Real Estate Illiquidity and Returns: A Time-Varying Regional Perspective

Michael Ellington*◇, Xi Fu*, Yunyi Zhu*

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Abstract

This paper proposes two new measures of illiquidity for real estate markets utilising concepts from asset pricing. Segregating real estate through a regional lens, we provide an in-depth analysis of real estate returns and illiquidity for the US and UK. Our results provide statistically significant and economically meaningful evidence that real estate illiquidity predicts real estate returns out-of-sample over and above a variety of control variables.

JEL: G12, G11, C58, R31.

Keywords: Real Estate, Liquidity, Forecasting, Time-Varying Parameter VAR, Network Connections.

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◇ Corresponding author. * University of Liverpool Management School, Chatham Building, Chatham Street, L69 7ZH, UK. ‡ Macquarie Group Limited, Ropemaker Place, 28 Ropemaker Street, London, EC2Y 9HD United Kingdom. Email addresses: Michael Ellington, m.ellington@liverpool.ac.uk; Xi Fu, fux@liverpool.ac.uk; Yunyi Zhu, Yunyi.Zhu@macquarie.com .

1 Introduction

Investors, financial market participants, and authorities rely on well functioning markets to facilitate the ease of trading assets. Liquidity conditions in asset markets, and indeed the liquidity of an asset itself are an important factor that drives prices. Liquidity conditions in asset markets may reveal the information set of investors regarding the future state of the economy (Ellington, 2018). Following the financial crisis in 2008, many studies confirm that liquidity in asset markets contains information regarding future economic activity (e.g. Næs et al., 2011). The financialisation and cyclical nature of real estate markets establish an intuitive link between the ability to sell these assets and their prices.

However, liquidity conditions within real estate markets are seldom discussed; with the majority of analysis being theoretical (Stein, 1995; Diaz and Jerez, 2013; Ngai and Tenreyro, 2014; He et al., 2015; Best and Kleven, 2017). From an empirical perspective, Ellington et al. (2017) use an aggregated measure of US real estate illiquidity and examine its influence on real GDP. Arguably, the lack of empirical literature is a by-product of the difficulties in tracking the (il)liquidity for illiquid assets. Liquidity can have many different meanings, and it is important for one to specify the dimension(s) they capture. This issue is far from trivial, especially when dealing with illiquid assets such as real estate.

In this paper, we propose two new measures of real estate illiquidity borrowing concepts from asset pricing and examine the dynamic links among real estate returns and illiquidity. Ideally, one looking to track real estate illiquidity would want to characterise individual assets in a similar manner to equities for example. However, this is extremely difficult for real estate, as each asset is unique. Therefore, one important issue is how to segregate real estate. Our approach focuses on regional aspects to identify heterogeneities within real estate markets. The attraction and intuition of separating real estate by region are that there is substantial evidence in favour of regional disparities in many real estate markets (Tsai, 2015; Flor and Klarl, 2017; Antonakakis et al., 2018).

We postulate that liquidity in real estate markets also has different dimensions; just like equity markets. However, we take an agnostic view on the specific dimension of illiquidity as we have no presumption on which is the most important for real estate markets. Our liquidity measures capture: i) the quantity dimension (or loosely speaking market-depth); and ii) price-impact. Borrowing from asset pricing literature, to proxy the quantity dimension, we use the inverse of regional trading volume (Lou and Shu, 2017). For price-impact, we use regional return-to-volume ratios (Amihud, 2002).

The main contribution of this paper is to provide a comprehensive out-of-sample analysis of the influence of our new real estate illiquidity measures on returns. We use US and UK data spanning 1985–2018 and 1998–2018, respectively. Our out-of-sample forecasting exercise ascertains whether real estate illiquidity holds predictive information for returns over and above additional economic and financial controls. Our results provide robust evidence in favour of utilising real estate illiquidity when forecasting returns. We show that time-varying parameter VAR (TVP VAR) models deliver the most favourable point and density forecasts. Examining the links over the forecasting samples shows that illiquidity becomes a prominent predictor of real estate returns from the early 2000s to the end of our sample[1]. To the best of our knowledge, this is the first study to provide an empirical investigation into the impact of liquidity conditions on returns in real estate markets.

Real estate markets, and indeed their liquidity conditions, are interesting and important for a number of reasons. First, in the US and the UK, citizens aspire to own their own homes. This cultural phenomenon feeds through into US and UK debt levels with mortgage debt of $9.56tn and £1.45tn as of March 2020 respectively. Second, in response to the property bust of 2008, both US and UK policy makers implemented schemes to revive their real estate markets[2]. Combining the above with the the view that, historically, recessions preceded by property busts are more severe than those without (see the Bank of England June 2014 Financial Stability Report), it is clear that the performance of, and indeed ease of trading within, US and UK real estate markets is linked to overall economic performance.

According to the Federal Reserve (British Property Federation), real estate comprises around 30% (21%) of total net wealth in the US (UK). In light of this, it is our conjecture that real estate is an admissible asset for investors and households to consider when making portfolio choices concerning risky and risk-free assets. As real estate is a legitimate asset that both people and financial institutions hold in their portfolios, it is necessary to examine the interaction between real estate liquidity and price changes.

This paper is pertinent to several strands of literature. Firstly, our work is particularly relevant to studies on regional property markets. Flor and Klarl (2017) use wavelet analysis to examine the synchronisation of metropolitan statistic areas of the US. Their analysis shows that discrepancies in cyclical synchronisation arise significantly from geographical location, and that co-movement in shorter cycles occurred following the crash in 2008. Antonakakis et al. (2018) build on earlier work (e.g. Gregoriou et al., 2014) using UK data, and show that the transmission of inter-regional property return shocks is an important contributor to return fluctuations.

Our study is also relevant to papers focussing on liquidity's predictive ability for real activity and returns. Næs et al. (2011) show that liquidity in the stock market is a leading indicator of economic activity using the US and Norwegian data. More recently, Chen et al. (2018) conduct a

[1] Additionally in the Online Appendix, we track network connections among our datasets and show that the network structure changes over time. However, there remains close connections among real estate illiquidity and returns which indicates that investors may use this information to hedge against regional spillovers.

[2] The US responded with the Troubled Asset Relief Program (TARP) and bailouts of major institutions including Fannie Mae and Freddie Mac. The UK responded with multiple 'Help to Buy' schemes, as well as a 'Funding for Lending' scheme. These responses from both nations are attempts to inject liquidity into the market by encouraging trading.

comprehensive examination of the explanatory power and out of sample forecasting ability of break adjusted, volatility-free stock market liquidity proxies for the US returns and economic activity. Chen et al. (2016) and Florackis et al. (2014) use non-linear models to examine the forecasting ability of stock market liquidity in the US and UK, respectively. Both studies reveal an important link with the business cycle and show that these specifications outperform linear alternatives.

This paper differs from the above in a variety of different ways. Those examining liquidity's role in the business cycle and forecasting returns focus primarily on the stock market. We extend on this by proposing new measures of illiquidity for the real estate market by utilising concepts grounded in asset pricing theory. This work examines the impact of real estate illiquidity shocks on property returns within regional markets and documents substantial heterogeneities in the transmission of these shocks. In doing so, we provide an in-depth analysis of the transmission mechanism and economic importance of illiquidity shocks in relation to real estate returns. Utilising large scale non-linear VAR models, we track regional spillovers and quantify the links between liquidity conditions and real estate returns across regions.

The remainder of the paper proceeds as follows: Section 2 provides details of our illiquidity proxies, discusses data, and provides an outline of our methodology. Our main results are in Section 3 and robustness analysis is in Section 4. Finally, Section 5 concludes.

2 Measuring Real Estate Illiquidity, Data, and Methodology

2.1 Measuring Real Estate Illiquidity

Our two new measures of real estate illiquidity utilize concepts from asset pricing. However, we note that the transaction process in the real estate market is fundamentally different to those in financial markets. A transaction is made only when a buyer is willing to pay a price greater than or equal to the seller's reservation price. In light of this, timing risk is the current convention to study real estate illiquidity. We conjecture that liquidity conditions in real estate markets also have different dimensions. Specifically, prospective sellers take into account when to list their assets for sale based on how regional markets are performing. Thus, measures capturing a combination of costs and quantity, or indeed market depth can provide a signalling channel to prospective sellers thereby influencing future prices; and subsequently returns.

i) *The quantity dimension:* Following Lou and Shu (2017), we compute the inverse of trading volume for region i over time interval D to proxy market-depth as:

$$\mathrm{V}_{i,D}^{-1} = \frac{1}{N_D} \sum_{d=1}^{D} \frac{1}{\mathrm{VOL}_{i,d}} \tag{1}$$

where $\text{VOL}_{i,d}$ represents month d's currency value of trading volume of properties for the ith region of the US or the UK. We take the average of the previous 12 months' inverse of trading volume for the ith region which makes N_D=12. Typically for stocks, the quantity dimension of liquidity is a price-quantity pair which is proxied by an average of offer and bid depth. It looks to capture, for example, the average quantity a trader can trade at the best price(s) (Holden et al., 2014). A stock's trading volume can act as a proxy for market-depth and indeed the quantity dimension of liquidity. However, market-depth for equity markets relates to the amount of stocks traded for a limit order for a given price. For real estate markets, trading volume is measured for each (unique) asset after price negotiations; there is no limit order book. The value trading volume in real estate markets is in fact a price-quantity pair. Thus, we postulate that real estate trading volume acts as a far more accurate proxy for the quantity dimension of liquidity relative to equity trading volume; with the technical caveat that we average over real estate within each region.

ii) *The price-impact dimension:* Price-impact essentially combines the cost and quantity dimension of liquidity and is the price elasticity of the asset with respect to trading volume. To proxy price-impact, we calculate the return-to-volume measure proposed in Amihud (2002) for the US or the UK's ith region over time interval D as:

$$\text{RtoV}_{i,D} = \frac{1}{N_D} \sum_{d=1}^{D} \frac{|R_{i,d}|}{\text{VOL}_{i,d}} \tag{2}$$

where $|R_{i,d}|$ is region i's absolute monthly property sector return in month d. $\text{VOL}_{i,d}$ is the ith region's monthly (currency value) trading volume during month d. As with $\text{V}^{-1}_{i,D}$, we take an average over the previous 12 months' return-to-volume ratios which makes N_D=12. For real estate markets, this measure tracks region i's average real estate price response to a 1 unit (in our case £) change in trading volume.

Note that we scale both $\text{VOL}_{i,d}$ and $\text{RtoV}_{i,D}$ by 10^8 for ease of reading descriptive statistics (Amihud, 2002; Acharya and Pedersen, 2005). In our main results we express real estate illiquidity as a % deviation from its 1-year moving average; stochastic de-trending in this manner is standard in the finance literature (see e.g. Chen et al., 2018). An increase in our illiquidity proxies constitutes a decline (surge) in liquidity (illiquidity). We use monthly data on regional average house prices and regional trading volumes to construct our measures of illiquidity for month D. We compute our measures of real estate illiquidity using both US and UK data.

The US is split into its four Census Bureau regions, which are: Midwest; North East; South; and West. The US sample we consider spans January 1985 to December 2018. The US house price indices are Freddie Mac repeat transaction indices and the data are taken from Thomson Reuters Datastream. These contain single family homes and condos. Specifically they measure the price appreciation, while holding constant property type and location, by comparing prices of the same property over two or more transactions. The corresponding volume series are the number of sold single family homes and condos for each US region.

The UK is split into 10 regions (excluding Scotland and Northern Ireland as trading volume data of these two regions begin in 2004 and 2005 respectively) which are: East England; East Midlands; London; North East; North West; Scotland; South East; South West; Wales; West Midlands; and Yorkshire and Humberside. The UK sample we consider spans January 1998 to December 2018. Estimation samples are dictated by data availability. We use Halifax regional house price data made available to us by IHS Markit and trading volume data from the Land Registry. The UK price indexes are average prices of residential real estate by region and sales volume is the number of residential real estate sales in a given region. Further details for all data we use in this study are in the Supplementary Appendix.

Table 1 reports the descriptive statistics for our regional real estate illiquidity measures. As can be seen from Panel A, the most liquid region of the US is the South, while the North East has the lowest levels of liquidity. Turning our attention to Panel B, the most liquid regions in the UK are London and the South East with Wales and the North East having the lowest levels of liquidity. Note also that the most illiquid regions are also the most volatile across both the US and the UK. For illustrative purposes, Figure 1 plots the median and 95% percentiles of the distribution of regional illiuqidity proxied by the inverse of trading volume, $\mathrm{V}_{i,D}^{-1}$ for the US (LHS plots) and UK (RHS plots). The top panels show the median and 95% coverage of the level of regional measures and the bottom panels reports the median and 95% coverage of the % deviations from their respective 1-year moving averages. As shown in the top panels, overall liquidity conditions in the US and the UK real estate markets in general improve. Note that liquidity conditions deteriorate during the bust of 2008, and remain persistent until around 2015. The bottom panels indicate liquidity drying up substantially during the bust of 2008 in both markets with increases of around 24% and 74% above the previous year's average in each respective market.

2.2 Economic and Financial Data

Here we outline the variables we use in our study as additional controls to explain and forecast real estate returns. Our focus is on examining the role of real estate illiquidity over and above the variables we introduce in this Section. Our choice of variables follows Ghysels et al. (2013) and Plazzi et al. (2010). The former use stock market returns, industrial production, inflation, and short-term interest rates to proxy for time-variation in the state of the economy. The latter use economic variables including employment, wages and housing starts.

Our economic data consists of: industrial production; consumer price inflation; the US or UK short-term interest rate (either Federal Funds Rate or the Bank of England Policy rate) that we splice with the shadow rate of Wu and Xia (2016) to account for unconventional monetary policies such as quantitative easing; the unemployment rate; wage growth; a weighted average of mortgage

Table 1: **Descriptive Statistics of Regional Illiquidity Measures in Levels for the US and UK**

Notes: Panel A of this table reports descriptive statistics for the two measures of regional real estate illiquidity using the US data. MW denotes Mid-West; NE denotes North East; S denotes South; and W denotes West. Panel B of this table reports descriptive statistics for the two measures of regional real estate illiquidity using the UK data. EE denotes East England; EM denotes East Midlands; LO denotes London; NE denotes North East; NW denotes North West; SE denotes South East; SW denotes South West; WA denotes Wales; WM denotes West Midlands; and YO denotes Yorkshire and Humberside. The LHS of each panel reports return-to-volume (RtoV) and the RHS reports inverse of trading volume (V^{-1}) respectively. Mean is the sample mean, Med is the sample median, and S.d is the sample standard deviation.

A: US Data January 1985 to December 2018						
		RtoV			$\mathbf{V^{-1}}$	
	Mean	Med	S.d	Mean	Med	S.d
MW	0.255	0.214	0.165	0.811	0.610	0.455
NE	0.429	0.251	0.573	0.841	0.663	0.406
S	0.137	0.127	0.081	0.452	0.320	0.266
W	0.206	0.160	0.170	0.493	0.347	0.309
B: UK Data January 1998 to December 2018						
		RtoV			$\mathbf{V^{-1}}$	
	Mean	Med	S.d	Mean	Med	S.d
EE	0.062	0.042	0.063	0.070	0.063	0.028
EM	0.118	0.081	0.112	0.135	0.115	0.055
LO	0.042	0.029	0.043	0.040	0.036	0.017
NE	0.293	0.209	0.273	0.320	0.278	0.131
NW	0.085	0.061	0.086	0.101	0.085	0.042
SE	0.033	0.022	0.034	0.038	0.035	0.014
SW	0.069	0.046	0.067	0.078	0.072	0.030
WA	0.238	0.160	0.247	0.267	0.226	0.112
WM	0.120	0.102	0.047	0.120	0.102	0.047
YO	0.120	0.082	0.120	0.142	0.119	0.060

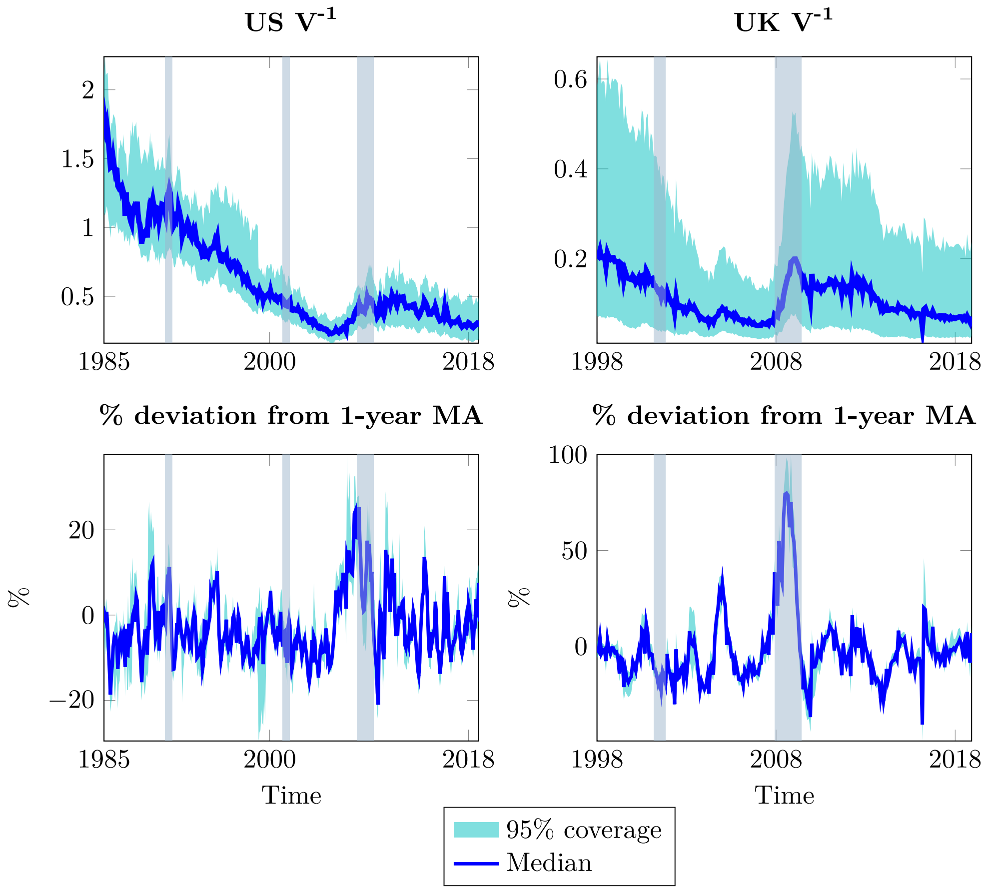

Figure 1: **The US and The UK Regional Real Estate Illiquidity: Level and % Deviations from 1-Year Moving Averages**

Notes: The LHS of this figure plots the median and 95% coverage for the inverse trading volume (V^{-1}) for the US regional data from January 1985 to December 2018. The top left plot shows levels and the bottom left plot expresses the US V^{-1} as a % deviation from its 1-year moving average. The RHS of this figure plots the median and 95% coverage for the inverse trading volume (V^{-1}) for the UK regional data from January 1998 to December 2018. The top right plot shows levels and the bottom right plot expresses the UK V^{-1} as a % deviation from its 1-year moving average. Grey bars indicate NBER recession dates.

rates; and the growth in housing starts. An additional variable we include is the the Economic Policy Uncertainty index of Baker et al. (2016).

Our financial data for the US includes the S&P500 composite market return and the Amihud (2002) measure of stock market illiquidity; with the latter using daily data of all individual stocks listed on the NYSE, AMEX, and NASDAQ. For the UK, we use the FTSE100 market return and the Amihud (2002) measure of stock market illiquidity using data for all individual stocks on the London Stock Exchange. We follow Ellington et al. (2017) and Ellington (2018) in constructing our measures of stock market illiquidity by using daily data on all stocks (both dead and alive) and standard filtering criteria. The market measure is an equally weighted average of individual stocks that remain after filtering. We then convert this to monthly frequency by taking an average of daily values within each month. In the Appendix, we provide tables with details of data sources and transformations.

2.3 Methodology

Our main model is the time-varying parameter VAR (TVP VAR) in Petrova (2019). This model permits time-variation in the VAR's coefficient matrices and covariance matrices in a non-parametric manner using a kernel weighting scheme. This specification permits the user to estimate and forecast complex large multivariate models in a computationally efficient manner; something that conventional methods such as Primiceri (2005) are unable to handle. We note here that the number of variables in our US dataset is 20 variables (4 regional real estate returns, their 4 corresponding illiquidity measures and 12 economic/financial variables). The UK dataset contains 30 variables (10 regional real estate returns, their 10 corresponding illiquidity measures, plus 12 economic/financial variables). Further details of are in the Supplementary Appendix.

3 Results

To determine whether our real estate illiquidity proxies carry information content for real estate returns, we conduct a recursive out-of-sample forecasting exercise in the following manner. We estimate the models over an expanding window using the first 60-months at the initial recursion. We produce forecasts of real estate returns h-steps ahead in an iterative manner, where $h = \{1, 3, 6, 12\}$; at $h > 1$ we analyse cumulative return forecasts. We analyse both point and density forecasts using root mean squared errors (RMSEs) and log predictive scores (LPS). The forecast sample using US data is from March 1990 to December 2017 and for UK data it is from March 2003 to December 2017.

We compare the performance of the Petrova (2019) TVP VAR containing our measures of market illiquidity against: i) AR(2) specifications; ii) time-varying parameter AR(2) (TVAR(2)) specifications that use an analogous algorithm to Petrova (2019) for univariate models; iii) standard Bayesian VARs with Minneosta Normal-Wishart priors (both with and without real estate illiquidity proxies) (BVAR(2)); and iv) TVP VARs containing no measure of real estate illiquidity. It is noteworthy to mention here that we also investigate whether our findings using regional real estate data hold when looking at national real estate data. In doing so we produce additional forecasts from all models of national real estate returns using national real estate illiquidity measures which are an equally weighted average of our regional measures.

3.1 Out-of-Sample Forecasting

We first analyse average forecast performance over the forecast sample. Tables 2 and 3 report average RMSE and LPS for regional and national real estate returns over the forecast sample from an array of different models at $h = \{1, 3, 6, 12\}$ month ahead horizons for US and UK data respectively. For each real estate return, and each horizon, we highlight in bold font the lowest RMSE and the highest LPS that show the most favourable forecasts.

Focussing on US real estate returns in Table 2, we can see that the most favourable point and density forecasts generally come from the TVP VAR model containing our V^{-1} measures of real estate illiquidity, although in some cases return forecasts from TVP VARs using RtoV are also preferable. Notably, density forecasts provide a stronger case for utilising real estate illiquidity measures. One possible explanation for this is that accounting for liquidity conditions provides a more precise estimate of the time-varying variance(s). Turning our attention to UK real estate returns in Table 3, both point on density forecasts suggest using TVP VAR models with our real estate illiquidity measures. Overall, it is clear that the TVP VAR models provide more accurate forecasts, on average, relative to a battery of simpler models.

These forecast metrics indicate that liquidity conditions capturing (regional) market depth and price impact are important predictors for real estate returns. Overall across both the US and UK, our quantity-based measures of real estate illiquidity provide the best out-of-sample predictions for real estate returns. This result may emerge due to the signalling channel stemming from market depth, and, as we discuss earlier, each trade in real estate is a price-quantity pair. In what follows for the sake of brevity, we focus on models using V^{-1} to assess the statistical significance of our forecasting models; results using RtoV measures are in the Online Appendix.

To investigate the statistical significance of forecasts, we use the pairwise tests of equal conditional predictive ability in conjunction with the decision rule approach of Giacomini and White (2006). Essentially this tests the null hypothesis of equal conditional predictive ability of forecasts from competing models/datasets using differences in loss functions. The decision rule procedure allows one to examine adaptively at time t a forecasting model/dataset for time $t + h$.

Table 2: **Average Forecast Performance of US Real Estate Returns from Competing Models from March 1990 to December 2017**

Notes: This table reports the average forecast performance for US regional and national real estate returns from competing models at the h month ahead horizon. The LHS of the table reports average root mean squared errors (RMSE) and the RHS reports average log predictive scores (LPS). MW, NE, S, and W denote the Midwest, North East, South and West regional return forecasts respectively, while US denotes the national real estate return forecast. AR(2) denotes a Bayesian AR(2) model with Normal inverse Gamma prior, TVP-AR(2) denotes a univariate version of the TVP VAR model of Petrova (2019), BVAR(2) denotes a standard Bayesian VAR(2) model with a Minnesota Normal-Wishart prior and TVPVAR(2) denotes the TVP VAR model in Petrova (2019). Multivariate models include all economic and financial controls. ILLIQ=N/A reports forecasts from a dataset with no measure of real estate illiquidity. ILLIQ=RtoV (ILLIQ=V^{-1}) report real estate return forecasts from datasets containing RtoV (V^{-1}) measures of real estate illiquidity. Numbers in bold font report the lowest RMSE for each real estate return and highest LPS for each real estate return at each forecast horizon across all models.

		RMSE						LPS				
		MW	**NE**	**S**	**W**	**US**		**MW**	**NE**	**S**	**W**	**US**
AR(2)	h=1	0.253	0.335	0.172	0.058	0.077	h=1	-0.912	-1.242	-0.899	-0.797	-0.976
	3	0.253	0.341	0.182	0.126	0.145	3	-1.393	-1.455	-1.389	-1.375	-1.321
	6	0.285	0.377	0.220	**0.188**	0.231	6	-1.727	-1.758	-1.729	-1.734	-1.529
	12	0.790	0.867	0.742	0.692	0.888	12	-1.775	-1.825	-1.785	-1.804	-1.633
TVP-AR(2)	h=1	0.268	0.344	0.184	**0.058**	**0.073**	h=1	-2.432	-2.918	-2.594	0.382	0.172
	3	0.287	0.357	0.208	**0.124**	**0.135**	3	-0.501	-1.298	-0.378	-0.213	-0.214
	6	0.320	0.392	0.247	0.192	**0.200**	6	-0.695	-0.839	-0.641	-0.599	-0.485
	12	0.657	0.742	0.614	0.555	0.643	12	-0.797	-0.940	-0.759	-0.774	**-1.074**
BVAR(2) ILLIQ=N/A	h=1	0.061	0.081	0.065	0.075	0.353	h=1	1.073	0.784	1.042	0.864	-0.356
	3	0.101	0.148	0.113	0.140	0.382	3	0.427	0.404	0.427	0.435	-0.661
	6	0.131	0.208	0.152	0.205	0.435	6	-0.542	0.149	-0.150	0.089	-1.072
	12	0.159	0.278	0.196	0.285	0.499	12	-4.187	-0.112	-1.637	-0.349	-2.071
BVAR(2) ILLIQ=RtoV	h=1	0.062	0.080	0.065	0.073	0.352	h=1	1.073	0.787	1.029	0.872	-0.356
	3	0.103	0.150	0.113	0.138	0.382	3	0.408	0.394	0.506	0.439	-0.659
	6	0.134	0.213	0.154	0.204	0.435	6	-0.691	0.123	-0.206	0.087	-1.015
	12	0.161	0.286	0.199	0.285	0.500	12	-4.252	-0.145	-1.314	**-0.329**	-1.738
BVAR(2) ILLIQ=V^{-1}	h=1	0.062	0.082	0.065	0.074	0.369	h=1	1.062	0.783	1.048	0.866	-0.386
	3	0.102	0.149	0.113	0.140	0.398	3	0.461	0.401	0.469	0.440	-0.715
	6	0.132	0.209	0.153	0.204	0.447	6	-0.351	0.147	-0.404	**0.096**	-1.026
	12	0.160	0.277	0.197	0.284	0.523	12	-3.329	**-0.111**	-1.588	-0.362	-1.642
TVPVAR(2) ILLIQ=N/A	h=1	0.060	0.078	0.065	0.076	0.089	h=1	1.134	0.928	1.119	0.953	**0.563**
	3	0.097	0.128	0.111	0.134	0.148	3	**0.658**	0.449	0.673	0.421	0.201
	6	**0.122**	**0.169**	**0.148**	0.191	0.202	6	0.502	0.131	0.501	-0.716	-0.118
	12	**0.147**	**0.213**	**0.187**	**0.260**	0.267	12	**0.764**	-0.694	-0.441	-5.727	-4.094
TVPVAR(2) ILLIQ=RtoV	h=1	0.061	**0.076**	0.065	0.076	0.088	h=1	0.563	-1.197	-0.090	**2.459**	0.265
	3	0.100	0.129	0.112	0.135	0.147	3	0.201	-0.568	0.315	**1.545**	**0.278**
	6	0.126	0.172	0.151	0.194	0.202	6	-0.118	-0.440	**0.525**	-0.742	-0.169
	12	0.151	0.217	0.191	0.264	0.267	12	-4.094	-0.354	**0.697**	-16.481	-3.218
TVPVAR(2) ILLIQ=V^{-1}	h=1	**0.060**	0.077	**0.064**	0.076	0.089	h=1	**1.150**	**0.935**	**1.130**	0.883	0.398
	3	**0.097**	**0.128**	**0.110**	0.134	0.148	3	0.643	**0.462**	**0.679**	0.448	0.264
	6	0.123	0.169	0.149	0.191	0.202	6	**0.633**	**0.149**	0.482	-0.282	**-0.081**
	12	0.147	0.214	0.188	0.261	**0.266**	12	0.729	-0.762	-0.269	-5.191	-3.355

Table 3: **Average Forecast Performance of UK Real Estate Returns from Competing Models from March 2003 to December 2017**

Notes: This table reports the average forecast performance for UK regional and national real estate returns from competing models at the h month ahead horizon. The first part of this table reports average root mean squared errors (RMSE) and the second part reports average log predictive scores (LPS). EE, EM, LO, NE, NW, SE, SW, WA, WM, and YO denote the East England, East Midlands, London, North East, North West, South East, South West, Wales, West Midlands, and Yorkshire and Humberside respectively. UK denotes the national real estate return forecast. AR(2) denotes a Bayesian AR(2) model with Normal inverse Gamma prior, TVP-AR(2) denotes a univariate version of the TVP VAR model of Petrova (2019), BVAR(2) denotes a standard Bayesian VAR(2) model with a Minnesota Normal-Wishart prior and TVPVAR(2) denotes the TVP VAR model in Petrova (2019). Multivariate models include all economic and financial controls. ILLIQ=N/A reports forecasts from a dataset with no measure of real estate illiquidity. ILLIQ=RtoV (ILLIQ=V^{-1}) report real estate return forecasts from datasets containing RtoV (V^{-1}) measures of real estate illiquidity. Numbers in bold font report the lowest RMSE for each real estate return and highest LPS for each real estate return at each forecast horizon across all models.

		RMSE										
		EE	**EM**	**LO**	**NE**	**NW**	**SE**	**SW**	**WA**	**WM**	**YO**	**UK**
AR(2)	h=1	0.657	0.681	0.836	0.817	0.693	0.696	0.611	0.778	0.637	0.618	0.488
	3	0.747	0.773	0.971	0.954	0.816	0.783	0.697	0.874	0.742	0.756	0.641
	6	0.807	0.840	1.044	1.046	0.884	0.835	0.750	0.958	0.813	0.818	0.720
	12	0.857	0.902	1.112	1.113	0.948	0.884	0.804	1.010	0.875	0.878	0.859
TVP-AR(2)	h=1	0.694	0.667	0.926	**0.782**	**0.637**	0.701	0.621	**0.724**	0.624	0.600	0.501
	3	0.816	0.783	1.064	**0.916**	0.763	0.822	0.733	**0.862**	0.737	0.722	0.676
	6	1.157	1.112	1.395	1.210	1.082	1.149	1.069	1.187	1.069	1.023	2.322
	12	90.478	68.435	79.079	60.755	66.017	97.891	74.902	61.888	89.991	70.108	4433.782
BVAR(2) ILLIQ=N/A	h=1	0.559	0.697	0.699	0.830	0.692	0.573	0.567	0.804	0.619	0.627	0.503
	3	0.720	0.836	0.923	0.995	0.829	0.729	0.711	0.947	0.766	0.770	0.681
	6	0.833	0.941	1.045	1.117	0.950	0.833	0.815	1.069	0.861	0.896	0.790
	12	0.961	1.082	1.167	1.260	1.084	0.957	0.953	1.204	0.991	1.049	0.906
BVAR(2) ILLIQ=RtoV	h=1	0.557	0.690	0.698	0.823	0.691	0.580	0.566	0.802	0.615	0.629	0.500
	3	0.721	0.826	0.931	0.989	0.826	0.727	0.712	0.947	0.752	0.767	0.682
	6	0.832	0.929	1.052	1.107	0.942	0.832	0.813	1.065	0.845	0.886	0.793
	12	0.962	1.079	1.171	1.255	1.079	0.960	0.952	1.200	0.984	1.047	0.909
BVAR(2) ILLIQ=V^{-1}	h=1	0.530	0.665	**0.680**	0.822	0.668	0.542	0.526	0.790	**0.589**	0.602	0.478
	3	0.663	0.791	0.878	0.966	0.794	0.675	0.672	0.932	0.713	0.742	0.644
	6	0.771	0.904	0.993	1.077	0.910	0.776	0.777	1.041	0.813	0.860	0.759
	12	0.943	1.086	1.150	1.244	1.071	0.947	0.960	1.194	0.987	1.048	0.910
TVPVAR(2) ILLIQ=N/A	h=1	0.529	**0.644**	0.683	0.819	0.656	0.540	0.528	0.806	0.598	0.581	0.460
	3	0.656	0.750	0.875	0.936	0.745	0.679	0.652	0.902	0.699	0.700	0.613
	6	0.729	0.802	0.972	0.989	0.813	0.755	0.712	0.928	0.753	0.757	0.699
	12	0.832	0.888	1.097	1.071	0.897	0.856	0.800	0.991	0.839	**0.839**	0.808
TVPVAR(2) ILLIQ=RtoV	h=1	0.531	0.645	0.686	0.818	0.658	0.540	0.529	0.810	0.598	0.585	0.462
	3	0.660	0.747	0.876	0.932	0.745	0.676	0.651	0.903	0.697	0.703	0.612
	6	0.728	**0.797**	0.968	0.987	0.811	0.748	0.709	**0.928**	0.750	0.755	0.696
	12	**0.832**	**0.888**	**1.094**	**1.069**	0.896	**0.851**	**0.797**	**0.990**	**0.836**	0.840	0.805
TVPVAR(2) ILLIQ=V^{-1}	h=1	**0.528**	0.651	0.685	0.822	0.651	**0.528**	**0.515**	0.797	0.603	**0.569**	**0.457**
	3	**0.653**	**0.746**	**0.866**	0.933	**0.727**	**0.661**	**0.635**	0.901	**0.693**	**0.682**	**0.601**
	6	**0.726**	0.803	**0.957**	**0.979**	**0.791**	**0.740**	**0.700**	0.928	**0.748**	**0.737**	**0.685**
	12	0.837	0.898	1.098	1.072	**0.887**	0.866	0.812	0.996	0.843	0.841	**0.804**

Table 3 Continued. **Average Forecast Performance of UK Real Estate Returns from Competing Models from March 2003 to December 2017**

Notes: This table reports the average forecast performance for UK regional and national real estate returns from competing models at the h month ahead horizon. The first part of this table reports average root mean squared errors (RMSE) and the second part reports average log predictive scores (LPS). EE, EM, LO, NE, NW, SE, SW, WA, WM, and YO denote the East England, East Midlands, London, North East, North West, South East, South West, Wales, West Midlands, and Yorkshire and Humberside respectively. UK denotes the national real estate return forecast. AR(2) denotes a Bayesian AR(2) model with Normal inverse Gamma prior, TVP-AR(2) denotes a univariate version of the TVP VAR model of Petrova (2019), BVAR(2) denotes a standard Bayesian VAR(2) model with a Minnesota Normal-Wishart prior and TVPVAR(2) denotes the TVP VAR model in Petrova (2019). Multivariate models include all economic and financial controls. ILLIQ=N/A reports forecasts from a dataset with no measure of real estate illiquidity. ILLIQ=RtoV (ILLIQ=V^{-1}) report real estate return forecasts from datasets containing RtoV (V^{-1}) measures of real estate illiquidity. Numbers in bold font report the lowest RMSE for each real estate return and highest LPS for each real estate return at each forecast horizon across all models.

		LPS										
		EE	**EM**	**LO**	**NE**	**NW**	**SE**	**SW**	**WA**	**WM**	**YO**	**UK**
AR(2)	h=1	-1.552	-1.546	-1.667	-1.613	-1.580	-1.572	-1.521	-1.605	-1.531	-1.523	-1.686
	3	-1.386	-1.372	-1.472	-1.426	-1.394	-1.400	-1.378	-1.393	-1.361	-1.383	-1.601
	6	-1.322	-1.310	-1.383	-1.370	-1.335	-1.333	-1.309	-1.333	-1.307	-1.324	-1.530
	12	-1.251	-1.252	-1.302	-1.319	-1.278	-1.257	-1.239	-1.274	-1.250	-1.264	-1.437
TVP-AR(2)	h=1	-1.637	-1.573	-1.788	-1.623	-1.585	-1.654	-1.585	-1.631	-1.556	-1.546	-1.503
	3	-1.405	-1.245	-1.776	-1.270	-1.195	-1.466	-1.354	-1.226	-1.228	-1.203	-1.336
	6	-1.444	-1.159	-2.099	-1.091	-1.037	-1.846	-1.299	-1.047	-1.127	-1.031	-1.254
	12	-1.760	-1.271	-6.268	-1.082	-1.031	-2.125	-1.419	-1.041	-1.237	-1.039	-1.349
BVAR(2) ILLIQ=N/A	h=1	-1.366	-1.549	-1.955	-1.537	-1.475	-1.618	-1.154	-1.648	-1.247	-1.225	-1.442
	3	-1.093	-1.131	-1.342	-1.249	-1.111	-1.131	-1.057	-1.226	-1.030	-1.060	-1.147
	6	-1.170	-1.293	-1.316	-1.236	-1.144	-1.374	-1.136	-1.182	-1.068	-1.118	-1.818
	12	-1.559	-1.619	-1.719	-1.403	-1.392	-2.343	-1.642	-1.373	-1.391	-1.434	-3.191
BVAR(2) ILLIQ=RtoV	h=1	-1.280	-1.663	-1.919	-1.544	-1.452	-1.381	-1.148	-1.643	-1.252	-1.222	-1.368
	3	-1.061	-1.078	-1.311	-1.224	-1.086	-1.065	-1.048	-1.223	-1.000	-1.036	-1.166
	6	-1.134	-1.123	-1.454	-1.205	-1.094	-1.222	-1.100	-1.160	-0.998	-1.071	-1.652
	12	-1.455	-1.576	-1.619	-1.392	-1.347	-1.968	-1.391	-1.329	-1.251	-1.429	-3.058
BVAR(2) ILLIQ=V^{-1}	h=1	-1.369	-1.761	-1.992	-1.541	-1.464	-1.651	-1.080	-1.546	**-1.203**	-1.195	-1.533
	3	-0.952	-1.007	-1.179	-1.210	-1.037	-0.942	-0.923	-1.199	-0.932	-0.993	-1.059
	6	-0.966	-1.050	-1.123	-1.155	-1.036	-0.969	-0.969	-1.118	-0.932	-1.007	-1.267
	12	-1.283	-1.427	-1.477	-1.343	-1.281	-1.463	-1.338	-1.301	-1.236	-1.326	-2.331
TVPVAR(2) ILLIQ=N/A	h=1	-1.217	-1.614	**-1.616**	-1.591	-1.327	**-1.168**	-1.079	**-1.500**	-1.237	-1.193	-1.310
	3	-0.870	-0.945	-1.180	-1.206	-0.984	-0.869	-0.855	-1.151	-0.893	-0.939	-0.843
	6	-0.808	-0.816	-1.036	-1.098	-0.881	-0.825	-0.784	-0.978	-0.786	-0.845	-0.864
	12	-1.002	-0.873	-1.087	-1.088	-0.895	-1.006	-0.880	-0.951	-0.814	-0.884	-1.216
TVPVAR(2) ILLIQ=RtoV	h=1	**-1.142**	**-1.455**	-1.744	**-1.535**	**-1.323**	-1.198	-1.082	-1.530	-1.286	-1.193	**-1.272**
	3	-0.863	**-0.937**	**-1.169**	-1.202	-0.976	-0.859	-0.837	**-1.148**	**-0.872**	-0.930	-0.842
	6	-0.805	**-0.803**	**-1.038**	-1.085	-0.871	-0.818	-0.762	**-0.970**	**-0.759**	-0.826	-0.934
	12	-0.920	-0.861	**-1.074**	**-1.075**	-0.867	-0.992	-0.861	**-0.950**	**-0.785**	-0.860	-1.318
TVPVAR(2) ILLIQ=V^{-1}	h=1	-1.457	-1.479	-1.684	-1.537	-1.394	-1.286	**-1.078**	-1.533	-1.254	**-1.185**	-1.421
	3	**-0.851**	-0.941	-1.183	**-1.197**	**-0.965**	**-0.842**	**-0.820**	-1.151	-0.881	**-0.898**	**-0.835**
	6	**-0.775**	-0.807	-1.042	**-1.082**	**-0.844**	**-0.780**	**-0.743**	-0.975	-0.765	**-0.766**	**-0.827**
	12	**-0.872**	**-0.853**	-1.076	-1.091	**-0.848**	**-0.946**	**-0.839**	-0.957	-0.792	**-0.818**	**-1.183**

Table 4: **Conditional Predictive Ability Tests for US Real Estate Return Forecasts, ILLIQ=$\mathbf{V^{-1}}$**

Notes: This table reports the results of pairwise tests of equal conditional predictive ability in Giacomini and White (2006) for forecasts of US real estate returns. The entries are p-values of the test of equal conditional predictive ability where we benchmark our TVP VAR model (TVPVAR(2)) containing regional (or national) measures of real estate illiquidity and economic and financial variables againsts: i) a Bayesian AR(2) model with Normal inverse-Gamma priors (AR(2)); ii) a Bayesian time-varying parameter AR(2) model (a univariate version of Petrova (2019)) (TVAR(2)); iii) a Bayesian VAR(2) model with Minnesota Normal-Wishart prior (BVAR(2)); and iv) a TVP VAR model (Petrova, 2019) that contains all economic and financial data apart from the measures of real estate illiquidity (TVPVAR(2) No ILLIQ). The loss function is either root mean squared errors (RMSEs) or log predictive scores (LPS). Numbers in parenthesis report the proportion of times our TVPVAR(2) model outperforms one of the alternative specifications over the forecast sample. p-values in bold font indicate a rejection of the null hypothesis of equal conditional predictive ability and that our TVPVAR(2) model outperforms the alternative at least 50% of the time. Parenthesis in italic font indicate that our TVPVAR(2) model outperforms the alternative at least 50% of the time. MW, NE, S, and W denote the Midwest, North East, South and West regional return forecasts respectively, while US denotes the national real estate return. Panels A and B reports results using our RtoV and V^{-1} real estate illiquidity measures respectively.

		RMSE					**LPS**				
		MW	**NE**	**S**	**W**	**US**	**MW**	**NE**	**S**	**W**	**US**
TVPVAR(2) vs.	h=1	**0.000**	**0.000**	**0.000**	**0.000**	**0.004**	**0.000**	**0.000**	**0.000**	**0.000**	**0.002**
AR(2)		*(0.895)*	*(0.95)*	*(0.851)*	*(0.09)*	*(0.251)*	*(0.991)*	*(0.994)*	*(0.985)*	*(0.997)*	*(0.994)*
	3	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
		(0.938)	*(0.978)*	*(0.858)*	*(0.294)*	*(0.644)*	*(0.994)*	*(0.988)*	*(1)*	*(0.988)*	*(0.981)*
	6	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
		(0.941)	*(0.991)*	*(0.988)*	*(0.393)*	*(0.867)*	*(0.988)*	*(0.991)*	*(0.997)*	*(0.963)*	*(0.932)*
	12	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.348**	**0.303**
		(0.957)	*(0.969)*	*(0.969)*	*(0.774)*	*(0.892)*	*(0.985)*	*(0.913)*	*(0.947)*	*(0.433)*	*(0.402)*
TVPVAR(2) vs.	h=1	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.003**	**0.000**	**0.000**	**0.569**
TVAR(2)		*(0.904)*	*(0.954)*	*(0.833)*	*(0.102)*	*(0.077)*	*(0.876)*	*(1)*	*(0.824)*	*(0.904)*	*(0.402)*
	3	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
		(0.944)	*(0.963)*	*(0.898)*	*(0.257)*	(0.508)	*(0.966)*	*(0.892)*	*(0.957)*	*(0.851)*	*(0.892)*
	6	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
		(0.966)	*(0.997)*	*(1)*	*(0.195)*	(0.539)	*(0.978)*	*(0.96)*	*(0.978)*	*(0.724)*	*(0.768)*
	12	**0.000**	**0.000**	**0.000**	**0.000**	**0.002**	**0.000**	**0.000**	**0.000**	0.487	0.433
		(0.985)	*(0.985)*	*(0.991)*	*(0.749)*	*(0.715)*	*(0.975)*	*(0.437)*	*(0.839)*	*(0.353)*	*(0.238)*
TVPVAR(2) vs.	h=1	**0.000**	**0.006**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	0.884	**0.091**
BVAR(2)		(0.452)	*(0.625)*	(0.455)	*(0.467)*	*(0.994)*	*(0.724)*	*(0.839)*	*(0.628)*	*(0.768)*	*(0.997)*
	3	**0.000**	**0.002**	**0.000**	**0.000**	**0.000**	0.398	**0.000**	0.102	**0.000**	**0.000**
		(0.455)	*(0.929)*	(0.396)	*(0.622)*	*(0.966)*	*(0.409)*	*(0.796)*	*(0.563)*	*(0.554)*	*(0.997)*
	6	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.042**	**0.000**	0.179	0.221	**0.001**
		(0.511)	*(1)*	(0.471)	*(0.703)*	*(0.889)*	(0.467)	*(0.65)*	*(0.598)*	(0.238)	*(0.96)*
	12	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	0.061	0.236	0.469	0.357	0.301
		(0.474)	*(0.96)*	(0.492)	*(0.783)*	*(0.861)*	(0.458)	(0.232)	*(0.557)*	(0.176)	(0.464)
TVPVAR(2) vs.	h=1	0.135	**0.003**	**0.054**	0.120	0.213	0.130	**0.052**	**0.003**	0.464	0.335
TVPVAR(2) No ILLIQ		*(0.83)*	*(0.817)*	*(0.851)*	(0.375)	(0.536)	*(0.978)*	*(0.824)*	*(0.898)*	(0.325)	(0.05)
	3	0.166	**0.008**	**0.006**	**0.018**	**0.032**	0.409	**0.030**	**0.002**	0.566	0.410
		(0.954)	*(0.786)*	*(0.845)*	(0.319)	*(0.783)*	*(0.712)*	*(0.802)*	*(0.802)*	(0.895)	*(0.923)*
	6	**0.030**	**0.051**	**0.089**	**0.046**	**0.070**	0.456	0.461	0.484	0.176	0.496
		(0.659)	*(0.576)*	(0.43)	*(0.551)*	*(0.591)*	*(0.981)*	*(0.768)*	(0.254)	*(0.985)*	*(0.963)*
	12	**0.014**	0.122	**0.075**	0.131	**0.092**	0.604	0.686	0.263	0.490	0.508
		(0.421)	*(0.616)*	(0.458)	(0.319)	*(0.901)*	(0.009)	(0.152)	*(0.598)*	*(0.957)*	*(0.765)*

Table 5: **Conditional Predictive Ability Tests for UK Real Estate Return Forecasts, ILLIQ=$\mathbf{V^{-1}}$**

Notes: This table reports the results of pairwise tests of equal conditional predictive ability in Giacomini and White (2006) for forecasts of UK real estate returns. The entries are p-values of the test of equal conditional predictive ability where we benchmark our TVP VAR model (TVPVAR(2)) containing regional (or national) measures of real estate illiquidity and economic and financial variables againsts: i) a Bayesian AR(2) model with Normal inverse-Gamma priors (AR(2)); ii) a Bayesian time-varying parameter AR(2) model (a univariate version of Petrova (2019)) (TVAR(2)); iii) a Bayesian VAR(2) model with Minnesota Normal-Wishart prior (BVAR(2)); and iv) a TVP VAR model (Petrova, 2019) that contains all economic and financial data apart from the measures of real estate illiquidity (TVPVAR(2) No ILLIQ). The loss function is either root mean squared errors (RMSEs) or log predictive scores (LPS). Numbers in parenthesis report the proportion of times our TVPVAR(2) model outperforms one of the alternative specifications over the forecast sample. p-values in bold font indicate a rejection of the null hypothesis of equal conditional predictive ability and that our TVPVAR(2) model outperforms the alternative at least 50% of the time. Parenthesis in italic font indicate that our TVPVAR(2) model outperforms the alternative at least 50% of the time. EE, EM, LO, NE, NW, SE, SW, WA, WM, and YO denote the East England, East Midlands, London, North East, North West, South East, South West, Wales, West Midlands, and Yorkshire and Humberside respectively. UK denotes the national real estate return. Panels A and B reports results using our RtoV and V^{-1} real estate illiquidity measures respectively.

		RMSE										
		EE	**EM**	**LO**	**NE**	**NW**	**SE**	**SW**	**WA**	**WM**	**YO**	**UK**
TVPVAR(2) vs.	h=1	**0.001**	0.562	**0.004**	0.774	0.287	**0.000**	**0.014**	0.621	0.549	0.088	**0.039**
AR(2)		*(1)*	*(0.85)*	*(0.862)*	*(0.725)*	*(0.964)*	*(0.958)*	*(1)*	*(0.413)*	*(0.904)*	*(0.85)*	*(0.796)*
	3	**0.000**	**0.064**	**0.000**	**0.005**	**0.003**	**0.000**	**0.001**	**0.012**	**0.017**	**0.005**	**0.000**
		(0.916)	*(0.838)*	*(0.988)*	*(0.922)*	*(0.976)*	*(0.91)*	*(0.958)*	*(0.653)*	*(0.796)*	*(0.964)*	*(0.85)*
	6	**0.004**	**0.058**	**0.001**	**0.012**	**0.001**	**0.002**	**0.014**	**0.013**	**0.005**	**0.007**	**0.000**
		(0.886)	*(0.916)*	*(0.928)*	*(0.922)*	*(0.904)*	*(0.898)*	*(0.856)*	*(0.85)*	*(0.76)*	*(0.904)*	*(0.934)*
	12	**0.009**	**0.005**	**0.002**	**0.005**	**0.001**	**0.001**	**0.005**	**0.002**	**0.003**	**0.006**	**0.000**
		(0.922)	*(0.737)*	*(0.689)*	*(0.671)*	*(0.826)*	*(0.719)*	*(0.515)*	*(0.563)*	*(0.701)*	*(0.659)*	*(0.904)*
TVPVAR(2) vs.	h=1	**0.000**	0.108	**0.000**	0.343	0.478	**0.001**	**0.031**	0.142	0.343	0.174	0.052
TVAR(2)		*(0.94)*	*(0.683)*	*(0.892)*	(0.569)	(0.635)	*(0.916)*	*(0.994)*	(0.18)	*(0.754)*	(0.946)	*(0.97)*
	3	**0.000**	**0.002**	**0.000**	**0.043**	**0.280**	**0.000**	**0.007**	**0.308**	**0.007**	**0.205**	**0.002**
		(0.916)	*(0.838)*	*(0.934)*	*(0.754)*	*(1)*	*(0.904)*	*(0.946)*	*(0.359)*	*(0.874)*	*(0.982)*	*(0.94)*
	6	**0.000**	**0.000**	**0.000**	**0.006**	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**
		(0.982)	*(0.994)*	*(0.994)*	*(0.988)*	*(0.946)*	*(0.994)*	*(0.994)*	*(0.934)*	*(1)*	*(1)*	*(1)*
	12	**0.002**	**0.000**	**0.001**	**0.000**	**0.002**	**0.012**	**0.000**	**0.000**	**0.002**	**0.000**	**0.044**
		(1)	*(1)*	*(1)*	*(0.964)*	*(0.964)*	*(1)*	*(1)*	*(0.958)*	*(1)*	*(0.976)*	*(1)*
TVPVAR(2) vs.	h=1	**0.746**	0.685	0.805	0.162	**0.008**	0.477	0.459	**0.002**	0.290	**0.007**	**0.268**
BVAR(2)		*(0.766)*	*(0.683)*	(0.15)	(0.563)	*(0.743)*	*(0.94)*	*(0.874)*	*(0.503)*	*(0.246)*	(0.287)	*(0.838)*
	3	**0.001**	**0.001**	**0.001**	**0.006**	**0.000**	**0.002**	**0.000**	0.366	**0.002**	**0.000**	**0.010**
		(0.802)	*(0.982)*	*(0.635)*	*(0.94)*	*(0.946)*	*(0.922)*	*(0.892)*	*(0.826)*	*(0.82)*	*(0.826)*	*(0.784)*
	6	**0.056**	**0.001**	**0.008**	**0.000**	**0.000**	**0.022**	**0.028**	**0.001**	**0.000**	**0.000**	**0.004**
		(0.874)	*(0.964)*	*(0.701)*	*(0.946)*	*(0.958)*	*(0.856)*	*(0.802)*	*(0.862)*	*(0.916)*	*(0.868)*	*(0.916)*
	12	**0.046**	**0.002**	**0.019**	**0.001**	**0.000**	**0.036**	**0.040**	**0.000**	**0.001**	**0.000**	**0.016**
		(0.85)	*(0.976)*	*(0.605)*	*(0.826)*	*(0.922)*	*(0.719)*	*(0.928)*	*(0.85)*	*(0.94)*	*(0.868)*	*(0.766)*
TVPVAR(2) vs.	h=1	0.931	0.343	0.939	0.913	0.724	0.284	**0.079**	**0.048**	0.519	0.272	0.176
TVPVAR(2) No ILLIQ		(0.419)	(0.305)	(0.485)	*(0.677)*	(0.868)	*(0.886)*	*(0.94)*	*(0.623)*	(0.192)	*(0.946)*	*(0.707)*
	3	0.149	**0.038**	**0.055**	**0.035**	**0.091**	0.260	**0.007**	0.261	**0.055**	0.210	**0.053**
		(0.79)	*(0.784)*	*(0.659)*	*(0.862)*	*(0.874)*	*(0.976)*	*(0.784)*	*(0.85)*	*(0.832)*	*(0.994)*	*(0.904)*
	6	0.346	0.176	0.141	0.174	0.145	0.395	**0.029**	**0.099**	**0.045**	0.214	**0.097**
		(0.491)	*(0.383)*	*(0.629)*	*(0.958)*	*(0.958)*	*(0.886)*	*(0.707)*	*(0.838)*	*(0.892)*	*(0.958)*	*(0.952)*
	12	0.251	0.210	0.125	0.123	0.117	0.112	**0.021**	0.232	**0.035**	0.125	**0.081**
		(0.323)	(0.299)	(0.353)	*(0.844)*	*(0.976)*	(0.246)	(0.126)	(0.347)	(0.365)	(0.371)	*(0.91)*

Table 5 continued: **Conditional Predictive Ability Tests for UK Real Estate Return Forecasts, ILLIQ=V^{-1}**

Notes: This table reports the results of pairwise tests of equal conditional predictive ability in Giacomini and White (2006) for forecasts of UK real estate returns. The entries are p-values of the test of equal conditional predictive ability where we benchmark our TVP VAR model (TVPVAR(2)) containing regional (or national) measures of real estate illiquidity and economic and financial variables againsts: i) a Bayesian AR(2) model with Normal inverse-Gamma priors (AR(2)); ii) a Bayesian time-varying parameter AR(2) model (a univariate version of Petrova (2019)) (TVAR(2)); iii) a Bayesian VAR(2) model with Minnesota Normal-Wishart prior (BVAR(2)); and iv) a TVP VAR model (Petrova, 2019) that contains all economic and financial data apart from the measures of real estate illiquidity (TVPVAR(2) No ILLIQ). The loss function is either root mean squared errors (RMSEs) or log predictive scores (LPS). Numbers in parenthesis report the proportion of times our TVPVAR(2) model outperforms one of the alternative specifications over the forecast sample. p-values in bold font indicate a rejection of the null hypothesis of equal conditional predictive ability and that our TVPVAR(2) model outperforms the alternative at least 50% of the time. Parenthesis in italic font indicate that our TVPVAR(2) model outperforms the alternative at least 50% of the time. EE, EM, LO, NE, NW, SE, SW, WA, WM, and YO denote the East England, East Midlands, London, North East, North West, South East, South West, Wales, West Midlands, and Yorkshire and Humberside respectively. UK denotes the national real estate return. Panels A and B reports results using our RtoV and V^{-1} real estate illiquidity measures respectively.

		LPS										
		EE	**EM**	**LO**	**NE**	**NW**	**SE**	**SW**	**WA**	**WM**	**YO**	**UK**
TVPVAR(2) vs.	h=1	**0.765**	**0.000**	**0.928**	**0.039**	**0.265**	**0.158**	**0.000**	**0.434**	**0.001**	**0.000**	**0.313**
AR(2)		*(0.515)*	*(0.766)*	*(0.473)*	*(0.886)*	*(0.946)*	*(0.964)*	*(0.994)*	*(0.772)*	*(0.928)*	*(1)*	*(0.982)*
	3	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
		(1)	*(1)*	*(0.988)*	*(1)*	*(1)*	*(1)*	*(0.976)*	*(0.994)*	*(0.982)*	*(1)*	*(1)*
	6	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
		(0.988)	*(1)*	*(1)*	*(0.976)*	*(0.97)*	*(1)*	*(0.994)*	*(0.97)*	*(1)*	*(0.988)*	*(0.976)*
	12	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
		(0.946)	*(0.94)*	*(0.952)*	*(0.766)*	*(0.904)*	*(0.904)*	*(0.832)*	*(0.844)*	*(0.94)*	*(0.832)*	*(0.743)*
TVPVAR(2) vs.	h=1	**0.613**	**0.001**	**0.844**	**0.024**	**0.245**	**0.018**	**0.000**	**0.270**	**0.000**	**0.000**	**0.955**
TVAR(2)		*(0.563)*	*(0.754)*	*(0.605)*	*(0.844)*	*(0.928)*	*(0.97)*	*(0.994)*	*(0.533)*	*(0.922)*	*(0.97)*	*(0.629)*
	3	**0.000**	**0.000**	**0.001**	**0.002**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
		(0.964)	*(0.982)*	*(0.976)*	*(0.892)*	*(0.904)*	*(0.946)*	*(0.97)*	*(0.683)*	*(0.964)*	*(0.892)*	*(0.994)*
	6	**0.000**	**0.000**	**0.003**	**0.000**	**0.000**	**0.014**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
		(0.916)	*(0.946)*	*(0.994)*	*(0.629)*	*(0.766)*	*(1)*	*(0.976)*	*(0.695)*	*(0.994)*	*(0.808)*	*(0.868)*
	12	**0.002**	**0.000**	**0.308**	**0.000**	**0.000**	**0.044**	**0.003**	**0.000**	**0.000**	**0.000**	**0.007**
		(0.982)	*(0.874)*	*(1)*	*(0.545)*	*(0.832)*	*(1)*	*(0.79)*	*(0.707)*	*(0.898)*	*(0.826)*	*(0.497)*
TVPVAR(2) vs.	h=1	0.685	0.317	0.336	0.844	0.658	0.409	0.516	0.573	0.243	0.564	0.813
BVAR(2)		(0.12)	*(0.826)*	*(0.731)*	(0.461)	(0.096)	*(0.731)*	(0.389)	(0.246)	(0.024)	*(0.078)*	*(0.838)*
	3	**0.001**	**0.000**	**0.004**	0.176	**0.002**	**0.084**	**0.000**	0.119	**0.058**	**0.001**	**0.006**
		(0.856)	*(0.904)*	*(0.246)*	*(0.569)*	*(0.844)*	*(0.898)*	*(0.695)*	*(0.503)*	*(0.88)*	(0.323)	*(0.838)*
	6	**0.005**	**0.000**	**0.034**	**0.004**	**0.000**	**0.019**	**0.001**	**0.000**	**0.000**	**0.000**	**0.046**
		(0.952)	*(0.988)*	*(0.593)*	*(0.731)*	*(0.904)*	*(0.862)*	*(0.796)*	*(0.683)*	*(0.904)*	*(0.772)*	*(0.904)*
	12	**0.001**	**0.000**	0.291	**0.000**	**0.000**	**0.061**	**0.000**	**0.000**	**0.000**	**0.000**	**0.064**
		(0.964)	*(1)*	*(0.808)*	*(0.796)*	*(0.916)*	*(0.934)*	*(0.994)*	*(0.778)*	*(0.988)*	*(0.874)*	*(0.94)*
TVPVAR(2) vs.	h=1	0.367	0.279	0.413	0.627	0.172	0.260	0.439	0.799	0.255	0.535	0.347
TVPVAR(2) No ILLIQ		(0.108)	*(0.976)*	(0.012)	*(0.94)*	(0.162)	(0.329)	*(0.527)*	(0.054)	(0.437)	*(0.892)*	(0.359)
	3	**0.075**	**0.084**	0.543	0.118	**0.036**	**0.038**	**0.068**	**0.047**	**0.093**	0.229	0.477
		(0.485)	*(0.689)*	(0.12)	*(0.88)*	*(0.91)*	*(0.904)*	*(0.976)*	*(0.76)*	*(0.76)*	*(0.964)*	*(0.838)*
	6	0.117	**0.023**	**0.030**	0.122	**0.019**	0.125	**0.049**	**0.006**	**0.073**	0.152	0.409
		(0.575)	*(0.832)*	(0.269)	*(0.832)*	*(0.838)*	*(0.772)*	*(0.754)*	*(0.719)*	*(0.725)*	*(0.928)*	*(0.94)*
	12	0.468	**0.028**	**0.063**	**0.015**	0.128	**0.058**	**0.071**	**0.018**	**0.067**	0.168	0.484
		(0.868)	*(0.898)*	(0.485)	*(0.784)*	*(0.88)*	*(0.862)*	*(0.76)*	*(0.551)*	*(0.862)*	*(0.934)*	*(0.952)*

Tables 4 and 5 report results for pairwise conditional predictive ability tests using US and UK data respectively from tests based on RMSEs and LPSs. Each table compares forecasts of real estate returns from the TVP VAR of Petrova (2019) using our V^{-1} real estate illiquidity measures against alternatives. Entries are p-values of pairwise conditional predictive ability tests and the numbers below indicate the proportion of times forecasts from our benchmark specification outperforms those from one of the alternative models/datasets. p-values in bold font indicate a rejection of the null hypothesis of equal conditional predictive ability such that the TVP VAR produces favourable forecasts that are significantly different to those from an alternative specification. Proportions in italic font indicate that the decision rule of Giacomini and White (2006) selects TVP VARs with measures of real illiquidity forecast relative to one of the alternative methods over at least 50% of the forecast sample.

On the whole, it is clear that the TVP VARs containing measures of real estate illiquidity produce more favourable point and density forecasts of real estate returns forecasts than AR(2), TVAR(2) and BVAR(2) models from a statistical sense at all forecast horizons. The statistical evidence is less strong when comparing against forecasts from the TVP VAR models containing no measures of real estate illiquidity. However, we posit that forecasts from from TVP VARs using our measures of real estate illiquidity are economically meaningful. This is because the proportion of times the decision rule selects forecasts from the TVP VAR with measures of real estate illiquidity is far greater than those coming from the TVP VAR fitted to datasets without real estate illiquidity.

To further investigate the benefits of our real estate illiquidity measures throughout the forecasting sample, we compute log Bayes factors in the spirit of Geweke and Amisano (2010). Figures 2 and 3 plot the log predictive Bayes factors using the US and the UK data, respectively. The solid lines report Bayes factors of real estate returns at a h=12 month horizon of the TVP VARs using RtoV real estate illiquidity versus the TVP VAR containing no illiquidity measures, and the dashed lines report analogous Bayes factors of the TVP VARs using V^{-1} real estate illiquidity versus the TVP VAR containing no illiquidity measures. Positive values indicate a higher LPS from the TVP VAR using measures of real estate illiquidity.

In general, across both datasets, the predictive performance of models using real estate illiquidity becomes prominent in the early to mid 2000s. This corresponds with the respective booms in real estate markets within the US and UK. In the US, forecasts of Midwest and Northeast returns provide higher LPSs using RtoV relative to forecasts with no measure of illiquidity. However, both measures provide forecasting gains in the South and West following the burst of the dot-com bubble. At a national level, we see gradual gains from utilising real estate illiquidity in the early 2000s, and again around 2005 until the end of the sample. In the UK at a regional level we observe gradual increases in log Bayes factors. However, at a national level using RtoV to forecast returns there is an abrupt decline at the beginning of the 2008 recession with negligible differences in density forecasts thereafter[3]. In general, log Bayes factors support those results we provide in Tables 2–5. They go further in showing when forecasting gains (losses) occur; typically these coincide with real estate booms (busts).

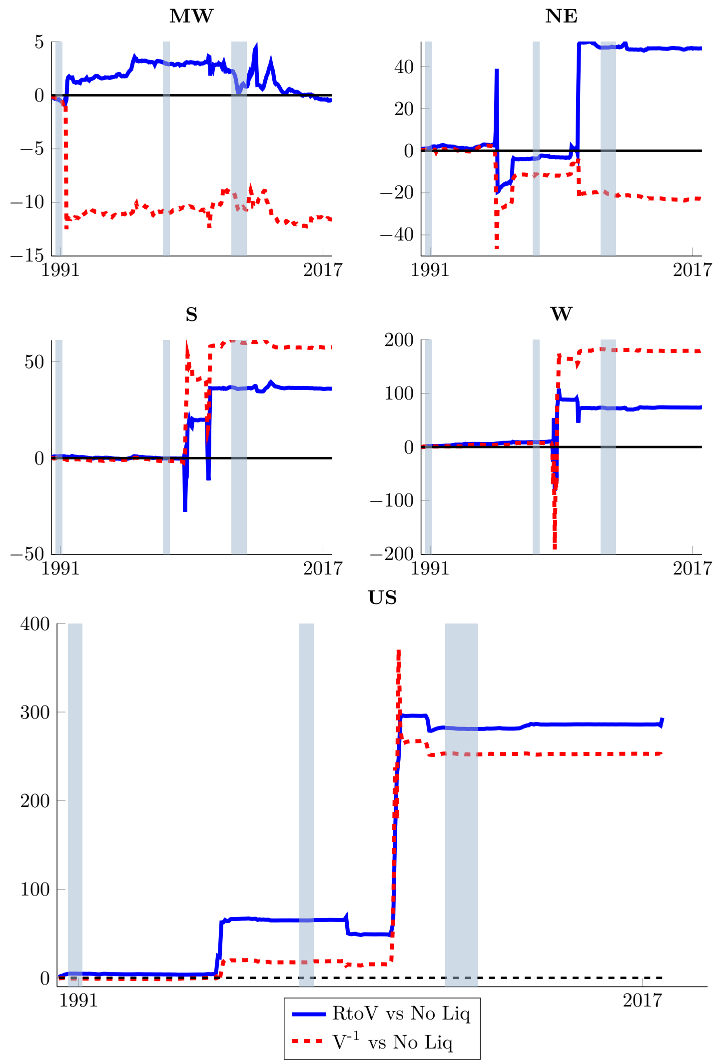

Figure 2: **Log Predictive Bayes Factors for the US Regional and National Real Estate Returns**

Notes: This figure plots log predictive Bayes factors of Geweke and Amisano (2010) for the US real estate returns from March 1990 to December 2017. These plots summarise the difference between cumulative log scores of TVP VARs containing measures of real estate illiquidity and TVP VARs with no measures of real estate illiquidity at a 12-month horizon. The solid line reports RtoV vs. no illiquidity and dashed lines reports V^{-1} vs. no illiquidity. Positive values indicate a higher cumulative LPS for the model using a measure of real estate illiquidity. The top four quadrants stem from the TVP VAR using regional real estate data and the bottom plot reports results from the TVP VAR using national data. Grey bars indicate NBER recession dates. MW denotes the Mid-West; NE denotes North East; S denotes South; W denotes West.

[3] The average forecast performance we report earlier does not pick up these large surges and declines we observe in the plots because they are influenced by a single–or very few–forecasts.

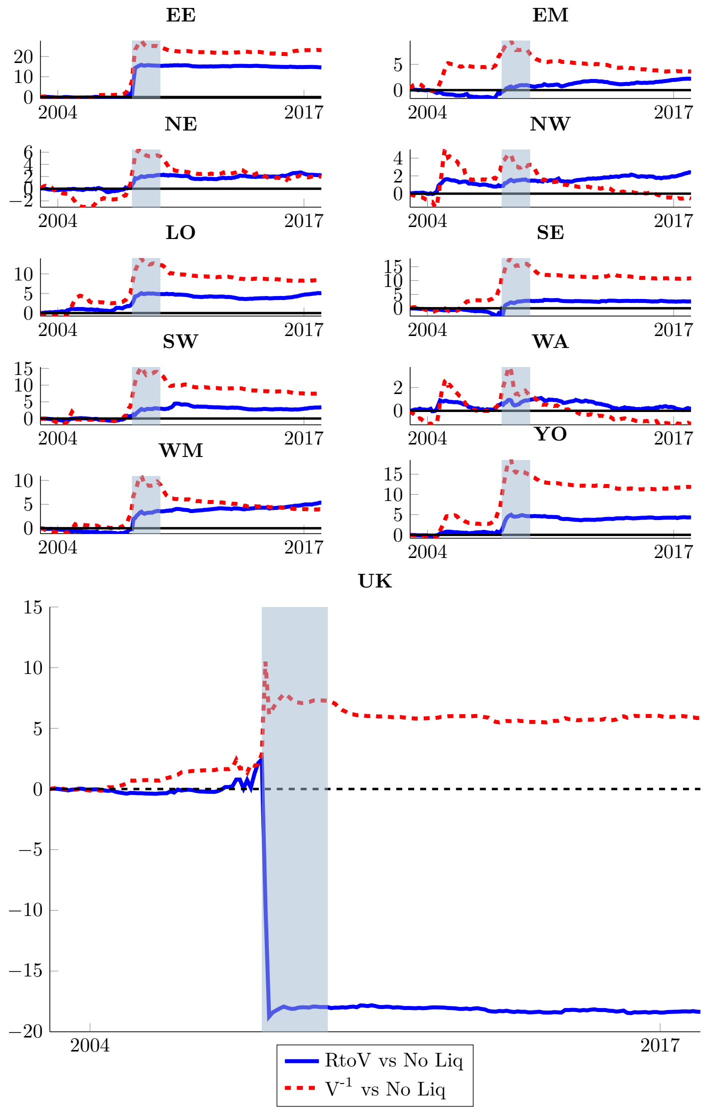

Figure 3: **Log Predictive Bayes Factors for the UK Regional and National Real Estate Returns**

Notes: This figure plots log predictive Bayes factors of Geweke and Amisano (2010) for the UK real estate returns from March 2003 to December 2017. These plots summarise the difference between cumulative log scores of TVP VARs containing measures of real estate illiquidity and TVP VARs with no measures of real estate illiquidity at a 12-month horizon. The solid line reports RtoV vs. no illiquidity and dashed lines reports V^{-1} vs. no illiquidity. Positive values indicate a higher cumulative LPS for the model using a measure of real estate illiquidity. The top ten plots stem from the TVP VAR using regional real estate data and the bottom plot reports results from the TVP VAR using national data. Grey bars indicate NBER recession dates. EE denotes East England; EM denotes East Midlands; LO denotes London; NE denotes North East; NW denotes North West; SE denotes South East; SW denotes South West; WA denotes Wales; WM denotes West Midlands; and YO denotes Yorkshire and Humberside.

Taken together, our out-of-sample forecasting results provide statistically significant and economically meaningful evidence in favour of using our real estate illiquidity measures to forecast real estate returns. Giacomini and White (2006) tests highlight the need to incorporate time-variation into the modelling process and our TVP VAR approach outperforms a battery of alternative models. Including our real estate illiqudiity measures into the TVP VAR generate at least as good, if not better, forecasts than those from TVP VARs without real estate illiquidity. Giacomini and White (2006) decision rules over the forecast sample show for both US and UK real estate data that the TVP VAR model using real estate illiquidity outperforms the analogous specification with no measure of illiquidity. Log Bayes factor plots further convey the economic importance of utilising real estate illiquidity for forecasting real estate returns.

4 Robustness Analysis

4.1 Regional Real Estate Illiquidity vs. a Common Factor?

Table 6: **Relative Root Mean-Squared Errors and Log Predictive Score Differences for US real Estate Returns: Regional Illiquidity versus a Common Factor**
Notes: The LHS of this table reports root mean squared errors (RMSEs) of US real estate returns at a h-month ahead horizon from TVP VAR models using a common factor extracted from regional real estate illiquidity measures (either RtoV or V^{-1}) relative to the corresponding TVP VAR model containing all the regional (or aggregated) measures. The RHS of this table reports corresponding log predictive score (LPS) differences. Relative RMSEs greater than 1 indicate that TVP VARs containing the regional or aggregated illiquidity measures outperform point forecasts from those using a common factor and are in bold font. Positive LPS differences indicate that TVP VARs containing the regional or aggregated illiquidity measures outperform density forecasts from those using a common factor and are in bold font. MW, NE, S, and W denote the Midwest, North East, South and West regional return forecasts respectively, while US denotes the national real estate return.

		Relative RMSEs					**LPS differences**				
		MW	**NE**	**S**	**W**	**US**	**MW**	**NE**	**S**	**W**	**US**
TVPVAR(2)	h=1	**1.042**	**1.091**	**1.076**	**1.084**	**1.142**	-0.517	-2.044	-1.124	**1.664**	**0.340**
ILLIQ=RtoV	3	**1.019**	**1.064**	**1.049**	**1.070**	**1.142**	-0.535	-0.998	-0.345	**1.112**	**0.118**
	6	**1.020**	**1.040**	**1.050**	**1.064**	**1.140**	-0.803	-0.605	-0.003	-0.858	-0.066
	12	**1.041**	**1.027**	**1.071**	**1.084**	**1.152**	-4.805	-0.250	**0.359**	-15.972	-1.748
TVPVAR(2)	h=1	**1.040**	**1.069**	**1.067**	**1.084**	**1.101**	**0.063**	**0.084**	**0.093**	**0.089**	**0.348**
ILLIQ=V^{-1}	3	**1.027**	**1.061**	**1.050**	**1.078**	**1.106**	-0.098	**0.018**	**0.008**	**0.011**	**0.100**
	6	**1.025**	**1.045**	**1.047**	**1.076**	**1.106**	-0.101	-0.070	-0.069	-0.403	-0.033
	12	**1.044**	**1.029**	**1.071**	**1.094**	**1.115**	-0.003	-0.694	-0.649	-4.868	-2.408

From Figure 1 it is clear that there is strong co-movement among our regional real estate illiquidity proxies. This suggests there may be a common factor driving a portion of variation within our measures[4]. A natural question to consider is whether extracting a common factor from regional illiquidity proxies generates better forecasts relative to including the regional measures. To investigate, for each real estate illiquidity measure, we extract the common factor among our regional measures at each forecast recursion following McCracken and Ng (2016) and use this in TVP VARs to produce forecasts of regional and national real estate returns. We then benchmark these against the TVP VARs we use in our baseline results in the form of relative RMSEs and LPS differences.

Table 7: **Relative Root Mean-Squared Errors and Log Predictive Score Differences for UK real Estate Returns: Regional Illiquidity versus a Common Factor**
Notes: The top half of this table reports root mean squared errors (RMSEs) of UK real estate returns at a h-month ahead horizon from TVP VAR models using a common factor extracted from regional real estate illiquidity measures (either RtoV or V^{-1}) relative to the corresponding TVP VAR model containing all the regional (or aggregated) measures. The bottom half of this table reports corresponding log predictive score (LPS) differences. Relative RMSEs greater than 1 indicate that TVP VARs containing the regional or aggregated illiquidity measures outperform point forecasts from those using a common factor and are in bold font. Positive LPS differences indicate that TVP VARs containing the regional or aggregated illiquidity measures outperform density forecasts from those using a common factor and are in bold font. EE, EM, LO, NE, NW, SE, SW, WA, WM, and YO denote the East England, East Midlands, London, North East, North West, South East, South West, Wales, West Midlands, and Yorkshire and Humberside respectively. UK denotes the national real estate return.

							Relative RMSEs					
		EE	**EM**	**LO**	**NE**	**NW**	**SE**	**SW**	**WA**	**WM**	**YO**	**UK**
TVPVAR(2) ILLIQ=RtoV	h=1	**1.025**	**1.069**	**1.020**	**1.047**	**1.013**	**1.037**	**1.021**	**0.988**	**1.006**	**1.051**	**1.038**
	3	**1.049**	**1.089**	**1.045**	**1.077**	**1.050**	**1.043**	**1.012**	**1.017**	**1.028**	**1.089**	**1.061**
	6	**1.058**	**1.072**	**1.050**	**1.107**	**1.041**	**1.038**	**1.014**	**1.035**	**1.027**	**1.109**	**1.052**
	12	**1.002**	**1.029**	**1.022**	**1.102**	**1.018**	**0.985**	**0.981**	**1.040**	**0.996**	**1.087**	**1.005**
TVPVAR(2) ILLIQ=V^{-1}	h=1	**1.032**	**1.066**	**1.021**	**1.042**	**1.035**	**1.068**	**1.051**	**1.005**	**0.989**	**1.092**	**1.048**
	3	**1.058**	**1.104**	**1.055**	**1.077**	**1.077**	**1.075**	**1.036**	**1.017**	**1.023**	**1.128**	**1.078**
	6	**1.060**	**1.082**	**1.058**	**1.115**	**1.067**	**1.059**	**1.023**	**1.030**	**1.022**	**1.144**	**1.066**
	12	**0.999**	**1.038**	**1.015**	**1.100**	**1.027**	**0.980**	0.964	**1.031**	**0.984**	**1.093**	**1.009**
							LPS differences					
		EE	**EM**	**LO**	**NE**	**NW**	**SE**	**SW**	**WA**	**WM**	**YO**	**UK**
TVPVAR(2) ILLIQ=RtoV	h=1	**0.076**	-0.003	-0.203	**0.094**	**0.046**	**0.008**	**0.043**	**0.092**	**0.000**	**0.065**	-0.193
	3	**0.288**	**0.320**	**0.230**	**0.312**	**0.263**	**0.248**	**0.225**	**0.233**	**0.277**	**0.298**	**0.224**
	6	**0.384**	**0.468**	**0.337**	**0.481**	**0.383**	**0.310**	**0.346**	**0.404**	**0.412**	**0.469**	**0.189**
	12	**0.330**	**0.512**	**0.345**	**0.578**	**0.429**	**0.208**	**0.329**	**0.480**	**0.457**	**0.526**	-0.078
TVPVAR(2) ILLIQ=V^{-1}	h=1	-0.240	-0.056	-0.213	**0.072**	-0.031	-0.102	**0.048**	**0.067**	**0.024**	**0.078**	-0.338
	3	**0.291**	**0.318**	**0.205**	**0.317**	**0.268**	**0.264**	**0.247**	**0.233**	**0.267**	**0.331**	**0.233**
	6	**0.413**	**0.473**	**0.327**	**0.486**	**0.403**	**0.356**	**0.358**	**0.404**	**0.408**	**0.529**	**0.290**
	12	**0.390**	**0.526**	**0.341**	**0.559**	**0.446**	**0.279**	**0.347**	**0.477**	**0.450**	**0.578**	**0.051**

Tables 6 and 7 report results that we average over the forecast sample using US and UK data

[4]In the Appendix we present impulse response and forecast error variance analysis that supports this view.

respectively. Relative RMSEs greater than 1 indicate that forecasts using regional measures of real estate illiquidity generate lower RMSEs relative to the analogous forecasts we obtain using the common factor and are in bold font. Positive LPS differences indicate density forecasts from our baseline results outperform forecasts from TVP VARs with the common factor and are in bold font. It is evident that our baseline models almost always outperform both point and density forecasts of real estate returns relative to when we use the common factors. This provides evidence in favour of the so called ripple effect in real estate markets (e.g. Tsai, 2015) in that explicitly accounting for regional interdependencies among returns and illiquidity leads to improvements in out-of-sample return predictions.

4.2 The Influence of Additional Supply Side Variables

Our next robustness check looks to control for additional supply side factors. Our baseline datasets contain many demand-side variables for real estate markets and only one supply-side variable. Specifically, our baseline datasets include housing starts growth as a supply side variable at a national level. This might produce bias in our main results[5]. In order to check, we include additional supply-side variables. For the US, we remove national housing starts growth and include: i) growth rates in housing starts at a regional level; ii) growth rates in regional housing completions; and iii) growth rates in regional building permits. For the UK, we remove the national housing starts growth and include regional housing starts growth and regional housing completion growth[6]. Note here we lose Wales due to a lack of data availability.

In Table 8 and 9 we report average relative RMSEs and LPS differences over the forecast sample using US and UK data respectively. These results benchmark the datasets containing additional supply-side variables against our baseline datasets using TVP VAR models. If our baseline forecasting models have a large upward or downward bias then one would expect large deviations from unity in relative RMSEs and large deviations from zero in LPS differences. Overall, relative RMSEs are close to one and the LPS differences are close to zero. This shows that accounting for additional supply-side real estate variables does not substantially influence our forecasting results. It also indicates that the inclusion of more granular supply-side real estate data does not diminish the importance of our real estate illiquidity measures.

We note here that we conduct the following additional robustness checks that are in the Online Appendix. First we use models with different forms of time-variation following Chan (2020). These results convey the same message as the main results we present above. Next, we examine network structures among our datasets. These results indicate close connections among real estate illiquidity and returns. This implies that investors may be able to successfully diversify away, or hedge against, regional spillover exposure. As an additional robustness check to our US dataset,

[5] We thank an anonymous referee for this comment

[6] The US data is from Census.gov. and the UK data is from ONS.gov.uk.

Table 8: **Relative Root Mean-Squared Errors and Log Predictive Score Differences for US real Estate Returns: The Influence of Additional Supply Side Variables**
Notes: The LHS of this table reports root mean squared errors (RMSEs) of US real estate returns at a h-month ahead horizon from TVP VAR models including additional regional supply-side real estate market variables relative to our baseline TVP VAR models. The RHS of this table reports corresponding log predictive score (LPS) differences. Relative RMSEs greater than 1 indicate that TVP VARs containing the regional or aggregated illiquidity measures outperform point forecasts from those including additional supply-side variables and are in bold font. Positive LPS differences indicate that TVP VARs containing the regional or aggregated illiquidity measures outperform density forecasts from those including additional supply-side variables and are in bold font. MW, NE, S, and W denote the Midwest, North East, South and West regional return forecasts respectively, while US denotes the national real estate return.

		Relative RMSEs					LPS differences				
		MW	**NE**	**S**	**W**	**US**	**MW**	**NE**	**S**	**W**	**US**
TVPVAR(2)	h=1	**1.003**	0.995	0.999	**0.993**	0.994	-0.013	-0.007	0.000	**0.026**	**0.424**
ILLIQ=N/A	3	0.999	0.998	**1.003**	0.994	0.996	-0.086	-0.016	-0.018	-0.057	-0.007
	6	**1.003**	0.999	**1.002**	0.998	0.998	-0.221	-0.028	-0.020	-0.486	-0.010
	12	**1.005**	**1.004**	**1.004**	**1.003**	**1.001**	**0.047**	-0.255	-0.361	-2.881	-0.786
TVPVAR(2)	h=1	0.995	0.997	**1.000**	0.992	0.996	-0.579	-2.144	-1.215	**1.599**	**0.023**
ILLIQ=RtoV	3	0.997	0.998	**1.003**	0.994	0.998	-0.536	-1.044	-0.368	**1.125**	-0.015
	6	**1.002**	0.999	**1.003**	**1.000**	**1.000**	-0.699	-0.621	**0.033**	-0.403	-0.099
	12	**1.005**	**1.004**	**1.006**	**1.005**	**1.002**	-4.851	**0.192**	**0.985**	-11.298	-1.032
TVPVAR(2)	h=1	0.996	0.991	0.999	0.991	0.992	**0.004**	-0.008	**0.003**	-0.073	-0.056
ILLIQ=V^{-1}	3	0.998	0.997	**1.003**	0.994	0.995	**0.005**	-0.015	**-0.011**	-0.013	**0.087**
	6	**1.001**	0.999	**1.001**	0.999	0.999	**0.053**	-0.019	-0.005	-0.082	**0.006**
	12	**1.003**	**1.003**	**1.003**	**1.003**	**1.001**	**0.003**	-0.369	-0.094	-0.402	-0.793

Table 9: **Relative Root Mean-Squared Errors and Log Predictive Score Differences for UK real Estate Returns: The Influence of Additional Supply Side Variables**
Notes: The top half of this table reports root mean squared errors (RMSEs) of UK real estate returns at a h-month ahead horizon from TVP VAR models including additional regional supply-side real estate market variables relative to our baseline TVP VAR models. The bottom half of this table reports corresponding log predictive score (LPS) differences. Relative RMSEs greater than 1 indicate that TVP VARs containing the regional or aggregated illiquidity measures outperform point forecasts from those including additional supply-side variables and are in bold font. Positive LPS differences indicate that TVP VARs containing the regional or aggregated illiquidity measures outperform density forecasts from those including additional supply-side variables and are in bold font. EE, EM, LO, NE, NW, SE, SW, WM, and YO denote the East England, East Midlands, London, North East, North West, South East, South West, West Midlands, and Yorkshire and Humberside respectively. UK denotes the national real estate return.

						Relative RMSEs					
		EE	**EM**	**LO**	**NE**	**NW**	**SE**	**SW**	**WM**	**YO**	**UK**
TVPVAR(2)	h=1	**1.013**	0.990	**1.015**	**1.008**	**1.007**	0.998	0.985	**1.004**	**1.013**	0.994
ILLIQ=N/A	3	**1.012**	0.997	0.990	**1.000**	**1.012**	**1.031**	0.990	0.999	**1.006**	0.987
	6	**1.009**	**1.001**	0.987	0.998	**1.006**	**1.054**	0.990	0.996	0.999	0.988
	12	**1.005**	**1.005**	0.993	**1.000**	**1.005**	**1.066**	0.996	0.998	**1.002**	0.995
TVPVAR(2)	h=1	**1.010**	**0.990**	**1.017**	**1.010**	**1.006**	**1.004**	0.988	**1.005**	**1.009**	0.988
ILLIQ=RtoV	3	**1.010**	**1.002**	0.993	**1.005**	**1.012**	**1.031**	0.995	**1.003**	**1.006**	0.986
	6	**1.010**	**1.005**	0.992	**1.002**	**1.009**	**1.054**	0.996	**1.003**	**1.004**	0.988
	12	**1.005**	**1.005**	0.998	**1.002**	**1.006**	**1.068**	1.000	**1.002**	**1.003**	0.995
TVPVAR(2)	h=1	**1.011**	**1.000**	**1.017**	**1.012**	**1.012**	**1.021**	**1.001**	**1.009**	**1.008**	0.997
ILLIQ=V^{-1}	3	**1.018**	**1.013**	**1.003**	**1.008**	**1.022**	**1.047**	**1.007**	**1.010**	**1.011**	0.990
	6	**1.013**	**1.005**	**1.003**	**1.007**	**1.021**	**1.060**	**1.000**	**1.003**	**1.012**	0.990
	12	**1.003**	0.998	0.999	**1.004**	**1.011**	**1.061**	0.994	0.997	**1.005**	0.997
						LPS differences					
		EE	**EM**	**LO**	**NE**	**NW**	**SE**	**SW**	**WM**	**YO**	**UK**
TVPVAR(2)	h=1	**0.005**	**0.084**	**0.007**	**0.034**	**0.011**	**0.132**	**0.003**	**0.114**	**0.013**	**0.316**
ILLIQ=N/A	3	**0.025**	**0.035**	-0.014	**0.002**	**0.016**	**0.008**	**-0.013**	**0.011**	**0.001**	-0.008
	6	**0.019**	**0.029**	-0.004	**0.005**	**0.018**	**0.000**	**-0.019**	**-0.008**	**-0.008**	-0.046
	12	-0.089	**0.010**	-0.025	**0.005**	**-0.001**	-0.052	-0.043	-0.021	-0.030	**0.027**
TVPVAR(2)	h=1	-0.025	**0.171**	-0.286	**0.011**	**0.013**	-0.093	**0.001**	-0.012	**0.014**	**0.076**
ILLIQ=RtoV	3	**0.033**	**0.030**	-0.004	**0.003**	**0.022**	**0.007**	**0.002**	**0.027**	**0.008**	-0.011
	6	**0.011**	**0.030**	-0.009	**0.010**	**0.021**	**-0.007**	**0.003**	**0.011**	**0.008**	-0.006
	12	-0.011	**0.002**	-0.005	**0.008**	**0.022**	-0.035	-0.037	**0.005**	-0.006	-0.001
TVPVAR(2)	h=1	-0.201	-0.027	-0.029	**0.062**	-0.045	-0.088	-0.005	-0.002	**0.015**	**0.037**
ILLIQ=V^{-1}	3	**0.038**	**0.039**	**0.010**	**0.014**	**0.030**	**0.021**	**0.014**	**0.026**	**0.026**	-0.005
		0.026	**0.034**	0.005	**0.005**	**0.038**	**0.020**	**0.010**	**0.021**	**0.028**	**-0.048**
		0.007	**0.017**	-0.003	-0.004	**0.031**	-0.023	-0.014	**0.003**	**0.012**	-0.145

we also look at more granular US data by constructing illiquidity proxies for the constituents of the S&P 20 city composite index and track network connections among real estate returns and illiquidity. These results provide similar conclusions to splitting the US into its four metropolitan statistical areas.

5 Conclusion

This paper proposes two new measures of illiquidity for real estate markets and assesses their relationship with real estate returns. Utilising measures from the asset pricing literature, we segregate assets through a regional lens. We use US and UK data and provide robust evidence that our real estate illiquidity measures predict returns out-of-sample, over and above a number of additional controls. We show that the relationship is time-varying and provide statistical evidence in favour of using TVP VAR models relative to a variety of other specifications. Our analysis reveals that real estate illiquidity becomes an influential predictor for real estate returns from the early 2000s to the end of our sample. This corresponds well with the booms in the US and the UK real estate markets during this period and highlights the increasing importance of real estate illiquidity throughout our sample. A natural extension to our work would be to explore further segregation of real estate markets and illiquidity conditions; perhaps by price or property type. With the emergence of big data for these markets from vendors such as Zillow, we see this as a promising avenue for further research.

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