1866)	(0.0171)	(53.7240)	(0.0195)
Buyer-type$_b$ = 1	102.6242**	0.1050***	49.2333	0.1057***	81.9775**	0.0987***
	(44.0357)	(0.0184)	(44.5592)	(0.0174)	(39.1683)	(0.0163)
Comparison	28.6089	0.0284*	-70.8755	0.0395**	-7.9711	0.0523***
	(42.2298)	(0.0161)	(40.1716)	(0.0156)	(50.306)	(0.0173)
Fixed Effects						
District	Yes	Yes	Yes	Yes	Yes	Yes
Region × Time	Yes	Yes	Yes	Yes	Yes	Yes
Household-level	Yes	Yes	Yes	Yes	Yes	Yes
N	122,296	122,296	122,296	122,296	122,296	122,296

The table presents coefficient estimates for Equation 5 for home purchases that occurred during the period 2013-2018 across different buyer types. All regressions include district-level fixed effects and region-by-time fixed effects. Standard errors are clustered at the district level. ***, **, 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 Local Demand**

	Non-tradable Employment			Tradable Employment			Income		
	All Districts	Excl. London	Propensity Score	All Districts	Excl. London	Propensity Score	All Districts	Excl. London	Propensity Score
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Pre_t \times$ Exposure	2.179	-1.605	3.166	2.118**	2.764***	3.091**	-0.129	0.138	0.279
	(4.396)	(3.061)	(6.961)	(0.839)	(0.754)	(1.268)	(0.076)	(0.076)	(0.708)
$Post_t \times$ Exposure	7.525**	10.704***	10.040*	-1.360*	-0.626	-1.365	0.280***	0.713***	1.248**
	(3.817)	(2.726)	(6.044)	(0.724)	(0.641)	(1.012)	(0.090)	"(0.229)"	"(0.630)"
Fixed Effects									
District	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,790	3,460	1,710	3790	3460	1710	555	545	357
R^2	0.994	0.995	0.990	0.981	0.983	0.984	0.8218	0.8338	0.6281

The table presents coefficient estimates for Equation 2 for the period 2009-2018, and shows the effect of HTB on various variables capturing local demand. Pre is a dummy variable equal to 1 for the period 2009-2011. Post is a dummy variable equal to 1 for the period 2013-2018. 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 2005-2007 divided by the total number of mortgages in 2005-2007. In columns 7 to 8, Exposure equals the average exposure across the districts assigned to the region. The dependent variable $Y_{d,t}$ is: non-tradable employment in columns 1-3, tradable employment in in columns 4-6, and household income in columns 7-9. Standard errors are multi-clustered at the district and time level and are shown in parentheses. ***, **, and * indicate statistical significance at the 1 percent, 5 percent and 10 percent confidence level, respectively.

Table 9: **The Effect of Help-to-Buy on Construction**

	All Districts	All Districts	Excl. London	Propensity Score	All Districts	All Districts	Excl. London	Propensity Score
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pre_t	0.006				0.024			
	(0.036)				(0.078)			
Post_t	0.153***				-0.010			
	(0.035)				(0.067)			
$\text{Pre}_t \times$ Exposure	-0.007	0.120	0.151	-0.035	-0.025	0.176	0.226	-0.058
	(0.157)	(0.196)	(0.161)	(0.305)	(0.177)	(0.211)	(0.247)	(0.345)
$\text{Post}_t \times$ Exposure	-0.035	-0.320*	-0.457***	-0.750***	0.161	0.033	-0.013	-0.512*
	(0.148)	(0.177)	(0.133)	(0.265)	(0.153)	(0.180)	(0.226)	(0.303)
$\text{Pre}_t \times$ Elasticity					-0.019	0.038	0.042	-0.016
					(0.065)	(0.067)	(0.067)	(0.083)
$\text{Post}_t \times$ Elasticity					0.164***	0.237***	0.247***	0.165**
					(0.061)	(0.061)	(0.067)	(0.075)
Fixed Effects								
District	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Time	No	Yes	Yes	Yes	No	Yes	Yes	Yes
N	3,250	3,250	2,920	1,780	3,220	3,220	2,890	1,760
R^2	0.680	0.704	0.727	0.687	0.683	0.706	0.730	0.688

The table presents coefficient estimates for Equation 1 for the period 2009-2018, and shows the effect of HTB on home starts. Pre is a dummy variable equal to 1 for the period 2009-2011. Post is a dummy variable equal to 1 for the period 2013-2018. The base year is 2012. 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. Elasticity is 1 minus the "Share of Developable Land" measure of Hilber and Vermeulen (2016), where values close to 1 (zero) proxy elastic (inelastic) housing supply. The dependent variable is the number of home starts in a given district and year. Standard errors are multi-clustered at the district and time level and are shown in parentheses. ***, **, and * indicate statistical significance at the 1 percent, 5 percent and 10 percent confidence level, respectively.

Internet Appendix

10 Living Costs and Food Survey Data

10.1 Background about the Living Cost and Food Survey

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.

10.2 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.

10.3 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*

10.4 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.

10.5 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.

10.6 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.

11 Money Dashboard Data

11.1 Household Consumption Categories from Transaction-level Money Dashboard Data

There are around 300 distinct "tags" to categorize transactions in the Money Dashboard (MDB) app. We use this tag information for debit transactions and 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. Table 10 describes how each Money Dashboard transaction tag is classified using our approach.

Table 10: Expenditure Categorization for Money Dashboard and ClearScore Tags

Home-related Expenditures	Non-durable Consumption	Non-durable Consumption	Non-durable Consumption
Home	Food, Groceries, Household	Eye care	Hotel/B&B
Furniture, Furnishing, Gardens	Groceries	Dental treatment	Insurance
Furniture	Supermarket	Medical treatment	Insurance - other
Lighting	Take-away	Physiotherapy	Vehicle insurance
Garden	Alcohol	MOT	Motorbike Insurance
Home and garden - other	Clothes	Service / Parts / Repairs	Breakdown cover
Soft furnishings	Clothes - Everyday or Work	Road charges	Mobile phone insurance
Appliances or Electrical	Clothes - Designer or Other	Vehicle Running Costs	Health insurance
Personal Electronics	Child - Clothes	Public Transport	Dental insurance
Home electronics	Clothes - other	Transport	Life insurance
Kitchen / Household Appliances	Designer clothes	Transport - other	Income insurance
Electrical equipment	Workwear	Taxi	Home insurance
Domestic supplies	Shoes	Taxis or Vehicle Hire	Home appliance insurance
Art	Fuel	Parking	Contents or Other Insurance
Antiques or Other	Art Supplies	Parking or Tolls	Payment Protection Insurance
Antiques	Lifestyle - other	Vehicle hire	Pet Insurance
Art, Antiques or Other	Child - Toys, Clubs or Other	Road/traffic fines	Bank charges
Stationery	Children - other	Vehicle tax	Banking Charges
Stationery & consumables	Toys	Flights	Interest charges
Office Supplies	Pet - Everyday or Food	Cycling	Penalty charges
Printing	Pet - Toys, Training, Other	Device rental	Financial - other
Home DIY or Repairs	Pet housing/care	Driving Lessons	Phone (landline)
DIY	Pet food	Gym Membership	Mobile
Tradesmen fees	Pet toys	Sports Club Membership	Phone or Internet
	Pets - other	Memberships	Broadband
Durable Expenditures	Photography	Social club	Media bundle
Vehicle	Flowers	Hobby Club Membership	Web hosting
Vehicle purchase	Hobby Supplies	Hobbies or Activities	Postage / Shipping
Caravan/Camping	Medication	Hobbies - other	One-off or Other
Hire Purchase	Beauty products	Entertainment, TV, Media	Nursery Fees
Software	Toiletries	Mobile app	Child - Everyday or Childcare
Games and gaming	Personal Care - Other	Administration - other	Childcare Fees
Gym Equipment	Appearance	TV / Movies Package	Childrens Club fees
Sports Equipment	Tobacco	TV Licence	School fees
Cycling	Books / Magazines / Newspapers	Music	Course and Tuition Fees
Musical Equipment	Gift	Museum/exhibition	Education - other
Jewellery	Gifts or Presents	Concert & Theatre	Clothing hire
Books & Course Materials	Gifts - other	Cinema	Dry cleaning and laundry
	Birthday present	Going out - other	Legal
	Christmas present	Enjoyment	Beauty treatments
	Irregular Income or Gifts	Gambling	Hairdressing
	Accessories	Gambling account	Hairdressing, Health, Other
	Bills	Pet training	Personal Training
	Council Tax	Vet	Spa
	Ground Rent or Service Charge	Sports event	Advertising
	Water	Zoo/theme park	Charity - other
	Energy (Gas, Elec, Other)	Religious Celebration	Donation to organisation
	Electricity	Lunch or Snacks	Religious Donation
	Gas and electricity	Dining or Going Out	One-off or Other Payment
	Gas	Dining and drinking	
	Coal/Oil/LPG/other	Holiday	
	Medical, Dental, Eye Care	Holidays	

11.2 Main Data Cleaning Steps

- We remove duplicate transactions that arise for all transactions of some users.
- We exclude business accounts, which are identified as those users that are paying staff costs, wages, income or dividends.
- We consider only users that are between 16 and 100 years of age.
- Approximately 10 percent of transactions have no tag information and so we exclude these. Many of the transactions with no tag appear to be transfers however, rather than expenditure items.
- We create filters to exclude Money Dashboard users that have periods for which they have no data or substantially missing data. This occurs when a user's online banking details change and the user doe not immediately update their details within the Money Dashboard app, leaving the app unable to collect the information for a period. Observations and/or users are identified and excluded as those with mean total consumption in the top and bottom percentile, as well as the standard deviation of mean total consumption in the top percentile, and consumption observations than drop below 25 percent of a users mean consumption.

11.3 Money Dashboard to Product Sales Database Merge

Here we outline how information from the PSD is merged with MDB data. The following table describes the specific variables used for the merge:

Match fields	MDB Variable	PSD Variable
1. Sector postcode	Sector postcode	Full postcode
2a. Birth year	Birth year	Date of birth main borrower
2b. Birth year	Birth year	Date of birth second borrower
3. Mortgage payment	Mortgage payment (transaction)	Mortgage payment (required) from PSD007
4. Date	Mortgage payment transaction date	Mortgage payment PSD007 balance date
4. Mortgage lender	Lender details extracted from merchant or transaction description field	Current lender

A merge on the sector postcode[39], birth year, mortgage payment and mortgage lender can provide a fuzzy match between the PSD and MDB datasets. Precise matches between the two datasets should occur for fixed rate mortgage products and when the mortgagor does not overpay or go into arrears. Reasonably good matches should also be possible for floating, tracker and discount mortgage products, whereby payments can vary from month to month and the PSD provides information about the half-yearly payment requirements as at 30 June and 31 December. The mortgage payment transaction reported in the MDB may otherwise differ from from the required mortgage payment due to over-payment (which is permitted for fixed mortgage products, for example) or mortgage performance issues.

We merge the PSD and MDB for the period 2013-2018, where we take the following iterative approach to the merge:

Table 11: Money Dashboard to Product Sales Database Merge

Match	Birth year	Mortgage payment rounding	MDB mortgage payment definition	Mortgage lender
1	Main borrower	Nearest 1[40]	Mortgage payment transactions	Required matching field
2	Second borrower	Nearest 1	Mortgage payment transactions	Required matching field
3	Main borrower	Nearest 1	Mortgage payment transactions	Not required as matching field
4	Second borrower	Nearest 1	Mortgage payment transactions	Not required as matching field
5	Main borrower	Floor 1	Mortgage payment transactions	Not required as matching field
6	Second borrower	Floor 1	Mortgage payment transactions	Not required as matching field
7	Main borrower	Ceiling 1	Mortgage payment transactions	Not required as matching field
8	Second borrower	Ceiling 1	Mortgage payment transactions	Not required as matching field
9	Main borrower	Nearest 1	Aggregate monthly payments	Not required as matching field
10	Second borrower	Nearest 1	Aggregate monthly payments	Not required as matching field

[39]The sector postcode comprises the postcode district (i.e. the outward code), the single space, and the first character of the inward code.

[40]For each unique match between a Money Dashboard user and a household in the PSD, we require the mortgage payment transaction to match on two different values OR where the mortgage payment transaction matches in two different half

12 Business Structure Database (BSD)

12.1 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.

12.2 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).
- *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 15 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).

year periods and matches 10 times or more.

13 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:

$$\begin{aligned} Y_{d,t} = \quad & \beta_1 \text{Pre}_t \times \text{Exposure}_d + \beta_2 \text{Post}_t \times \text{Exposure}_d \\ & + \boldsymbol{\gamma} \text{District}_{d,t-1} + \delta_d + \theta_t + u_{d,t} \end{aligned} \tag{6}$$

where d indexes a district and t is the year. The dependent variable $Y_{d,t}$ is now Net Migration Flows$_{d,t}$, which equals the number of persons that move from another UK district to district d, less the number of people that move from district d to another UK district, in a given year scaled by the population in district d. The rest of the model is the same as Equation 2.

The results are presented in Table 16. The first column shows the average effect of relaxing the down payment constraint on net migration flows. It indicates that after HTB came into effect, we find a decrease in net migration flows in high exposure districts (column 1). This result holds when we exclude districts in the London area (column 2). This suggests that *increased* migration into high exposure areas cannot be driving our results, which is consistent with the 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 bolstered due to HTB-induced endogenous moves.

14 Alternative Household Survey Panel Construction

14.1 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 (2009-2012) and the post-HTB period (2013-2018). 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.

14.2 Help-to-Buy and Household Expenditures

We estimating the following cross-sectional regression model:

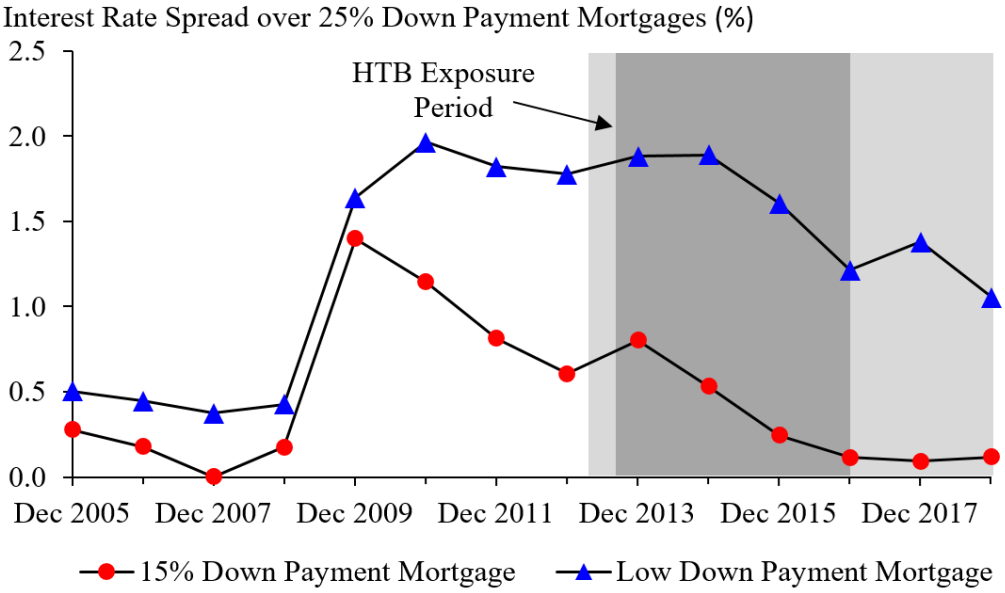
$$\triangle \text{Consumption}_{d,Post} = \beta_1 \text{Exposure}_d + \boldsymbol{\gamma} \triangle \text{Cohort}_{d,Post} + \lambda \triangle \text{House Prices}_{d,Post} + u_d \quad (7)$$

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, $\textbf{Cohort}_{d,t}$, which includes the same controls described in Section 7.2, 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 17 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.

15 Additional Figures and Tables

Figure 13: 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 12: **Comparison Low- and High-Down Payment First-time Buyers**

	Low-Down Payment (EL)	Low- Down Payment (Non-EL)	High-Down Payment
Age (years)	30.20	30.26	31.61
	(6.36)	(6.31)	(7.65)
Gross Income (£)	49,085.32	48,783.63	47,728.62
	(30,113.26)	(48,497.93)	(17,4405.9)
Down Payment (£)	11,845.32	18,236.48	62,851.95
	(5,733.42)	(19,636.17)	(10,3257.1)
Property Value (£)	220,680.75	183,306.54	216,252.79
	(93,887.55)	(94,827.17)	(201,452.2)

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 2018. All variables are deflated to 2016 values.

Table 13: **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 14: **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
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 15: **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	Non-tradable
33.15	Repair and maintenance of ships and boats	Non-tradable
45.11-45.19	Sale of motor vehicles	Non-tradable
45.32	Retail trade of motor vehicle parts and accessories	Non-tradable
45.40	Sale, maintenance and repair of motorcycles and related parts and accessories	Non-tradable
47.11-47.99	Retail trade, except of motor vehicles and motorcycles	Non-tradable
56.10-56.30	Food and beverage service activities	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 16: **The Effect of Help-to-Buy on Internal Migration**

	All Districts	Excl. London	Propensity Score
	(1)	(2)	(3)
$\text{Pre}_t \times \text{Exposure}_d$	0.2070	0.2272	0.3108
	(0.369)	(0.340)	(0.656)
$\text{Post}_t \times \text{Exposure}_d$	-0.9378***	-0.7534**	-0.9014*
	(0.334)	(0.325)	(0.529)
Fixed Effects			
District	Yes	Yes	Yes
Region × Time	Yes	Yes	Yes
N	3900	3570	1780
R^2	0.6429	0.6323	0.6271

The table presents coefficient estimates for Equation 6 for the period 2009-2018, and shows the effect of HTB on net internal migration flows. The dependent variable is district-level net internal migration flows (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 2009-2011. Post is a dummy variable equal to 1 for the period 2013-2018. The base year is 2012. Exposure equals the number of low-down payment mortgages in a district in the period 2005-2007 divided by the total number of mortgages in 2005-2007. Column 2 presents estimates from a specification that excludes all London districts. Column 3 presents estimates for the propensity score matched sample. Standard errors are multi-clustered at the district and time level and are shown in parentheses. ***, **, and * indicate statistical significance at the 1 percent, 5 percent and 10 percent confidence level, respectively.

Table 17: **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 7, and shows the effect of HTB on household consumption. The dependent variable is either total household consumption, home-related expenditures, non-durable and services consumption or durable expenditures, in the post-HTB period (2013-2018) compared with the pre-HTB period (2009-2012). 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 2005-2007 divided by the total number of mortgages in 2005-2007. 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.