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Macroprudential Policy, Mortgage Cycles and Distributional Effects: Evidence from the UK*

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Abstract

We analyse the distributional effects of macroprudential policy on mortgage cycles by exploiting the UK mortgage-register and a 2014's 15%-limit imposed on lenders' high loan-to-income (LTI) mortgages. Constrained lenders issue fewer and more expensive high-LTI mortgages, with stronger effects on low-income borrowers. Unconstrained lenders strongly substitute high-LTI loans in local-areas with higher constrained-lender presence, but *not* high-LTI loans to low-income borrowers—consistent with adverse selection problems—implying lower overall credit to low-income borrowers. Consistently, policy-affected areas experience lower house-price growth post-regulation and, following the Brexit referendum (negative aggregate shock), better house-price growth and lower mortgage defaults for low-income borrowers.

JEL Classification: E5; G01; G21; G28; G51.

Key words: macroprudential policy; mortgages; credit cycles; inequality; house prices.

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1 Introduction

Household leverage has received intense academic scrutiny as a source of financial instability. The empirical literature provides evidence that strong mortgage expansion to households was the underlying cause of the 2007-09 US financial crisis—as well as some previous financial crises in history—with associated high mortgage defaults, house price contractions, and overall negative real effects (Schularick and Taylor (2012); Favara and Imbs (2015); Adelino et al. (2016); Mian et al. (2017); Di Maggio and Kermani (2017); Piskorski and Seru (2021)). The theoretical literature shows settings in which unrestricted lending to households can lead to housing booms and to negative externalities during periods of adverse macroeconomic conditions, with strong negative effects on house prices (fire sales) and bank loan defaults; thereby advocating macroprudential policies to limit household leverage during booms (Lorenzoni (2008); Corbae and Quintin (2015); Farhi and Werning (2016); Korinek and Simsek (2016); Favilukis et al. (2017); Dávila and Korinek (2017); Greenwald (2018)). Consistent with this view, policymakers across the world have introduced macroprudential regulations on household leverage, especially after the global financial crisis.¹ Despite the academic and policy importance of macroprudential policy on household leverage, the empirical literature is scant, especially so in analysing the effects during booms *and* adverse aggregate conditions.

In this paper, we analyse the distributional effects of macroprudential policy on mortgage cycles. For empirical identification, we utilise the UK mortgage-register in conjunction with a 15%-limit imposed on lenders' high loan-to-income (LTI) mortgages. These lenders are differentially affected based on their pre-policy share of high-LTI loans in their mortgage portfolio. Moreover, we exploit the unexpected outcome of the Brexit referendum, a negative aggregate shock that led to a strong house price growth correction across the UK, to analyse the effects of macroprudential policies implemented during booms at times of negative aggregate shocks.

The macroprudential policy limiting high-LTI lending was announced by the UK regulator in

¹E.g., regulators in many countries around the world, including the U.S., and some European and Asian countries, have introduced restrictions on household leverage. A complete list of jurisdictions that have regulated household leverage is available in the iMaPP database (IMF). Some of these policies are on debt/loan-to-income ratios or debt service-to-income ratios, which may affect low-income borrowers more; however, it is not clear that the so-called 2007-08 U.S. *subprime* financial crisis was caused by the leverage of low-income borrowers as compared to the middle-class (see Adelino et al. (2016)).

June 2014. We exploit the loan-level data on mortgages issued in the UK during 2012Q3-2016Q2 from the mortgage-register in conjunction with this LTI regulation. The loan-level data includes information on borrower characteristics such as income, age and employment status, on the issuing lender, and on characteristics of the loan itself, such as origination date, loan amount, interest rate, interest rate type (fixed or floating), mortgage term, property value and full postcode. We merge the loan-level data with lenders' balance-sheet data. We also match mortgage data with house price growth at the full postcode local-area level for different house price quantiles between 2012Q3 and 2018Q2, and loan-level mortgage default status to exploit the unexpected outcome of the Brexit referendum in mid-2016. Therefore, we create a rich dataset that allows us to exploit time, borrower, lender, and location characteristics to study the effects of the policy.

Our research design hinges on the restriction on high-LTI lending binding at the lender-level for some lenders. At the time of the policy's introduction, the economy was performing well and, moreover, the overall lending of high-LTI loans was just 10%, i.e. far away from the 15% limit. However, there were differences in exposure across lenders. This provides a variation across UK lenders based on the share of high-LTI loans in their mortgage portfolio during the year before the policy's introduction. We use the high-LTI shares to classify UK lenders into two groups: constrained and unconstrained lenders. Constrained lenders issued just over a fifth of all mortgages in our sample. Constrained and unconstrained lenders are similar across a wide range of balance sheet characteristics (such as size, liquidity ratio, core funding ratio, return on assets, CET1 ratio, share of household credit) and mortgage characteristics (such as volume, interest rate, rate type, loan-to-value (LTV), maturity). We use both a specification without controls and a highly saturated specification to study changes in the mortgage portfolio of constrained lenders in response to the policy. We also test in all key results that there are no differential pre-trends.

Our results show that the introduction of the macroprudential regulation affects mortgage lending. First, after the regulation, and compared to unconstrained lenders, constrained lenders cut their share of high-LTI mortgages (by 3.9%) and charge higher loan rates (by 13 bp, 4.5% higher) for those loans, thereby suggesting bank-driven (credit supply) restrictions due to the policy. Moreover, the fewer high-LTI loans issued by constrained lenders after the regulation contain 6.1%

fewer loans to borrowers in the lowest income-quintile. That is, the regulation affects low-income borrowers through two distinct channels: the reduction in high-LTI loans (which they are more likely to borrow) and the drop in their presence within high-LTI loans issued by constrained lenders. Importantly, all the key effects happen only after the regulation is implemented (i.e., no pre-trends, which serve as a placebo test).

Second, we analyse credit substitution since the regulation is on lenders (not on households), is not binding at the aggregate (unconstrained lenders have substantial slack to substitute), and business cycle conditions are good around the policy’s introduction. We find imperfect credit substitution.

We find evidence that low-income borrowers are more likely to receive loans with LTI lower than 4.5 from constrained (vs. unconstrained) lenders, leading to no change in the proportion of loans to low-income borrowers by constrained banks. However, this does not imply that intra-lender substitution is perfect, as the credit substitution is via lower-seized loans (e.g., weighting loans by their size, constrained banks do cut the proportion of loans to low-income borrowers) and, in addition, constrained banks cut average loan volumes to low-income borrowers (by 3.7%).

Moreover, there is *no* substitution of high-LTI loans to low-income borrowers by unconstrained lenders, as these lenders reduce high-LTI loans to low-income borrowers and increase their loan price in areas with a higher pre-policy presence of constrained lenders (and hence with higher cut in high-LTI loans to low-income borrowers).² This finding highlights a third channel through which the regulation negatively affects lending to low-income borrowers. Thus, low-income borrowers suffer a triple credit crunch since unconstrained lenders’ substitution is strong for high-LTI loans in general, but inexistent for high-LTI loans to low-income borrowers.

Furthermore, the cut in credit that we document (i.e., lack of substitution for high-LTI loans to low-income borrowers from unconstrained lenders) is consistent with adverse selection problems. The increases in loan prices for low-income borrowers in high-LTI loans are monotonically increasing for lenders that have more capacity to substitute and are the highest for the unconstrained lenders

²Differently, in areas with a higher pre-policy presence of constrained lenders (higher credit substitution possibilities), unconstrained lenders expand high-LTI loans in general and reduce their loan price (i.e., higher credit supply).

furthest away from the regulatory limit, i.e. lenders with lower pre-policy presence (proxying for less knowledge) in this market. These effects are even stronger in areas with higher pre-policy presence of constrained lenders and hence higher substitution possibilities. These results are consistent with winner’s curse problems for unconstrained lenders only in the substitution for the segment of low-income borrowers within high-LTI loans. Moreover, the increase in loan prices of high-LTI loans to low-income borrowers is strongest in areas with higher competition among unconstrained lenders (proxied by Herfindahl-Hirschman index) and with higher potential for credit substitution (i.e., areas with higher presence of constrained lenders). This result is consistent with theories of adverse selection under differential bank competition (e.g., [Marquez \(2002\)](#)) in which higher bank competition exacerbates adverse selection problems since lenders are afraid that available borrowers have been rejected by other lenders, thus raising loan prices due to winner’s curse problems.

As results suggest that credit substitution is imperfect, we analyse the overall lending to low-income borrowers stemming from the policy. We aggregate mortgage lending by time (quarterly), local areas (equivalent to boroughs) and income-quintiles. Estimated coefficients show that low-income borrowers in areas with a pre-policy one standard deviation higher exposure to constrained lenders experience a 10.8% decline in the total value of lending (in £) after the introduction of the regulation. Consistently, after the regulation there is a drop in the growth rate of the 25th percentile of house price transactions (a quantile that is more linked to low-income borrowers) in local areas more affected by the regulation—i.e., areas more exposed to constrained lenders and with a higher concentration of low-income borrowers.

Third, we exploit the unexpected outcome of the Brexit referendum in June 2016 which led to a strong drop in house price growth across the UK; for instance, growth in the 25th percentile of house prices in the UK fell from a peak of 11% annually just before the referendum to 2% two years later. Also, there was a substantial increase in the number of local areas with negative house price growth (from less than 9% in the two years before the referendum to 25% by 2018Q2). Our results suggest that local areas more affected by the 2014 macroprudential policy have a relatively lower cooling in house price growth after the referendum, especially for lower-quantiles of house price transactions, consistent with the reduced lending to low-income borrowers post-regulation. We also find that the

areas more affected by the 2014 macroprudential policy do not respond differently to past negative aggregate shocks (2007-08 financial crisis), which serves as a placebo test. Moreover, low-income borrowers in the more affected local areas experience relatively lower mortgage defaults after the Brexit referendum. This post-referendum positive effect from the 2014 macroprudential policy is consistent with the relatively lower decline in house price growth in those affected areas as well as the lower leverage due to the policy’s introduction.

Literature Review. Our main contribution to the literature is to show the effects of macroprudential regulation of household leverage during both a boom and after a negative aggregate shock (cycle), including its distributional effects—e.g., the triple credit crunch to low-income borrowers, including the lack of credit substitution from unconstrained lenders due to adverse selection problems, and the effects on lower defaults for low-income borrowers due to the policy—thereby showing costs and benefits of macroprudential policies on households.

To the best of our knowledge, there is currently no paper which studies the effects of macroprudential regulation of household leverage during periods of both booms and adverse aggregate conditions. This is not only due to scarcity of administrative data on mortgages (most credit-registers are on corporate loans), but also due to relative recency of such regulation because of which there have not been negative overall shocks to check the potential benefits of limiting household leverage during a boom.³ The UK offers an ideal setting as it has a mortgage-register, a macroprudential policy which restricted high-LTI lending, and a negative aggregate shock (with a strong reduction in house price growth) stemming from the unexpected result of the Brexit referendum. Even though the LTI regulation is on lenders and not on households, business cycle conditions were good when the policy was introduced, and the banking system was not constrained at all (constrained lenders represented only a fifth of lending and aggregate share of high-LTI loans was 10% as opposed to the 15% policy limit), we find that the policy restricts credit to low-income households during the boom, and consistently, lower mortgage defaults and better house price growth during adverse aggregate conditions.

³There has been the COVID-19 pandemic in 2020-22. However, many different policy measures have been introduced in many countries around the world (including the UK) during the COVID-19 period, including strong expansive fiscal policies, as well as policies supporting lenders (liquidity facilities) and borrowers (loan moratoria).

Other papers studying the effects of household leverage regulation introduced post-2008 financial crisis (e.g. [DeFusco et al. \(2020\)](#), [Bekkum et al. \(2019\)](#) and [Acharya et al. \(2022\)](#) based on regulations in the US, Netherlands and Ireland, respectively, and [Belgibayeva \(2020\)](#) and [Benetton \(2021\)](#) based on regulations in the UK) have analysed the effects of the macroprudential policy only around its introduction and not during an episode of negative aggregate shock. Importantly, by analysing the beneficial effects during negative aggregate shocks, we provide suggestive evidence on a key prediction of the theoretical models highlighted in the first page of the Introduction, i.e. the reduction in leverage during booms can have an impact on house prices and loan defaults during adverse macroeconomic conditions. Our results, which show a reduction in household leverage resulting from the UK macroprudential policy despite *no restriction at the borrower level*, suggest that there are important frictions in substituting credit across differently affected lenders during a *boom* period. Our evidence is consistent with adverse selection problems in credit (mortgage) markets (e.g. [Shaffer \(1998\)](#); [Marquez \(2002\)](#); [Freixas and Rochet \(2008\)](#)), which further distinguishes our study from the other papers analysing macroprudential policy.⁴

We also contribute to the literature on credit and house prices. Household leverage closely interacts with house prices on the way to affecting the macroeconomy. The literature has emphasized the amplification loop that exists between changes in lending standards or expectations, household leverage and subsequent changes in house prices ([Mayer et al. \(2009\)](#); [Mian and Sufi \(2009\)](#); [Favara and Imbs \(2015\)](#); [Jordà et al. \(2015\)](#); [Bhutta and Keys \(2016\)](#); [Di Maggio and Kermani \(2017\)](#); [Adelino et al. \(2017\)](#); [Johnson \(2020\)](#)). Our results suggest that the macroprudential regulation (introduced during a boom in response to increases in household leverage) is associated with a subsequent reduction in house-price growth in local areas more affected by the regulation, and importantly, with better house price dynamics and mortgage defaults after the Brexit referendum (a negative aggregate shock). That is, consistent with the reduction in lending to low-income borrowers due to the macroprudential policy, after the Brexit referendum and in areas affected by the

⁴Our results on the absence of substitution of high-LTI loans to low-income borrowers by unconstrained lenders, despite the substantial capacity among unconstrained lenders to do so and mortgage lending being more transactional than SME lending, expands our understanding on credit frictions. On the transactional nature of mortgage lending, see e.g. [Nguyen \(2019\)](#) in which competitor banks are more likely to substitute mortgages than SME loans when faced with rival bank-branch closures.

2014 policy, there are lower mortgage defaults (notably for low-income borrowers) and relatively better house price growth (especially stronger for houses in the 25th percentile).

There is also a growing literature which has varyingly attributed the secular rise in income and wealth inequality to taxation (Piketty and Saez (2003)), globalization (Autor et al. (2013)) and automation (Autor and Dorn (2013)). Papers have also studied the redistributive effects of policies, such as those for monetary policy (Auclert (2019), Andersen et al. (2022)) and for policies aimed at financial access (Rajan (2011); Agarwal et al. (2012)). We contribute to this literature by linking debt, inequality and macroprudential policies and showing an important trade-off. Our results suggest that, on the one hand, macroprudential policies aimed at limiting high leverage can strongly reduce mortgage lending to low-income borrowers, but on the other hand, such macroprudential policies are associated with benefits—in terms of a lower house price growth correction and lower mortgage defaults for low-income borrowers—during an episode of negative aggregate shock.

Organization. The rest of the paper is organized as follows. Sections 2 and 3 discuss the regulation and the data, respectively. Section 4 presents the empirical strategy and the results. Section 5 concludes.

2 Institutional Background

Mortgages are one of the largest items on the balance sheets of both UK lenders and households; indeed, they are the largest liability for UK households.⁵ Therefore, non-performing mortgages can pose direct risks to the resilience of the UK banking system and to financial stability. In the event of a negative aggregate shock, households may increase loan defaults and/or adjust their real estate assets, which could have significant indirect effects on the rest of the economy. The macroprudential policy authority in the UK, the Bank of England’s Financial Policy Committee (FPC), monitors developments in the housing and mortgage markets in order to mitigate these risks to financial and economic stability.

At its June 2014 meeting, the FPC assessed risks to lenders and the wider economy from an increase in UK household indebtedness. At that time, there were signs that the UK housing market

⁵Lending to households consistently accounts for roughly half of all the credit issued to the private non-financial sector by banks in the UK (Source: FRED Economic Data). In 2017Q2, mortgages (£1.3 trillion) made up more than 80% of the £1.6 trillion stock of household debt (Bank of England (2017c)).

was heating up. There was strong recovery in the housing market, and house prices were rising faster than household income. These developments were associated with a significant increase in the share of high-leverage mortgages. For instance, the share of mortgages with loan-to-income ratios (LTI) at or greater than 4.5 rose from 6.5% in the immediate pre-crisis period during 2005-07 to 10% between 2013Q2-2014Q1. Therefore, as insurance against the risk of a loosening in underwriting standards and a significant increase in the number of highly indebted households, the FPC recommended the Prudential Regulation Authority (PRA) and Financial Conduct Authority (FCA) to ensure that mortgage lenders do not extend more than 15% of their new residential mortgages with LTI at or greater than 4.5.⁶

The PRA and the FCA implemented the FPC’s recommendation as of 1 October 2014. The policy was implemented on a quarterly basis and excludes remortgages with no change to the outstanding principal and lifetime mortgages. The policy applies to mortgage lenders whose annual residential mortgage lending is in excess of £100 million in value and 300 in number of mortgages. According to the policy, a mortgage lender part of a banking group is allowed to allocate all or part of its high LTI allowance to any other regulated entity within that group. When the rules came into effect on 1 October 2014, there were 32 banking groups within the scope of the policy. During the period of interest of this study, mortgage lenders inside the scope of the policy account for 99% and 98% percentage of the total number and total value of mortgage lending, respectively.

3 Data

We draw upon multiple data sources for our empirical analysis. These are: the PSD001 database which includes the universe of newly issued residential mortgages in the UK; the PSD007 database which includes the stock of mortgages in the UK; the balance sheet and income statement data

⁶The PRA is responsible for prudential regulation and supervision of banks, building societies, credit unions, insurers and major investment firms in the UK. The FCA is the conduct regulator for financial services firms and financial markets in the UK. Along with the cap on the proportion of mortgages with $LTI \geq 4.5$, the FPC also introduced an affordability test for lenders where they must assess the affordability of each mortgage issued to ensure that borrowers could still afford the mortgage if the Bank of England’s base rate were to increase by 300 basis points (stress rate) within 5 years of the origination of the mortgage. However, these tests had already been introduced by the FCA in 2012 and UK lenders were using stress tests of 250-300 basis points when the 2014 regulation was introduced. See [Bank of England \(2014\), Box 5](#) for details. The 4.5 LTI-limit was calibrated to ensure a cap on the mass of borrowers who may face debt-servicing ratios of around 35-40%. This is an inflection point beyond which the proportion of borrowers experiencing repayment difficulties can rise sharply. See [Bank of England \(2017b\), page 8](#) for details.

from lenders; and the UK land registry for data on housing transactions.

PSD001 (Product Sales Database 001), updated quarterly by the Financial Conduct Authority (FCA), contains information on the universe of newly issued residential mortgages subject to the limit on high loan-to-income (LTI) lending introduced in 2014.⁷ We exclude from our sample instances of external remortgaging without a change in the principal of the loan and life-time mortgages since these types of contracts are not in the scope of the regulation. Our sample covers mortgages originated between 2012Q3-2016Q2, covering two years around the announcement of the regulation in June 2014. The data from PSD001 provide a wide range of borrower characteristics, such as borrower’s gross income, age, employment status, and whether the borrower is a home-mover, first-time-buyer or remortgagor. Moreover, the database contains information on mortgage characteristics such as loan amount, interest rate, the price of the property, LTI, loan-to-value (LTV), mortgage term, type of repayment, and the location of the property. We report summary statistics of our sample in Table 1.

[Table 1 around here]

The dataset also includes the date of origination, the issuing lender, and highly disaggregated information on the property’s location at the 6-digit postcode level. Therefore, we can use these data to study changes in the mortgage portfolio of lenders more, or less, constrained by the limit on high-LTI lending, test whether some borrower cross-sections are disproportionately affected by the regulation, and also explore the geographic dimensions across which these adjustments take place following the regulation. To this dataset, we merge information on the sales channel (i.e., whether the mortgage is sold directly by the lender or via a mortgage broker) provided by the FCA.

PSD007 (Product Sales Database 007) contains information on the stock of UK mortgages. This dataset has been obtained by the FCA bi-annually starting 2015. It includes information on the

⁷The database includes the full set of mortgages that UK regulators use to assess compliance with the regulation. PSD001 excludes loans such as second-charged, commercial, and buy-to-let mortgages, none of which are under the scope of the regulation. The database includes external remortgages (also known as external product transfers), but not internal ones—i.e. refinancing without changing lender and property. Importantly, the high-LTI limit does *not* apply to remortgages without a change in principal. Remortgages, both internal and external, should be less affected by the regulation compared to other types of mortgages: borrowers remortgage their loans typically after the initial fixed-rate period (two or five years); as they have paid part of the mortgage for a period of time, they are likely to have lower LTI than when acquiring the initial mortgage. Consistent with this intuition, in unreported results, we find that external remortgagors, when compared with first time buyers, are significantly less affected by the regulation.

performance of extant mortgages in a given period, such as whether the mortgage is in payment arrears or under forbearance; the latter refers to mortgages under repayment difficulties which have received modified terms from lenders in the form of payment suspension or reduction, term extension etc. The stock dataset includes the date of origination, issuing lender, and the location of the related property. We use this information to track whether a mortgage in our original sample is under default (i.e., under payment arrear or forbearance or possession order) by the end of 2017. This allows us to study the impact of the 2014 LTI regulation on mortgage defaults (for loans issued before vs. after the policy) following the Brexit referendum which led to a substantial house price correction in the UK.

In addition, we have data on balance sheet positions and income statements reported by lenders to the Bank of England at a quarterly frequency. The dataset includes lender size, liquidity and core funding from balance sheets; return on assets from income statements; and the share of household credit and capital ratio from other regulatory reports.

Finally, the HM Land Registry’s Price Paid Data contain information on the price paid, date, location (at 6-digit postcode level) and house type (flat, terraced, semi-detached or detached) of all residential housing transactions in England and Wales. We use this dataset to study house prices dynamics immediately after the policy’s introduction as well as during the correction in the housing market following the Brexit referendum, and focus on the period between the second half of 2012 (two years before the introduction of the regulation) and the first half of 2018 (two years after the referendum). The key feature of this dataset—disaggregated location (6-digit postcodes) and house types—allows us to also create a house price index at a full postcode-house type level which we use to study changes in house price dynamics.

We construct a house-price series that controls for the quality of the properties transacted while retaining a house-price distribution within local areas.⁸ The UK has approximately 1.75 million unique postcodes at the most disaggregated level for a population of approximately 27.5 million households in 2018, with around 4,500 unique postcodes in each local area in the UK. This level of disaggregation is quite uncommon: for comparison, the US only has 41,689 different zip codes for

⁸We expand on the construction of the index in Online Appendix Section C.

a much bigger territory and population. For each period, we aggregate the data at postcode-house type pair, while taking the average price in cases where there is more than one transaction in a given period. We create a balanced panel of postcode-house type pairs that are transacted every period. We thus control for the quality (proxied by the full postcode-house type unit) of transacted houses in local areas over time, while retaining a house-price distribution for each local area.

4 Empirical Strategy and Results

Lenders in the UK are differentially affected by the 2014 loan-to-income (LTI) regulation based on their pre-policy share of high-LTI loans. We first define the criteria for classifying lenders into two groups: ‘constrained’ and ‘unconstrained’ lenders. We use this variation to analyse lending, both at loan-level as well as aggregated, and house prices and loan defaults.

The 2014 LTI regulation sets a 15% limit on the proportion of new residential mortgages that lenders could issue every quarter with LTI at or greater than 4.5. We use the lenders’ quarterly shares of high-LTI loans in the run up to its announcement (from 2013Q3 to 2014Q2) to identify lenders more likely to be constrained by the regulation. There are five lenders, which issue just over a fifth of all mortgages in our sample, whose average level of high-LTI loans is greater than (or very close to) 15%. We refer to these five lenders as ‘constrained’ lenders. The remaining lenders are well below the 15% limit and hence less constrained by the regulation.⁹ We refer to these lenders as ‘unconstrained’ lenders. Apart from the shares of high-LTI lending (Figure 1), constrained lenders do not significantly differ from unconstrained lenders in other key characteristics of their balance sheets such as size, liquidity, and capital ratio (Appendix Table A.4); or (apart from the average LTI) in the underlying characteristics of their mortgage portfolio, such as loan volume, loan interest rate, rate type, loan-to-value (LTV), or maturity (Appendix Table A.5).

Our empirical strategy relies on the differential exposure to the regulation for constrained and unconstrained lenders. We use data on lending two years prior to and two years after the announcement of the regulation at the end of 2014Q2, i.e. all the mortgages issued during 2012Q3-2016Q2. We drop all mortgages issued during 2014Q3 from our sample since the regulation was announced towards the end of 2014Q2 but came into effect only in 2014Q4. We restrict our study to mortgages

⁹We cannot share the lender *specific* shares of high-LTI loans because of data confidentiality requirements.

issued until 2016Q2 when the UK held the so-called Brexit referendum to leave the European Union. Exploiting the Brexit referendum shock, we analyse house prices (with data until 2018Q2, i.e. two years after the referendum) and loan defaults in areas differentially affected by the regulation.

4.1 Loan-level analysis

4.1.1 Share, pricing, and redistribution of high-LTI mortgages

We study the differential impact of the regulation on high-LTI lending by constrained lenders using loan-level data in Equations 1, 2 and 3. The baseline specification (Equation 1) tests whether mortgages issued by constrained lenders are less likely to be high-LTI loans ($LTI \geq 4.5$) following the regulation. The outcome variable, $\text{HighLTI}_{i,l,b,t}$, indicates whether a loan issued to borrower i in local area l by bank b in quarter t has $LTI \geq 4.5$; the key regressor is $\text{Post}_t \times \text{Constrained}_b$, where Post_t and Constrained_b are dummies which indicate periods after the implementation of the regulation (2014Q4 onwards) and constrained lenders, respectively. The controls in the highly saturated specification are borrower and loan characteristics ($X_{i,l,b,t}$), bank $\times$ time controls ($X_{b,t}$), local area $\times$ bank fixed-effects ($f_{l,b}$) and time fixed-effects (f_t).¹⁰ l refers to the location of the underlying property at Local Administrative Unit Level 1 (LAU1) level.¹¹ The coefficient β reflects the change in the share of high-LTI loans in the portfolio of constrained lenders after the introduction of the policy.

$$\text{HighLTI}_{i,l,b,t} = \beta \cdot \text{Post}_t \times \text{Constrained}_b + \gamma_1 \cdot X_{i,l,b,t} + \gamma_2 \cdot X_{b,t} + f_{l,b} + f_t + \varepsilon_{i,l,b,t} \quad (1)$$

Table 2 (A) presents estimates of β (Equation 1) based on our loan-level sample during 2012Q3-2016Q2.¹² The negative and significant estimate of β suggests that constrained lenders reduce high-

¹⁰Borrower controls include borrower type, employment status, age, income and whether joint or sole applicant. Loan controls include type of rate, term, type of repayment, loan value, property value, and income verification. Bank controls include size, liquidity and core funding ratios, return on assets, CET1 ratio, and the share of household lending. These variables are described in Appendix Tables A.1 and A.2. In unreported results, we also test for robustness to inclusion of local area $\times$ time fixed-effects (throughout all tables and columns when possible); our results are qualitatively and quantitatively similar with these fixed-effects.

¹¹The Office of National Statistics provides an overview of the administrative geographies for the United Kingdom [here](#). LAU1 is the second lowest level of administrative geography, followed by electoral wards. There are 415 LAU1 local areas in the UK with an average population of around 158,000 residents (2016).

¹²Our loan-level data includes 2.9 million mortgages issued during the period of our study. 1.8 million of these have information on all our controls and form the basis of our loan-level regressions. The drop is primarily due to missing observations for loan-level controls described in Appendix Table A.1. We include Post_t and Constrained_b

LTI mortgages in the aftermath of the regulation. The coefficient is robust and highly significant as we add loan-level controls (column 2 (c.2)), bank $\times$ time controls (c.3), local area $\times$ bank fixed-effects (c.4), and time fixed-effects (c.5). In c.5, which includes all the controls, the coefficient indicates that the share of high-LTI mortgages in the portfolio of constrained lenders drops by roughly 3.9% following the regulation, down from 16.6% when policy was introduced (2014q2).

[Table 2 (A) around here]

Figure 1 (A) shows the share of high-LTI loans in the portfolio of constrained and unconstrained lenders, with a clear decline of high-LTI loans in the portfolio of constrained lenders following the regulation. Figure 1 (B) plots the coefficients obtained by regressing Constrained_b interacted with the full set of time-dummies (except 2014Q2, the reference time period) and the controls described in Equation 1. The resulting coefficients are negative and significant *only* in periods after the introduction of the regulation. The pre-policy coefficients are quantitatively and statistically not different from 0, consistent with the lack of pre-trends.

[Figure 1 around here]

Pricing of high-LTI loans. Columns 1 and 2 of Table 2 (B) show results from regressing $\text{Rate}_{i,l,b,t}$ —interest rate of the mortgage issued to borrower i in local area l by bank b in quarter t —on $\text{Post}_t \times \text{Constrained}_b$ in sub-samples of low-LTI ($\text{LTI} < 4.5$) and high-LTI ($\text{LTI} \geq 4.5$), respectively. The coefficient in sub-sample of high-LTI loans is positive (6.5 bp), while that in sub-sample of low-LTI loans is quantitatively insignificant (-0.7 bp).

$$\text{Rate}_{i,l,b,t} = \beta_{rate} \cdot \text{Post}_t \times \text{Constrained}_b \times \text{HighLTI}_{i,l,b,t} + \gamma_1 \cdot X_{i,l,b,t} + \gamma_2 \cdot X_{b,t} + f_{l,b} + f_t + \varepsilon_{i,l,b,t} \quad (2)$$

[Table 2 (B) around here]

We further estimate β_{rate} using Equation 2 and our loan-level data to test whether constrained lenders charge different interest rates on high-LTI loans after the introduction of the regulation.

as standalone variables when not absorbed by fixed-effects; estimated coefficients for either variable are positive and smaller in magnitude than the one for on $\text{Post}_t \times \text{Constrained}_b$.

Columns 3-7 show estimates of β_{rate} on the triple interaction term first without any controls, and progressively with the controls used to saturate the specification (same in Equations 1 and 2). β_{rate} is positive and robust to the inclusion of controls. Further, β_{rate} is statistically significant in columns 4-7 as the standard errors go down with the inclusion of controls that also substantially increase the R^2 . The coefficient in c.7 shows a 4.5% increase in interest rates of high-LTI loans issued by constrained lenders, up 13 bp in comparison to the average interest rate of 290 bp for such loans at policy’s introduction. The results this far—lower volume and higher price—suggest that the drop in high-LTI lending in Table 2 (A) is lender-driven (credit supply).

Redistribution of high-LTI loans across borrowers. We use Equation 3 to investigate the impact of the regulation on borrower income in the sub-sample of high-LTI mortgages. We classify mortgages into income-quintiles based on the distribution of reported income of borrowers of all mortgages issued in periods before the introduction of the regulation and assign them a dummy $\mathbb{D}(\text{Inc} = j)$, where $j \in \{1, 2, 3, 4, 5\}$. For each borrower i , we use information on the location of the underlying property to position them in their corresponding quintile j based on the income-distribution of all mortgages issued at a regional level.¹³

$$\mathbb{D}(\text{Inc}=j)_{i,l,b,t} = \beta_j \cdot \text{Post}_t \times \text{Constrained}_b + \gamma_1 \cdot X_{i,l,b,t} + \gamma_2 \cdot X_{b,t} + f_{l,b} + f_t + \varepsilon_{i,l,b,t} \quad (3)$$

The estimated β_j shown in Table 3 reflects a stark change in the distribution of borrower-incomes in the high-LTI portfolio of constrained lenders following the policy. Column 1 shows that constrained lenders decrease the share of high-LTI loans issued to borrowers in the lowest income-quintile by 6.1% (down from 30.5% at policy’s introduction). This decline is matched by an increase in the proportion of high-LTI loans obtained by borrowers in the higher income-quintiles (c.4, c.5). Figure 2 shows a lack of pre-trends in the share of low-income borrowers in high-LTI loans by constrained lenders, with the negative effect only coming after the introduction of the policy. Interestingly, in Appendix Table A.8, there is no change in the age composition of high-

¹³We use a localized distribution, rather than the national distribution, to account for regional differences across the UK. The income-quintile classification is based on all mortgages issued at 40 Local Administrative Unit 2 (LAU2) level in the UK. LAU2 is at a higher level than LAU1, the level at which we aggregate lending data in Section 4.2. The main reason for using LAU2 instead of the more granular LAU1 to classify borrowers is the presence of very few mortgages for some LAU1 local areas in pre-policy periods to generate reliable quintile thresholds.

LTI mortgages issued by constrained lenders in Post_t periods (also without pre-trends, Appendix Figure A.4). Thus, the contraction in high-LTI loans by constrained lenders has a stronger effect on low-income borrowers. These households are negatively affected by both the reduction in the share of high-LTI loans (which they are more likely to borrow) and the drop in their share *within* high-LTI loans.¹⁴

[Table 3 around here]

[Figure 2 around here]

4.1.2 Substitution

We analyse credit substitution since the regulation is on UK lenders and not on households, and business cycle conditions were good around the policy’s introduction: borrowers who could not receive high-LTI loans from constrained lenders (i.e., low-income borrowers) could either receive a loan with $\text{LTI} < 4.5$ from those lenders or obtain a (high-LTI) loan from an unconstrained lender.

We analyse the first possibility in Table 4. We regress the dummy indicating low-income borrowers (LowInc_i , which corresponds to $\mathbb{D}(\text{Inc}=1)$ in the previous table) on $\text{Post}_t \times \text{Constrained}_b$ in different sub-samples of LTI bands (four bands in c.1-4 are based on quartiles for mortgages with $\text{LTI} < 4.5$, $\text{LTI} \geq 4.5$ in c.5 and for all loans in c.6). Table 4 emphasises the role of substitution by constrained lenders via smaller loans to low-income borrowers. Columns 1-4 of the table show a 2.2 pp increase (up from 15.1% at policy’s introduction) in the share of low-income borrowers in lower-LTI loans issued by constrained lenders after the regulation, while c.5 corresponds to a 6.1% reduction in the share of low-income borrowers in high-LTI loans.

[Table 4 around here]

When combining the different LTI groups in c.6, there is a zero differential change in the share of loans to low-income borrowers between constrained and unconstrained lenders. However, this

¹⁴In Online Appendix Table A.7, we find that constrained lenders increase average loan size, property value, and LTV of high-LTI loans after the policy; they also reduce the average LTI and increase borrower income (controlling for loan size). The increase in average borrower incomes is over and above any (mechanical) increase driven by the increase in loan size (reported in column 1 of the same table).

does not suggest that intra-lender substitution is perfect since substitution in c.1-4 is towards (on average) smaller low-LTI loans (within low-income borrowers), while the contraction in c.5 is in the larger high-LTI loans. Consistent with the shift towards smaller low-LTI loans for low-income borrowers, an estimate of c.6 using loan size as weights is negative and statistically significant at the 0.05 level. Further, c.7 shows a 3.7% reduction in the average size of loans to low-income borrowers following the regulation (while c.8 shows that there is no corresponding reduction in the average size of loans to borrowers with higher incomes).

Heterogeneous substitution of high-LTI loans. To further study substitution (given the substantial reduction in high-LTI loans (Table 2 (A)) and the disproportionate reduction of low-income borrowers receiving high-LTI loans (Table 3)), we focus on the behaviour of unconstrained lenders who had substantial slack to substitute constrained lenders. We classify unconstrained lenders into three groups based on the share of high-LTI loans in their portfolio a year before the introduction of the regulation. Least_Unconstr. $_b$ is the group of lenders closest to the 15% limit (with a share of high-LTI loans around 10% before the regulation), Mid_Unconstr. $_b$ comprises lenders further away from the limit (share of high-LTI loans around 5% before the regulation), and Most_Unconstr. $_b$ are lenders furthest away from the limit (share of high-LTI loans around 1% before the regulation). We test whether these three lender groups substitute high-LTI loans, and particularly to low-income borrowers among the high-LTI loans, in areas with a higher exposure to constrained lenders (i.e., areas with a higher credit substitution potential), and whether they do so differentially with respect to their available slack.

$$\text{HighLTI/LowInc}_{i,l,b,t} = \beta_h \cdot \text{Post}_t \times \text{ConstrShare}_l + \gamma_1 \cdot X_{i,l,b,t} + \gamma_2 \cdot X_{b,t} + f_{l,b} + f_t + \varepsilon_{i,l,b,t} \quad (4)$$

We estimate Equation 4 *in the sample of loans issued by unconstrained lenders* to study the substitution of high-LTI loans by these lenders. First, we regress a dummy for high-LTI loans ($\text{HighLTI}_{i,l,b,t}$) on the interaction between Post_t and ConstrShare_l . ConstrShare_l is the demeaned share of lending by constrained lenders in local area l in periods before the introduction of the regulation. β_h , if positive (negative), shows whether there is an overall expansion (contraction) in lending of high-LTI loans by unconstrained lenders in areas with higher exposure to constrained

lenders (and hence higher potential to substitute high-LTI loans in general or to low-income borrowers). We include lower-level interaction terms and controls described in Equation 1.

Table 5 c.1 shows that unconstrained lenders are more likely to provide high-LTI mortgages in areas with higher pre-policy presence of constrained lenders after the policy is introduced (up by 0.5pp in areas with one standard deviation higher exposure to constrained lenders). Further, in c.2, the triple-interaction between $Post_t$, $ConstrShare_l$ and the lender groups shows that this substitution of high-LTI loans is a lot stronger for the two lender-groups further away from the 15% limit: $Mid_Unconstrained_b$ and $Most_Unconstrained_b$. This result is consistent with the residualized shares of high-LTI loans shown in Appendix Figure A.3, with a strong decline for constrained lenders, and an increase for unconstrained lenders following the regulation.

[Table 5 around here]

Yet, is this substitution of high-LTI loans homogeneous? We have seen that the reduction of high-LTI lending by constrained lenders (Table 2 (A)) affects low-income borrowers through two distinct channels: first because they are over-represented in the high-LTI segment, and second because constrained lenders shift their high-LTI lending away from low-income borrowers (Table 3). Do unconstrained lenders substitute high-LTI mortgages to low-income borrowers? Or are there impediments that do not allow low-income borrowers to benefit from substitution?

Table 5 c.3-4 show estimates of β_h in Equation 4 by regressing the dummy for low-income borrowers ($LowInc_{i,l,b,t}$) in the sub-sample of high-LTI loans issued by unconstrained lenders. Column 3 shows that β_h for low-income borrowers is negative and statistically significant. That is, in their substitution of high-LTI loans, unconstrained lenders reduce lending to low-income borrowers in areas with higher share of constrained lenders—areas with more possibilities for substitution. Local areas with a one standard deviation higher share of constrained lenders experience a 5.7 pp decline (down from 35.2%) in the share of low-income borrowers in high-LTI loans issued by unconstrained lenders. This lack of substitution of high-LTI loans for low-income borrowers is despite the reduction in lending of high-LTI loans to low-income borrowers by constrained (compared to unconstrained) lenders (Table 3), available slack, and overall good economic and financial conditions. Further, c.4 shows that this decline is driven by all three unconstrained lender groups.

Mechanisms underlying substitution pattern. We explore mechanisms behind the heterogeneous substitution pattern described above. First, we test whether unconstrained lenders adjust their pricing of high-LTI mortgages after the policy. We estimate Equation 5, where the dependent variable is the same as in Equation 2, but the sample is again restricted to loans issued by unconstrained lenders.

$$\text{Rate}_{i,l,b,t} = \beta_{rate}^s \cdot \text{Post}_t \times \text{HighLTI}_{i,l,b,t} + \gamma_1 \cdot X_{i,l,b,t} + \gamma_2 \cdot X_{b,t} + f_{l,b} + f_t + \varepsilon_{i,l,b,t} \quad (5)$$

Estimate of β_{rate}^s in Table 6 c.1 shows that unconstrained lenders reduce loan rates for high-LTI loans compared to other loans after the policy is introduced, consistent with a willingness to substitute for these loans. This 12 bp reduction in loan rates (against an average price of 315 bp for high LTI loans by unconstrained lenders at policy’s introduction) is present for all three unconstrained lender groups (c.2) as well as in areas with high (c.3) and low (c.4) shares of constrained lenders before the policy. That is, results are consistent with higher credit supply of high-LTI loans by unconstrained lenders after the regulation in areas with higher pre-policy share of constrained lenders.

[Table 6 around here]

Given the heterogeneous substitution pattern of high-LTI loans by unconstrained lenders (i.e., not to low-income borrowers), we study whether these results are more consistent with borrower frictions or lender frictions by analysing the pricing of this segment. We use Equation 6 for the sub-sample of *high-LTI loans issued by unconstrained lenders*: a negative $\beta_{rate}^{s'}$ would suggest that unconstrained lenders try to attract low-income borrowers in high-LTI mortgages but, given the results in Table 5 (c.3-4), are unsuccessful because of borrower frictions; a positive $\beta_{rate}^{s'}$ would be more consistent with a restriction of credit supply driven by lender-side frictions.

$$\text{Rate}_{i,l,b,t} = \beta_{rate}^{s'} \cdot \text{Post}_t \times \text{LowInc}_{i,l,b,t} + \gamma_1 \cdot X_{i,l,b,t} + \gamma_2 \cdot X_{b,t} + f_{l,b} + f_t + \varepsilon_{i,l,b,t} \quad (6)$$

As shown in Table 7, the pricing of high-LTI loans to low-income borrowers experiences a very

different pattern than the pricing of high-LTI loans in general. Column 1 shows that, on average, unconstrained lenders increase the price of high-LTI loans issued to low-income borrowers after the policy, while reducing loan volumes (as shown in Table 5 c.3-4). This increase in loan prices is significantly higher in areas with a higher pre-policy share of constrained lenders (c.3) compared to areas with a lower share (c.4).¹⁵ The coefficient in c.3 implies an increase in the loan interest rate of almost 15 basis points.¹⁶ Moreover, in c.2 and c.5, we find that the increase in loan interest rates of high-LTI loans to low-income borrowers monotonically increases with unconstrained lenders' pre-policy amount of slack to substitute—for the `Most_Unconstrainedb` group, the coefficient implies an increase of over 70 basis points, approximately 23% of the average loan interest rate in the quarter of the policy announcement.

[Table 7 around here]

These results suggest that lender-level frictions prevent low-income borrowers from substituting the drop in high-LTI lending from constrained lenders via unconstrained lenders. There are two types of frictions that are consistent with the results in Table 7: market power and adverse selection. This is because the increase in the pricing and the decrease in volume of high-LTI loans to low-income borrowers by unconstrained lenders could be explained by both problems of adverse selection of low-income borrowers for unconstrained lenders, or by the higher market power acquired by unconstrained lenders post-regulation.

First, for high-LTI loans in general, lenders with more available slack (i.e., `Most_Unconstr.b`) are the ones with more aggressive cuts in loan prices and higher increases in loan volume (Table 5 c.2 and Table 6 c.2).¹⁷ This is the exact opposite of what we find in the pricing for high-LTI loans to low-income borrowers. As shown in Table 7 c.2 and c.5, the increases in the prices of high-LTI

¹⁵Note also that constrained lenders increase loan price more than unconstrained lenders, as the regulation is binding for the former, but after the regulation, unconstrained lenders increase loan prices to low-income borrowers in areas with higher pre-policy presence of constrained lenders (and hence where there are possibilities of credit substitution).

¹⁶The average interest rate for such loans before the announcement of the policy was just above 3%.

¹⁷Note also that the results on the substitution of high-LTI loans in general are not consistent with market power playing a key role, since there is a strong decrease, rather than increase, in the prices of high-LTI loans by unconstrained lenders after the regulation (Table 6). Moreover, this decrease is of similar magnitude precisely in areas where unconstrained lenders have acquired more market power to potentially increase loan prices, i.e. those areas where constrained lenders have a higher pre-policy presence, and hence there is a higher cut in high-LTI loans by constrained lenders.

loans to low-income borrowers are monotonically increasing for lenders that have more capacity to substitute, i.e. lenders with less pre-policy presence (proxying for less pre-policy knowledge) in this market. The increase is also stronger in areas where there are more possibilities for substitution, i.e. areas where constrained lenders have a higher pre-policy presence (Table 7 c.3 vs c.4), while they cut loan volumes (Table 5 c.4). These results are consistent with winners' curse problems for unconstrained lenders only in the substitution for the segment of low-income borrowers within high-LTI loans.

Second, we compare the pricing of high-LTI loans to low-income borrowers in areas with different levels of competition (proxied by the Herfindahl-Hirschman index based on the local area share of lending among unconstrained lenders) *and* higher substitution possibilities (i.e., higher pre-policy share of constrained lenders). If market power is the main driver of the increase in pricing, we expect this increase to be the highest in areas with low competition. If adverse selection is driving the results, the result should be the opposite since winner's curse problems are theoretically more intense in higher competition areas (Marquez (2002)). Higher bank competition exacerbates adverse selection problems since lenders are afraid that available borrowers have been rejected by other lenders, and raise loan prices and cut loan volumes due to winner's curse problems.

In c.1-2 of Table 8, we report that the increase in price of high-LTI loans to low-income borrowers by unconstrained lenders is present in areas with high and low competition, although it is significantly larger in areas with higher competition. Importantly, as shown in columns 3-6, this increase in prices is the strongest (over 14 bp, a 4.5% increase vs. the average level for high-LTI loans at policy's introduction) in areas with higher bank competition among unconstrained lenders *and* higher pre-policy share of lending by constrained lenders (and hence more possibilities of credit substitution).¹⁸ We show in Appendix Table A.10 that the difference in the interest rate charged between high-competition and low-competition areas is statistically significant within areas with higher pre-policy share of constrained lenders (c.2). These results further suggest a key role of

¹⁸High competition areas are those where the Herfindahl-Hirschman index based on intra-unconstrained lender share of lending is in the bottom 50th percentile; high share areas are those where the pre-policy share of lending by constrained lenders is greater than the 50th percentile. Results are qualitatively and quantitatively similar using the Herfindahl-Hirschman index based on intra-unconstrained lender share specifically in the market segment of low-income borrowers receiving high-LTI loans (see Appendix Table A.11).

adverse selection in preventing substitution of high-LTI loans to low-income borrowers.

[Table 8 around here]

Robustness of reported coefficients to substitution pattern. While the heterogeneous substitution patterns described above suggest that substitution for high-LTI loans is strong, we show that coefficients estimated in Section 4.1.1 are robust to the exclusion of the lenders further away from the LTI limit, which use their available slack to strongly substitute for high-LTI loans (Table 5 c.1-2). We replicate Tables 2 (A), 2 (B), and 3 after excluding mortgages issued by the Mid_Unconstrained_{*b*} and Most_Unconstrained_{*b*} lenders, and report results in Appendix Table A.9. The reported coefficient in Appendix Table A.9 (A) for the most saturated specification is negative, quantitative and statistically significant, and somewhat smaller than the one reported in Table 2 (A), consistent with a stronger substitution of high-LTI loans by the excluded lender groups with substantial slack to substitute.¹⁹ The results on high-LTI pricing and shifting away from low-income borrowers by constrained banks (Appendix Tables A.9 (B) and (C)) are similar to the ones in the main tables, if anything somewhat stronger.

4.2 Overall lending to low-income borrowers

As credit substitution is imperfect, we now turn to the overall effect of these multiple channels on lending to low-income borrowers in areas with a higher pre-policy presence of constrained lenders.

To study the net effect of the aforementioned channels on lending to low-income borrowers, we combine lending by constrained and unconstrained lenders. We create a time series of aggregate lending volumes (in $\mathcal{L}$) and use the specification described in Equation 7 to check whether the regulation has an overall effect on lending to low-income borrowers in local areas more exposed to constrained lenders after the regulation. In Equation 7, we regress the lending data aggregated by quarter $\times$ local area $\times$ income-quintile on $\text{Post}_t \times \text{ConstrShare}_l \times \text{LowInc}_j$, where ConstrShare_l is the demeaned share of constrained lenders (described in Section 4.1.2 previously) and LowInc_j is a

¹⁹This result is also consistent with the overall change and Oaxaca-Blinder decomposition of the LTI distribution for constrained and unconstrained lenders shown in Appendix Figure A.2 (I) and A.2 (II), respectively. The decomposition shows that changes in LTI quantiles for constrained lenders are primarily attributable to the 2014 regulation, while that for unconstrained lenders is largely explained by underlying covariates (and hence can be controlled for in our saturated regression specifications).

dummy variable which indicates lending to low-income borrowers (i.e., borrowers in the bottom income-quintile). β_{Inc} indicates whether there is a drop in lending to low-income borrowers after the regulation in areas with higher pre-policy presence of constrained lenders.

$$\log(L_{j,l,t}) = \beta_{Inc} \cdot \text{Post}_t \times \text{ConstrShare}_l \times \text{LowInc}_j + f_{j,l} + f_{j,t} + f_{l,t} + \varepsilon_{j,l,t} \quad (7)$$

We report the results on changes in lending volumes in Table 9. We start by splitting the sample by low-income (c.1) vs. higher-income (c.2) quintiles. Consistent with the loan-level evidence, the presence of constrained lenders is associated with a reduction in lending after the policy only for the lowest income-quintile. In c.3-6 we test whether this difference is statistically significant using the triple interaction specified in Equation 7. The coefficient β_{Inc} is negative and significant, showing a contraction in total lending to borrowers in the lowest income-quintile in local areas more exposed to constrained lenders after the regulation.²⁰ We gradually saturate the specification with local area $\times$ time ($f_{l,t}$), local area $\times$ income-quintile ($f_{l,j}$) and income-quintile $\times$ time ($f_{j,t}$) fixed-effects. These allow for strong identification since we control for factors that may impact borrowers in a specific income group or a specific local area at a given time, such as a demand shock common to low-income borrowers or local areas following the regulation.²¹

[Table 9 around here]

The estimated coefficients show that borrowers in the bottom income-quintile in local areas with a one standard deviation higher pre-policy share of constrained lenders experience a 10.8% drop in the total loan amount (in $\mathcal{L}$) following the regulation. Similarly, these areas experience a 8.6% drop in the total number of loans (Appendix Table A.14), which shows that the overall drop

²⁰Appendix Table A.12 shows results by weighting each observation with the size of local area’s pre-policy total lending portfolio; i.e. the effects are not driven by the relative size of local areas. Appendix Table A.13 shows that the contraction in lending for low-income borrowers in c.1 of Table 9 is particularly driven by constrained lenders, and is substantially weaker for unconstrained lenders. The strong contraction in lending to low-income borrowers is also present in the residualized shares of low-income borrowers in high-LTI loans shown in Appendix Figure A.5 with a strong decline for constrained lenders, which is not compensated by unconstrained lenders, following the regulation. Finally, the contraction in lending to low-income borrowers in areas more exposed to constrained lenders is ameliorated by the presence of brokers, and is stronger in their absence (Appendix Table A.15).

²¹In unreported results, we use the Oster (2019) test and find that our results are robust to concerns of selection and omitted variable biases (we find identical conclusions in the loan-level analysis, e.g. on Table 2 (A)). Moreover, the results are also robust to the inclusion of alternate controls, such as those based on local area share of high-LTI loans and regional house-price and GDP growth.

in lending to low-income borrowers is driven by both a drop in number of loans and the average size of loans. We also regress the aggregated lending data on $\text{ConstrShare}_l \times \text{LowInc}_j$ interacted with the full set of time-dummies: Figure 3 shows that the resulting estimates are zero in periods *before* 2014Q2 and show a contraction in lending to low-income borrowers only in periods *after* the introduction of the regulation (showing lack of pre-trends). The strong contraction in lending to low-income borrowers is in contrast with the overall effect on high-LTI lending (Table A.16) which, though negative, is economically a lot weaker and statistically insignificant.

[Figure 3 around here]

4.3 House prices

In this section, we study the behaviour of house prices after the introduction of the policy. While the policy was introduced during a housing boom, the Brexit referendum two years later (June 2016) was followed by a house price growth correction across the UK (Appendix Figure A.6 (A)). We analyse whether the areas more affected by the macroprudential policy are associated with lower house price growth during good times (as lending to low-income borrowers goes down) and higher house price growth during a negative aggregate shock (as low-income borrowers were less leveraged due to the 2014 policy).

We use Equation 8 to analyse house prices during 2012H2-2018H1 in more affected areas. We regress annual changes in the logarithm of house price indices in local area l at year t , on $\text{Post}_t \times \text{Constr}_l \times \text{LowInc}_l$ and $\text{BrexitRef}_t \times \text{Constr}_l \times \text{LowInc}_l$, where Post_t indicates periods 2014H2 onwards, BrexitRef_t indicates periods 2016H2 onwards, and $\text{Constr}_l \times \text{LowInc}_l$ indicate *affected* local areas with high pre-policy share of constrained lenders ($>$ median) and mortgages to low-income borrowers ($>$ 75th percentile). β_{pol} reflects trends in house price growth in affected areas post-policy; β_{ref} reflects trends in house price growth in affected areas after the Brexit referendum. We include highly disaggregate fixed-effects: for instance $\text{County} \times \text{Time}$ fixed-effects ($f_{c,t}$) compares trends across geographically proximate local areas with differential exposures to the regulation.

$$\begin{aligned} \Delta \log(P_{l,t}) = & \beta_{pol} \cdot \text{Post}_t \times \text{Constr}_l \times \text{LowInc}_l + \beta_{ref} \cdot \text{BrexitRef}_t \times \text{Constr}_l \times \text{LowInc}_l \\ & + f_l + f_{r,t} + f_{c,t} + \varepsilon_{l,t} \end{aligned} \quad (8)$$

Table 10 (A) shows affected areas are associated with a drop in house-price growth (-3pp, c.1) at the lower-end of the house-price distribution after the policy. This trends reverses after the Brexit referendum (+5.9pp, c.1) and holds for both the 25th percentile (c.1 and 2) and the bottom-tercile (c.4) of the distribution, irrespective of whether indices are based on all transactions (c.1) or repeat postcode-house type combinations which control for mix of transacted houses (c.2 and c.4). These results are consistent with the credit reduction to low-income borrowers from the policy affecting house-price growth at the lower-end of the price distribution. Consistent with the lack of an effect on higher-income borrowers, the coefficients for the higher end of the price distribution (c.3 and 5) are not statistically significant. Placebo test (c.6) shows affected areas did not respond differentially in a separate episode of negative aggregate shock (2007-08 financial crisis).²²

[Table 10 (A) around here]

These results suggest that the triple credit crunch on low-income borrowers following the regulation are associated with subsequent lower house price growth in the lower end of the house price distribution in policy-affected areas, and with relatively lower drop in house price growth after a negative aggregate shock. While these results are consistent with previous contributions on interactions between house prices and household leverage, we note the relatively short two-year windows after the policy and after the Brexit referendum as limitations to making stronger claims on the effects of the 2014 regulation on house prices.

4.4 Defaults

Results suggest that the 2014 macroprudential policy leads to a contraction in lending to low-income borrowers (Table 9), and policy-affected areas (areas with higher pre-policy exposure to constrained lenders and higher concentration of low-income borrowers) experience relatively lower house price drop following a negative aggregate shock (Table 10 (A)). We now test whether affected

²²Appendix Table A.17 shows that results are not driven by Greater London, local-area housing supply constraints, share of high-LTI mortgages, and differential exposures to the regional shocks. We run 1,048,575 different regressions to test the sensitivity of the estimated coefficients and their statistical significance to observed characteristics (a la Brodeur et al. (2020) in Appendix Figure A.6 (C)) and results are robust. Our estimates are also robust to concerns of selection and omitted variable biases (i.e., unobservables) using the tests described in Oster (2019) and Altonji et al. (2005). Appendix Figure A.6 (B) shows lack of pre-trends in house price growth in affected local areas.

areas, consistent with pre-referendum reduction in leverage, are also associated with lower mortgage defaults following the negative aggregate shock (referendum).

We use the *stock* data on mortgages to track performance of the mortgages in our sample. A mortgage is classified as under default in case it is under payment arrear (or shortfall), forbearance, or a possession order. We focus on mortgage performance in 2017H2 (18 months following the Brexit referendum)²³ and compare mortgages issued before (2012Q3-2014Q2) and after (2014Q4-2016Q2) the introduction of the policy to test whether mortgages issued post-policy in affected areas experience relatively lower rates of defaults vs. other areas and, within affected areas, whether low-income borrowers experience lower defaults vs. other borrowers.

We use Equation 9 to estimate the effects of the 2014 LTI regulation on mortgage defaults using a Poisson model, i.e. we assume that the number of defaults in a local area in a given quarter is Poisson distributed. We take loan-level data matched with mortgage performance in 2017H2 to create an aggregated dataset of the *number of mortgages* under default ($ND_{j,l,t}$) for income-quintile j , in local area l and period of mortgage origination t (quarter), and the total number of mortgages ($M_{l,t}$, i.e. the exposure variable) issued in local area l in quarter t . The Poisson model is appropriate to study the count of local area defaults given the low number of defaults at the level of disaggregation (income-band $\times$ local area $\times$ time). We estimate the coefficient β_d^{ext} on $Post_t \times Constr_l \times LowInc_l \times LowInc_j$, where $Constr_l \times LowInc_l$ refers to policy-affected areas, and $LowInc_j$ refers to borrowers in the bottom income-quintile, which shows differences in the relative-risk of being under default by end-2017, conditioned on being issued to low-income borrowers in affected areas after the introduction of the policy. The equation is estimated in the presence of lower-level interaction terms, and the same set of fixed-effects as Equation 8.²⁴

$$\frac{ND_{j,l,t}}{M_{l,t}} = e^{-\lambda_{j,l,t}}, \text{ where } \lambda_{j,l,t} = \beta_d^{ext} \cdot Post_t \times Constr_l \times LowInc_l \times LowInc_j + f_l + f_{r,t} + f_{c,t} + \varepsilon_{j,l,t} \quad (9)$$

In Table 10 (B), c.1–2, we report the coefficient on $Post_t \times Constr_l \times LowInc_l$ in split-samples by

²³Appendix Figure A.7 shows an increase in the default rate for mortgages in our sample with $LTI \geq 4.5$ and mortgages to low-income borrowers following the Brexit referendum.

²⁴We exclude local area $\times$ time fixed-effects to report the coefficient on $Post_t \times Constr_l \times LowInc_l$.

income-quantile: c.1 shows the results for low-income borrowers (borrowers in the lowest income-quintile), c.2 shows the results for the rest of the borrowers. We find that mortgages issued in affected areas after the introduction of the policy experience lower default only for low-income borrowers, not for the rest. This result is confirmed using the coefficient on the quadruple interaction shown in c.3-5 which suggests that areas affected by the 2014 macroprudential policy are associated with a lower *number* of mortgage defaults (vs. less affected areas) following the Brexit referendum, driven by lower defaults for low-income borrowers (vs. higher-income borrowers) in those areas (again consistent with the macroprudential policy). The coefficient in c.5 shows a relative-risk (of being under default) of 0.66 for low-income borrowers (i.e., 34% lower defaults) conditioned on their mortgage being issued after the policy in an affected area.

[Table 10 (B) around here]

5 Conclusion

We analyse the distributional effects of macroprudential policy on mortgage cycles. To the best of our knowledge, this is the first paper which studies the effects of macroprudential regulation of household leverage both during a boom and following a negative aggregate shock. For empirical identification, we use the UK mortgage-register in conjunction with a 15%-limit imposed on lenders' high loan-to-income (LTI) mortgages. These lenders are differentially affected based on their pre-policy share of high-LTI loans in their mortgage portfolio. Moreover, we exploit the unexpected outcome of the Brexit referendum, that led to a strong house price growth correction across the UK, to analyse potential effects of macroprudential policies implemented during booms at times of negative aggregate shocks.

Our robust results show that constrained lenders issue fewer and more expensive high-LTI mortgages. This reduction affects low-income borrowers through two distinct channels: first because they are over-represented in the high-LTI segment, and second because constrained lenders shift their high-LTI lending towards higher-income borrowers; low-income borrowers, hence, suffer a double crunch. Credit substitution for low-income borrowers is imperfect. We find substitution towards smaller low-LTI loans to low-income borrowers when comparing constrained vs. un-

constrained lenders. Furthermore, substitution by unconstrained lenders is heterogeneous: they strongly substitute high-LTI loans in general, but do not extend these loans to low-income borrowers. We document wide-ranging evidence which suggests that this heterogeneous substitution lending pattern is driven by lender-side frictions, in particular consistent with concerns around adverse selection of low-income borrowers. This highlights a third channel which negatively affects lending to low-income borrowers, i.e. low-income borrowers suffer a triple crunch in lending resulting from the regulation. The net result of these multiple channels is that low-income borrowers experience a strong contraction in lending in areas more exposed to constrained lenders (i.e. lower loan volumes).

Our results show that market frictions are an important channel in the transmission of macroprudential regulations to credit markets. The lack of substitution by unconstrained lenders occurs despite the regulation being aimed at lender (not household) level, despite multiple lenders (and aggregate banking system) with sufficient slack to substitute constrained lenders, and despite good financial and economic conditions around the introduction of the regulation, which are all a testament to the strength of those market frictions. Consideration of these market frictions is a key implication of our results for both policy and theory on the effects of macroprudential policies on credit markets.

We document house price and default dynamics consistent with the contraction in lending to low-income borrowers. We find that local areas more affected by this contraction are associated with a dampening of house prices following the regulation. Our results suggest that during the strong drop in house price growth across the UK following the Brexit referendum, these affected areas experience relatively lower drops in house price growth; moreover, low-income borrowers in the affected areas experience relatively lower mortgage defaults concurrent with the better house price growth. These potential costs and benefits of macroprudential regulation are highly topical given the widespread interest in introducing such regulations as a way to ensure financial stability, and potential implications for inequality due to their burden on low-income borrowers.

In sum, on the one hand, we document a triple credit crunch of mortgages to low-income borrowers in high-LTI loans, with imperfect credit substitution consistent with adverse selection

problems, leading to an overall reduction in lending to low-income borrowers. But on the other hand, following a negative aggregate shock and consistent with the drop in leverage for low-income borrowers, policy-affected areas are associated with relatively lower subsequent drops in house prices (particularly at the lower-end of house price distribution) and lower loan defaults (particularly for low-income borrowers).

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Tables

Table 1: Summary statistics of loan and borrower level data

Total sample of mortgages						
Variable	count	mean	sd	p25	p50	p75
Loan Value (£)	1,849,952	165,138	119,625	90,000	136,093	202,995
Property Value (£)	1,849,952	270,612	215,928	145,000	210,000	318,000
Mortgage Term	1,849,952	23.4	7.7	18	25	30
Loan-to-Income	1,849,952	3.0	1.1	2.2	3.1	3.8
Loan-to-Value	1,849,952	66.0	22.3	51.9	73.1	84.9
Borrower Income (£)	1,849,952	58,535	45,396	33,000	46,706	68,001
Borrower Age	1,849,952	38	9.8	30	37	45
Sample of high loan-to-income (LTI) mortgages						
Variable	count	mean	sd	p25	p50	p75
Loan Value (£)	149,988	235,599	140,741	142,100	199,999	284,995
Property Value (£)	149,988	362,146	259,518	201,000	286,950	426,000
Mortgage Term	149,988	28.16	6.17	25.00	30.00	34.00
Loan-to-Income	149,988	4.85	0.30	4.63	4.77	4.99
Loan-to-value	149,988	69.8	15.5	60.3	73.5	80.6
Borrower Income (£)	149,988	48,763	31,636	29,262	41,000	58,720
Borrower Age	149,988	35.00	8.24	29.00	34.00	40.00

This table shows summary statistics based on loan and borrower level data of residential mortgages issued in the UK during 2012Q3-2016Q2 that were under the purview of the 2014 regulation.

Table 2 (A): Loan level: Share of high-LTI loans ($LTI \geq 4.5$)

Variable	$\leftarrow$ Dummy for high-LTI loans ($\text{HighLTI}_{i,l,b,t}$) $\rightarrow$				
	(1)	(2)	(3)	(4)	(5)
$\text{Post}_t \times \text{Constrained}_b$	-0.0474*** (0.0116)	-0.0578*** (0.0102)	-0.0513*** (0.0093)	-0.0401*** (0.0087)	-0.0387*** (0.0079)
Observations	1,849,952	1,849,952	1,849,952	1,849,952	1,849,952
R^2	0.0124	0.0641	0.0657	0.117	0.118
Borrower, Loan Controls		Yes	Yes	Yes	Yes
Bank Controls			Yes	Yes	Yes
Local Area $\times$ Bank FE				Yes	Yes
Time FE					Yes

The dependent variable in this table is $\text{HighLTI}_{i,l,b,t}$, a binary variable that equals 1 if the mortgage granted by lender b to borrower i in quarter t in local area l has a loan-to-income ratio (LTI) equal or above 4.5, and 0 otherwise. The sample period is from 2012Q3 to 2016Q2, excluding 2014Q3. Post_t is a binary variable that equals 1 for quarters after 2014Q3, 0 for quarters before. Constrained_b is a binary variable that equals 1 if lender b is at or very close to the limit of 15% share of high-LTI mortgages in the four quarters before the announcement of the policy (2013Q3-2014Q2), 0 otherwise. All regressions are estimated using ordinary least squares. Borrower, loan, and bank controls, as well as fixed-effects are either included ("Yes") or not included. Online Appendix Section A shows the definition of the main controls. Post_t and Constrained_b are included as standalone variables when they are not absorbed by fixed-effects. Robust standard errors double-clustered at bank-quarter and local area level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Table 2 (B): Loan level: Pricing of high-LTI loans

Variable	← Interest rate ($\text{Rate}_{i,l,b,t}$) →						
Sub-sample	Low-LTI	High-LTI	All				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{Post}_t \times \text{Constrained}_b$	-0.0068 (0.130)	0.0647 (0.151)	-0.0068 (0.130)	0.0433 (0.132)	-0.0055 (0.130)	0.0396 (0.127)	0.0597 (0.0353)
$\text{Post}_t \times \text{Const.}_b \times \text{HighLTI}_j$			0.0715 (0.085)	0.145** (0.0643)	0.131** (0.0629)	0.123** (0.0517)	0.128*** (0.0447)
Observations	1,694,823	150,845	1,845,668	1,845,668	1,845,668	1,845,668	1,845,668
R^2	0.0878	0.156	0.0964	0.281	0.292	0.356	0.428
Borrower, Loan Controls				Yes	Yes	Yes	Yes
Bank Controls					Yes	Yes	Yes
Local Area $\times$ Bank FE						Yes	Yes
Time FE							Yes

The dependent variable in this table is the interest rate charged on a mortgage by lender b to borrower i in quarter t in local area l . The sample period is from 2012Q3 to 2016Q2, excluding 2014Q3. The sample is restricted to mortgages with a loan-to-income ratio (LTI) less than (column 1) or greater than or equal to (column 2) 4.5, while columns 3-7 include full sample. Post_t is a binary variable that equals 1 for quarters after 2014Q3, 0 for quarters before. Constrained_b is a binary variable that equals 1 if lender b is at or very close to the limit of 15% share of high-LTI mortgages in the four quarters before the announcement of the policy (2013Q3-2014Q2), 0 otherwise. HighLTI_j is a binary variable that equals 1 for mortgages with $\text{LTI} \geq 4.5$, 0 for the rest. All regressions are estimated using ordinary least squares. Borrower, loan, and bank controls, as well as fixed-effects are either included (“Yes”) or not included. Online Appendix Section A shows the definition of the main controls. Lower-level interactions are included as standalone variables when they are not absorbed by fixed-effects. Robust standard errors double-clustered at bank-quarter and local area level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Table 3: Loan level: Income quintiles in high-LTI loans

Variable	$\leftarrow$ Dummy for income quintiles ($\mathbb{D}(\text{Inc}=\text{j})_{i,l,b,t}$) $\rightarrow$				
j =	I	II	III	IV	V
$\text{Post}_t \times \text{Constrained}_b$	-0.0608*** (0.0159)	-0.0221* (0.0096)	-0.0069 (0.0092)	0.0309*** (0.0089)	0.0588*** (0.0119)
Observations	149,988	149,988	149,988	149,988	149,988
R^2	0.338	0.0654	0.079	0.140	0.207
Borrower, Loan Controls	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes
Local Area $\times$ Bank FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

The dependent variables are binary variables indicating whether borrower i associated to a mortgage granted by lender b in quarter t in local area l belongs to a particular income quintile (1) or not (0). Each column corresponds to the binary variables for a specific quintile-group, with I being the bottom and V the top quintile of the income distribution. The quintiles are constructed using the sample from the pre-policy period. The sample period is from 2012Q3 to 2016Q2, excluding 2014Q3. The sample is restricted to mortgages with a loan-to-income ratio (LTI) ≥ 4.5 . Post_t is a binary variable that equals 1 for quarters after 2014Q3, 0 for quarters before. Constrained_b is a binary variable that equals 1 if lender b is at or very close to the limit of 15% share of high-LTI mortgages before the announcement of the policy (2013Q3-2014Q2), 0 otherwise. All regressions are estimated using ordinary least squares. All regressions include borrower, loan, and bank controls, as well as fixed-effects. Online Appendix Section A shows the definition of the main controls. Robust standard errors double-clustered at bank-quarter and local area level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Table 4: Loan level: Substitution in lending to low-income borrowers

Variable	← Dummy for low-income borrowers ($\mathbb{D}(\text{Inc}=1)$) →						log(Loan Size)	
	LTI $\in$ (0,2.09)	LTI $\in$ [2.09,2.87)	LTI $\in$ [2.87,3.57)	LTI $\in$ [3.57,4.5)	LTI $\geq$ 4.5	All	Low Income	Non-low Income
Sub-sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Post}_t \times \text{Constrained}_b$	0.0128* (0.0057)	0.0243*** (0.0071)	0.0249** (0.0078)	0.0313*** (0.0073)	-0.0608*** (0.0159)	0.0038 (0.0058)	-0.0366* (0.0203)	-0.0094 (0.0149)
Observations	404,346	417,799	428,022	445,371	149,988	1,849,962	278,524	1,570,212
R^2	0.173	0.200	0.207	0.245	0.338	0.189	0.488	0.528
Borrower, Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Local area $\times$ Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable in columns 1-6, $\text{LowInc}_{i,l,b,t}$, is a binary variable indicating whether the income of borrower i associated to a mortgage granted by lender b in quarter t in local area l is in the bottom quintile of the income distribution among borrowers. The dependent variable in columns 7-8, $\log(\text{Loan Size}_{i,l,b,t})$, is the logarithm of the total amount of mortgage granted by lender b to borrower i in quarter t in area l . The sample period is from 2012Q3 to 2016Q2, excluding 2014Q3. The quartiles of the loan-to-income (LTI) distribution is calculated based on the pre-policy period. In each column 1-4, the sample is restricted to mortgages with an LTI inside that particular quartile. In column 5, the sample is restricted to mortgages with $\text{LTI} \geq 4.5$. Column 6 includes full sample. Columns 7 (8) contains mortgages to low-income (non-low-income) borrowers only. Post_t is a binary variable that equals 1 for quarters after 2014Q3, 0 for quarters before. Constrained_b is a binary variable that equals 1 if lender b is at or very close to the limit of 15% share of high-LTI mortgages before the announcement of the policy (2013Q3-2014Q2), 0 otherwise. All regressions are estimated using ordinary least squares. All regressions include borrower, loan, and bank controls, as well as fixed-effects. Online Appendix Section A shows the definition of the main controls. Robust standard errors double-clustered at bank-quarter and local area level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Table 5: Loan level: Substitution by unconstrained lenders

Variable	Dummy for high-LTI loans		Dummy for low-income borrowers within high-LTI loans	
	$\leftarrow (\text{HighLTI}_{i,l,b,t}) \rightarrow$		$\leftarrow (\text{LowInc}_{i,l,b,t}) \rightarrow$	
	All		High-LTI loans	
Sub-sample	(1)	(2)	(3)	(4)
$\text{Post}_t \times \text{ConstrShare}_l$	0.0007* (0.0004)		-0.0083*** (0.0017)	
$\text{Post}_t \times \text{ConstrShare}_l \times \text{Least_Unconstr.}_b$		-0.0010** (0.0004)		-0.0056*** (0.0018)
$\text{Post}_t \times \text{ConstrShare}_l \times \text{Mid_Unconstr.}_b$		0.00134** (0.0005)		-0.0081*** (0.0022)
$\text{Post}_t \times \text{ConstrShare}_l \times \text{Most_Unconstr.}_b$		0.00144** (0.0006)		-0.001 (0.0244)
Observations	1,233,127	1,233,127	75,103	75,103
R^2	0.0942	0.0950	0.331	0.332
Borrower, Loan Controls	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
Local Area $\times$ Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

The dependent variables are $\text{HighLTI}_{i,l,b,t}$ (c. 1-2), a binary variable that equals 1 if a mortgage granted by lender b to borrower i in quarter t in local area l has a loan-to-income ratio (LTI) equal or above 4.5, and 0 otherwise; and $\text{LowInc}_{i,l,b,t}$ (c. 3-4), a binary variable indicating whether the income of borrower i associated to a mortgage granted by lender b in quarter t in local area l is in the bottom quintile of the income distribution among borrowers. The sample includes *all* mortgages issued by unconstrained lenders (c. 1-2) and *high-LTI* mortgages issued by unconstrained lenders (c. 3-4). Unconstrained lenders are classified into three groups— Least_Unconstr._b refers to unconstrained lenders whose share of loans with $\text{LTI} \geq 4.5$ in 2013Q3-2014Q2 is closest to the 15% limit; Most_Unconstr._b refers to unconstrained lenders furthest from the 15% limit; Mid_Unconstr._b refers to unconstrained lenders with an intermediate share of high-LTI loans. Post_t is a binary variable that equals 1 for quarters after 2014Q3, 0 for quarters before. ConstrShare_l equals the demeaned share of lending by constrained lenders in local area l in periods before the announcement of the policy. All regressions are estimated using ordinary least squares. Lower-level interactions are included as standalone variables when they are not absorbed by fixed-effects. Borrower, loan, and bank controls, as well as fixed-effects are included. Online Appendix Section A shows the definition of the main controls. Robust standard errors double-clustered at bank-quarter and local area level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Table 6: Loan level: Pricing of high-LTI loans by unconstrained lenders

Variable	← Interest rate ($\text{Rate}_{i,l,b,t}$) →			
Sub-sample	All		High constr. share	Low constr. share
	(1)	(2)	(3)	(4)
$\text{Post}_t \times \text{HighLTI}_{i,l,b,t}$	-0.121*** (0.0306)		-0.125*** (0.0260)	-0.116*** (0.0342)
$\text{Post}_t \times \text{HighLTI}_{i,l,b,t} \times \text{Least_Unconstr.}_b$		-0.131*** (0.0498)		
$\text{Post}_t \times \text{HighLTI}_{i,l,b,t} \times \text{Mid_Unconstr.}_b$		-0.050** (0.0219)		
$\text{Post}_t \times \text{HighLTI}_{i,l,b,t} \times \text{Most_Unconstr.}_b$		-0.244** (0.122)		
Observations	1,228,827	1,228,827	244,208	984,619
R^2	0.482	0.483	0.495	0.479
Borrower, Loan Controls	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
Local Area $\times$ Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

The dependent variable is the interest charged on a mortgage at the time of origination. The sample includes mortgages issued by unconstrained lenders only. Unconstrained lenders are classified into three groups—Least_Unconstr._b refers to unconstrained lenders whose share of loans with loan-to-income (LTI) ≥ 4.5 in 2013Q3-2014Q2 is closest to the 15% limit; Most_Unconstr._b refers to unconstrained lenders furthest from the 15% limit; Mid_Unconstr._b refers to unconstrained lenders with an intermediate share of high-LTI loans. Post_t is a binary variable equal to 1 for quarters after 2014Q3, 0 for quarters before. ConstrShare_l equals the demeaned share of lending by constrained lenders in local area l in periods before the announcement of the policy. The sample is restricted to areas with a ConstrShare_l above (c.3) or below (c.4) the 75th percentile. All regressions are estimated using ordinary least squares. Lower-level interactions are included as standalone variables when not absorbed by fixed-effects. Borrower, loan, and bank controls, as well as fixed-effects are included. Online Appendix Section A shows the definition of the main controls. Robust standard errors double-clustered at bank-quarter and local area level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Table 7: Loan level: Pricing of high-LTI loans to low-income borrowers

Variable	← Interest rate ($\text{Rate}_{i,l,b,t}$) →				
Sub-sample	High-LTI loans		High constr. share	Low constr. share	High constr. share
	(1)	(2)	(3)	(4)	(5)
$\text{Post}_t \times \text{LowInc}_{i,l,b,t}$	0.105*** (0.0325)		0.145*** (0.0409)	0.0860*** (0.0322)	
$\text{Post}_t \times \text{LowInc}_{i,l,b,t} \times \text{Least_Unconstr.}_b$		0.0111 (0.0383)			0.0365 (0.0565)
$\text{Post}_t \times \text{LowInc}_{i,l,b,t} \times \text{Mid_Unconstr.}_b$		0.0965*** (0.0323)			0.113*** (0.0414)
$\text{Post}_t \times \text{LowInc}_{i,l,b,t} \times \text{Most_Unconstr.}_b$		0.272 (0.322)			0.705** (0.312)
Observations	75,008	75,008	25,444	49,564	25,444
R^2	0.536	0.537	0.556	0.525	0.558
Borrower, Loan Controls	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes
Local area $\times$ Bank FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

The dependent variables is the interest charged on a mortgage at the time of origination. The sample includes high loan-to-income (LTI) mortgages issued by unconstrained lenders only. Unconstrained lenders are classified into three groups—Least_Unconstr._b refers to unconstrained lenders whose share of loans with $\text{LTI} \geq 4.5$ in 2013Q3-2014Q2 is closest to the 15% limit; Most_Unconstr._b refers to unconstrained lenders furthest from the 15% limit; Mid_Unconstr._b refers to unconstrained lenders with an intermediate share of high-LTI loans. Post_t is a binary variable that equals 1 for quarters after 2014Q3, 0 for quarters before. ConstrShare_l equals the demeaned share of lending by constrained lenders in local area l in periods before the announcement of the policy. The sample is restricted to areas with a ConstrShare_l above (c.3 and c.5) or below (c.4) the 75th percentile. All regressions are estimated using ordinary least squares. Lower-level interactions are included as standalone variables when not absorbed by fixed-effects. Borrower, loan, and bank controls, as well as fixed-effects are included. Online Appendix Section A shows the definition of the main controls. Robust standard errors double-clustered at bank-quarter and local area level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Table 8: Loan level: Competition and pricing of high-LTI loans to low-income borrowers by unconstrained lenders

Variable	$\leftarrow$ Interest rate ($\text{Rate}_{i,l,b,t}$) $\rightarrow$					
Sub-sample	All		High Share		Low Share	
	High Comp	Low Comp	High Comp	Low Comp	High Comp	Low Comp
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Post}_t \times \text{LowInc}_j$	0.126*** (0.0332)	0.085** (0.0383)	0.142*** (0.0394)	0.086* (0.0465)	0.0874** (0.0384)	0.0852** (0.0409)
Observations	48,169	26,839	35,726	15,723	12,443	11,116
R^2	0.544	0.527	0.550	0.538	0.528	0.509
Borrower, Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Local Area $\times$ Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable is the interest charged on a mortgage at the time of origination. The sample includes high loan-to-income (LTI) mortgages ($\text{LTI} \geq 4.5$) issued by unconstrained lenders only. Columns 1 and 2 include all observations. Columns 3 and 4 restrict the sample to areas with a higher share of constrained lenders (share above the median), while columns 5 and 6 focus on areas with a lower share of constrained lenders (below the median). Each sample is divided between high-competition (areas with a Herfindahl-Hirschman Index (HHI) below the median) and low-competition (HHI above the median) areas, based on market shares among unconstrained lenders. Post_t is a binary variable that equals 1 for quarters after 2014Q3, 0 for quarters before. LowInc_j is a binary variable indicating whether the income of borrower associated to a granted mortgage is in the bottom quintile of the income distribution among borrowers. All regressions are estimated using ordinary least squares. Lower-level interactions are included as standalone variables when they are not absorbed by fixed-effects. All regressions include borrower, loan, and bank controls, as well as fixed-effects. Online Appendix Section A shows the definition of the main controls. Robust standard errors double-clustered at bank-quarter and local area level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Table 9: Overall lending to low-income borrowers

Variable	$\leftarrow$ Total value (in £) of mortgages($\log(\mathbb{L}_{j,l,t})$) $\rightarrow$					
Sub-sample	Low income	Non-Low income	All			
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Post}_t \times \text{ConstrShare}_l$	-0.0156*** (0.0024)	0.0012 (0.0012)	0.0012 (0.0012)			
$\text{Post}_t \times \text{ConstrShare}_l \times \text{LowInc}_j$			-0.0169*** (0.00252)	-0.0168*** (0.00259)	-0.0168*** (0.00260)	-0.0168*** (0.00258)
Observations	6,200	24,852	31,045	31,045	31,043	31,043
R^2	0.958	0.813	0.841	0.841	0.863	0.864
Local Area FE	Yes	Yes	Yes	-	-	-
Time FE	Yes	Yes	Yes	-	-	-
Local Area $\times$ Time FE				Yes	Yes	Yes
Local Area $\times$ Income-quintile FE					Yes	Yes
Time $\times$ Income-quintile FE						Yes

The dependent variable is the logarithm of the total value (in £) of mortgages granted in quarter t in local area l to borrowers in the income-quintile j . The sample period is from 2012Q3 to 2016Q2, excluding 2014Q3. Post_t is a binary variable that equals 1 for quarters after 2014Q3, 0 for quarters before. ConstrShare_l equals the demeaned share of lending by constrained lenders in local area l in periods before the announcement of the policy. LowInc_j indicates the bottom income-quintile. Column 1 restricts the sample to lending to low-income borrowers (i.e., borrowers in the bottom income-quintile), while column 2 restricts the sample to lending to the rest of the borrowers (i.e., 2nd-5th income-quintiles). Columns 3-6 use the full sample. All regressions are estimated using ordinary least squares. Lower-level interactions are included as standalone variables when they are not absorbed by fixed-effects. Fixed-effects are either included ("Yes"), spanned by other fixed-effects ("-"), or not included. Robust standard errors clustered at local area level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Table 10 (A): House price growth in affected local areas

Variable	← House price growth ($\Delta \log(\text{House Price}_{l,t})$) →					
Index	25 th perc.	25 th perc.	75 th perc.	Bottom tercile	Top tercile	25 th perc.
	(1)	(2)	(3)	(4)	(5)	(6)
BrexitRef _t × Constr _l × LowInc _l	0.059** (0.022)	0.081*** (0.020)	-0.035 (0.050)	0.093*** (0.022)	0.007 (0.035)	
Post _t × Constr _l × LowInc _l	-0.030* (0.016)	-0.059** (0.027)	0.014 (0.043)	-0.073** (0.031)	0.017 (0.042)	
Fin.Crisis _t × Constr _l × LowInc _l						0.005 (0.023)
Observations	3,072	1,536	1,536	1,536	1,536	1,024
R ²	0.553	0.475	0.439	0.463	0.423	0.904
Local Area FE	Yes	Yes	Yes	Yes	Yes	Yes
Region × Constr × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Region × LowInc × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
County × Time FE	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable is the (annual) change in the logarithm of house price indices for local area l , calculated using all transactions (c.1) or repeat postcode-house type transactions (c.2-6). The indices are based on: 25th percentile (c.1, 2, 6); 75th percentile (c.3); average price paid in bottom (c.4) and top (c.5) tercile of house transactions. The sample spans from 2012H2-2018H1 (c.1-5) and 2004H2-2009H1 (c.6). Post_t indicates periods 2014H2-2018H1 (i.e. post-policy); BrexitRef_t indicates 2016H2 - 2018H1 (i.e. post Brexit referendum). Constr_l and LowInc_l indicate *affected* local areas with high pre-policy share of constrained lenders (>p50) and mortgages to low-income borrowers (>75th percentile), respectively. Fin.Crisis_t indicates the period 2007H2 - 2009H1. All regressions are estimated using ordinary least squares. All lower-level interactions are included. Fixed-effects are either included (“Yes”), spanned by other fixed-effects (“-”), or not included. Robust standard errors clustered at local area level show significance at 1% level; **: significant at 5% level; *: significant at 10% level.

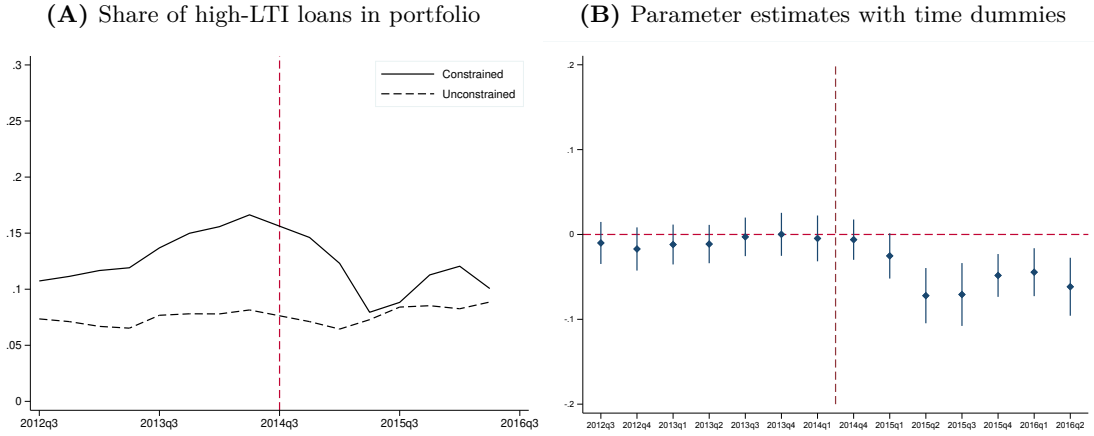
Table 10 (B): Mortgage defaults

Variable	← Number of mortgages under default ($ND_{j,l,t}$) →				
Sub-sample	Low Income	Non-Low Income	All		
	(1)	(2)	(3)	(4)	(5)
$Post_t \times ConstrShare_l \times LowInc_l$	-0.24** (0.0969)	0.0245 (0.0568)	0.0262 (0.0562)	0.161 (0.1)	0.0473 (0.121)
$Post_t \times ConstrShare_l \times LowInc_l \times LowInc_j$			-0.265** (0.111)	-0.259** (0.113)	-0.408*** (0.13)
Observations	3,599	5,615	9,214	9,214	5,868
Time FE	Yes	Yes	Yes	-	-
Local Area FE	Yes	Yes	Yes	Yes	Yes
Region $\times$ Constr $\times$ Time FE				Yes	Yes
Region $\times$ LowInc $\times$ Time FE				Yes	Yes
County $\times$ Time FE					Yes

The dependent variable is the total number of mortgages under default in December 2017 aggregated by borrower income-quintile j , quarter t , local area l . The sample includes existing mortgages in 2017H2 which were originated between 2012Q3 to 2016Q2, excluding 2014Q3. $Post_t$ is a binary variable that equals 1 for quarters after 2014Q3, 0 for quarters before. $Constr_l$ and $LowInc_l$ are local area level variables which indicate local areas with higher share of constrained lenders ($>p50$) and higher share of lending to low-income borrowers ($>p75$), respectively. $LowInc_j$ is a binary variable that equals 1 for the bottom income-quintile, 0 for the rest. Column 1 restricts the sample to lending to low-income borrowers (i.e., borrowers in the bottom income-quintile), while column 2 restricts the sample to lending to the rest of the borrowers (i.e., 2-5 income-quintiles). Columns 3-4 include full sample. Regressions are estimated using Poisson regression. Lower-level interactions are included as standalone variables when they are not absorbed by fixed-effects. Fixed-effects are either included (“Yes”), spanned by other fixed-effects (“-”), or not included. Online Appendix Section A shows the definition of the main controls. Robust standard errors clustered at local area level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

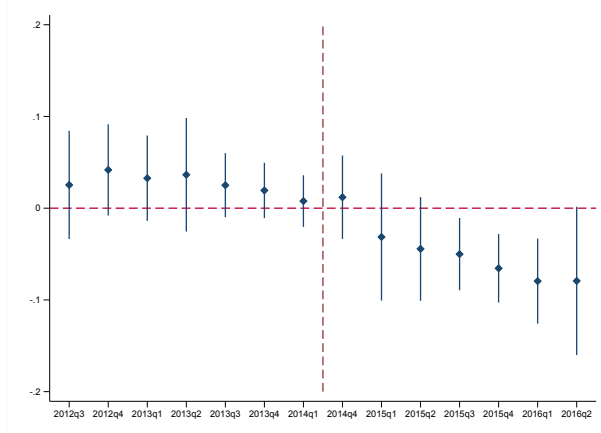
Figures

Figure 1: Loan level: Share of high-LTI loans



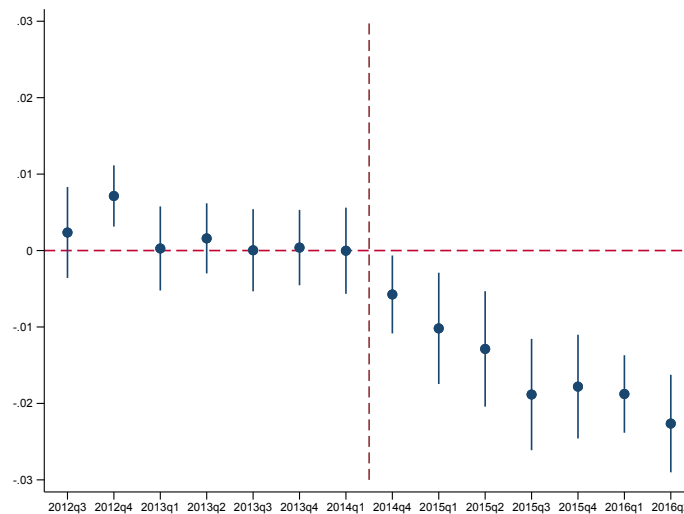
Panel (A) shows the quarterly share of the number of high loan-to-income (LTI) mortgages for the period of 2012Q3 to 2016Q2 for constrained and unconstrained lenders. Panel (B) shows the estimated coefficients of the interaction of Constrained_b , a binary variable that equals 1 if lender b is at or very close to the limit of 15% share of high-LTI mortgages in the four quarters before the announcement of the policy (2013Q3-2014Q2), 0 otherwise, and the full set of time (quarter)-dummies (excluding 2014Q2, the reference time-period). The dependent variable is $\text{HighLTI}_{i,l,b,t}$, which is a binary variable that equals 1 if the mortgage granted by lender b to borrower i in quarter t in local area l has an LTI equal or above 4.5. The bands represent the 95% confidence interval based on robust standard errors double-clustered at the bank $\times$ quarter and local area level. The vertical dashed line shows the date of the announcement of the policy. The sample period is from 2012Q3 to 2016Q2, excluding 2014Q3. The regression is estimated using ordinary least squares, and includes borrower, loan, and bank controls, as well as local area $\times$ bank and quarter fixed-effects. The definition of the main independent variables can be found in Online Appendix Section A.

Figure 2: Loan level: Share of low-income borrowers in high-LTI loans



This figure shows the estimated coefficients of the interaction of Constrained_b , a binary variable that equals 1 if lender b is at or very close to the limit of 15% share of high loan-to-income (LTI) mortgages in the four quarters before the announcement of the policy (2013Q3-2014Q2), 0 otherwise, and the full set of time (quarter)-dummies (excluding 2014Q2, the reference time-period). The dependent variable is $\mathbb{D}(\text{Inc}=1)$ (LowInc_i), which is a binary variable that equals 1 if the income of the borrower is in the bottom quintile of the income distribution, 0 otherwise. The bands represent the 95% confidence interval based on robust standard errors double-clustered at the bank $\times$ quarter and local area level. The vertical dashed line shows the date of the announcement of the policy. The sample period is from 2012Q3 to 2016Q2, excluding 2014Q3, and it only includes mortgages with an $\text{LTI} \geq 4.5$. The regressions are estimated using ordinary least squares, and include borrower, loan, and bank controls, as well as local area $\times$ bank and time fixed-effects. The definition of the main independent variables can be found in Online Appendix Section A.

Figure 3: Lending to low-income borrowers in areas with more constrained lenders



This figure shows the estimated coefficients of the interaction of ConstrShare_l (a variable that equals the total share of lending by constrained lenders in local area l in periods before the announcement of the policy), LowInc_j (a binary variable that equals 1 for the bottom income-quintile, 0 for the rest), and the full set of time (quarter)-dummies (excluding 2014Q2, the reference time-period). The dependent variable is the logarithm of the total value (in £) of mortgages granted in quarter t in local area l to borrowers in the income-quintile j . The bands represent the 95% confidence interval based on robust standard errors clustered at local area level. The vertical dashed line shows the date of the announcement of the policy. The sample period is from 2012Q3 to 2016Q2, excluding 2014Q3. The regressions are estimated using ordinary least squares and include local area $\times$ time, local area $\times$ income quintile and time $\times$ income quintile fixed-effects.

INTERNET APPENDIX

The following tables and figures are a part of the online appendix for the paper ‘*Macroprudential Policy, Mortgage Cycles and Distributional Effects: Evidence from the UK*’. These additional results are referenced in the main paper and organized as follows.

Section [A](#) describes the main loan-level, bank-level and local area level variables. This section also shares summary statistics of the balance sheet and the mortgage portfolio by the constrained and unconstrained lenders. Section [B](#) describes the variation across UK local areas of exposure to the 2014 LTI regulation by share of lending by constrained lenders and share of lending to low-income borrowers. We also present an illustrative example of our identification strategy using a counties in a specific UK region. Section [C](#) describes the house price index used for analysing the effect of the 2014 LTI regulation on local area house prices. Finally, Section [D](#), which comprises the bulk of the appendix, shares additional tables and figures in support of the main results in the paper.

A Description of loan, bank-time, and local area level controls

Table A.1: Loan level controls

Variable	Description
Borrower type	Includes <i>first-time buyers, home-movers, refinancers</i>
Rate type	<i>Fixed</i> or <i>floating</i>
Deal type	Duration of initial teaser rates
Employment	Employment status of the primary borrower
Age	Age of the primary borrower
Applicant type	Sole, joint or unreported
Mortgage term	Duration of payment period
Repayment	Type of repayment, for e.g. <i>interest-only</i>
Loan value (£)	Total loan amount issued to the borrower
Property value (£)	Value of the property
Income verified	Yes, no or unreported

Source: PSD001

Table A.2: Bank-time level controls

Variable	Description
Size	Logarithm of total assets
Liquidity ratio	Cash and government bonds over total assets
Core funding ratio	Retail deposits over total assets
Return on assets	Profits over total assets
CET1 ratio	Common Equity Tier 1 capital over risk-weighted assets
Share of household credit	Household lending over total lending

Source: Statistical and regulatory data reported by financial institutions to the Bank of England (BT/PL/AL forms) and PRA.

Table A.3: Local area level controls

Variable	Description
Age	Median age of residents in 2011
Density	Number of residents per hectare in 2011
Earnings	Median gross annual salary for full-time employees in 2011
Unemployment	Unemployment rate in 2011
Population	Population in 2011
Owned	% of households that own their property in 2011
Correlation	Correl. of local house price growth with regional trend (1996-2011)
Detached	% of detached houses among the transactions
Developed	% of land that is developed in 2001
Coastal	Dummy variable equal to 1 if the local area is coastal, 0 otherwise

Sources: 2011 Census, Office for National Statistics, Price Paid dataset, Hilber and Vermeulen (2016).

Table A.4: Balance sheet of constrained and unconstrained lenders

Variable	Constrained	Unconstrained	<i>t</i>	<i>p</i>
Size	10.54	9.94	1.07	0.29
Liquidity (%)	9.33	9.95	-0.47	0.64
Core funding (%)	66.3	73.3	-1.31	0.19
Return on assets (%)	0.12	0.14	-0.38	0.7
CET1 Ratio (%)	18.39	16.14	1.4	0.17
Share of household credit (%)	65.36	71.88	-1.04	0.3
Share of high LTI loans	0.18	0.05	10.32	0.00

The above table shows the difference in the averages of the bank-level control variables for constrained and unconstrained lenders based on quarterly data for the period 2013Q3 - 2014Q2. A constrained lender is defined as a lender that is at or very close to the 15% limit on the share of high loan-to-income mortgages in the four quarters before the announcement of the policy (2013Q3-2014Q2). Column 1 shows the averages for constrained banks; column 2 shows the averages for unconstrained banks; column 3 provides the t-statistic for the null hypothesis of equal means, and column 4 provides the corresponding p-value. The definition of these variables can be found in Table A.2.

Table A.5: Characteristics of loans by constrained and unconstrained lenders

Variable	Constrained		Unconstrained		Mean Difference	
	mean	sd	mean	sd	b	t-test
Age	39.81	2.63	38.87	4.33	(0.94)	(0.46)
Gross income (£)	80,633	60,969	58,190	12,525	(22,443)	(0.82)
Property value (£)	401,773	316,367	253,678	62,981	(148,095)	(1.04)
Loan value (£)	225,777	158,121	158,014	31,002	(67,763)	(0.95)
Loan-to-value	63.90	4.78	68.13	8.25	4.23	1.10
Loan-to-income	3.20	0.06	2.88	0.22	(0.32)	(6.36)***
Loan interest rate	3.35	0.36	3.65	0.65	0.30	0.88
Repayment: Interest-only	0.11	0.12	0.07	0.10	(0.04)	(0.84)
Rate type: Fixed	0.79	0.11	0.82	0.19	0.04	0.42
Income verified	0.95	0.07	0.97	0.09	0.02	0.43
Sole mortgagor	0.45	0.14	0.42	0.08	(0.04)	(0.60)
Mortgage term	22.56	1.62	23.07	2.07	0.51	0.52

The above table shows the difference in averages of mortgage characteristics between constrained and unconstrained lenders. A constrained lender is defined as a lender that is at or very close to the 15% limit on the share of high loan-to-income mortgages in the four quarters before the announcement of the policy (2013Q3-2014Q2). Columns 1 and 2 show the averages and standard deviations for constrained banks; columns 3 and 4 show the averages and standard deviations for unconstrained banks; column 5 provides the difference in averages between constrained and unconstrained lenders; and column 6 presents the t-statistic for the null hypothesis of equal means (based on either an equal variance t-test or unequal variance t-test suggested by an F-test at 10% level). ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Table A.6: Summary statistics of local area level data

House price growth: Repeat postcode-house type transactions						
Variable	count	mean	sd	p25	p50	p75
$\Delta \log(25^{th} \text{ percentile house price})$	2,082	0.047	0.065	0.007	0.048	0.088
$\Delta \log(75^{th} \text{ percentile house price})$	2,082	0.050	0.066	0.006	0.049	0.093
$\Delta \log(\text{avg. house price bottom tercile})$	2,082	0.060	0.063	0.023	0.058	0.098
$\Delta \log(\text{avg. house price top tercile})$	2,082	0.040	0.070	-0.003	0.043	0.087
House price growth: All transactions						
Variable	count	mean	sd	p25	p50	p75
$\Delta \log(25^{th} \text{ percentile house price})$	4,176	0.050	0.050	0.017	0.047	0.082

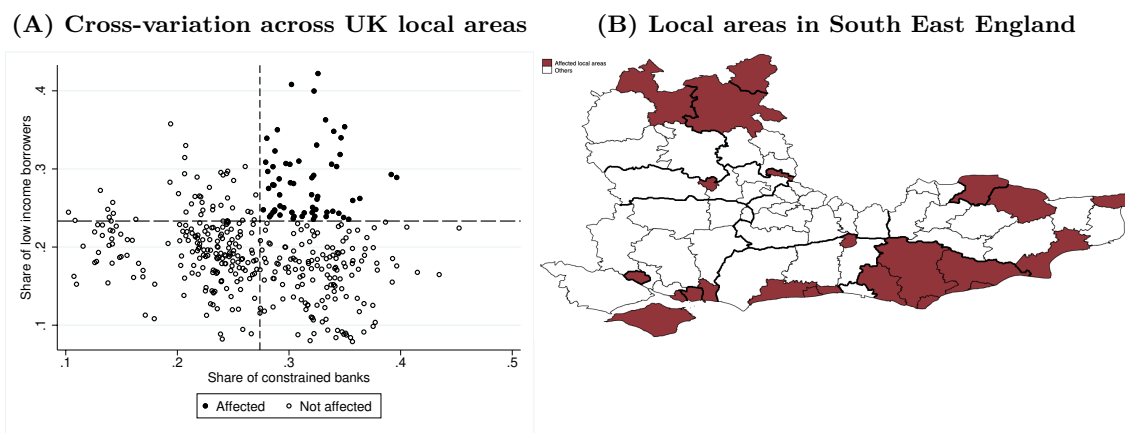
This table shows summary statistics based on data available for house price growth for local areas in the UK (LAU1 - lower local administrative units, or equivalently boroughs). House price growth is calculated as the annual change in the logarithm of the house price index for local area l . The index is computed either using a repeat postcode-house type approach ("Repeat postcode-house type transactions") or using all transactions ("All transactions") for the period under study (2012Q3 - 2018Q2), and corresponds to the dependent variables in Tables 10 (A) and A.17 .

B Variation across UK local areas of exposure to constrained lenders and share of low-income borrowers

Our analysis shows that (1) local areas more affected by the regulation experienced a cooling down of house prices after the regulation, and (2) experienced relatively lower house price declines and mortgage non-performance rates during the house price correction in the UK following the so-called Brexit referendum. “Affected” local areas are those with a higher share of constrained lenders and a higher share of low-income borrowers.

The figure in Panel (A) shows that there is a sufficient cross-variation between the share of constrained lenders and the share of mortgages received by low-income borrowers. “Affected” local areas are reflected as shaded dots in Panel (A). The figure in Panel (B) shows the spatial distribution of “affected” local areas in the region of South East England as an example.

Figure A.1: Variation across UK local areas of exposure to constrained lenders and low-income borrowers



Panel (A) shows the cross-variation between the share of constrained lenders and the share of borrowers in the bottom income-quintile across local areas in the United Kingdom. As shown in the figure, the share of constrained lenders and the share of low-income borrowers is not highly correlated. Panel (B) shows the spatial distribution of the local areas more affected by the policy in the region of South East England. These are the local areas where the share of constrained lenders before the policy is greater than the median share *and* here the share of loans received by low-income borrowers is above the 75th percentiles. The darker lines indicate the borders of the different counties.

C Construction of the house price indices

We detail the construction of the different house price indices used in Section 4.3. The approach, which we call “repeat postcode-house type”, seeks to control for the quality of the houses being transacted while retaining a house price distribution within each local area and period.

The UK has approximately 1.75 million unique postcodes at the most disaggregated level for a population of approximately 27.5 million households in 2018, with around 4,500 unique postcodes in each local area in the UK. The housing transactions data includes the full postcode as well as the type of the transacted properties (flat, terraced, semi-detached, or detached house). From these two variables we construct a unit which corresponds to a particular postcode-house type pair.

Then, for each period, we aggregate the data at postcode-house type level, taking the average price paid in those instances where more than one house within this unit is transacted in the same period. The underlying assumption is that quality heterogeneity of the houses being transacted in each period is greatly reduced at postcode-house type level, given the granularity of full postcodes in the UK.

We then take only postcode-house type units that are transacted in every period of our sample. This gives us a balanced panel at postcode-house type level, while retaining a price distribution within local area in each period. From this balanced panel, we construct two price indices.

The first price index corresponds to a particular percentile of the underlying price distribution. In the paper, we use the 25th and 75th percentiles of price paid. Note that this means that, for each period and local area, we sort postcode-house price units in terms of price paid and take the one which is above the 25% or 75% of the postcode-house type pairs.

The second price index is constructed by sorting postcode-house price units within a local area *ex ante*. In particular, we look at the price distribution a year before the start of our sample and classify postcode-house type units as belonging to the bottom or the top tercile in a local area. Then, for each subset of postcode-house type units (which is kept fixed), we calculate the average price paid in each period in each local area. Table A.6 shows the summary statistics of growth in these house price indices across UK local areas.

D Supplementary results

Overall changes in the loan-to-income (LTI) distribution of lenders

We now discuss the effect of the regulation on the overall LTI distribution of mortgages issued by constrained and unconstrained lenders. Figure A.2 (I) shows the LTI distribution of the mortgages in periods before (2012Q3 - 2014Q2, Pre_t) and after (2014Q4 - 2016Q2, Post_t) the introduction of the regulation in colours blue and red for constrained (left panel) and unconstrained lenders, respectively. The LTI distribution of mortgages issued by the constrained lenders shows a clear shift to the right in Post_t periods, with an increase in the mass of mortgages with LTI close to and below 4.5. We use a counterfactual distribution estimation technique, the so-called Oaxaca-Blinder decomposition, to provide a breakdown of the changes in quantiles of the LTI distribution between Pre_t and Post_t periods attributable to the regulation and to changes in the underlying distribution of covariates plausibly unrelated to the regulation.

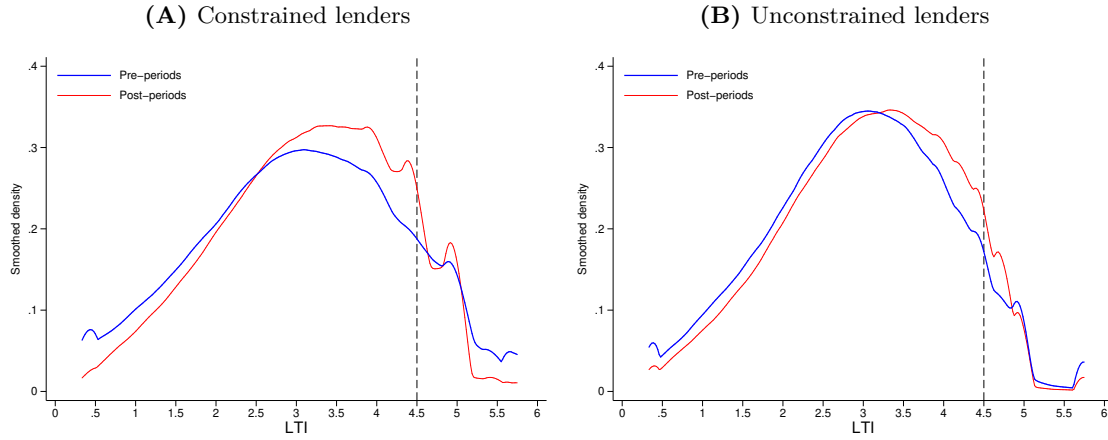
We use the technique described in Chernozhukov et al. (2013) to estimate a counterfactual LTI distribution for Post_t periods for the two lender groups. As per the technique, we take the distribution of covariates (bank $\times$ time, borrower, and loan controls described in Table A.1) in Post_t periods and estimate a counterfactual LTI distribution based on the likelihood of obtaining a LTI for a given combination of covariates in Pre_t periods.

Figures A.2 (II) (A) and (B) show the Oaxaca-Blinder decomposition for the constrained and unconstrained lenders, respectively. The decomposition is based on a breakdown of the total change (solid line) in the quantiles of the LTI distribution into two driving forces—changes in underlying covariates (dotted line) and the effect of the regulation (dashed line).²⁵ Figure A.2 (II) (A) shows that changes in LTI quantiles for the constrained lenders in Post_t periods are largely attributable to the regulation; the changes driven by differences in underlying covariates is quantitatively a lot smaller, and consistently so across the different quantiles. On the other hand, changes in the quantiles of the LTI distribution for unconstrained lenders in Figure A.2 (II) (B) are largely explained by the changes in underlying covariates. The effect of the regulation on the LTI quantiles

²⁵A simple way to understand the decomposition is that the effect of changes in covariates is equal to the differences between the estimated counterfactual and the Pre_t period LTI distribution; differences between the Post_t period and the estimated counterfactual LTI distribution show the effect of the regulation.

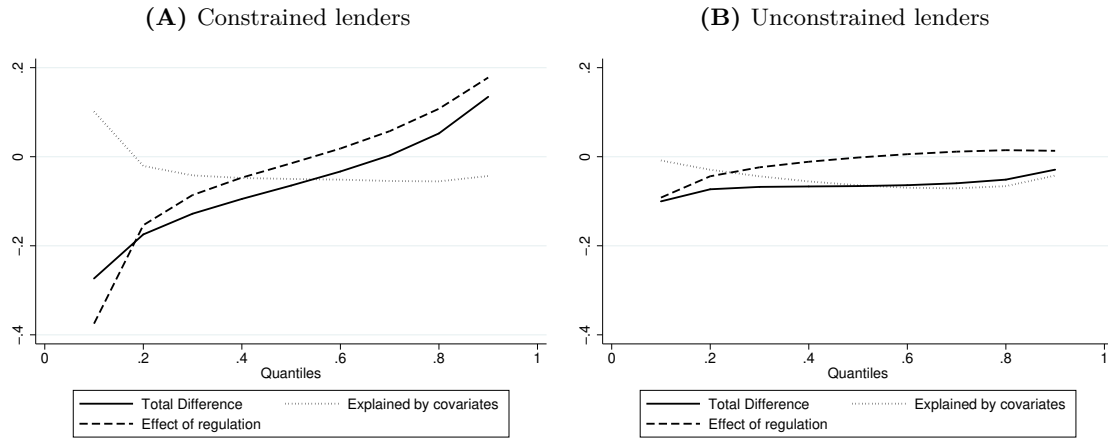
of unconstrained lenders is estimated to be close to 0.

Figure A.2 (I): Distribution of LTI for constrained and unconstrained lenders



The above figures show a histogram of the loan-to-income (LTI) ratios of mortgages issued by the constrained (left panel) and unconstrained lenders (right panel) in periods before (2012Q3-2014Q2; Pre-periods) and after (2014Q4-2016Q2; Post-periods) the introduction of the limit on high-LTI lending by UK regulators. The underlying data is the universe of newly issued residential mortgages in the UK from PSD001.

Figure A.2 (II): Oaxaca-Blinder decomposition for constrained and unconstrained lenders



The above figure shows the Oaxaca-Blinder decomposition for the change in the loan-to-income (LTI) distribution of mortgages issued by constrained (left panel) and unconstrained lenders (right panel) in Pre_t and $Post_t$ periods. The decomposition is based on a counterfactual distribution estimated using the technique described in [Chernozhukov et al. \(2013\)](#). The technique uses a set of covariates for all mortgages issued in $Post_t$ periods and estimates a counterfactual distribution based on the likelihood of obtaining a certain LTI for the set of covariates in Pre_t periods. The difference between the quantiles of the $Post_t$ period LTI distribution and the counterfactual distribution is attributable to the regulation (dashed line); the difference between the quantiles of the counterfactual and Pre_t period LTI distribution is explained by changes in the distribution of covariates in the mortgages issued by the lender in Pre_t and $Post_t$ periods (dotted line).

Figure A.3: Share of high-LTI loans by lender groups



The figure shows the share of high loan-to-income (LTI) loans issued by constrained and unconstrained lenders over the sample period (2012Q3-2016Q2). Unconstrained lenders include Most_Unconstrained (unconstrained lenders furthest from the 15% limit) and Mid_Unconstrained (unconstrained lenders with an intermediate share of high-LTI loans). The shares are residualized using the controls described in Equation 1.

Table A.7: Loan level: Size, property value, LTV, LTI, and borrower income of high-LTI loans

Variable	log(Loan Size)	log(Prop. Value)	LTV	LTI	log(Borr. Inc.)
	(1)	(2)	(3)	(4)	(5)
$\text{Post}_t \times \text{Constrained}_b$	0.0981*** (0.0203)	0.0707*** (0.0163)	1.472* (0.568)	-0.0768*** (0.018)	0.0308*** (0.0062)
Observations	149,988	149,984	149,984	149,988	149,988
R^2	0.612	0.722	0.354	0.205	0.955
Borrower, Loan Controls	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes
Local Area $\times$ Bank FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

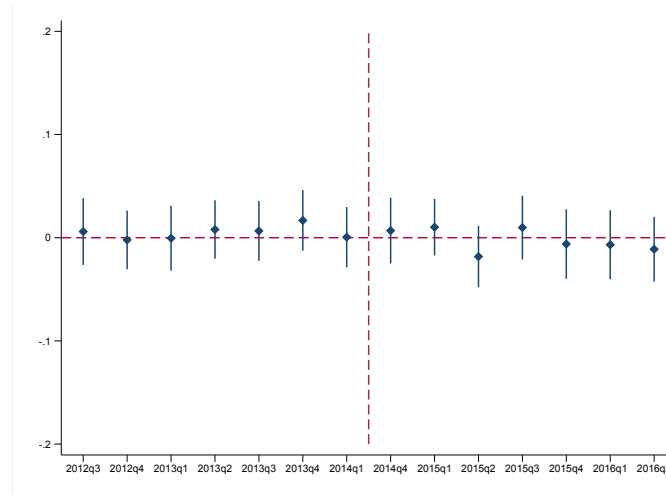
The dependent variables are: $\log(\text{Loan Size}_{i,l,b,t})$, the (log of the) value of a mortgage granted by lender b to borrower i in quarter t in local area l (column 1); $\log(\text{Prop. Value}_{i,l,b,t})$, the (log of the) value of a property associated with a mortgage granted by lender b to borrower i in quarter t in local area l (column 2); $\text{LTV}_{i,l,b,t}$, the loan-to-value ratio (in percentage points) of a mortgage granted by lender b to borrower i in quarter t in local area l (column 3); $\text{LTI}_{i,l,b,t}$, the loan-to-income ratio of a mortgage granted by lender b to borrower i in quarter t in local area l (column 4); and $\log(\text{Borr. Inc.}_{i,l,b,t})$, the (log of the) annual gross income of borrower i associated to a mortgage granted by lender b in quarter t in local area l (column 5). The sample period is from 2012Q3 to 2016Q2, excluding 2014Q3. The sample is restricted to mortgages with a loan-to-income ratio (LTI) ≥ 4.5 . Post_t is a binary variable that equals 1 for quarters after 2014Q3, 0 before. Constrained_b is a binary variable that equals 1 if lender b is at or very close to the limit of 15% share of high-LTI mortgages in the four quarters before the announcement of the policy (2013Q3-2014Q2), 0 otherwise. All regressions are estimated using ordinary least squares. All regressions include borrower, loan, and bank controls, and Local Area $\times$ Quarter and Local Area $\times$ Bank fixed-effects. Column 5 also controls for the size of the loan (in thousand pounds). Online Appendix Section A shows the definition of the main controls. Robust standard errors double-clustered at bank-quarter and local area level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Table A.8: Loan level: Age quintiles in high-LTI loans

Variable	$\leftarrow$ Dummy for age-quintiles ($\mathbb{D}(\text{Age}=j)_{i,l,b,t}$) $\rightarrow$				
j =	I	II	III	IV	V
$\text{Post}_t \times \text{Constrained}_b$	-0.0071 (0.0064)	-0.0033 (0.0059)	-0.0006 (0.0049)	0.0061 (0.0046)	0.0049 (0.0037)
Observations	149,988	149,988	149,988	149,988	149,988
R^2	0.320	0.0876	0.0706	0.146	0.369
Borrower, Loan Controls	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes
Local Area $\times$ Bank FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

The dependent variables are binary variables indicating whether borrower i associated to a mortgage granted by lender b in quarter t in local area l belongs to a particular age quintile (1) or not (0). In each column, the dependent variable is a binary variable equal to 1 if the age of the borrower is in that particular quintile (with I being the bottom and V the top quintile) of the age distribution. The quintiles are constructed using the sample from the pre-policy period. The sample period is from 2012Q3 to 2016Q2, excluding 2014Q3. The sample is restricted to mortgages with a loan-to-income ratio (LTI) ≥ 4.5 . Post_t is a binary variable that equals 1 for quarters after 2014Q3, 0 for quarters before. Constrained_b is a binary variable that equals 1 if lender b is at or very close to the limit of 15% share of high-LTI mortgages before the announcement of the policy (2013Q3-2014Q2), 0 otherwise. All regressions are estimated using ordinary least squares. All regressions include borrower, loan, and bank controls, and local area $\times$ quarter and local area $\times$ Bank fixed-effects. Online Appendix Section A shows the definition of the main controls. Robust standard errors double-clustered at bank-quarter and local area level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Figure A.4: Loan level: Share of young borrowers in high-LTI loans



The figure above show the estimated coefficients of the interaction of Constrained_b , a binary variable that equals 1 if lender b is at or very close to the limit of 15% share of high-LTI mortgages in the four quarters before the announcement of the policy (2013Q3-2014Q2), 0 otherwise, and the full set of time(quarter)-dummies (excluding 2014Q2, the reference time-period). The dependent variable is $\mathbb{D}(\text{Age}=1)$, which is a binary variable that equals 1 if the age of the main borrower is in the bottom quintile of the age distribution, 0 otherwise. The figure represents the regression result in Table A.8 column 1. The bands represent the 95% confidence interval based on robust standard errors double-clustered at the bank $\times$ quarter and local area level. The vertical dashed line shows the date of the announcement of the policy. The sample period is from 2012Q3 to 2016Q2, excluding 2014Q3, and it only includes mortgages with an LTI ≥ 4.5 . The regressions are estimated using ordinary least squares, and include borrower, loan, and bank controls, as well as local area $\times$ quarter and local area $\times$ bank fixed-effects. The definition of the main independent variables can be found in Table A.1.

Table A.9: Loan level: Replicated results for Tables 2 and 3 excluding unconstrained lenders further away from the regulatory limit

(A) Table 2 (A)

Variable	$\leftarrow$ Dummy for high-LTI loans ($\text{HighLTI}_{i,l,b,t}$) $\rightarrow$				
	(1)	(2)	(3)	(4)	(5)
$\text{Post}_t \times \text{Constrained}_b$	-0.0339*** (0.0132)	-0.0478*** (0.0096)	-0.0348*** (0.0084)	-0.0256*** (0.0099)	-0.0238*** (0.0090)
Observations	1,123,965	1,123,965	1,123,965	1,123,965	1,123,965
R^2	0.00527	0.0695	0.0714	0.123	0.124
Borrower, Loan Controls		Yes	Yes	Yes	Yes
Bank Controls			Yes	Yes	Yes
Local Area $\times$ Bank FE				Yes	Yes
Time FE					Yes

(B) Table 2 (B)

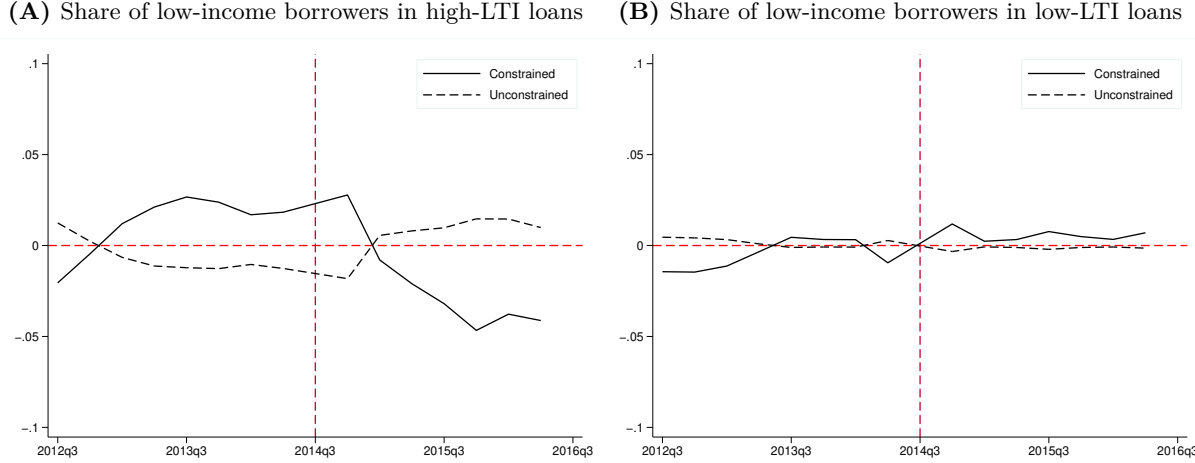
Variable	$\leftarrow$ Interest rate ($\text{Rate}_{i,l,b,t}$) $\rightarrow$						
	Sub-sample		All				
	Low-LTI	High-LTI					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{Post}_t \times \text{Constrained}_b$	-0.0746 (0.150)	0.0845 (0.170)	-0.0746 (0.150)	0.0306 (0.150)	-0.0901 (0.146)	0.0177 (0.139)	0.0258 (0.0504)
$\text{Post}_t \times \text{Const.}_b \times \text{HighLTI}_j$			0.159 (0.0967)	0.223*** (0.0708)	0.190*** (0.0722)	0.184*** (0.0622)	0.179*** (0.0555)
Observations	1,007,622	116,357	1,123,979	1,123,979	1,123,979	1,123,979	1,123,979
R^2	0.0677	0.144	0.0792	0.283	0.298	0.362	0.426
Borrower, Loan Controls				Yes	Yes	Yes	Yes
Bank Controls					Yes	Yes	Yes
Local Area $\times$ Bank FE						Yes	Yes
Time FE							Yes

(C) Table 3

Variable	$\leftarrow$ Dummy for income quintiles ($\mathbb{D}(\text{Inc}=j)_{i,l,b,t}$) $\rightarrow$				
	I	II	III	IV	V
$\text{Post}_t \times \text{Constrained}_b$	-0.123*** (0.0201)	-0.0439*** (0.0125)	0.0167 (0.0113)	0.0645*** (0.0094)	0.0853*** (0.0140)
Observations	115,940	115,940	115,940	115,940	115,940
R^2	0.349	0.0569	0.0732	0.131	0.208
Borrower, Loan Controls	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes
Local Area $\times$ Bank FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

This table replicates: in panel (A), Table 2 (A); in panel (B), Table 2 (B); and in panel (C), Table 3, excluding the Mid_Unconstr._b and Most_Unconstr._b lenders, which are the lenders with an intermediate share of high-LTI loans and those furthest away from the 15% limit, respectively.

Figure A.5: Share of low-income borrowers by lender groups and LTI bands



The figure shows the share of loans issued to low-income borrowers by constrained and unconstrained lenders in sub-sample of high-LTI ($LTI \geq 4.5$, Panel (A)) and low-LTI (i.e. loans with $LTI < 4.5$, Panel (B)) over the sample period (2012Q3-2016Q2). The shares are residualized using the controls described in Equation 1.

Table A.10: Loan level: Competition and pricing of high-LTI loans to low-income borrowers by unconstrained lenders

Variable	← Interest rate →		
	Col. 1 vs 2	Col 3 vs 4	Col. 5 vs 6
Table 8 comparison	(1)	(2)	(3)
$Post_t \times LowInc_j \times Comp_l$	0.0581* (0.0304)	0.0687* (0.0391)	0.0277 (0.0471)
Observations	75008	51449	23559
R^2	0.536	0.545	0.516
Borrower, Loan Controls	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes
Local area $\times$ Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

The dependent variable is the interest charged on a mortgage at the time of origination. The sample includes high loan-to-income (LTI) mortgages ($LTI \geq 4.5$) issued by unconstrained lenders only. Columns 1-3 use triple interactions to show t-stats for the difference between the coefficients reported in columns 1-2, 3-4 and 5-6, respectively, of Table 8. $Post_t$ indicates period after 2014Q3. $LowInc_j$ indicates whether the mortgage belongs to a borrower in the bottom quintile of the income distribution. $Comp_l$ indicates high-competition areas with a Herfindahl-Hirschman Index (HHI) below the median based on market shares among unconstrained lenders. All regressions are estimated using ordinary least squares. Lower-level interactions are included as standalone variables when they are not absorbed by fixed-effects. Online Appendix Section A shows the definition of the main controls. Robust standard errors double-clustered at bank-quarter and local area level show significance at ***: 1% level; **: 5% level; *: 10% level.

Table A.11: Loan level: Competition and pricing of high-LTI loans to low-income borrowers by unconstrained lenders: Robustness

Variable	$\leftarrow$ Interest rate ($\text{Rate}_{i,l,b,t}$) $\rightarrow$					
Sub-sample	All		High Share		Low Share	
	High Comp	Low Comp	High Comp	Low Comp	High Comp	Low Comp
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Post}_t \times \text{LowInc}_j$	0.126*** (0.0354)	0.073** (0.0348)	0.132*** (0.0386)	0.0639 (0.0465)	0.0987** (0.0383)	0.0765** (0.0382)
Observations	50,590	24,400	41,784	9,652	8,806	14,748
R^2	0.541	0.529	0.548	0.535	0.508	0.524
Borrower, Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Local Area $\times$ Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable is the interest charged on a mortgage at the time of origination. The sample includes high loan-to-income (LTI) mortgages ($\text{LTI} \geq 4.5$) issued by unconstrained lenders only. Columns 1 and 2 include all observations. Columns 3 and 4 restrict the sample to areas with a higher share of constrained lenders (share above the median), while columns 5 and 6 focus on areas with a lower share of constrained lenders (below the median). Each sample is divided between high-competition (areas with a Herfindahl-Hirschman Index (HHI) below the median) and low-competition (HHI above the median) areas, based on market shares of high-LTI loans to low-income borrowers among unconstrained lenders. Post_t indicates period after 2014Q3. LowInc_j indicates whether the mortgage belongs to a borrower in the bottom quintile of the income distribution. All regressions are estimated using ordinary least squares. Lower-level interactions are included as standalone variables when they are not absorbed by fixed-effects. Online Appendix Section A shows the definition of the main controls. Robust standard errors double-clustered at bank-quarter and local area level show significance at ***: 1% level; **: 5% level; *: 10% level.

Table A.12: Overall lending to low-income borrowers - WLS

Variable	← Total value (in £) of mortgages($\log(\mathbb{L}_{j,l,t})$) →					
Sub-sample	Low income	Non-Low income	All			
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Post}_t \cdot \text{ConstrShare}_l$	-0.0153*** (0.00129)	-0.00115 (0.00145)	-0.00115 (0.00145)			
$\text{Post}_t \cdot \text{ConstrShare}_l \cdot \text{LowInc}_j$			-0.0141*** (0.00142)	-0.0141*** (0.00142)	-0.0141*** (0.00142)	-0.0141*** (0.00142)
Observations	6200	24852	31053	31045	31043	31043
R^2	0.962	0.749	0.789	0.799	0.826	0.827
Lower-level interactions	-	-	-	-	-	-
Local area FE	Yes	Yes	Yes			
Time FE	Yes	Yes	Yes			
Local area×Time FE				Yes	Yes	Yes
Local area×Income quint. FE					Yes	Yes
Time×Income quint. FE						Yes

The dependent variable is the logarithm of the total value (in £) of mortgages granted in quarter t in local area l to borrowers in the income-quintile j . The sample period is from 2012Q3 to 2016Q2, excluding 2014Q3. Post_t indicates periods after 2014Q3. ConstrShare_l is a variable that equals the demeaned share of lending by constrained lenders in local area l in periods before the announcement of the policy. LowInc_j is a binary variable that equals 1 for the bottom income-quintile, 0 for the rest. Column 1 restricts the sample to lending to low-income borrowers (i.e., borrowers in the bottom income-quintile), while column 2 restricts the sample to lending to the rest of the borrowers (i.e., 2nd-5th income-quintiles). Columns 3-6 use the full sample. All regressions are estimated using weighted least squares using pre-policy local area volume of lending as weights. Lower-level interactions are included as standalone variables when they are not absorbed by fixed-effects. Fixed-effects are either included ("Yes"), spanned by other fixed-effects ("-"), or not included. Robust standard errors clustered at local area level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Table A.13: Overall lending to low-income borrowers: By constrained and unconstrained lenders

Variable	← Loans (in £) to low-income borrowers →		
Lenders	All	Constrained	Unconstrained
$\text{Post}_t \times \text{ConstrShare}_l$	-0.0156*** (0.0024)	-0.0358*** (0.004)	-0.0083*** (0.0014)
Observations	6,200	6,068	6,198
R^2	0.958	0.866	0.949
Lower-level interactions	-	-	-
Time FE	Yes	Yes	Yes
Local Area FE	Yes	Yes	Yes

The dependent variables is the logarithm of the total value (in GBP) of mortgages granted in quarter t in local area l to borrowers in the income-quintile j . The sample period is from 2012Q3 to 2016Q2, excluding 2014Q3. Post_t indicates periods after 2014Q3. ConstrShare_l is a variable that equals the demeaned share of lending by constrained lenders in local area l in periods before the announcement of the policy. LowInc_j is a binary variable that equals 1 for the bottom income-quintile, 0 for the rest. Estimates reported in column 1 are based in a sub-sample of local areas where the share of broker-intermediated mortgages is less than the 75th percentile for that measure across UK local areas; estimates reported in column 2 are based in the remaining sub-sample where the share of broker-intermediated mortgages is greater than the 75th percentile. All regressions are estimated using ordinary least squares. Lower-level interactions are included as standalone variables when they are not absorbed by fixed-effects. Fixed-effects are either included ("Yes"), spanned by other fixed-effects ("-"), or not included. Robust standard errors clustered at local area level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Table A.14: Overall lending to low-income borrowers (number of loans)

Variable	← Total number of mortgages($\log(\mathbb{L}_{j,l,t})$) →					
Sub-sample	Low income	Non-Low income	All			
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Post}_t \times \text{ConstrShare}_l$	-0.0132*** (0.0014)	-0.00009 (0.0020)				
$\text{Post}_t \times \text{ConstrShare}_l \times \text{LowInc}_j$			-0.0132*** (0.00272)	-0.0132*** (0.00272)	-0.0133*** (0.00273)	-0.0132*** (0.00271)
Observations	6200	24852	31045	31045	31043	31043
R^2	0.957	0.870	0.870	0.870	0.901	0.903
Lower-level interactions	-	-	-	-	-	-
Local area FE	Yes	Yes	Yes			
Time FE	Yes	Yes	Yes			
Local area $\times$ Time FE				Yes	Yes	Yes
Local area $\times$ Income quint. FE					Yes	Yes
Time $\times$ Income quint. FE						Yes

The dependent variable is the logarithm of the total number of mortgages granted in quarter t in local area l to borrowers in the income-quintile j . The sample period is from 2012Q3 to 2016Q2, excluding 2014Q3. Post_t indicates periods after 2014Q3. ConstrShare_l is a variable that equals the demeaned share of lending by constrained lenders in local area l in periods before the announcement of the policy. LowInc_j is a binary variable that equals 1 for the bottom income-quintile, 0 for the rest. Column 1 restricts the sample to lending to low-income borrowers (i.e., borrowers in the bottom income-quintile), while column 2 restricts the sample to lending to the rest of the borrowers (i.e., 2nd-5th income-quintiles). Columns 3-6 use the full sample. All regressions are estimated using ordinary least squares. Lower-level interactions are included as standalone variables when they are not absorbed by fixed-effects. Fixed-effects are either included (“Yes”), spanned by other fixed-effects (“-”), or not included. Robust standard errors clustered at local area level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Table A.15: Overall lending to low-income borrowers: Presence of brokers

Variable	$\leftarrow$ Total value (in £) of mortgages ($\log(\mathbb{L}_{j,l,t})$) $\rightarrow$		
	Brokered - Low	Brokered - High	All
$\text{Post}_t \times \text{ConstrShare}_l \times \text{LowInc}_j$	-0.0173*** (0.0021)	-0.0045 (0.0044)	-0.0045 (0.0044)
$\text{Post}_t \times \text{ConstrShare}_l \times \text{LowInc}_j \times \text{LowBrok}_l$			-0.0128** (0.0048)
Observations	23,318	7,725	31,043
R^2	0.867	0.772	0.864
Local Area $\times$ Income-quintile FE	Yes	Yes	Yes
Local Area $\times$ Time FE	Yes	Yes	Yes
Time $\times$ Income-quintile FE	Yes	Yes	Yes

The dependent variables is the logarithm of the total value (in £) of mortgages granted in quarter t in local area l to borrowers in the income-quintile j . The sample period is from 2012Q3 to 2016Q2, excluding 2014Q3. Post_t indicates periods after 2014Q3. ConstrShare_l equals the demeaned share of lending by constrained lenders in local area l in periods before the announcement of the policy. LowInc_j indicates the bottom income-quintile. Estimates reported in column 1 are based in a sub-sample of local areas where the share of broker-intermediated mortgages is below p75; estimates reported in column 2 are based in the remaining sub-sample. All regressions are estimated using ordinary least squares. Lower-level interactions are included; fixed-effects are either included (“Yes”), spanned by other fixed-effects (“-”), or not included. Robust standard errors clustered at local area level show significance at: ***: 1% level; **: 5% level; *: 10% level.

Table A.16: Overall lending of high-LTI loans

Variable	$\leftarrow$ Total value (in £) of mortgages ($\log(\mathbb{L}_{j,l,t})$) $\rightarrow$					
	Non-HighLTI $_j$	HighLTI $_j$	All			
Sub-sample	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Post}_t \times \text{ConstrShare}_l$	0.0022 (0.0017)	-0.0020 (0.0026)	0.0023 (0.0017)			
$\text{Post}_t \times \text{ConstrShare}_l \times \text{HighLTI}_j$			-0.0054 (0.0041)	-0.0051 (0.0038)	-0.0045 (0.0037)	-0.0046 (0.0037)
Observations	24,746	6,214	30,952	30,952	30,952	30,952
R^2	0.712	0.947	0.719	0.719	0.743	0.744
Local Area FE	Yes	Yes	Yes			
Time FE	Yes	Yes	Yes			
Local Area $\times$ Time FE				Yes	Yes	Yes
Local Area $\times$ Income-quintile FE					Yes	Yes
Time $\times$ Income-quintile FE						Yes

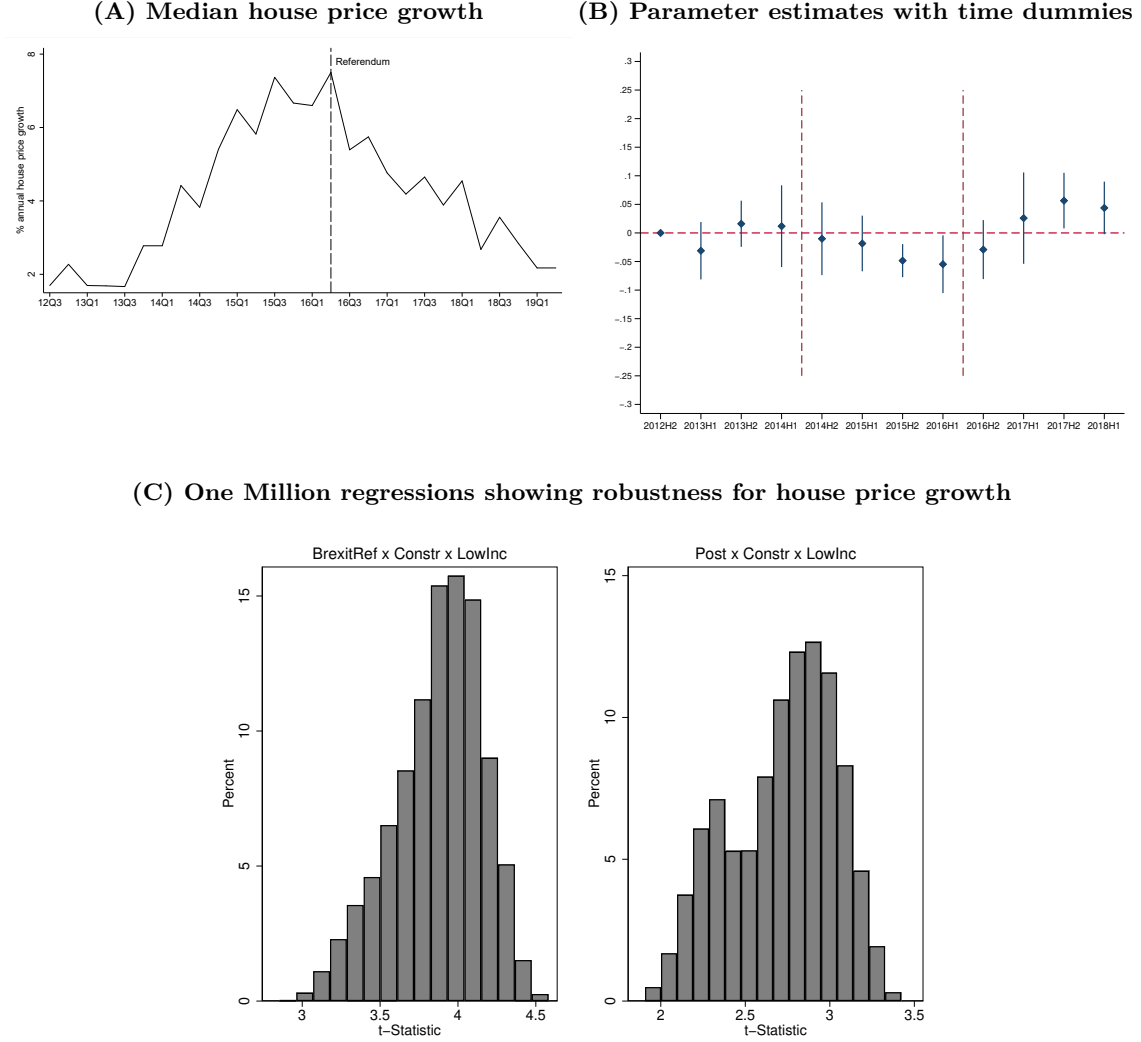
The dependent variables is the logarithm of the total value (in GBP) of mortgages granted in quarter t in local area l to borrowers in LTI group j . The sample period is from 2012Q3 to 2016Q2, excluding 2014Q3. Post_t is a binary variable that equals 1 for quarters after 2014Q3, 0 for quarters before. ConstrShare_l equals the demeaned share of lending by constrained lenders in local area l in periods before the announcement of the policy. HighLTI_j is a binary variable that equals 1 for mortgages with $\text{LTI} \geq 4.5$, 0 for the rest. All regressions are estimated using OLS. Fixed-effects are either included (“Yes”), spanned by other fixed-effects (“-”), or not included. Robust standard errors clustered at local area level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Table A.17: Repeat postcode-house type index growth in affected local areas: Robustness

Variable	$\leftarrow \Delta \log(25\text{th percentile house price}_{l,t}) \rightarrow$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BrexitRef _{<i>t</i>} × Constr _{<i>l</i>} × LowInc _{<i>l</i>}	0.081*** (0.020)	0.089*** (0.022)	0.084*** (0.022)	0.081*** (0.022)	0.070*** (0.021)	0.081*** (0.020)	0.081*** (0.020)	
Post _{<i>t</i>} × Constr _{<i>l</i>} × LowInc _{<i>l</i>}	-0.059** (0.027)	-0.070*** (0.025)	-0.060** (0.027)	-0.065** (0.027)	-0.034 (0.040)	-0.063** (0.026)	-0.059** (0.027)	
$\Delta \log(P_{r,t}) \times \text{Constr}_l \times \text{LowInc}_l$								0.045 (0.132)
Observations	1,338	1,476	1,536	1,536	1,536	1,536	1,536	4,064
R^2	0.424	0.486	0.475	0.476	0.475	0.475	0.475	0.621
Local area FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Constr × Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × LowInc × Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County × Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robustness	Excl. London	Housing constraints	HighLTI _{<i>l</i>} vs. Constr _{<i>l</i>}	HighLTI _{<i>l</i>} vs. LowInc _{<i>l</i>}	HP cycle	GDP cycle	Interest rate	Exposure to cycle

The dependent variable is the change in the logarithm of the 25th percentile price paid using a repeat postcode-house type method at local area l in the twelve-month period t compared to the same period in the year before. Column (1) excludes the region of London. Column (2) includes the variables Refusal rate_{*l*}, % developed_{*l*}, and Range_{*l*} interacted with BrexitRef_{*t*} and Post_{*t*} as controls. Column (3) includes two additional triple interactions, where Constr_{*l*} is replaced by HighLTI_{*l*}, a dummy variable equal to 1 if local area l has a number of high-LTI mortgages ($\text{LTI} \geq 4.5$) above the median before the policy, 0 otherwise. Column (4) includes two additional triple interactions, where LowInc_{*l*} is replaced by HighLTI_{*l*}. Column (5) includes as controls the interaction of Constr_{*l*} and LowInc_{*l*} with the regional change of house prices, GDP, and the change in interest rates. The sample spans from 2012H2 to 2018H1. Post_{*t*} indicates the period 2014H2 - 2018H1 (i.e. after the introduction of the policy); BrexitRef_{*t*} indicates the period 2016H2 - 2018H1 (i.e. after the Brexit referendum). Constr_{*l*} indicates local areas in which the mortgage market share of constrained lenders is above the median before the announcement of the policy. LowInc_{*l*} indicates local areas in the top quartile in terms of share of low-income borrowers before the announcement of the policy. All regressions are estimated using ordinary least squares. All lower-level interactions are included. Robust standard errors clustered at local area level show significance at ***: 1% level; **: 5% level; *: 10% level.

Figure A.6: House price growth in affected areas

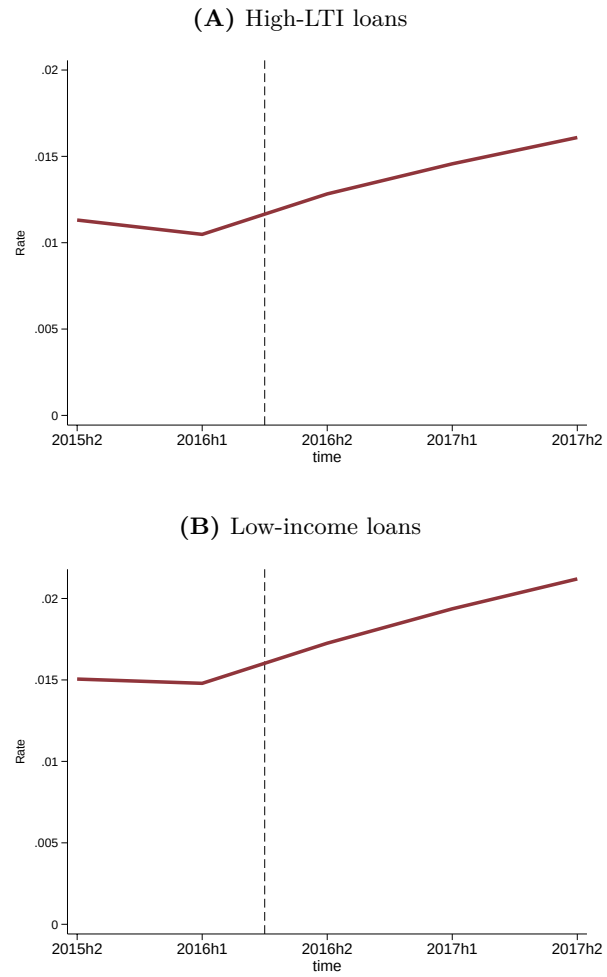


Panel (A) shows the annual growth rate of median house prices in England and Wales. The vertical dashed line denotes the date of the Brexit referendum. The data is from the House Price Statistics for Small Areas (HPSSAs) Dataset 9: Median price paid for administrative geographies.

Panel (B) shows the estimated coefficients of the interaction of $\text{Constr}_l \times \text{LowInc}_l$, and the full set of time (half-year)-dummies (excluding 2012H2, the reference time-period), corresponding to the specification in Table 10 (A), column 1. The dependent variable is the annual change in the logarithm of the 25th percentile house price in local area l in half-year t . The bands represent the 90% confidence interval based on robust standard errors clustered at local area level. The vertical dashed lines show the date of the announcement of the policy and the Brexit referendum.

Panel (C) shows the distribution of the t-statistics for the coefficients of $\text{BrexitRef}_t \times \text{Constr}_l \times \text{LowInc}_l$ and $\text{Post}_t \times \text{Constr}_l \times \text{LowInc}_l$ using the specification in Table 10 (A), column 2 and adding all possible combinations of the local-area controls in Online Appendix Table A.3 interacted with Post_t and BrexitRef_t . These amount to a total of $2^{20} - 1 = 1,048,575$ different combinations (only the interactions are included since the levels are spanned by the local area fixed-effects). This approach and the algorithm to implement it come from Brodeur et al. (2020).

Figure A.7: Mortgage default rates



The figures above show the mortgage default rates for mortgages in our sample with high-LTI ($LTI \geq 4.5$, panel (A)), and those by low-income borrowers (panel (B)) at half-yearly snapshots of the UK mortgage stock.