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

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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 using time-varying parameter VAR models. Density forecasts show real estate illiquidity holds prominent predictive power for returns over and above a variety of control variables. Our models reveal that illiquidity shocks significantly depress returns and are economically meaningful explaining up to 28% of regional return variation. Network analysis uncovers substantial heterogeneities in the influence of illiquidity shocks over time with the implication that real estate investors may be able to diversify away, or hedge against, regional spillover exposure.

JEL: G12, G11, C58, R31.

Keywords: Time-Varying Parameter VAR, Quasi-Bayesian Local Likelihood Methods, Real Estate, Liquidity, Density Forecasts, Network Connections.

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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 (see 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)[1]. 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 hope to capture. This issue is far from trivial; especially when dealing with illiquid assets such as real estate[2].

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[3]. 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

[1] He et al. (2015) state that house prices contain a liquidity premium because people are able to use housing as collaterals when credit markets are imperfect. Stein (1995) develops a model where demand for housing is conditional on the amount of liquidity within the sector, and Best and Kleven (2017) extend Stein's model, and show that declines in transaction taxes stimulate activity in the real estate markets in which leverage amplifies the mechanism. Furthermore, Glaeser and Nathanson (2017) develop a model to match time-series observations for the US real estate market.

[2] The calibrations of search and matching models in Diaz and Jerez (2013) and Ngai and Tenreyro (2014) use sales volume data to imply US time-on-the-market (TOM) as a proxy for real estate illiquidity. Both US and UK time-on-the-market data is not publicly available.

[3] In this paper, we focus on market liquidity, i.e., trading volume based liquidity, instead of accounting liquidity, which has been examined in the previous literature. For example, Genesove and Mayer (1997) show that, if the owner has a high loan-to-value ratio, he/she tends to set a higher asking price, a higher expected time on the market, and receives a higher price from the sale. Brown (2000) provides evidence that the credit problems of highly leveraged owners lead to the decline in commercial real estate values during the period of the late 1980s to early 1990s.

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 an in-depth examination on the importance of real estate illiquidity for returns. We use US and UK data spanning 1985–2018 and 1998–2018 respectively. First, we explore whether the real estate illiquidity holds predictive information for returns over and above a number of controls used within the literature. Second, we explore the time-varying transmission mechanism and economic importance of regional illiquidity shocks for returns by using novel time-varying parameter (TVP) VAR models of considerable size. Our final set of results tracks dynamic regional spillovers among liquidity conditions and returns. 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[4]. 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[5]. 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 market 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.

Our main results document significant time-variation in the relationship between real estate illiquidity and returns. First, our out-of-sample density forecasting exercises show that real estate illiquidity has increasing predictive ability for returns from the early 2000s to the end of our sample. This corresponds well with the boom in the US and UK markets. Second, we document significant contractions in regional returns with respect to shocks to their corresponding illiquidity measures.

[4]See e.g. https://www.forbes.com/sites/fredpeters/2019/04/08/the-american-dream-of-homeownership-is-still-very-much-alive/ and https://www.theguardian.com/money/2016/jan/14/why-are-brits-so-obsessed-with-buying-their-own-homes.

[5]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.

The average contraction over the 2008 recession for US regions ranges from 0.6%–1.7% and for UK regions ranges from 2%–5.7%. In the same period, the percent of forecast error variance attributable to real estate illiquidity shocks is as high as 28% in both countries. Third, using network connectedness measures of Diebold and Yılmaz (2014), we uncover substantial differences in regional spillovers of real estate illiquidity. In particular, we uncover so called "ripple effects" in both nations with illiquidity becoming shock transmitters and returns becoming shock receptors following the 2008 property bust.

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 using the UK data, such as Gregoriou et al. (2014), and show that the transmission of inter-regional property return shocks is an important contributor to return fluctuations.

We also contribute to the real estate literature examining dynamics between price and trading volume (Charles et al., 2002; Leung and Feng, 2005). These papers look to examine why correlation exists between real estate prices and volume and outline what drives price-trading volume correlation using commercial real estate data respectively. Wong et al. (2013) examines spatial autocorrelation and confirms a role for trading volume in the real estate price discovery process. In particular, this study provides evidence against constant correlations. Our work adds to this stream by proposing measures of real estate illiquidity. In doing so, we provide a specific interpretation of the interactions between returns and liquidity conditions from volume based measures. Our analysis reveals a dynamic relationship between returns and illiquidity both in-, and out-of-sample.

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 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 of the US and the UK data, respectively. Both studies reveal an important link with the business cycle and show that these specifications outperform linear alternatives[6].

This paper differs from the above in a variety of different ways. Those examining liquidity's role

[6] We also contribute to the growing literature that fits TVP VAR models to macroeconomic and financial data (Prieto et al., 2016; Hubrich and Tetlow, 2015; Ellington, 2018). In general, these papers examine the financial sector's role for the economy. However, these models are emerging within studies of asset markets with particular reference to connectedness measures as in Diebold and Yılmaz (2014). For example, Demirer et al. (2018) use LASSO methods on a large dataset for banks to span network connectedness. Our innovation applies these methods to real estate data in a time-varying framework; the former use rolling VAR models.

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 Regional 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 asset for sale based on how regional markets are performing. Thus, measures capturing market depth can provide a signalling channel to prospective sellers thereby influencing future prices; and in turn, returns.

We note that assets in real estate markets are unique. However, real estate markets are subject to substantial regional segregation (Tsai, 2015). Therefore, a natural way to approach this is through a regional lens. This makes sense because prospective buyers and sellers looking to buy/sell in particular area naturally search for prices in that area. This is in order to guide listing prices and also provide prospective buyers of their purchasing power. The argument above is intuitive, and allows one to build a hypothesis that market depth may be an important dimension of real estate illiquidity. However, we impose no presumption on which dimension we favour apriori and look to capture a number of different dimensions of illiquidity.

One popular aspect of illiquidity is to proxy the cost of trading. Measures of the cost dimension for financial assets are in Roll (1984) and Fong et al. (2017); with the latter using measures stemming from high frequency data, which are unavailable for real estate markets. It is entirely possible to compute measures in the spirit of Roll (1984) for real estate data, and we have done this[7]. However, the implicit assumption of using this measure is that market efficiency holds. It is difficult to argue in favour of market efficiency in real estate markets because the price real estate lists at is not necessarily what the asset sells for. Also, the time taken to sell an real estate is considerable.

Coupling the above with the amount of time taken to communicate to the market the actual selling price of the asset, as well as the difficulty for market participants to retrieve this information, it is clear real estate markets lack efficiency. Therefore, first order autocovariances can capture any number of factors that cause prices to change. Thus, while possible to construct the Roll (1984) measure, we do not advocate its use when examining real estate illiquidity due to a lack of theoretical justification for market efficiency.

The caveat to our approach is that regional real estate markets can be further segregated by prices. However, granular time-series data that captures regional price disparities is sparse and in general insufficient for the purpose of our study. Therefore, in what follows, our results on regional real estate markets can be thought averaging out price disparities within regions[8]. Given the time-series limitations in real estate markets, we propose two measures that capture i) the quantity dimension; and ii) price impact, respectively. The latter captures both the quantity and cost dimension of illiquidity.

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 $\mathrm{VOL}_{i,d}$ represents month d's currency (in this case £) 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

[7]Note the Roll (1984) measure, is not defined when the first order autocovariance of returns is positive. The asset pricing literature sets the value to zero when this is the case. When applying this measure to US data, there are more zeros than non-zero values, which means we are unable to reliably estimate our models. This is not the case for the UK data and we have results using the Roll (1984) measure that are available on request.

[8]We also estimate models we describe below using levels of (log) illiquidity, prices, and economic and financial data. However, we run into convergence issues as parameter draws are explosive and the model by definition assumes variables follow a stable heteroskedastic TVP VAR.

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[9].

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:

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

where $|R_{i,d}|$ is region i's absolute monthly property sector return in month d. $\mathrm{VOL}_{i,d}$ is the ith region's monthly (currency value) trading volume during month d. As with $\mathrm{V}_{i,D}^{-1}$, 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 $\mathrm{VOL}_{i,d}$ and $\mathrm{RtoV}_{i,D}$ 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 (Chen et al., 2018) in the Finance literature[10].

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 indexes and the data are taken from Thomson Reuters Datastream. These indices contain single family homes and condos[11]. 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

[9] Lou and Shu (2017) find that the pricing of the Amihud (2002) illiquidity measure for equities is driven by the trading volume component.

[10] Using regional trading volume directly in these models results in qualitatively similar results and conclusions to those we report in the main text. We choose to express the quantity dimension in this manner in order to remain consistent with our other measure of illiquidity. It is also consistent to other studies focusing on equity markets (Lou and Shu, 2017).

[11] 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.

house price data made available to us by IHS Markit and trading volume data from the Land Registry[12]. 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: **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: The 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: The 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

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, and the North East possesses

[12] The Halifax house price indexes use a hedonic regression model where prices reflect the valuation from a purchaser's perspective on a set of locational and physical charactersitics of the property itself. Note that UK house price indexes at regional level are available from other vendors. Nationwide provides regional quarterly prices and only a monthly aggregate price index. The Land Registry regional price data are available at a monthly frequency but require seasonal adjustment. While we have computed seasonally adjusted measures using these data, they seem to inject substantially more volatility into our RtoV illiquidity estimates relative to the Halifax price index data.

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, $V_{i,D}^{-1}$ 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.

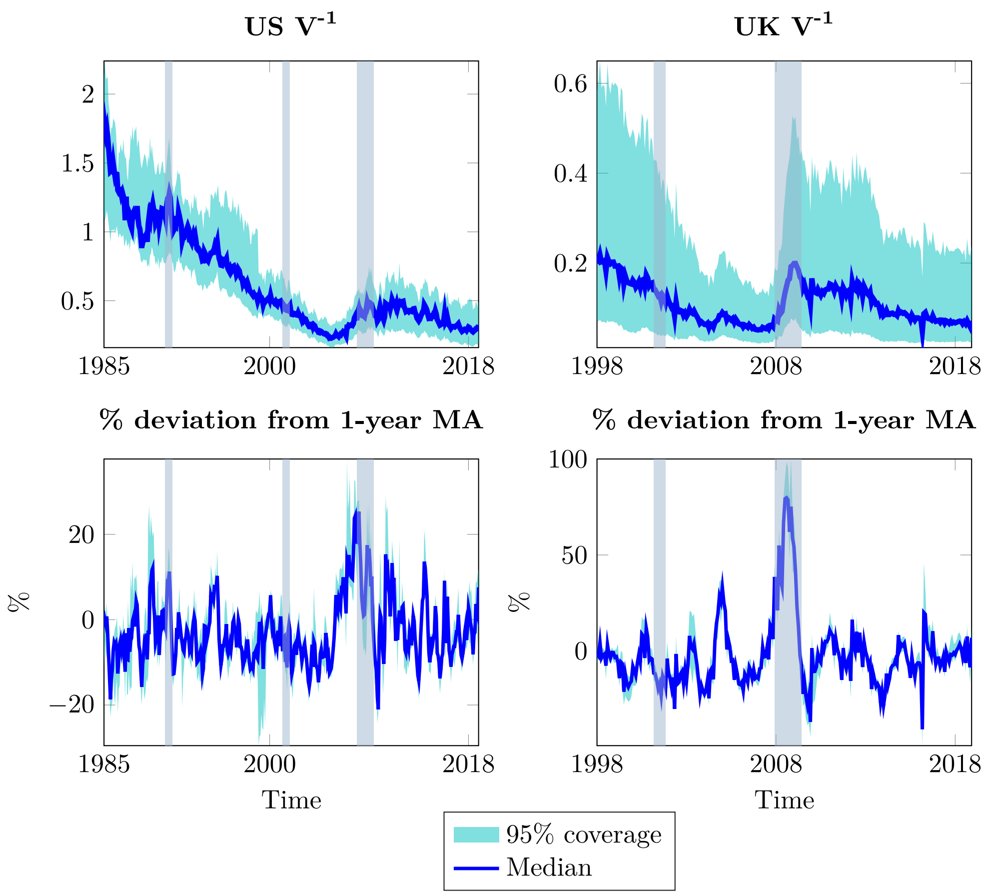


Figure 1: **The US and The UK Regional Real Estate Illiquidity: Level and % Deviations from 1-Year Moving Averages**

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.

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 economic and financial data is guided by prior studies; an extensive summary is given in Ghysels et al. (2013). In particular, they use stock market returns, industrial production, inflation, and short-term interest rates to proxy for time-variation in the state of the economy. Furthermore, studies such as Plazzi et al. (2010) and many others, 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 rates; and the growth in housing starts.

With regards to financial data, for the US we use the S&P500 composite market return and the Amihud (2002) measure of stock market illiquidity 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[13]. An additional variable we include is the Economic Policy Uncertainty index of Baker et al. (2016). The Supplementary Appendix provides details of transformations and data sources. In the Appendix, we provide tables with details of data sources and transformations[14].

2.3 Methodology

Following Petrova (2019), let y_t be an $N \times 1$ vector generated by a stable time-varying parameter (TVP) heteroskedastic VAR model with L lags:

$$y_t = \mathbf{B}_{0,t} + \sum_{p=1}^{L} \mathbf{B}_{p,t} y_{t-p} + \varepsilon_t, \;\; \varepsilon_t = \mathbf{\Xi}_t^{-\frac{1}{2}} \kappa_t, \;\; \kappa_t \backsim \text{NID}(0, \mathbf{I}_N) \tag{3}$$

where $\mathbf{B}_{0,t}, \mathbf{B}_{p,t}$ contain the time-varying intercepts and autoregressive matrices, respectively. Note that all roots of the polynomial, $\psi(z) = \det\left(\mathbf{I}_N - \sum_{p=1}^{L} z^p \mathbf{B}_{p,t}\right)$, lie outside the unit circle, and $\mathbf{\Xi}_t^{-1}$ is a positive definite time-varying covariance matrix. Stacking the time-varying intercepts and autoregressive matrices in the vector θ_t with $\mathbf{X}_t' = (\mathbf{I}_N \otimes x_t)$, $x_t = \left(1, y_{t-1}', \ldots, y_{t-L}'\right)$ and $\otimes$

[13] We follow Ellington et al. (2017) and Ellington (2018) in constructing these measure 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.

[14] The contemporaneous correlations between our measures of real estate illiquidity and stock market illiquidity for the US range from -0.01 to 0.20, and for the UK the correlations range from 0.08 to 0.38. The correlations between our measures of real estate illiquidity and Economic Policy Uncertainty range from 0.05 to 0.16 for the US and -0.12 to 0.20 for the UK.

denotes the Kronecker product, the model can be written as:

$$y_t = \mathbf{X}_t' \theta_t + \mathbf{\Xi}_t^{-\frac{1}{2}} \kappa_t \tag{4}$$

The time-varying parameters of the model are estimated by employing Quasi-Bayesian Local Likelihood (QBLL) methods (Petrova, 2019).

Estimation of the model in Equation (4) requires re-weighting the likelihood function. Essentially, the weighting function gives higher proportions to observations surrounding the time period whose parameter values are of interest. The local likelihood function at time period k is given by:

$$\mathrm{L}_k\left(y|\theta_k, \mathbf{\Xi}_k, \mathbf{X}\right) \quad \propto \quad |\mathbf{\Xi}_k|^{\mathrm{trace}(\mathbf{D}_k)/2} \exp\{-\frac{1}{2}(y - \mathbf{X}'\theta_k)'\left(\mathbf{\Xi}_k \otimes \mathbf{D}_k\right)(y - \mathbf{X}'\theta_k)\} \tag{5}$$

The $\mathbf{D}_k$ is a diagonal matrix whose elements hold the weights:

$$\mathbf{D}_k = \mathrm{diag}(\vartheta_{k1}, \ldots, \vartheta_{kT}) \tag{6}$$

$$\vartheta_{kt} = \phi_{T,k} w_{kt} / \sum_{t=1}^{T} w_{kt} \tag{7}$$

$$w_{kt} = (1/\sqrt{2\pi}) \exp((-1/2)((k-t)/H)^2), \text{ for } k, t \in \{1, \ldots, T\} \tag{8}$$

$$\phi_{Tk} = \left(\sum_{t=1}^{T} w_{kt}^2\right)^{-1} \tag{9}$$

where ϑ_{kt} is a normalised kernel function. w_{kt} uses a Normal kernel weighting function. ϕ_{Tk} gives the rate of convergence and behaves like the bandwidth parameter H in Equation (5), and it is the kernel function that provides greater weight to observations surrounding the parameter estimates at time k relative to more distant observations.

Using a Normal-Wishart prior distribution for $\theta_k|\,\mathbf{\Xi}_k$ for $k \in \{1, \ldots, T\}$:

$$\theta_k|\mathbf{\Xi}_k \backsim \mathcal{N}\left(\theta_{0k}, (\mathbf{\Xi}_k \otimes \mathbf{\Omega}_{0k})^{-1}\right) \tag{10}$$

$$\mathbf{\Xi}_k \backsim \mathcal{W}\left(\alpha_{0k}, \mathbf{\Gamma}_{0k}\right) \tag{11}$$

where θ_{0k} is a vector of prior means, $\mathbf{\Omega}_{0k}$ is a positive definite matrix, α_{0k} is a scale parameter of the Wishart distribution ($\mathcal{W}$), and $\mathbf{\Gamma}_{0k}$ is a positive definite matrix.

The prior and weighted liklihood function implies a Normal-Wishart quasi posterior distribution for $\theta_k|\,\mathbf{\Xi}_k$ for $k = \{1, \ldots, T\}$. Formally let $\tilde{\mathbf{X}} = (x_1', \ldots, x_T')'$ and $\tilde{\mathbf{Y}} = (y1, \ldots, y_T)'$ then:

$$\theta_k|\mathbf{\Xi}_k, \tilde{\mathbf{X}}, \tilde{\mathbf{Y}} \quad \backsim \quad \mathcal{N}\left(\tilde{\theta}_k, \left(\mathbf{\Xi}_k \otimes \tilde{\mathbf{\Omega}}_k\right)^{-1}\right) \tag{12}$$

$$\mathbf{\Xi}_k \quad \backsim \quad \mathcal{W}\left(\tilde{\alpha}_k, \tilde{\mathbf{\Gamma}}_k^{-1}\right) \tag{13}$$

with quasi posterior parameters

$$\tilde{\theta}_j = \left(\mathbf{I}_N \otimes \tilde{\mathbf{\Omega}}_k^{-1}\right)\left[\left(\mathbf{I}_N \otimes \tilde{\mathbf{X}}'\mathbf{D}_k\tilde{\mathbf{X}}\right)\hat{\theta}_k + \left(\mathbf{I}_N \otimes \mathbf{\Omega}_{0k}\right)\theta_{0k}\right] \tag{14}$$

$$\tilde{\mathbf{\Omega}}_k = \tilde{\mathbf{\Omega}}_{0k} + \tilde{\mathbf{X}}'\mathbf{D}_k\tilde{\mathbf{X}} \tag{15}$$

$$\tilde{\alpha}_k = \alpha_{0k} + \sum_{t=1}^{T}\vartheta_{kt} \tag{16}$$

$$\tilde{\mathbf{\Gamma}}_k = \mathbf{\Gamma}_{0k} + \tilde{\mathbf{Y}}'\mathbf{D}_k\tilde{\mathbf{Y}} + \mathbf{\Theta}_{0k}\mathbf{\Gamma}_{0k}\mathbf{\Theta}_{0k}' - \tilde{\mathbf{\Theta}}_k\tilde{\mathbf{\Gamma}}_k\tilde{\mathbf{\Theta}}_k' \tag{17}$$

where $\hat{\theta}_k = \left(\mathbf{I}_N \otimes \tilde{\mathbf{X}}'\mathbf{D}_k\tilde{\mathbf{X}}\right)^{-1}\left(\mathbf{I}_N \otimes \tilde{\mathbf{X}}'\mathbf{D}_k\right)y$ is the local likelihood estimator for θ_k. The matrices $\mathbf{\Theta}_{0k}$, $\tilde{\mathbf{\Theta}}_k$ are conformable matrices from the vector of prior means, θ_{0k}, and a draw from the quasi posterior distribution, $\tilde{\theta}_k$, respectively.

The motivation for employing the QBLL approach over the conventional method of Primiceri (2005) are threefold. First, we are able to estimate large systems that the former framework do not permit. This is because the state-space representation of an N-dimensional TVP VAR (L) requires an additional $N(3/2 + N(L + 1/2))$ state equations for every additional variable. Conventional Markov Chain Monte Carlo (MCMC) methods fail to estimate larger models, which in general confine one to (usually) fewer than 6 variables in the system. Second, the standard approach is fully parametric and requires a law of motion. Imposing a parametric relationship can distort inference if the true law of motion is misspecified (Petrova, 2019). Third, the methods used here permit direct estimation of the VAR's time-varying covariance matrix, which has an inverse-Wishart density and is symmetric positive definite at every point in time. Finally, we also note the computational convenience of our framework as we are able to estimate models using parallel computing which means we are able to estimate sophisticated models in an efficient manner.

More generally, we note that one may opt to use alternative models that incorporate time-varying parameters such as the Generalised Autoregressive Score framework of Creal et al. (2013) which emcompasses Engle (2002). Applications of dynamic models for real estate data are in Kau et al. (2011) and Babii et al. (2019). Both use frailty models to examine defaults with the latter utilising Creal et al. (2013) to model factor dynamics. However, these alternative frameworks incorporate time-variation in a parametric manner and therefore may misrepresent inference if we misspecify the true law of motion; similar to the case of conventional TVP VAR models as in Primiceri (2005)[15].

In estimating the TVP VAR model in equation (3), we use L=2 and a Minnesota Normal-Wishart prior with a shrinkage value $\varphi = 0.05$ and centre the coefficient on the first lag of each variable to 0.5 in each respective equation. The prior for the Wishart parameters are set following Kadiyala and Karlsson (1997). For each point in time, we run 5000 simulations of the model to

[15] Another notable reference is Koopman and Lucas (2008). Their model allows one to draw common and specific risk factors from panels of data modelling default probabilities. Our goal is to examine interdependencies within regional real estate data in a time-varying framework and therefore deem this model more suitable in the context of our paper. An analysis on disaggregated data modelling regional mortgage default probabilities would be an interesting application for the model of Koopman and Lucas (2008).

generate the (quasi) posterior distribution of parameter estimates[16].

Our empirical models using US data contain 20 variables (4 regional real estate returns, 4 regional illiquidity measures, plus 12 economic/financial variables), and using UK data contain 30 variables (10 regional real estate returns, 10 regional illiquidity measures, plus 12 economic/financial variables). It is noteworthy to mention here that we use aggregated measures of the US and the UK economic data in our models of regional real estate markets. In the spirit of Pesaran (2006), we interpret these as cross-sectional averages capturing cross-sectional dependencies in the data[17]. The dimension of our models therefore requires an alternative method over Primiceri (2005) and the ensuing literature. One could also opt to use rolling VAR models, however this often induces jumps in parameters and covariances when rolling through the window, which may reflect a less accurate approximation of the DGP relative to more sophisticated models; such as the above. In the Appendix, we provide out-of-sample forecasting results using rolling Bayesian VAR models and show the TVP VAR of Petrova (2019) provides more favourable point and density forecasts[18].

2.3.1 Forecasting Methodology

We conduct a recursive forecasting exercise for the US and UK TVP VAR models in the following manner. We estimate forecasting models recursively over an expanding data window using the first 60 months for the initial recursion. For the US data, the forecasting sample spans March 1990 to December 2017. For UK data, the forecasting period spans March 2003 to December 2017. We examine forecast horizons of $h = \{1, 6, 12\}$ months and we obtain forecasts at $h > 1$ recursively and analyse cumulative growth rates. We estimate marginal predictive densities using kernel methods to account for the non-linear nature of our models. We examine root mean square errors (RMSE) which are the mean of the predictive densities. We evaluate the accuracy of the predictive densities using log-scores (LS) which measures the log-likelihood the model assigns to actual observations based on lagged data.

Typically, log-scores allow one to compare the average forecast performance of a set of models over a given forecast sample[19]. However, perhaps a more pertinent issue is how a real estate

[16] Note we experiment with various lag lengths, $L = \{2, 3, 4, 5\}$; shrinkage values, $\varphi = \{0.01, 0.25, 0.5\}$; and values to centre the coefficient on the first lag of each variable, $\{0, 0.05, 0.2, 0.5\}$. All results provide similar conclusions to those we report below.

[17] We thank an anonymous referee for this suggestion. While regional data are available for most variables, for housing starts there are only aggregated national measures. Interpreting national economic data in this manner allows us to reduce the dimension of the models whilst allowing for regional spillovers within the real estate markets.

[18] One may opt to select a prior in each region's return equation to allow the first lag of the corresponding illiquidity measure to have a non-zero coefficient. Apriori, this presumes that each region's illiquidity conditions bear more importance to their corresponding return. We experiment with these choices and results provide the same qualitative conclusions as those we report; results are available upon request. However, we prefer to let the data speak for itself and only specify lagged dependent dynamics in each equation of the VAR model. Note that if one wished to specify an alternative prior such as allowing for variable selection, then this may result in the need to derive the posterior distribution or adding extra blocks into the sampler.

[19] In the Supplementary Appendix, we report the average performance of TVP VAR models in forecasting regional and national real estate returns using each of our proposed illiquidity measures relative to a benchmark TVP VAR

investor looking to forecast returns chooses between incorporating real estate illiquidity into the information set on the basis of real-time information. We investigate this issue by computing log-predictive Bayes factors that summarise cumulative differences between a TVP VAR containing real estate illiquidity measures and a TVP VAR that does not at each month of the forecast sample (Geweke and Amisano, 2010)[20].

Formally, given a pair of models (A, B) and a variable x_t, the log Bayes factor at period t and forecast horizon h is:

$$\mathrm{BF}_{t,h}^{A,B} = \sum_{\tau=1}^{t} \left[\ln(LS_{\tau,h}^{A}) - \ln(LS_{\tau,h}^{B}) \right] \tag{18}$$

where $LS_{\tau,h}^{i} = p(x_{\tau}^{o}|Y_{\tau-1})$ is the predictive density from model i for x_t that we evaluate at the actual observation x_t^o. These statistics tell us the overall relative forecasting performance of a model up to period t.

2.3.2 Impulse Responses, Variance Decompositions and Network Analysis

Since there is no theoretical model suggesting how an illiquidity shock should affect the return in a regional context, we compute generalised impulse response functions using the algorithm in Pesaran and Shin (1998), and use these to analyse forecast error variance decompositions.

Formally the generalized impulse response function for variable j due to a shock in variable k is

$$\mathrm{GIRF}_{j,k,t} = \xi_{kk,t}^{-\frac{1}{2}} \sum_{h=0}^{H} \left(\boldsymbol{\Psi}_{h,t} \boldsymbol{\Xi}_t \right)_{j,k} \tag{19}$$

where $\xi_{kk,t}^{-\frac{1}{2}}$ is the square root of the time t diagonal element of $\boldsymbol{\Xi}_t$, $\xi_{kk,t} = (\boldsymbol{\Xi})_{kk,t}$, $\boldsymbol{\Psi}_{h,t}$ is the time t $N \times N$ matrix of moving average coefficients at horizon h which we obtain from the Wold decomposition. The forecast error variance decomposition matrix, $\boldsymbol{\Lambda}_{H,t}$ at horizon H and time t contains information regarding future variance attributable to each variable in the system. In

containing only regional (or national) real estate returns and economic/financial data. For the US, average results are mixed with models containing illiquidity measures generally generating lower RMSEs for all forecast horizons; log scores show superior performance of models using real estate illiquidity for the South, West, and on a national scale at 6 and 12 month horizons. For the UK, average RMSEs are marginally higher for models containing measures of real estate illiquidity. However, when looking at log scores, TVP VARs using real estate illiquidity outperform the benchmark model across all horizons and regions. We also report, in the Supplementary Appendix, the average forecast performance of real estate returns using weighted log scores emphasising the models' accuracies in the left tail of the distribution (Amisano and Giacomini, 2007). This enables us to examine density forecasts that assign higher weight to extreme left tail values thereby corresponding with predictions of large declines in the real estate market. Results and conclusions here are similar to those using simple log scores. The main implication is that using real estate illiquidity in these models provides more accurate predictions of large declines in real estate returns. Note that in general, average discrepancies between model forecasts are small. Overall, examining forecasting performance on the basis of averages makes it difficult to ascertain whether and when real estate illiquidity holds predictive information for returns.

[20] Note we can also use this as a way of deciding between models.

particular, variable k's contribution to j's H-step ahead generalised forecast error variance at time t, for $H = 1, \ldots, H$ is:

$$\left(\mathbf{\Lambda}_{H,t}\right)_{j,k} \quad = \quad \frac{\xi_{kk,t}^{-1} \sum_{h=0}^{H} \left(\left(\mathbf{\Psi}_{h,t} \mathbf{\Xi}_t \right)_{j,k} \right)^2}{\sum_{h=0}^{H} \left(\mathbf{\Psi}_{h,t} \mathbf{\Xi}_t \mathbf{\Psi}'_{h,t} \right)_{j,j}} \tag{20}$$

with $\mathbf{\Psi}_{h,t}$ is the time t $N \times N$ matrix of moving average coefficients at horizon h, $\xi_{kk,t}$ is the time t k^{th} diagonal element of $\mathbf{\Xi}_t$, $\xi_{kk,t} = (\Xi)_{kk,t}$. Therefore, $\left(\mathbf{\Lambda}_{H,t}\right)_{j,k}$ denotes the time t contribution of variable k to the variance of forecast error of variable j at horizon H. Since rows of the variance decomposition matrix do not necessarily sum to one, each entry is normalised by the row sum. Denoting this normalised matrix as $\tilde{\mathbf{\Lambda}}_{H,t}$, the sum of all elements are equal to N by construction.

Building on variance decomposition analysis, we note that there is empirical evidence in favour of real estate markets possessing interdependencies across regions (see e.g. Antonakakis et al. (2018) and Flor and Klarl (2017)). Therefore, in order to track regional spillovers, we manipulate the normalised forecast error variance decomposition matrix we present in Equation 20, $\tilde{\mathbf{\Lambda}}_{H,t}$ that provides the H-step ahead forecast error variance of variable x_j that is due to shocks in $x_k, \forall j \neq k$ (Diebold and Yılmaz, 2014).

Time t system-wide connectedness is defined as ratio of the sum of off-diagonal elements to the sum of all elements in the matrix:

$$\mathcal{C}_{H,t} = 100 \cdot \left(1 - \frac{\mathrm{Tr}\{\tilde{\mathbf{\Lambda}}_{H,t}\}}{\sum \tilde{\mathbf{\Lambda}}_{H,t}} \right) \tag{21}$$

where $\mathrm{Tr}\{\bullet\}$ denotes the trace operator. System-wide connectedness is interpreted as the relative contribution of forecast error variances from variables in the system minus the influence of own shocks. Therefore, the higher the connectedness measure, the more central network is, and ultimately the riskier the system is.

Note also that $\left(\tilde{\mathbf{\Lambda}}_{H,t}\right)_{j,k}$ provides measures of time t pairwise connectedness at horizon H. Therefore, the respective directional connectedness transmitted by variable k to all other variables, and received by variable k from all other variables are:

$$\mathcal{C}_{\bullet \leftarrow k,t} \quad = \quad 100 \cdot \left(\frac{\sum_{k=1, k \neq j}^{N} \left(\tilde{\mathbf{\Lambda}}_{H,t}\right)_{k,j}}{\sum \tilde{\mathbf{\Lambda}}_{H,t}} \right) \tag{22}$$

$$\mathcal{C}_{k \leftarrow \bullet,t} \quad = \quad 100 \cdot \left(\frac{\sum_{k=1, k \neq j}^{N} \left(\tilde{\mathbf{\Lambda}}_{H,t}\right)_{j,k}}{\sum \tilde{\mathbf{\Lambda}}_{H,t}} \right) \tag{23}$$

This provides information regarding the total influence variable k has on all other variables, and how the remaining j variables influence variable k. It is generally more convenient to work with spillovers in terms of net directional connectedness. The difference between Equation (20) and

Equation (21) provides net directional connectedness:

$$\mathcal{C}_{k,t,H} = \mathcal{C}_{\bullet \leftarrow k,t} - \mathcal{C}_{k \leftarrow \bullet,t} \tag{24}$$

where positive (negative) values denote that at time t, variable k is a net transmitter (receiver) at horizon H[21]. Therefore, if $\mathcal{C}_{k,t,H} > 0$, the shocks to the k^{th} variable is influencing the fluctuations, in net terms, of other variables within the system; and vice versa.

3 Empirical Results

3.1 Out-of-Sample Forecasting

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 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 log score from the models using measures of real estate illiquidity.

For the US, and for both measures of illiquidity, we can see that for the Mid-West (North East), there are negligible differences in the Bayes factors for the first two-thirds (one third) of the forecasting sample before models using no measures of illiquidity perform better. The South and Mid-West however show negligible differences for the first half of the forecasting sample, then models using measures of real estate illiquidity begin to outperform those without. We can also see this holds true when we aggregate US regions from the bottom plot in Figure 2. Turning to Figure 3, it is clear that models using measures of real estate illiquidity produce more accurate predictive densities relative to those without, especially when using V^{-1}; both regionally and on a national scale.

In general, across both the US and the UK data, the predictive performance of models using real estate illiquidity becomes prominent in the early 2000s, which largely corresponds with the respective booms in real estate markets within the US and the UK. Furthermore, relative to the benchmark, these results suggest that V^{-1} yields more accurate predictive densities for real estate returns. Our analysis also shows that these links appear when aggregating from regional real estate data to national real estate data.

[21] Note however, even if we observe variable k being a net transmitter (receiver) at time t, it is not necessarily dominating all variables within the network. Therefore, net pairwise directional connectedness can be defined, which enables us to focus on and track the net directional connectedness between region i's real estate illiquidity shock and region j's return. These results are available on request, and are not reported as we have $N^2 - N$ pairwise net directional connectedness measures to consider.

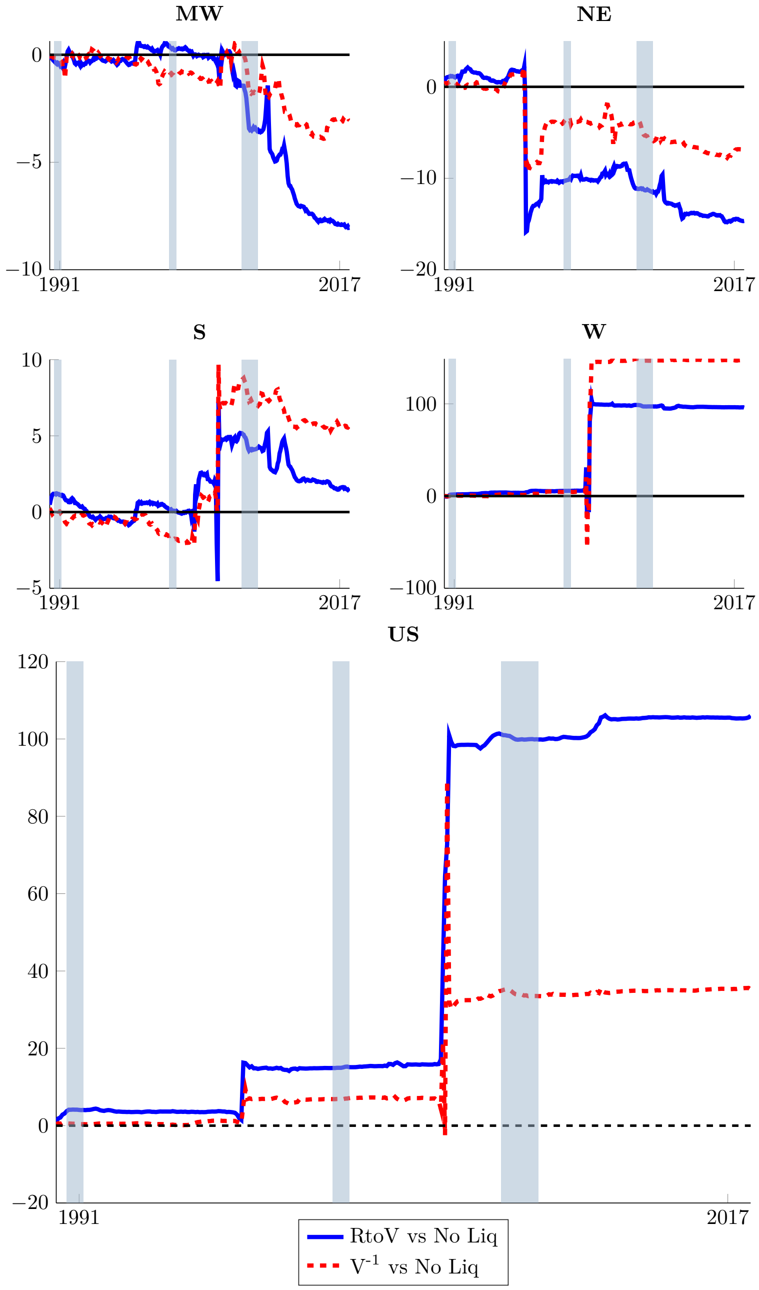


Figure 2: **Log Predictive Bayes Factors for the US Regional and National Real Estate Returns**

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 LS 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.

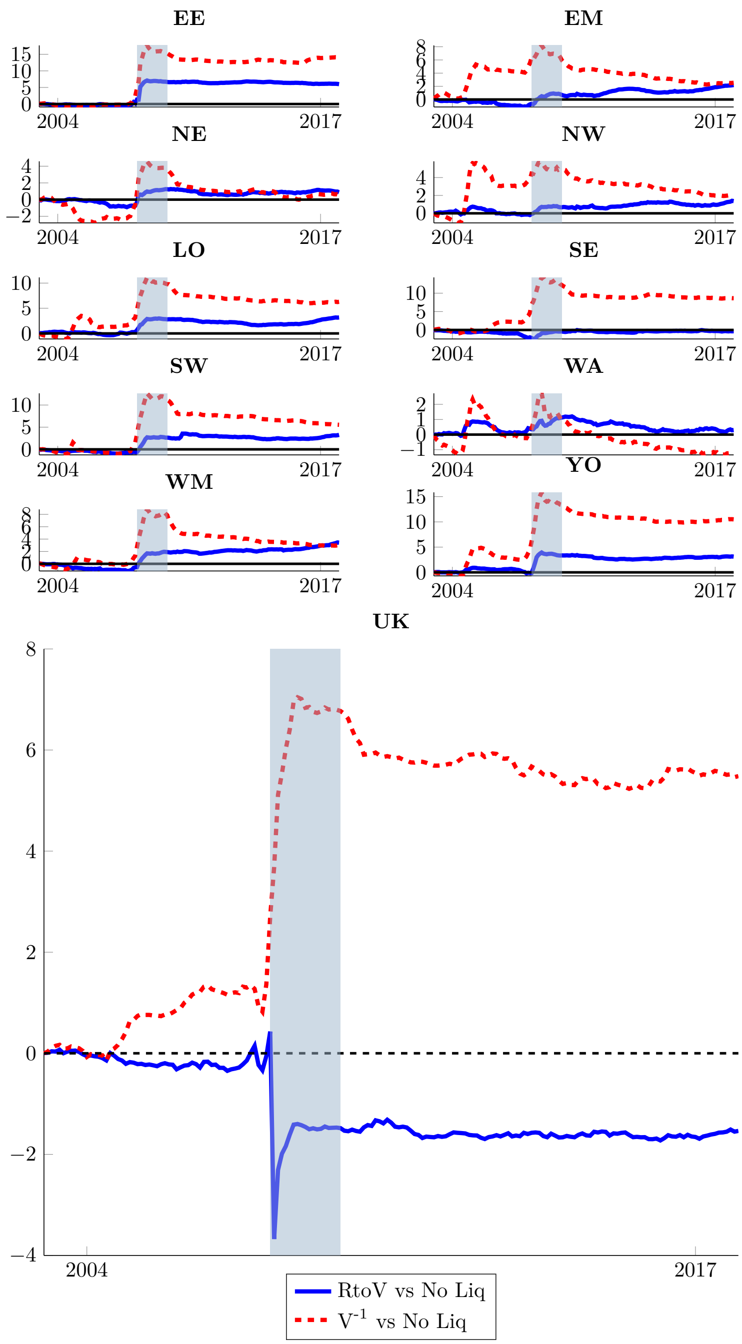


Figure 3: **Log Predictive Bayes Factors for the UK Regional and National Real Estate Returns**

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 LS 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.

3.2 Illiquidity Shocks and Returns

In what follows, we present results using the inverse of trading volume, V^{-1}. Results and conclusions using RtoV are qualitatively similar to those we report below and are available upon request. Having shown a dynamic out-of-sample relationship between real estate returns and real estate illiquidity, we now focus on the impact of illiquidity shocks for real estate returns.

Figures 4 and 5 plot the posterior median and 68% equal-tailed point-wise probability bands of the average impulse response function of region j's real estate return with respect to an illiquidity shock in region j over the Great Recession for the US and the UK data respectively[22]. For both the US and the UK, and across all regions, we can see that the regional illiquidity shocks are persistent throughout the Great Recession with these shocks remaining prominent for 10-12 months. The most sensitive region in the US is the Mid-West with a drop in the return of an average of 2% during this period. For the UK, the most sensitive regions are East England, London and the South East. The returns in these regions fall by an average of 5.8%, 5.5%, and 4.2%, respectively.

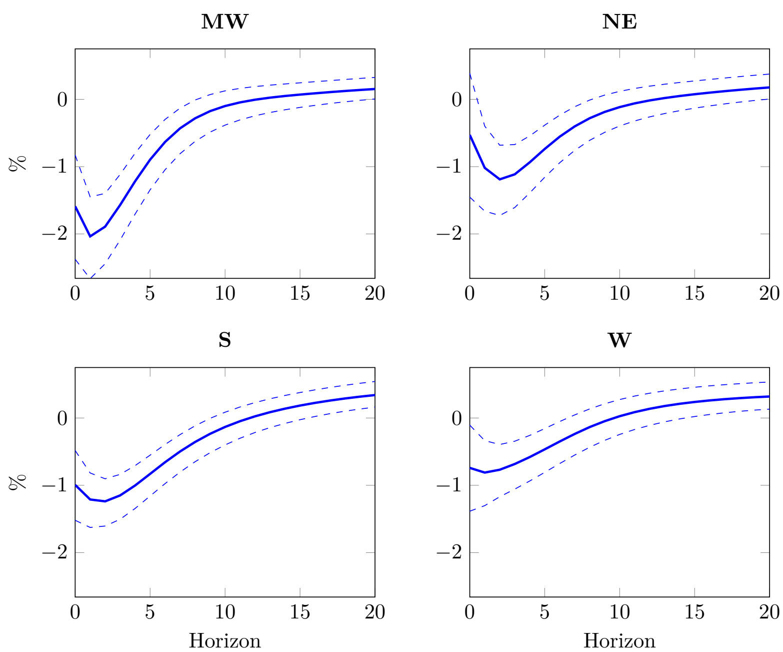


Figure 4: **Impulse Response Functions of the US Regional Real Estate Returns with Respect to an Illiquidity Shock in the Corresponding Region: Average Response over the Great Recession**

Notes: This figure plots the posterior median and 68% equal-tailed point-wise posterior probability bands of the average response of return in region j with respect to an illiquidity shock in region j over a 20-month horizon during the Great Recession (defined by NBER recession dates). MW denotes the Mid-West; NE denotes North East; S denotes South; W denotes West.

[22] The Supplementary Appendix reports posterior median response functions throughout time which document substantial time-variation in the response of regional real estate returns. It is also clear from these plots that the sensitivity of returns with respect to the corresponding region's illiquidity shock intensifies during the Great Recession.

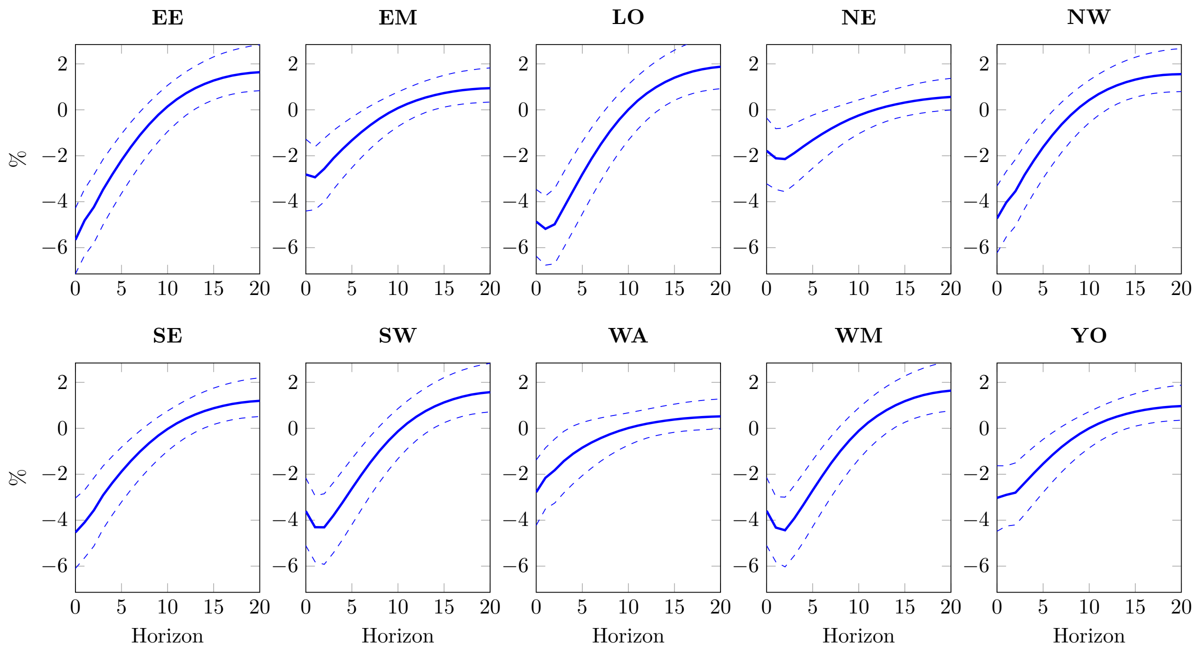


Figure 5: **Impulse Response Functions of the UK Regional Real Estate Returns with Respect to an Illiquidity Shock in the Corresponding Region: Average Response over the Great Recession**

Notes: This figure plots the posterior median and 68% equal-tailed point-wise posterior probability bands of the average response of return in region j with respect to an illiquidity shock in region j over a 20-month horizon during the Great Recession (defined by 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.

To assess the economic importance of regional illiquidity shocks, we report the posterior median of the proportion of forecast error variance explained by all regional illiquidity shocks for each region's real estate return for the US and the UK in Figures 6 and 7 respectively. Forecast error variance shares are at a 20 month horizon throughout each respective estimation sample. For the US, the proportion of variance explained by illiquidity shocks surges during the burst of the dot-com bubble and again in 2005 prior to the 2008 recession. During the most recent recession, the percentage of regional return variance explained by illiquidity shocks ranges between 16%–28%. In the UK, with the exception of the North East, Wales, and Yorkshire, the importance of these shocks builds prior to the Great Recession before peaking in late-2008. The proportion of variance explained by illiquidity shocks ranges from 10%–28% during the most recent recession. What we observe in the North East, Wales, and Yorkshire is increases in the importance of illiquidity shocks following the 2008 recession, which may suggest that the impact of the 2008 property bust took time to influence real estate markets in these regions.

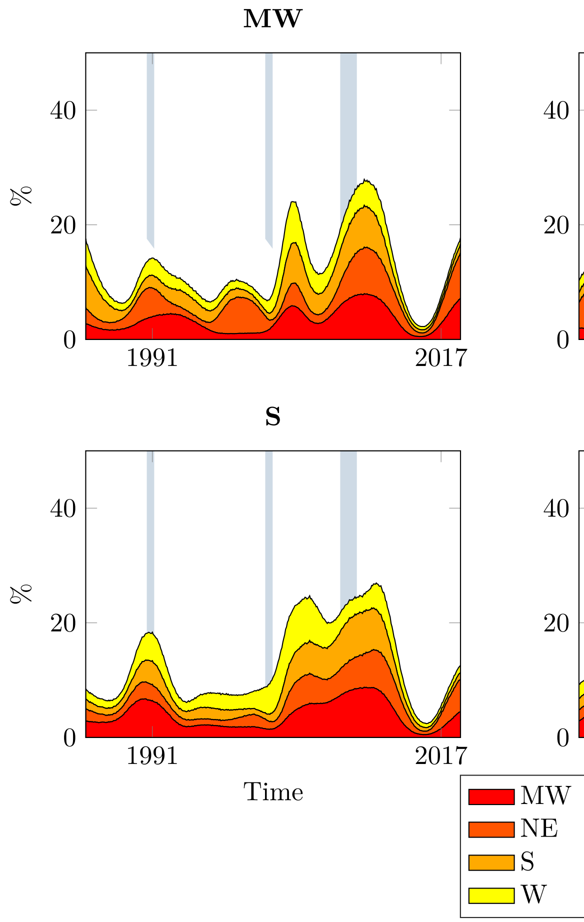


Figure 6: **Percentage Share of Forecast Error Variance Explained by Regional Illiquidity Shocks for Regional US Real Estate Returns from 1985 to 2018**
Notes: This figure plots the posterior median of percentage of forecast error variance of region j's real estate return explained by all regional illiquidity shocks from January 1985 to December 2018 at a 20-month horizon. Grey bars denote NBER recession dates. MW denotes the Mid-West; NE denotes North East; S denotes South; W denotes West.

To put the influence of illiquidity shocks for regional return variation into context, shocks to the short-term interest rate and mortgage rates explain around 4%–7% and 2%–6% during the Great Recession. The percent of forecast error variance associated to stock market returns, stock market illiquidity and economic policy uncertainty are negligible. Notably, the prime driver of future regional return variation implied by these models are the corresponding regional returns themselves explaining over half of total forecast error variance over the respective estimation samples.

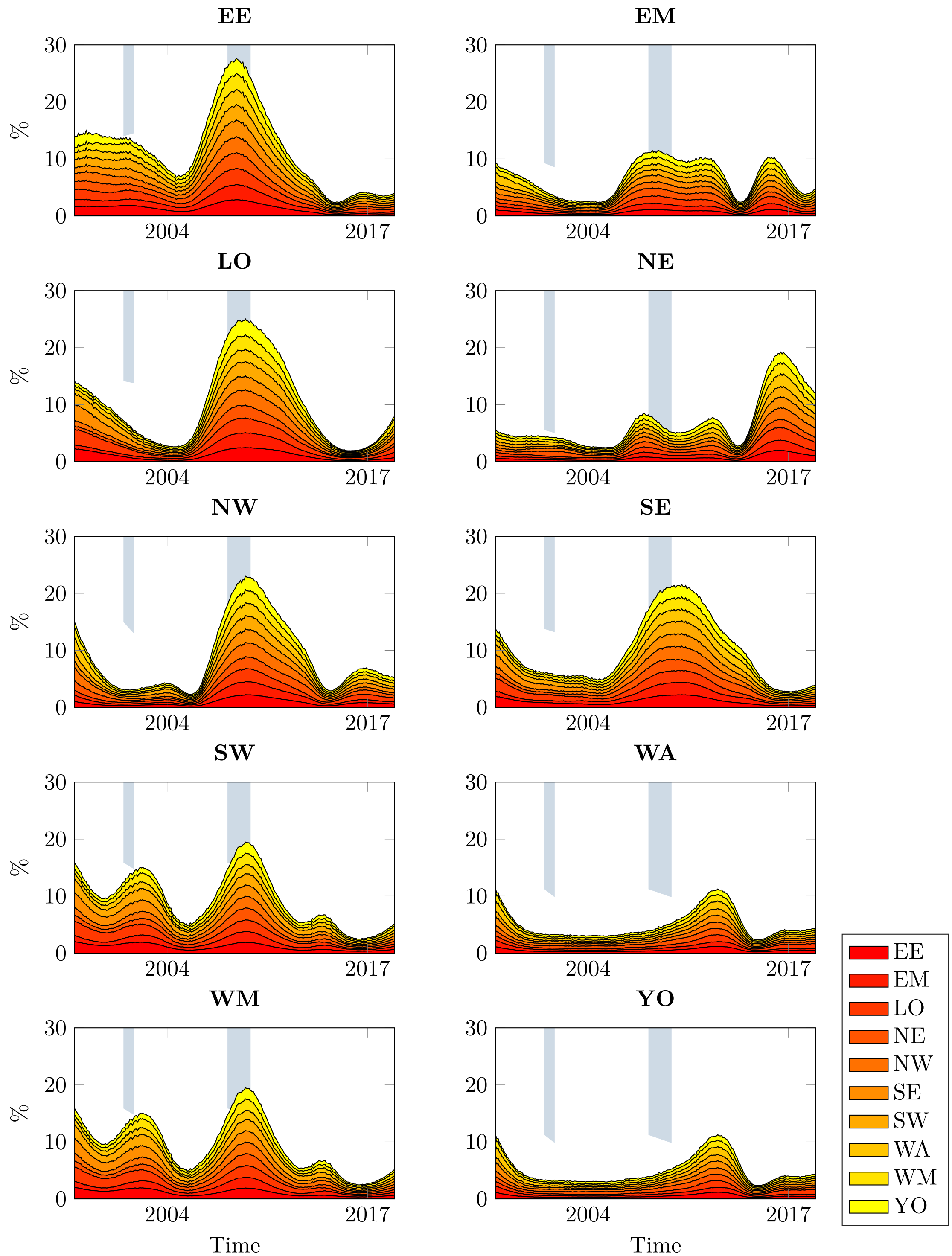


Figure 7: **Percentage Share of Forecast Error Variance Explained by Regional Illiquidity Shocks for Regional UK Real Estate Returns from 1998 to 2018**
Notes: This figure plots the posterior median of percentage of forecast error variance of region j's real estate return explained by all regional illiquidity shocks from January 1998 to December 2018 at a 20-month horizon. Grey bars denote 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.

Overall, these results uncover important regional heterogeneities in the overall importance of illiquidity shocks across different areas of the US and the UK. For example, surges in the economic importance of illiquidity shocks for the US real estate returns in the West rise prior to both the 1991 and 2008 recession. In the UK, regional illiquidity shocks bear little influence to East Midlands, North East, Wales, and Yorkshire and Humberside during the 2008 recession. The explanatory power of these shocks for return variation rise following the most recent recession. However, although we observe differences in the overall importance of illiquidity shocks throughout time, the contribution of each individual region's illiquidity shock to the regional return at any given time period are similar. This suggests a strong common component that drives regional illiquidity shocks that in turn explains, on aggregate, a sizable proportion of regional return variation.

In general, these results show significant declines in regional returns during the most recent recession; the Supplementary Appendix uncovers considerable time-variation in both the persistence and impact of these shocks for their corresponding region's real estate return. Comparing the US to the UK, the impact of regional illiquidity shocks in the UK result in larger contractions during the Great Recession. With regards to their economic importance, overall the analysis shows considerable time variation with surges during recessions. The immediate implication is that regional illiquidity conditions are significantly related to real estate price movements over and above other variables that relate with drive price changes.

3.3 Regional Spillovers

Figures 8 and 9 plot net directional connectedness measures for regional real estate returns and regional illiquidity using the US and the UK data respectively. Panel A of each figure reports net directional connectedness of regional real estate returns and Panel B of each figure plots net directional connectedness of regional real estate illiquidity.

First, considering the US, there are notable differences in the net directional connectedness of returns. We can see that the Mid-West, North East and South rise during the 1991 recession. With the exception of the North East, all region's net directional connections begin to rise in 2005 and gradually continue to do so until the 2008 recession; thereby acting as net transmitters in the system. Then, as the US economy recovers, all regional return net directional connectedness are negative (from posterior median estimates) thus showing that returns on average are prone to shocks from the system. Turning to net directional connectedness of regional illiquidity, all regions illiquidity measures appear to be net transmitters following the 2008 recession thereby influencing other variable's dynamics in the system; namely returns.

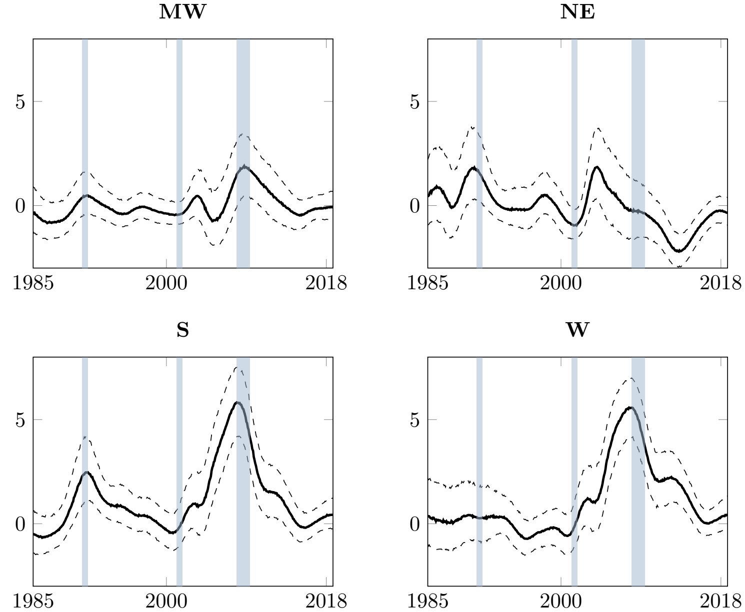
Now, turning to the UK, we can see that all regional returns are net receivers during the build up to the 2008 recession; with the North West, Wales and Yorkshire and Humberside returns being most receptive to shocks. During the latter years of the sample, these regional returns appear to be relatively more insulated to shocks from the system relative to regions such as London and South West. From the net directional connectedness of regional illiquidity measures, we can see that all regions act as net transmitters throughout the estimation sample; with peaks surrounding the most recent recession. Following the 2008 recession to the end of the sample, London, the South East, and South West are the most influential transmitters within the system.

In general, the dynamics of net-directional connections provide evidence that regional illiquidity shocks display some degree of co-movement for both nations; particularly for the UK. This ties in well with our results from variance decompositions in Figures 6 and 7. It also implies that these shocks possess a common component that influences regional returns. Building on this, the time-varying nature of our models uncovers regional differences for net-directional connections of real estate returns and how they respond to shocks coming from the system.

Taken, our analysis uncovers quite different network dynamics within the US and the UK, but these differences in how returns transmit and receive shocks indicate periods in which we observe the so-called "ripple effects"of Tsai (2015). Specifically, in the US we find that the influence of illiquidity conditions in the Mid-West, South and West, become significant in influencing regional real estate returns from 2010 to 2018 while returns become shock receivers. For the UK however, our analysis suggests peaks in illiquidity shock transmission during the 2008 recession, which correspond with regional real estate shock reception. We also find evidence of a so-called "ripple effect" from the Southern regions' illiquidity conditions for all regional returns from 2010 to 2018.

Uncovering these regional differences in how returns respond to shocks combined with documenting the dynamic connections of regional illiquidity shocks, suggests that our results also have an important implication for real estate investors in US and UK markets. In particular, following property busts that precede recessions, those with assets located in the North East of the US should monitor liquidity conditions in other regions of the US as they act as significant transmitters within the network. Furthermore, those with assets in the regions of the UK should pay attention to London and the South East of England for the same reason. Ultimately, accounting for connectedness at a systemic or directional level, may aid in investors successfully diversifying away, or hedging against, regional spillover exposure. Understanding liquidity conditions within these regions and their impact on other areas may influence the hedging and/or rebalancing decisions of portfolio managers who hold Mortgage Backed Securities (MBS).

A: Net Directional Connectedness for Regional Returns



B: Net Directional Connectedness for Regional Illiquidity

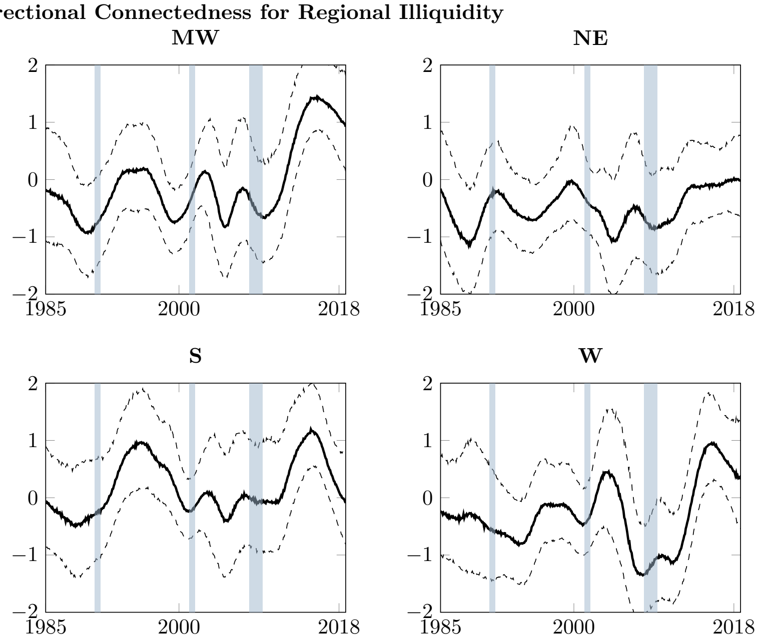


Figure 8: **Total Net Directional Connectedness of the US Regional Real Estate Returns and Illiquidity from 1985 to 2018**

Notes: This figure plots the posterior median (solid line) and 68% equal-tailed point-wise posterior probability bands (dashed lines) of the total net directional connectedness of the US regional real estate returns (Panel A) and illiquidity (Panel B) at a 20-month horizon from January 1985 to December 2018 using the methods proposed in Diebold and Yılmaz (2014). Grey bars denote NBER recession dates. MW denotes the Mid-West; NE denotes North East; S denotes South; W denotes West.

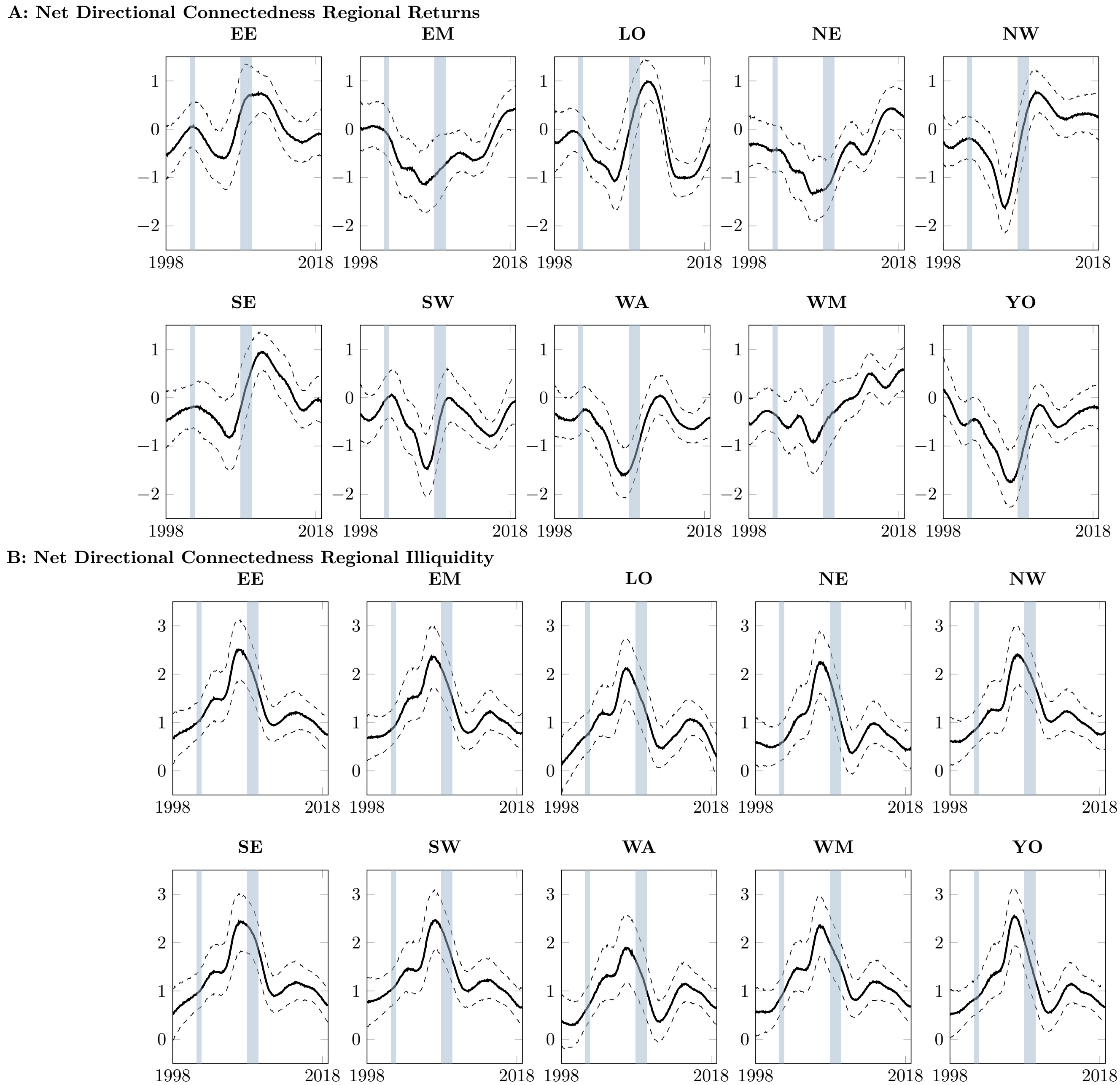


Figure 9: **Total Net Directional Connectedness of the UK Regional Real Estate Returns and Illiquidity from 1998 to 2018**

Notes: This figure plots the posterior median (solid line) and 68% equal-tailed point-wise posterior probability bands (dashed lines) of the total net directional connectedness of the UK regional real estate returns (Panel A) and illiquidity (Panel B) at a 20-month horizon from January 1998 to December 2018 using the methods proposed in Diebold and Yılmaz (2014). Grey bars denote 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.

4 Robustness Analysis

4.1 Forecasting with VAR Models under Alternative Forms of Time-variation

We now investigate whether our forecasting results hold for different VAR models with alternative forms of time-variation. Chan (2020) deduces various Bayesian VAR models under different forms of heteroskedasticity and serial correlation that we utilise to examine the robustness of our forecasting models. In particular, we repeat the recursive forecasting exercise for each nation using: i) a Bayesian VAR with common stochastic volatility, BVAR-CSV; ii) a Bayesian VAR with common stochastic volatility with t-distributed errors, BVAR-CSV-t; and iii) a Bayesian VAR with common stochastic volatility that follow t-distributed MA(1) errors, BVAR-CSV-t-MA(1)[23]. Our priors are identical to those in Chan (2020) and we set the lag length equal to 2 and allow for 6,000 simulations, discarding the first 1,000 as burn-in, in each of these alternative specifications and use the first 60 months for the initial recursion. For the sake of brevity, we report results from models using our RtoV measure of illiquidity; results are similar for models using V^{-1} and available on request.

Figures 10 and 11 report log Bayes factors for 12-month ahead forecasts of regional real estate returns in the US and UK respectively. First looking at the US, we can see that returns in the Northeast benefit most from including real estate illiquidity proxies. The Bayes factors from all specifications gradually increase throughout the forecast sample. Real estate return forecasts in the South and West benefit from the inclusion of real estate illiquidity during the first half of the forecast sample, while the Midwest sees considerable gains following the 2008 recession only. Turning our attention to the UK, across all models and all regions, models containing measures of real estate illiquidity generate more accurate forecasts for returns. In particular, the predictive accuracy of these models increases gradually throughout the forecast sample with largest gains occurring during the 2008 recession.

On the whole, we can see that our main result holds under alternative specifications of time-variation. Notably for the US, we observe some differences in regions that benefit most from using real estate illiquidity for forecasting. However, the models still uncover an important role for real estate illiquidity in forecasting returns. For the UK, these results further highlight the importance of accounting for real estate illiquidity when forecasting returns. Note also that we carry out this exercise for national measures of real estate returns and illiquidity. These results are available on request and convey the same message as those we report in Figures 2 and 3.

[23]Code for the Bayesian VARs with common stochastic volatility are taken from Joshua Chan's webpage. We also repeat our analysis using adaptive hierarchical priors in Korobilis and Pettenuzzo (2019); these results are available on request and conform with our main findings.

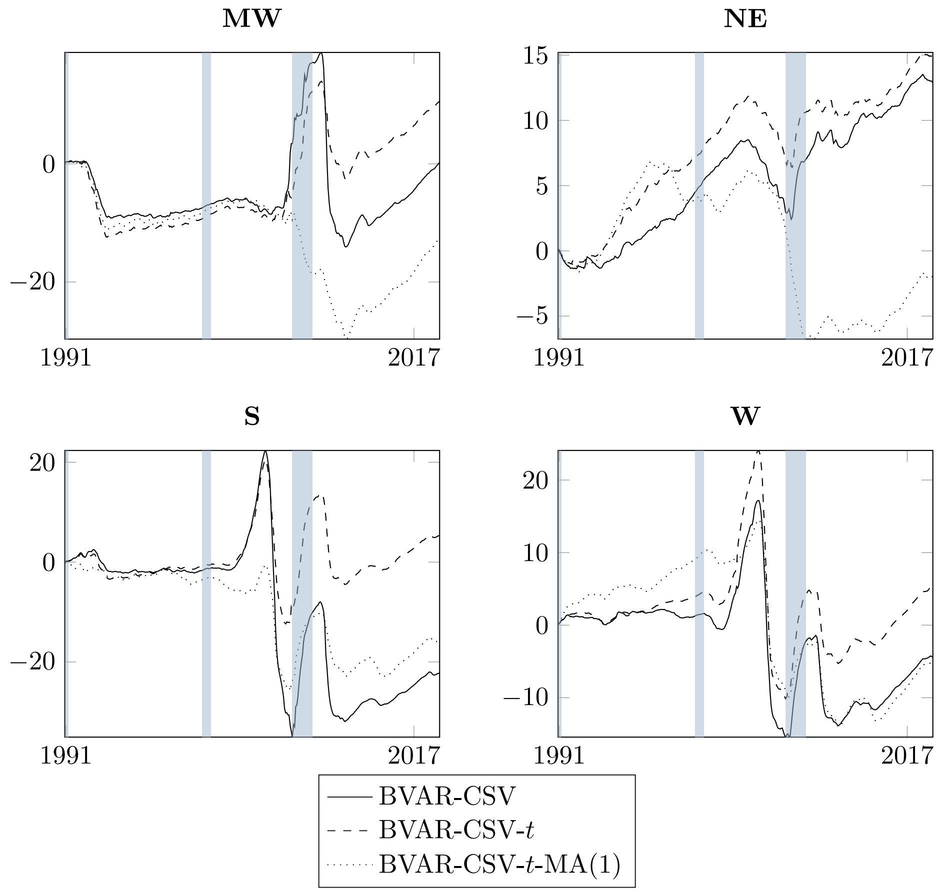


Figure 10: **Log Predictive Bayes Factors for the US Regional and National Real Estate Returns**

Notes: This figure plots log predictive Bayes factors of Geweke and Amisano (2010) for the US real estate returns from November 1990 to December 2017. These plots summarise the difference between cumulative log scores of: i) a BVAR with common stochastic volatility (BVAR-CSV) containing real estate illiquidity and a BVAR-CSV with no measures of real estate illiquidity at a 12-month horizon (solid line); ii) a BVAR with common stochastic volatility with $t-$distributed errors (BVAR-CSV-t) containing real estate illiquidity and a BVAR-CSV-t with no measures of real estate illiquidity at a 12-month horizon (dashed line); and iii) a BVAR with common stochastic volatility with $t-$distributed MA(1) errors (BVAR-CSV-t-MA(1)) containing real estate illiquidity and a BVAR-CSV-t-MA(1) with no measures of real estate illiquidity at a 12-month horizon (dotted line). All models use RtoV as the measure of real estate illiquidity. Positive values indicate a higher cumulative LS for the model using a measure of real estate illiquidity. Grey bars indicate NBER recession dates. MW denotes the Mid-West; NE denotes North East; S denotes South; W denotes West.

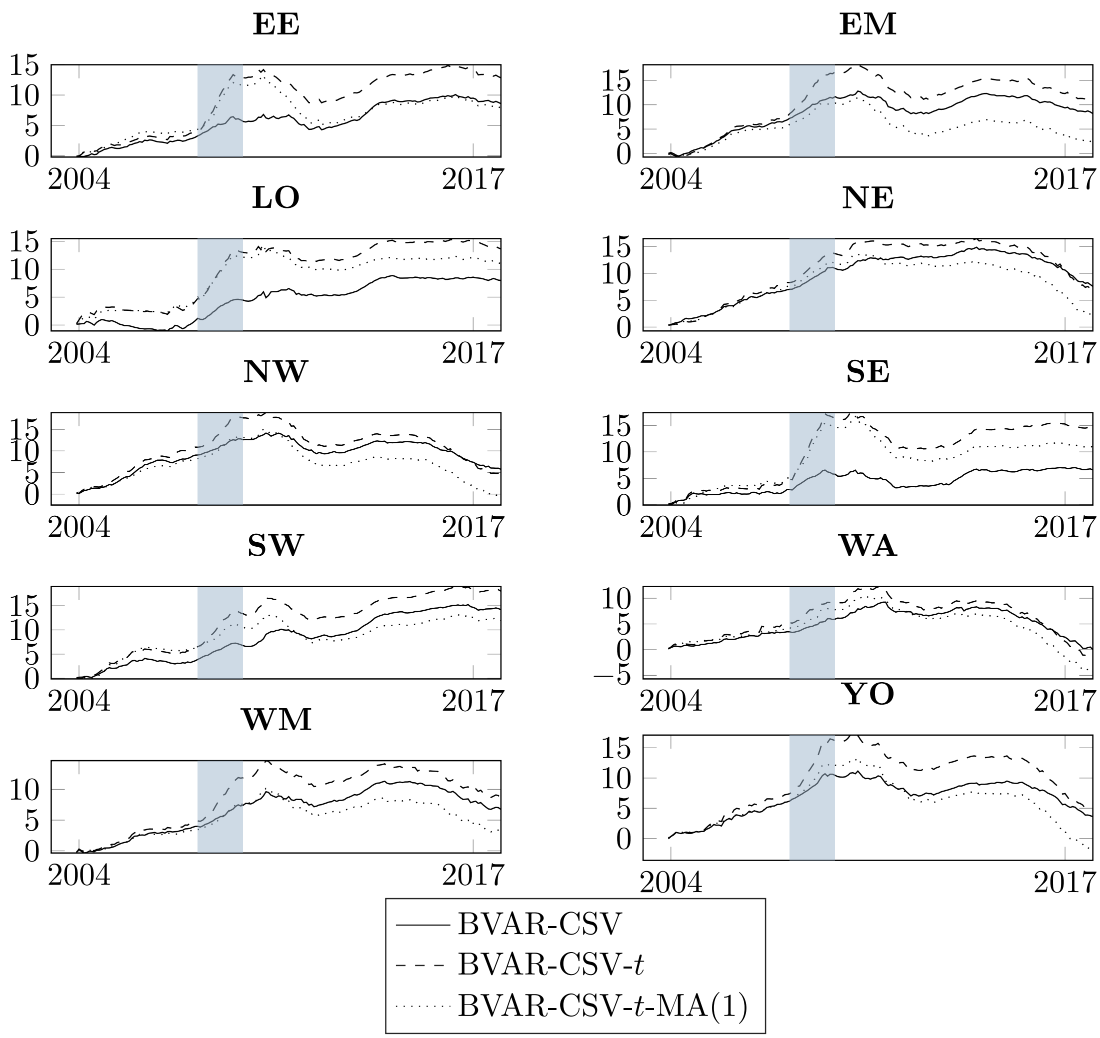


Figure 11: **Log Predictive Bayes Factors for the UK Regional and National Real Estate Returns**

Notes: This figure plots log predictive Bayes factors of Geweke and Amisano (2010) for the UK real estate returns from October 2003 to December 2017. These plots summarise the difference between cumulative log scores of: i) a BVAR with common stochastic volatility (BVAR-CSV) containing real estate illiquidity and a BVAR-CSV with no measures of real estate illiquidity at a 12-month horizon (solid line); ii) a BVAR with common stochastic volatility with $t-$distributed errors (BVAR-CSV-t) containing real estate illiquidity and a BVAR-CSV-t with no measures of real estate illiquidity at a 12-month horizon (dashed line); and iii) a BVAR with common stochastic volatility with $t-$distributed MA(1) errors (BVAR-CSV-t-MA(1)) containing real estate illiquidity and a BVAR-CSV-t-MA(1) with no measures of real estate illiquidity at a 12-month horizon (dotted line). All models use RtoV as the measure of real estate illiquidity. Positive values indicate a higher cumulative LS for the model using a measure of real estate illiquidity. Grey bars indicate NBER recession dates. 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.

4.2 Regional Spillovers using more Granular US Data

We now investigate whether our main results concerning the transmission of illiquidity shocks using US data hold at a more granular level of disaggregation. In particular, we take the constituents of the S&P 20 city composite index and examine illiquidity measures for these cities; except for Dallas, TX. This is because price and volume data for Dallas begins in 2000 which would result in a small sample. US real estate price and volume data are from the FRED economic data and these make up 19 of the 20 metropolitan areas in the USA used to calculate the S&P Case and Shiller 20 city composite index.

Our disaggregation of the US is no split into 19 regions. These are: Boston MA (BOS); Chicago IL (CHIC); Denver CO (DENV); Las-Vegas NV (LAS-V); Los Angeles CA (LOS-A); Miami FL (MIAM); New York (NY); San-Diego CA (SAN-D); San-Francisco CA (SAN-F); Washington DC (WASH); Atlanta GA (ATLA); Charlotte NC (CHAR); Cleveland OH (CLEV); Detroit MI (DET); Minneapolis MN (MINN); Phoenix AZ (PHNX); Portland OR (PORT); Seattle WA (SEAT); and Tampa Fl (TAMPA). Our time series for these models begin in March 1991 due to data availability[24]. Therefore we estimate TVP VARs as in equation 3 with N=50 variables (i.e. 19 regional real estate returns, 19 regional real estate illiquidity measures, and the 12 economic/financial variables as controls we outline in Section 2.2)[25].

Figure 12 reports the posterior median and 68% equal-tailed point-wise posterior probability bands for net-directional connectedness measures of regional returns and V^{-1} illiquidity measures in Panels A and B respectively. There are two main takeaway points from this Figure. First from Panel A, we can see that the majority of returns act as net recipients of shocks, from posterior median estimates, within the system with the exception of Charlotte NC from 2006 onwards; error bands indicate little evidence of significance.

Second from Panel B, it is clear that there are substantial differences in the impact of illiquidity shocks. Note that illiquidity in Eastern-central cities (i,.e. DET and MINN) are net shock recipients. Illiquidity measures that act as dominant transmitters of shocks to the system appear from cities located in the West and Mid-West; as well as the US capital. Specifically, the main drivers of illiquidity shock transmission throughout the sample are: DENV; LOS-A; SAN-D; SAN-F; PHNX; and WASH. Then following the 2008 recession illiquidity conditions in CHAR; PORT; SEAT; and TAMPA all act as shock transmitters too.

Overall at this level of aggregation, our analysis indicates that differences in the impact of illiquidity conditions within US regions is more prominent than at Census Bureau level. We observe statistically significant shock transmission and reception of real estate illiquidity that varies throughout time. The consistency with our main results is the transmitting nature of real

[24]These indices also track the sale of single-family homes. The construction of these price indices also follow the repeat-sales methodology that those in our main results use.

[25]Note we also estimate forecasting models at this level of disaggregation and find that in 8 of the 19 areas including illiquidity measures provides more accurate density forecasts of regional returns. We also show that computing aggregate illiquidity measures from these 19 areas results in quantitatively similar results to those we present in Figure 2. These results are available on request.

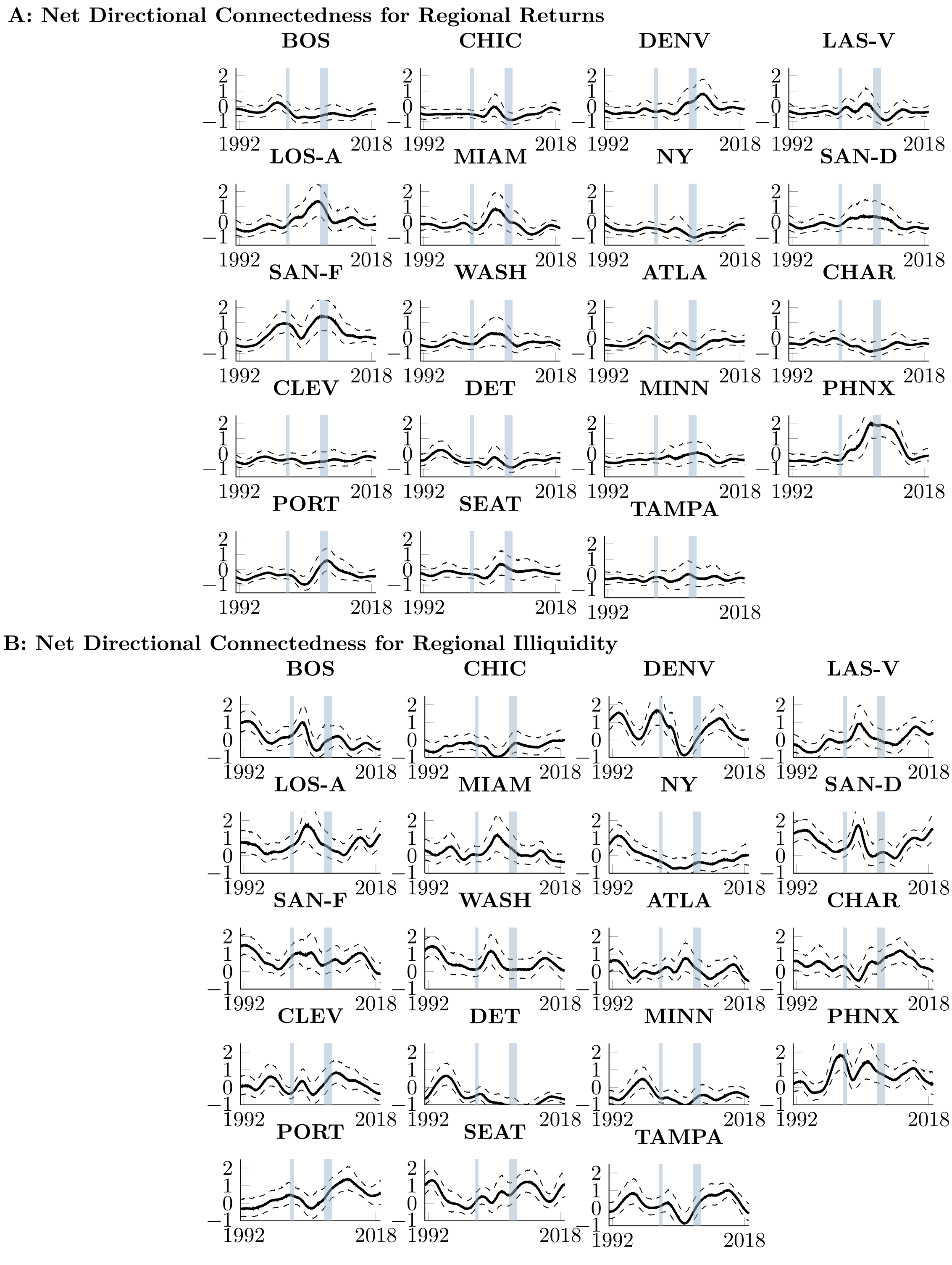


Figure 12: **Total Net Directional Connectedness of the US Regional Real Estate Returns and Illiquidity from 1985 to 2018**

Notes: This figure plots the posterior median (solid line) and 68% equal-tailed point-wise posterior probability bands (dashed lines) of the total net directional connectedness of the US regional real estate returns (Panel A) and illiquidity (Panel B) at a 20-month horizon from March 1991 to December 2018 using the methods proposed in Diebold and Yılmaz (2014). Grey bars denote NBER recession dates. BOS denotes Boston; CHIC denotes Chicago; DENV denotes Denver; LAS-V denotes Las-Vegas; LOS-A denotes Los Angeles; MIAM denotes Miami; NY denotes New York; SAN-D denotes San-diego; SAN-F denotes San-Francisco; WASH denotes Washington; ATLA denotes Atlanta; CHAR denotes Charlotte; CLEV denotes Cleveland; DET denotes Detroit; MINN denotes Minneapolis; PHIL denotes Philadelphia; PORT denotes Portland; SEAT denotes Seattle; and TAMPA denotes Tampa.

estate illiquidity stemming from cities located in Mid-West and West and therefore further evidence of Tsai (2015)'s ripple effect. The implication here, similar to our main findings, is that those with real estate in other areas within the US should monitor the liquidity in these metropolitan areas as they have an influential effect on returns elsewhere in the US.

5 Conclusion

This paper proposes two new measures of illiquidity for real estate markets and assesses their impact on returns. Utilising measures from the asset pricing literature, we segregate assets through a regional lens. Using the US and the UK data, we fit non-linear VAR models to explore the link between regional real estate illiquidity and returns after controlling for a variety of economic and financial variables. Density forecasts show that real estate illiquidity holds predictive content 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.

We examine the impact of regional illiquidity shocks on their corresponding real estate returns and document significant contractions. These contractions tend to be more prevalent during periods of recession and are most severe during the property bust of 2008. For example, average monthly contractions in the US and the UK regional markets range from 0.6% to 1.7%, and 2% to 5.7%, respectively. During the same period, the proportion of return variance attributable to real estate illiquidity shocks is as high as 28% in both the US and the UK. Using measures of dynamic network connectedness uncovers substantial heterogeneities in regional spillovers of real estate illiquidity. In particular, we find evidence of the so-called "ripple effect" in both countries. For the US, regional illiquidity shocks stemming from the Mid-West, South, and West are dominant shock transmitters from 2010 to 2018, with all regional returns becoming shock receptors over the same period. For the UK, shock transmission is highest from all regional illiquidity shocks during the 2008 recession, then from 2010 to 2018 illiquidity conditions in the South of England become most influential. In both time periods, returns are shock receptors.

Overall, our results document significant regional differences, as well as confirming time-varying linkages, between the relationship between real estate returns and illiquidity. Our ressults are robust to alternative VAR models that allow for various forms of time-variation, and also for disaggregation at a more granular level. 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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