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Abstract

What is the role of lending in transmitting shocks to residential real estate? We consider this question by examining an adverse and salient shock to a segment of the property market in England and Wales. This shock, arising from a tragic event which resulted in significant loss of life, affected high-rise properties.[1] Using comprehensive administrative data on all residential mortgage and property transactions, combined with property-level rent data, we study responses in these markets. Consistent with the idea of credit being a 'financial accelerator', we document a decline in mortgage originations following the shock, with the sharpest contraction observed among first-time buyers. We also highlight the role of cash buyers and lender size in dampening the overall impact of the shock. Additionally, the paper provides a conceptual framework that integrates multiple administrative data sets to understand how salient shocks, including those related to climate risks, may affect the property market. It offers valuable insights for financial policymakers on how these shocks propagate through credit and housing markets.

Key words: Residential real estate, mortgage market, collateral shocks.

JEL classification: D14, G21.

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[1]The authors of this paper recognise the suffering and hardship the Grenfell disaster has brought to those affected and acknowledge the significant personal and social impacts it has had, which extend beyond the scope of the empirical analysis. This academic paper is focused on the financial stability implications arising from shocks to residential properties. The authors also refrain from commenting on the actions of the decision-makers involved. Any views expressed are solely those of the authors and should not be taken to represent those of the Bank of England or as a statement of Bank of England policy. This paper should not be reported as representing the views of any members of the Bank's committees.

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1 Introduction

Real estate properties are regularly impacted by shocks, such as extreme weather events, pandemics, disasters (e.g. structural failures or fire) or unexpected policy interventions. These shocks can impact the value of real estate properties. As properties serve as collateral for mortgage loans, lenders are not only exposed to these shocks but they might also play a crucial role in their transmission by adjusting their lending decisions. The established view is that lenders may amplify shocks by restricting lending to borrowers that face high agency cost (Bernanke et al., 1996).[2] Understanding the feedback effects of shocks to the property market is important as residential real estate constitutes a significantly large asset class for banks and households. Increased shocks may therefore impact the economy by lowering households' ability to accumulate wealth (Bhatia, 1987) and decreasing aggregate investments in an economy (Bahaj et al., 2020).

This paper revisits the role of lending in transmitting shocks within the real estate market. To that end, we study a specific, adverse shock arising from a disaster that affects, for the purposes of this academic paper, an important class of residential properties in England & Wales. Our analysis focuses on the property market in London given the concentration of the affected properties in the capital.[3] Consistent with the financial accelerator hypothesis, our analysis reveals a sharp contraction in the number of mortgages originated against affected properties following the shock. This effect is particularly pronounced for first-time buyers, which are typically more information opaque. Additionally, we uncover evidence of compensatory adjustments within the rental market and among cash-buyers concurrent with the decline in lending. These findings underscore the pivotal role that cash-buyers and the rental market play in stabilizing both prices and transaction volumes amidst lending contractions induced by shocks.

Typically, identifying the transmission of such real estate shocks and measuring their impact is difficult for several reasons. They can be geographically concentrated, such as extreme weather events, which makes it difficult to disentangle them from other changing local economic conditions (Giglio et al., 2021). Moreover, they might be salient but slow-moving, such as sea level rise, which makes it difficult to isolate from changing expectations of economic agents, such as home-buyers or mortgage lenders. Last, the time scales over

[2] At the core of this "financial accelerator" dynamic is asymmetric information between lenders (principal) that cannot costlessly acquire information about characteristics of the borrower (agent). After an economic shock, borrowers facing high agency costs, should receive a relatively lower share of credit extended ("the flight to quality") and hence should account for a proportionally greater part of the decline in economic activity.

[3] We define London observations as those starting with postcodes E, EC, N, NW, SE, SW, W, WC, BR, CM, CR, DA, EN, HA, IG, SL, TN, KT, RM, SM, TW, UB, WD.

which they occur are uncertain and some of these shocks might be infrequent and small. These factors make the data challenging to interpret.

We overcome such empirical challenges examining a salient and material shock arising from a disaster to a distinct class of residential real estate in the United Kingdom. The shock that we study encompasses two events: (i) a severe fire of the Grenfell Tower, a high-rise residential tower block in London, which was a tragic event that resulted in significant loss of life and which raised concerns about the safety of a specific type of property, and (ii) public guidance which delineated the subset of properties under risk and suggested remedies for affected properties.[4] The first event precedes the second by more than one year. Both events highlighted an increased perceived risk of living in the affected property type.[5] In response to the second event, owners of affected properties needed to undertake renovations to restore the safety of their properties, which came with uncertain but size-able costs.[6] Both, higher risk and renovation costs, led to a decrease in property valuations and added uncertainty about their true values. Studying this shock is particularly informative as it came unexpected to market participants. Moreover, exposure to the risk depended on a property characteristic instead of the property's spatial location. This helps us isolate the effect of risk from confounding changes to local economic conditions. Last, it was salient to all markets that we study.

Our empirical analyses examine how this shock changes transaction prices of affected properties. Moreover, we examine the role of lending in transmitting the shock to the property market. While we recognize the broader impact of the shock on peoples' lives, these implications lie beyond the scope of this paper. We reason that increased maintenance costs and changes in risk perception meant that buyers were faced with more uncertainty about the true values of affected properties and might have valued them lower. The resulting decreased demand for affected properties are expected to have lowered their transaction prices.[7] Mortgage lending might have played a role in exacerbating the shock as mortgage

[4]The authors of this paper recognize the suffering and hardship the Grenfell disaster has brought to those affected and acknowledge the significant personal and social impacts it has had, which extend beyond the scope of our empirical analysis. This academic paper is focused on the financial stability implications arising from shocks to residential properties. The authors also refrain from commenting on the actions of the decision-makers involved.

[5]There are parallels between this shock and the two main channels through which climate change can affect asset values. The physical event relates to the notion of "physical risks", adjustments of property values that arise from climate- and weather-related events. The public guidance relates to the notion of "transition risks", reassessments of property values as costs become apparent (Carney, 2015).

[6]The second event gave central guidance on what constituted an "affected" property and what actions were required to be taken for such a property to be deemed safe. While these actions were not required legally, sellers were effectively required to abide by them as many lenders made the extension of loans contingent on the completion of these tasks (https://www.insidehousing.co.uk/insight/advice-note-14-explained-what-is-it-and-why-is-it-stopping-the-sale-of-so-many-properties-63981).

[7]Potential buyers' willingness to pay should reduce because of the potential costs of renovating affected

lenders may have become more reluctant to offer mortgages against affected properties due to increased uncertainty around true property values (as well as those decreases in property values that are not reflected in loan-to-value (LTV) ratios). Lower credit volumes may have tightened credit constraints and could have further reduced the demand for affected properties. At the same time, potential cash-buyers were unconstrained and could have offset the demand for affected properties by stepping into the property market. They might have passed on higher maintenance cost to renters if they rented out these purchased properties.

To test these hypotheses, we leverage detailed administrative data of the universe of all mortgage transactions in England & Wales, but we focus our main analyses on London. We complement these data with detailed administrative data on and all property transactions and data on rental listings in London. All data sets include information on the property type that allows us to coarsely identify those properties that are affected by the shock.[8] They also include details on the location of the property which allows us to (i) control for granular spatial fixed effects at the postcode-level in our analysis of prices and rents; and (ii) measure differences in the evolution of transaction volumes for different types of properties across space.[9]

We employ these data in a dynamic Difference-in-Difference (DiD) research design. It allows us to estimate the effects of the shock on key outcomes of interest in the property, mortgage and rental markets. We compare changes in property prices and volumes of mortgage-based transactions of properties affected by the shock relative to those unaffected. The time dimension of our data allows us to estimate event studies to examine the dynamic effects of the shock. We study when exactly the financial effects of the shock materialized on the property marketand whether they were temporary or persistent. It also allows us to study the pre-shock period corroborating our assumption that the shock was not anticipated.

We find an economically significant and persistent decrease in property prices following the shock. Our study also highlights the role that mortgage lending may have played in propagating the shock. Specifically, we observe a sharp decline in the number of mortgages issued against affected properties. This decrease cannot be solely attributed to a general decrease in demand for several reasons. First, we do not observe a corresponding sharp

properties as well as the risk perceptions due to safety of living in them. This should be reflected in lower demand and lower transaction prices.

[8]In our analysis, we classify all flats as being affected by the shock because we lack data on building height and cladding. In reality, it became ultimately known that only a subset of flats – high rise flats with combustible cladding – were directly affected by the shock. This implies that our estimates will understate the true effects of the shock since the treatment group may also include control units which were not directly impacted by the shock. We thus interpret our estimates as a lower bound of the true causal effect.

[9]These data also allow us to construct property identifiers which allows us to track them over time and enables us to mitigate concerns of the composition of the housing stock changing over time.

decrease in overall transaction volumes for these properties. Instead, we document that this decrease in mortgage issuance is more pronounced for borrowers facing higher agency costs. In particular, we document a decrease in mortgage issuance to first-time buyers (FTB) who tend to have less transparent financial profiles compared to existing homeowners, pointing to a crucial role of information asymmetries between lenders and borrowers in the propagation of the shock. Moreover, our estimates indicate that the drop in mortgage originations was larger for loans with high Loan-to-Income (LTI) ratios.[10] However care must be taken when interpreting the difference in originations by LTI since the point estimates are noisy and does not allow us to reject the null of equality. Lastly, we find that rents did not decrease in the immediate aftermath of the first shock and increased after the public guidance suggesting that the willingness-to-pay to live in affected properties did not fall as a result of the shocks.

Our findings reveal the pivotal role played by cash-buyers and lender heterogeneity in alleviating the impact of the shock. We note a significant increase in the proportion of cash-buyers following the shock, indicating that this cohort of non-credit-constrained buyers may help offset some of the reduced demand for affected properties. These findings align with evidence showing a notable uptick in rents in response to the shock, suggesting that cash-buyers passed on short-term increases in property maintenance costs to renters through higher rental rates. Additionally, we observe that contractions in lending appear to be less pronounced among the largest lenders.

Our analysis does not directly pinpoint how changing credit conditions affect property prices and mortgage origination volumes for affected properties. To isolate the impact of credit conditions accurately, we would need a specific setup that examines shocks independently of demand for the affected properties, a scenario not present in our data. Instead, we focus on identifying the causal effect of the shock on the housing market overall. Additionally, we uncover further evidence supporting our prior, indicating a reduction in lending to high-risk borrowers associated with affected properties.

Related literature: Our paper contributes to the literature on the role of credit in propagating shocks to the economy (Kiyotaki and Moore, 1997; Brunnermeier, 2009; Bernanke et al., 1996). Consistent with the concept of credit serving as a "financial accelerator" (Bernanke et al., 1996), we observe a decrease in collateralized mortgage lending to households following an adverse shock to residential property values. In line with this notion,

[10] Since the LTI constraint was binding prior to the shock, the documented pattern of heterogeneity cannot solely be explained by falling prices for affected properties. A drop in prices not only reduces the value of the loan, but it also reduces the minimum borrower income to qualify for a given LTI constraint. Therefore, a drop in prices is not sufficient to generate a drop in the LTI. On the other hand, a downward adjustment of lenders' LTI tolerances is sufficient to generate the observed drop in LTI.

our paper complements existing evidence on the relationship between property values and lending to firms (e.g., Chaney et al. (2012); Gupta et al. (2021)). Recent research indicates that firms seek new debt following an increase in the value of their real estate, but they tend to opt for unsecured borrowing rather than secured borrowing (Campello et al., 2022). Consistent with the notion of reduced risk appetite[11], our findings indicate that the decline in mortgage lending is most significant for informationally-opaque borrowers. Specifically, we observe a decrease in mortgage lending among borrowers with high loan-to-income (LTI) ratios exceeding 4.5, a regulatory constraint in the United Kingdom (Peydró et al., 2023; Kashyap, 2020). This finding aligns with the work of Almeida et al. (2006), who noted that mortgage lending is more sensitive to shocks in countries where Loan-to-Value (LTV) limits become binding. In terms of opaqueness, we find evidence of a decline in mortgage lending to First-time-buyers (FTB) that are more informationally opaque given their shorter credit history. This underscores the role of information asymmetries between lenders and borrowers (Sufi, 2007) in constraining lending (Stiglitz and Weiss, 1981). In this context, our findings on residential mortgages complement research on corporate lending, which also demonstrates evidence of credit rationing among younger firms (Kirschenmann, 2016; Ferri and Murro, 2015). Overall, our study provides valuable evidence on residential mortgage lending which comes with implications for household finance, expanding our understanding beyond the scope of existing literature focused primarily on lending to firms.

The established view of real estate collateral's role in economic fluctuations has faced recent challenges from empirical studies (e.g., Mian and Sufi (2011)).[12] We contribute to this literature by introducing two additional perspectives. Firstly, we highlight the crucial role of cash-buyers and lender heterogeneity in mitigating the effect of adverse shocks to real estate. Previous research has suggested that heterogeneity in risk beliefs can explain why drops in property values are less severe than expected (Baldauf et al., 2020; Bakkensen and Barrage, 2021). We complement this literature by providing evidence that the heterogeneity in financing sources for property purchases also plays a relevant role in understanding shocks to property prices. Specifically, our findings indicate that the proportion of cash-buyers in the property market is a significant factor influencing the impact of shocks on property values.

Our paper also contributes to the literature on how lenders respond to such shocks to real estate which acts as collateral for mortgage lending.[13] It documents heterogeneous

[11] In line with the concept of a "flight for safety" (Bernanke et al., 1996).

[12] They argue that the primary transmission channel of financial shocks to the real economy during the Great Recession was the significant reduction in aggregate demand driven by declines in household net worth.

[13] The existing literature has examined responses to tightening credit limits and interest rates (Cerqueiro et al., 2016; Nguyen et al., 2022), securitization decisions (Ouazad and Kahn, 2021) and property valuations

responses with respect to banks' levels of capitalization (Schüwer et al., 2018) and diversification (Chavaz, 2016). We contribute to this literature by documenting nuanced differences across bank size where small lenders react more strongly after the shock while larger lenders' lending decreases less strongly (potentially because they are more diversified). We also complement to it by documenting a lagged effect on mortgage lending which dropped only following public guidance is issued but not immediately after the physical shock.[14]

Implications for financial stability policy and firm supervision: Our paper comes with several implications that are relevant for financial stability policymakers and supervisors of financial institutions.

In terms of its results, our paper suggests that cash-buyers can act as automatic stabilizers of shocks to property values by stepping into the property market once such shocks materializes. This is relevant to financial stability policymakers as drops in historical property values might not be as strong as expected if there is, ex-ante, a higher share of potential cash-buyers in the market. Second, our results suggest that lenders react to such shocks in a correlated way after a salient public guidance signals the riskiness of those mortgages that are collateralised by those properties affected by the shock. It points to the importance of public guidance about the riskiness of certain properties beyond the shock itself.

Our paper also offers an analytical approach for policymakers to study other, related shocks including those from climate risks. Specifically, our paper provides a conceptual framework on the transmission of shocks to real estate values via the mortgage market. Moreover, it showcases a methodological approach on how these transmission channels can be quantified using available data. By doing so, our paper showcases how one can leverage multiple data sources to estimate the effects of shocks to properties. By documenting the appeal but also limitations of the data and methodology we employ, our paper highlights the necessity of collecting data at an appropriate level of granularity to study such effects. This informs the public debate on whether and how to address data gaps to find appropriate responses to emerging risks of shocks to property values, including those from climate change (Garbarino and Guin, 2021).

[14] Our paper also links to the literature studying dynamic responses to shocks to real estate both in terms of prices and transaction volumes. It shows that there is a lead-lag structure which means property transaction volumes fall first and then prices only fall later in the presence of a slow-moving shock from sea level rises (Keys and Mulder, 2020) which can be rationalized by optimistic homeowners continue listing properties at high price and only gradually update their asking prices which explains the sluggish drop in prices (DeFusco et al., 2022). By contrast, our results suggest in the presence of an unexpected and salient shock both transaction volumes and prices fall immediately. For the mortgage market, our results suggest in fact a reversed lead-lag relationship, i.e. valuations fell immediately whereas volumes responded more than a year later, suggesting that mortgage lenders update their valuations immediately.

(Financial Stability Board, 2022; Basel Commitee on Banking Supervision, 2021a).[15]

2 Conceptual framework

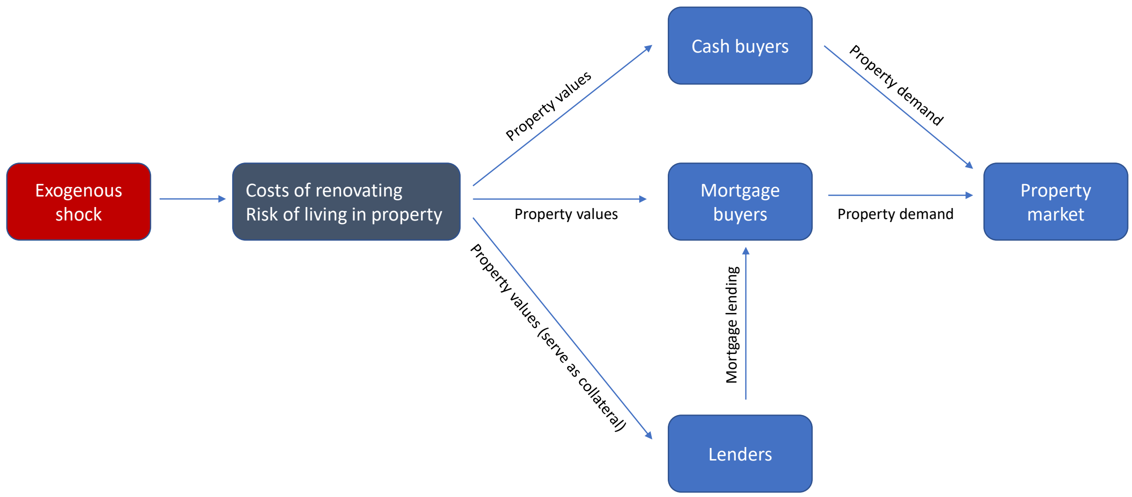
In this section, we present a conceptual framework that sets out how shocks to properties transmit to the property market which motivates our empirical analyses (Figure 1).[16] Once a shock such as an extreme weather event disaster occurs, it may impact the risk perception associated with a certain class of properties, i.e. it reduces households' willingness to live in affected properties. Moreover, it may generate costs to homeowners to renovate affected properties. Both higher perceived risk and elevated costs reduce the valuation of affected properties by prospective buyers. Moreover, they can increase the uncertainty of the true collateral value of mortgages assessed by lenders, who might respond to such drops by reducing mortgage originations against affected properties. In response, buyers taking out mortgages experience a tightening of their credit constraints which will further reduce demand for affected properties. We therefore expect a lowering of property prices in response to severe shocks. By contrast, cash buyers are unaffected by credit availability. Their own property valuations might not fall as risk perceptions are less relevant in the case they buy properties to let them as an investment. For these reasons, there might be a dampening price effect from cash buyers depending on their share in the property market.[17]

[15]In this spirit, our paper can also be seen as a response to calls for further research to better understand such climate risk drivers, or "shocks", and their transmission channels to financial institutions (Basel Commitee on Banking Supervision, 2021b). Using a non-climate risk driver our methodological approach allows us to understand and quantify the transmission channels to the mortgage market and, thereby, lenders' risk exposures.

[16]It follows the spirit of BCBS's Climate-related risk drivers and their transmission channels (Basel Commitee on Banking Supervision, 2021b).

[17]Lastly, a contraction in lending could have a feedback effect on the housing market if the willingness to lend against affected properties falls beyond the willingness to own in the housing market.

Figure 1: Transmission of shocks to the property market

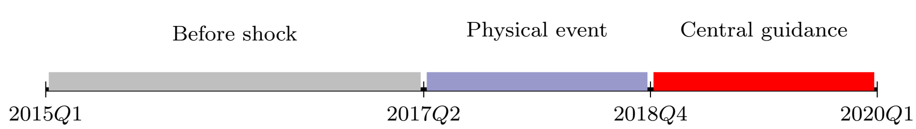


3 Overview of the shock and data

3.1 Timeline of events

In this paper, we study market dynamics around a specific shock to properties in the UK, which encompasses two events that occurred consecutively. They break our sample up into three periods (Figure 2).

Figure 2: Timeline of Events



The first event was a severe fire that affected a specific building located in London which resulted in the tragic loss of life.[18] This disaster raised concerns about the safety

[18] The Grenfell Tower Inquiry was created to examine the circumstances leading up to and surrounding

of flats in other high-rise buildings because of cladding which was identified to be highly combustible. It also had further, significant personal and social impacts on peoples' lives, which extend beyond the scope of our academic analysis. The second event occured in December 2018 when the government released central guidance, the so-called Advisory Note 14. From the perspective of our analyses, it served two purposes. First, it defined the subset of flats that were at risk and those that were not, specifically those high-rise flats with exterior wall cladding. Second, it suggested remedies for these affected properites. For building owners, it mentioned the measures they should take to ensure their buildings were safe. Specifically, it guided owners of flats to check whether their property was constructed using unsafe materials and to remove such material if found, which comes with costs.[19] For the purpose of our empirical analyses, we restrict our sample to start in 2015 Q1.[20] We choose to end the sample period in 2020 Q1 because of the first COVID lockdown in the UK that ocurred at the time which may conflate our analyses.

3.2 Data

In our analysis, we employ transaction-level data from the Product Sales Database (PSD). It records the universe of residential mortgage originations and refinancings in the UK during our period of interest and it is well-established in the literature (e.g., Benetton (2021); Benetton et al. (2021); Peydró et al. (2023); Arnould et al. (2020)). In terms of geographical information, we observe the six-digit postcode of each mortgage transaction.[21] In our sample of mortgage originations in England & Wales between 2015 and 2020, about 13% of all mortgage transactions are flats (remaining ones are non-flats). We observe on average 19 transactions of non-flats and 3 transactions of flats per postcode district and month before the shock. The average price paid for a mortgage-financed flat is £283,565 and the average price of a mortgage-financed non-flat is £296,667. We use these data to quantify the number of property transactions and average prices by property type, geographic area and time. We employ postcode district as the geographic area and the year-month level as our time dimension. In terms of property type, our data allows us to differentiate between flats and non-flats. However, we are neither able to observe whether flats are in high-rise buildings nor can we observe their wall construction such as cladding.

Whilst the PSD provides rich data to study trends in property prices and the number

the fire at Grenfell Tower on the night of 14 June 2017. More information can be found at https://www.grenfelltowerinquiry.org.uk/

[19] Such costs include (higher) insurance costs for affected properties as well as costs of maintenance and renovations.

[20] Choosing 2015 Q1 ensures that the time before the event roughly equals the time after the event.

[21] A six-digit postcode can consist of around 10 properties.

of mortgages originated, it does not contain information on those property transaction that are cash-financed. We therefore combine PSD with the Land Registry Price Paid Dataset (PPD) to separately analyse the dynamics in the cash- and mortgage-financed segments of the housing market. The latter records the universe of all residential property transactions in England and Wales and it is also well-established in the existing literature (e.g., Bracke et al. (2018)). For each transaction, we observe the property type, the exact transaction date as well as the price paid for the property. In our sample of all transactions in England & Wales between 2015 and 2020, about 19% of all property transactions are flats (remaining ones are non-flats). We observe on average 26 transactions of non-flats and 6 transactions of flats per postcode district and month before the shock. The average price paid for a property is £289,947 in the sample period. The average price for a flat is £293,332 and the average price of a non-flat is £289,163 in the Land Registry.

Combining PPD with PSD allows us to back out the implied number of all cash purchases for flats and non-flats at the postcode district × year-month level by subtracting the number of mortgage transactions in PSD from the number of property transactions in PPD.[22] Between 2015 and 2020, the share of cash transactions among all properties was approximately 37%. This number compares well with aggregate statistics[23] and the share reported by Bracke and Tenreyro (2021) for the UK.

We complement these two datasets with data on rental listings from Zoopla which are processed by WhenFresh Ltd.[24] It is the second most popular property portal in the United Kingdom in terms of traffic and covers 70% of the whole-of-household privately rented housing stock in the UK (Bracke, 2021). The dataset contains information on the address of properties, listing sale/rental prices, and property attributes (such as property type and number of bedrooms). This dataset includes listings of rentals including the asking rent but we do not observe whether a specific property was actually rented. In the Zoopla data between 2015 and 2020 for London, the median weekly rent was £375 for all properties, £369 for flats and £398 for non-flats (see Table 1 in the Appendix for summary statistics).

[22] PPD classifies transactions as 'Additional Price Paid' if they were "transfers under a power of sale/repossessions, buy-to-lets (where they can be identified by a mortgage), transfers to non-private individuals and sales where the property type is classed as 'Other'." Importantly, a Buy-to-Let transaction is not classified as Additional Price Paid if it was financed entirely with cash. The set of properties not tagged as Additional Price Paid therefore include all standard residential transactions (financed either with cash or mortgages) as well as Buy-to-Let transactions financed only with cash. The number of all cash purchases (including Buy-to-Let) can thus be backed out by taking the difference in the number of PPD non-Additional Price Paid transactions and all PSD transactions.

[23] www.gov.uk/government/news/uk-house-price-index-new-data-reveals-number-of-cash-buyers, retrieved on 24 September 2023.

[24] *WhenFresh Ltd* is a major provider of UK residential property data (https://whenfresh.com).

4 Research Design

For our empirical analyses, we employ a dynamic Difference-in-Difference (DiD) research design. It allows us to estimate the effects of the shock on outcomes in the property, mortgage and rental markets. Specifically, we examine how outcomes of properties affected by the shock compare to outcomes of unaffected properties before and after the shock. The long time dimension and high frequency of our data allows us to examine the dynamic effects of the shock. Specifically, we can study when exactly the effects of the shock materialized and whether they were temporary or persistent.

Employing this dynamic DiD research design is appealing given the nature of the shock in question and the data at our disposal. First, the shock was *unexpected and was unprecedented*.[25] This mitigates concerns that market participants' anticipation might explain some of the effects on outcomes in the property and mortgage markets.[26] Second, our setting and data allow us to *identify a set of properties affected by the shock*, our treatment group, which we can compare to a set of unaffected properties which form our control group.[27] As the treatment is assigned by the type and not by the spatial location of the property, concerns of changing local economic conditions explaining some of the estimated effects are mitigated.[28] Last, the dynamic DiD allows us to estimate the incremental effects of the two subsequent events, the physical shock and central guidance, of the shock that we study.

To implement the dynamic DiD, we estimate two types of regressions. The first set of regressions allows us to study outcomes at the transaction level, for example changes in the transaction prices of affected properties. The second set of specifications allows us to study changes to the number of transactions at the postcode district × time × property-type level. We estimate our regressions for transactions both in London as well as outside London, as dynamics and the share of affected properties across these markets might differ. In all regressions, the reference period that we compare outcomes to is 2017Q2, the quarter when

[25] We argue that the shock that we study was unexpected for two reasons. First, prior to it, there was not much coverage of the risks associated with cladding issues which were responsible for it. Second, there was not much coverage of the fact that these cladding issues were particularly problematic for flats as opposed to other types of buildings.

[26] By contrast, in other settings news of expected changes to policy or risk is available well in advance of the actual shock. It is difficult to identify the effects of the actual event as individuals may respond in advance in anticipation of it. This issue is particularly relevant for climate change since many climate-related events such as changes to sea levels, temperature, and rainfall can be forecasted by households.

[27] This is because the shock only increased risk perceptions and costs associated with living in high-rise flats while leaving non-flats unaffected.

[28] By contrast, for instance, sea-level rise impacts all coastal properties. Similarly, floods, droughts, heat waves, and forest fires tend to impact all properties within a large catchment area. Failure to account for such spatially granular time-trends can bias estimates of effects if the treated and control units are located in different locations and these locations face different time-trends.

the physical event occurred.

The DiD regressions at the transaction level take the following generic form:

$$\ln y_i = \beta_0 + \sum_{\tau=2015Q1}^{2020Q1} \alpha_\tau \ \mathbb{1}(i \in \text{flat}, t(i) = \tau) + \gamma_{\text{flat}} \mathbb{1}(i \in \text{flat}) + \gamma_{t(i)} + \rho(i) + \varepsilon_i \tag{1}$$

where i indexes each transaction; y_i is the outcome variable of interest; $\gamma_{t(i)}$ is an indicator for quarter-year $t(i)$ for transaction i; α_τ is the difference-in-difference coefficient for quarter-year τ; and γ_{flat} is the fixed effect for flats. Depending on the exercise, $\rho(i)$ is either a fixed effect at the property level or at the postcode × number of rooms level for transaction i. Of interest are the estimates of α_τ which measure the evolution of outcomes of affected properties relative to unaffected properties, e.g. prices of flats relative to non-flats.

To study the evolution of the number of transactions, we estimate Poisson regressions with the dependent variable defined as the count of transactions of flats or non-flats at the postcode district × month-year level. The regression specification takes the following form:

$$\ln \mu_{ift} = \beta_0 + \sum_{\tau=2015Q1}^{2020Q1} \alpha_\tau \times \mathbb{1}(f = \text{flat}, t \in \tau) + \gamma_\tau + \gamma_f + \rho(i) \tag{2}$$

where i indexes each postcode district (our measure of the local area); t indexes each year-month (the time dimension); f indexes flats and non-flats (the property type); μ_{ift} is the expected count of the relevant transactions of type-f properties during month-year t; γ_τ is an indicator for quarter-year τ; γ_f is the fixed effect for properties of type-f; $\rho(i)$ is the postcode district fixed effect; and α_τ is the difference-in-difference coefficient for quarter-year τ.

5 Results

5.1 Effect on property prices

This section studies how the shock which is composed of two subsequent events, the physical event and the central guidance, affected transaction prices for flats. We find that prices (and therefore the value of mortgage collateral) for flats fell significantly and persistently relative to non-flats following the physical event.

5.1.1 Evolution of property prices over time

We first examine the historical price dynamics across the two types of properties, flats and non-flats. Specifically, we study the evolution of mean purchase prices in log units for flats and non-flats that were purchased using a mortgage. To account for heterogeneity in price dynamics across regions, we illustrate the evolution of prices separately for transactions within London and outside of it. The reported, estimated means adjust for time trends as well as compositional differences due to unobserved and observed characteristics at the postcode × number of rooms level which might influence the price of the transacted properties. Specifically we estimate four different regressions, for flat and non-flat transactions both within and outside London.

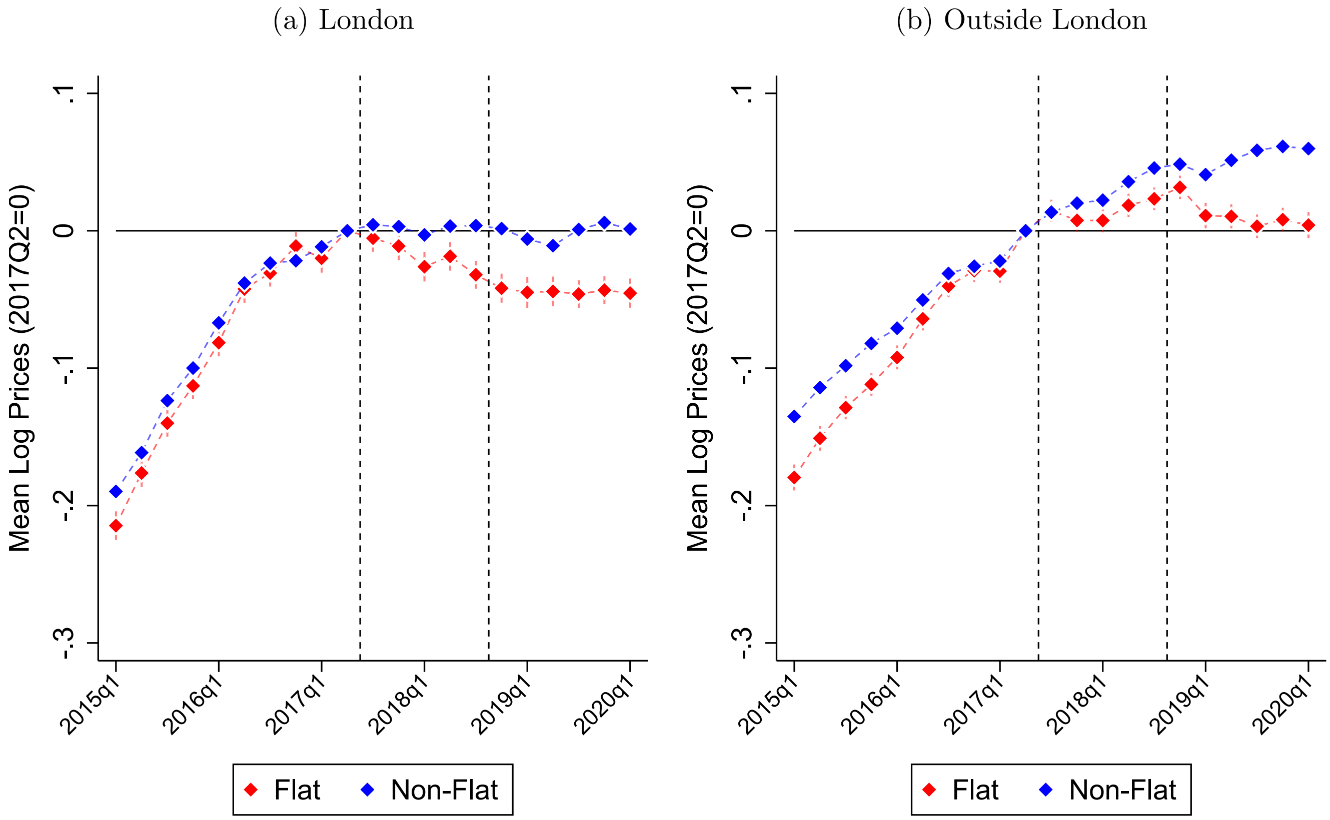
$$\ln p_i = \beta_0 + \gamma_{t(i)} + \rho(i) + \varepsilon_i \tag{3}$$

where i indexes each transaction, $\gamma_{t(i)}$ is an indicator for quarter-year $t(i)$ for transaction i, and $\rho(i)$ is the postcode × number of rooms fixed effect for i. All regressions presented in this paper exclude the quarter-year indicator for 2017Q2, the quarter when the physical event occurred. Therefore all quarter-year parameters γ_t represent deviations from the mean in 2017Q2. We report robust standard errors unless stated otherwise.

The granular postcode × number of rooms fixed effects allow us to control for any time-invariant characteristics which generate price differences across postcodes, property sizes, and the interaction of postcode and property size. These fixed effects isolate any change in prices that may occur due to changes in the composition of transacted properties along these dimensions over time. The evolution of the estimated γ_t thus captures quarterly changes in prices due to factors other than changes in the composition of transacted properties along these dimensions. Figure 3 plots estimates of γ_t and their confidence intervals using data from the Product Sales Data 001.

The estimates in Figure 3 show an abrupt change in the evolution of flat prices relative to non-flat prices beginning in 2017Q2, the quarter of the physical event. Whereas prior to 2017Q2 in London the percentage difference in prices between flats and non-flats was weakly decreasing, this percentage difference abruptly started increasing after 2017Q2. The relative decline in flat prices continued for 6 quarters after which the percentage difference between non-flats and flats stayed approximately constant at around 6%. Figure 3 shows that transactions outside London also exhibit an abrupt change in the relative evolution of flat and non-flat prices in 2017Q2. Whereas prior to 2017Q2 the percentage difference between flat and non-flat prices was falling due to significantly greater growth in flat prices, this pattern was reversed in 2017Q2 when the growth in non-flat prices suddenly began to outpace the growth in flat prices. As with London, by 2020Q1, the percentage difference in prices between non-flats and flats had reached approximately 6% for transactions outside London.

Figure 3: Log Purchase Price for Mortgage-Financed Property Transactions



Note: This figure presents estimates from two different regressions. Each figure plots the quarterly mean log purchase price for transactions of flats and non-flats in London and outside London respectively along with the 95% confidence interval estimated from a normal distribution. The estimates adjust for fixed effects at the postcode $\times$ number of rooms level. All estimates are relative to 2017Q2. The figure uses vertical dashed lines to mark two events: the leftmost vertical dashed line represents the period of the physical event whereas the rightmost vertical dashed line represents the central guidance.

5.1.2 Effect on property prices: Difference-in-Difference analyses

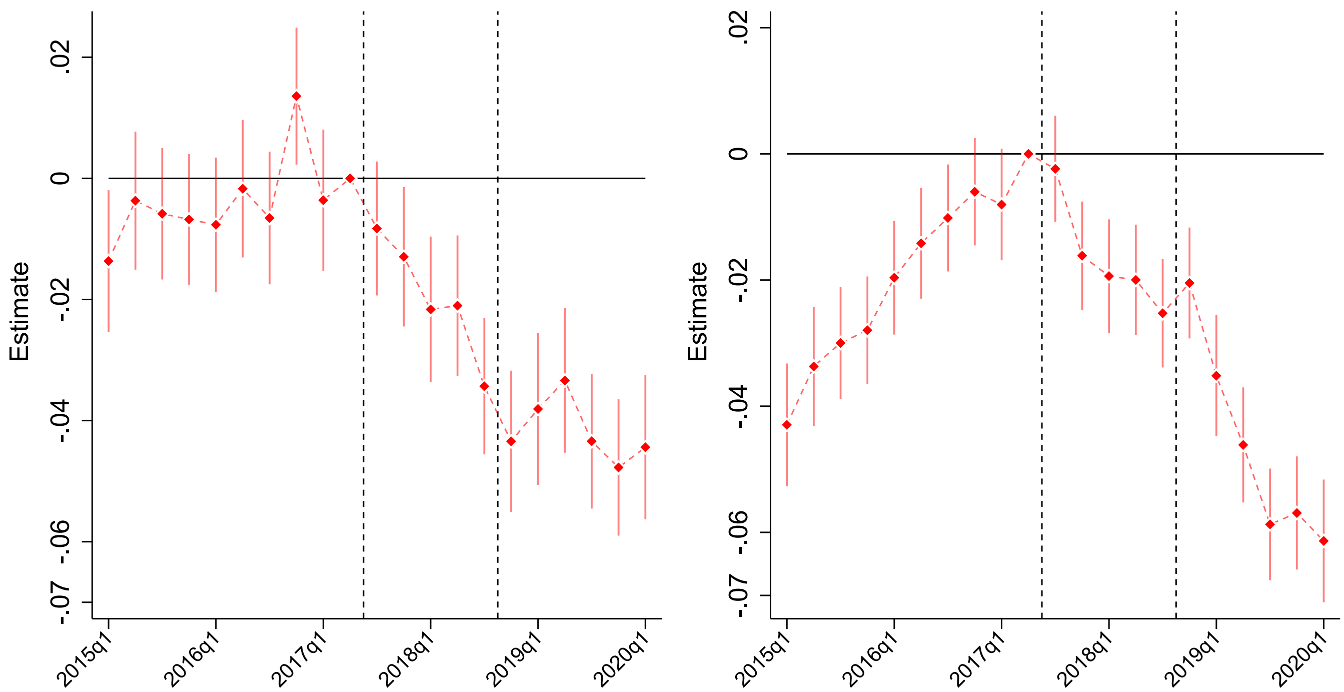
Our previous descriptive analyses of the evolution of transaction prices suggested that the price growth for flats outpaced non-flats prior to 2017Q2. By contrast, after 2017Q2 this pattern reversed abruptly. In this subsection, we formally test these differences in the relative change of transaction prices. To that end, we conduct a dynamic difference-in-differences analysis. We estimate the following specification separately for transactions within and outside London:

$$\ln p_i = \beta_0 + \sum_{\tau=2015Q1}^{2020Q1} \alpha_\tau \, \mathbb{1}(i \in \text{flat}, t(i) = \tau) + \gamma_{\text{flat}} \mathbb{1}(i \in \text{flat}) + \gamma_{t(i)} + \rho(i) + \varepsilon_i \qquad (4)$$

where i indexes each transaction; $\gamma_{t(i)}$ is an indicator for quarter-year $t(i)$ for transaction i; $\rho(i)$ is the postcode $\times$ number of rooms fixed effect for i; α_τ is the difference-in-difference coefficient for quarter-year τ; and γ_{flat} is the fixed effect for flats. Of our interest are the estimates of α_τ which gauge how much prices of flats have evolved compared to non-flats relative to the 2017Q2, the quarter of the physical event.

Figure 4: Flat vs. Non-Flat Difference in Log Purchase Prices
for Mortgage-Financed Property Transactions

(a) London (b) Outside London



Note: This figure presents difference-in-difference estimates from two different regressions. Each figure plots the quarterly difference in mean log purchase price between mortgage-financed flat and non-flat transactions in London and outside London respectively along with the 95% confidence interval estimated from a normal distribution. The estimates adjust for fixed effects at the postcode × number of rooms level. All estimates are relative to 2017Q2. The figure uses vertical dashed lines to mark two events: the leftmost vertical dashed line represents the period of the physical event whereas the rightmost vertical dashed line represents the central guidance.

Figure 4 plots these dynamic difference-in-difference estimates. They provide empirical evidence that flat prices reversed abruptly relative to non-flats in 2017Q2. In London, the point estimates for the difference in mean log prices are increasing before 2017Q2, although they are not statistically significantly different than zero at the 5% level. We conclude that there is no statistical evidence for the existence of a pre-trend in the difference in log prices between flats and non-flats. However, the difference in log prices between flats and non-flats begins to abruptly fall after 2017Q2, such that within two quarters (2017Q4) the difference is statistically significantly negative and different from zero. By 2020Q1 the difference in mean log prices has fallen statistically significantly to approximately -0.05 log points which represents a 5% drop in the prices of flats relative to 2017Q2 and the quarters prior. Outside London, there is strong evidence for a reversal of the relative evolution of prices between flats and non-flats. Unlike in London, in the time period before the physical event, we see a strong and statistically significant increase of 4% in prices of flats relative to non-flats. Yet, this pattern completely reverses in 2017Q2 such that flat prices drop statistically significantly by ∼2% within two quarters (2017Q4) and by ∼6% by 2020Q1. Overall, this evidence presented so far provides strong evidence that the physical event reduced prices for flats purchased with mortgages by 5% - 6% in the span of two years in England & Wales. On an annualized basis, the physical event reduced flat prices by approximately 3% per year.

5.2 The role of lending

Consistent with our priors, our previous analyses suggest that there is an economically significant and persistent negative effect of the shock on the prices of affected properties relative to unaffected ones. In this section, we examine the dynamics of mortgage lending which serves to finance property purchases. Reduced market values of properties reduces the value of collateral where there is an outstanding mortgage. Lenders might respond to uncertanity of property values by reducing mortgage originations against affected properties.

5.2.1 Contraction in mortgage lending against affected properties

First, we examine whether mortgage lending against affected properties changed in response to the shock. To that end, we study the relative change in the number of mortgage transactions when affected properties serve as collateral compared to non-flats. As our dependent variable is a count variable, we employ a Poisson regression model. Specifically, we estimate the following dynamic difference-in-differences specification:

$$\ln \mathbb{E}[Q_{ift} \mid \cdot] = \beta_0 + \sum_{\tau=2015Q1}^{2020Q1} \alpha_\tau \times \mathbb{1}(f = \text{flat}, t \in \tau) + \gamma_\tau + \gamma_f + \rho(i) \tag{5}$$

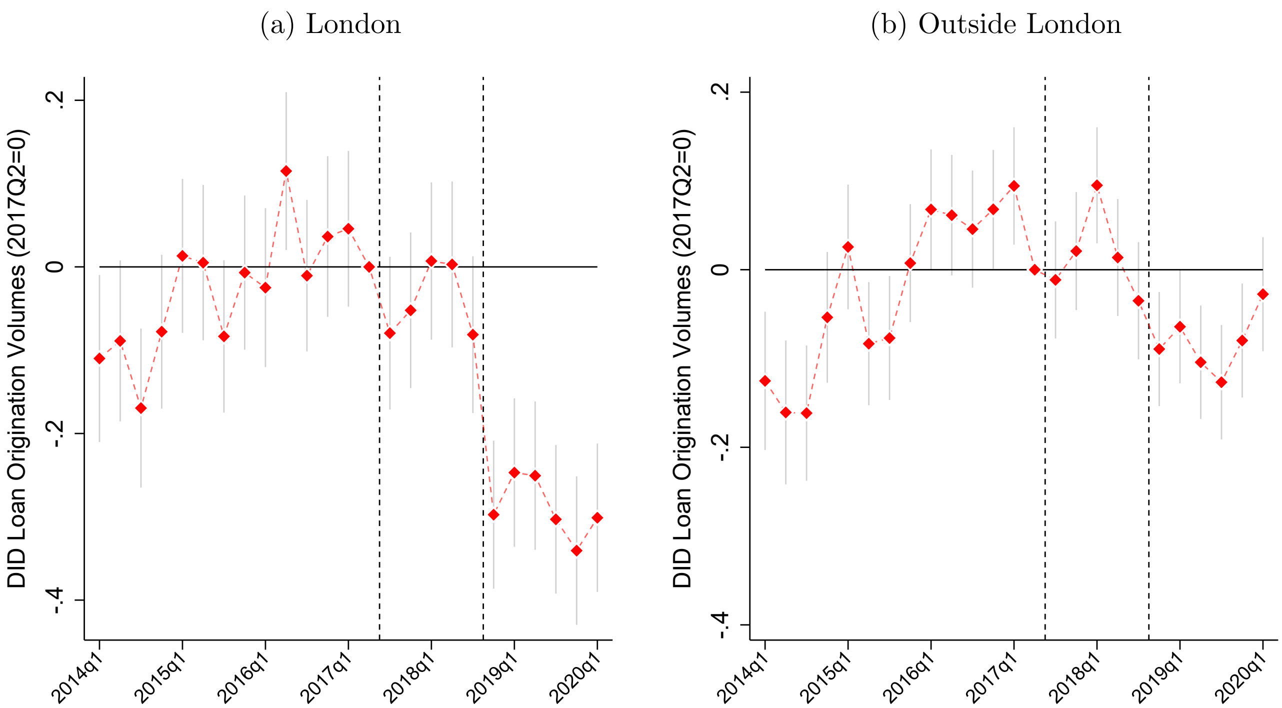
where i indexes each postcode district; t indexes each year-month; f indexes flats and non-flats; Q_{ift} is the count of originations of type-f properties during month-year t; γ_τ is an indicator for quarter-year τ; γ_f is the fixed effect for properties of type-f; $\rho(i)$ is the postcode district fixed effect; and α_τ is the difference-in-difference coefficient for quarter-year τ. We present the difference-in-difference estimates of α_τ. We estimate this regression for two different subpopulations, both within London as well as outside London (Figure 5).[29]

The difference-in-differences estimates presented in Figure 5 document a sharp drop in mortgage originations against flats in 2018Q4, the quarter when the central guidance was published across both regions. However, the drop is significantly more pronounced in London where the number of mortgages against flats fell sharply and persistently by 30-40%. In comparison, flat originations dropped by around 10-20% outside London. The fact that originations dropped by an additional ∼20 percentage points in London is consistent with ex-ante expectations since the central guidance targeted high rise properties which are proportionally more common among flats in London. This evidence further strengthens our interpretation that the post-2018Q4 drop was indeed caused by the central guidance as it rules out any competing explanations for the drop in 2018Q4 that cannot also simultaneously explain the pattern of heterogeneity documented in Figure 5.

By contrast, estimates of the 19 quarters preceding 2018Q4 do not suggest anticipation effects because estimates before 2018Q4 are close to zero (with the only statistically significant departure from zero being due to yearly seasonal trends which drive up the estimate predictably in the first quarter of each year). The exact coincidence of the central guidance with this significant and sustained departure from the pre-2018Q4 trend provides strong evidence that this ∼20% drop in flat originations was caused by the central guidance. In contrast, the data shows no significant evidence that the physical event had an impact on mortgage originations.

[29] We also document results for England & Wales, as shown Figure 12 in the Appendix.

Figure 5: Flat vs. non-Flat Difference in Log Number of Originations by Region



Note: This figure presents difference-in-difference estimates from two different Poisson regressions. Each figure plots the quarterly difference in mean log number of mortgages originated for flats and non-flats within and outside London along with the 95% confidence interval estimated from a normal distribution. The estimates adjust for postcode district fixed effects. All estimates are relative to 2017Q2. The figure uses vertical dashed lines to mark two events: the leftmost vertical dashed line represents the period of the physical event whereas the rightmost vertical dashed line represents the central guidance.

5.2.2 Less credit to constrained borrowers?

Our previous results suggested that originations of mortgages against affected properties fell sharply and in a sustained manner after the central guidance, with the largest drops occurring in London. This might have further reduced demand for affected properties if it was mainly already credit-constrained borrowers affected by a tightening in underwriting standards. In this section, we explore heterogeneity in origination numbers against affected properties by a combination of borrower × loan characteristics. Consistent with the idea of a lower risk appetite[30], declines in mortgage lending should be more pronounced for credit-constrained borrowers. Specifically, we examine lending depending on the loan-to-income (LTI) and loan-to-value (LTV) ratios. The first ratio, LTI, is a measure of initial affordability of a mortgage. The shock, in particular the central guidance, increased insurance costs for affected properties as well as costs of maintenance and repairs (FCA, 2022; DLUHC, 2022). It might have changed lenders' perceptions about the risk of non-repayment due to an increase in non-mortgage costs associated with the ownership of flats. The second ratio, LTV, is a measure of borrower leverage. The shock reduced prices of affected properties and increased uncertainty around the true value. This might have changed lenders' willingness to lend against high-LTV mortgages following the physical event and central guidance.

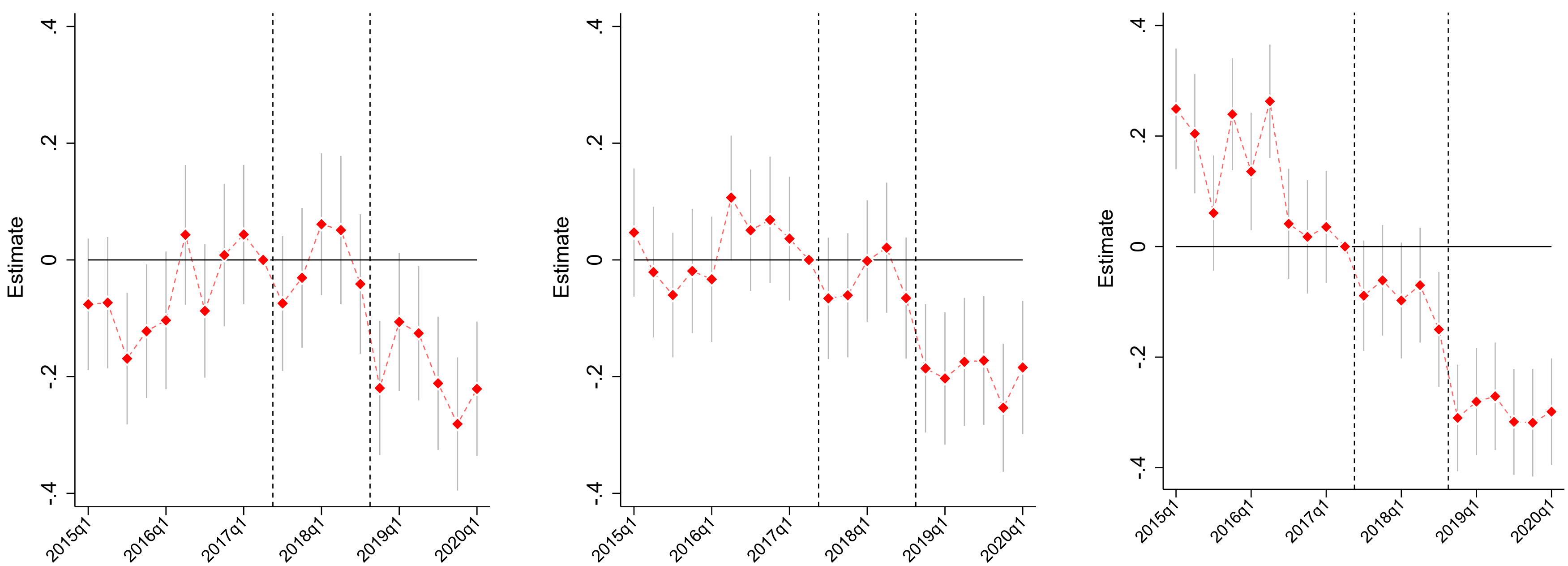
Loan-to-Income Ratio (LTI): To explore heterogeneity in origination by LTI, we estimate Equation 5 for three different LTI bands. For the first regression, we restrict the sample to only include mortgage originations with LTI between 0-4, i.e. those mortgages that are least risky. We define the count Q_{iflt} in Equation 5 using only mortgage originations in this sample—this count measures the number of originations with LTI between 0-4. We similarly conduct this exercise for a medium LTI band ($4 \leq$ LTI ≤ 4.5) and a high LTI band (LTI> 4.5), i.e. those mortgages that are riskiest. For each band, we define the count variable to only include originations of mortgages within the relevant LTI band.

Figure 6 plots the difference-in-differences coefficients from these regressions. We observe that the contraction in lending in response to the central guidance is increasing in the LTI. The point estimates indicate that originations for mortgages on flats with LTIs below 4.5 fell by around ∼20%. By contrast, mortgages on flats with higher LTIs experienced a larger contraction in originations of ∼30%. This difference of ∼10 percentage points in the point estimates is consistent with the central guidance increasing lenders' concerns that flat owners would be unable to service their monthly mortgage payments. However we should be cautious in interpreting this difference as the estimates are noisy and do not appear to be statistically significant as judged by the overlap of the confidence intervals.

[30] In the spirit of a "flight for safety" (Bernanke et al., 1996).

Figure 6: Flat vs. Non-Flat Difference in Log Number of Mortgage Originations in London, by Borrower LTI Band

(a) Low LTI: 0 to 4 (b) Medium LTI: 4 to 4.5 (c) High LTI: ≥ 4.5



Note: This figure presents difference-in-difference estimates from three different Poisson regressions. Each figure plots the quarterly difference in mean log number of mortgages originated for flats and non-flats in England & Wales by borrowers with different LTIs along with the 95% confidence interval estimated from a normal distribution. The estimates adjust for postcode district fixed effects. All estimates are relative to 2017Q2. The figure uses vertical dashed lines to mark two events: the leftmost vertical dashed line represents the period of the physical event whereas the rightmost vertical dashed line represents the central guidance.

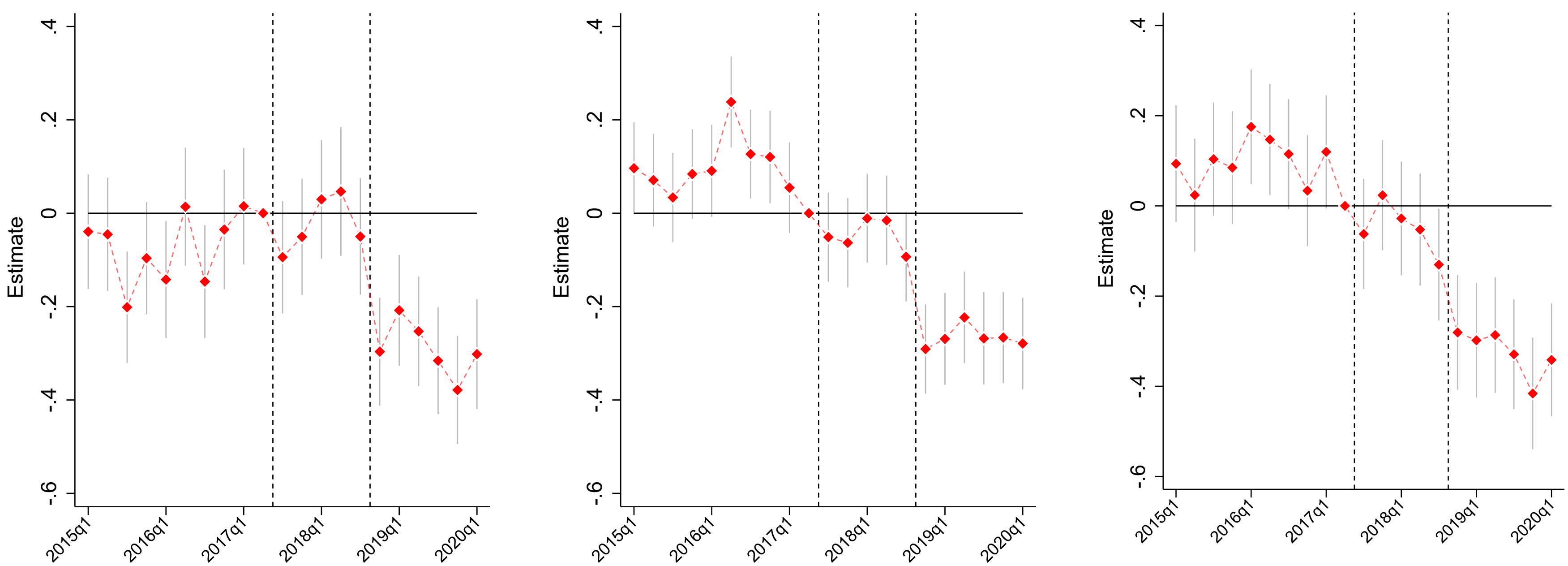
Loan-to-Value Ratio: We next study heterogeneity in the evolution of the number of mortgages against flats across different LTV bands. Analogously to our earlier analysis of heterogeneity across LTI bands, we re-estimate Equation 5 for three different LTV bands.

For the first regression, we restrict the sample to only include mortgage originations with LTV between 0% and 75%, i.e. those mortgages that are least risky. We define the count Q_{iflt} in Equation 5 using only mortgage originations in this sample—this count measures the number of originations with LTV between 0% and 75%. We similarly conduct this exercise for a medium LTV band (75% $\leq$ LTV $\leq$ 90%) and a high LTV band (LTV$>$ 90%), i.e. those mortgages that are riskiest.[31] For each band, we define the count variable to only include originations of mortgages within the relevant LTV band. The estimates plotted in Figure 7 show that unlike in the LTI analysis, there is no systematic correlation between LTV and evolution of the number of mortgages against flats. The contraction in flat originations around 2018Q4 appears approximately the same across all LTV bands. The lack of heterogeneity along LTV suggests that the central guidance did not change lenders' perceptions about borrower leverage. One explanation is that LTV might already reflect the effect of the shock as property prices dropped in responses to the shock. Lenders might have adjusted loan amounts in order to keep target LTV values constant.

[31] These are the same bands used by the Financial Conduct Authority (FCA) in their Quarterly Commentary on Mortgage lending statistics.

Figure 7: Flat vs. Non-Flat Difference in Log Number of Mortgage Originations in London, by Borrower LTV Band

(a) Low LTV: 0% to 75% (b) Medium LTV: 75% to 90% (c) High LTV: 90% to 100%



Note: This figure presents difference-in-difference estimates from three different Poisson regressions. Each figure plots the quarterly difference in mean log number of mortgages originated for flats and non-flats in London by borrowers with different LTVs along with the 95% confidence interval estimated from a normal distribution. The estimates adjust for postcode district fixed effects. All estimates are relative to 2017Q2. The figure uses vertical dashed lines to mark two events: the leftmost vertical dashed line represents the period of the physical event whereas the rightmost vertical dashed line represents the central guidance.

5.2.3 Less credit to First-time buyers (FTB) that are information opaque?

Our previous analyses studied how declines in mortgage lending were related to liquidity-constrained borrowers with high LTI ratios. Consistent with the idea of a “flight for safety” (Bernanke et al., 1996), declines in mortgage lending should also be pronounced for borrowers that are informationally opaque to lenders as information asymmetries between them and borrowers can restrict mortgage lending (Stiglitz and Weiss, 1981).

In this section, we explore the heterogeneity of the shock on mortgage lending to First-time buyers (FTB) given their shorter credit histories.[32] To that end, we estimate Equation 6 on the subsamples of First-time buyers (FTB), which we compare to Home Movers. The estimates in Figure 8 shows the quarterly difference in mean log number of mortgages originated for flats and non-flats in England & Wales by these two types of borrowers, Home movers vs. First-time buyers (FTB). The results suggest that flat originations dropped by close to 50% for First-time buyers (FTB). By contrast, the drop of mortgage lending to home movers amounted to ∼30%. Overall, this evidence suggests that mortgage lending to First-time buyers (FTB) decreased more. This contractionary response in mortgage lending can be indicative of delaying entry into the property ladder for young home buyers that are most credit-constrained and reliant on mortgage finance.[33]

Combining with the results of section 5.2.2 that showed liquidity-constraints become more binding after the shock, our results point to credit-constrained borrowers being most likely to be impacted by shock since they are most reliant on mortgages. Affected properties are flats which tend to be the point of entry into home-ownership, i.e. the lowest end of the so-called “property ladder”. From this perspective, our results point to further consequences for home-ownership: shocks to collateral values seem to create frictions for First-time buyers (FTB)’s access to credit thereby adding barriers for them to enter home-ownership.[34]

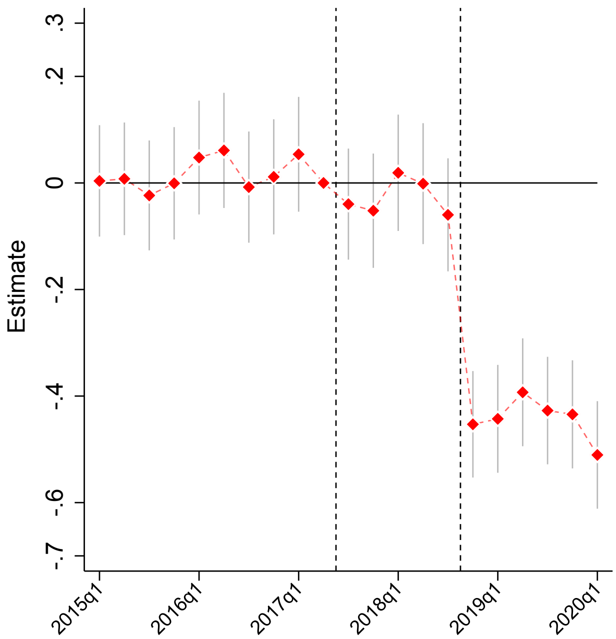
[32] We compare them to home movers that have a longer credit history.

[33] We acknowledge that FTB usually have higher LTIs as they are borrowing a higher proportion of the properties’ cost. Given this positive correlation, we might be seeing the LTI results through a different lens.

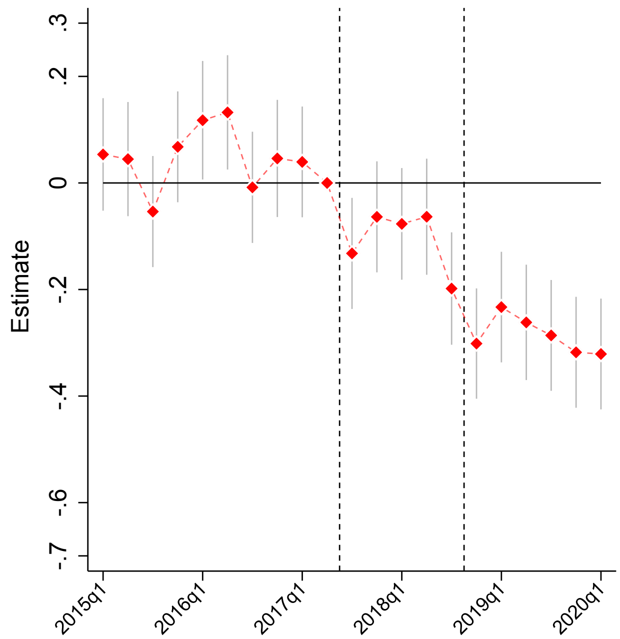
[34] Moreover, it might have prevented existing property owners from increasing property size, or progressing up along the ladder, as they were less able to sell affected properties.

Figure 8: Flat vs. Non-Flat Difference in Log Number of Mortgage Originations in London, by Type of Borrower

(a) First-time Buyers (FTB)



(b) Home Movers



Note: This figure presents difference-in-difference estimates from two different Poisson regressions. Each figure plots the quarterly difference in mean log number of mortgages originated for flats and non-flats in London by different types of borrowers along with the 95% confidence interval estimated from a normal distribution. The estimates adjust for postcode district fixed effects. All estimates are relative to 2017Q2. The figure uses vertical dashed lines to mark two events: the leftmost vertical dashed line represents the period of the physical event whereas the rightmost vertical dashed line represents the central guidance.

5.3 Mitigants to the effects of the shock

5.3.1 The heterogeneous response by lender size

Our previous results show that mortgage lending dropped sharply following the central guidance. Yet, these results do not shed light on whether this drop in originations was common across mortgage lenders. There are reasons to expect that large lenders react differently to the shock than small lenders. Their mortgage portfolios might be better diversified. Moreover, they might be in a better position to absorb shocks to collateral values. For these reasons, their reaction to the shock might be less sensitive.

In this section, we examine heterogeneity in the number of mortgage originations against affected properties by lender size. In England & Wales, the top four lenders take up the largest fraction of the residential mortgage market. Specifically, the mortgage market for flats is highly concentrated among these lenders who account for approximately 90% of mortgage originations against flats and 50% of mortgage originations against non-flats. The remaining lenders account for the residual share of mortgage lending.

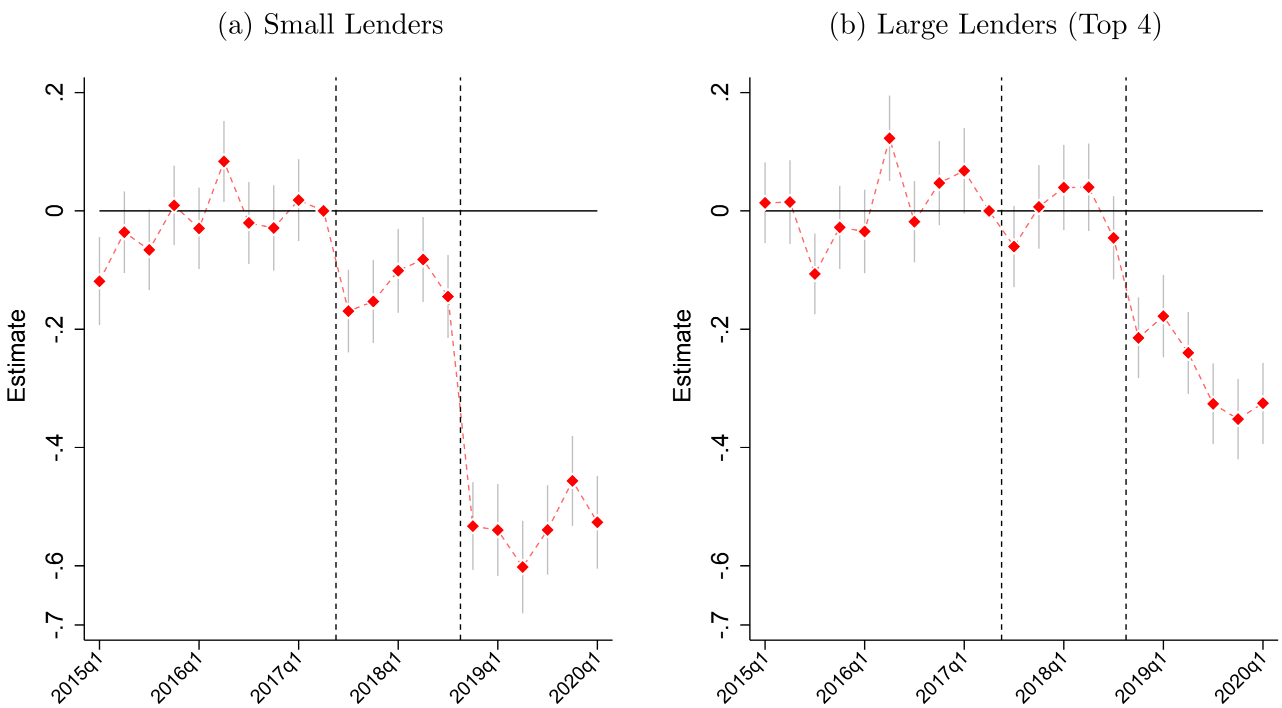
To capture potential differences by lender size, we estimate two separate regressions, one for the top four lenders and another one for all other lenders. To study the heterogeneity in mortgage originations by lender size, we estimate a slightly augmented and more granular version of the Poisson regression in Equation 5. The regressions take the following form:

$$\ln \mathbb{E}[Q_{iflt} \mid \cdot] = \beta_0 + \sum_{\tau=2015Q1}^{2020Q1} \alpha_\tau \times \mathbb{1}(f = \text{flat}, t \in \tau) + \gamma_\tau + \gamma_f + \gamma_l + \rho(i) \tag{6}$$

where i indexes each postcode district; t indexes each year-month; f indexes flats and non-flats; l indexes each lender; Q_{iflt} is the count of originations of type-f properties originated by lender-l during month-year t; γ_τ is an indicator for quarter-year τ; γ_f is the fixed effect for properties of type-f; γ_l is a lender fixed effect; $\rho(i)$ is the postcode district fixed effect; and α_τ is the difference-in-difference coefficient for quarter-year τ. Figure 9 plots estimates of α_τ and its confidence intervals for London.

The estimates in Figure 9 reveal that following the central guidance, small lenders reduced flat originations by nearly ∼60% while the top four lenders only reduced originations up to ∼40%. Overall, this difference of ∼20 percentage points suggests that large lenders' mortgage lending is less sensitive to the shock than lending by small lenders. As credit availability is relevant for buyers taking out mortgage debt to purchase properties, we take these results as evidence that lender size being a relevant dimension in the propagation of the shock to property values.

Figure 9: Flat vs. Non-Flat Difference in Log Number of Mortgages Originated by Lenders of Different Sizes in London



Note: This figure presents difference-in-difference estimates from two different Poisson regressions. Each figure plots the quarterly difference in mean log number of mortgages originated for flats and non-flats in London by lenders of different sizes along with the 95% confidence interval estimated from a normal distribution. The estimates adjust for postcode district and lender fixed effects. All estimates are relative to 2017Q2. The figure uses vertical dashed lines to mark two events: the leftmost vertical dashed line represents the period of the physical event whereas the rightmost vertical dashed line represents the central guidance.

5.3.2 The role of cash-buyers

Our previous results suggest that mortgage lending dropped significantly in response to the shock. Yet, debt-financed purchases make up only around two thirds of the property market. In this section, we examine whether the drop in mortgage lending against affected properties was partially or fully offset by cash-buyers that do not take out mortgage lending to finance their property purchase.

To that end, we construct a new measure for cash purchases as such data is not publicly available. Specifically, we combine data on property transactions with those on mortgage transactions. First, we use data from the Land Registry Price Paid data (PPD) to construct a count of all flat and non-flat transactions respectively that occurred in each month-year in each postcode district. Second, we use mortgage data from the Product Sales Data (PSD) to construct analogous counts for mortgage-financed transactions.[35] We then take the difference of the first set of counts measuring all transactions with the second set of counts measuring only mortgage-financed transactions to yield a new set of counts which measure the implied number of cash transactions at the postcode district×month-year level for flats and non-flats respectively. The count of these cash transactions allows us to calculate the share of cash transactions relative to all transactions per postcode district.

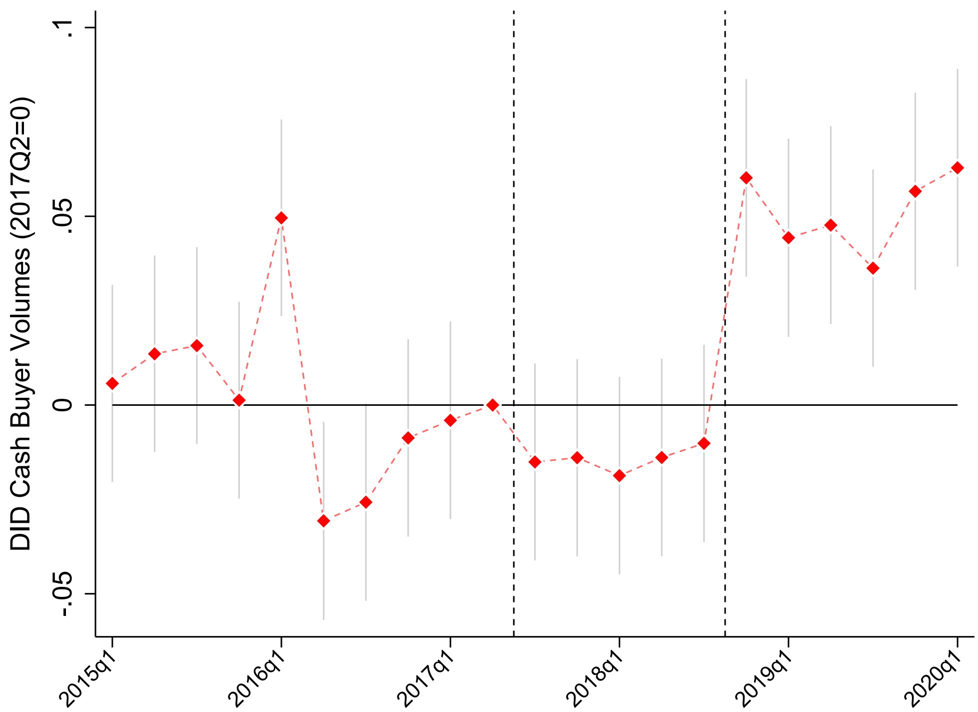
We employ this share variable as the dependent variable on a regression estimated using the subsample of properties located in London.[36] In particular, we estimate a version of Equation 5 where the dependent variable is defined to measure the share of purchases of properties of type-f in postcode district i during month-year t that is financed with cash. These estimates are presented in Figure 10. It shows that the share of cash-transactions against affected properties increased by approximately 5% following the central guidance relative to unaffected ones.

The results show that there is a significant increase in the share of flat purchases financed solely with cash. This result suggests that the contraction in the financing of flat purchases was offset by increased financing from another source, namely, by cash-buyers. Combining these results with those on the impact on cash-buyers in section 5.2.3, our analyses suggest that there is reshuffling in the composition of the residential property market. Specifically, we observe that the decrease in first time buyers (FTB) coincides with increase in cash buyers. This suggests that some FTB might have been crowded out of the property market.

[35] These counts of mortgage transactions are the same counts we use when estimating Equation 5.

[36] We restrict the sample geographically given the size of our final data set.

Figure 10: Flat vs. Non-Flat Difference in Cash Share of Sales in London

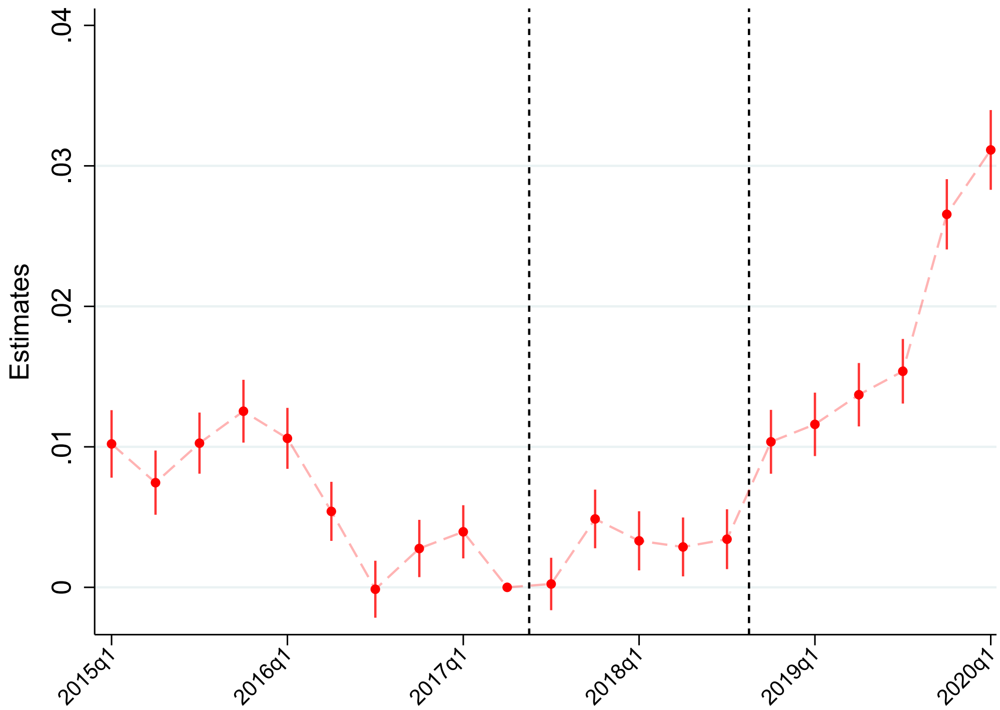


Note: This figure difference-in-difference estimates. The figure plots the quarterly difference in mean cash share of sales for flats and non-flats in London The estimates adjust for postcode district fixed effects. All estimates are relative to 2017Q2. The figure uses vertical dashed lines to mark two events: the leftmost vertical dashed line represents the period of the physical event whereas the rightmost vertical dashed line represents the central guidance.

5.3.3 Rental market: Increases in rents

Our previous results illustrated the propagation of the shock on prices in the property market through the mortgage market. In this section, we investigate whether and how the rental market adjusted to the physical event and the central guidance. We interpret the empirical evidence through the lens of a standard user-cost model, which suggests that (i) the post-shock drop in prices and number of mortgages were not generated by a decline in the willingness to reside in flats; and (ii) landlords pass short-run increases in user-costs on to renters through increased rents, but do not adjust rents in response to changes in prices.

Figure 11: Flat vs. Non-Flat Difference in Log Rents of Rental Listings in London



Note: This figure presents difference-in-difference estimates. The plot reports the quarterly difference in mean log rents of rental listings for flats and non-flats along with the 95% confidence interval estimated from a normal distribution. The estimates adjust for property fixed effects. All estimates are relative to 2017Q2. The figure uses vertical dashed lines to mark two events: the leftmost vertical dashed line represents the period of the physical event whereas the rightmost vertical dashed line represents the central guidance.

To study how rents reacted to the shock, we make use of proprietary data from Zoopla, the second most popular property portal in the United Kingdom. We estimate the following dynamic difference-in-differences specification with property fixed effects for all available rental listings in London:

$$\ln \text{rent}_i = \beta_0 + \sum_{\tau=2015Q1}^{2020Q1} \alpha_\tau \, \mathbb{1}(i \in \text{flat}, t(i) = \tau) + \gamma_{t(i)} + \rho(i) + \varepsilon_i \tag{7}$$

where i indexes each rental listing; $\gamma_{t(i)}$ is an indicator for quarter-year $t(i)$ for listing i; $\rho(i)$ is a fixed effect for property i; and α_τ is the difference-in-differences coefficient for quarter-year τ. Notice that a flat indicator which would be included in a traditional difference-in-differences specification is excluded here since it is absorbed by the property fixed effect. Figure 11 plots estimates of α_τ and its confidence intervals.

There are two patterns worth noting. First, Figure 11 shows that rents did not adjust immediately following the physical event in 2017Q2. In contrast, our preceding analysis shows that prices responded immediately (see Figure 4). This evidence allows us to rule out the possibility that the decrease in prices immediately following the physical event was due to a drop in the willingness to reside in flats arising either due to changes in the perceived quality or risk associated with residing in flats. Second, Figure 11 shows that rents of affected properties adjusted sharply upwards in response to the central guidance by an annualized rate of ∼2%. In comparison, the growth of flat prices in London appear to not have dropped sharply following central guidance (see Figure 4)

.

Interpreting the evidence: user-cost model. We use the standard user-cost model of home-ownership (see e.g., Poterba, 1984) to interpret these patterns. It provides a simple framework to understand the joint dynamics of prices and rents. Under standard assumptions of perfect competition, the user-cost model implies that the price of owning a property today p_t is a function of the rent that the owner would otherwise pay to reside in the same property r_t, various user-costs that the owner must incur this period c_t, and the discounted expected price of the property tomorrow were the owner to sell it p_{t+1}:[37]

$$p_t = r_t - c_t + \beta\, \mathbb{E}[p_{t+1}] \tag{8}$$

We can interpret this model from the perspective of an investor buying a flat to let it at the two moments of the event:

1. Physical event. Following this first event, rents r_t for flats did not fall (Figure 11), which suggests that the willingness-to-pay to reside in flats did not decrease. The user-cost model then implies that the drop in prices must have either been due to an increase in user-costs c_t or due to a decrease in the expected future price p_{t+1} of flats. While we cannot separately identify the changes in user costs and price expectations, anecdotal evidence suggests that user-costs did not increase immediately following the physical shock since it took more than a year for central guidance to be released which resulted in increases in insurance, maintenance, and repair costs. This leads us to conclude that the drop in prices for flats immediately following the physical event is

[37] In a perfectly competitive market, there is zero profits associated with home ownership. To see why the expression in Equation 8 follows from the assumption of perfect competition, simply define the profits of owning a home this period and selling it next period as π and set it to zero:

$$\pi = -p_t + r_t - c_t + \beta\, \mathbb{E}[p_{t+1}]$$

likely to have been generated by changes in the expected future prices of flats.

2. Central guidance. A different pattern emerges in the period following the central guidance. Figure 11 shows that the relative rents r_t for flats increase rapidly following the guidance at an annualized rate of $\sim 2\%$. This abrupt increase in rents is not accompanied by any abrupt drop in flat prices in London (see Figure 4). Instead it coincides with reported increases in costs associated with the insurance, maintenance, and repair of flats induced by the central guidance. We take it as evidence suggesting that landlords passed on increases in user costs induced by the central guidance to renters by increasing rents.

6 Conclusion

In this paper, we study complementary responses in the mortgage, property and rental markets to an adverse and salient shock to the residential properties in England & Wales. We leverage detailed administrative data on the universe of all residential mortgage and property transactions complemented with property-level data on rents in England & Wales. Our paper offers a more nuanced perspective to the idea of credit being a "financial accelerator" (Bernanke et al., 1996). Whilst we document a decline in property prices and mortgage lending which is most pronounced for information opaque borrowers, our results also uncover a crucial role of cash-buyers and lender heterogeneity in mitigating the effect of the shock.

Beyond these immediate results, our paper offers an analytical approach for financial stability policymakers to study other, related shocks including those from climate risks. Moreover, it showcases a methodological approach on how these transmission channels can be quantified using available data. By doing so, our paper demonstrates how one can leverage multiple data sources to estimate the effects of shocks to properties. By documenting the appeal but also limitations of the data and methodology we employ, our paper highlights the necessity of collecting data at an appropriate level of granularity to study such effects.

Our paper opens several avenues for future research. First, our set-up allows us to demonstrate the dynamics of both in the property and mortgage markets. But we do not seek to establish whether the property market leads the mortgage market, or if the mortgage market drives the property market. Future research can explore the exact dynamics between these two markets.

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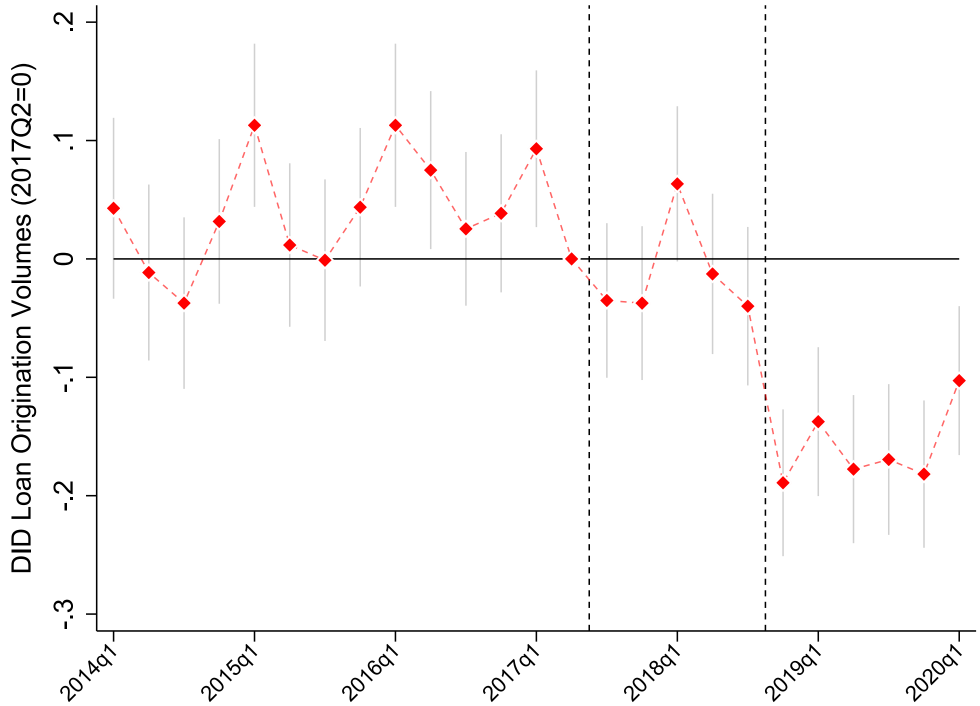
A Appendix

Table 1: Summary statistics of key variables in our data sets

	Mean	Median	St.Dev.
Mortgage transactions (PSD)			
Price £	295,002	235,000	373,310
First time buyer	0.477	0	0.499
Home mover	0.523	1	0.499
Number of rooms	3.07	3	3.88
Number of transactions	3,114,559		
Property transactions (PPD)			
Price £	289,947	225,000	317,890
Number of transactions	4,639,365		
Rental listings (Zoopla)			
Rent	467	375	340.15
Number of observations	4,470,104		

Note: This table presents summary statistics for the three datasets used in the analysis. The statistics for PPD and PSD are based on data for England & Wales between 2015 and 2020. The statistics for Zoopla is based on data for listings in London.

Figure 12: Flat vs. non-Flat Difference in Log Number of Originations in England & Wales



Note: This figure presents difference-in-difference estimates from a Poisson regression. The plot reports the quarterly difference in mean log number of flats and non-flats along with the 95% confidence interval estimated from a normal distribution. All estimates are relative to 2017Q2. The figure uses vertical dashed lines to mark two events: the leftmost vertical dashed line represents the period of the physical event whereas the rightmost vertical dashed line represents the central guidance.