Bank of England

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Developing a house price-at-risk framework for the UK

Tihana Škrinjarić[1]

Abstract

This paper develops a house price-at-risk framework for the UK. The model allows me to track and decompose different parts of the distribution of house price growth. The analysis covers both the national level, and nine English regions, along with Wales, Scotland, and Northern Ireland. I employ a comprehensive set of variables and indicators that could help to explain house price dynamics. My main findings are that since the 1970s, the most important predictors for the tail of the distribution have been transaction growth, changes in mortgage rate, credit to GDP gap, and financial stress. I utilise several forecasting horizons and demonstrate that this framework can be applied to forecast downside risks to house price growth and the probability of negative growth up to two years ahead. At the regional level, the analysis reveals considerable variation in the estimated coefficients for mortgage interest rates, with supply-inelastic regions showing higher values than other areas. Finally, I find that an increase in the housing supply in most regions is associated with subsequent easing of price pressures in regional markets.

Key words: House price dynamics, financial stability, quantile regression, sub-national house price growth.

JEL classification: C22, E32, E44, E58, G01, G28.

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1. INTRODUCTION

House price dynamics, together with credit dynamics, have been shown to be among the best predictors of financial crises (Borio, 2012, Jordá et al., 2015). In the UK, house prices have increased by more than 160% since the mid-1990s, representing the fastest growth among OECD nations (Mulheirn, 2019). These developments are significant for banks, households, and firms, as housing represents a long-term investment. Furthermore, mortgages are one of the largest components of the balance sheets and cash flows of both UK lenders and households. Property accounts for 36% of household wealth (ONS 2022), with a third of income spent on rent (Gov UK, 2024) and 20% on mortgage payments (Gov UK, 2023). These figures highlight the central role of housing, suggesting that substantial changes on the UK housing market could have direct implications for financial stability (FS). Thus, analysing vulnerabilities in the housing market is essential for monitoring risks that could potentially arise. Macroprudential policymakers focus on mitigating systemic risks, which are associated with the tail risks of macro-financial variables (Galán and Rodríguez-Moreno, 2020), including house prices.

Moreover, the UK housing market is far from homogeneous, with substantial structural and behavioural differences across regions. Academic analyses document strong but uneven interdependencies (Zhang et al., 2021), and regional housing markets exhibit significant heterogeneity in demand, supply, and spatial diffusion patterns (Bhattacharjee and Jensen-Butler, 2024). UK house prices form multiple convergence clusters rather than a single national trend (Montagnoli and Nagayasu, 2015). Since the Global Financial Crisis (GFC), regions such as London and East Anglia have experienced increases in prices of over 110% and 88% respectively, whereas regions such as Scotland and Northern Ireland have seen growth of around 41% and 42% (Nationwide, 2024).

This paper develops a house price at risk model for UK, both at the national and subnational levels (covering nine English regions, Wales, Scotland, and Northern Ireland). I investigate and decompose nominal[1] house price growth, with a particular focus on tail risks. I apply quantile regression (QR) to decompose nominal house price dynamics over the past few decades. By adopting this approach, I can focus on tail risks, which are especially important from a financial stability perspective. To achieve this, I collect a considerable number of variables and indicators that could assist in modelling house price growth. I examine approximately fifty different indicators, making this analysis one of the most comprehensive works in the house price modelling literature.

The main contributions of this paper are twofold. Firstly, this study presents the first empirical analysis of house price growth using the quantile regression approach. This enables me to capture the heterogeneous relationship between different variables and house price growth across its distribution. It also enables a focus on the *at-risk* aspect, allowing me to assess the tail risk to future house price growth. I show how the results from my model can be used to track the vulnerabilities in the house price dynamics.

The second contribution lies in demonstrating the added value of conducting the analysis at the regional level: it captures local market conditions, enabling a more effective assessment of regional housing market dynamics, and the identification of supply constraints.

The main results show that the most important factors for predicting the tail risk of nominal house price growth are transaction growth, mortgage rate changes, the credit to GDP gap, and financial stress. I utilise several forecasting horizons and find that this framework can be used to forecast downside risks to house price growth and the probability of negative growth up to two years ahead.

At the regional level, my analysis reveals considerable variation in the estimated coefficients between the tail and the median estimates for mortgage rates, with supply-inelastic regions displaying higher coefficient values than other areas. In these supply-inelastic regions, increases in mortgage interest rates may be followed by more pronounced price drops, as the supply cannot adjust in the short term. Simultaneously, the higher cost of borrowing discourages demand. Finally, I find that an increase in the housing supply in most regions is associated with future alleviation of price pressures in regional markets.

The remainder of the paper is organised as follows. Section 2 reviews the main findings in the related literature. Subsequently, section 3 details the variables, with particular emphasis on the housing supply indicator I derive. Section 4 sets out the main methodology employed. The empirical analysis is presented in sections 5 and 6: the former examines UK-wide results, while the latter focuses on sub-national outcomes. Finally, section 7 concludes the paper.

[1] Throughout the paper, I refer to the nominal house price growth, unless it is explicitly stated about real house price growth.

2. LITERATURE REVIEW

Research conducted since GFC has deepened understanding of how real estate market dynamics impact financial stability and the broader economy. Key factors influencing house prices include income, mortgage rates, demographics, construction costs, economic activity, building permits, unemployment, leverage, credit constraints, regulatory restrictions, and speculative bubbles (Algieri, 2013; Mian and Sufi, 2016; Favara and Imbs, 2015; Hilber and Vermeulen, 2016; Cerutti et al., 2017). In the UK, supply-side regulatory constraints are found to drive high and volatile house prices, while physical constraints are less significant (Hilber and Vermeulen, 2016). Evidence of speculative bubbles is mixed, with some studies finding none (Cameron et al., 2006), and others confirming their presence (Barrell et al., 2004; Zhou and Sornette, 2003). There has been a simultaneous decline in mortgage rates since the 1980s alongside rising house prices. Theoretical models suggest that a 1% rise in mortgage rates could reduce real house prices by about 20% (Miles and Monro, 2019), though critiques highlight possible over-simplifications of some empirical approaches (Duca et al., 2021).

Sub-national analyses have explored price ripple effects[2] and regional co-movements (Meen, 1999; Holmes and Grimes, 2008; Cook and Watson, 2016). Recent studies indicate spillovers from London to other regions and persistent interactions across the UK, with certain regions acting as shock transmitters (Lo Cascio, 2021; Antonakakis et al., 2018). Regional cycles differ, with Southern and Eastern England and the Midlands displaying quicker reactions to economic changes, while other regions experience higher growth during booms (Chowdhury and Maclennan, 2014). Herding behaviour is evident in several sub-national markets, with London standing out due to high demand and the presence of institutional investors (Ngene and Gupta, 2022).

The House Price at Risk (HPaR) approach to forecasting house price growth is increasingly utilised, particularly in central banks' financial stability reports[3]. The IMF's framework monitors downside risks, finding that financial conditions are strong predictors of short-term house price risks, while credit booms influence medium-term risks, especially in emerging economies (IMF, 2019; Adrian et al., 2020). Macroprudential policies, notably limits on loan-to-value (LTV) and debt service-to-income (DTI) ratios, are effective in mitigating risks. Studies at both city and national levels highlight varying risk dynamics (Alter and Mahoney, 2020). In emerging Europe, income growth is the principal driver of house prices, with mortgage rates exerting a dampening effect on prices (Cevik and Naik, 2022). Ganics and Rodriguez-Moreno (2022) argue that monitoring nominal house price growth is important in Spain for macroprudential reasons, as banks use nominal values for collateral and households base decisions on these figures. Škrinjarić and Sabol (2023, 2024) apply a house price-at-risk model to Croatia, finding regional differences driven by factors like foreign demand and diverse dwelling types. Comparative studies of Spain and Portugal examine how similar macroeconomic conditions can yield divergent housing market dynamics (Lmyenço et al., 2024).

This paper addresses several important gaps in the literature on house price modelling. First, I incorporate a broad set of explanatory variables potentially linked to house price movements. While many previous studies focus on a single group of indicators—either demand- or supply-side—my approach draws on an extensive list informed by related research, the specific characteristics of the UK housing market, and data availability. This helps reduce omitted variable bias and enhances the accuracy of both estimates and forecasts. It enables us to capture complexity and better understand how different factors affect house prices, and it improves the accuracy of the model. On top of that, I aimed to collect the longest time series possible, to capture several boom-bust periods to learn from different types of housing cycles. Some of the variables that I will evaluate start in mid 1950s and onward for the national, and mid 1970s for the sub-national level.

Second, whereas some studies develop theoretical models based on stylised facts and then calibrate them to replicate housing market dynamics, my approach is data-driven. I allow the data to determine the optimal combination of indicators based on historical co-movements, offering a more flexible and empirically grounded framework. This methodology enables me to identify and incorporate relationships within the data that may not be captured by rigid theoretical models, thus enhancing the robustness and relevance of my analysis. By leveraging a broad dataset and empirical techniques, my model adapts to the specificities of the UK housing market over time, capturing shifts in relationships among variables that may result from policy changes, economic cycles, or other. This data-driven process also minimises the risk of model misspecification, as I am not bound to pre-set assumptions but instead rely on observed evidence to guide the selection and weighting of

[2] The ripple effect refers to the way house price changes in one region, typically London or the South East, spread to other regions over time.

[3] HPaR models are regularly applied by central banks, including the ECB, Deutsche Bundesbank, Bank of Spain, and Danish National Bank, (ECB, 2021; Kennedy and Wosser, 2020; Hafemann, 2023; Galán and Rodríguez-Moreno, 2020; Cucic et al., 2022). For a background on at risk approach, see Škrinjarić (2024, 2025).

explanatory factors. As a result, my findings are more likely to reflect true market dynamics and provide actionable insights for both policymakers and practitioners.

Third, I explicitly account for regional heterogeneity by estimating separate models for each region. This is crucial for applications such as valuation models and stress testing, where regional dynamics can significantly influence outcomes. By employing this comprehensive framework, both policymakers and financial institutions can generate more nuanced forecasts and better monitor vulnerabilities in the housing market. Local factors that reflect supply issues and different housing affordability can exhibit great heterogeneities (Ferreira and Gyourko, 2012) and can contribute to different house price dynamics across regions. That is why national approach may not be able to capture this. Examining these is important to understand pockets of risks.

3. DATA DESCRIPTION & SUPPLY INDICATOR DERIVATION

In this section, I describe the data collected for the empirical analysis. I then derive the housing supply indicators used alongside other variables in the main HPaR model. One of key contributions of this study is the development of these indicators, which inform us about how effectively supply is adjusting to demand and other factors. This is the first study to provide time series indicators of this kind.

3.1. Data description

For the empirical part of the analysis, I collected data for both the UK and the sub-national level from various sources. The main variable of interest, house prices, refers to the Nationwide Building Society[4] house price indices for the UK and sub-national markets, based on nominal prices for all properties. Sub-national house price indices cover the nine English regions (North East, North West, East Midlands, West Midlands, Yorkshire and the Humber, East Anglia, South East, South West, and London), as well as Scotland, Northern Ireland, and Wales. The time series for UK-level house prices begins in the mid-1950s, while regional price series commence in the mid-1970s. Appendix 1 Table provides full details on variable definitions, the available time spans, and sources.

The majority of the variables are transformed into growth rates, differences, or other relevant formats prior to the main analysis. I have included a wide range of indicators at both the national and sub-national levels. All explanatory variables are standardised to enable comparative analysis. The factors helping to explain house price movements are categorised into several groups: financial, demand, supply, non-fundamental, and other factors, consistent with previous literature reviews and classifications by Droes and van den Minne (2017), the Bank of England (2020), and the comprehensive analysis conducted by Duca et al. (2021).

3.2. Deriving housing supply constraints indicator

Economic model indicator

One of the challenges found in literature on the UK housing market is the inelastic supply (Hilber and Vermeulen, 2016; Meen, 1999). Markets that have inelastic long-run supply, subject to given increase in the demand, result in greater increases of prices (Anundsen, 2016; Cavalleri et al. 2019). Sources of inelasticity could come from regulation on land use and permit procedures or can be natural (topographical). Importantly, while previous literature has discussed various aspects of supply constraints and their implications for house price dynamics, it has not defined a time series indicator of supply constraint that can be directly incorporated as a variable in an empirical model in the way I intend to use it here. My approach, therefore, fills this gap by constructing and applying such an indicator within the main HPaR model, enabling a more precise analysis of the role of supply constraints over time.

I estimate a model that can derive a supply (in)elasticity coefficient subject to house price changes and a supply misalignment indicator that compares observed supply on the market to an "optimal" one. To do so, I follow Caldera and Johansson (2013), and Cavalleri et al. (2019) by estimating system (1-2). It is derived from the Meen (2002) model (see Appendix 3 for the theoretical model) and describes how housing supply (eq. 1) and demand (eq. 2) should behave in an economy or area, based on macro-financial and demographic characteristics:

$$i_t = \beta_0 + \beta_1 p_t + \beta_2 pop_t + \beta_3 ppi_t + e_t \text{ ... (S)} \qquad (1)$$

$$p_t = a_0 + a_1 s/pop_t + a_2 y_t + a_3 pop_t + a_3 irate_t + u_t \text{ ... (D)} \qquad (2)$$

where all variables are denoted with small letters indicating log levels, i_t is the output of construction on new housing from ONS (2024), p_t is nominal house price index (Nationwide, 2024), pop_t is total population from OECD (2024), ppi_t is the producer price index from ONS (2024) estimating construction costs, s_t is the total stock of

[4] Although other sources of house price data exist, this is the longest one, especially for the sub-regional analysis.

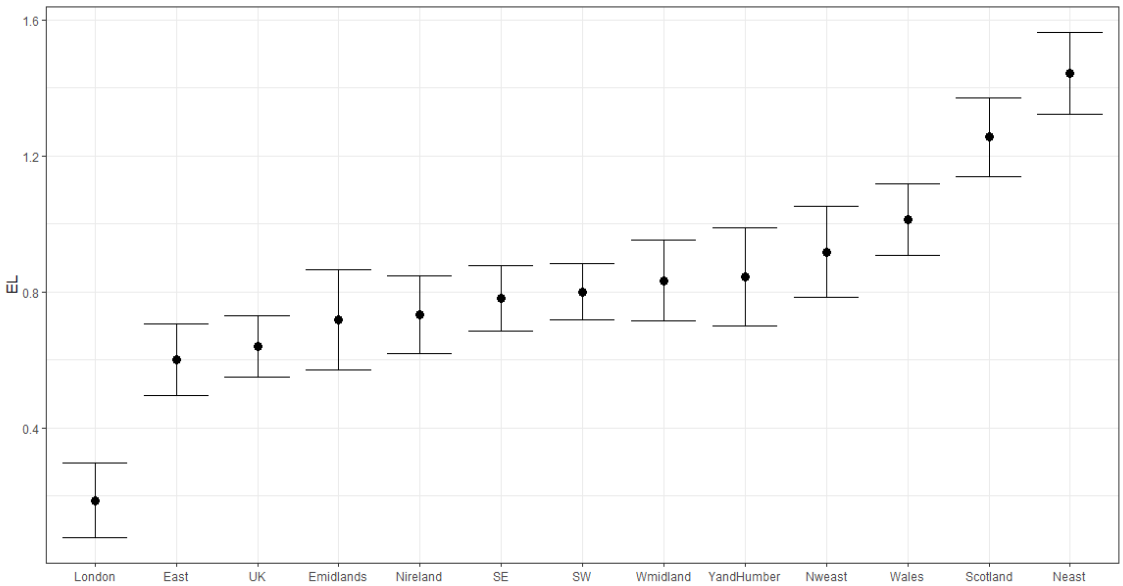
dwellings (Gov.UK, 2024, 2024), y_t is the total personal disposable income per capita from ONS (2024), and $irate_t$ is the 3y fixed rate mortgage rate from Building Societies Association (2024). I estimate model (1-2) via seemingly unrelated equation (SUR[5]) for the UK and every region for period Q1 1980 - Q2 2024. Additionally, the model is also estimated on a panel SUR approach for the panel of all regions.

From the model I obtain two important outputs: the first one is the supply misalignment indicator, defined as the percentage deviation[6] of the observed supply on the market (i) from the estimated value ($\hat{\imath}$). This will be one of the supply-side inputs in the main model that forecasts house prices. The second output is the supply elasticity, measured by the coefficient β_1 in the supply equation. I use this coefficient below to test the validity of my results to related literature that has commented on the supply (in)elasticity.

As related literature on supply (in)elasticity has some comparable findings, I start with showing the estimates of coefficient β_1. I compare my results to related findings to check for the validity of my approach first. Then, I comment on the derived supply misalignment indicator that will be used in the main forecasting model. Figure 1 shows the estimates of the supply (in)elasticity coefficient for the UK and across all regions. On the national level, the supply elasticity is estimated to be ~ 0.64% (95% confidence interval is (0.55, 0.73)), which is comparable to 0.40% of Caldera and Johansson (2013), and 0.80% in Cavalleri et al. (2019). However, the national level (in)elasticity can mask significant regional differences.

Estimates on the sub-national level shown in Figure 1 indicate that London supply is the least elastic, and Northeast, Scotland and Wales have most reactive supplies to price changes. These differences can be explained with supply constraint stemming from the local authorities, where London, East Anglia, East Midlands, North Ireland, and Southeast and have highest refusal rates on new housing (Appendix 4 Figure, left panel), as found in Hilber and Vermeulen (2016), and Mayer and Somerville (2000). The later study found that land use regulation lowers new construction and elasticity of supply. Also, Glaeser et al. (2008) found that house price growth in US was much stronger in metro areas with inelastic supply; and to less extent topographical characteristics (Appendix 4 Figure, right panel). Thus, my findings are in line with existing literature.

Figure 1: Confidence intervals for UK and sub-national supply elasticity

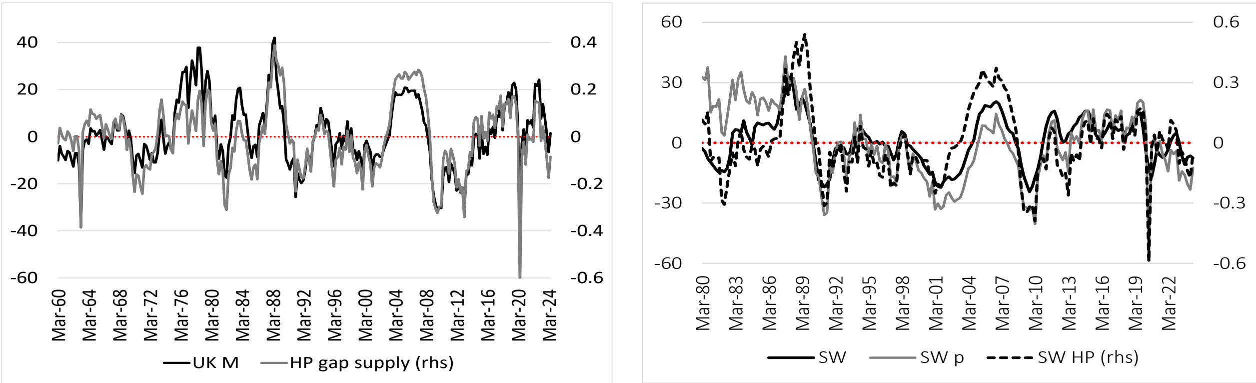


Note: Figure shows interval estimates of elasticity of supply for UK and sub-national areas for model (1-2). Black dots indicate point estimate, and whiskers are 95% confidence intervals. East – East Anglia, Emidlands- East Midlands, Neast – Northeast, Nwest – Northwest, SE – Southeast, SW – Southwest, Wmidlands – West Midlands, YandHumber – Yorkshire and Humber.

[5] This is the first approach to explicitly account for the correlation between the error terms of supply and demand equations. I additionally estimate an IV (instrumental variable) regression model where instruments in the first step are previous values of supply and demand. I also estimate another version of IV regression where the instrument for the supply the lagged value of *ppi* is, whereas for demand its lagged value remains the instrument as in the previous IV version. The results remain broadly the same.
[6] Thus, I calculate the following: (observed investment – optimal investment) / optimal investment * 100%, where optimal investment is the estimated investment from model (1-2).

I now look at the time series of the supply misalignment indicator presented in Figure 2 for the entire UK (left panel, black curve), and SW[7] region (right panel, black and grey curves; see Appendix 5 Figure for all regions). Higher values of the indicator suggest that the observed supply in the market is able to keep pace with the demand, whereas lower values, particularly those that are negative, indicate that supply is declining and not aligned with macro-financial fundamentals. The dynamics are intuitive to interpret; for instance, during the GFC downturn, all indicators fell, and in some regions, it took considerable time for recovery. Values of supply misalignment coincide with real economic growth, implying that the broader economic climate has also been significant for the construction industry.

Figure 2: Supply misalignment from model (1-2) and from statistical filter, UK – left, SW - right



Note: The left panel compares supply misalignment from model (1-2) (UK M) to the HP gap (HP gap supply, RHS – Right Hand Side) for the case of UK. The right panel compares supply misalignment from model (1-2) (SW) to the same model on a panel basis (p), and to the HP gap (SW HP, RHS) for the case of South-West region. When the indicators increase in their value, supply can follow demand on the market and should alleviate house price pressures. See Appendix 5 Figure for all regions.

Statistical filter indicator

Although the model in previous section has economic foundations, it could still suffer from omitted variable bias, as there could be many factors affecting both supply and demand side of the market but could not be measured or captured. As an alternative measure, I utilise a statistical filter (HP – Hodrick Prescott[8]) to obtain the gap value, measured as the difference between the observed value of house investments, and the "optimal", i.e. trend value that is estimated via the filter, as it is interpreted as the long-term trend. I recognise that this is a very simplistic way of obtaining a misalignment indicator, as it does not depend on economic fundamentals. Figure 2 shows that this alternative approach is very similar to the previous one, both for the case of UK (grey curve, left panel), and SW region (dashed black curve, right panel, see Appendix 5 Figure for all regions). In the main model specification, I will test both supply misalignment indicators to see which one is better for house price growth prediction.

4. METHODOLOGY DESCRIPTION

The benefits of using quantile regression and the at-risk approach to model different parts of the distribution of house price growth are well established in the literature. This methodology enables the examination of downside risks and provides a framework to analyse the key predictors of future price growth across various parts of the distribution and forecasting horizons (Prasad et al., 2019). Furthermore, unlike many other approaches to modelling financial cycles, this framework does not require the prior identification of boom-and-bust periods (Adrian et al., 2020). I briefly describe the methodology I apply below. Moreover, due to the reduced-form setup of the model where I project future values of the house price growth, I am presenting the results in form of covariates that can predict HP growth the best, and not in the form of causal results.

4.1. Quantile regression

Following Koenker (2005), quantile regression is a model in which the dependent variable y is regressed on a set of explanatory variables X at different parts of the distribution of y as follows:

[7] Used here as an example to interpret the results.

[8] Thus, I calculate: (observed investment – trend investment) / trend investment * 100%, where trend investment is the trend value estimated in the HP filter. The smoothing parameter is 25K, which means that the house price cycle lasts for about 15.5 years (Pitros and Arayici, 2016) or 16.5 (Rünstler and Vlekke, 2016). For more details on smoothing parameters and relations between business and credit cycles, see Škrinjarić and Bukovšak (2022a,b).

$$Q_{y|\boldsymbol{X}}(\tau) = \alpha^{\tau} + \sum_{i \in I} \beta_i^{\tau} X_i + \varepsilon^{\tau}, \tag{3}$$

where τ is the observed quantile, *i* is the *i*-th explanatory variable, and ε^{τ} is the error term, i.e. equation (3) describes the τ-th quantile of the conditional probability distribution of y given X. Model (3) is estimated at τ such that coefficients β_i^{τ} are chosen to minimize the sum of quantile weighted absolute errors:

$$\widehat{\boldsymbol{\beta}}^{\boldsymbol{\tau}} = \arg_{\boldsymbol{\beta}} \min \sum_{i=1}^{I} (\tau \cdot 1_{y_i \geq \boldsymbol{X\beta}} \, |y_i - \boldsymbol{X\beta}| + (1-\tau) \cdot 1_{y_i < \boldsymbol{X\beta}}) |y_i - \boldsymbol{X\beta}|), \tag{4}$$

where 1(.) is an indicator function equal to 1 if the condition $y_i \geq \boldsymbol{X\beta}$ is satisfied, or 0 otherwise. The dependent variable is defined as the annualized growth *h* periods ahead, *h* = 1, …, 16:

$$y_{t+h} = (Price_{t+h}/Price_t - 1)/(h/4). \tag{5}$$

From the main models I derive a couple of probability indicators. One is of Alessandri et al. (2019), called Forward Looking Recession Probability (FLRP), that calculates the net contraction of an economic variable over a predefined time interval, calculated as $P(\hat{y}_{t+h} < 0 | \, I_t) = E\,(\hat{y}_{t+h}^{\tau} < 0)$, where I calculate the probability of house price growth at horizon *h* to be less than zero value. Second measure is the Distance to tail (DTT), calculated as the difference between the median and the lower tail estimate. Finally, following Busetti et al. (2021), I also calculate Expected Shortfall (ES) as the expected value of the left tail, $ES(\tau) = E(\hat{y}_{t+h} | \hat{y}_{t+h} < q(\tau))$.

To select the best-performing models, I applied several criteria. First, I retained only those models for which the Dynamic Quantile (DQ) test at the 5th[9] percentile did not reject the null hypothesis, as my focus is on accurately capturing tail dynamics. Next, I ranked the models based on the Akaike Information Criterion (AIC) and pseudo-R2 values at the 5th and 50th percentiles. Information criteria such as AIC (Akaike) evaluates the overall fit and penalises number of parameters in the model. Pseudo R-squared compares a model without explanatory variables to the one where I include the covariates, at each quantile. Another measure I used is the dynamic quantile test of Engle and Manganelli (2004), where I jointly test independence of violations and correct coverage of a quantile[10]. Next, I compared CRPS[11] (Continuous Rank Probability Score), as the generalisation of mean squared error applied to probabilistic forecasts, with lower value meaning better accuracy. I also verified the signs and significance of the estimated parameters to ensure they were interpretable and consistent with theoretical expectations. Models with better goodness-of-fit but with insignificant or incorrectly signed variables were excluded from consideration.

Next, I will fit the probability distribution function as described in Azzalini and Capitanio (2003), where the skewed t-distribution is estimated such that I minimise the distance between the selected estimated quantiles and the corresponding quantiles of the t-distribution $\hat{Q}_{y|\boldsymbol{X}}(\tau|\boldsymbol{X})$:

$$\widehat{\boldsymbol{\beta}}^{\tau} = \underset{\mu, \sigma, \alpha, \upsilon}{\arg\min} \left(\sum_{\tau} \hat{Q}_{y|\boldsymbol{X}}(\tau|\boldsymbol{X}) - F^{-1}(\tau;\, \mu, \sigma, \alpha, \upsilon)\right)^2 \;\; , \tag{6}$$

where F^{-1} is the quantile of the skewed t-distribution, and its corresponding parameters μ, σ, α and υ, i.e. location, scale, shape and fatness. I select the 5th, 25th, median, 75th and 95th quantiles to do so. Thus, at each point in time *t*, I produce the distribution of the estimated house price growth.

4.2. Panel quantile regression

For the case of individual regions, I will examine both the univariate approach as for the UK, and the panel quantile regression. For the univariate approach, I re-estimate a similar model as described in the previous subsection (depending on data unavailability at sub-national level). For the panel case, I follow Canay (2011), where a linear panel model is estimated to derive the fixed effects for each region *i*:

$$y_{i,t} = a_i + \sum_{j=1}^{J} b_j x_{j\; it-h} + e_{i,t}, \tag{7}$$

where *J* is the number of regressors *x*. Then, estimated values of $\hat{a}_i$ are purged from values $y_{i,t}$, and the new value $y_{i,t} - \hat{a}_i$ is used in the second step for the main quantile regression model. In the panel approach, I estimate a model where sub-national house prices depend on the previous UK- level house price growth (to capture ripple[12] effects), with additional sub-national-level information.

[9] As there is not enough data to have reasonable estimates for lower percentiles when using macro variables, I focus on the fifth percentile, as is done in related literature (see references in the literature review section, authors observe the 5th or even sometimes the 10th percentile).

[10] A "hit" variable is defined as $I(y_{t+h} \leq \hat{Q}_{y|X}(\tau)) - \tau$, where *I* is the indicator function, and measures if the realisation is below the estimated quantile, and should be equal to τ under the null hypothesis. The hit variable is regressed on previous values and regressors from the model to test if I have calibrated quantile forecasts correctly.

[11] Let the *X* be a continuous random variable, and *F* the CDF defined in previous footnote. CRPS between *x* and *F* is defined as CRPS(*F*,*x*) = $-\int_{-\infty}^{\infty}(F(y) - 1(y-x))^2 dy$, where 1(.) is the indicator function equal to 1 if the argument is positive or zero, or 0 otherwise.

[12] Ripple effect is a well-known characteristic of the UK housing market (see literature review). In this study, I conducted a full additional analysis of these effects both on a static and dynamic approach before moving on to the main HPaR model for regions. These results are available upon request.

5. EMPIRICAL RESULTS - UK LEVEL

In this section I present the main estimation results for a House Price at Risk model for the entire UK. Due to having many different variables to consider, I take the following approach. I estimate various combinations of variables and indicators to cover all possible categories listed in Appendix 1 Table, aiming to identify the best model for a forecasting horizon of *h*=4. In total, I compared over 9 mil models. Due to strong correlations between some variables within the same category, I opted to estimate combinations using one variable or the other, but not both simultaneously. All variables were standardized prior to estimation, ensuring that the coefficients in the models are directly comparable. I select a few models that cover all variable categories listed in Table 1, varying some variables within each category to conduct an initial robustness check.

5.1. Main results – one year ahead

Table 1 presents the final selected models for the nominal house price growth one year ahead[13], while Appendix 6 provides the corresponding results for the real house price growth. I discuss in this section the most important findings for the tail of the distribution to track downside risks for house price growth. Appendix 7 comments the most important results for the median. I look at several models at once, as they provide further robustness checks (see section 5.3).

Financial factors

Changes in mortgage interest rates[14] are found to be an important predictor: declining rates lower borrowing costs and stimulate demand (Geng, 2018; Basco, 2014; Courchane and Holmes, 2014). Borrowers may also accelerate repayments in anticipation of future mortgage rate increases, further boosting prices (Courchane and Holmes, 2014). From an investment perspective, lower mortgage interest rates reduce returns on alternative assets, increasing the attractiveness of real estate[15]. My results indicate that the year-over-year change in mortgage interest rates has a significant negative relationship with tail risk of house price growth, and this relationship is more pronounced in the lower tail of the distribution than at the median. This suggests that rising mortgage interest rates have disproportionately greater correlation with the downside risk of nominal house prices, increasing the dispersion of the growth distribution. These findings are consistent with Adrian et al. (2020) and Hafemann (2023), who also highlight the asymmetric relationship between mortgage interest rate changes and house price growth at different parts of its distribution.

The credit-to-GDP gap (C2GDP gap) exhibits a significant negative relationship with future tail risk of house price growth. This is consistent with findings by Adrian et al. (2020). This supports the notion that credit expansions often precede economic downturns. Bauer (2014) demonstrates that credit-to-GDP ratios are useful in forecasting housing market turning points, as restrictive policies frequently precede price corrections. Similarly, Jimenéz and Saurina (2006) find that loans issued during credit booms are more likely to default than those granted during periods of slower credit growth. The stronger coefficient I estimate at the tail aligns with these findings. In my analysis, I also interpret the credit-to-GDP gap as a proxy for capturing structural changes in the financial system over time. While I cannot directly observe or quantify long-term structural shifts, prior literature has linked credit supply shocks to declines in bank capital (Gerali et al., 2010), or deteriorating asset quality in the banking sector (Gertler and Karadi, 2011). Therefore, although I lack a dedicated indicator for structural financial changes, the mortgage credit supply component embedded in the credit-to-GDP gap may reflect some of these underlying dynamics.

Stock market movements show a significant negative relationship with future tail risk of house price growth, suggesting a substitution effect could exist between financial and property markets. This is particularly relevant in the UK, where institutional investment in private property has become increasingly prominent (Livingstone, 2022). My findings align with Muellbauer (2018) as well, who argues that when returns on non-housing assets are low, investors tend to leverage into housing.

Financial stress, measured by the Composite Indicator of Systemic Stress[16] (CISS), shows a significant negative relationship with the lower tail of the future nominal house price growth distribution. This finding aligns with related such as Galán and Rodríguez-Moreno (2020). Elevated levels of financial stress are typically associated with more severe economic downturns, during which house prices tend to decline (Duprey et al., 2017).

[13] I have also estimated the model one quarter, two and three years ahead to evaluate the results over time. Results are available upon request.

[14] During certain stages of the financial cycle, risk misperception can lead credit institutions to extend loans to riskier borrowers, making lending conditions—measured through mortgage interest rates or spreads—important to monitor (Škrinjarić, 2023).

[15] Conversely, rising mortgage interest rates can deter buyers and dampen demand (Macdonald, 2010).

[16] See Table 1 in Appendix on full variable description and sources.

Supply

Supply sometimes has a positive association with the one year ahead house price growth, which is consistent with Zahirovic-Herbert and Gibler (2014). This study found that in high-cost, built-up areas, new construction can be expensive and limited, driving up prices. However, in my study, association between supply and future house price growth becomes negative after one year ahead (see next section), indicating that some time is needed before the supply builds up to be able to have some effects on the market. Furthermore, as will be visible in the subnational results section, these results become significant on individual region level. This is important, as the national model cannot capture the supply side regional differences in a manner that can be representative of the differences among them.

Other factors: uncertainty, transactions, consumer confidence; non-fundamental and AR

Economic and broader forms of uncertainty, such as political or geopolitical, have become increasingly prominent in macro-financial models over the past decade (Chen et al., 2024).[17] In my analysis, economic policy uncertainty[18] (EPU) shows a positive relationship with the lower tail of house price growth. These findings are broadly consistent with Choudhry (2018), who, focusing on UK regions, found that uncertainty has a positive short-term effect on house price growth.

Transactions (YoY transaction growth) have a positive relationship with future nominal house price growth, consistent with findings by Meen and Whitehead (2020). They argue that transaction volumes can serve as early indicators of nominal house price dynamics: during downturns, sellers are often reluctant to lower prices, leading to longer time-on-market and a decline in transaction volumes before prices begin to adjust. As such, falling transactions typically precede falling prices.

Exuberance[19], or bubble-like behaviour, demonstrates a strong positive relationship with the future tail risk of house price growth. The autoregressive (AR) term captures movements somewhat like those indicated by the exuberance measure and the growth in the price-to-rent ratio. However, while these variables reflect the influence of omitted factors and general market momentum, the exuberance variable more directly captures irrational or speculative dynamics. Moreover, the AR term is mostly insignificant in my models, likely due to its high correlation with both the exuberance and price-to-rent indicators. As exuberance effectively captures the dynamics that the AR term would otherwise represent, I have chosen to exclude the AR term from the final model specification (see Appendix Figure 8-5 for comparisons).

[17] The IMF's Global Financial Stability Report (2024) highlights that elevated macroeconomic uncertainty significantly increases downside risks to financial stability, especially when macro-financial vulnerabilities are already high. However, the theoretical foundation for the role of uncertainty dates back further: Friedman (1984) and Dreman (1979) argued that in times of high uncertainty, investors tend to suppress their private beliefs and rely more on the behaviour of others, potentially leading to herding and speculative bubbles.

[18] See Table 1 in Appendix on full variable description and sources.

[19] See Appendix 8 for a full explanation from a theoretical point of view, as well as the empirical approach to estimating bubble-like behaviour. In short, the bubble-like behaviour indicator measures whether the current growth is explosive compared to the recent trend. Its importance in the HPaR model is interpreted as follows: if the bubble-like behaviour indicator is high in the current quarter, one can expect with high probability that house price growth will be higher in the next few quarters. Since house price growth is regressed on past values of bubble-like behaviour, the interpretation is "if house price growth is high today, I expect it to be high tomorrow as well". This indicator is therefore correlated with the AR component and the price-to-rent ratio growth, as all of them display similar dynamics. That is why, in models where I include all three of these variables, the latter two become insignificant. I tested several specifications of these models: including only the AR term, only the price-to-rent ratio growth, and both, to compare with the model in the main text. The coefficients of the other variables do not change, and the best performing model remains the one from the main text. Results are compared in Appendix Figure 8-5.

Table 1: Best house price models for the case of nominal price growth, UK level, 4-quarter ahead

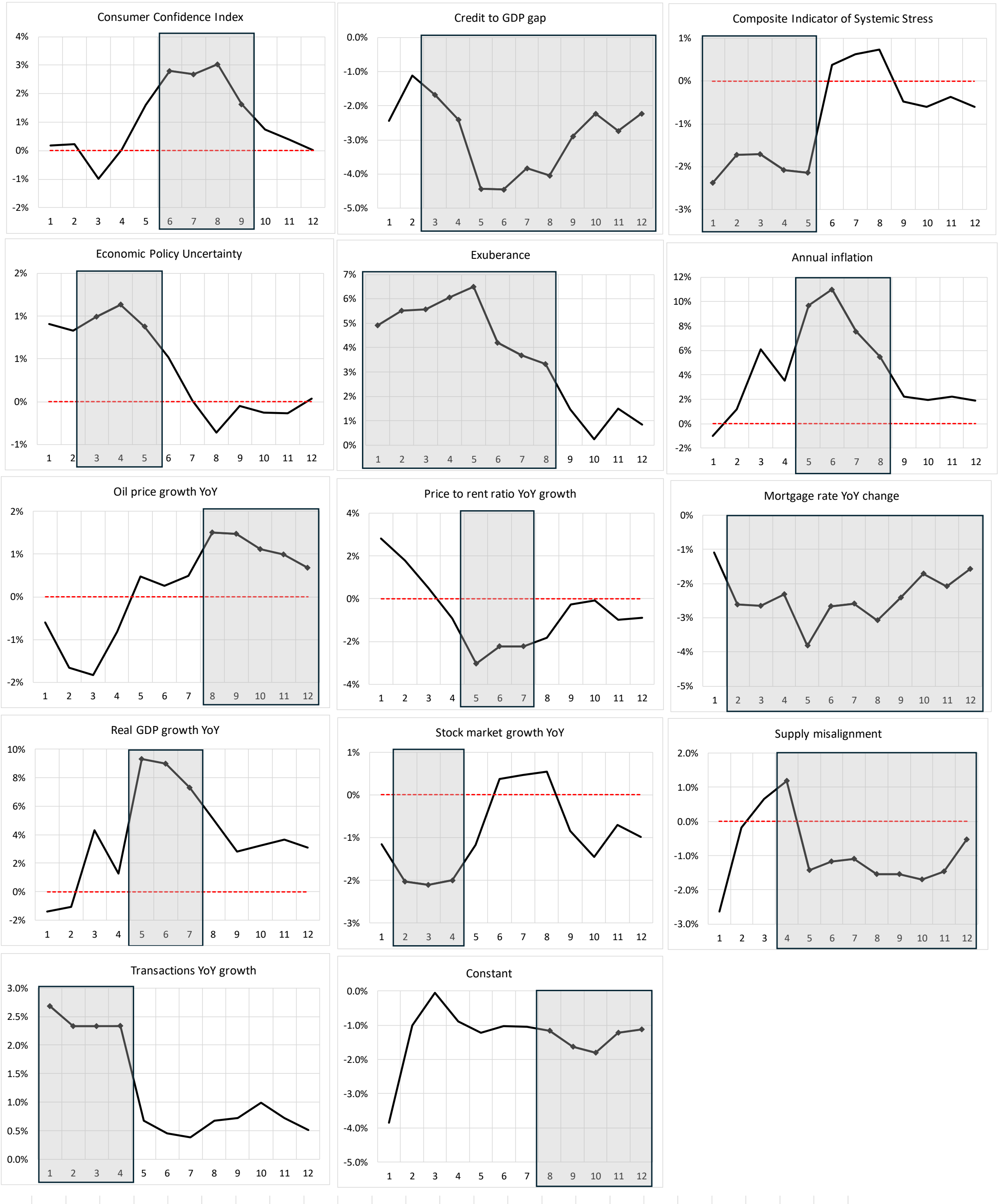
Category	Variable	5th 1	5th 2	5th 3	5th 4	5th 5	5th 6	5th 7	5th 8	50th 1	50th 2	50th 3	50th 4	50th 5	50th 6	50th 7	50th 8
Demand	YoY real GDP growth	0.013	0.008	0.013	0.008	0.006	0.006	0.013	0.015	0.038**	0.036**	0.038**	0.036**	0.040**	0.036**	0.040**	0.036**
		(0.052)	(0.023)	(0.052)	(0.023)	(0.021)	(0.041)	(0.025)	(0.039)	(0.017)	(0.016)	(0.017)	(0.016)	(0.017)	(0.017)	(0.018)	(0.017)
Supply	YoY investment growth	0.012	0.014	0.012	0.014	0.014**	0.015	0.012*	0.011	-0.01	-0.007	-0.01	-0.007	-0.011*	-0.008	-0.011	-0.007
		(0.009)	(0.009)	(0.009)	(0.009)	(0.007)	(0.012)	(0.007)	(0.009)	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)
Supply	YoY oil price growth	-0.008	-0.007	-0.008	-0.007	-0.006	-0.007	-0.008	-0.007	-0.007	-0.009**	-0.007	-0.009**	-0.008	-0.009	-0.007	-0.009
		(0.006)	(0.009)	(0.006)	(0.009)	(0.005)	(0.008)	(0.007)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.005)
Financial	YoY mortgage rate_1 change	-0.024**	-0.025**	-0.024**	-0.025**	-0.028***	-0.026**	-0.023***	-0.027***	-0.018***	-0.017***	-0.018***	-0.017***	-0.018***	-0.016***	-0.016**	-0.017***
		(0.010)	(0.011)	(0.010)	(0.011)	(0.006)	(0.012)	(0.008)	(0.008)	(0.007)	(0.006)	(0.007)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)
Financial	Spread_2		-0.002		-0.002		0.002		-0.004		-0.006		-0.006		-0.002		-0.006
			(0.010)		(0.010)		(0.011)		(0.010)		(0.005)		(0.005)		(0.004)		(0.005)
Financial	C2GDP gap	-0.024***	-0.025***	-0.024***	-0.025***	-0.028***	-0.026***	-0.024***	-0.027***	-0.017***	-0.019***	-0.017***	-0.019***	-0.015***	-0.014**	-0.018**	-0.019**
		(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.010)	(0.005)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.005)	(0.006)	(0.007)	(0.007)
Financial	YoY diff stock market	-0.028*	-0.029**			-0.015	-0.015			-0.038***	-0.036***			-0.033***	-0.031***		
		(0.014)	(0.015)			(0.010)	(0.015)			(0.011)	(0.011)			(0.010)	(0.011)		
Financial	YoY stock market growth			-0.019*	-0.020**			-0.020***	-0.022**			-0.026***	-0.025***			-0.026***	-0.027***
				(0.010)	(0.010)			(0.005)	(0.010)			(0.008)	(0.007)			(0.008)	(0.007)
Financial	YoY price to rent growth	-0.012	-0.014	-0.012	-0.014	-0.017	-0.016	-0.009	-0.012	-0.006	-0.003	-0.006	-0.003	-0.014**	-0.012*	0.004	0.003
		(0.032)	(0.019)	(0.032)	(0.019)	(0.010)	(0.020)	(0.006)	(0.010)	(0.013)	(0.014)	(0.013)	(0.014)	(0.007)	(0.007)	(0.008)	(0.006)
Financial	YoY Inflation	0.034	0.025	0.034	0.025	0.017	0.02	0.035**	0.034	0.021	0.021	0.021	0.021	0.016	0.012	0.032	0.028
		(0.055)	(0.026)	(0.055)	(0.026)	(0.017)	(0.027)	(0.017)	(0.026)	(0.019)	(0.018)	(0.019)	(0.018)	(0.017)	(0.017)	(0.020)	(0.020)
Financial	CISS	-0.02	-0.020*	-0.02	-0.020*	-0.023***	-0.021*	-0.021***	-0.021*	0.009	0.011**	0.009	0.011**	0.009	0.010*	0.009	0.01
		(0.016)	(0.011)	(0.016)	(0.011)	(0.008)	(0.011)	(0.008)	(0.012)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)
Non fund	Exuberance	0.061***	0.063***	0.061***	0.063***	0.059***	0.057***	0.061***	0.064***	0.041***	0.041***	0.041***	0.041***	0.041***	0.039***	0.043***	0.041***
		(0.012)	(0.010)	(0.012)	(0.010)	(0.009)	(0.011)	(0.007)	(0.012)	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)	(0.009)	(0.008)
Other	YoY transaction growth	0.023***	0.023***	0.023***	0.023***	0.013**	0.014*	0.023***	0.021***	0.010*	0.011**	0.010*	0.011**	0.008	0.008*	0.013**	0.013**
		(0.008)	(0.006)	(0.008)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Other	CCI	0.0003	-0.001	0.0003	-0.001	-0.005	-0.004	0.0004	0.001	0.016*	0.016*	0.016*	0.016*	0.015*	0.013	0.019**	0.017*
		(0.013)	(0.013)	(0.013)	(0.013)	(0.007)	(0.011)	(0.009)	(0.012)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)
Other	EPU	0.011*	0.011**	0.011*	0.011**	0.009***	0.010*	0.011**	0.011**	-0.005	-0.007	-0.005	-0.007	-0.005*	-0.005	-0.006	-0.006
		(0.007)	(0.005)	(0.007)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.003)	(0.004)	(0.004)	(0.004)
	AR term	-0.019	-0.019	0.003	0.003					-0.013	-0.018	0.015	0.01				
		(0.029)	(0.019)	(0.026)	(0.019)					(0.015)	(0.016)	(0.016)	(0.017)				
	Const	-0.008	-0.009	-0.009	-0.01	-0.014**	-0.014	-0.009	-0.009	0.068***	0.071***	0.067***	0.069***	0.066***	0.067***	0.070***	0.070***
		(0.010)	(0.007)	(0.010)	(0.008)	(0.006)	(0.013)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)
AIC		-459.496	-457.801	-459.495	-457.800	-457.398	-455.507	-461.084	-459.500	-515.959	-514.812	-515.959	-514.812	-515.634	-513.925	-516.994	-516.369
Pseudo R2		0.666	0.666	0.666	0.666	0.662	0.662	0.665	0.666	0.615	0.616	0.615	0.616	0.613	0.613	0.614	0.616

Note: *, ** and *** denote statistical significance at 10%, 5%, and 1% (2 way test). The table depicts estimated coefficients across tail (5th) and median (50th) for 8 different models. The coefficients are fully comparable across variables, as they are standardised. Interpretation of coefficients can be done such that they are multiplied with 100%. Thus, increase of any of the variable by one standard deviation is related to β·100 p.p. change of house price growth 4-quarter ahead. I also estimated the model one quarter, as well as two and three years ahead. Results are available upon request.

5.2. Impulse response analysis

To effectively track tail risks, it is essential to monitor the estimated relationships over time. Accordingly, I have plotted the estimated coefficients for all variables from one to twelve quarters ahead for the lower tail (i.e. the 10th percentile). The results, displayed in Figure 3, indicate that some variables exert greater correlation with house price growth in the short term, whereas others become more significant over the medium to longer term. For policymakers, timely access to information regarding potential movements in tail risk is vital, as it allows for preventative measures to be implemented at the appropriate juncture.

Figure 3: Association between variables in the model and future tail risk (10th percentile) of house price growth, from one to twelve quarters ahead.



Note: panels depict the estimated coefficient for a given variable over time (x-axis represents quarters), where the grey shaded area denotes statistical significance. For the description of the variables, see Appendix Table A1.

Main findings are as follows:

In the short term (up to four quarters ahead), significant predictors of house price growth include financial stress, transaction growth, stock market growth, and changes in economic policy uncertainty. The importance of financial stress as a predictor of tail risks in the short term is well established in the literature—originating from growth-at-risk models and extending to house price modelling as well (see Adrian et al., 2020). However, after one year, its significance disappears entirely. Policymakers could treat spikes in financial stress as a signal of elevated near-term downside risk in the housing market. The roles of stock market growth and economic policy uncertainty in forecasting house prices in the short term are consistent with Antonakakis et al. (2016), who provide evidence that stock market performance and policy uncertainty are significant drivers of near-term housing market movements. Strong co-movement of house prices with stock market performance and policy uncertainty means the housing market is sensitive to broader investor sentiment. Policymakers could be alert to spillovers from financial market volatility into housing, especially when uncertainty jumps (e.g., geopolitical events, elections, policy shifts).

In the medium term (5 to 8 quarters), significant predictors become consumer confidence index, credit to GDP gap, inflation, price to rent ratio growth, and real GDP growth. The literature (Ling et al., 2015) shows that consumer expectations do not quickly revert to fundamentals, giving them stronger medium-term predictive power. Credit to GDP gap is a known mid to long term predictor of growth and house price at risk. My results are in line with Drehman and Yetman (2020) who show that the gap is a robust medium-horizon indicator of financial instability. A widening gap could signal accumulating leverage and could warrant tighter macroprudential policy (e.g., stricter LTV/DTI limits). Findings for inflation are in line with Rufai et al. (2024), and Kishor (2023), where a authors show that inflation plays an important role in driving house price growth over medium-term horizons. Price to rent ratio growth has the expected negative sign in the medium term. From asset pricing theory, rent can be observed as the future dividend or return on the housing investment (Courchane and Holmes, 2014). Thus, property prices should reflect the present value of those future dividend flows (Black et al., 2006). As house stock cannot react to changes immediately, decrease of rents would lead to decreased demand for housing, which would decrease house prices (Gholipour, 2013), as the user cost of housing becomes more expensive than renting. Higher real GDP growth is associated with a reduction in downside risk, in line with findings of Adrian et al. (2020), and vast growth at risk literature.

In the long term (8 to 12 quarters), the most important predictors of tail risks are supply, oil price growth, and the credit to GDP gap remains an important predictor. Although in this study I utilise the cyclical movement of supply, it still takes time for it to become significant. This is due to new house build could require the development of new infrastructure. These projects are often complex and time-consuming. As a result, the effects of supply expansion tend to be felt only after a considerable lag, once construction and infrastructure improvements are fully completed and integrated into the community. Regarding oil prices, literature suggests that rising energy costs can increase construction expenses and thus housing prices (Büyükkara et al., 2023), while oil price shocks may also shift investor behaviour toward alternative assets like gold (Shakil et al., 2018; Imran and Ahad, 2023).

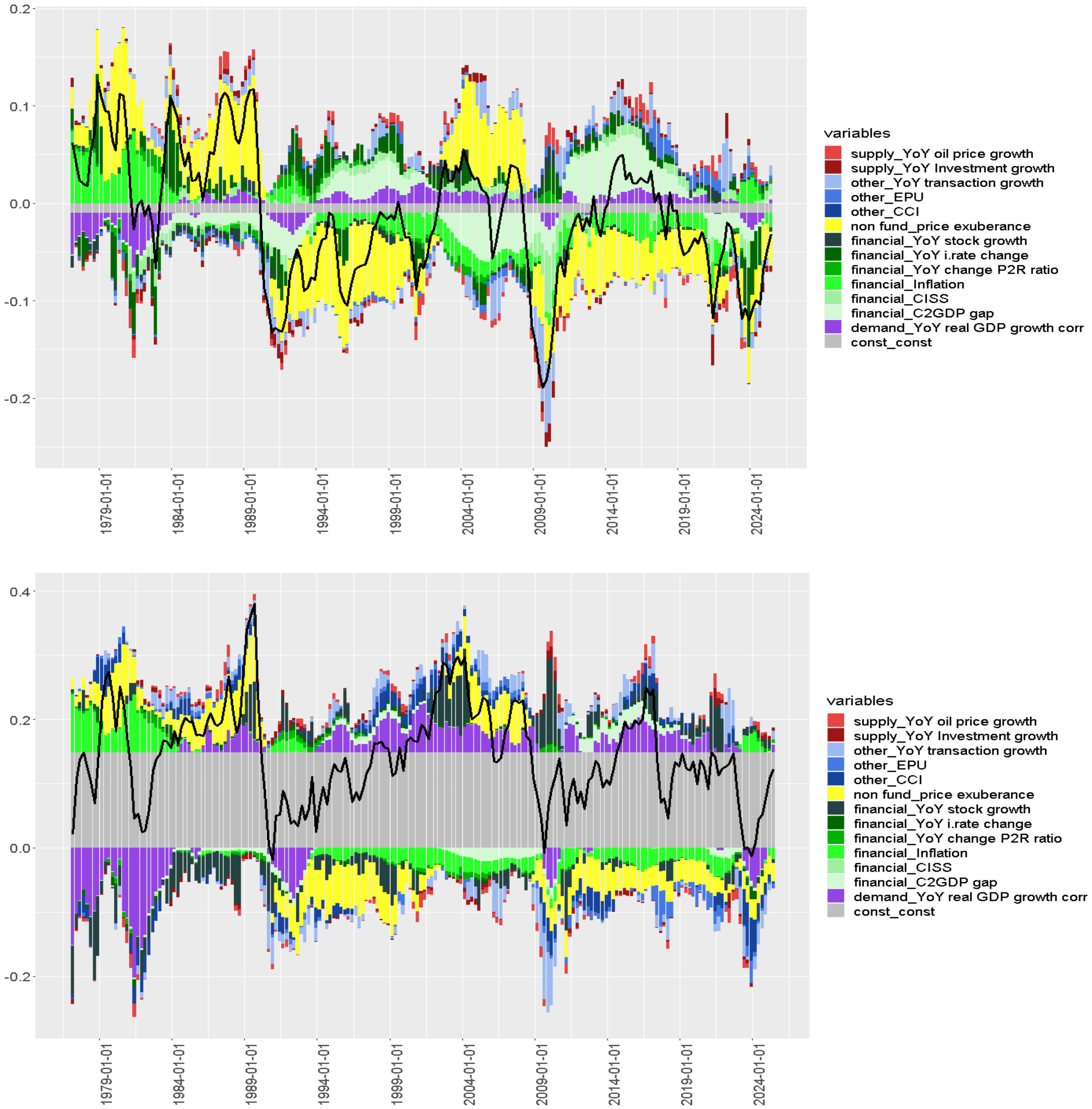
5.3. Robustness checks

Before continuing with the applications of the model, I have conducted different robustness tests. Firstly, I observe that across the final eight models in Table 1 —where variable definitions are varied or certain variables are excluded—the coefficients for the same variables remain stable. This consistency enhances my confidence in interpreting the results. However, I do provide additional robustness testing in Appendix 9. I compare estimated results by doing a recursive approach of adding one quarter information at a time, and by rolling window approach where I shift the available data one quarter at a time. Furthermore, I estimate the model in the pre-GFC era to look if there were some structural changes of parameters compared to the full sample estimation. Finally, I estimate one model that excludes only the Covid-19 period (i.e. 2020-2021), and another one that stops with data in 2019 (i.e. does not include 2022 period onward). My model is shown to be robust with respect to all these additional estimations.

5.4. Decomposing the main model

In the next step after estimating the main model and testing its robustness, I want to decompose the forecasted house price growth. To do so, I select Model (7) from Table 1, as it performs comparably to other models while including the highest number of statistically significant variables. Figure 4 presents the decomposition of the 5th percentile nominal HPaR and the median growth. The model clearly captures periods of booms and busts, with the tail risk component more effectively identifying downturns than the median estimate. In contrast, a standard linear regression model would fail to capture these busts—just as the median estimate in the lower panel of Figure 4 does not adequately reflect the dynamics of GFC.

Figure 4: Decomposition of the 5th (upper) and median (lower) of nominal house price growth



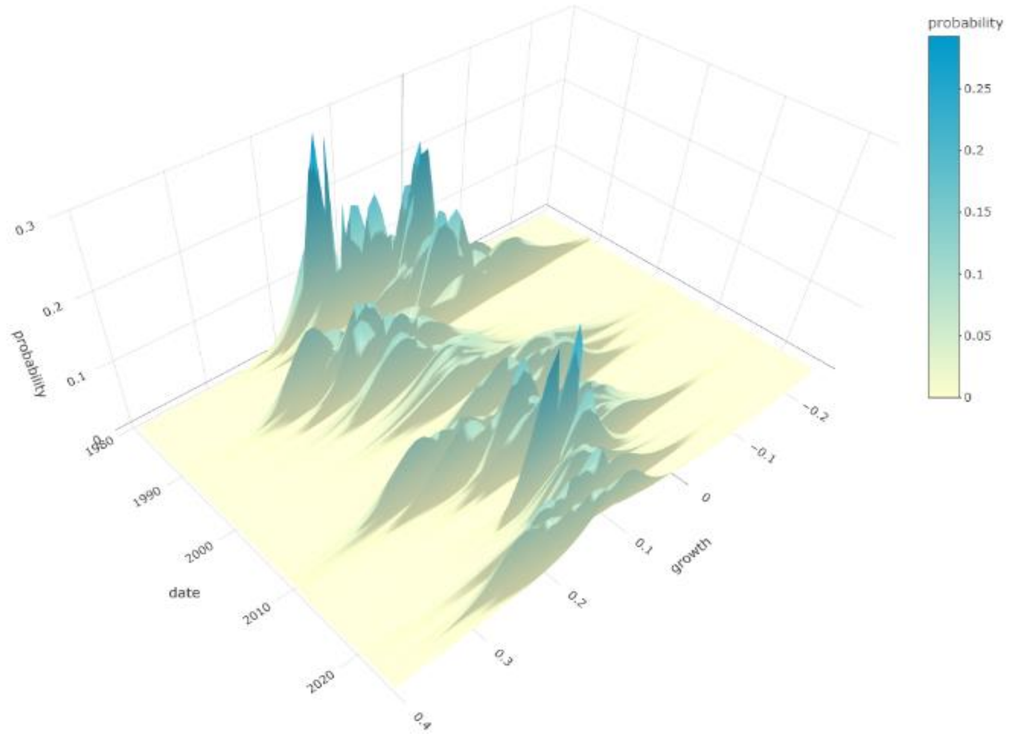
Note: The Figure shows the decomposition of the tail risk (upper panel) and of the median growth (lower panel) on factors from Table 2. Estimates shown such that values in 2024 Q3 reflect forecasts based on 2023 Q3 data. Black curves are the 5th and median HP growth estimate. 95th percentile estimate decomposition is shown in Appendix 10 Figure.

If I focus on the tail risks (upper panel, Figure 3), I observe that the declines in nominal house prices during the early 1980s, 1990s, the GFC, and the recent period were explained by different factors. In the early 1980s, the initial drop in nominal house prices was primarily linked to the oil price shock and a concurrent economic recession, followed by sharp increases in mortgage interest rates. The downturn in the 1990s also began with a recession, but the bursting of a housing bubble—reflected in a sharp decline in exuberance—played a more prominent role. This was compounded by a dramatic fall in credit activity and a significant drop in transactions in preceding quarters. During the GFC, transaction volumes made the largest forecasting contribution to the decline, followed by heightened financial stress and a contraction in credit supply. In the most recent downturn, the decline began with a slowdown in transactions, rising mortgage interest rates, and a drop in exuberance. Both the tail and median nominal house price growth have been trending downward since 2016, consistent with findings by Nguyen and Vergara-Alert (2023), although this period did not present a major tail risk event. In contrast, during the strongest boom periods (see Appendix Figure 10), stock market performance, real GDP growth, and exuberance were the key predictors positively correlated with rising nominal house price growth.

5.5. Distribution forecasting

I examine how the distribution of estimated house price growth evolves over time. To do this, I fit a skewed t-distribution to the model in each quarter and illustrate its progression in Figure 5[20]. Recessions are clearly visible, typically followed by an increase in the dispersion of the distribution, reflecting heightened uncertainty. In the most recent period, I initially observe a leftward shift of the entire distribution, driven by rising mortgage interest rates—consistent with Hafemann's (2023) findings for the German housing market. However, a recovery is evident in subsequent quarters, as the pace of increase in key contributing factors has slowed. Importantly, by examining the full shape of the distribution—rather than just the median or mean forecast—we gain a more comprehensive understanding of the range and direction of potential future outcomes. This approach enhances my ability to interpret the model's forecasts in the context of evolving economic conditions.

Figure 5: Nominal house price growth distribution over time



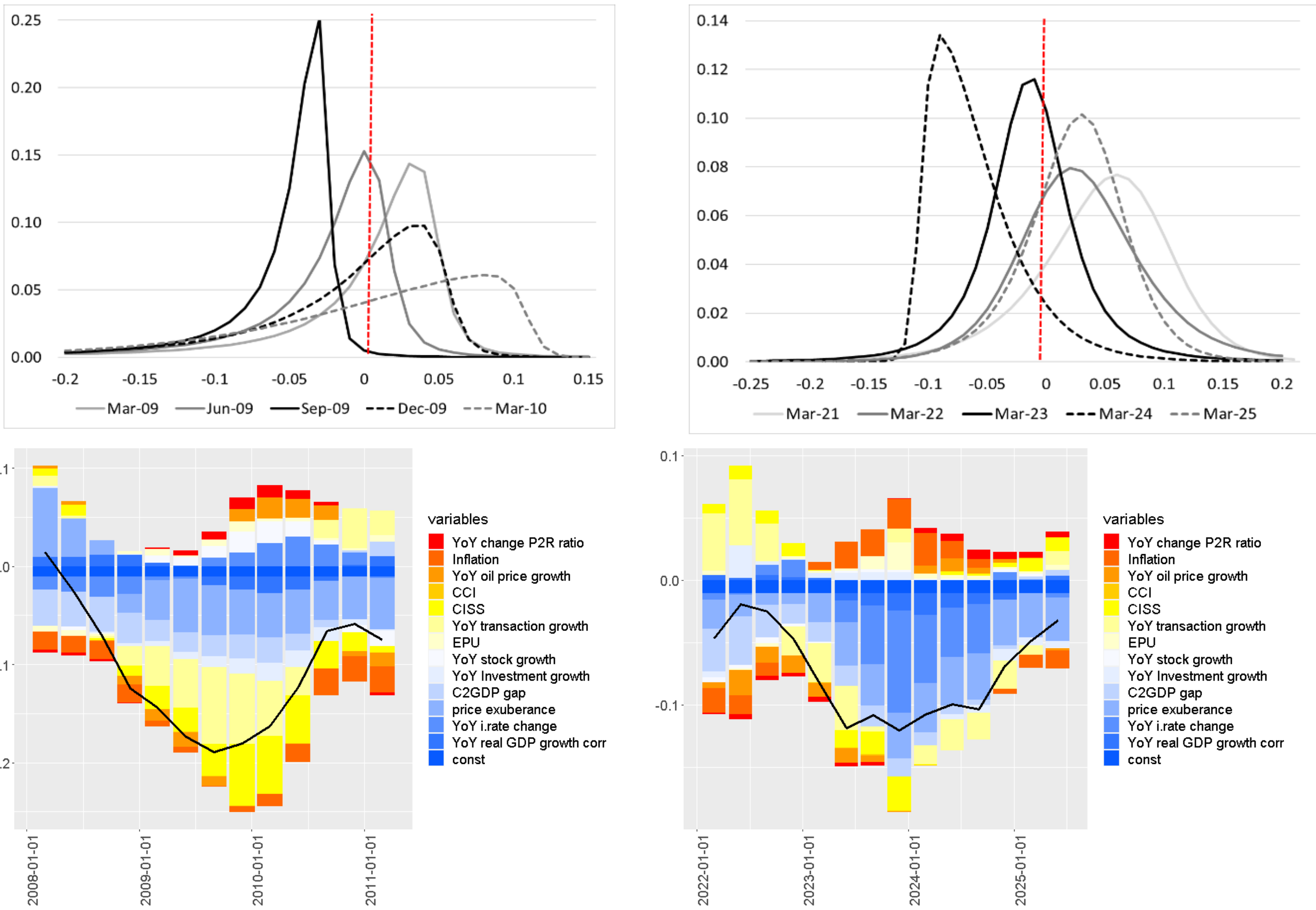
Note: Distribution depicted at a certain quarter in a given year is estimated based on information from the same quarter from previous year. The figure shows the probability (vertical axis) of obtaining growth in each period (date axis). Appendix 11 shows the time series of the estimated parameters of the distribution.

I want to showcase how in specific periods the distribution changed over time, and what were the most prominent factors that helped in decomposing the HP growth. Specifically, I highlight the pre-GFC and GFC period (Figure 6, left), and the most recent period (Figure 6, right). Since the framework is forward-looking—meaning the estimates are based on information available one year prior—tracking the distribution during the pre-GFC era reveals early warning signs of an impending shift. These include a slowdown in transactions, booming credit activity, and rising financial stress. Similarly, the recent decline in nominal house prices, which began to emerge around Q1 2021, could also have been anticipated with transaction growth drop, business confidence decline,

[20] Estimated parameters of the fitted distribution as time series are shown in Appendix 11.

and mortgage rate increase, alongside low exuberance, and spike of financial stress. At that time, the left tail of the distribution began to fatten, indicating increased downside risk[21]. Reasons this time are different except for the transactions again, now the increase of mortgage interest rate alongside exuberance declining rapidly were the main contributors to such dynamics.

Figure 6: HP growth distribution (upper panel) and decomposition of the 5th percentile (lower), one year ahead



Note: In the upper panel, the red dashed line denotes zero value on x-axis. X-axis denotes nominal house price growth values while Y-axis denotes the probability. Upper panel shows several distributions from selected points in time. In the lower panel, I decompose the 5th percentile growth across time for selected sub-periods.

5.6. Forward looking measures of house price vulnerability

I calculate several forward-looking risk measures based on the estimated distributions for the one-year ahead model: tail risk (5th percentile), distance to tail, expected shortfall, and the probability of negative growth—presented in Figure 5. Since these measures are derived from models that forecast one year ahead, they offer potential as rapid, forward-looking tools for monitoring housing market risk.

Tail risk is an intuitive measure, as it tells us what the potential fifth percentile house price growth could be one year ahead; lower values indicate greater risk. As shown in Figure 7 (upper left panel), tail risk was able to anticipate house price downturns in the early 1990s, GFC, and the latest downturn in 2023–2024.

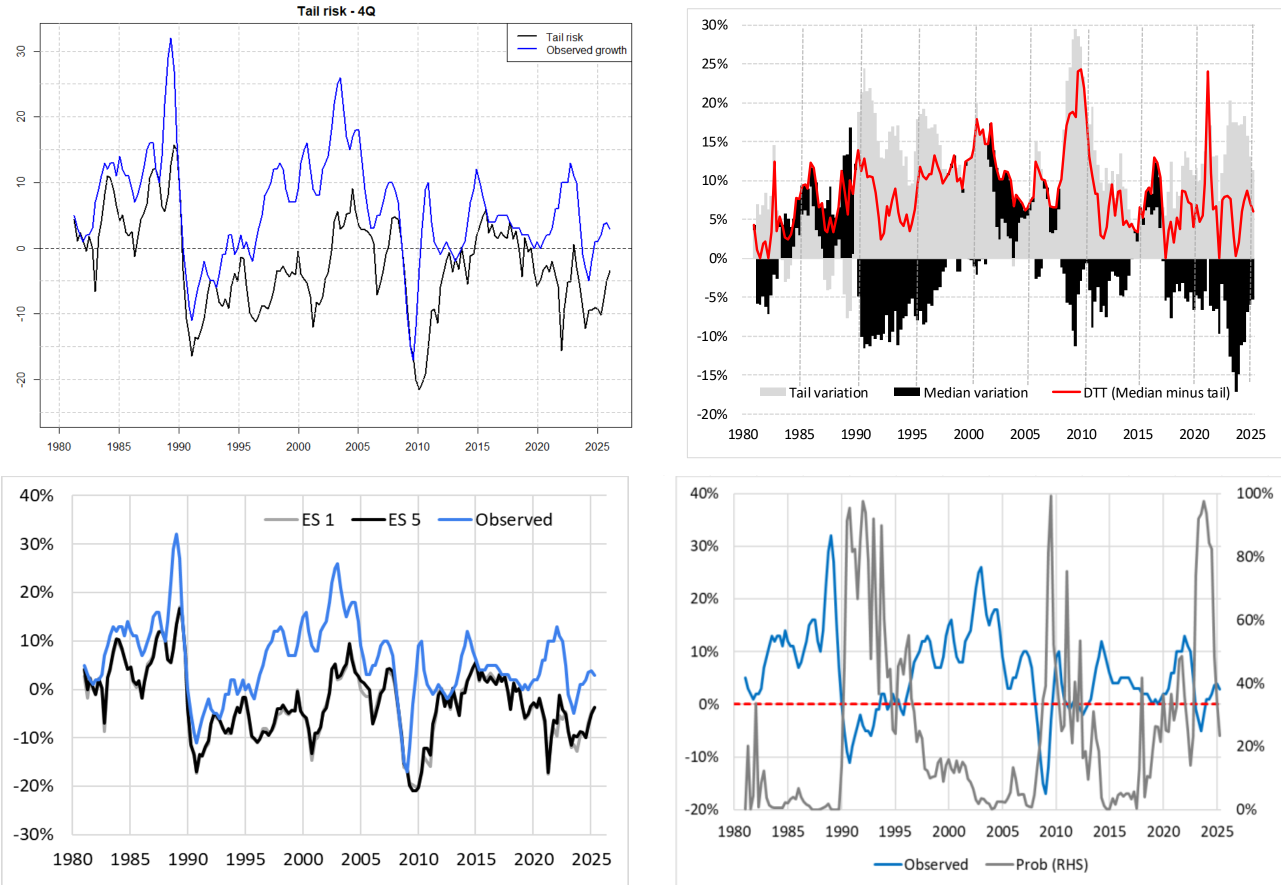
Distance to tail (Figure 7, upper right panel) is the difference between the median and tail risk growth. An increasing gap between the median and lower-tail forecasts may signal growing vulnerabilities. To better understand the source of this uncertainty, I decompose it into contributions from movements in the median and the tail. When tail estimates diverge from the median, the lighter grey area increases; conversely, when the

[21] Final thing to note is that although the distribution in March 2024 had a peak lower than the GFC peaks, the standard deviation of the recent distributions is much lower than around GFC. Thus, although it seems that the recent drop is harsher than the GFC, what is reflected is that the estimate for the median and tail growths is now much closer than what was estimated to be for GFC. The lower panel of figure 6 shows the decomposition of the lower tail for both sub-periods, where I can see that the 5th percentile for the GFC case is much lower than the corresponding percentile in the case of most recent developments.

median moves away from the tail, the darker grey area becomes more prominent. A notable spike in uncertainty is observed during the COVID-19 shock, though it dissipates quickly, as expected. Also consistent with expectations, median estimates tend to converge towards the tail during crises, coinciding with a drop in standard deviation. The expected shortfall (right panel) effectively captures the evolving characteristics of the distribution over time.

Expected shortfall (lower left panel) is the expected average growth at a certain quantile. I focus on the first and fifth percentiles and how ES anticipated future potential house price drops. Like tail risk, these measures could predict increases in vulnerabilities of house price growth one year ahead. Finally, I also forecast the probability of negative house price growth one year ahead (Figure 7, lower right panel). The model is successful in predicting such periods when house prices would drop significantly, in the aforementioned periods.

Figure 7: Tail risk (upper left), distance to tail and its decomposition (upper right), expected shortfall (lower left), probability of negative house price growth (lower right), one year ahead

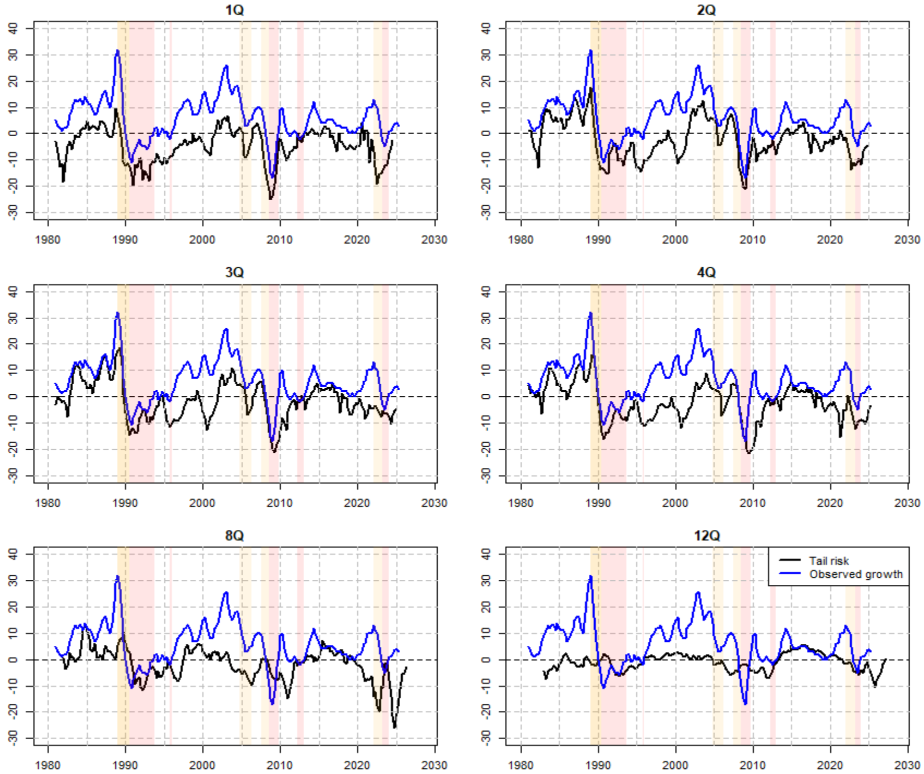


Note: Tail risk refers to the house price growth at 5th percentile. Uncertainty is calculated as house price growth at median minus house price growth at 5th percentile. Decomposition in the upper right panel shows how the uncertainty between median and 5th percentile is changing due to changes in median and the left tail respectively. ES1, ES5 and observed growth stand for expected shortfall at 1%, 5%, and the observed HP growth respectively. Estimates at a certain quarter of a year are based on information from the same quarter in the previous year.

Policymakers may be interested in monitoring changes in house prices over a period longer than one year. This is particularly relevant when assessing the effects of a particular policy or tracking the build-up of certain vulnerabilities. Therefore, I repeat some of the exercises across different time horizons to evaluate the effectiveness of the modelling approach presented in this paper. Figure 8 illustrates the downside risk that I forecasted one, two, three, four, eight, and twelve quarters ahead, and compares these forecasts to periods of significant house price declines (orange shaded areas) and episodes of negative house price growth (red shaded areas).

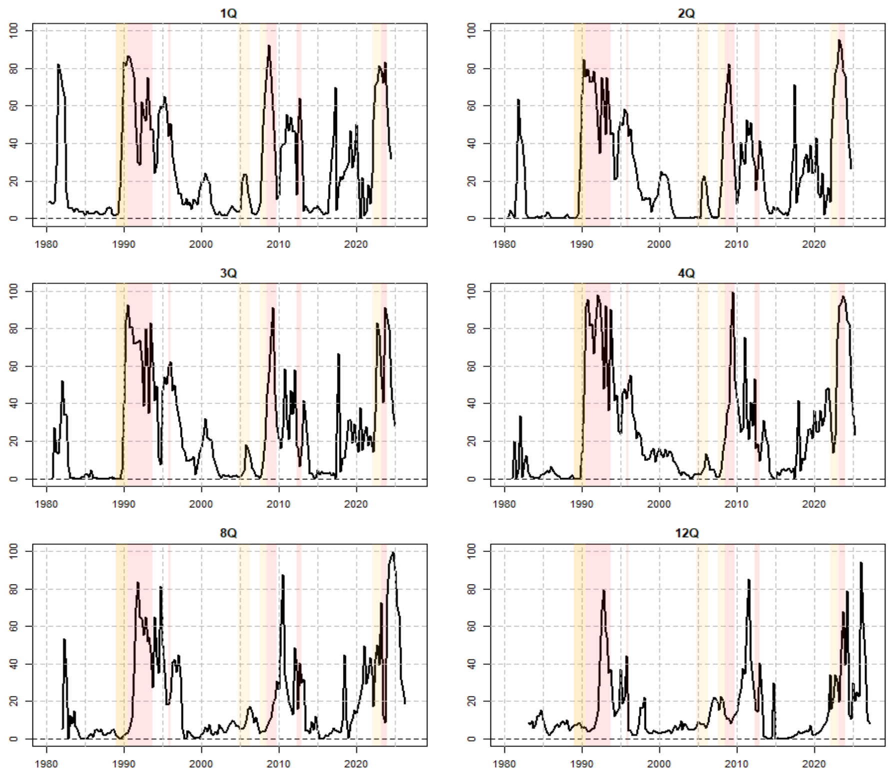
Models that forecast house price tail risk up to four quarters ahead prove highly effective in predicting major house price drops. The same holds true for forecasts eight quarters ahead. However, at the twelve-quarter horizon, the model becomes less informative. Consequently, using these measures to monitor potential downside risks may be valuable for up to two years.

Figure 8: Tail risk of house price growth at different prediction horizons



Note: orange shaded areas denote great drop of house price growth, whereas red shaded areas denote periods when the house price growth became negative. 1Q, 2Q, 3Q, 4Q, 8Q, and 12Q denote one, two, three, four, eight, and twelve quarters ahead. Tail risk denotes the forecasted 10th percentile of future house price growth, observed growth is the actual consumption growth.

Figure 9: Probability of negative house price growth for *h* quarters ahead



Note: orange shaded areas denote great drop of house price growth, whereas red shaded areas denote periods when the house price growth became negative. 1Q, 2Q, 3Q, 4Q, 8Q, and 12Q denote one, two, three, four, eight, and twelve quarters ahead.

Another useful metric I propose from this framework is the probability of negative house price growth *h* quarters ahead. In Figure 9, I plot this probability for various time horizons and contrast it with periods when house prices underwent a substantial decline (orange shaded areas) and entered negative territory (red shaded areas). Similar conclusions can be drawn as in the previous figure: at all horizons except for the twelve-quarter forecast, the model successfully predicts significant decreases in house price growth, particularly negative growth. To utilise such models effectively, it is important to detect these types of movements.

6. EMPIRICAL RESULTS - SUB-NATIONAL LEVEL

6.1. Model description

This section focuses on estimating the house price growth model at the sub-national level. As Meen (1999) suggests, factors that affect sub-national housing prices can be classified into two groups: those that are common across all regions, and those that reflect economic and structural differences specific to individual regions. Some authors assert that house price dynamics are a local phenomenon (Himmelberg et al., 2005), and there exist great heterogeneities across regional housing markets (Ferreira and Gyourko 2012). Rapaport (1997) shows that consumers do not decide only on how much housing to consume, but also where to consume it. Due to limitations in data availability, I incorporate national-level variables used in the UK model from the previous section, alongside region-specific indicators. These include measures of supply and demand misalignment and sub-national gross disposable income (GDI) dynamics. This approach allows us to capture both the shared macroeconomic influences and the localized factors that shape housing market behaviour across different regions. Firstly, I estimate a model on a panel basis, where I look at several different specifications:

i) Model 1 - model that has all the variables included as on the national level – i.e. replicating the same model I observed in the previous section.
ii) Model 2 - model where instead of GDP dynamics I include sub-national GDI growth – i.e. all the variables stay the same as in Model 1, but I swap the GDP with the GDI dynamics.
iii) Model 3 - a simpler model that has fewer variables included compared to Models 1 or 2. I base the selection of these variables on their correlation to the dependent variable. Here, I include the AR component of HP growth, that can capture the ripple effect.
iv) Model 4 – is same as Model 3 with inclusion of interaction between mortgage interest rate change and supply misalignment indicator. The rationale on this is that the panel approach assumes equal parameters for the covariates, and I have seen previous discussions on the supply inelasticity varying across regions both in literature (Cameron et al., 2006; Vonlanthen, 2023). Aastveit and Anundsen (2022) explicitly interact interest rate shocks with local housing supply elasticities in their regression models, as authors explain that effects of interest rate shocks differ with respect to the proximity of house prices to the minimum profitable construction costs. If the distance is smaller, area is considered supply elastic. Thus, I opt to include this somehow in the panel setting by including not only the mortgage interest rate change and supply misalignment indicator, but also their interaction[22].

Secondly, I estimate models for each region individually. I start with the full model specification again (as Model 1 above, but for an individual region). Then, I estimate Models 2 and 3 as above, but again, on an individual region basis. There is no need to estimate Model 4, as now individual models will capture differences between coefficients among regions. In the next section, I report on the main results regarding the lower tail of the growth distribution (i.e. the fifth percentile).

6.2. Main results – lower tail estimates

Panel results

Appendix 12 Table presents the results of four estimated models using a panel-based approach. For Models 1 and 2, most parameter estimates align with those from the national-level model, with a few notable exceptions. Specifically, the coefficients for the credit-to-GDP gap become positive, and both inflation and price-to-rent growth emerge as statistically significant. These deviations may reflect regional heterogeneities that are not fully captured by the panel framework. This interpretation is supported by the correlations I observe for each region

[22] To the knowledge of the author, there do not exist other studies that try to interact other variables besides these one that were examined here, and this could be explored in the future.

individually[23], which illustrate that the relationships between individual variables and regional nominal house price growth can vary significantly—not only in magnitude but also in sign—across different regions.

A similar pattern is observed in Models 3 and 4, particularly for the income and exuberance variables. It is important to acknowledge that, within this modelling framework, I assume uniform effects of macro-financial variables across all regions and identical ripple effects. This assumption may limit the model's ability to fully reflect region-specific dynamics. This is explored in the rest of this section.

Region-specific results

In the next step, I estimate individual sub-national models. The results for all three model specifications are presented in Appendix tables 12, 13, and 14. These estimations reveal several important and insightful findings compared to the panel-based models, which tended to produce more constrained results compared to the individual region-specific models.

Due to regional differences, I observe instances where the same variable has coefficients with opposite signs across regions. This suggests that changes in national-level variables may lead to divergent regional responses. Increase in income might shift demand from one region to another, rather than uniformly boosting housing demand across all regions. I find that demand has different sign of its coefficient across regional models. As expected, greatest positive relationship is found with London, SW, SE, and East regions. This is in line with Ministry of Housing's (2010) findings that some regions accumulate more human and physical capital from growth than others, affecting how income and housing demand respond to GDP cycles. This finding could be helpful for economic policies that try to stimulate demand, especially from the regional point of view.

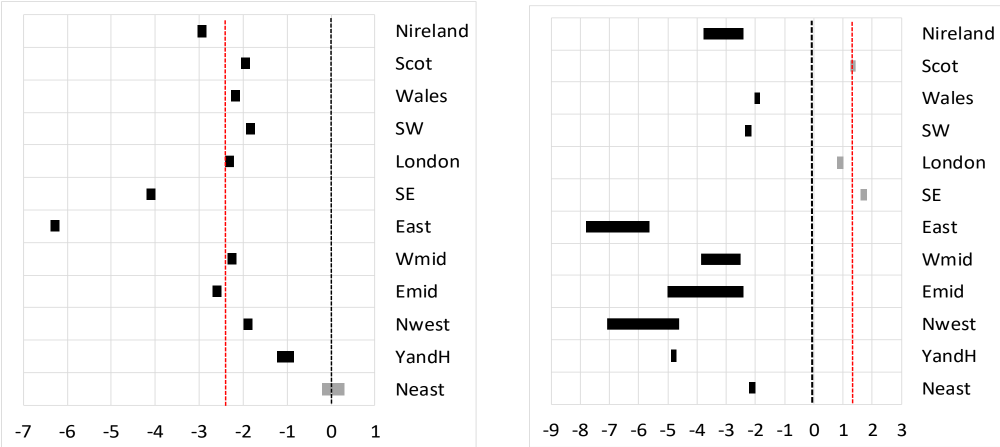
Credit to GDP gap similarly has a positive and a negative relationship with different regions. A region that is already "overheated" may see a negative future effect of a rising credit-to-GDP gap (predicting corrections), while another region in an earlier phase of the cycle may still show positive price growth responses. This is in line with conclusions of Albuquerque et al. (2005). I find that the greatest negative relationship is found for London, SE, SW, and East – regions that the exuberance measure tracked greatest increase of house price growth overall. Thus, combining overvaluation metrics with the credit to GDP gap could be useful to differentiate the potential downside risks of house price growth between regions.

Mortgage interest rate and supply effects have been widely discussed in the literature. To explore these dynamics further, I compare the estimated effects across all models in Figure 10. The coefficients for mortgage interest rate changes are notably stronger in regions that are more supply-constrained, consistent with findings from Cameron et al. (2006), Aastveit and Anundsen (2022), Vonlanthen (2023), and Walker (2023). I follow the symmetric interpretation of interest rate increases with respect to elastic or inelastic areas as in Duca et al. (2021), alongside focusing on the one year ahead forecast, which allows for the assumption of supply not reacting to changes of interest rates. In supply-inelastic regions, rising mortgage interest rates can result with sharper house price declines, as supply cannot adjust in the short term, while higher borrowing costs suppress demand. Conversely, when mortgage interest rates fall, prices in these regions tend to rise more quickly, as new construction cannot respond immediately to increased demand. These results also align with Meen (1999), who noted that debt-gearing capacity is higher in the southern regions of the UK. This implies that these areas may be more vulnerable to short-term liquidity constraints during periods of rising mortgage interest rates. I further examine the term structure of mortgage interest rate effects in Figure 11. The results confirm that southern regions not only react more strongly but also more quickly than other regions—particularly within the first two years following a mortgage rate change.

On the supply side (right panel, Figure 10), I observe that in most regions, increased housing supply helps to alleviate price pressures. However, there are notable exceptions: London, SE, and Scotland. For the first two, the results align with the findings of Zahirovich-Herbert and Gibler (2014), who argue that in large, built-up metropolitan areas, new supply can lead to higher house prices. This is due to elevated land costs, stringent development constraints, and the potential need for brownfield remediation. Farris (2001) further suggests that upgrading existing infrastructure in such areas can contribute to rising prices. In Scotland, beyond the previously discussed regulatory and policy differences, new housing developments may enhance local amenities and reduce crime. As Gleeson (2023) describes, these improvements can stimulate demand for existing housing stock, thereby pushing up prices. For the remaining regions, the results are consistent with Caldera and Johansson (2013), who find that in areas with less elastic supply, an increase in housing stock tends to be followed by a decrease in prices.

[23] I look at the correlations for each region on its own. Figures for the regional analysis are available upon request.

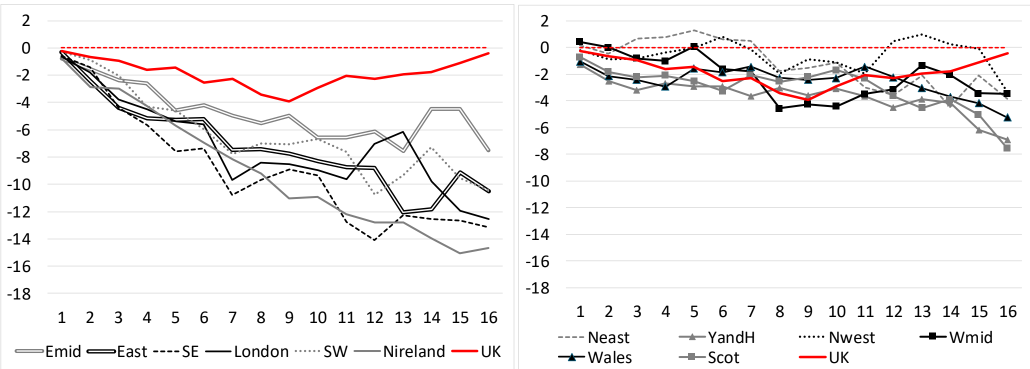
Figure 10: Range of estimates for mortgage rate change (left), and supply misalignment (right)



Note: Grey bars indicate non-significance. Estimates refer to the left tail. Red dashed line is the UK estimate. Supply misalignment is interpreted as follows: the greater its value is, the more housing supply is provided on the market. Higher supply misalignment therefore should be followed by decrease of nominal house prices.

Additionally, the results for Northern Ireland and Scotland often differ from those of other UK regions. This is not surprising, given their distinct economic and institutional contexts. Northern Ireland, for example, is more closely tied to the Republic of Ireland's economy (see Brownlow, 2023)[24]. Since the late 1990s, it has gained greater autonomy from the UK government in areas such as social security and housing market taxation (McKee et al., 2017). Stevenson (2004) also identified strong cross-border investment linkages between Northern Ireland and the Republic of Ireland, suggesting that housing market developments in Dublin may influence prices in Northern Ireland. Scotland has its own housing regulations and broader housing policy framework, which differ from those in England and Wales (Gibb, 2019). These institutional and policy differences help explain the regional variation observed in the model estimates.

Figure 11: Term structure of mortgage interest rate coefficient in sub-national models



Note: The figure shows how the estimated coefficients for mortgage interest rate change across time and regions for the lower tail. Estimated coefficients are based on model from Appendix 13 table.

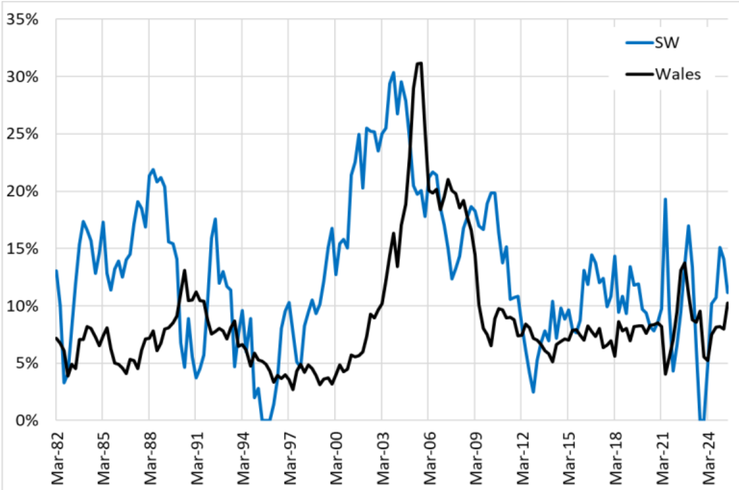
Region-specific probabilities of negative growth and distance to tail

We derive distributions over time for each region, as was done for the case of national model, and calculate the one year ahead probability of negative nominal house price growth in Appendix 16 Figure. The model is successful to predict periods of future negative growth, despite having shorter time series on sub-national level. Thus, I have confidence in future usage of these sub-national models, as they can distinguish between individual idiosyncrasies, while taking into consideration factors that have been found important on the national level. Including downside risks of regional house prices in the monitoring toolkit can strengthen the financial stability framework.

[24] Moreover, historical developments of Northern Ireland nominal (and real) house prices are different to the rest of the UK as noted in McCord et al. (2011) and Muellbauer and Murphy (1997); with government policy advocating homeownership in addressing the social and economic disparity.

Finally, I also derive the distance to tail indicator for individual regions. I showcase an example of contrast of results in Figure 12 on an example of SW and Wales. Other region-specific differences are presented in Appendix 17 Figure. The build-up of vulnerabilities, measured by increasing distance to tail indicator, is different across the regions in terms of magnitude and the timing. The build-up was more prominent in SW region in the late 1980s, and the new build-up in the pre-GFC era was sooner and faster as well. Thus, this measure needs to be tracked individually, as some regions will have build-up of vulnerabilities sooner than others. Furthermore, eventual actions of certain policies could also be reflected at different points in time. Whereas the previous indicator, probability of negative growth gave us information on what is the likelihood of breaching negative growth, the distance to tail tells us on increased uncertainty, or the divergence between the most probable outcome and that one that is considered as tail risk. That is why I consider them as complementary measures.

Figure 12: Distance to tail for South-West (SW) and Wales



Note: SW denotes South-West. Figure shows distance to tail (median minus the tail risk forecast) one year ahead.

7. CONCLUSION

Developments in the housing market have material implications for financial stability, as demonstrated during the GFC. My model captures risks to financial stability by estimating both the median and the tail of the nominal house price growth distribution, for the case of UK and its sub-national markets. Overall, the modelling framework provides a basis for analysing the drivers of downside risks to house prices. At the national level, the model delivers a coherent and informative picture of tail risks and their key macro-financial determinants. However, the regional results add important additional insights, revealing substantial heterogeneity across regions. In particular, the results for variables such as GDP growth, the credit-to-GDP gap, and mortgage rate changes varies markedly at the sub-national level. These differences mean that regional dynamics cannot be fully captured or replicated through aggregation to the national level. Taken together, the results highlight the value of considering both national and regional models to obtain a more comprehensive and nuanced understanding of house price tail risks, especially when using the framework for forecasting or "what-if" exercises. A combined approach may offer a more nuanced and comprehensive understanding of housing market dynamics.

My main findings are as follows. Higher demand – denoted by an increase in real GDP growth – is associated with a reduction in downside risks. However, this may also be followed by increased median house price growth, potentially raising financial stability risks in the longer term. My sub-national analysis reveals heterogeneity in demand sensitivity. Additionally, housing supply was generally found to alleviate price pressures in most sub-national markets, offering useful insights for policies aimed at stimulating housing investment. Changes in mortgage interest rates are an important factor that help to predict house price growth by affecting mortgage borrowing costs and housing wealth. The sub-national results indicate that the relationship between nominal house price developments and mortgage rate changes is not uniform but rather varies across different regions.

The framework developed in this paper can be used for regular macroprudential risk monitoring. My model enables the assessment of risks and vulnerabilities in house prices driven by macro-financial indicators. To the extent that higher credit growth predicts a fall in house price growth at the 5th percentile, my results imply that policies aimed at moderating credit growth would reduce tail risks to house prices.

Although the framework developed in this study has proven useful, several limitations must be acknowledged. One key constraint is data availability - particularly the lack of regional macro-financial variables, which was the most significant limitation. This may partly explain why the results from the regional approach cannot be aggregated in a way that would fully replicate the national estimates, due to the substantial regional disparities discussed earlier. More broadly, many of the variables used in the analysis only begin in the 1960s or 1970s, which restricts my ability to capture earlier cycles in nominal house price growth. Additionally, there are important region-specific factors and research questions explored in other studies that I could not incorporate into my framework.

My model performs best when more data is available, meaning that some interesting questions could not be explored due to the absence of long time series for certain variables. Furthermore, the framework is designed for cyclical analysis and is not suited to assessing structural changes. While I attempt to capture some structural shifts, such as changes in the banking system, through variables like credit availability, and I test for structural breaks over time, the model itself is not structural. As such, it does not allow us to infer true causality. Instead, I interpret the results in terms of the relative strength of different variables as predictors of potential future nominal house price growth.

This study sets out an initial framework for considering the risks to nominal house prices. However, there are several possible avenues for future research. If better sub-national data become available—particularly on demand—these should be incorporated and tested. Ripple effects could also be explored further, as this study assumed they occur one year after the initial price movements in the originating regions.

We could also deepen the sub-national analysis by examining convergence clubs of nominal house price growth (groups of regions that exhibit similar behaviour over time and converge in their growth). This would allow for the estimation of smaller panel models, potentially yielding more precise estimates than those based on the overall panel, while still offering more data points than individual region-specific models.

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Appendix 1 - Table A1: Variable description

CATEGORY	VARIABLE	TIME SPAN	SMYCE, ADDITIONAL INFO
DEPENDENT	UK house price index	Q4 1952 – Q3 2024	Nationwide building society (2024), based on nominal prices Index and in £. Index for all house prices instead of new houses, as the two indices are very similar
	Sub-national house price indices	Q4 1973 – Q3 2024	Nationwide building society (2024), based on nominal prices 12 sub-national indices; Index and in £
FOR DEPENDENT VARIABLE IN REAL TERMS	Final consumption expenditure deflator	Q1 1955 – Q2 2024	Index to be used to deflate price series, and other relevant variables of interest ONS (2024). Index
FINANCIAL FACTORS	Mortgage interest rate[25]	Q1 1960 – 3Q 2024 Spliced dataset: 3Q 1939 – Q1 2017	2y, and 3y fixed rate 75% LTV Building Societies Association (2024), FRED (2024), OECD (2024 a) Spliced dataset: BoE research data; Percentage Using two series: 10y government bond yield, and historical research data rate spliced with 2y, and 3y rate
	Mortgage debt stock	Q2 1963 – Q2 2024	Stock, historical data up to 1987 from BoE Research database (2024), from 1987 from BoE (2024) In mil £
	Mortgage debt flow	Q3 1963 – Q2 2024	Stock, historical data up to 1987 from BoE Research database (2024), from 1987 from ONS (2024) In mil £
	Stock market index	Q4 1957 – Q3 2024	FRED (2024).
	CISS UK	Q1 1980 – Q3 2024	ECB (2024) Index, 0 to 1.
	CLIFS UK	Q1 1970 – Q3 2024	ECB (2024) Index, 0 to 1.
	Bank of England rate	Q1 1946 – Q3 2024	Historical data from Fred (2024) Newer data from BoE (2024)
	Treasury bill rate	Q1 1946 – Q3 2024	Historical data up until 2017 from BoE (2024) Newer data from Investing (2024)
	Spread	Q1 1960 – 3Q 2024	Spread between the mortgage interest rate on mortgages (see above) and the treasury bill rate Spliced dataset: 3Q 1939 – Q1 2017
	Rent index	Q1 1962 – Q3 2024	ONS (2024) for newer data Historical data from Gov (2024 a, b) To be used for the price to rent ratio
	M4 money supply	Q1 1963 – Q3 2024	BoE (2024)
DEMAND FACTORS	Gross disposable income (GDI) UK	Q4 1952 – Q2 2024	ONS (2024); In mil £
	GDI Sub-national	Q4 1973 – Q4 2022	GDI in monetary units from ONS (2024) for 1997 to 2022 ONS (2016) for 1976 to 1996 In mil £. Annual interpolated into quarterly with linear interpolation. Growth from 2022 applied to 2023 and 2024
	Population uk	Q1 1960 – Q2 2024	OECD (2024), annual interpolated into quarterly with linear interpolation ONS (2021) estimates for 2023 and 2024
	SUB-NATIONAL population	Q4 1973 – Q2 2024	ONS (2024), annual interpolated into quarterly with linear interpolation. Growth from 2022 applied to 2023 and 2024
	GDP UK	Q1 1955 – Q2 2024	ONS (2024) In mil £

[25] The mortgage interest rate post 1999 was collected from Building Societies Association (BSA, the 2y and 3y fixed rates with 75% LTV). However, as I need longer time series, I proceed with the following approaches to extend the series in the past. One is using the "Spliced variable mortgage rate" from the BoE's research data (See sheet "M12. Secured and unsecured personal borrowing rates, 1939-2016), as in the period 1999 onward, it coincides with the 2y and 3y fixed rates, with the 97% and 95% correlation between the two mortgage interest rates and the spliced series. Thus, the spliced series in pre 1999 era was used, and onward I use the BSA values. The other approach is following related papers, who use the 10y government bond yields. I observe the correlation between the bond yields and the spliced rate to be also high (see Figure A2-4, 92%). Moreover, the correlation between the bond yields and the 2y and 3y fixed rates is also very high (see Figure A2-4, 94% and 96%). Thus, as an alternative approach, I use the government bond yield data.

SUPPLY FACTORS	Output of construction industry on new housing, Sub-national	Q1 1980 – Q2 2024	ONS (2024), for North Ireland Nistra (2024), interpolation for North Ireland before 2000. In mil £
	Output of construction industry on new housing uk	Q1 1955 – Q2 2024	ONS (2024) In mil £
	Producer price inflation	Q1 1960 – Q2 2024	BoE Research dataset for values before 2013, ONS (2024) and ONS (2024) for latest few quarters
	Stock of dwellings, UK and Sub-national		Gov.UK (2024, 2024). For Scotland: Gov.Scot (2024). For Wales: Gov.Wales (2024). For North Ireland: Department of Finance N. Ireland (2024). Annual data interpolated into quarterly.
	Investment (supply) misalignment UK	Q1 1960 – Q2 2024	Description in *section 3.2. in main text*: 1) Model based 2) HP filter gap
	Sub-national investment (supply) misalignment	Q1 1980 – Q2 2024	Description in *section 3.2. in main text*: 1) Model based – individual 2) Model based – panel 3) HP filter gap
	Producer price index	Q1 1960 – Q2 2024	ONS (2024)
	Oil price	Q1 1946 – Q3 2024	FRED (2024). Spot Crude Oil Price: West Texas Intermediate (WTI), Dollars per Barrel
NON-FUNDAMENTAL FACTORS	Price misalignment UK	Q1 1960 – Q2 2024	Description in *Appendix 3* 1) Model based 2) Exuberance measure for nominal prices 3) Exuberance measure for real prices 4) HP gap for price to income ratio
	Sub-national price misalignment	Q1 1980 – Q2 2024	Description in *Appendix 3* 1) Model based – individual 2) Model based – panel 3) Exuberance measure for nominal prices 4) Exuberance measure for real prices HP gap for price to income ratio
OTHER	Composite consumer confidence indicator UK	Q4 1957 – Q3 2024	OECD (2024). Before 1977: CLI values. Balance, 100 = neutral, above 100 = positive, below 100 = negative.
	Composite business confidence indicator UK	Q4 1957 – Q3 2024	OECD (2024). Before 1974: CLI values. Balance, 100 = neutral, above 100 = positive, below 100 = negative.
	Composite leading indicator (CLI) UK	Q4 1957 – Q3 2024	OECD (2024). Balance, 100 = neutral, above 100 = positive, below 100 = negative.
	EPU	Q1 1900 – Q3 2024	EPU (2024). Historical dataset and new one merged such that 100 = March 2003.
	Housing transactions UK	Q2 1977 – Q2 2024	Data until 2005 from ONS archives. Data from 2005 onward: ONS (2024)

Source: author's compilation based on sources in last column
Note: table summarises all variables used in the empirical part of the study, with sources and timespan availability.

Appendix 2 - Table A2: Abbreviations description

Abbreviation	Description	Sign
dlog.gdi	YoY growth rate of GDI	+
dlog.gdipc	YoY growth rate of GDI p.c.	+
r.dlog.gdi	YoY growth rate of real GDI	+
r.dlog.gdipc	YoY growth rate of real GDI p.c.	+
d.rate_1	QoQ change of Irate_1	-
d4.rate_1	YoY change of Irate_1	-
d.rate_2	QoQ change of Irate_2	-
d4.rate_2	YoY change of Irate_2	-
dlogpop	YoY growth rate population	+
dlogp2i	YoY growth rate of price to income ratio	+
dloginv	YoY growth rate of investment in new housing	-
dlogppi	YoY growth rate of PPI	+
price_mis_exu	Exuberance test value for house prices, UK Exuberance test value for house prices, individual region	+
price_mis_hp	HP gap of house price misalignment, UK / HP gap of house price misalignment, individual region	+
price_mis_model	Gap of house price misalignment from economic model (1-2), UK	+
price_mis_model_ind	Gap of house price misalignment from economic model (1-2), individual region	+
price_mis_model_panel	Gap of house price misalignment from economic model (1-2), panel approach	+
dlogmorts	YoY growth rate of mortgage credits - stock	+
dlogmorts_qoq	QoQ growth rate of mortgage credits - stock	+
mort_f	Flow of mortgage credits	+
growth	YoY GDP growth	+
growth.corr	YoY GDP growth, with Covid-19 correction	+
r.growth	YoY real GDP growth	+
r.growth.corr	YoY real GDP growth, with Covid-19 correction	+
dm2gdp.s.corr	YoY change of mortgage to (corrected) GDP ratio	+
dm2gdp.s.sum.corr	YoY change of mortgage to (corrected) sum of GDP ratio, sum refers to current and previous 3 Q - stock	+
m2sum.gdp.gap.s.corr	HP gap of mortgage to (corrected) sum of GDP ratio - stock	+
m2gdp.gap.s.corr	HP gap of mortgage to (corrected) GDP ratio - stock	+
f2gdp.gap.corr	HP gap of mortgage to (corrected) GDP ratio - flow	+
inv_mis_hp	HP gap of investment misalignment, UK / HP gap of investment misalignment, individual region	-
inv_mis_model	Gap of investment (supply) misalignment from model (1-2), UK	-
inv_mis_model_ind	Gap of investment (supply)misalignment from model (1-2), individual region	-
inv_mis_model_panel	Gap of investment (supply) misalignment from model (1-2), panel approach	-
stocks.qoq	QoQ stock market returns	+/-
stocks.yoy	YoY stock market returns	+/-
clifs	CLIFS index	-
ciss	CISS index	-
diff.yoy	Difference between YoY stock market and house price returns	-
diff.qoq	Difference between QoQ stock market and house price returns	-
epu	EPU indicator	+
transactions	Number of house price transactions	+
Cci	Consumer confidence index	+
Bci	Business confidence index	+
lci	Leading composite index	+
Boe	Bank of England interest rate	-
Inflation	YoY CPI inflation	+
Spread_1	Spread between Rate_1 and treasury bill rate	+
Spread_2	Spread between Rate_2 and treasury bill rate	+
Boom1	Indicator variable equal to 1 when m2sum.gdp.gap.s.corr is above 0	+/-
Boom2	Indicator variable equal to 1 when m2gdp.gap.s.corr is above 0	+/-
Boom3	Indicator variable equal to 1 when f2gdp.gap.corr is above 0	+/-
Boe	Bank of England interest rate	-
D4boe	YoY change of Boe	-
dboe	QoQ change of Boe	-
P2r	YoY growth rate of price to rent ratio	-
yi	House price growth *i* quarters ahead, i = 1 to 16	/

Source: author’s compilation based on sources in Table 1 in main text.
Note: All variables are transformed to be changes or growth rates where needed, and are normalised before the analysis. Sign – expected sign at median estimate.

Appendix 3 – Estimating supply misalignment indicator - basis

Model (1-2) from main text

System of equations (1-2) in the main text are derived from a stock-flow model (Di Pasquale and Wheaton, 1994), where supply S is defined through new investing I, and the amortisation rate from previous period λ:

$$S_t = I(X, P) + (1-\lambda)S_{t-1}\ , \qquad \text{(A4-1)}$$

where investment depends on P (house prices) and other factors in X (e.g. construction costs). Demand is defined as function of prices and other factors in Y (permanent income and development in population, user cost of housing, Meen, 2001), i.e. $D = f(Y, P)$, and in the equilibrium, I have $S = D$, i.e.

$$I(X, P) + (1-\lambda)S_{t-1} = f(Y, P). \qquad \text{(A4-2)}$$

The model has an advantage of looking at housing as capital investment, and a consumption good. Since the housing market moves slowly, the equilibrium is reached in the long run. There have been several variations of variables that are included in X and Y (see Cavalleri et al., 2019).

Alternative version of model (1-2)

Besides the main approach in the text, I also tested the version of Meen's (2001) life cycle model where there exists substitution between housing and consumption, related to selling price and user cost of capital. In this model, house price is defined as:

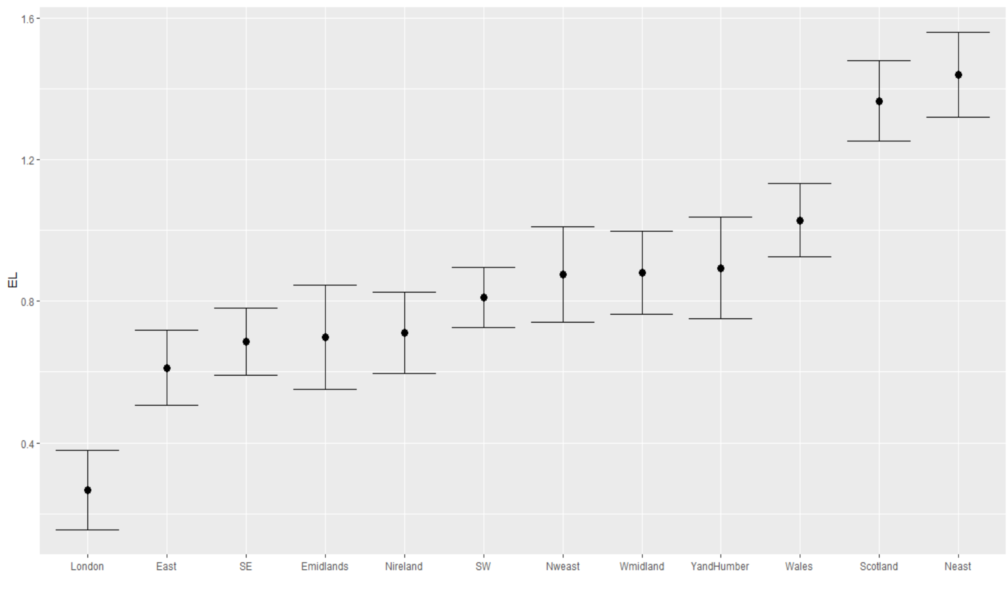
$$P(t) = \frac{R(t)}{(1-\theta)i(t) - \pi + \lambda - \frac{dg/dt}{g(t)}}\ , \qquad \text{(A4-3)}$$

where R is the real rental price, θ is the household marginal tax rate, i is the market interest rate, π is the inflation rate, and remaining ratio is the expected real capital gain from housing. As Cavalleri et al. (2019) show, rental prices have been estimated as function of the real income, number of households and real income, and by substituting that estimate in (A4-2), the empirical equation to be estimated is:

$$p_t = a_0 + a_2 y_t + a_3 pop_t + a_3 real\_irate_t + u_t\ . \qquad \text{(A4-4)}$$

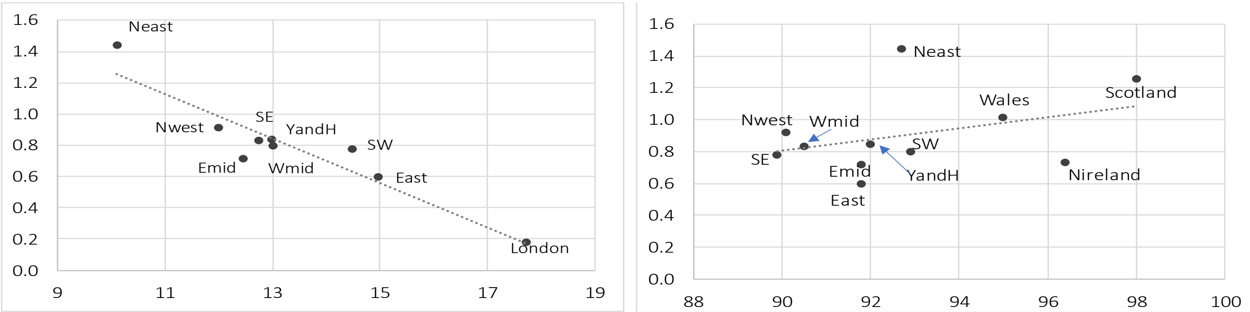
When I compare this equation to model (2) in the main text, I see that instead of using nominal, in (A4-3) I use real mortgage interest rates. Thus, I re-estimated the model (1-2) with having this into mind, but the overall results did not change, which is visible in figure A4.

Figure A4: Confidence intervals for sub-national supply elasticity, with real mortgage interest rates



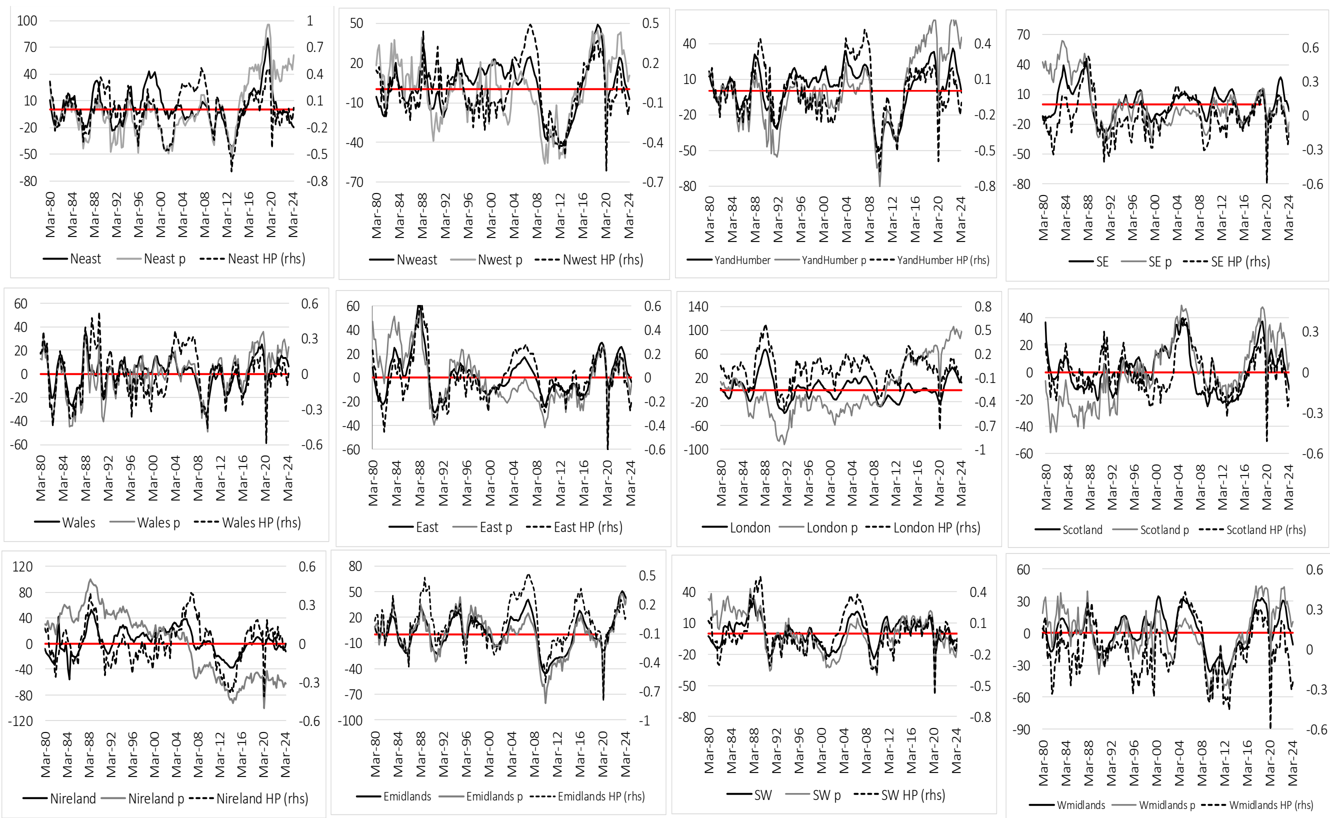
Note: black dots indicate point estimate, whereas whiskers denote 95% CIs. East – East Anglia, Emidlands- East Midlands, Neast – Northeast, Nwest – Northwest, SE – Southeast, SW – Southwest, Wmidlands – West Midlands, YandHumber – Yorkshire and Humber.

Appendix 4 – Figure: Correlation between estimated supply elasticities and average refusal rate on new built (left panel); and between share of non-developed land



Source: Gov.UK (2024a, 2024b)
Note: Figure compares estimated elasticity coefficients across regions from Figure 1 (on y axis) against: left panel the average refusal rate on new built, and right panel share of non-developed land. Correlation on the left is stronger compared to the one on the right, as in line with literature.

Appendix 5 – Figure: Supply misalignment from model (1-2) in main text and from statistical filter, regions



Note: Region name refers to misalignment derived from model (1-2), p denotes the same model on panel basis, HP refers to the gap obtained from the HP filter. RHS is right hand side. Figure shows indicators of supply misalignment for regions across time, and compares it based on a single region model (name of the region), panel model (name of region with p) and a HP gap filter results (HP gap, RHS). The higher the value of the indicators, supply is able to follow demand more and should have alleviating effect on prices.

Appendix 6 – Real house price growth model results

Results from the real HP growth shown in Table A3-1 are similar to those of the discussed nominal HP growth. However, there are some differences that I discuss here. Firstly, some of the variables become insignificant for the real house price dynamics, such as EPU, transactions and CISS. Policy uncertainty and financial stress can be affected by inflation, as in terms of higher inflation they could increase, thus, making them insignificant when the house prices are deflated. Housing transactions affect mostly the nominal prices, as these are the ones buyers need to pay for. Because of these variables becoming insignificant, the AR term becomes significant in the real HP specification, which picks up some other possible effects that I did not include in the model. However, these effects are not big, as the coefficient besides the AR term is between 0.16 to 0.29. Oil price dynamics becomes significant in this specification, which could be in line with explanations that increased oil prices increase production costs, which leads to fall in domestic output, and this affects house prices as consumers cut back on spending (see Antonakakais et al., 2016; Mohsen and Ghodsi, 2020; Sheng et al., 2021; Breitenfellner et al., 2015). Price to rent ratio dynamics now becomes sometimes positively related to the future house price growth. However, this is in the case of models that do not have the AR component, which could mean that this component is stronger in the price dynamics than the effect of the rent in the price to rent ratio.

Table A3-1: Best house price models for case of real price growth, UK level

	5th 1 (1)	5th 2 (2)	5th 3 (3)	5th 4 (4)	5th 5 (5)	5th 6 (6)	5th 7 (7)	5th 8 (8)	50th 1 (9)	50th 2 (10)	50th 3 (11)	50th 4 (12)	50th 5 (13)	50th 6 (14)	50th 7 (15)	50th 8 (16)
r.growth.corr	-0.066	-0.078*	-0.081*	-0.049	0.0003	-0.028	-0.011	-0.031	0.018	0.023	0.035*	0.034**	0.035*	0.039*	0.043**	0.042*
	(0.078)	(0.041)	(0.041)	(0.042)	(0.064)	(0.098)	(0.085)	(0.098)	(0.020)	(0.020)	(0.018)	(0.014)	(0.019)	(0.023)	(0.021)	(0.022)
d4.rate_1	-0.071***	-0.060	-0.068	-0.088***	-0.082***	-0.078***	-0.084	-0.081***	-0.056***	-0.065***	-0.061***	-0.069***	-0.068***	-0.071***	-0.067***	-0.066***
	(0.026)	(0.036)	(0.047)	(0.030)	(0.024)	(0.029)	(0.079)	(0.026)	(0.015)	(0.016)	(0.018)	(0.016)	(0.018)	(0.015)	(0.017)	(0.018)
price_mis_exu	0.040***	0.023*	0.032	0.040***	0.030**	0.029	0.018	0.019	0.023***	0.023**	0.025***	0.025***	0.012	0.015	0.016	0.017*
	(0.015)	(0.014)	(0.020)	(0.011)	(0.014)	(0.021)	(0.026)	(0.017)	(0.008)	(0.009)	(0.008)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)
m2gdp.gap.s.corr	-0.030**	-0.040***	-0.023	-0.039***	-0.027**	-0.023	-0.022	-0.019	0.002	-0.002	-0.0003	-0.002	0.005	0.002	0.003	0.003
	(0.013)	(0.011)	(0.015)	(0.008)	(0.012)	(0.014)	(0.021)	(0.015)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)
dloginv	0.032*	0.022*	0.036**	0.019*	0.015	0.020	0.011	0.016	-0.003	-0.007	-0.007	-0.008	-0.006	-0.007	-0.007	-0.007
	(0.019)	(0.013)	(0.015)	(0.010)	(0.020)	(0.024)	(0.022)	(0.016)	(0.007)	(0.007)	(0.007)	(0.006)	(0.009)	(0.010)	(0.010)	(0.010)
diff.yoy	0.004	0.032**			-0.028	-0.027			-0.011	-0.014			-0.029***	-0.029***		
	(0.018)	(0.014)			(0.020)	(0.028)			(0.010)	(0.013)			(0.009)	(0.011)		
stocks.yoy			-0.011	-0.016			-0.031	-0.028			-0.016*	-0.016*			-0.014*	-0.014
			(0.018)	(0.013)			(0.027)	(0.023)			(0.008)	(0.009)			(0.008)	(0.008)
epu	0.010	0.002	0.010	0.004	-0.010	-0.013	-0.023**	-0.024**	-0.011*	-0.013**	-0.013**	-0.011**	-0.018***	-0.018***	-0.018***	-0.018***
	(0.015)	(0.012)	(0.015)	(0.011)	(0.017)	(0.026)	(0.011)	(0.012)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.007)	(0.006)	(0.005)
dlogtrans	0.021	0.049	0.025	0.056	0.026	0.025	0.021	0.020	0.032**	0.032**	0.030*	0.035*	0.010	0.015	0.008	0.008
	(0.047)	(0.046)	(0.041)	(0.039)	(0.044)	(0.056)	(0.069)	(0.056)	(0.015)	(0.016)	(0.016)	(0.019)	(0.015)	(0.017)	(0.016)	(0.018)
ciss	-0.010	0.0005	-0.007	-0.015	-0.010	-0.006	-0.008	-0.005	0.004	0.002	-0.0002	-0.001	-0.001	0.001	0.003	0.004
	(0.011)	(0.013)	(0.012)	(0.013)	(0.021)	(0.017)	(0.015)	(0.010)	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)
cci	0.045	0.059	0.040	0.025	-0.044	-0.020	-0.018	-0.004	0.013	0.009	0.003	0.0001	-0.009	-0.018	-0.019	-0.019
	(0.078)	(0.049)	(0.052)	(0.047)	(0.065)	(0.101)	(0.089)	(0.101)	(0.024)	(0.024)	(0.022)	(0.021)	(0.028)	(0.031)	(0.030)	(0.030)
oil	-0.013	-0.011	-0.022***	-0.013	-0.019*	-0.023**	-0.024***	-0.026***	-0.014***	-0.014**	-0.015***	-0.013***	-0.016***	-0.015***	-0.015***	-0.015***
	(0.011)	(0.008)	(0.008)	(0.009)	(0.010)	(0.011)	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
p2r	-0.034	-0.024	-0.011	-0.046**	-0.001	0.007	0.031	0.035*	-0.031**	-0.027*	-0.029**	-0.028**	0.002	0.0001	0.025***	0.024**
	(0.030)	(0.020)	(0.053)	(0.021)	(0.020)	(0.033)	(0.021)	(0.020)	(0.015)	(0.015)	(0.014)	(0.013)	(0.009)	(0.011)	(0.009)	(0.009)
ar_term	0.216*	0.290***	0.159	0.251***					0.204***	0.165***	0.230***	0.229***				
	(0.110)	(0.081)	(0.168)	(0.081)					(0.056)	(0.052)	(0.048)	(0.043)				
spread_2		-0.022**		-0.019**		0.006		0.007		-0.004		-0.003		-0.003		-0.001
		(0.010)		(0.008)		(0.020)		(0.008)		(0.007)		(0.008)		(0.007)		(0.007)
Constant	0.063	0.099***	0.041	0.086***	-0.018*	-0.023	-0.015	-0.019	0.163***	0.143***	0.176***	0.176***	0.071***	0.073***	0.070***	0.070***
	(0.047)	(0.036)	(0.076)	(0.032)	(0.011)	(0.015)	(0.018)	(0.015)	(0.028)	(0.025)	(0.025)	(0.024)	(0.008)	(0.008)	(0.008)	(0.008)
AIC	-392.145	-392.716	-392.065	-392.550	-383.661	-381.872	-384.223	-382.640	-487.460	-486.166	-490.054	-488.553	-475.930	-474.203	-469.917	-467.978
Pseudo R2	0.592	0.595	0.592	0.595	0.580	0.580	0.581	0.581	0.580	0.581	0.583	0.584	0.564	0.564	0.556	0.556

Note: *, ** and *** denote statistical significance at 10%, 5%, and 1% (2 way test). Description of abbreviations is given in Table A1. 5^{th} and 50^{th} denote model estimated at lower tail or median, 1 to 8 denote model 1 to model 8. The coefficients are fully comparable across variables, as they are standardised. Interpretation of coefficients can be done such that they are multiplied with 100%. Thus, increase of any of the variable by one standard deviation is related to β·100 p.p. change of house price growth 4 Q ahead. Price_mis_exu refers to the bubble test measure on real house prices.

Appendix 7 – Results of the estimated model – at median

We comment on the results of Table 1 in the main text that refer to the median estimates.

Demand - In my study, annual real GDP growth is found to be positively and significantly associated with nominal house price growth at the median (see the final eight columns in Table 1). This result is consistent with the findings of Claussen (2013), Case and Shiller (2003), and Ortalo-Magné and Rady (2005). Furthermore, the estimated coefficient at the median—ranging from 0.043 to 0.051—corresponds closely with the typical estimate of approximately 0.04 reported by Williams (2016), who reviews the wider literature on this topic.

Supply - Supply—measured by year-over-year investment growth—shows a mixed relationship with nominal house prices. Sometimes it is negative at the median, aligning with Coulson and McMillen (2007), who argue that new construction improves housing quality and shifts demand.

Financial factors

Price to rent factor (YoY price to rent growth) has the expected negative sign in the lower tail of the nominal house price growth distribution. This aligns with asset pricing theory, where rents are viewed as the future dividends of a housing investment (Couchane and Holmes, 2014). Just as investors prefer stocks with strong expected payouts—reflected in lower price-to-dividend ratios—the same logic applies to housing: when the price-to-rent ratio is high, it signals that property prices may be overvalued relative to rental income, reducing the attractiveness of housing as an investment. Gallin (2008) explains that high house price-to-rent ratios are typically followed by periods of faster rent growth and slower real house price growth, as demand shifts from buying to renting. This dynamic reflects a correction in perceived overvaluation[26]. In my analysis, while the price-to-rent variable generally behaves as expected, it is not consistently significant across all models. This suggests only weak evidence that investors systematically reduce housing demand in response to expectations of lower future rental yields.

Interestingly, there are instances where CISS is positively related to median nominal house price growth, which may reflect a flight-to-safety behaviour—where investors and households view housing as a more stable and reliable investment during periods of financial market volatility. Inflation becomes particularly relevant during periods of high price growth, as it may prompt households to hedge by investing in real estate. Several studies have found that higher inflation is associated with rising house prices, supporting the idea of housing as an inflation hedge (Bond and Seiler, 1998; Kenny, 1999). In my analysis, inflation generally exhibits the expected positive sign but is not statistically significant in most models. This suggests limited evidence that households increase housing demand as a precautionary response to general price level increases. However, the larger coefficients observed in the lower tail of the distribution compared to the median are consistent with findings by Christou et al. (2018), who show that consumer and house price indices are cointegrated primarily at lower quantiles—indicating that house prices may over-hedge inflation during downturns or periods of heightened uncertainty.

Other factors - Confidence indicators are also widely used in macro-financial forecasting and are relevant for housing markets, particularly under the rational expectations permanent income hypothesis (Turner and Wachter, 2010; Heining and Nanda, 2018). Higher confidence reflects optimism about the economy and personal financial stability, which can encourage large purchases like housing, thereby increasing demand and pushing prices upward. In my results, consumer confidence (CCI) is positively associated with median HP growth, in line with Kholodilin and Siliverstovs (2014). However, during periods of severe downturns—captured in the lower tail of the distribution—CCI is not significant, suggesting that optimism alone is insufficient to reverse price declines from a trough.

Appendix 8 - house price exuberance/bubble like behaviour background

The concept of a house price bubble/exuberance and overvaluation are well established in the literature. They typically refer to a significant increase in real estate prices beyond their intrinsic value, often driven by investor expectations that prices will continue to rise, even when fundamental factors cannot justify such valuations (Stiglitz, 1990). I estimate bubble like behaviour and overvaluation to track time series of it over time, to test if this can be a good predictor of house price growth. Before estimating them, I summarise them from the theoretical point of view, and describe the empirical strategy.

Defining bubble like behaviour

Case and Shiller (2003) argue that a (rational) bubble can occur when expectations of future price increases lead to temporarily inflated prices. Arce and López-Salido (2011) suggest that in a low-interest-rate environment, creditors may seek alternative investment opportunities, with speculative housing investment becoming an attractive option. Additionally, excess liquidity—another byproduct of low interest rates—can fuel housing demand and, consequently, drive up prices (Kim and Min, 2011).

Levin and Wright (1997) investigate bubble dynamics in the UK housing market, including sub-national regions, and identify several potential drivers of speculative behaviour. One key factor is the timing of property transactions: capital gains can arise from house price increases occurring between the date contracts are exchanged for a new purchase and the date contracts are exchanged for the sale of an existing property. This timing mismatch can incentivise speculative behaviour, particularly among households that commit to purchasing a new home before finalising the sale of their current one.

[26] According to Black et al. (2006), property prices should reflect the present value of expected future rental flows. However, because housing supply cannot adjust immediately, rising rents can eventually reignite demand for home purchases, pushing prices back up (Gholipmy, 2013).

Another contributing factor is anticipatory upgrading, where households purchase larger or higher-quality properties in expectation of future price increases. This behaviour can further inflate prices beyond levels justified by fundamentals. To model such dynamics, researchers have developed equilibrium correction models that incorporate bubble-like behaviour. A notable example is the "bubble-builder and bubble-buster" model proposed by Abraham and Hendershott (1996), which captures both the formation and correction of speculative price surges. If a house price bubble does exist, it can have long-term negative effects on economic growth. As Grossman and Yanagawa (1993) argue, bubbles represent unproductive assets that divert capital away from more productive investments. In empirical research, this often involves testing the time series properties of house prices. In addition to testing for house price bubbles, the literature has also used corresponding indicators to explain the onset of financial crises. Anundsen et al. (2016) find that the probability of a crisis increases significantly when bubble-like price behaviour coincides with high household leverage, based on an analysis of 20 OECD countries.

In asset pricing theory, house prices (HP) should equal the expected present value of future rents (R)[27]:

$$HP_t = E_t\left[\sum_{i=1}^{\infty}\left(\frac{1}{1+r}\right)^i R_{t+i}\right], \tag{A7-1}$$

which stems from solving the forward recursive equation:

$$HP_t = E_t\left[\sum_{i=1}^{j}\left(\frac{1}{1+r}\right)^i R_{t+i} + \left(\frac{1}{1+r}\right)^i HP_{t+j}\right], \tag{A7-2}$$

where it is assumed that transversality condition holds: $\lim_{j\to\infty}\left(\frac{1}{1+r}\right)^i HP_{t+j} < \infty$, which excludes explosive behaviour of *HP*. If this does not hold, then the house prices in (A7-1) are also affected with an explosive bubble component *B*. Campbell and Shiller (1987) representation of house price that includes bubbles is written as:

$$HP_t - \frac{1}{r}R_t = \frac{1+r}{r}E_t\left[\sum_{i=1}^{\infty}\left(\frac{1}{1+r}\right)^i \Delta R_{t+i}\right] + B_t, \tag{A7-3}$$

and if a bubble *B* is of large value, it will disconnect from the fundamental value, and to test this out, one looks at explosive behaviour in the observed house price time series.

If the rent is assumed to be $R_t = a + bR_{t-1} + e_t,\ \ e_t \sim WN\ (0, \sigma_e^2)$, where *abs*(*b*) < 1, then the rent is stationary, or in case of *b* = 1, it becomes a RW with drift. If there are no bubbles (*B* = 0), then the house prices are at their fundamental value, and are either stationary or have a unit root, depending on the rent *R*. On the opposite side, if there exists a bubble (*B* ≠ 0), there exists an explosive bubble component in house prices.

Empirical test for bubble like behaviour

Existence of house price bubbles or exuberance is based on unit root testing. Phillips et al. (2015a, 2015b) define a recursive testing procedure to identify periods of exuberance in time series, where explosive behaviour tested in an ADF-like (Augmented Dickey Fuller) regression approach. Idea is to test the null hypothesis of a unit root versus explosive behaviour in a given subsample of the time series. Besides research[28] applications, this approach is also used on regular basis at UK Housing Observatory (2024).

The standard ADF test regression:

$$\Delta y_t = \mu + \rho y_{t-1} + \sum_{j=1}^{p}\gamma\Delta y_{t-j} + \varepsilon_t \tag{A6-4}$$

is augmented into a recursive version of a sup ADF (SADF):

$$\Delta y_t = \mu_{r_1,r_2} + \rho_{r_1,r_2} y_{t-1} + \sum_{j=1}^{p}\gamma_{r_1,r_2}\Delta y_{t-j} + \varepsilon_t \tag{A6-5}$$

where r_i is equal to T_i / T, *i* ∈ {1, 2}, *T* is the total number of observations and T_i are sample starting and end points. If the ρ_{r_1,r_2} is equal to zero (null hypothesis), it implies that the time series *y* is integrated of order one. If, on the other hand, $\rho_{r_1,r_2} > 0$ (alternative), then the time series is explosive. In case of more than one bubble testing, GSADF (generalised SADF) approach is made (Phillips et al. 2015a, 2015b), where the sample starting, and end points can change. To detect house price bubbles in US, Dallas FED uses this approach (FED, 2024), and for the case of the UK market, the same approach is made by UK Housing Observatory (2024).

[27] As rent is regarded as the future dividend, i.e. the return on investment in houses (Cmychane and Holmes, 2014), is the main component of forming fundamental house price.

[28] See Pavlidis et al. (2021), Anundsen et al. (2016), Cincinelli et al. (2024). See also Banco de España (2021) and some explanations there on how prices are regressed on specific macroeconomic variables, alongside using statistical filters.

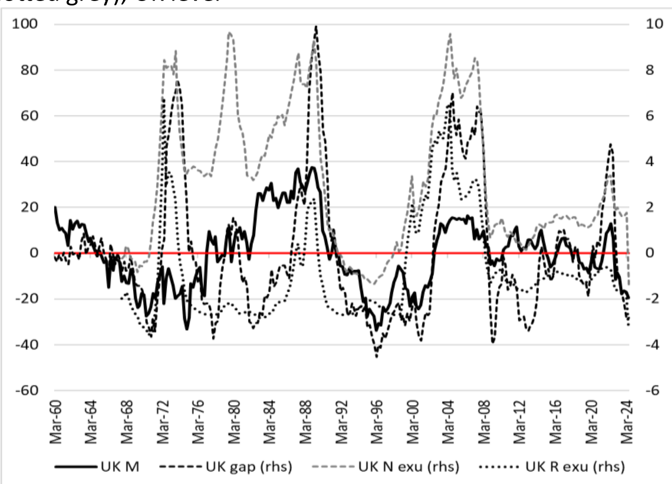
House price overvaluation

Overvaluation has also gotten attention in the related literature (Ganics and Rodríguez-Moreno, 2022; Jarmulska et al., 2022; Bowe et al., 2023), as it refers to house prices being overvalued compared to the "optimal" value or the value determined with economic fundamentals. Overvaluation is flagged as a source of systemic risk (Muellbauer, 2022). Whereas exuberance testing mostly refers to evaluating statistical property of the house price time series, overvaluation focuses more on economic reasoning on why prices deviate from what should be "optimal". Literature has shown that overvaluation is one of the best predictors of signalling future financial crises see Borio, 2012; Jordá et al., 2015). I estimate the house price overvaluation as the percentage deviation of the real house prices from estimated prices from model (1-2) in main text. This is the analogue approach I have done for the supply misalignment indicator.

Estimated results for bubble like behaviour and overvaluation

Figures A7-1 and A7-2 show all of the derived measures: exuberance empirical statistics both for nominal and real house price values, the overvaluation measure from model (1-2) on individual and panel estimation basis, and the HP filter-based measure of the house price to income gap. What is remarkable is that all measures are very much aligned, irrespective of being calculated from a theoretical model point of view, or from a pure statistical approach. It is not surprising that the greatest difference is captured in the dynamics around Covid-19 shock, as some macro-financial variables have this effect in them, whereas the house prices exhibited strong resilience in that period, which means that applying statistical filtering did not capture this period.

Figure A7-1: Exuberance in house prices (black full and dotted curves), price misalignment from model ((1-2), grey) and affordability (dotted grey), UK level

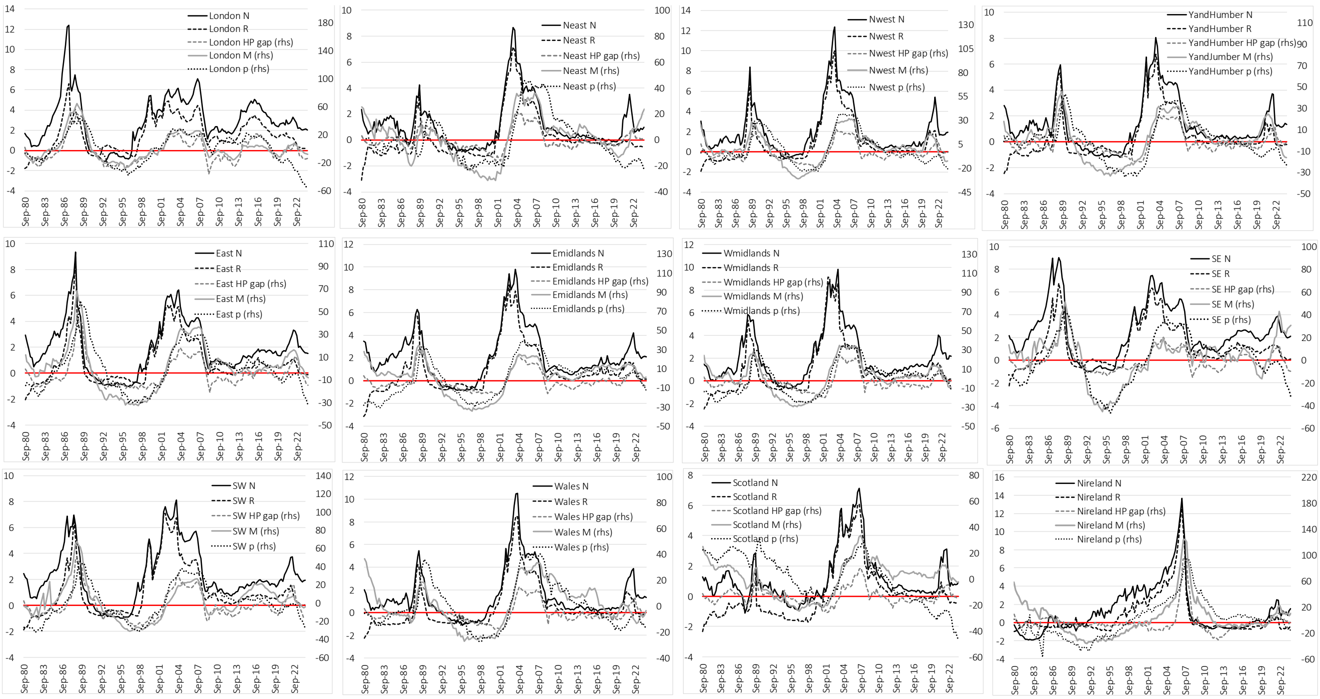


Note: M, N, R denote "Model", "Nominal", "Real" respectively, exu and gap are exuberance and HP filter gap, RHS denotes right hand side. The measures from left to right are: model (1-2) based price gap / price misalignment, HP gap based on price to income ratio, nominal and real price based exuberance empirical value (reduced by theoretical test value).

Generally, the results are in line with UK Housing Observatory (2024), especially for the same indicators that I use. Results around 2007 are in line with Clark et al. (2010), who claim that the UK house price bubble ended mid-2007 with the start of US subprime crisis. Real house price test results are in line with Black et al. (2006), who evaluated the estimated model real house prices to the fundamentals, and found several periods of overvaluation, that are in line with my results. Nominal house price test results are in line with Anundsen et al. (2016) for UK. The rest of the results are in line with Chowdhury and Maclennan (2014) who examined sub-national house price growth from the regime switching point of view, and the spikes in series in figures A6-1 and A6-2 are in line with the periods of extreme price growth in the mentioned study. The results for the earlier period are in line with Levin and Wright (1997) who found little house price speculation for Northern Ireland, Wales and Scotland for period 1972 to 1994, as my measures are lowest in that period for the mentioned regions. Highly speculative house price behaviour was found to be South East and South West, East Anglia and London in Levin (1997), and the spikes in my series in Figure A7-2 confirm that. Increases of the indicators in the post-Covid reopening of the economy for other regions than London is also captured nicely in my approach, as tenants moved away from the capital, due to flexible ways of working (see Bellpepper, 2021), and this finding is in line with finings of Bricongne et al. (2023).

Another important thing to notice is that the exuberance indicators have preceded the other indicators, which could affect forecasting capabilities of individual series. This is in line with Pavidlis et al. (2016), who explain that fundamental economic growth caused price increase during the tech boom in late 1990s and early 2000s, with the boom turning into a bubble. When focusing on the UK level (Figure A7-1), I can see that the nominal house prices experienced much greater values of the exuberance test statistic from mid-1960s to 1980s compared to other measures, as it is a purely statistical approach and was capturing the extreme growth rates in that period. Otherwise, the pattern of behaviour is similar to sub-national results.

Figure A7-2: Exuberance in house prices (black full and dotted curves), price misalignment from model ((1-2), grey) and affordability (dotted grey)



Note: N, R, M, and p denote nominal, real, single model and panel-based estimates respectively. RHS is right hand side, and HP gap is the Hodrick-Prescott filter gap in %, obtained from the ratio of house price to income ratio. Exuberance empirical values are obtained from the GSADF test, and are reduced by the critical value of the test.

Housing affordability

Additionally, I observe housing affordability to compare to the previously defined measures. For the affordability, I employ a simple approach of observing the ratio between house price and the gross disposable income per capita for each region (due to data unavailability), and calculate the respective HP filter gap based deviation of the ratio (as in Bowe et al., 2023). The main idea of this indicator is to show capability of households to balance housing costs. This was also one of the indicators I wanted to test out based on previous literature. When I looked at its dynamics, I observed that it is very much correlated to the overvaluation and exuberance measures. Thus, I also plot the affordability measure in Figure A7-1, and A7-2 alongside the other two (the HP "gap" indicator).

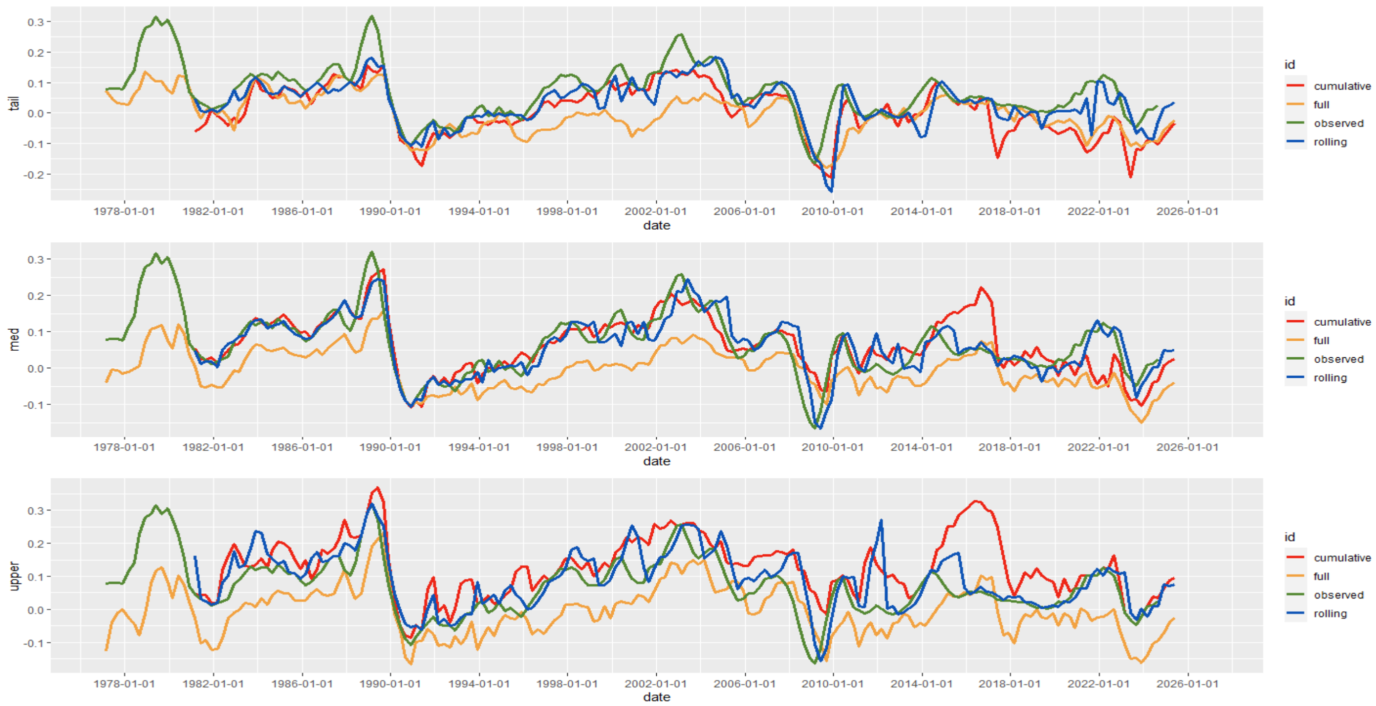
Appendix 9 - Robustness checking

Initial robustness checking

We assess the robustness of my results from the main text and the models presented in Table 1 using several approaches. The baseline model was estimated on the full sample. I then apply a recursive (cumulative) estimation approach: starting with the first 100 quarters of data, I estimate the model and generate a one-year-ahead forecast. Next, I add the subsequent quarter of data, re-estimate the model, and produce a new forecast. This process is repeated sequentially, mimicking real-time forecasting as new data become available, until the sample period concludes. The second approach is rolling window estimation, whereby the model is estimated on a fixed 50-quarter window. For each new data point added, the oldest observation is dropped, and the model is re-estimated on the updated window. This method places greater emphasis on more recent data, allowing the influence of older observations to gradually diminish and eventually be excluded.

Both approaches help to assess the stability and predictive consistency of the model over time. The results are displayed in Figure 8-1, which demonstrates stable outcomes. It is reasonable to expect some differences due to the approaches described. Nonetheless, I observe that all methods succeed in capturing certain periods of boom and bust. The full-sample approach captures all peaks and troughs and is therefore closest to the observed values. Nevertheless, the rolling window approach most accurately represents median movements.

Figure 8-1: Lower tail (upper panel), median (middle panel), upper tail (lower panel) estimates based on different approaches



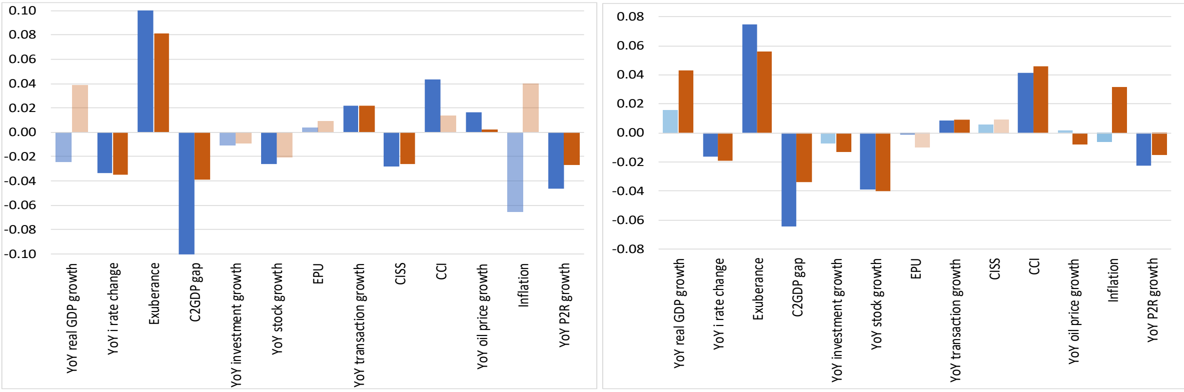
Note: observed stands for the observed nominal house price growth, cumulative, full and rolling refer to the way of estimating the model described in the main text. All of the estimates at a certain Q of a year are based on information from the same Q in previous year.

GFC structural changes

Another important robustness check to consider is whether the post-GFC reforms and structural changes to the financial system—particularly within the banking sector—have altered the correlations between house price dynamics and the key factors under examination. To investigate this, I first estimate a model for the pre-GFC period and then compare it with the full-sample estimates from the main text. I opt not to estimate the model for the post-GFC period alone, as the limited data available would not provide reliable estimates, especially for the tails of the distribution. Estimated coefficients are compared in Figure 8-2. Most coefficients remain broadly consistent, indicating that my results are robust. However, one notable change is that the inflation coefficient for median growth becomes significant and positive in the full sample, whereas it was not in the pre-GFC period. This shift is reasonable, as recent data likely capture inflation effects more clearly. Real GDP growth also becomes significant in the full sample.

During the pre-GFC era—characterised by looser financial conditions and less regulation—some variables, such as GDP growth, may not have exerted as strong an effect as they do in the more regulated post-GFC environment, where demand-side factors in the housing market play a larger role. Another key change is the reduced significance of the credit-to-GDP gap for both median and tail growth. This is expected, given the post-GFC reforms, and aligns with earlier explanations that this variable reflects structural changes in the banking system. A healthier, more capitalised financial system today may be reflected in the diminished importance of the credit-to-GDP gap.

Figure 8-2: Pre-GFC (blue) and full sample (red) estimates of coefficients, 5th percentile (left) and median (right)



Note: Size of the estimated parameters are depicted with bars. Transparent bars denote statistical insignificance. Left panel shows estimates for the lower tail and right panel for the median estimate.

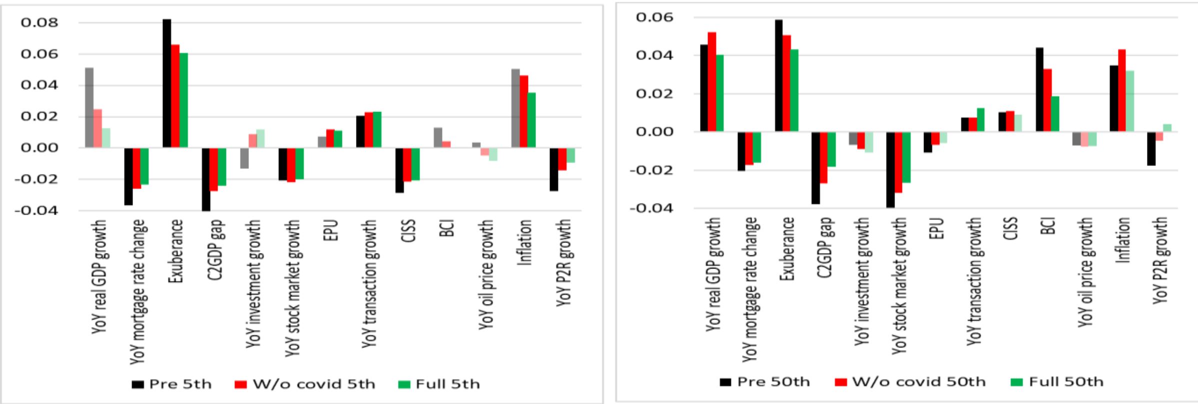
Covid-19 analysis

Many housing markets around the world demonstrated strong resilience during the COVID-19 shock. Duca et al. (2021) note that this shock affected house prices differently compared to previous recessions, due in part to stricter lending standards in the years leading up to the pandemic and a well-capitalised banking system. Additionally, the scale of government support and regulatory responses was unprecedented. As a result, the effects of the COVID-19 shock vary across different analyses and among economic agents. Although I previously adjusted for GDP dynamics in my analysis, the effects of the pandemic have not been fully excluded. To assess how these effects influence my results, I estimate a model using data up to 2020, and then a second model that includes data from the two years following the shock, 2023-2024. These are compared to the full model specification discussed in the main text. The estimated coefficients for both the tail and median are presented in Figure 8-3. In most cases, the coefficients remain very similar, although their magnitudes have generally decreased. This is likely because nominal house prices remained relatively stable during the pandemic, while other macro-financial variables experienced more pronounced reactions. Consequently, previously established relationships between these variables and house prices have weakened. This outcome is expected, given that the nature of the pandemic shock differs significantly from that of earlier recessions and crises.

We also compare the predicted tails and median nominal house price growth from the model based solely on pre-COVID data with my full-sample approach, as shown in Figure 8-4. Unsurprisingly, there are almost no differences in how the models' forecast values in the period leading up to 2020. However, as previous crises are not comparable to the COVID-19 shock, a model based only on pre-COVID data would predict a sharper decline in nominal house prices for both the median and upper tail cases. The lower tail estimates, however, remain very similar across both models. This result holds even after adjusting GDP, transaction volumes, and investment in new housing to account for the sharp one-quarter drop in all three series during the initial lockdown. The decline in inflation throughout 2020 contributed to the expected price drops. However, rising household savings and shifts in consumer preferences led to actual outcomes that diverged from model forecasts. Duca et al. (2021) found that in both the UK and US, price increases were concentrated in detached houses. Similarly, Fazio and Harper (2022) reported that approximately 50% of the total nominal house price growth during this period could be attributed to changes in preferences—not only regarding property type but also location. Therefore, when applying the framework developed here, it is important to recognise that models of this kind cannot fully capture such behavioural shifts.

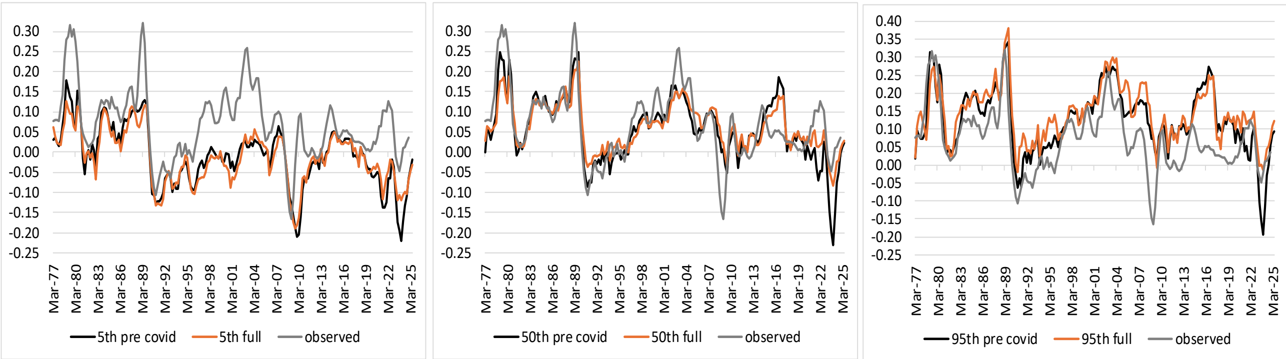
Finally, another interesting insight emerges from this exercise. At the end of the sample period, both models predict a decline in house prices during 2023–2024, attributed to rising mortgage interest rates. However, the full-sample model indicates a less pronounced trough compared to the model estimated using only pre-COVID data. This difference arises because the full model incorporates the effects of the most recent cycle of mortgage interest rate increases, as well as the unique characteristics of the pandemic shock—such as unprecedented government support, central bank interventions, and a surge in forced savings. In contrast, the pre-COVID model does not account for such a sharp rise in mortgage interest rates, leading it to overestimate the impact of these changes. This finding reinforces my earlier point about the importance of including sufficient peaks and troughs in the estimation period. Models of this kind are most effective when they can capture the full range of economic or financial cycles, thereby allowing for more accurate and nuanced forecasting.

Figure 8-3: Coefficients comparison, pre-Covid, full period without Covid, and full period with Covid shock



Note: 5th and 50th denote estimates for the 5th tail and median. Pre, W/o covid and Full denote estimation based on pre-Covid data, full dataset with Covid subperiod exclusion (i.e. until 2024, without 2020 and 2021), and the full dataset (i.e. original model). Transparent colmys denote insignificant parameters.

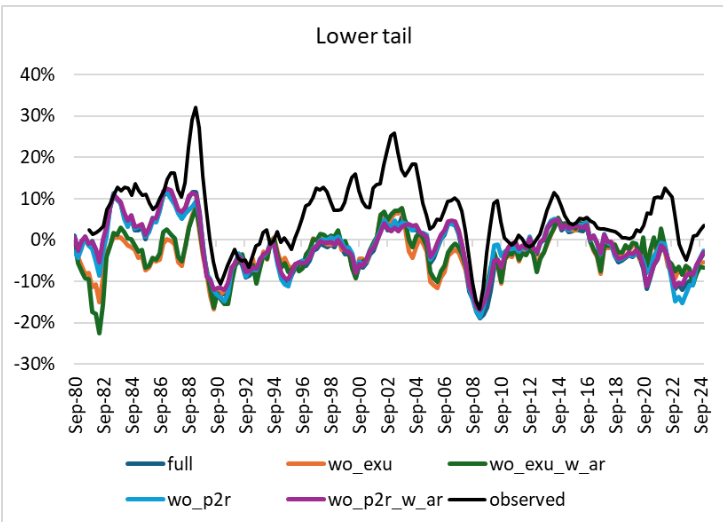
Figure 8-4: Estimated nominal house price growth comparison, pre Covid and full sample

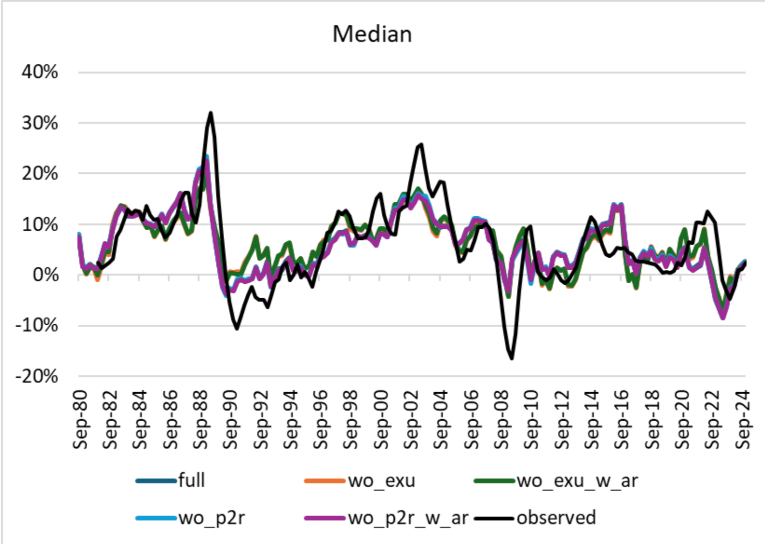


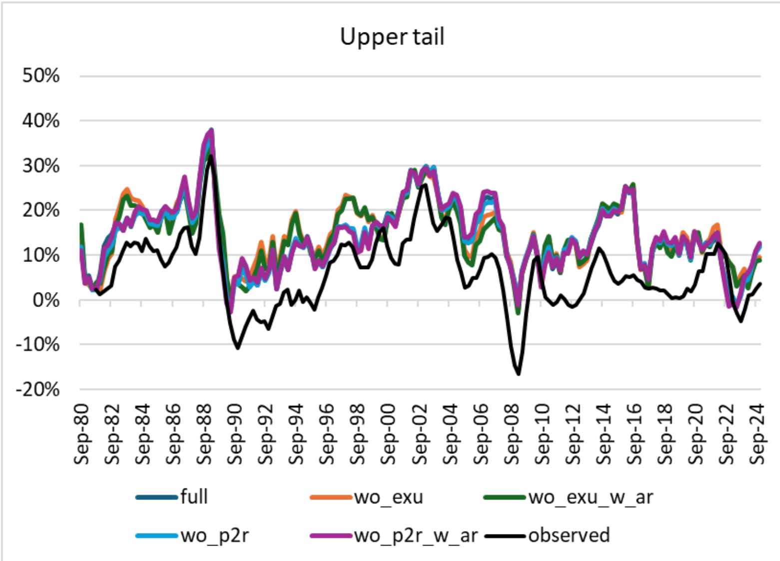
Note: 5th, 50th and 95th denote estimates for the 5th tail, median, and 95th tail respectively. Figures show how estimates change for samples of full model, pre-covid period, compared to observed data.

Finally, we compare the estimates between the original model, and the one that does not have the exuberance component in Figure 8-5.

Figure 8-5: Estimated lower (upper panel), median (mid), and upper tail (lower panel) based on full model specification, and the one without the exuberance measure

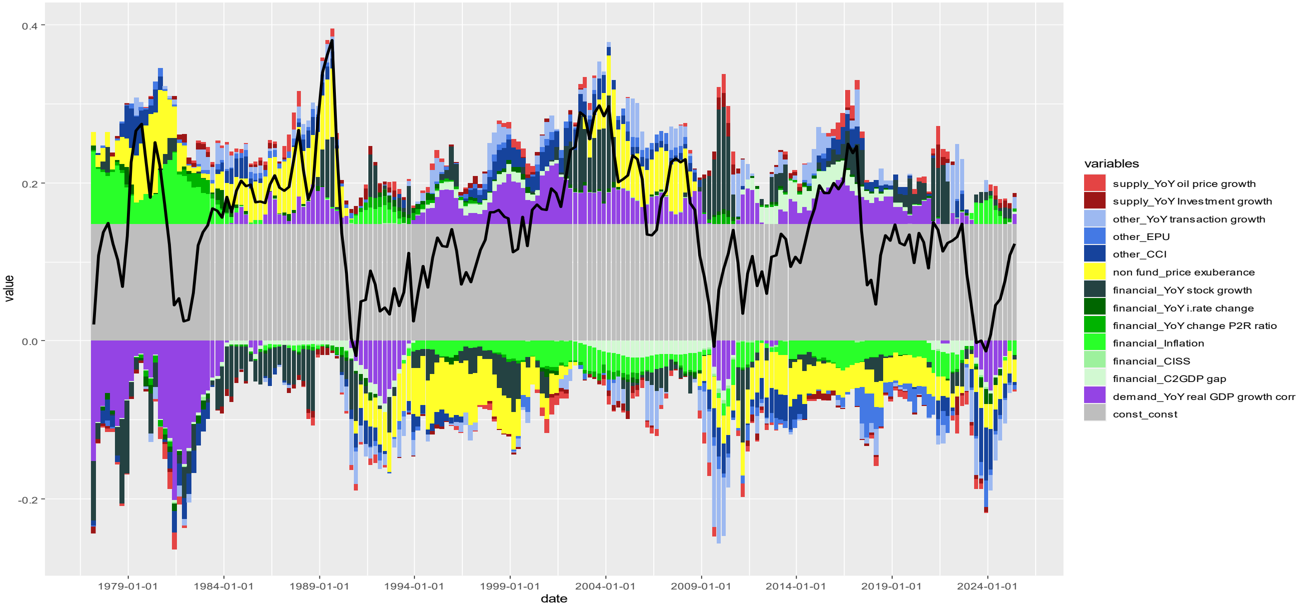






Note: lower tail, median, and upper tail denote estimates for the 5^{th} tail, median, and 95^{th} tail respectively. “full”, “wo_exu”, “wo_exu_w_ar”, “wo_p2r”, “wo_p2r_w_ar“ denote the full model from the main text, model with all the same variables as the original model without exuberance measure, model with all the same variables as the original model without exuberance measure and with the AR term, model with all the same variables as the original model without price to rent ratio, model with all the same variables as the original model without price to rent ratio and with AR term. Observed refers to the observed annual house price growth.

Appendix 10 Figure: Decomposition of tail risks for the 95th percentile decomposition

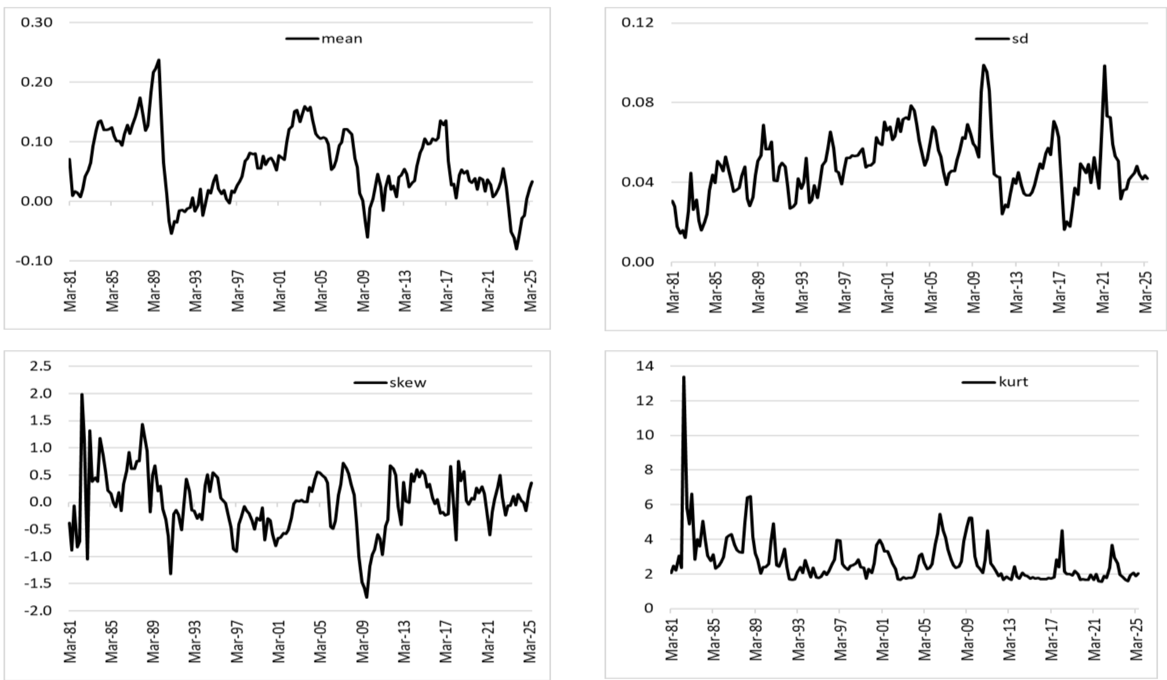


Note: Variable description in Table A1. Upper panel focuses on crises periods and decomposes how 5th percentile evolved during those periods. Lower panel decomposes the 95th house price growth for model (7) and table 2 in main text.

Appendix 11 – Estimated parameters for the fitted distribution of HP growth

The distributions shown in main text in Figure 4 are based on estimated parameters of the skewed t-distribution, which I further illustrate in Figure 10-1 to highlight their evolution over time. The standard deviation exhibits an upward trend during booming periods, likely reflecting idiosyncratic differences across regions that contribute unevenly to nominal house price growth. Skewness tends to increase negatively during recessions, capturing the leftward shift in the distribution. Meanwhile, kurtosis appears to rise when mean estimates are at their highest, often preceding recessions or significant drops in nominal house price growth. These dynamics provide deeper insight into the changing nature of uncertainty and asymmetry in the housing market across different economic cycles.

Figure 10-1: Estimated mean, standard deviation, skewness, and kurtosis



Note: All of the estimates at a certain Q of a year are based on information from the same Q in previous year. Figure shows how parameters of the distribution on Figure 11 evolve over time.

Appendix 12 Table: Panel regression results for sub-national model

Variable	Model 1			Model 2			Model 3			Model 4		
	5th	Median	95th	5th	Median	95th	5th	Median	95th	5th	Median	95th
(Intercept)	**-4.59**	**6.92**	**18.40**	**-6.350**	**5.636**	**19.097**	**-6.331**	**6.050**	**19.738**	**-12.086**	**-0.802**	**12.425**
YoY real GDP pc growth	2.08	**4.29**	**12.55**	/	/	/	0.810	**-1.701**	-0.954	0.958	**-0.760**	*-1.348*
YoY real GDI pc growth	/	/	/	-0.254	-0.041	**2.229**	/	/	/	/	/	/
Exuberance	**-2.18**	**1.16**	**3.30**	**-2.460**	**0.742**	**4.074**	**-2.510**	**1.529**	**6.339**	**-2.142**	**0.570**	**4.169**
Investment gap	**-1.61**	**-1.93**	-0.29	**-1.103**	**-1.742**	0.513	**-0.215**	**-1.905**	*-1.173*	**-0.725**	*-1.640*	**-1.301**
YoY transaction growth	**3.16**	**1.22**	**1.67**	**3.108**	**1.186**	**2.602**	**2.735**	**0.903**	**1.280**	**2.197**	**0.518**	**0.235**
YoY m.rate change	-0.32	**-1.01**	**-2.03**	-0.387	**-0.891**	**-1.474**	-0.759	**-0.553**	**-0.987**	**-1.533**	**-0.893**	**-1.306**
YoY inflation	**2.95**	**5.98**	**11.30**	0.958	**3.097**	**5.561**	/	/	/	/	/	/
C2GDP gap	**1.15**	**1.27**	**1.18**	**0.778**	**1.016**	-0.504	/	/	/	/	/	/
YoY oil price growth	**-0.72**	**-1.35**	**-2.20**	**-0.698**	**-1.197**	**-1.840**	/	/	/	/	/	/
CCI	0.42	**2.60**	**1.59**	0.588	**3.001**	**3.213**	**1.435**	**2.871**	**4.471**	**1.612**	**2.191**	**3.680**
CISS	**-2.49**	-0.05	**1.07**	**-2.347**	-0.151	0.502	/	/	/	/	/	/
YoY stock growth	**-2.96**	**-2.62**	**-4.62**	**-2.954**	**-2.302**	**-4.294**	/	/	/	/	/	/
EPU	**1.10**	**-0.39**	**-1.83**	0.613	**-0.670**	**-2.043**	/	/	/	/	/	/
YoY P2R growth	**3.50**	**0.76**	**1.44**	**3.692**	**1.652**	**2.360**	/	/	/	/	/	/
AR	/	/	/	/	/	/	**1.637**	**1.199**	0.515	**2.506**	**3.210**	**3.6371**
I(YoY m.rate change *Investment gap)	/	/	/	/	/	/	/	/	/	**-2.541**	**-1.107**	0.033
AIC	-3701.36	-4994.45	-2866.06	-3664.76	-4981.59	-2771.25	-3471.88	-4842.53	-2164.33	-3607.93	-4870.70	-2111.74
Pseudo R2	.26	.20	.34	.25	.20	.36	.21	.17	.25	.24	.18	.25

Note: bolded numbers indicate statistical significance at 1%, underlined at 5%, and italic at 10%. Description of abbreviations is in Table A1. Model is estimated in two steps as described in methodology section: panel fixed effects regression is run on the mean to extract the fixed effect for each region. Then the quantile regression is estimated as the second step. Bolded values indicate significance.

Appendix 13 Table: Full variable specification results for regions, fmy quarters ahead

Variable	Median											
	Neast	YandH	Nwest	Emid	Wmid	East	SE	London	SW	Wales	Scot	Nireland
(Intercept)	**6.089**	**6.252**	**6.548**	**5.714**	**5.353**	**5.624**	**6.383**	**7.447**	**5.878**	**4.697**	**5.479**	**6.32**
YoY real GDP pc growth	2.92	0.147	2.732	**6.903**	**4.686**	**4.596**	**3.941**	**4.025**	**7.714**	3.447	-1.76	0.481
YoY m.rate change	**-1.162**	-1.023	-0.847	**-1.847**	**-0.852**	-1.248	**-1.719**	**-1.398**	**-2.045**	**-1.819**	**-0.967**	-0.59
Exuberance	**-1.716**	**-2.211**	-1.251	1.514	-0.53	**2.425**	**1.939**	-0.091	1.415	**-2.909**	**-2.144**	**2.674**
C2GDP gap	**2.000**	**2.354**	**2.879**	0.215	0.757	-1.085	-0.462	-0.168	0.414	**4.081**	**3.052**	**1.175**
YoY investment growth	-0.388	-0.649	-1.14	**-1.866**	-0.823	1.132	1.479	1.112	-0.863	0.222	0.197	0.418
YoY stock growth	**-4.431**	**-5.304**	**-3.708**	**-3.273**	**-2.691**	-0.829	-1.311	-0.498	**-1.546**	**-4.804**	**-1.93**	-0.739
EPU	-0.838	**-0.817**	0.141	-0.507	-0.325	**-1.826**	**-2.372**	**-2.716**	**-1.296**	-0.33	**-0.829**	-0.27
YoY transaction growth	**1.885**	**2.005**	0.553	**2.383**	**1.438**	0.657	**1.529**	1.082	**1.339**	**1.504**	**1.276**	-0.628
CISS	0.393	-0.303	-0.615	1.38	1.015	**2.249**	**1.852**	**2.183**	**1.746**	-0.524	-0.187	**-3.75**
CCI	0.927	**2.36**	**2.164**	**2.62**	**2.805**	**2.828**	**2.200**	**1.919**	**2.045**	0.711	**1.506**	1.238
YoY oil price growth	-0.307	-0.884	-0.534	**-1.317**	**-1.104**	**-1.964**	**-3.235**	**-3.327**	**-2.262**	-0.856	**-0.998**	-0.113
YoY Inflation	**8.394**	**5.681**	**7.250**	**8.847**	**6.057**	3.549	2.952	**3.273**	**7.31**	**4.083**	1.958	-0.023
YoY P2R growth	**3.845**	**4.208**	**3.545**	**1.945**	**2.062**	-0.391	-0.139	1.086	0.424	**4.016**	**1.997**	-1.182
Pseudo R2	0.400	0.379	0.436	0.383	0.414	0.369	0.420	0.428	0.400	0.396	0.514	0.394

						5th						
Variable	**Neast**	**YandH**	**Nwest**	**Emid**	**Wmid**	**East**	**SE**	**London**	**SW**	**Wales**	**Scot**	**Nireland**
(Intercept)	**-2.747**	**-2.538**	**-1.447**	**-2.446**	-0.828	**-7.314**	**-4.871**	**-4.293**	**-4.81**	**-1.241**	0.947	**-7.641**
YoY real GDP pc growth	**-7.171**	**-10.785**	**-8.802**	0.265	-4.295	4.250	-1.997	3.045	3.614	**-6.473**	**-4.557**	-1.126
YoY m.rate change	0.398	-1.227	**-1.783**	**-2.583**	**-2.153**	0.410	0.079	-0.194	-0.943	**-2.062**	**-1.857**	-1.834
Exuberance	**-2.431**	**-5.892**	**-5.498**	-1.931	**-4.530**	0.374	-2.963	**-4.45**	-2.714	**-6.526**	**-3.717**	**-5.808**
C2GDP gap	-0.847	**1.505**	**2.422**	0.236	0.862	**-2.709**	-0.932	-1.344	-0.953	**2.957**	**1.557**	**2.973**
YoY investment growth	**-2.007**	0.653	**2.208**	**-2.426**	-1.207	-1.131	1.920	0.376	-1.075	-0.053	**1.139**	0.718
YoY stock growth	-1.282	**-5.608**	-2.315	**-5.638**	**-6.200**	-0.598	**-4.046**	-0.948	-2.13	**-3.727**	**-3.924**	**-2.298**
EPU	-0.24	**-3.142**	-1.249	-0.794	-1.38	0.898	-0.657	-0.422	0.451	**-2.042**	**-1.514**	0.768
YoY transaction growth	0.032	0.700	1.000	**3.958**	**2.504**	**5.266**	**3.582**	**2.866**	**4.37**	1.265	0.808	**2.238**
CISS	-1.401	-0.806	-1.05	**-1.923**	**-1.833**	-1.943	-1.038	-0.096	-0.622	-1.016	0.026	**-7.192**
CCI	0.337	0.33	0.474	-0.962	-0.339	**2.929**	0.137	2.356	0.373	-0.254	**1.187**	0.263
YoY oil price growth	-0.807	**-1.364**	**-1.377**	**-2.176**	-1.242	1.021	-1.762	-0.957	0.852	-0.994	-0.472	**-1.566**
YoY Inflation	-2.608	-2.287	-3.108	5.036	3.297	4.637	-0.23	1.667	6.021	0.037	2.283	-0.733
YoY P2R growth	**7.492**	**10.974**	**5.952**	**6.886**	**8.99**	-3.427	3.642	**4.57**	2.849	**8.676**	**3.764**	0.034
Pseudo R2	0.399	0.523	0.450	0.484	0.460	0.472	0.502	0.519	0.452	0.455	0.528	0.561

						95th						
Variable	**Neast**	**YandH**	**Nwest**	**Emid**	**Wmid**	**East**	**SE**	**London**	**SW**	**Wales**	**Scot**	**Nireland**
(Intercept)	**19.683**	**17.606**	**17.925**	**17.171**	**16.996**	**16.326**	**15.29**	**17.547**	**15.249**	**16.846**	**13.124**	**18.482**
YoY real GDP pc growth	-1.116	**25.049**	**8.236**	**23.664**	**21.364**	-1.639	3.002	**-10.545**	4.697	**20.031**	**8.583**	**-9.095**
YoY m.rate change	1.894	-1.629	-0.852	-2.588	**-3.463**	-0.702	-0.688	-1.277	-1.295	**-3.78**	**-2.163**	0.15
Exuberance	-2.945	2.519	2.087	**5.397**	3.515	**8.826**	**6.093**	1.705	**7.119**	-0.176	-0.664	**9.363**
C2GDP gap	2.332	1.843	-0.118	0.753	2.482	-0.871	**-1.741**	**-3.021**	-0.768	**3.605**	**3.58**	**4.092**
YoY investment growth	**4.206**	-2.056	-0.408	-0.901	-0.143	-2.57	-0.444	**-2.568**	-1.177	**1.999**	**-0.242**	-1.377
YoY stock growth	**-4.978**	**-9.131**	**-6.379**	**-8.988**	-3.461	**4.28**	**-2.737**	**1.424**	-1.068	**-9.034**	**-2.695**	1.781
EPU	**-2.202**	-0.114	-0.828	-1.217	-1.577	**-3.25**	**-2.89**	**-4.553**	-0.107	-0.638	**-0.859**	0.001
YoY transaction growth	0.202	**2.83**	**2.138**	**3.64**	1.345	**2.099**	**2.96**	**2.239**	**2.557**	**2.431**	-0.425	**2.958**
CISS	-0.518	1.28	0.795	1.645	2.703	**2.766**	1.378	1.146	1.164	0.21	-0.189	**-3.031**
CCI	-0.371	-0.011	1.102	0.022	-1.243	**4.507**	**3.545**	0.607	**4.908**	-2.673	**-3.902**	**3.375**
YoY oil price growth	**-3.836**	-0.043	-1.427	0.661	-1.57	**-2.338**	**-2.528**	**-4.327**	**-1.926**	0.79	-0.051	0.868
YoY Inflation	4.438	**23.691**	**14.319**	**17.656**	**16.031**	-6.573	0.035	**-8.85**	2.225	**17.106**	**10.662**	**-9.567**
YoY P2R growth	**4.989**	0.543	**6.233**	-2.59	1.805	-1.042	**-2.054**	**4.072**	-1.53	0.749	**3.724**	**-2.009**
Pseudo R2	0.594	0.561	0.624	0.490	0.479	0.600	0.638	0.612	0.589	0.562	0.610	0.589

Note: bolded numbers indicate statistical significance at 10%. Description of abbreviations is given in Table A1.

Appendix 14 Table: House price model (A) estimates for regions, nominal, 4 quarters ahead

						Median						
Variables	Neast	**YandH**	**Nwest**	**Emid**	**Wmid**	**East**	**SE**	**London**	**SW**	**Wales**	**Scot**	**Nireland**
(Intercept)	**4.538**	**5.164**	**5.42**	**5.551**	**5.599**	**5.649**	**6.305**	**7.108**	**6.166**	**4.572**	**5.254**	**4.816**
YoY real GDP pc growth	-1.085	-0.74	**-1.462**	1.018	1.13	1.839	**2.245**	1.921	**2.538**	-0.088	**-1.513**	**2.033**
YoY mortgage rate change	-0.311	**-1.514**	-0.168	**-1.475**	-0.568	**-1.994**	**-2.209**	-1.366	**-1.75**	-0.465	**-1.641**	-0.34
Exuberance	-0.667	0.776	-0.15	**2.319**	**1.527**	**3.469**	**2.122**	0.728	**3.389**	-0.517	**-1.186**	0.619
C2GDP gap	**2.355**	**2.649**	**3.637**	0.874	**1.18**	-0.983	-0.68	**-1.281**	0.601	**2.684**	**3.312**	**3.387**
Investment gap	**-2.083**	**-2.999**	**-3.161**	**-2.99**	**-2.565**	**-2.433**	-1.404	-0.905	**-4.164**	**-1.718**	-0.429	**-3.161**
EPU	-0.064	0.162	**0.762**	0.046	-0.332	**-1.687**	**-1.85**	**-2.733**	**-0.836**	-0.146	**-0.832**	-0.103
YoY transaction growth	**1.436**	**1.307**	0.271	**1.525**	**1.374**	**1.309**	**1.956**	**1.519**	**1.543**	**1.436**	**1.531**	0.203
CISS	-0.433	**-1.566**	**-1.672**	0.85	0.033	1.462	**2.152**	**2.092**	1.203	-0.348	**-1.05**	-2.13
CCI	**2.139**	**2.521**	**3.661**	**3.306**	**2.776**	**2.414**	**1.957**	**2.808**	**2.39**	**2.82**	**1.182**	**1.306**
YoY stock market growth	**-1.456**	**-3.132**	**-2.372**	-1.191	**-1.661**	-0.693	-0.704	-0.312	-0.095	**-2.762**	**-1.981**	-0.17
Pseudo R2	0.350	0.362	0.404	0.394	0.384	0.343	0.470	0.403	0.360	0.363	0.366	0.419

						5th						
Variables	**Neast**	**YandH**	**Nwest**	**Emid**	**Wmid**	**East**	**SE**	**London**	**SW**	**Wales**	**Scot**	**Nireland**
(Intercept)	**-4.044**	**-6.695**	**-4.888**	**-5.615**	**-4.193**	**-6.711**	**-6.46**	**-6.091**	**-5.087**	**-4.609**	**-1.186**	**-7.745**
YoY real GDP pc growth	-2.58	**4.907**	-0.306	**5.298**	-0.78	**3.791**	1.932	2.181	2.528	-1.858	**-2.382**	**3.376**
YoY mortgage rate change	**1.957**	-0.835	-0.502	**-1.633**	1.045	-2.213	-0.201	-2.213	-0.427	1.546	-0.081	**-2.828**
Exuberance	1.592	**1.807**	0.249	**1.375**	-0.434	**4.779**	0.069	0.183	1.022	**-2.69**	**-3.889**	**-7.397**
C2GDP gap	-0.331	0.749	1.848	0.253	-0.268	**-2.74**	**-1.658**	**-2.377**	-1.308	0.097	**1.572**	**4.854**
Investment gap	**-3.611**	**-4.747**	**-4.618**	**-5.016**	**-2.505**	**-7.797**	-0.457	0.809	-1.709	-1.728	0.346	**-2.428**
EPU	0.468	-1.04	**-3.293**	**-3.065**	-0.564	**-3.765**	0.388	**-1.722**	-0.738	0.624	0.087	0.561
YoY transaction growth	**1.858**	1.118	1.233	**1.161**	**2.863**	**2.46**	**3.948**	**4.442**	**2.349**	0.467	**1.352**	**3.349**
CISS	-1.326	**-3.357**	-1.397	**-2.687**	-1.595	-1.538	**-2.908**	-0.093	**-2.334**	-1.684	0.152	**-5.901**
CCI	**2.247**	1.2	**2.948**	1.188	**2.986**	-0.792	1.856	-0.242	0.326	**3.896**	**1.24**	0.559
YoY stock market growth	**-2.269**	**-5.389**	**-3.584**	**-4.347**	**-2.289**	-0.97	**-2.945**	-0.883	-1.223	0.102	-1.412	**-3.82**
Pseudo R2	0.3722	0.4592	0.3542	0.500	0.376	0.363	0.458	0.575	0.475	0.472	0.454	0.455

						95th						
Variables	**Neast**	**YandH**	**Nwest**	**Emid**	**Wmid**	**East**	**SE**	**London**	**SW**	**Wales**	**Scot**	**Nireland**
(Intercept)	**17.609**	**19.005**	**17.078**	**17.628**	**18.341**	**17.513**	**17.143**	**19.269**	**15.061**	**18.825**	**12.48**	**19.379**
YoY real GDP pc growth	1.136	**4.786**	**5.969**	**6.552**	**7.544**	3.282	1.459	-0.311	**3.561**	**7.533**	1.339	-4.518
YoY mortgage rate change	0.547	-0.44	-0.55	0.008	-1.781	-2.225	**-1.941**	-0.845	-1.042	1.207	**-1.335**	-0.11
Exuberance	1.425	0.664	**4.669**	**5.127**	**7.171**	**7.148**	**6.171**	**5.143**	**6.782**	0.39	-0.633	**11.542**
C2GDP gap	**4.354**	-0.545	0.137	-2.117	-1.457	-0.498	-0.647	**-4.316**	0.231	0.974	**5.574**	**4.43**
Investment gap	-1.323	2.57	3.146	1.283	1.131	-1.305	**-1.81**	**-3.081**	-2.061	**2.838**	**-2.554**	**-3.067**
EPU	-1.621	**-4.403**	**-3.11**	**-3.282**	**-3.469**	**-3.295**	**-2.154**	**-3.317**	-1.562	**-3.363**	**-1.213**	0.562
YoY transaction growth	1.255	2.131	**1.592**	**3.427**	**2.595**	**2.341**	**2.688**	**2.511**	**3.76**	1.392	0.067	1.434
CISS	-0.782	2.921	1.631	**7.324**	**7.836**	2.369	**1.769**	**3.83**	2.644	**4.885**	**-1.764**	**-4.179**
CCI	4.051	**3.446**	1.379	**2.93**	1.204	**2.865**	**3.431**	**3.9**	**2.91**	**4.548**	0.12	**1.735**
YoY stock market growth	**-7.884**	**-8.689**	**-6.935**	**-4.1**	-0.091	-1.188	**-1.673**	1.411	-0.545	**-5.938**	**-3.773**	0.446
Pseudo R2	0.527	0.494	0.523	0.478	0.498	0.505	0.551	0.562	0.558	0.600	0.544	0.56

Note: bolded numbers indicate statistical significance at 10%. Description of abbreviations is given in Table A1.

Appendix 15 Table: House price model (B) estimates for regions, nominal, 4 quarters ahead

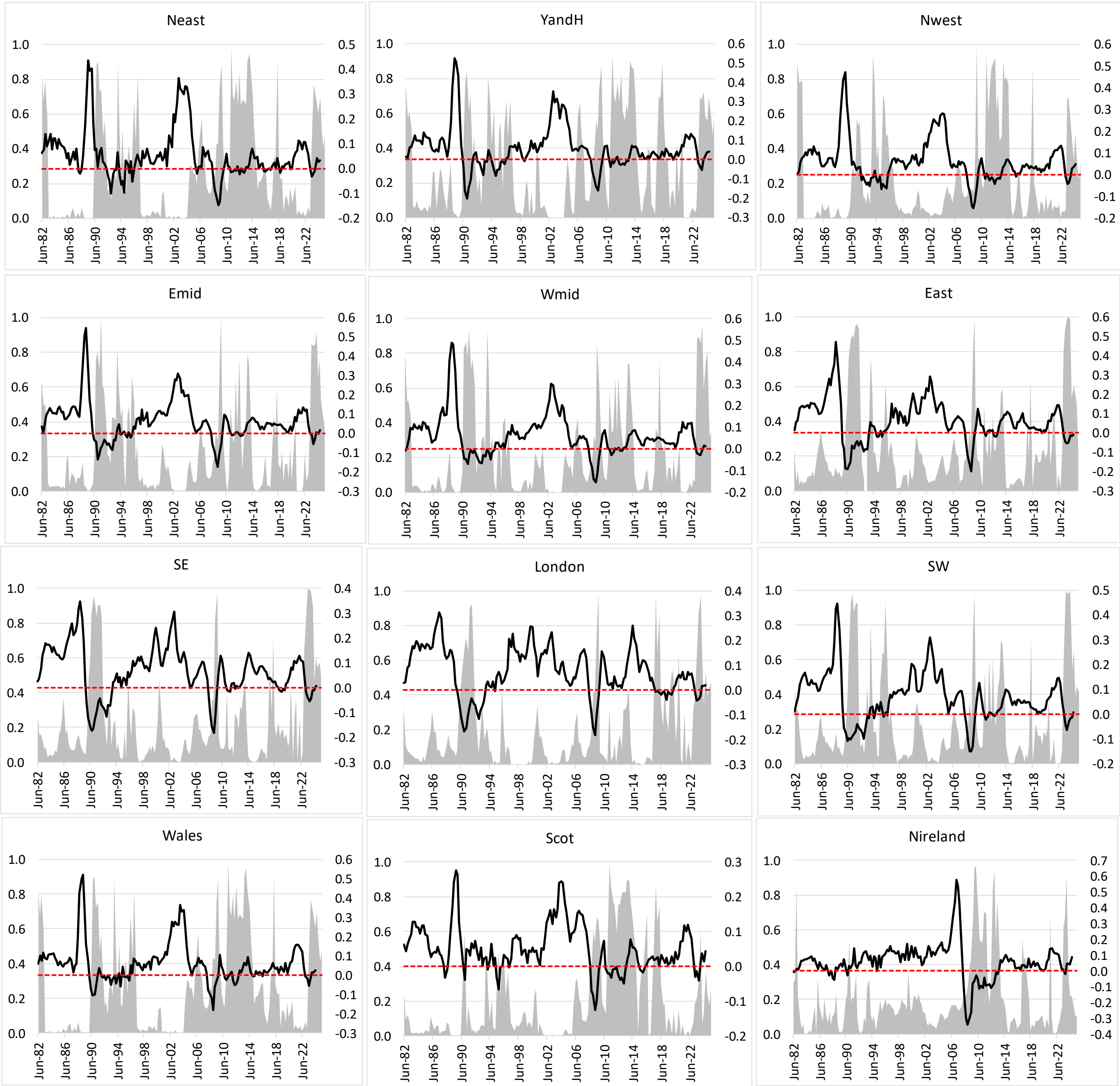
	Median											
Variable	**Neast**	**YandH**	**Nwest**	**Emid**	**Wmid**	**East**	**SE**	**London**	**SW**	**Wales**	**Scot**	**Nireland**
(Intercept)	**5.78**	**4.993**	**6.144**	**6.107**	**5.713**	**5.883**	**6.042**	**7.553**	**6.492**	**4.768**	**5.765**	**5.818**
YoY real GDP pc growth	**-3.442**	-1.141	**-3.425**	0.71	0.261	0.806	1.434	1.189	0.508	-1.038	**-3.58**	-0.792
Exuberance	-0.295	**1.393**	0.154	**1.982**	**1.22**	**2.796**	**1.867**	-0.095	**4.07**	0.984	-0.532	**3.27**
Investment gap	**-1.338**	**-2.368**	-0.695	**-2.825**	**-1.799**	**-2.433**	**-2.29**	-0.872	**-4.353**	**-1.76**	**0.925**	**-0.96**
YoY transaction growth	0.109	-0.229	-0.259	0.367	**0.752**	**1.375**	1.21	**2.196**	**1.248**	0.415	0.335	**1.099**
YoY mortgage rate change	0.235	-0.345	-0.114	**-1.285**	0.009	**-1.625**	**-1.722**	**-1.768**	**-1.984**	-0.099	**-0.623**	-0.44
UK AR	**4.597**	**1.789**	**3.739**	**2.837**	**1.882**	0.329	0.883	1.813	-0.084	**1.943**	**2.895**	0.284
CCI	**1.212**	**3.627**	**2.55**	**2.719**	**2.411**	**2.234**	**1.764**	**2.287**	**2.558**	**2.533**	**2.014**	**2.419**
Pseudo R2	0.311	0.304	0.333	0.396	0.386	0.337	0.324	0.295	0.409	0.297	0.370	0.344

	5th											
Variable	**Neast**	**YandH**	**Nwest**	**Emid**	**Wmid**	**East**	**SE**	**London**	**SW**	**Wales**	**Scot**	**Nireland**
(Intercept)	**-2.540**	**-4.05**	**-2.305**	**-4.812**	**-2.994**	**-9.441**	**-8.612**	**-7.143**	**-6.473**	**-2.824**	**-0.348**	**-9.197**
YoY real GDP pc growth	**-3.397**	**-4.304**	**-1.653**	-1.337	-0.767	**7.931**	4.884	**6.929**	2.224	**-3.304**	**-3.61**	-1.257
Exuberance	**-3.900**	**-4.542**	-1.932	-2.487	**-2.523**	**4.893**	-0.559	**-4.993**	-0.581	**-5.085**	**-2.449**	**-5.933**
Investment gap	-0.188	-0.19	**-2.166**	-0.261	-1.160	**-5.645**	1.613	1.662	-2.146	**-1.838**	**1.245**	**-3.77**
YoY transaction growth	1.081	**2.236**	-0.536	**3.01**	**1.467**	**2.477**	**4.789**	**2.748**	**2.36**	-0.727	0.52	0.442
YoY mortgage rate change	0.325	1.842	-0.395	-1.637	-1.604	**-6.181**	**-4.022**	-1.390	-1.718	0.887	-0.774	-1.726
UK AR	**4.347**	**4.625**	**4.890**	**5.067**	**5.639**	-0.448	-0.025	**1.628**	2.395	**3.918**	1.643	**5.401**
CCI	0.491	2.078	0.891	0.487	-0.196	-1.357	1.145	**3.381**	-1.997	**2.195**	**1.485**	2.308
Pseudo R2	0.355	0.381	0.413	0.403	0.375	0.399	0.411	0.434	0.363	0.384	0.439	0.466

	95th											
Variable	**Neast**	**YandH**	**Nwest**	**Emid**	**Wmid**	**East**	**SE**	**London**	**SW**	**Wales**	**Scot**	**Nireland**
(Intercept)	**23.219**	**25.78**	**18.502**	**15.172**	**18.371**	**18.928**	**17.676**	**20.637**	**15.919**	**24.533**	**14.858**	**19.643**
YoY real GDP pc growth	**-4.078**	-5.796	-3.985	0.792	-0.862	-2.186	0.005	-2.12	2.041	-3.799	-1.89	-0.896
Exuberance	**-4.058**	**-6.524**	0.651	6.104	**8.568**	**9.624**	**8.349**	**3.832**	**9.54**	-3.845	0.364	**10.951**
Investment gap	-0.892	-0.066	-0.53	-2.471	-0.538	-0.54	**-1.993**	**-3.149**	**-2.477**	2.545	1.209	**2.229**
YoY transaction growth	**-5.076**	**-3.059**	-1.325	0.895	3.723	**3.298**	**2.776**	**5.629**	**3.416**	-2.049	-0.89	1.806
YoY mortgage rate change	**2.045**	-3.617	-1.333	0.618	**-2.838**	**-2.718**	**-1.701**	**-4.581**	-1.156	-3.886	-1.817	0.75
UK AR	**9.476**	**13.556**	6.188	-1.682	-1.542	**-6.555**	**-5.43**	-2.823	-4.119	**13.885**	**5.232**	-2.35
CCI	**6.438**	3.813	**4.272**	**6.337**	**3.275**	**7.026**	**5.525**	**3.02**	**3.469**	-2.657	0.232	1.263
Pseudo R2	0.494	0.369	0.409	0.373	0.403	0.546	0.567	0.492	0.545	0.373	0.475	0.528

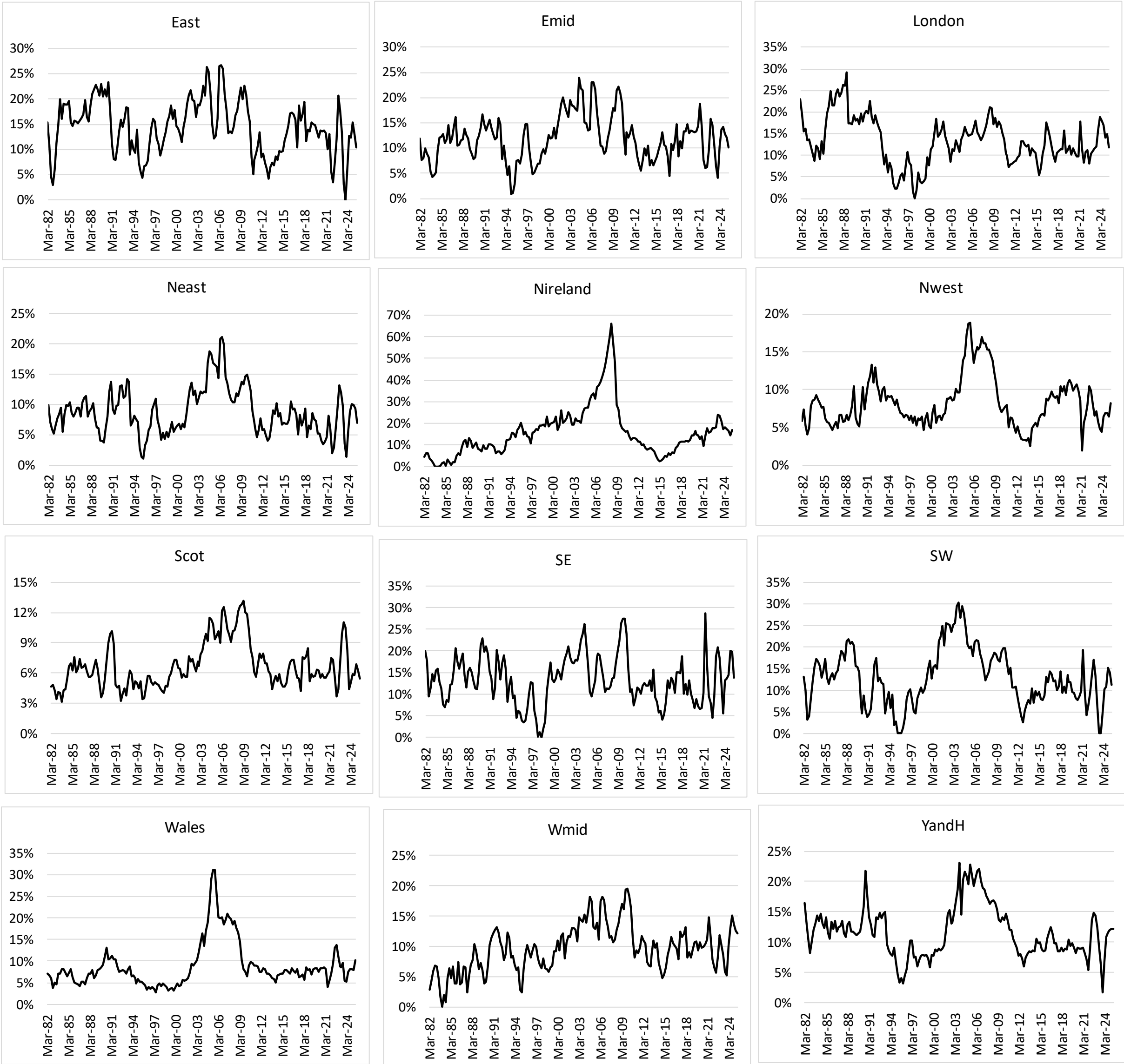
Note: bolded numbers indicate statistical significance at 10%. Description of abbreviations is given in Table A1.

Appendix 16 Figure: Probabilities of negative growth for sub-national models



Note: calculations based on full model specification, see Table A6 in Appendix. Grey shaded area is the probability of negative growth in a given quarter (left hand side). Black curves is the observed house price growth (right hand side).

Appendix 17 Figure: Distance to tail for sub-national models



Note: distance to default is calculated as the difference between the median and tail (5th percentile) estimate.