How much of the housing price increase during the Covid pandemic was driven by a change in household preferences?

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Executive summary

The Covid-19 (Covid) pandemic, and measures put in place to contain it, brought about an unprecedented contraction in economic activity. Despite this, housing prices in a range of advanced economies continued to grow throughout the pandemic, and housing price growth in the UK reached its highest rate in over a decade. The absence of a contraction in housing prices can in part be explained by measures put in place to support the broader economy, including a loosening of the monetary policy environment and fiscal measures such as the Coronavirus Job Retention Scheme. The market was also directly supported by the temporary reduction in Stamp Duty Land Tax (SDLT).

But standard macroeconomic factors are not sufficient to explain the full extent of the increase in housing prices observed during the pandemic. Alongside these macro factors, there have been some indications that household preferences for different types of housing and locations changed during the pandemic. This may have taken place if, for example, households were more willing and able to work from home. In this paper, we aim to quantify the extent to which changes in household preferences contributed to housing price growth during the pandemic.

We built a version of the Office for National Statistics (ONS)/HM Land Registry (HMLR) house price index using price paid data on each residential property transaction that took place in England and Wales between 2010 and end-2021. We combined this with information on the characteristics of the properties from their Energy Performance Certificates, and with ONS information on the local area each property is located in. We then investigate changes in buying habits, alongside changes in households' willingness to pay for houses relative to flats, and for properties outside of the Greater London area.

[1] The authors would like to thank Mai Daher who was involved in an early stage of this analysis. Additionally we would like to thank Sarah Venables, Matt Waldron, Sevim Kösem, Alexandra Varadi, and Renée Horrell for their comments and suggestions in preparing this paper.

Our analysis suggests that just under 50% of the total growth in housing prices observed since the start of the pandemic can be explained by shifts in household preferences, especially around property type and location. However, the impact of these factors varied over the course of the pandemic. For example, while households placed consistently more value on houses compared to flats, the effect of changes in valuation across areas of the UK – in particular London compared to less densely populated areas – was more short-lived.

The paper allows policymakers to consider how preferences for housing could affect demand and prices, alongside more traditional macroeconomic factors. However, this paper does not seek to account for all of the factors at play during the pandemic and so cannot disentangle other Covid-related factors such as the temporary changes to SDLT from a shift in preferences. Future work could explore changes in preferences in more detail by accounting for additional characteristics that households may value, such as the size of the garden attached to a property.

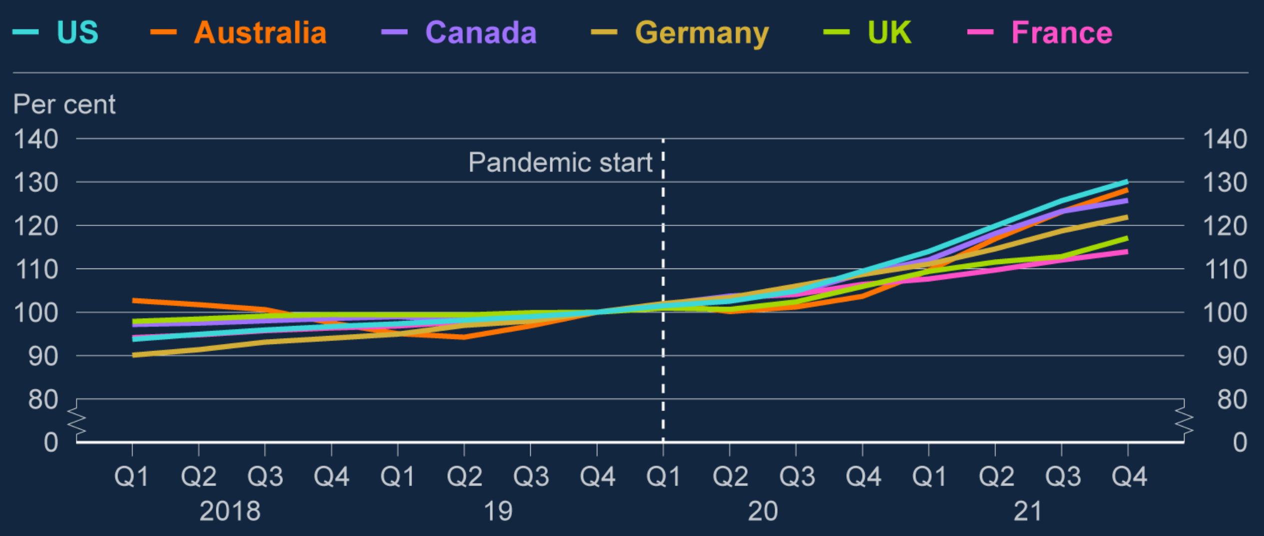
1: Introduction

Unlike in most recessions, housing prices broadly continued growing over the course of the Covid pandemic.

The Covid pandemic, and the measures put in place to contain it, brought about an unprecedented contraction in economic activity. Historically, pandemic episodes have been associated with reductions in housing prices, but during the Covid pandemic housing prices largely continued growing in a range of advanced economies (Chart 1).[2, 3] In the case of the UK, prices grew at their highest rate in over a decade.

Chart 1: Housing prices grew rapidly across a range of advanced economies from March 2020

Growth in housing prices across a range of advanced economies



Sources: Organisation for Economic Co-operation and Development and Bank calculations.

Rapid increases in housing prices are often associated with excessive build-ups of mortgage debt, which has historically been an important source of risk to both the UK financial system and broader economy (December 2021 Financial Stability Report). This is particularly true when housing price increases are driven by speculative activity, often indicated by an increase in riskier lending and activity in buy-to-let markets. Therefore, understanding the

2 Francke and Korevaar (2021) for the impact of pandemic episodes on housing prices historically.

3 Typically 'house prices' refers to prices of all residential properties, including houses and flats. As this paper specifically focuses on the difference in prices of houses and flats, we have used 'housing prices' to refer to prices of all types of property, and used 'house' or 'flat prices' when referring to either types of property.

drivers of a period of strong growth in housing prices can help determine whether risks to financial stability have grown alongside it.

The measures put in place by the authorities, which helped sustain demand, and the relatively short-lived shock to housing supply may have supported housing prices.

At the onset of the pandemic, strict public health measures briefly brought housing markets across the globe to a halt. On the supply side, construction of new-build homes stopped as building sites shut down, and the supply of ancillary services to the housing market, such as valuation surveys and house viewings, also came to a halt. But the shock to housing supply was relatively short-lived. For example, according to **ONS statistics**, completion of new build homes in 2020 Q2 dropped to around half the 2019 level, but by 2020 Q3 it had largely recovered. More broadly, throughout the remainder of the pandemic, housing markets were able to reopen and function normally, in spite of periodic reimposition of more stringent restrictions.

On the demand side, the initial stage of the pandemic brought expectations of a reduction in housing demand, given increased uncertainty, reductions in income and a tightening in credit supply. In the early stages of the pandemic lenders withdrew a lot of mortgage products from the market, and accessing a mortgage became more difficult. But this trend was also short-lived, as by the end of 2020 the number of mortgage products available had tripled compared to the low levels seen early on in the pandemic.

And unprecedented interventions from the authorities helped to alleviate the decrease in income. Across developed nations, packages of government support, such as the Coronavirus Job Retention Scheme in the UK, were introduced to support household incomes. Additionally, government-sponsored initiatives to offer mortgage payment holidays also helped families reduce their outgoings, while maintaining consumption in other areas. There is evidence that households with healthier balance sheets also availed themselves of this type of measure, allowing them to increase their savings.[4] More generally, 'forced' savings due to more limited opportunities for recreational spending is also likely to have played a role in sustaining demand for housing, especially for the wealthiest households.[5]

Authorities across the globe also intervened by loosening monetary policy, which likely contributed to supporting housing demand. For example in the UK, the Monetary Policy Committee (MPC) reduced Bank Rate from 0.75% to 0.1% in March 2020. Although the pass-through from policy rates to mortgage rates was only partial and not uniform across all mortgage products, the loosening likely helped keep mortgage rates lower than they may otherwise have been, especially at lower loan to value ratios (LTVs).[6] From 2020 Q1 to

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4 **Albuquerque and Varadi (2022)** for UK evidence.
5 For the UK, see **Franklin et al (2021)**.
6 See **Fuster et al (2021)** for evidence in the US, and the **December 2020 Financial Stability Report** for UK evidence.

2021 Q4 the MPC also nearly doubled gilt holdings in the Asset Purchase Facility. The loosening in monetary policy resulted in lower long-run interest rates, with 10-year gilt yields decreasing from an average of around 0.70% in January 2020 to a low of around just under 0.13% in August 2020, only recovering in mid-2021. The initial drop in long-run interest rates may have signalled a decrease in discount rates, helping to support housing prices.[7]

Demand for housing in the UK also received support from the temporarily reduced rates of SDLT. This meant the first £500,000 'slice' of housing transactions was moved into the nil tax bracket, in effect exempting transactions of £500,000 or less from SDLT (the 'SDLT exemption').

> **Standard macroeconomic factors are insufficient to explain the growth during the pandemic, pointing to a change in consumers' preferences for housing.**

Low interest rates are often considered a key driver of fast housing price increases.[8] But **Zhao (2020)** finds that the response of housing demand to lower mortgage rates in the US during the Covid crisis has exceeded that of any previous crisis, consistent with a fundamental change in household behaviour during the pandemic. And **Duca et al (2021)**, point out that economic factors alone are not sufficient to explain European and US housing price increases during Covid, therefore indicating behavioural factors as a potentially important contributor.

There is also little evidence that strong housing price growth in the UK can be attributed to supply-side factors, which in general tend to be country and location specific.[9] In the UK, new builds are a small fraction of the housing stock (**Barker (2004)**), and supply has been historically relatively irresponsive to price dynamics (**Hilber and Vermeulen (2016)**). This suggests that the temporary disruption to housing supply is unlikely to have played a large role in driving UK housing price increases during the pandemic.

Alongside the role of policy interventions in preventing a collapse in the demand for housing, the pandemic may have also resulted in a shift in household preferences for housing in general, as well as for housing with certain characteristics. In the US, evidence emerged of housing demand shifting to less densely populated areas, with housing prices and rents declining in city centres and increasing away from city centres.[10] Working from home has been indicated as an important contributor to this phenomenon.[11] And individuals who work

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[7] **Cochrane (2000)** postulates how asset prices (among which are housing prices) are negatively related to discount rates, as they should correspond to the sum of the expected discounted flows of service they provide.

[8] **Duca et al (2021)** for a comprehensive review of the role of interest rates, incomes and other macroeconomic factors in driving house price cycle. **Miles and Monro (2021)** for evidence in the UK, **Duca et al (2011)** and **Garriga et al (2019)** for US evidence.

[9] See **Glaeser et al (2008)** on the role of different supply elasticities across locations in determining house prices dynamics and sustainability.

[10] **Liu and Su (2021)** and **Gupta et al (2021)**.

[11] See **Ramani and Bloom (2021)** and **Mondragon and Wieland (2022)**.

remotely have a higher share of housing consumption in total expenditure.[12] Others highlighted the shift in importance of both social and professional networks over the pandemic when choosing the neighbourhood to live in.[13]

Beside evidence from the literature, Bank Agency intelligence as well as the popular media have also noted the emergence of a 'race for space'. This suggests an increased preference for larger properties, and for houses over flats in areas further away from city centres.[14]

This paper focuses on changes in willingness to pay for certain property attributes and a shift in buying habits to explain housing price growth during the pandemic.

In this paper, we look at the role of changes in buying habits and willingness to pay for different housing characteristics in explaining strength in housing price growth during the pandemic. We adopt a 'hedonic regression' approach, a technique that allows to decompose the price of a complex good, such as housing, into the value consumers place on specific tangible characteristics.

These methods were first pioneered by **Rosen (1974)** and then refined by **Bartik (1987)**. The simple model we provide to interpret our estimates, set out in **Box A**, represents a special case in which hedonic regressions can precisely recover preferences.[15] But this may not be possible under more general assumptions.

We focus on pandemic-specific drivers of housing price growth related to changes in demand for housing. As a result, our model embodies an assumption that housing supply remains irresponsive to changes in price. We think that this framework is a reasonable approximation of the UK housing market, given the irresponsiveness of the supply of new housing to price changes, especially in the short run.[16] We note that the cyclicality of housing price movements could have been dampened by other factors related to the existing housing stock, which are outside the scope of this work, such as sellers anchoring their asking price to what they paid when they purchased their house.[17]

The rest of the paper is organised as follows. As a prelude to the analysis, Section 2 explores historical patterns of housing prices across different housing types and locations in the UK, with a focus on recent trends since the pandemic. Section 3 discusses the scope of our analysis, how it can be linked to a simple model of preferences, and the econometric

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12 **Stanton and Tiwari (2021)** estimate the cost of remote work using pre-pandemic data.

13 **Ferreira and Wong (2022)**.

14 The Guardian '**Race for space fuelling busiest UK housing market since 2007**', '**House prices shoot up in UK towns as 'race for space' continues apace**'.

15 **Feenstra (1995)**.

16 See the Barker Review (2004) in relation to housing supply inflexibility in the UK.

17 **Bracke and Tenreyro (2016)** and **Duca et al (2021)**.

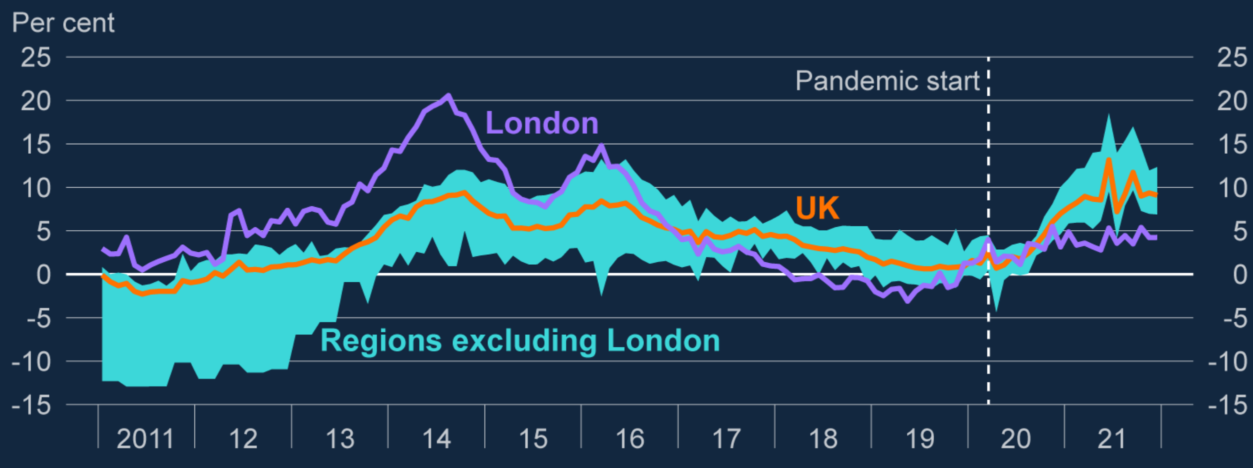
framework used. Section 4 presents our key results and the potential for future work. We discuss some policy implications and draw conclusions in Section 5.

2: UK housing market trends and how they have changed since March 2020

During the pandemic, housing price growth reached its highest rate in over a decade. As noted in Section 1, housing price growth accelerated across advanced economies during the Covid pandemic. Up to the end of 2021, annual housing price inflation peaked at 13.2% in the UK, its highest level in over a decade (Chart 2). The rapid growth since March 2020 was accompanied by an increase in the volatility of growth rates, particularly between July and September 2021. This coincided with the Stamp Duty Land Tax exemption tapering.[18] But growth remained strong even after the tapering, with housing prices in 2021 H2 growing at an annual rate of 9.3% on average, faster than any H2 period since 2006.

However, there was considerable variation across regions. This is most pronounced when looking at London compared to the rest of the UK. For a large part of the decade prior to the pandemic, housing price growth was faster in London than in any other region of the UK. But the rate of housing price growth in London increased only moderately during the pandemic, while growth in other areas of the UK was significantly stronger.

Chart 2: Housing price growth accelerated during the pandemic, but growth in London lagged behind other areas of the UK
Year-on-year housing price growth rates in London and other UK regions



Sources: ONS and Bank calculations.

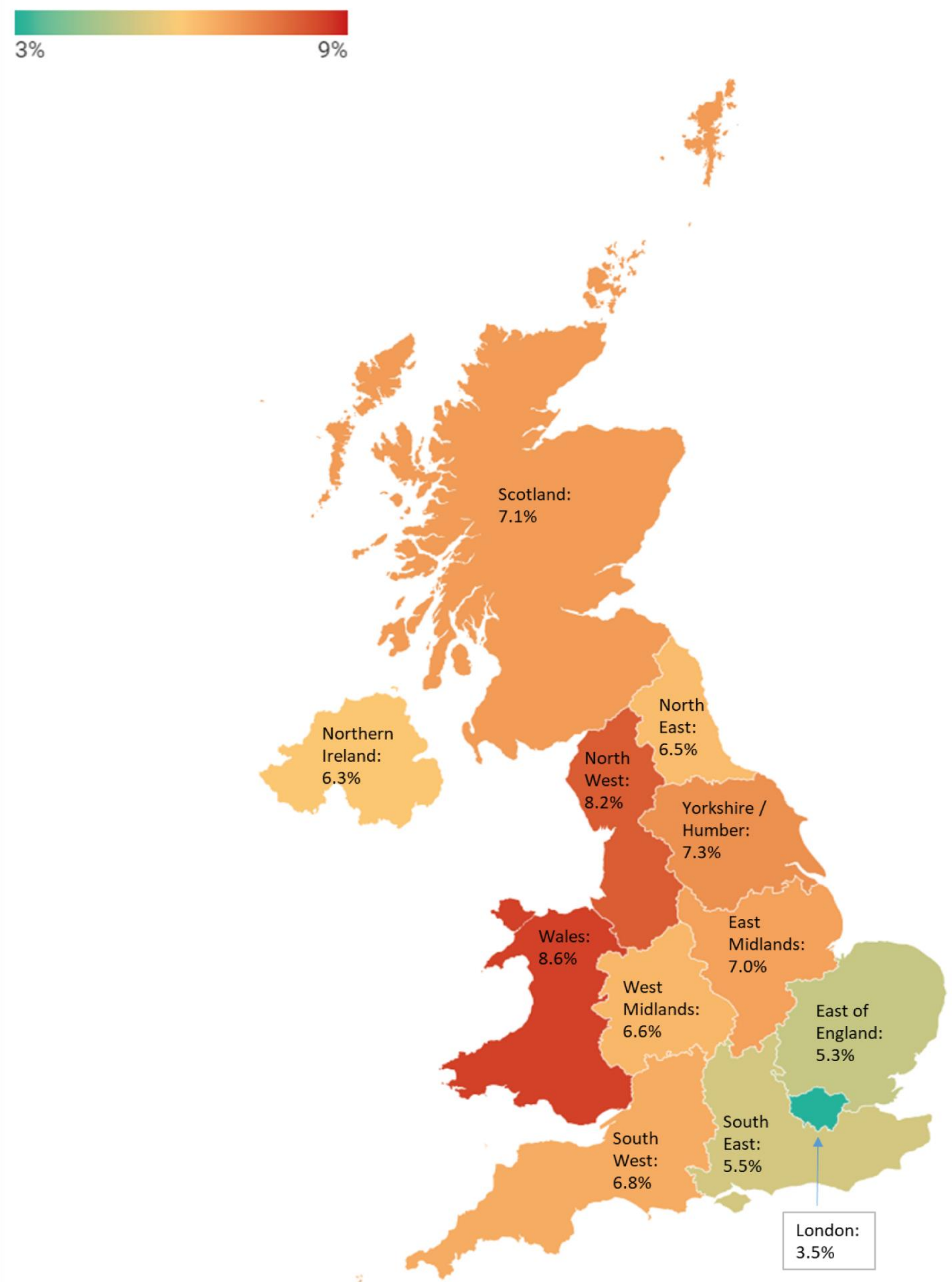
[18] Similar although not identical policies were also introduced in Wales and Scotland and the same regulation for England also applied in Northern Ireland.

Some regions of the UK saw unusually strong housing price growth.

From March 2020 to December 2021, housing prices grew the quickest in more northern regions of England, as well as across Wales and Scotland. For example, across Wales and in the North West of England, housing prices grew at an average annual rate of 8.6% and 8.2% respectively, compared to 3.5% in London (Figure 1).

Figure 1: From the start of the pandemic to the end of 2021, housing prices grew more rapidly in the North and West than in the South and London

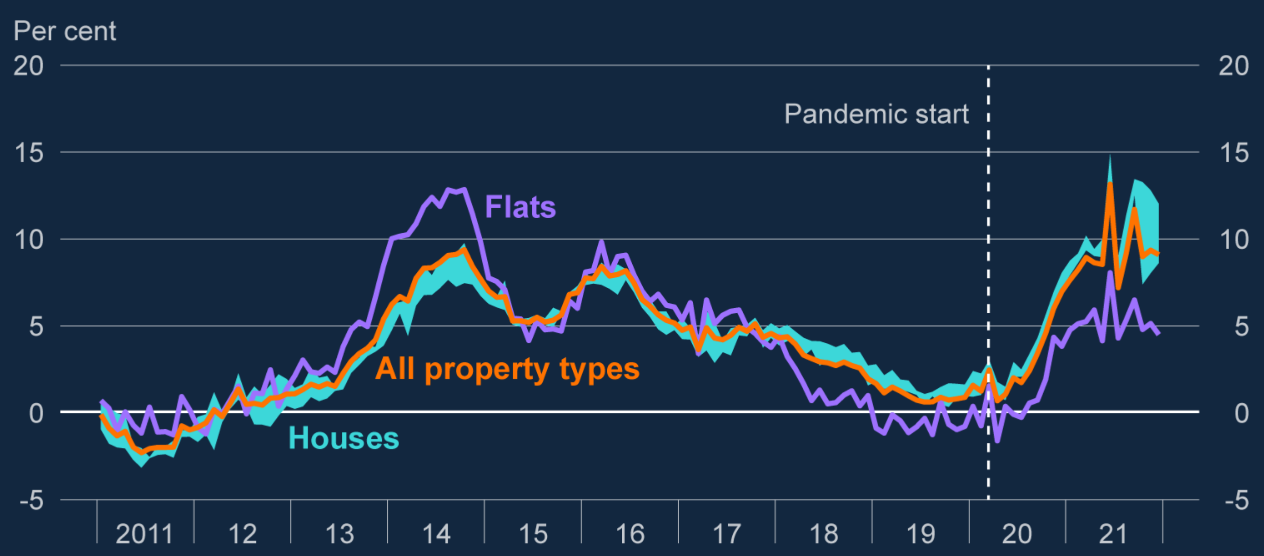
Average 12-month housing price growth from March 2020 to December 2021



Sources: ONS and Bank calculations.

Prices of houses grew more quickly than prices of flats over this period.
The pandemic also saw a widening gap between the growth in prices of flats compared to other types of property, reversing trends seen after the global financial crisis (GFC). On average the price of flats and houses grew by around 3.9% and 3.4% respectively per year since the end of the GFC. But the relatively similarity of the two masks a high degree of volatility in flat price growth, while house price growth was relatively more stable (Chart 3). In particular, strong flat price growth in the early 2010s slowed and partially reversed between 2019 and 2020, and then decreased by 0.8% in the year to December 2019.

Chart 3: Growth in flat prices has been somewhat more volatile than in houses, but both have grown at a similar rate on average
Year-on-year price growth rates in flats and houses across the UK



Sources: ONS and Bank calculations.

Growth rates for both houses and flats increased after March 2020. Between March 2020 and December 2021 the average 12-month growth rate for flats was 3.4%. Growth rates in house prices increased even more sharply than for flats, rising from 1.2% in December 2019 to 7.3% annually on average since March 2020. This pattern of slower price growth for flats than houses over the pandemic holds across all UK regions, and it is therefore independent from the regional trend illustrated above.

3: Scope and framework for our analysis of the effect of changes in household preferences

Our analysis focuses on how household preferences for housing characteristics changed during the pandemic.

The changes in the UK housing market trends set out in Section 2 are consistent with a shift in household preferences having affected housing prices. To test this hypothesis, we use the HMLR Price Paid data set, covering all housing transactions that took place in England and Wales, to estimate the value attached to individual housing characteristics.[19] We then use this information to create a housing price index and decompose it into different key factors that may have contributed to the increase observed during the pandemic. In Box A we show that under certain assumptions, the observed changes in households' willingness to pay for certain property characteristics can be attributed to a shift in consumer preferences during the pandemic.

Our analysis focuses exclusively on the link between changes in preferences and housing price growth, but it is possible that some other contributors may have had similar effects on the housing market as those we found in our analysis.

First, the temporary SDLT exemption – alongside its counterparts in the devolved UK nations – allowed households to save on the cost of purchasing a property, and is likely to have influenced the pattern and timing of housing price growth observed. However, the rate of growth of housing prices remained elevated even after the withdrawal of this policy, which suggests that other more persistent factors played an important role.

Second, the increase in savings observed during the pandemic may have been channelled towards the housing market, enabling an increased demand for housing. While detailed data on the use of accumulated savings is lacking, we note this could also be a contributing factor to the strength in housing price growth over the course of the pandemic, perhaps facilitating the observed shift in buying habits.

To analyse the link between changes in consumer preferences and housing price growth, we followed the ONS's methodology for producing the house price index (HPI).

The ONS and HMLR **HPI** is a key indicator of how housing prices change over time in the UK. The series is monitored by the Financial Policy Committee when considering how risks to UK financial stability from the housing market are evolving.[20] HPIs are produced at an

[19] Similar data covering Northern Ireland and Scotland were not available to us.
[20] See the **December 2021 Financial Stability Report** for an example of this.

aggregate level for the UK, as well as for each of the constituent nations of the UK, and down to each individual Local Authority District (LAD).

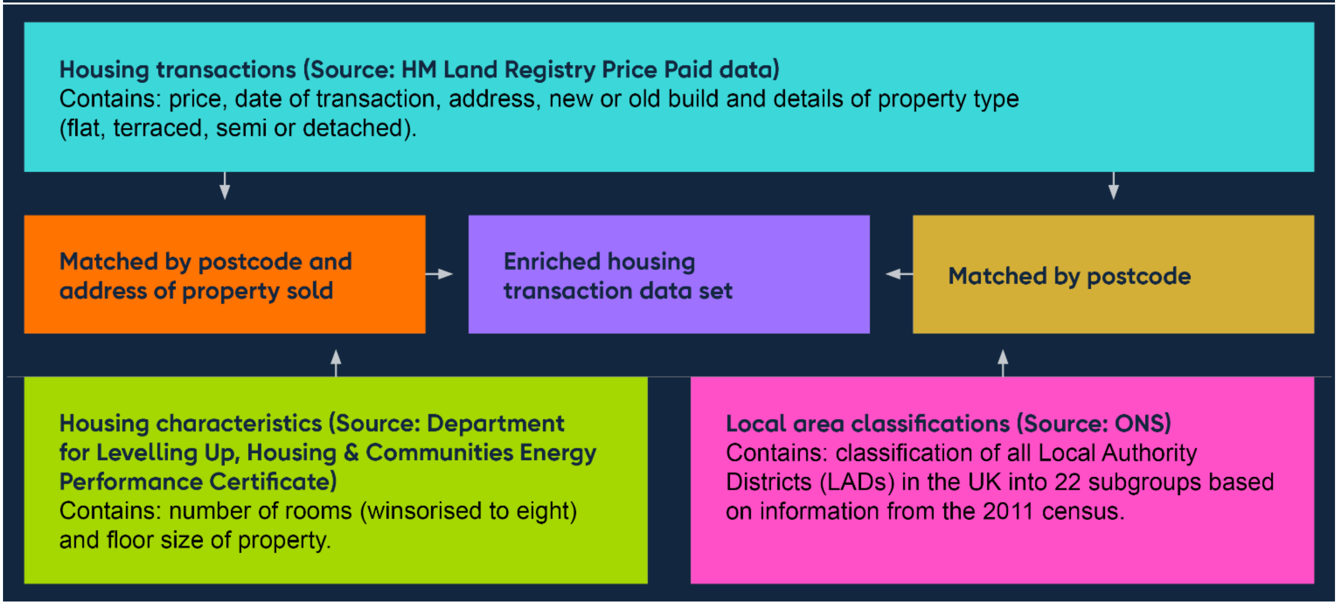
To understand how changes in preferences may have influenced increases in housing price growth during the pandemic, we followed the HMLR and ONS's **methodology** to produce the HPI. This allowed us to reproduce our own version of the index, decompose it into constituent parts, and track the key factors behind its recent trends. Due to the heterogeneity of the housing stock, it is crucial to distinguish between actual price movements, and changes in the characteristics of properties sold over time, as the latter do not reflect genuine price shifts. The HPI does so through its mix adjustment, which corrects for the impact of differences in the quality of properties being purchased.[21] The mix-adjustment is updated yearly, to ensure that the index remains representative of housing sales over time.

We created a data set of each housing transaction in England and Wales, together with information on location and characteristics of each property.

Our analysis was based on a data set combining transaction level data from the HMLR **Price Paid** data set. We enriched this with data from the Department for Levelling Up, Housing & Communities (DLUHC) on the **Energy Performance Certificates** (EPCs) for each property transacted, as well as with ONS information on the **characteristics of the LAD** where each property was sold in. A graphical representation of our approach to merging the data, and the information we utilise from each of the source is shown in Figure 2.

Figure 2: Our analysis matches HMLR transaction-level price paid data with two other sources

Data sources for our analysis and information taken from each



[21] See Section 3.4.1 of '**Official House Prices Explained**' for a worked example of the need for mix-adjustment.

After cleaning the data, our data set comprises more than 8.7 million residential property transactions from January 2010 to December 2021, around 60,000 per month on average. We observe a large degree of variability in the variables in our data set. For example, the average price paid for a property has increased from less than £230,000 in 2011 to around £340,000 in 2021 but prices vary significantly even within the same year across regions and property types.

To append characteristics on each property sold, we match the Price Paid and EPC data based on the address and postcode of each property. Our matching approach has a success rate of just under 90% on average, but with some variation. In particular, the matching rate drops to around 75% in June 2021 before partially recovering from September 2021 onwards. More details on the uneven matching rate over time, which could have an effect on the reliability of our estimates, can be found in **Box B**.

In line with the ONS, we carry out 'hedonic regressions' to estimate the marginal contribution of housing characteristics to housing prices.

Following the ONS, we adopted a 'hedonic regression' approach when calculating how households' valuation of different housing characteristics could influence the price they are willing to pay. This approach is typically used to break down the price of a complex good into the value consumers place on its tangible characteristics.

In determining the price households are willing to pay for a property, they may attach value to whether a property is a flat, terraced, or detached house, to the floor size that a property offers and the number of rooms a property has. Households may also place value on the area a property is located in and its characteristics, such as crime rates and local amenities. While each of these characteristics will play a role in determining the price a household is willing to pay for a given property, they typically cannot be valued in isolation. In Box A we show how such a hedonic regression can be linked to households' preferences for different housing characteristics.

To examine the contribution of various housing characteristics to the prices households pay, and how these have changed over time, we split our data set into monthly observations. For each month we regress the natural logarithm of prices paid against a set of variables of interest.

Specifically, we look at the contribution of the following characteristics:

- the type of property – whether a flat or a detached, semi-detached or terraced house;
- the number of rooms, where houses with eight or more rooms are grouped together;
- the size of the floor area of the property in square meters;
- whether the property is a new or an old building;
- the region the property is located in; and

- a qualitative **classification** of the LAD that the property is located in, comprising 21 subgroups, based on information from the UK 2011 census.

This leads to the following set of regressions:

$$\ln P_t^k = \beta_{0t} + \beta_{1t}Prop.type^k + \beta_{2t}Room.no^k + \beta_{3t}Floor.size^k + \beta_{4t}New.build_t^k + \beta_{5t}Region^k + \beta_{6t}LAD.classification^k + \epsilon_t^k$$

Where *k* represents an individual property in our sample, *t* represents the month, and β_{nt} with *n = 1,…,6* represents the set of households' marginal valuations for the characteristics considered in a particular month.

In practice, there are other characteristics that could affect the price households are willing to pay for a property, such as its age and condition. Following the ONS's approach, we do not account for these, and with the exception of new build status, we also do not track changes in the characteristics of properties sold more than once in our data set, such as modifications to a property that could increase floor space or number of rooms.

In line with the ONS's methodology, we do not include interaction terms in our regressions, but we recognise they may be important for understanding changes in household preferences. As an example, households' valuation of new buildings may vary across locations, but because we do not interact new build status with regions, we can only observe the average effect in England and Wales. We also do not include any information relating to buyers' characteristics, largely due to the lack of available data that tracks households over time. But we note that this type of data would provide useful information about preference changes across different households.[22]

As a sensitivity check, we perform alternative estimations replacing the LAD classification with a set of variables capturing information on the area where a property is located, such as average income, average size of gardens and population density etc. Our estimates do not appear to change substantially using this alternative approach, and so for simplicity, we adopt the specification with LAD characteristics as our main regression.

The coefficients we estimate show households' valuation of housing characteristics relative to an old build, one-bed flat in London.

With the exception of floor size, all our regressors are categorical variables, which can be represented with a series of dummies, taking on values of 0 or 1 depending on whether a property belongs to a certain category, such as whether it is a terraced, semi-detached, or detached house.

22 See Rosen's second stage approach and more recent papers using the same idea combined with modern identification techniques, for example **Bishop and Murphy (2019)**.

To avoid perfect multicollinearity in our estimation, we keep the intercept but remove one category for every qualitative variable. In our setting, the intercept represents an old-build one-room flat in London in an area with LAD classification ‘London Cosmopolitan’. Following the ONS’s approach to producing a non-seasonally adjusted index, we choose not to seasonally adjust the dependent variable. This implies that the intercept will also capture seasonality in the housing market, which has a big impact on price fluctuations.[23] Likewise, the impact of seasonality may differ across regions, and this will be captured by the coefficients on the regional dummies.

The estimated coefficients for all the regressors need to be interpreted in relation to the property encapsulated in the intercept. For example, the coefficient on a three-room dummy captures the extra willingness to pay for two additional rooms, while a detached house dummy measures the added value of that property type, on top of the value of a flat.

We used our estimations to produce an index of prices for an ‘average’ house in line with the ONS and HMLR’s methodology.

In line with the ONS and HMLR’s methodology, we use the estimated coefficients from the monthly regressions to fit prices paid and construct an average price for each month. To create this average price, we use weights that reflect the proportion of properties that were transacted in the previous year with a given combination of housing characteristics in our model. This ensures that temporary changes in the quality and types of houses sold does not affect our estimates.

For example, if the share of detached houses sold in January 2018 increases, this will not affect average prices in that month. However, if the trend continues throughout 2018, then the predicted prices for detached houses receive more weighting in the index throughout 2019.

We then use the series of average prices to create a house price index for all properties sold in England and Wales. In line with the ONS, our index uses January 2015 as the reference period.[24]

Despite some volatility in our model, our predicted index and growth rates broadly track trends in the ONS’s HPI.

Using this methodology we have predicted the HPI for properties sold in England and Wales from the start of 2011 to December 2021. Both the HPI and associated year-on-year growth rates produced by our analysis appears to track the broad trends in the HPI produced by the

[23] See **Ngai and Tenreyro (2014)**.

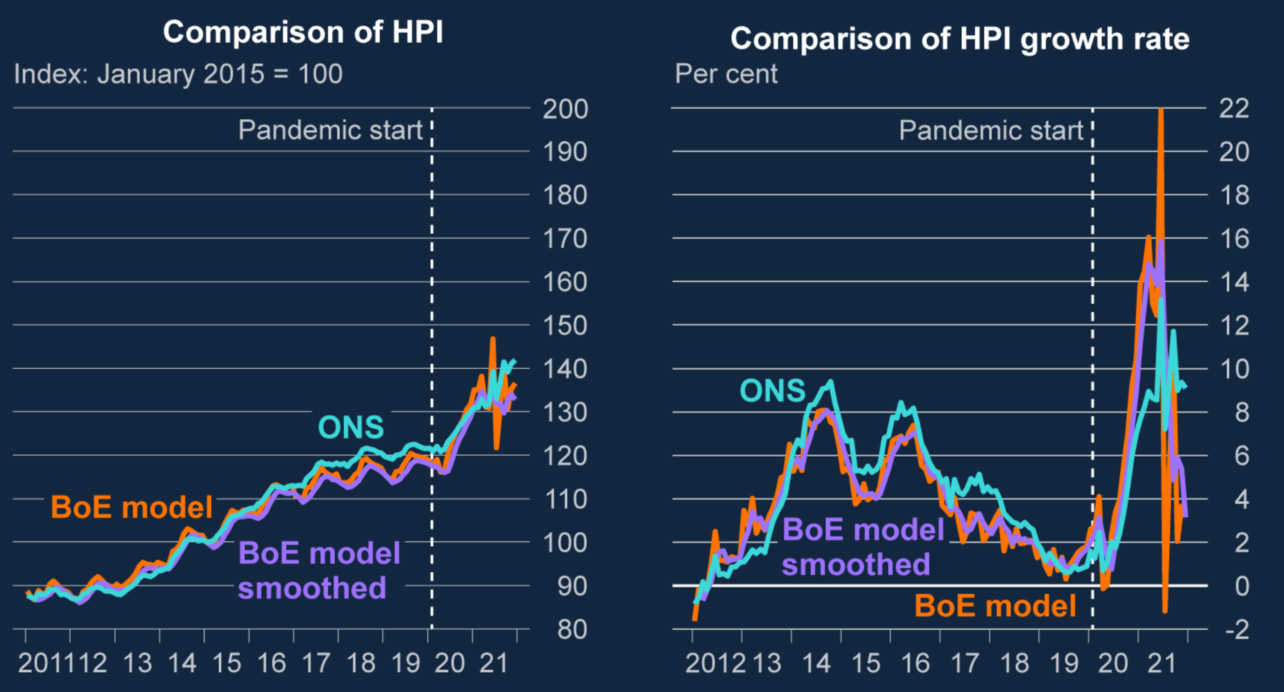
[24] Generally, the ONS updates this reference period every five years, and the whole index needs to be chain-linked accordingly after the update. However, they have not done this for 2020.

ONS. Our index mildly overestimates the ONS HPI from 2012 to 2015 and underestimates it between 2017 and 2020.

The index also displays excess volatility, especially from early 2020 onwards and with a particular spike in volatility around June and September 2021. This could reflect a range of factors, including the SDLT exemption tapering, which we do not include in our model, and the reduction in matching rates we observe around this period. Despite this volatility, our model does show that housing price growth accelerated during the pandemic, and it largely captures fluctuations in growth rates (Chart 4).

Chart 4: The HPI and growth rates produced by our model broadly track those produced by the ONS

HPI and growth rates produced by our analysis compared to the ONS series



Sources: Department for Levelling Up, Housing & Communities, HM Land Registry, ONS and Bank calculations.

To account for the excess volatility of our estimated index, we take a three-month moving average of the index and compute growth rates from this smoothed index (purple line in Chart 5). This helps reduce the most severe swings in housing price growth and brings our results more in line with the ONS's HPI.

4: Assessing the link between changes in preferences and the recent housing price growth

We found evidence that households' valuations of properties other than flats and, to a lesser extent, properties outside of London increased during the pandemic.

To decide which factors appeared important for the growth of housing prices during the pandemic, we looked at the trends displayed by our estimated coefficients. We observed a clear upward trend for the coefficients on properties other than flats, and for properties in areas outside London, although with more volatility. In particular, some regions display an upward trend since 2016 which continues during the pandemic and reverses somewhat in the second part of 2021. We did not observe clear trends around the Covid period in the coefficients on other characteristics such as additional square meters of floor space and extra rooms. The confidence intervals for these latter estimates were significantly wider, suggesting more uncertainty on their actual values. A time series of three-month averages for some of the estimated coefficients and confidence intervals are reported in Box B, alongside a summary table of the average coefficients before and during the pandemic.

Our analysis suggests that changes in household preferences were associated with just under 50% of the housing price growth from the start of the pandemic to December 2021.

To determine the link between changing housing preferences and the strength in housing price growth over the course of the pandemic, we focused on three separate drivers.

- First, we accounted for changes in the types of properties households bought. As set out above, if households persistently shift towards buying properties with more expensive characteristics (for example detached houses instead of flats), then the prices of those properties will have more weighting in the index over time. We control for this by fixing the weights for different property characteristics to reflect purchasing patterns in 2019 when calculating the index.
- Second, consistent with a shift in preferences towards certain property types, households may have increased their marginal valuation of houses over flats after the pandemic began. We control for this effect holding constant the value consumers placed on property types other than flats at their end-2019 level.
- Finally, households may have increased the value they place on properties across different regions of the UK, particularly for properties in less densely-populated areas outside London. Similarly to the above, this could increase the price households are willing to pay for properties in certain areas and therefore increase the overall house price index. We control for this by holding constant households' relative valuation of

properties in different areas of the UK, using London as a baseline, at their end-2019 level.

The value attached to the reference property, represented by the intercept in the regression, remains stable during the pandemic period (Chart F in Box B). This implies that any relative increase in the marginal contribution of characteristics we control for is not counteracted by a corresponding fall in the value of the reference property.

Overall, we find average housing price growth would have been 49% lower between the start of the pandemic and the end of 2021 in the absence of these changes (Table A).

Table A: Our model suggests that shifts in households' preferences were linked to just under 50% of housing price growth between 2020 and 2021

Average 12-month growth rates and the contribution of individual factors

	Total accounted for by changes in preferences	Of which due to the mix of properties bought	Of which due to increased premium for houses over flats	Of which due to changes in valuations across regions
Housing price growth explained between January 2020 and December 2021	49%	12%	38%	-1%

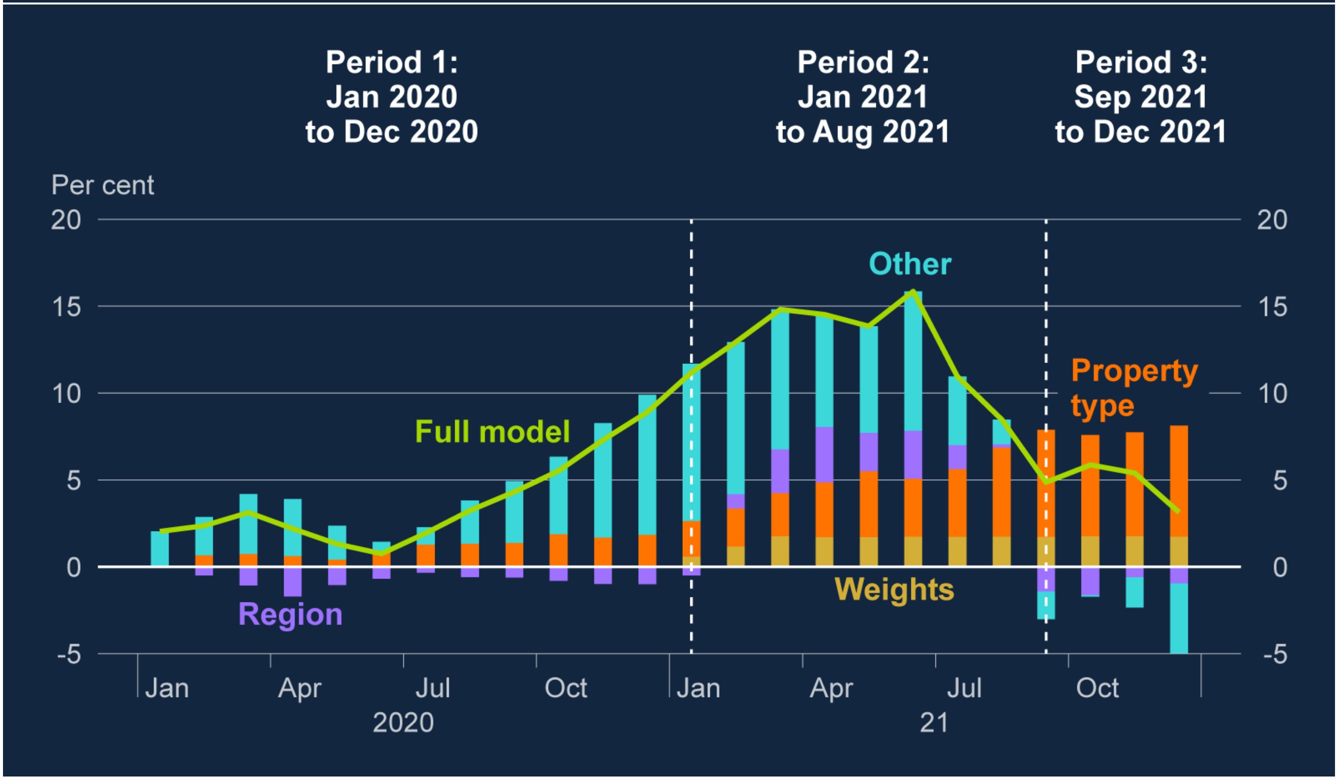
Sources: Department for Levelling Up, Housing & Communities, HM Land Registry, ONS and Bank calculations.

Of the factors examined, an increase in valuation of houses over flats appears to be the most important and least volatile.

The analysis suggests that around 38% of the increase in housing prices was consistently associated with an increase in households' marginal valuation of houses over and above the valuation of flats. The change in types of properties bought, reflecting buying habits, only began to have an influence on growth in 2021, given the use of one-year lagged weights in the construction of the index (Chart 5). But throughout the two years of the pandemic, around 12% of the increase is linked to changes in the mix of properties bought (Table A).

Chart 5: Our analysis suggests the effect of the three factors we account for varied over time

Effect of different factors on housing price growth since the pandemic started



Sources: Department for Levelling Up, Housing & Communities, HM Land Registry, ONS and Bank calculations.

The net effect of changes in households' valuation of properties in different areas of the UK relative to London has varied significantly over the course of the pandemic (Chart 5). In the first half of 2021, this shift in valuations contributed positively to growth on average. But outside of this period, the net effect on housing price growth was slightly negative. This could reflect the balance of preferences across the UK, with households increasing the value attached to living in some regions and reducing their valuation in others.

Chart 5 shows that the 'other' component switches from positive to negative after August 2021. So while some of the elements we control for contribute to raising the index, there could be other factors contemporaneously pushing it down. For example, the switch coincides with the unwind of the SDLT exemption. But it could also reflect excess volatility in our estimates and reduced matching underlying our index at the end of the sample.

The association between shifts in preferences and housing price growth is likely to also incorporate the effect of the SDLT exemption.

As set out earlier, our analysis does not account for a range of other factors that could influence housing prices. Among these is the SDLT exemption, and we note two ways the exemption could have affected the HPI in a similar way as a shift in preferences.

First, the properties that were transacted while the exemption was active may reflect the stronger incentive to move home for properties that were priced at around £500,000. So the basket of properties traded that we observe in 2021 may be influenced by the SDLT exemption, alongside a change in preferences.

Second, the stronger incentive to purchase properties at around £500,000 is likely to have increased demand, and competition, for properties in this segment of the market, which likely consists mostly of detached houses.[25] This, in turn is likely to have put upward pressure on prices offered for these properties, even absent a change in households' preferences.

However, we continue to see a positive effect on growth from the marginal valuation of property types other than flats, even after the stamp duty deadline. This suggests that changes in household preferences played a key role in the housing price growth we observed, even without the stamp duty exemption.

And further extensions to our analysis could improve our understanding of the factors behind the fast housing price growth during the pandemic.

Although our analysis suggests a significant proportion of the housing price growth during the pandemic can be explained by changes in consumer preferences, it does not include other factors that are also likely to have played a part. Here we list some of the possible extensions that would be useful to incorporate.

First, the scope of our dataset could be expanded to also include property transactions in Scotland and Northern Ireland, and the timeframe could be extended to a longer time horizon. The geographical extension would be useful to ensure that our results hold across the rest of the UK. The expansion of the time frame would allow us to test whether or not similar rapid increases in housing prices, such as in the run up to the GFC, were linked to changes in households' preferences.

Some housing characteristics that are not included in our analysis may have played an important role for households during the pandemic, such as an increased desire for outdoor space during lockdowns. The change in preferences we analyse could therefore be made more precise by adding information on garden size, available from the Ordnance Survey.

By contrast, the relevance of some other housing characteristics may have decreased during the pandemic, and accounting for this may also improve our analysis of preference shifts. For example, given a general increase in working from home, the ease of commuting into work arguably became less important during the pandemic.[26] More generally, introducing a proxy

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25 As of December 2019 the average price paid for a detached house in the UK was around £400,000 compared to £290,000 for flats and around £250,000 for semi-detached and terraced houses.
26 See **Morel (2022)** for an application to Canadian data.

to track changes in households' ability to work from home over time would also be a useful complement to our analysis.

Other macroeconomic factors affecting the dynamics of housing demand can be important when explaining changes in housing prices. Yet it is difficult to incorporate most of these time-varying factors in a simple hedonic regression setup. For example, we could extend our analysis to include the role of the SDLT exemption, but there are clear challenges with separately identifying the effect of changes in both households' preferences and the tax environment. One possible avenue for such analysis could be to separate out a time trend from the prices paid, which could be related to macroeconomic factors, and a hedonic component, using a version of our framework to predict prices on the basis of objective housing characteristics.[27]

[27] See also the work of **Graham and Makridis (2021)** on the use of hedonic regressions to construct an instrument for house prices to discern their impact on consumption.

5: Conclusion

> **Our analysis provides a framework for analysing the role of shifting preferences in driving housing price growth.**

Our analysis provides a framework for analysing how changes in households' preferences can contribute to changes in housing prices. This offers a new way for policymakers to understand the drivers behind evolving trends in housing prices, alongside more traditional macroeconomic factors such as incomes and interest rates.

This approach could be particularly beneficial when considering how housing prices evolve in response to shocks to housing demand. The factors we have analysed in this paper were likely a specific response from households to conditions that arose during the pandemic. For example, the shift in preferences may have reflected an increase in remote working. Our analysis suggests this could have resulted in households placing more value on certain characteristics of a given property or in an increased share of housing demand directed towards such property types in the aggregate, putting upward pressure on prices.

Our analysis also implies that housing price growth during the pandemic was not associated with a material increase in financial stability risks. A shift in preference is linked to almost half of the growth in housing prices, while both aggregate household indebtedness, as well as the share of highly indebted households remained relatively stable during the pandemic (**July 2022 Financial Stability Report**). And this is in line with the objectives of the **FPC's mortgage market Recommendations** guarding against a material loosening in mortgage underwriting standards, and an excessive build-up of mortgage debt.

To the extent that the rapid housing price growth was associated with shifts in household preferences that are specific to the pandemic, there is clearly uncertainty about what this means for the future outlook. If these changes in preferences turn out to be transitory – for example if households' willingness and ability to work from home falls back over time – then some of the growth seen during the pandemic could unwind.

On the other hand, it is possible that at least part of the observed preference shift is permanent, if the factors driving these changes prove long-lasting. In that case, we do not think the factors we have analysed would be likely to contribute to a housing price contraction.

Regardless of the permanence or otherwise of the shift in preferences induced by the pandemic, housing prices will continue to be influenced by macro-economic fundamentals like long-term interest rates and wage growth. The framework we have developed in this paper can be used in the future to examine how changing preferences for different housing characteristics affect housing price growth alongside these fundamentals.

Box A: Theoretical foundations of the model

In this box we describe a simple model in the spirit of **Rosen (1974)** to rationalise the estimates from hedonic regressions as arising from consumer preferences across housing characteristics. We focus on the market for existing housing and assume that supply is fixed, as is common in the literature. To this end, we set up a static consumer problem where households maximise their utility subject to their budget constraint.

Key modelling assumptions

While housing is a durable good, we model the choice of housing as static. This is equivalent to a dynamic set up under some simplifying assumptions, such as utility being time-separable, in the absence of borrowing limits and moving costs. In practice, moving costs exist and are non-negligible.[28] Importantly, for the period we focus on, the Stamp Duty Tax is an obvious and time-varying component of moving costs for home movers, which we abstract from. We refer to **Bishop and Murphy (2019)** for some examples on how to predict the size and direction of biases from incorrectly assuming a static model without fully developing a dynamic model, and to **Bishop and Murphy (2019)** for a fully-fledged dynamic model of the housing market.

Another important aspect of the model is that it provides a theory of rental prices, rather than sales prices. In a stable macroeconomic environment, the sale price is the sum of the expected discounted future values of housing services, the rental prices. But sale prices reflect the asset value of properties and can react to a host of factors and expectations about the future that do not affect current rents. The decline in the discount rate that took place during the period of analysis is one important factor that suggests our estimates should be interpreted with caution.

Following Rosen, we abstract from heterogeneity in consumer preferences and from unobserved product characteristics. In practice, both these assumptions are unlikely to hold. For example, some consumers are likely to choose bundles that are strictly dominated and therefore hard to rationalise in this set up if one only accounts for observed characteristics. And preference homogeneity, which Rosen relies on for identification, has been criticised as problematic at best, with consumers with stronger preferences for certain characteristics more likely to choose bundles with a large content of such characteristics, creating a simultaneity problem when trying to recover utility parameters. However, we also add an assumption regarding the utility function, meaning that we do not run a 'second-stage regression' in the spirit of Rosen to identify demand parameters. But we still choose to adopt these simplifications both because we have no information on consumer heterogeneity, and because our focus is on time-varying

[28] See **Kennan and Walker (2011)**.

preferences, which would be hard to disentangle from preference heterogeneity without looking for repeated sales.[29]

Consumers' maximisation problem

Household i period t utility is $u_{tij} = u_{ti}(\mathbf{z}_j, c)$, with $\mathbf{z}_j$ a vector of observable property characteristics and c a commodity, the price of which we normalise to 1 and use as unit of reference. The price of a unit of housing with set of characteristics $\mathbf{z}_j$ is determined by the time varying hedonic function $p_{tj} = \mathbf{p}_{\mathrm{t}}(\mathbf{z}_j)$. In every period, household choose housing of type j^* such that:

$$j^*(t,i) = \underset{j}{\operatorname{argmax}}\, u_{ti}(\mathbf{z}_j, c) \;\text{ subject to } c + \mathbf{p}_{\mathrm{t}}(\mathbf{z}_j) = y_i.$$

where y_i is consumer i's income. Considering continuous characteristics, such as floor size, the solution to this problem can be obtained by substituting the budget constraint into the utility function and taking the first order condition.

First order conditions

Consider a continuous housing characteristic $\boldsymbol{k}$. At the optimal choice, the following condition must hold:

Equation 1 $$\frac{\partial u_{tij}}{\partial z_j^k} - \frac{\partial u_{tij}}{\partial c} \cdot \frac{\partial p_{tj}}{\partial z_j^k} = \mathbf{0} \quad \Rightarrow \quad \frac{\partial u_{tij}/\partial z_j^k}{\partial u_{tij}/\partial c} = \frac{\partial p_{tj}}{\partial z_j^k}$$

Equation 1 indicates that at the optimal solution, continuous characteristics are chosen to ensure that the marginal rate of substitution between the characteristic and the commodity good exactly corresponds to the partial derivative of the hedonic price function with respect to the characteristic. In equilibrium, this hedonic price of characteristic k represents the rate at which the household would be willing to increase (if positive) expenditure on a house as the characteristic increases, while holding the utility level constant.

First stage: estimating hedonic prices

For each month in our sample, we run hedonic regressions to estimate the contribution of different characteristics to prices, assuming that the observed transaction for housing $j^*(t,i)$ is the results of household i's optimization at time t.

$$\ln p_{tj} = \textstyle\sum_{k=0}^{K} \alpha_t^k\, z_j^k + \epsilon_{tj}; \qquad \text{with } z_j^0 = 1 \text{ and } K \text{ the number of variables considered.}$$

With this approach, one can estimate how both continuous and categorical characteristics contribute to the price paid. However, the semi-log functional form means

[29] See Bajari et al (2012) for an approach using repeated sales.

that each characteristic cannot be priced in isolation. For example, the price paid for an extra room may vary depending on whether the property is a flat or a house.

For continuous characteristics, this regression additionally implies that we can approximate the marginal willingness to pay (MWTP) for a given characteristic with

Equation 2 $$\frac{\partial \boldsymbol{p}_{tj}}{\partial \boldsymbol{z}_j^k} = \boldsymbol{p}_{tj}\widehat{\boldsymbol{\alpha}}_t^k$$

the hedonic price of characteristic k. This can then be used in Equation 1 and represents the first step in Rosen's approach to estimate preferences. In particular, additional assumptions are required to model a second stage to identify the left-hand side of Equation 1.

A special case for the second stage: log-linear utility

Assume that the utility of all households has the same log-linear functional form, but the preference parameters for different characteristics $\left(\theta_t^k\right)$ may change over time.

$$u_{ti}\left(\mathbf{z}_j, c\right) = \sum_{k\in A} \theta_t^k \log z_j^k + \sum_{k\in B} \theta_t^k\, z_j^k + c$$

Where A and B represent the sets of continuous and categorical characteristics respectively. In our case, $A = \{Room.no, Floor.size\}$ and $B = \begin{Bmatrix} Prop.type, New.build, Region, \\ LAD.classification \end{Bmatrix}$.[30]

In this section, we focus on characteristics belonging to group A, for which $\frac{\boldsymbol{\partial u_{tij}}}{\boldsymbol{\partial z_j^k}} = \frac{\boldsymbol{\theta_t^k}}{\boldsymbol{z_j^k}}$ and $\frac{\boldsymbol{\partial u_{tij}}}{\boldsymbol{\partial c}} = \mathbf{1}$. This last expression represents a normalisation, so that the marginal rate of substitution between a certain housing characteristic and non-housing consumption only changes in response to variation in the marginal utility of housing characteristics.[31] Equation 1 can then be combined with Equation 2 to give:

Equation 3 $$\boldsymbol{\theta_t^k} = \boldsymbol{z_j^k} \cdot \frac{\boldsymbol{\partial p_{tj}}}{\boldsymbol{\partial z_j^k}} \quad \Rightarrow \widehat{\boldsymbol{\theta}}_t^k = \widehat{\boldsymbol{\alpha}}_t^k \boldsymbol{z_j^k} \boldsymbol{p_{tj}}$$

This implies that once we obtain an estimate of the hedonic prices of all continuous characteristics $\left(\frac{\partial p_{tj}}{\partial z_j^k}\right)$, and given that we can observe the quantity of characteristics consumed by households $\left(\boldsymbol{z}_j\right)$, we can recover a local estimate for the relevant preference parameters $\left(\hat{\theta}_t^k\right)$.

[30] While room number is clearly a discrete and not a continuous variable, we include it in the continuous group as it is a numerical variable, not a categorical one.
[31] This normalisation is an important step for identification of all utility parameters, see **Diewert (2003)** for more details.

A shift in consumer preferences inducing an increased marginal utility for a given characteristic can therefore arise from three separate sources: (1) an increase in the MWTP for such a characteristic $\hat{\alpha}_t^k$; (2) an increase in the quantity demanded for such a characteristic z_j^k; (3) a generic increase in the price of houses with that characteristic p_{tj}, perhaps not directly related to the characteristic itself.

Preference parameters for categorical characteristics

Variables belonging to group B are categorical, meaning that they can be summarised with a set of dummy variables. For these variables, no first order condition underpins the optimal choice of the consumer. Rather, households choose which category to buy based on a threshold rule. This indicates that consumers will buy housing belonging to a certain category, for example 'flat' as opposed to 'house', only if the marginal utility increase associated with a flat is larger than the difference in the price of a property with otherwise identical characteristics, but which is a flat $(\hat{\mathrm{z}}_{\mathrm{j}})$ rather than any other housing type $(\bar{\mathrm{z}}_{\mathrm{j}})$. If we define the variable 'property type' as a set of four dummy variables $\{D_f, D_t, D_s, D_d\}$ for flats, terraced, semi-detached and detached houses, with associated utility parameters $\{\theta_t^f, \theta_t^t, \theta_t^s, \theta_t^d\}$, then

$$D_f = 1 \;\; \Rightarrow \;\; \theta_t^f > \frac{p_t(\hat{\mathrm{z}}_{\mathrm{j}} | D_f = 1) - p_t(\bar{\mathrm{z}}_{\mathrm{j}} | D_f = 0)}{\Delta D_f}$$

Similar conditions for consumers' optimal choices also apply to all the other categorical variables.

Identification of the preference parameters associated with these variables is not as direct as for continuous variables, as observing consumer choices only indicate that their preference parameter is above a threshold. With additional information on consumers' characteristics, eg if the preference parameters depend on demographic variables, and by making distributional assumption on the error term, one can recover preferences for categorical variables too.[32]

However, we do not have access to household characteristics information and are therefore unable to exploit such a method. All that we can say about categorical variables is that an increase in the share of households choosing properties with a certain characteristic, such as eg terraced houses, is associated with either a reduction in the price premium for such a characteristic or an increase in the marginal utility extracted from terraced houses. If we observe the price differential for terraced houses and other housing types staying unchanged or even increasing, but a larger share of total sales in terraced houses, we interpret this as an increase in the marginal valuation of that characteristic.

[32] See **Bajari and Kahn (2005)** for one such example.

Box B: Data and estimations

In this box we discuss more details around the methodology we follow, the quality of the matching, the statistical significance of our estimated coefficients, as well as how to interpret them.

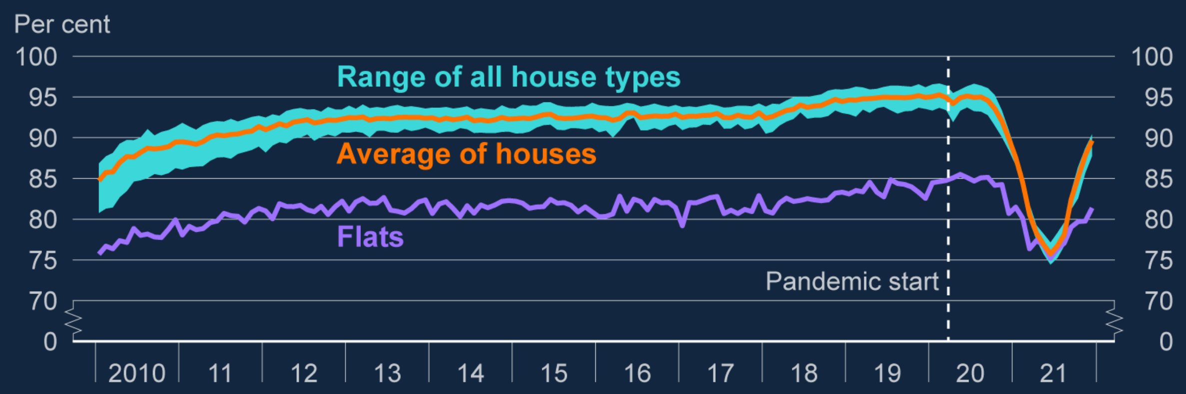
Matching between HMLR price paid data and the DLUHC Energy Performance Certificates

We follow a simple procedure for matching EPC information to the main HMLR data set, based on full address, postcode and county. When this does not work, we use the full address and postcode without the county. In principle, new certificates may be issued over time, meaning that a transaction could match to multiple certificates. But in practice more than 80% of EPCs are unique references, so for simplicity we remove the duplicates without introducing further matching rules based on the date of the transaction. For most of the period covered, our matching rate is similar to that achieved using more complex techniques, see eg **Chi et al (2019)**.

Our matching rate between the two key data sets is around 90% for most of the period we consider, but drops to 75% in 2021. We looked at whether there are patterns of heterogeneity behind this uneven matching. Our analysis suggests there was no clear geographical pattern to the matching deterioration. But we found that the matching rate for houses was typically far higher than that for flats, and in 2021 matching on houses deteriorated to broadly equalise with that of flats (Chart A). This suggests that our estimates in the most recent months may be less reliable, and in turn this could influence the construction of the HPI.

Chart A: EPC and Price Paid matching rates decreased significantly in late 2020 and remained below their average level

Matching rate between EPC and Price Paid data



Sources: Department for Levelling Up, Housing & Communities, HM Land Registry and Bank calculations.

Data cleaning and preparation

We start with a data set of 10,870,584 matched observations. Before proceeding with the analysis, we clean the data to ensure the transactions captured are realistic, complete and representative of the housing market.

We found that information on the number of rooms was missing for quite a large share of the data set, over 11%. Moreover, the pattern of non-available data was not random, increasing in the most recent period and for new builds. Therefore, where this was missing, we imputed it by rounding to the nearest integer the average number of rooms in a flat or house (as appropriate) in the LAD where the property in question was sold. While this may contribute to adding noise to the estimates for this characteristic, we consider this a better solution than removing these observations from the data set.

After imputing the room number, we follow the approach in **Chi et al (2019)**, which uses the same data set, and remove transactions that meet the specified rules for elimination listed in Table 1 below.

Table 1: Rules for data cleaning

Variable	Details	Number of transactions	Share of total transactions
Category type	B	1,068,025	10.14%
Floor size	0 or missing	1,036,275	9.84%
	More than 1017 square meters	544	0.01%
	Less than 13 square meters	1,624	0.02%
Number of rooms	0 or missing	4,716	0.04%
	More than 20	673	0.01%
Price per square meter	More than £500,000	192	0.00%
	Less than £200	1,031	0.01%
Square meter per room	More than 100 square meters	4,323	0.04%
	Less than 4.64 square meters	417	0.00%
Total		**2,117,820**	**20.11%**

Sources: Department for Levelling Up, Housing & Communities, HM Land Registry and Bank calculations.

Transactions belonging to Category B are excluded as they can reflect commercial transactions, and the price paid does not reflect market value. We also remove all transactions that do not report a floor size, with a total floor size of less than 13 square meters and above 1,017 square meters.[33] Housing with more than 20 rooms, with a price per square meter above £50,000 or below £200, or where the average floor size for each room is less than 4.64 square meters[34] are also discarded. In total, we remove just above two million observations or about 20% of all transactions, with the largest share due to the category type and the absence of floor area information. We are left with 8,752,764 observations covering the period from 2010 to 2021.

The ONS has reported that Covid has affected the timeliness of data from HMLR, potentially requiring more future revisions. This has particularly affected new builds, and so the ONS has adopted a **methodology** of pooling together new-build transactions two months at a time, starting from the second half of 2021. We follow their approach, so for example, new build transactions in June 2021 include new build transactions from May and June 2021.

Summary statistics

In Chart B, we report monthly information on the number of housing transactions in our data set. This statistic is subject to seasonality, and the number of transactions is exceptionally high in some specific months, such as March 2016 and July and September 2021. This coincided with changes in the SDLT regulation. More generally, volatility has increased since the start of the pandemic.

33 Range of floor area as reported by the **English housing survey**, updated to 2018.
34 Minimum room size for a child under 10 according to the **Licensing of Houses in Multiple Occupation 2018**.

Chart B: The number of monthly transactions shows the effect of seasonality, with excess volatility around SDLT changes and the pandemic

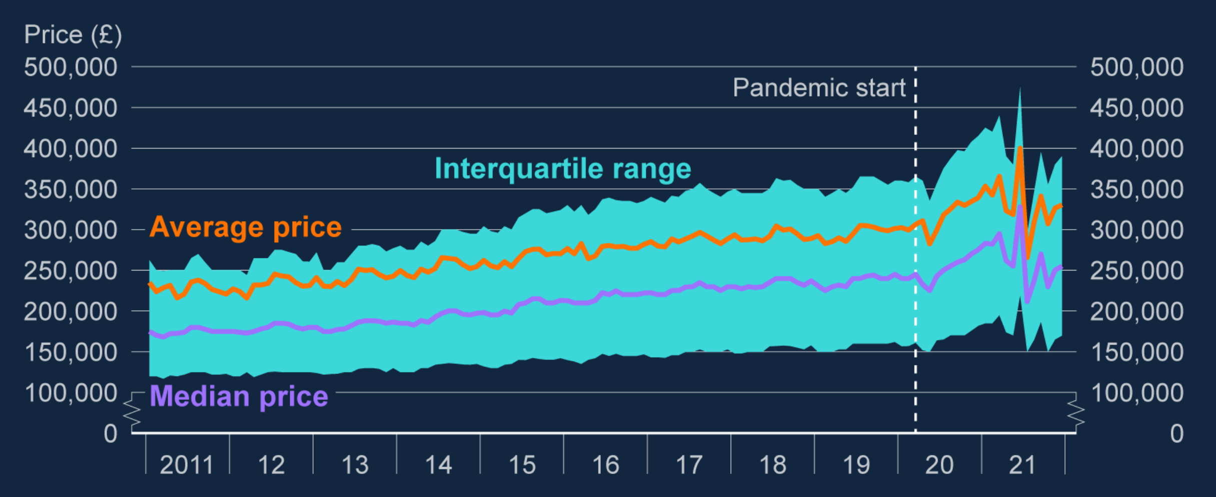
Monthly housing transactions

Sources: Department for Levelling Up, Housing & Communities, HM Land Registry and Bank calculations.

Chart C displays the mean, median and interquartile range for prices paid. The interquartile range of housing prices is relatively wide and becomes wider over time. The median stays consistently below the mean, pointing to a few very high transaction prices pushing up the mean. There is also a clear upward trend over time, which accelerates after the first few months of the pandemic and slows down by the end of 2021. Similarly to the volatility of the number of transactions, the Covid pandemic is associated with heightened variance in housing prices.

Chart C: Housing prices show excess volatility during the pandemic

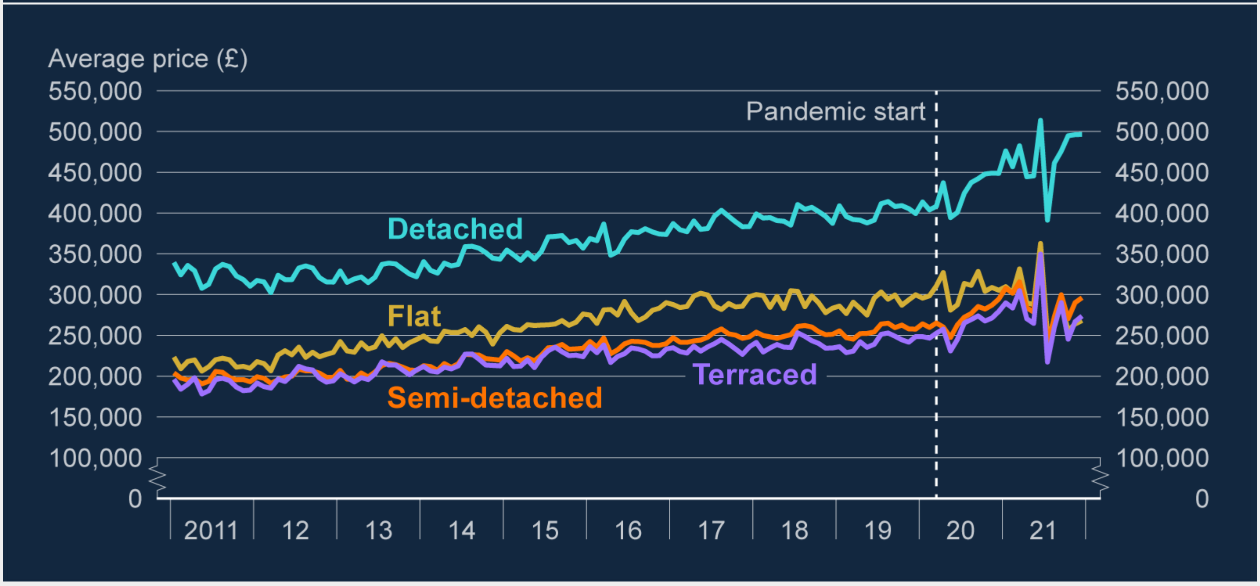
Mean, median, and interquartile range of housing prices over time



Sources: Department for Levelling Up, Housing & Communities, HM Land Registry and Bank calculations.

Charts D and E break down the aggregate figures displayed above into different property types and regions. Detached houses are sold at a large premium compared to other housing types (Chart D). The average price of flats has been the second highest for most of the period considered, perhaps reflecting a concentration of this type of housing in London. But during the pandemic, the average price of flats across all regions has gone down, with semi-detached homes now the second most expensive.

Chart D: The most expensive properties are detached, and since the second half of 2021, semi-detached houses
Average prices by property type

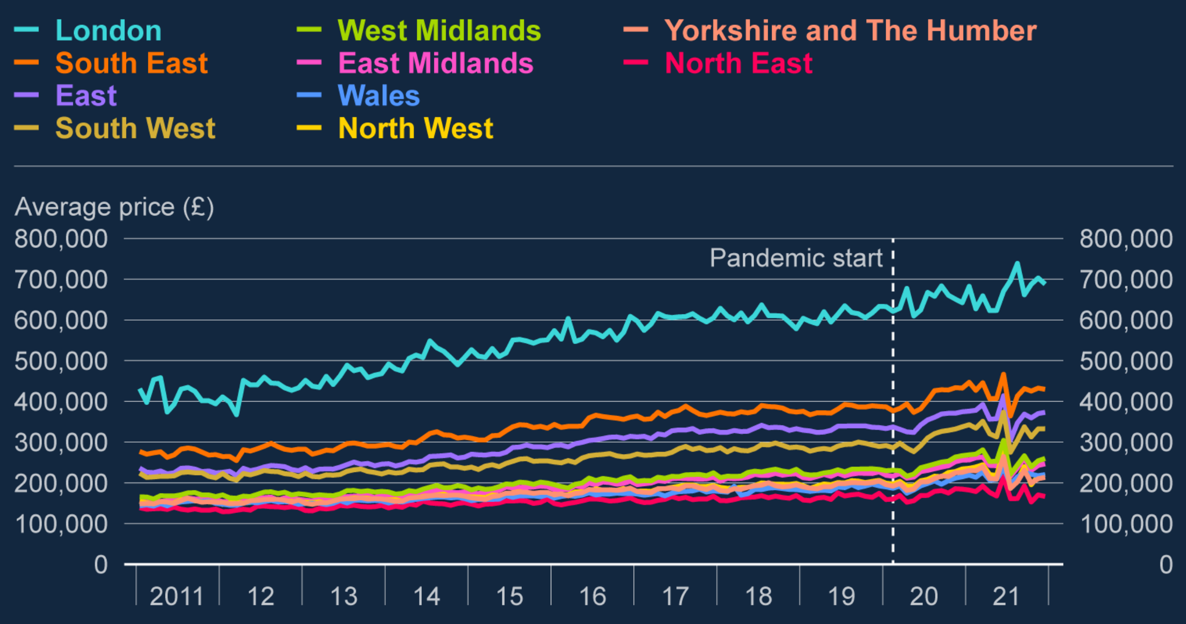


Sources: Department for Levelling Up, Housing & Communities, HM Land Registry and Bank calculations.

From a regional perspective, London stands out with very high and fast-increasing average prices, leading to an average price over one and a half times above the second highest regional average price (the South East) (Chart E). The East and the South of England display medium average housing prices. The Midlands, the North West and the Yorkshire regions, with typically lower prices, have seen faster housing price increases during the pandemic.

Chart E: The most expensive properties are located in London and the South East

Housing prices by region



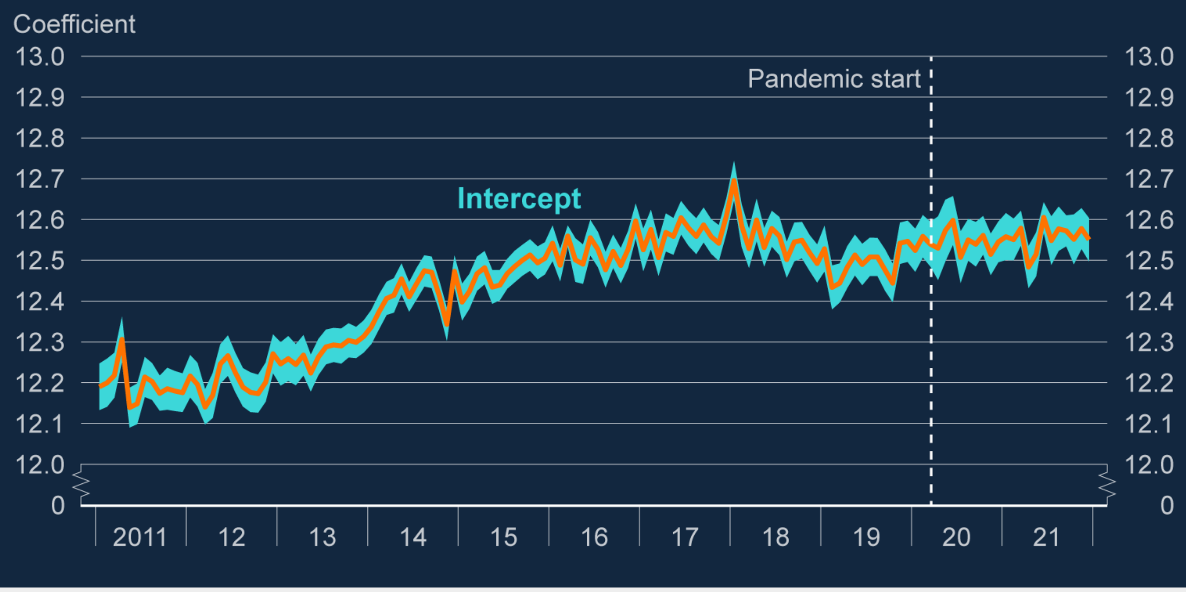
Sources: Department for Levelling Up, Housing & Communities, HM Land Registry and Bank calculations.

Time variation in estimated coefficients

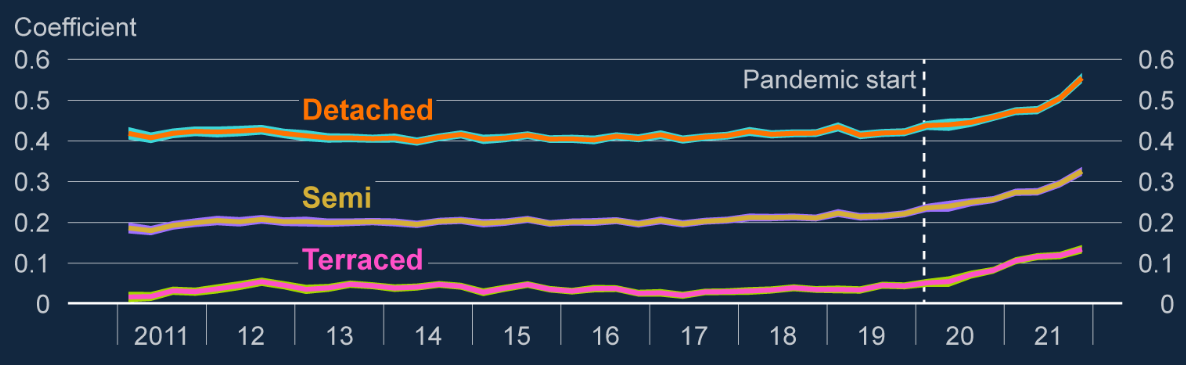
After running monthly regressions of the log of price paid on all dependent variables, we collect the estimated coefficients and their confidence intervals. Before plotting the coefficients, we take a three-month average to reduce their month-on-month volatility. Not all coefficients are estimated with the same degree of precision at all times, reflecting limited variation in some of the regressors in those time periods. Additionally, not all coefficients show a clear change in trend during the pandemic period. To ease the exposition, we only report here coefficients where a pattern emerges, corresponding to the factors that we control for in Section 4 of the paper (Chart F). We additionally report the intercept, to aid interpretation of the other coefficients.

Chart F: Only some coefficients display a break around the time of the pandemic

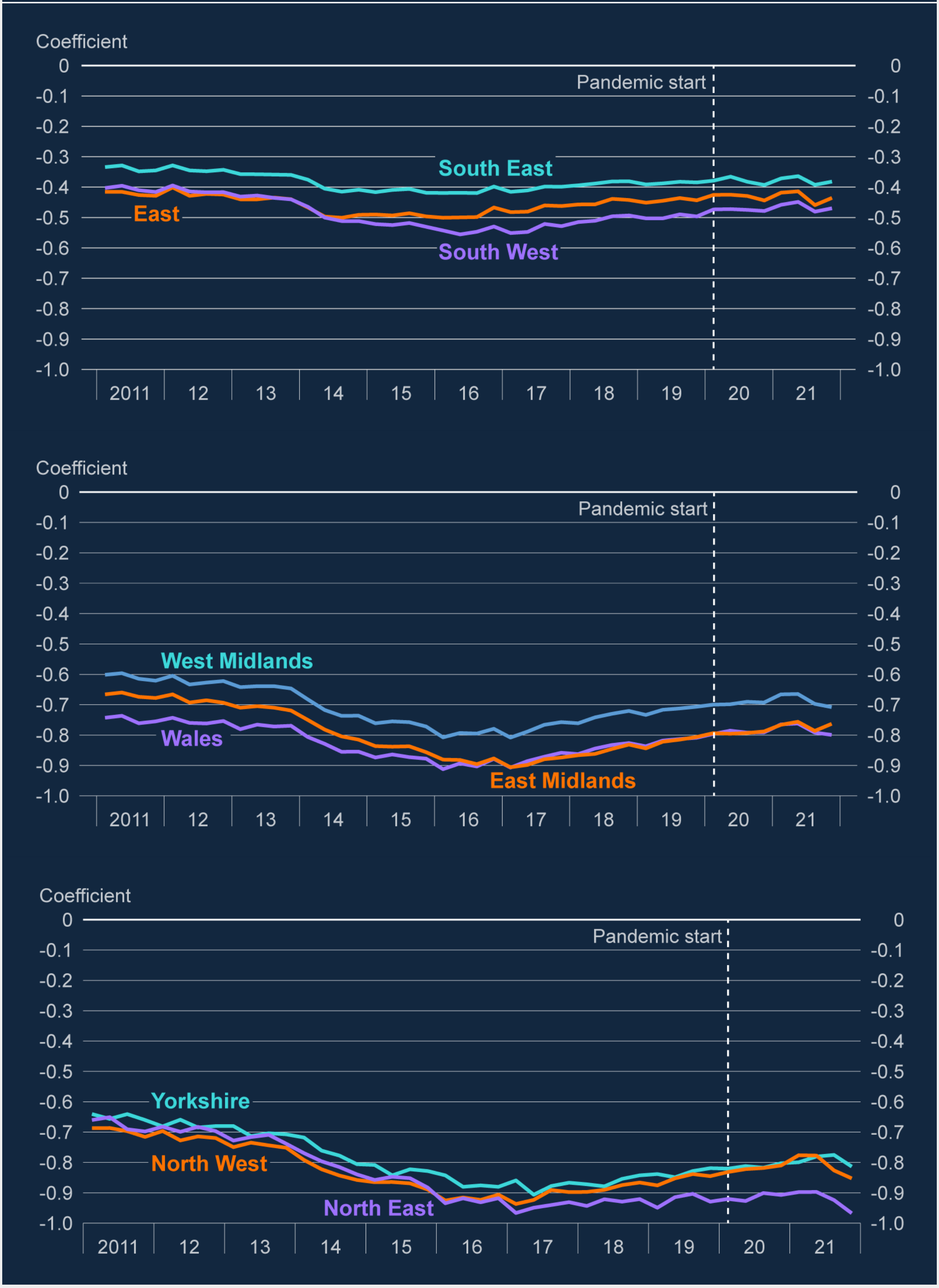
Intercept – confidence intervals shown in swathe



Property types – confidence intervals shown in swathes



Regional dummies – confidence intervals not plotted for legibility



Sources: Department for Levelling Up, Housing & Communities, HM Land Registry, ONS and Bank calculations.

These variables display a pattern of increase in recent years. For the regional dummies, a reduction in the implied discount had started taking place from the end of 2016. In this sense, the observed impact during the pandemic is likely to reflect a long-term trend that is not exclusively associated with Covid. On the other hand, for coefficients on property types other than flats, a clear acceleration took place from March 2020.

We complement this information with Table 2, reporting averages of coefficients before and during the pandemic. The coefficients on regions and property types show an increase on average during the pandemic period, whereas other coefficients do not display a similar trend.

Table 2: Average of estimated coefficients

Variables	Values	Long-term average of coefficients, Jan 2010 to Dec 2019	Average of coefficients, Jan 2018 to Dec 2019	Average of coefficients, Jan 2020 to Dec 2021
Intercept		12.39	12.53	12.55
Property type	Detached	0.41	0.42	0.47
	Semi-detached	0.20	0.22	0.27
	Terraced	0.04	0.04	0.09
Regions	East	-0.45	-0.45	-0.43
	East Midlands	-0.81	-0.83	-0.79
	North East	-0.81	-0.93	-0.92
	North West	-0.81	-0.87	-0.81
	South East	-0.38	-0.39	-0.38
	South West	-0.47	-0.50	-0.47
	Wales	-0.78	-0.84	-0.78
	West Midlands	-0.70	-0.73	-0.69
	Yorkshire	-0.77	-0.84	-0.80
ONS classification	Affluent rural	-0.46	-0.49	-0.51
	Ageing coastal living	-0.77	-0.79	-0.79

Variables	Values	Long-term average of coefficients, Jan 2010 to Dec 2019	Average of coefficients, Jan 2018 to Dec 2019	Average of coefficients, Jan 2020 to Dec 2021
	City periphery	-0.64	-0.55	-0.56
	Country living	-0.74	-0.73	-0.76
	Ethnically diverse metropolitan living	-0.59	-0.53	-0.53
	Expanded areas	-0.74	-0.69	-0.73
	Industrial and multi-ethnic	-0.91	-0.89	-0.90
	Larger towns and cities	-0.66	-0.63	-0.64
	Manufacturing legacy	-0.93	-0.93	-0.94
	Mining legacy	-1.04	-1.04	-1.05
	Older farming communities	-0.57	-0.59	-0.61
	Prosperous semi-rural	-0.63	-0.61	-0.64
	Prosperous towns	-0.64	-0.62	-0.65
	Rural growth areas	-0.51	-0.50	-0.53
	Rural urban fringe	-0.33	-0.33	-0.35
	Seaside living	-0.91	-0.88	-0.86
	Service economy	-0.83	-0.83	-0.85
	Sparse English and Welsh countryside	-0.82	-0.83	-0.85
	University towns and cities	-0.48	-0.46	-0.43
	Urban living	-0.84	-0.81	-0.82

Variables	Values	Long-term average of coefficients, Jan 2010 to Dec 2019	Average of coefficients, Jan 2018 to Dec 2019	Average of coefficients, Jan 2020 to Dec 2021
Rooms grouped[(a)]	2	0.15	0.15	0.15
	3 to 5	0.35	0.37	0.38
	6 or more	0.47	0.46	0.47
New build	0.16	0.18	0.15	0.15
Floor area	0.01	0.01	0.01	0.01

Sources: Department for Levelling Up, Housing & Communities, HM Land Registry, ONS and Bank calculations.

(a) For brevity, we report here a specification where the number of rooms have been grouped in three categories, but the results do not change when replacing this by the actual number of rooms.

Interpretation of regression output

The monthly regressions we run benefit from a very large number of observations. As the sample size approaches the population, the statistical inference used to assess the significance of the outcomes should take this into account, as small-sample inference may no longer be appropriate. In particular, the p-values of the estimates naturally converge to zero as the sample size increases, leading to statistically significant effects that might actually be of very little economic interest.

But even though p-values may not be very useful in large samples, confidence intervals remain valid, and are therefore a better measure for the reliability of our estimates. It is for this reason that reporting confidence intervals, as we have in the swathes in the chart above where possible, is especially important. We refer to the literature for further details on this issue.[35]

Goodness of fit

After running monthly regressions, we look at the performance of our model by reporting the adjusted R-squared each month. This appears to improve over time, reaching a peak of just under 78% of total variation in housing prices explained by the factors we considered in our model in September 2020. Paralleling the dip in the fraction of

[35] See **Lantz (2012)**.

observations matched for houses and flat in mid-2021, we also observe a similar drop in the percent of variation that can be explained around the same time.

The combination of these two things, the drop in matching and the drop in performance as measured by the R-squared, both point towards a careful interpretation of results in the second half of 2021.

Chart G: The fit of the regression temporarily drops in July 2021, at the same time as the SDLT tapering
Adjusted R squared

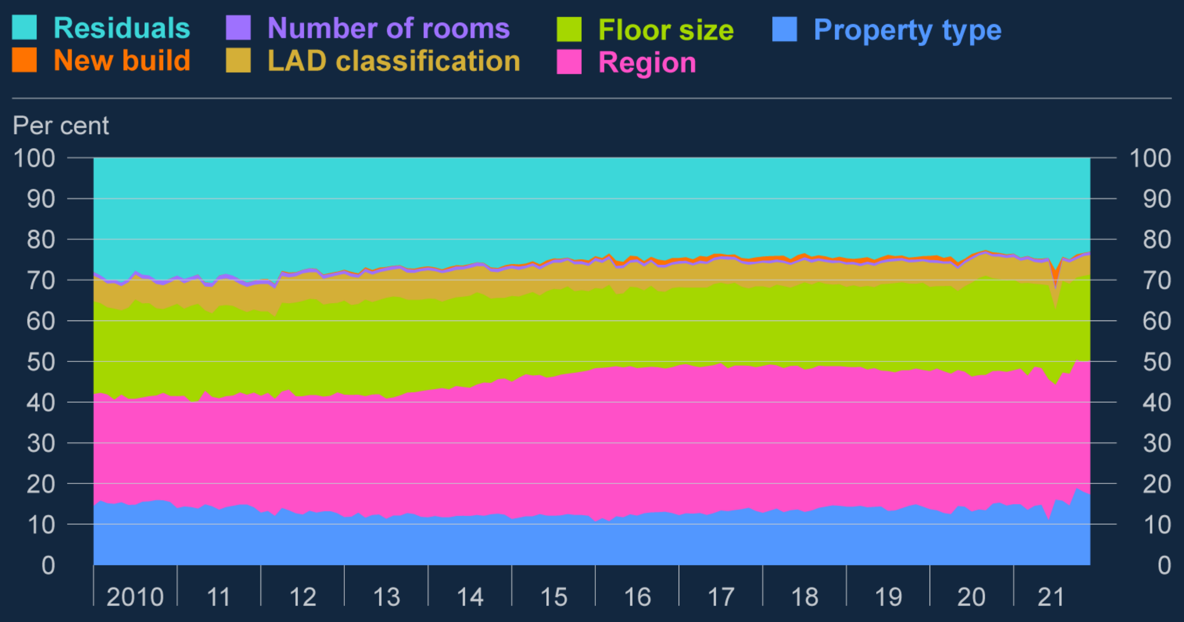
Sources: Department for Levelling Up, Housing & Communities, HM Land Registry, ONS and Bank calculations.

Contribution of different variables to explaining total variance in prices paid

Below we report a chart on the relative importance of each regressors for explaining housing prices. The three main contributors to explaining variation in housing prices are regions, types of properties and floor size, explaining almost 65% of the total variation on average over the period considered. The classification of the local area, the number of rooms and the new build status together only contribute to explaining around 8% of total variation. The importance of these factors varies over time, for example regions become a more important determinant from 2014. Finally, one can observe the increased role of property types in explaining prices over the past two years.

Chart H: Property type, floor size and region explain the largest proportion of variation in housing prices

Variance analysis



Sources: Department for Levelling Up, Housing & Communities, HM Land Registry, ONS and Bank calculations.

Robustness checks relating to measures of space in the regression

We perform a series of checks to ensure the robustness of our results and in particular, the importance of including two different proxies for the size of a property in the regression. These proxies are floor size and number of rooms, and the coefficients on both appear as rather volatile in our estimates, not displaying any clear trend. This is in contrast with the narrative of a 'race for space' in the housing market during the pandemic.

To investigate whether our regression may be mis-specified because of the introduction of both measures, we therefore run alternative regressions where we exclude one of floor size and number of rooms. As reflected in Chart H above, floor size explains a larger share of the variance of housing prices than room number, so that removing it from the regression reduces the adjusted R-squared significantly. Vice versa, removing the number of rooms barely changes the R-squared, and so we focus on this specification.

We find that if we remove the number of rooms, a clearer pattern emerges relating to the coefficient on floor size. We notice a decline in the value associated with floor size since the start of the pandemic, although volatility in the estimates persists. This appeared in direct contrast with the popular media narrative of a 'race for space'.

We further checked this reduction in valuations of floor size by introducing interaction terms of floor size with all other coefficients. We find that the decline is not present for flats but only in other house types. This seems to indicate a shift of importance from square meters to property type, such that households were less willing to spend on space, so long as they had access to houses instead of flats. We suspect that adding information relating to the presence of a garden for each property, as well as an indicator of location more precise than regions such as LADs or partial postcodes, may clarify this result further.

To be sure that this observed decline in the valuation of floor size would not overturn our results, we repeat the exercise of constructing a house price index and fix the valuation of floor size, alongside the other relevant regressors in the main analysis, at the beginning of the pandemic. We find that fixing this coefficient has a very small negative contribution to explained housing prices but does not change the key message of our results. We therefore choose not to report this in the main text.