Measuring Uncertainty in Illiquid Markets

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ABSTRACT

Employing a generalized Hamiltonian Monte Carlo Bayesian procedure we develop a new measure of real estate uncertainty that explicitly encapsulates conditional stochastic volatility and noise. When applied to commercial real estate (CRE) markets, results of Vector Autoregressive (VAR) modelling indicate that our measure outperforms conventional measures of volatility in predicting CRE price growth and transaction volume. Our novel uncertainty measure explains up to 11% or CRE price growth, and 30% of transaction volume in the US, making it highly suitable for measuring uncertainty in illiquid assets characterized by low trading frequency.

Keywords: Uncertainty, Stochastic Volatility, Noise, Valuation Uncertainty, Bayesian Estimation, Repeat Sales Model, Commercial Real Estate, Illiquid Markets.

JEL classification: C11, C33, C81, G11, G14, R30.

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I. Introduction

Understanding and measuring economic uncertainty is an important undertaking, as it became abundantly clear during global events like the Global Financial Crisis (GFC) and Covid. Investors and lenders alike measure uncertainty to set discount rates, ergo prices, and to determine capital allocation to different asset types in the capital markets. Policymakers can use time-varying risk measures to detect bubbles early. Industry and existing literature has primarily relied on proxies of uncertainty, such as the implied or realized volatility of (stock market) returns, the cross-sectional dispersion of firm profits, stock returns, or productivity, the cross-sectional dispersion of subjective (survey-based) forecasts, or the appearance of "uncertainty-related" key words in news publications (Soo, 2018).

Given the low-frequency trading nature of real estate, its heterogenous nature (Francke and van de Minne, 2020), the informational asymmetries (Lambson, McQueen, and Slade, 2004), and high levels of market segmentation (Cvijanović, Milcheva, and Van de Minne, 2020), measuring uncertainty in real estate prices is fraught with difficulty. For example, Peng (2016) shows that a cross-sectional approach that uses disaggregated property level data likely provides less biased and more efficient estimates relative to a time series approach that uses aggregate data such as real estate price indices. Further, taking the volatility of index returns, only provides a meaningful risk measure if price returns follow a random walk, which is not the case in real estate (Nagaraja, Brown, and Zhao, 2011; Van de Minne, Francke, Geltner, and White, 2019).

In this paper, we provide a new way to estimate uncertainty in illiquid markets. We produce real estate uncertainty indices that are as free as possible from the structure of specific theoretical models. Underpinning this approach is the notion that what matters for economic decision making is not whether particular economic indicators, such as real estate prices, have become more or less variable or dispersed *per se*, but rather whether the real estate prices have become more or less *predictable*; that is, more or less uncertain. Given the size and importance of real estate to the global economy, investment industry and household wealth, providing uncertainty measures that accurately reflect the nature of the asset class is an important while understudied topic not just for academics, but also for industry practitioners and real estate investors.[1]

Employing a generalized Hamiltonian Monte Carlo Bayesian procedure, the No-U-Turn-Sampler, (Hoffman and Gelman, 2014), we develop a novel way to measure uncertainty in real estate markets that explicitly encapsulates conditional stochastic volatility, and variation in model residuals. Using a repeated sales framework, we model conditional stochastic volatility (predictability in real estate prices over time) as a time-varying *signal*, and individual property uncertainty as *noise* in separate transition equations. We follow Jurado, Ludvigson, and Ng (2015) and others, in defining the signal as the conditional variance of the error term that is unforecastable from the perspective of economic agents. Assuming ARX (autoregressive plus explanatory variables) innovations, the volatility of the time-varying real estate values could be used to measure the signal, which is the *conditional stochastic* volatility, or the predictability in real estate prices over time. However, the uncertainty defined in this way does not take into account the uncertainty *within* real estate value *itself* (Francke and van de Minne, 2020). Similar in spirit to Sagi (2020), noise in our model captures the dispersion in transacting below or above the average transaction price (in our case within an MSA) and is associated with variation in model errors, which can we interpret as valuation uncertainty.

Our research contributes to the literature in several ways. First, we show how uncertainty can be measured using novel models which account for the illiquid nature of CRE assets. Second, we show how the resulting uncertainty indices can be applied to forecasting real estate prices and volumes. Third,

[1] On the CRE side, as of 2020, MSCI Inc. estimated that roughly US$10.5 trillion in global real estate assets were held for investment purposes under professional institutional management, while Nareit estimates that the 2018 total dollar value of CRE in the U.S. was $16 trillion. According to the Mortgage Bankers Association, total commercial debt outstanding was $3.98 trillion at the end of the second quarter of 2021,1 with banks accounting for 24.3% of total commercial loan volume. Total combined property values amount to approximately $30 trillion in the US alone, with about $ 10 trillion in debt, according to Sifma as of 2020.

in contrast to previous work assessing macroeconomic uncertainty (Jurado et al., 2015), our real estate uncertainty model can be estimated in a single step without having to collect additional macroeconomic variables. An additional advantage of our approach is that it lends itself to different choice of functional forms (i.e. Repeated Sales Model (RSM), hedonic models), which is of particular relevance for investors and policy makers. With our proposed methodology in hand, it becomes easier to measure real estate uncertainty on various subsets of data (i.e. by property type, or geo-location, or both). This is particularly important in real estate due to the segmented nature of the space markets (Geltner, Miller, Clayton, and Eichholtz, 2013). Finally, we also introduce the concept of time-varying *noise*. This is important for illiquid, infrequently traded assets such as real estate,[2] as it is difficult to diversify away such risks, due to the relative high price points.

Our empirical tests are built on a large sample of CRE transactions in the U.S. between 2000 and 2021, available through Real Capital Analytics (RCA). For each transaction, we obtain the transaction price and date at time of purchase and sale, as wall as the investor ownership structure.

Our model of real estate uncertainty is able to control for the stickiness of the real estate market and does a superior job in measuring real volatility beyond simply observing changes in general prices. We find evidence that signal is elevated during the dot-com bubble and peaks in 2008, coinciding with the GFC. At the same time, our noise index is much more volatile and less related to macroeconomic events. This is intuitive, since the noise captures the residual risk associated with the individual assets in each market segment and acts as an aggregate of the residual risks of individual transactions.

We deploy a Vector Autoregressive (VAR) model to examine the temporal causality between CRE prices, transaction volumes (as proxied by CRE investment activity) and our measures of real estate uncertainty. We find evidence that our uncertainty indices Granger cause CRE prices and transaction volumes, but not the other way around, implying that those can be

[2]Our model is particularly suitable for illiquid, less frequently traded assets, such as: art, municipal bonds and collectibles, among others.

used for forecasting purposes.

The VAR model also helps us understand the dynamic relationships between uncertainty indices and real estate prices and volumes. This ensures that we account for the simultaneity between uncertainty, returns, volumes and other macroeconomic variables, which are endogenous in our model.

We find that the effect of an unexpected shock to either signal or noise leads to a drop in real estate prices, however the effect is not statistically significant. However, an unexpected shock to either signal or noise leads to a significant drop in transaction volume. One standard deviation increase in signal leads to a 9% drop in transaction volume after three quarters and the effect lasts for about 5 years. An unexpected shock to noise leads to an instantaneous drop in transaction volume by as much as 8% in the first three quarters, after which it quickly recovers. Our results suggest that the effects of unexpected shocks to noise on transaction volume are impactful yet short-lived, whereas the effect of shocks to signal tend to be more persistent in the long run.

We next examine the contribution of our real estate uncertainty indices to the variance of real estate price growth and transaction volume, and compare that to other conventional measures of uncertainty, including the VIX and Macro Uncertainty (MU) by Jurado et al. (2015). We find that our uncertainty measure has the strongest explanatory power and the fastest impact, explaining up to 11% of real estate price growth after 5 quarters. In turn, VIX explains about 4% and the MU measure about 1%.

Furthermore, our uncertainty indices explain around 30% of variation in transaction volumes after 5 quarters and this effect is persistent. In turn, VIX and MU explain less than 5% of the variation in transaction volumes up until quarter 5. Taken together, these results suggest that our uncertainty measures have superior properties when it comes to measuring volatility of illiquid assets.

Finally, we provide an application of our uncertainty measures by producing indices at more granular levels and using both, a hedonic and a repeat sales framework.

Our paper fits within the broader set of literature on indexing real estate values within a state-space framework. For example, the RCA CPPIs use the methodology proposed by Van de Minne et al. (2019). Other papers include Goetzmann (1992); Schwann (1998); Francke and DeVos (2000); Francke (2010); Francke and Van de Minne (2022). It relates to the burgeoning literature on measuring real estate uncertainty or risk, which has so far mainly focused on housing. Nguyen Thanh, Strobel, and Lee (2020) show that their Real Estate Uncertainty (REU) measure accounts for twice as much of variation in housing prices—and starts compared to the MU by Jurado et al. (2015).[3] In the context of CRE, Holland, Ott, and Riddiough (2000) focus on analyzing the impact of uncertainty on investment decision making. They empirically examine the uncertainty-investment relationship using aggregate construction data from 1972 through 1992 on various types of commercial real estate, and find a significant short-term negative relationship between total uncertainty and the rate of investment for most types of commercial real estate.

Our paper is structured as follows. The methodology is given in Section II, followed by a description of the data in Section III. Section IV provides the results of our analysis, while in Section V we show further applications of our model. In Section VI we conclude.

II. Methodology

In this paper, we show how (1) conditional volatility indices and (2) noise indices can be constructed by using CRE transaction data in the US between 2001 and 2021. Our work is inspired by the methodological framework of macro uncertainty by Jurado et al. (2015), whose setup involves four steps: First, an econometrician collects a vector of macroeconomic time series variables that she suspects have an impact on the variable of interest. Secondly, the econometrician has to forecast all of these time series variables using a forecasting tool of choice. In a third step, the econometrician runs stochas-

[3]Other works examining the impact of uncertainty on the housing market include Childs, Ott, and Riddiough (2002), Yavas (2001), Strobel, Nguyen Thanh, and Lee (2020) and Choudhry (2020), among others.

tic volatility models on the residuals of the model in step 2, which gives the time-varying standard deviation of the unforecastable returns, i.e. the conditional volatility as we define it in this paper as well. Finally, the econometrician needs to average out all of these values, to get *one* uncertainty measure.

As mentioned, our real estate uncertainty model in turn can be estimated in a single step without having to collect additional macroeconomic variables. Another advantage of our uncertainty index is that it is time-varying and responds to new information about individual transactions.

Measuring time-series volatility of real estate assets is more challenging relative to equity volatility. This is due to the fact that real estate assets do not transact frequently, and also due to the assets themselves being very cost-intensive and impossible to divide into tradeable pieces. This has implications for how volatility is measured for direct real estate transactions or other illiquid assets, such as private equity, less frequently traded bonds, etc. Essentially, an uncertainty index of those assets will reflect their illiquid nature and naturally exhibit lower volatility and high autocorrelation.

We consider that the concept of signal in illiquid markets is associated with changes in the prices of individual transactions of a given market – i.e. Metropolitan Statistical Area (MSA), state, country. Signal captures the volatility of a market (i.e. the US as a whole) of the asset class over time. Increases in signal hence reflect increased exposure to unexpected macroeconomic shocks, that are not necessarily due to loss of liquidity, presence of block traders, or concerns with valuations.

In addition to signal, we also explore noise which is associated with the notion of valuation uncertainty. Noise captures the volatility of the market associated with changes in the standard deviation of the error terms of the model used. Noise stems from the residuals of the expected model values of CRE prices. Agents in CRE markets are more prone to "errors" in the estimation of CRE prices which can be linked to the illiquidity of the markets. Higher noise indicates there is more uncertainty in the real estate asset valuation than in previous episodes. This can happen as a result of thin trading, or it can be due to changes in the maturity of the market, or due to lack of information.

A. Measuring Noise

The foundation of tracking constant quality prices over time is based on Hedonic Price Models (HPM). Rosen (1974) explicated the formal microeconomic theory underlying HPMs, although the technique has older roots in consumer and marketing empirical analytics practice (Court, 1939). The basic idea is that heterogeneous goods can be described by their attributes (de Haan and Diewert, 2011). In other words, a good is a bundle of characteristics. In the case of real estate properties, the relevant bundle contains attributes of the building structure and location site of the property. For example, attributes might include the size, age, and type of building, and the distance of the site from downtown or the airport or the nearest subway station. There is no market for the individual characteristics as such, since they cannot be sold separately. In the market for property occupancy, demand and supply in the market for built space (the rental market) determine the characteristics' marginal contributions to the total value of the bundle. The price "index" can subsequently be captured by time of sale dummies. Regression-based techniques are typically used to estimate these marginal value contributions. Such a model is given by;

$$y_{it} = \mu_t + x_i\beta + \epsilon_{it}, \quad \epsilon_t \sim \mathcal{N}(0, \sigma_{\epsilon,t}), \quad i = 1, \ldots, P, \tag{1}$$

where i are the individual properties (with P total properties), t is time of sale, x are the covariates (with corresponding coefficient vector β) and ϵ are the residuals. The dependent variable (y) are the log of sales prices. The residuals are assumed to be normally distributed with mean zero and standard deviation σ, which is the noise in our study. The higher the standard deviation of the hedonic model, $\sigma_{\epsilon,t}$, is, the higher the noise in the market is. It means, it is more difficult to correctly predict (individual) transaction prices.

For example, if we have transaction prices of real estate buildings for New York between 2010 and 2020, we estimate a cross-sectional model for the entire New York area. The standard deviation of the residual, σ, will be the noise of the real estate market in New York between 2010 and 2020. In its simplest form, the noise is assumed to be constant, however, in Equation (1), we assume that the noise, σ, varies over time. We do this by explicitly modeling it as a random walk, so that:

$$\Delta\sigma_{\epsilon,t} \sim \mathcal{N}(0, \zeta_\epsilon). \tag{2}$$

However, HPMs – in particular for commercial real estate transactions – are in practice hard to develop. First, properties are heterogeneous in nature, implying many potential value drivers. A second compounding issue is that the number of recorded property characteristics is in most real estate databases quite limited: many value drivers are missing. And when they are sufficiently available, there is the risk of misspecification and overfitting (Francke and van de Minne, 2020). One way to solve this is by using the so-called repeat sales model (RSM), which was first introduced by Bailey, Muth, and Nourse (1963). With the RSM, we replace the time-invariant covariates, mostly associated with the property characteristics, with a dummy (δ) per property:

$$y_{it} = \mu_t + x_i\beta + \delta_i + \epsilon_{it}, \quad \epsilon_t \sim \mathcal{N}(0, \sigma_{\epsilon,t}), \quad i = 1, \ldots, P, . \tag{3}$$

This model is usually "first differenced" by subtracting the transaction price at sell from the transaction price at buy, allowing us to drop the property level fixed effect in its entirety. The model looks like:

$$y_{it} - y_{is} = \mu_t - \mu_s + (x_{it} - x_{is})\beta + \epsilon_{it} - \epsilon_{is}, \quad \epsilon_{ist} \sim \mathcal{N}(0, 2\sigma_{\epsilon,t}), \tag{4}$$

where s is the time of purchase, as opposed to t, which denotes the time of sale. Hyperparameter ϵ_{ist} is the difference between ϵ_{it} and ϵ_{is}. Covariates are in x_{it}, which only include variables that change between buy and sell. In the case of commercial real estate, the most obvious candidate is a change in space markets, measured by the NOI.[4]

Despite the advantage of the RSM to account for unobservered heterogeneity across transactions, it has its own caveats. One obvious issue is that we can only estimate this model on properties that sold at least twice, meaning we *potentially* lose some observations.[5] This issue becomes partly attenuated as databases mature, which is the case for our data. Another issue is that the property might "change" between sales that we do not observe as econometricians. This leads to additional heterogeneity across observations, which is still not accounted for in x. If it is an obvious change, like change in NOI, square footage or property use, we can either control for it, or omit the observation. (See Section III as well.) However, there are also a lot of possible changes between the sales that we do not observe. These are mostly related to operating expenses (OpEx) and capital expenditures (CapEx). OpEx and CapEx can be anything from regular maintenance (or the lack thereof) to new heating, ventilation, air-conditioning (HVAC) systems, for example. As a result, properties with a longer holding period might have a larger variance in sales prices (i.e. higher σ_ϵ). Case and Shiller (1987) solved this by estimating the RSM with weighted least squares, essentially putting less weight on properties with longer holding periods. We solve this by making the noise ϵ_{it} directly a function of the holding period, as measured in years. This is given by:

$$y_{it}-y_{is} = \mu_t-\mu_s+(x_{it}-x_{is})\beta+\epsilon_{it}-\epsilon_{is}, \quad \epsilon_{ist} \sim \mathcal{N}(0, 2\sigma_{\epsilon,t}\times\exp(h_{its}\theta)), \tag{5}$$

where h is the log holding period in years, and θ is the corresponding parameter, which we believe is going to be positive. We exponentiate the holding period times its corresponding covariate as to ensure no negative values for the standard deviation of the model, i.e. the noise. Note that properties

[4]Note that the interpretation of parameter vector μ_t is not that of overall price index of the market (as is usual with repeat sales models), unless there are no systematic dynamics in NOI over time. For $\beta \approx 1$, equation (4) tracks the dynamics of the Price/NOI over time (or the inverse of the "cap rate").

[5]You can also *potentially* lose many observations in a hedonic framework, if many observations lack characteristics. In our dataset for example, almost none of the observations have an entry for *all* characteristics (which is close to 200 in total).

with very short holding periods can pose a concern, as these might represent "flips" (Clapp and Giaccotto, 1999). Our data provider usually records when a property is bought with the intent to redevelop. Those properties are subsequently filtered out. The data provider also filters out repeat sales with holding periods of less than two years, which corresponds with academic practice (Clapp and Giaccotto, 1999).[6]

Finally, note that we also allow the noise ($\sigma_{\epsilon,t}$) to vary over time as we did with the HPM earlier. The noise index can be constructed at the national level or sub-national level, for as long as we have a large amount of repeat sales of commercial real estate units.

B. *Measuring Signal*

In order to estimate the overall real estate uncertainty, we explicitly model conditional stochastic volatility (predictability in real estate prices over time) as a time-varying *signal*, and idiosyncratic individual property uncertainty as *noise* in separate transition equations. Conditional stochastic volatility, or signal, denotes the non-diversifiable part of real estate uncertainty. Typically, asset uncertainty is measured by taking the volatility of the returns of a real estate index, i.e. the real estate return in a given market. However, by estimating the volatility of an already existing index, we would not account about the volatility within individual real estate values themselves (Francke and Van de Minne, 2017). Another caveat with applying financial risk modelling to real estate is due to the frictions observed in real estate markets. Trading in real estate is characterized by a double-sided search market, with relatively little information. As a result, there is a certain level of predictability in real estate prices, in particular in case of shorter frequencies, i.e. the so called momentum in stock markets. This can result in serial correlation. To account for these potential issues, sig-

[6]More recently, Sagi (2020) finds that properties with short holding periods also sell for more while controlling for CapEx. His reasoning is that such transactions almost never happen, but if they do occur, this must happen with a large premium to offset the hefty transaction costs (which can easily be 10% of the initial price) paid for by the owner of the real estate. Usually, long holding periods are a way to spread out such transaction costs over multiple years.

nal would only measure the variance around the unpredictable parts of real estate prices and not the entire price index.

To identify the unpredictable part of the real estate returns, we follow the general framework in Jurado et al. (2015). We specify a state equation which allows us to forecast future real estate returns. Signal is defined as the (stochastic) volatility of the residuals of the state equation. The specified state equation can be used for both hedonic pricing and repeat sales models. The state-equation is given by:

$$\Delta\mu_t \sim \mathcal{N}(\Delta v_{t-1}\omega, \sigma_{\mu,t}), \tag{6}$$

where v are the explanatory variables used to forecast changes in the price index ($\Delta\mu$), with its corresponding vector of covariates ω. In this paper, v has two components - an autoregressive term and the stock market return of publicly trades real estate investment trusts (REITs)[7]. First, previous literature (Nagaraja et al., 2011; Van de Minne et al., 2019; Sagi, 2020) found that real estate price returns can be described by an autoregressive model. As such, we introduce an autoregressive component in v. Secondly, as shown in Francke and van de Minne (2020); Barkham and Geltner (1995), prices of the properties held by REITs tend to lag the share prices of REITs.[8] Therefore, to predict direct real estate prices, we include REIT returns.

v is formalised as:

$$\Delta v_t = \Delta\mu_t\rho + \Delta r_t\alpha, \tag{7}$$

with $\Delta\mu_t\rho$ being the autoregressive component and r being the REIT return, with corresponding coefficients ρ (which is fixed to be between $-1 \geq \rho \geq 1$) and α.

We estimate the equations simultaneously using full Bayesian inference.

[7]REITs are publicly traded real estate firms that must invest at least three-quarters of their assets in, and derive at least three-quarters of their income from, commercial real estate (Mühlhofer, 2019). In reality this number is typically closer to 100% invested in real estate, see Geltner et al. (2013).

[8]The main reason for this lead-lag relationship is that REIT stocks are traded on stock exchanges allowing for a quicker transfer of information while properties transact in less frictionless markets.

More specifically, we estimate our model using the No-U-Turn-Sampler (NUTS), introduced by Hoffman and Gelman (2014), with mostly uninformative priors (Gelman, 2006). We use random starting values, over 6 chains, with 2,500 samples each, of which the first half will be used as a "warm-up". Model convergence is tested based on the Rhats of the individual variables, which has to be lower than 1.01 on average, and no one variable can exceed 1.1.

III. Data and Descriptive Statistics

Our analysis uses transaction data from Real Capital Analytics (RCA). RCA captures approximately 95% of all commercial property transactions in the United States over $2.5 million.[9] RCA have a dedicated research team of over 200 that finds - and enters into their database - real estate deals, even in non-disclosure states. RCA data runs from 2000 until 2021 and contains over half a million individual transactions. We look in particular at transactions that are repeat sales.

To identify repeat sales, we use the algorithm and filters provided to us by RCA. Only if the property did not change between sales (because a redevelopment or a major addition to a building), are multiple transactions of the same property considered to be repeat sales. Repeat sales with a holding period of a year or less are also excluded, as these can represent "flips." We estimate our repeat sales model for the entire US (Panel A in Table I) and industrial properties alone (Panel B in Table I.

In the Section V we also estimate hedonic models for retail properties in Phoenix between 2000 and 2021 (Panel C in Table I) and single family housing sales in West Hartford (CT) between 2017 and 2021, for which data was provided to us by the local MLS (Panel D in Table I). For the Phoenix retail properties we also include city fixed effects, and for the single family housing model we also include dummies for type of parking, architectural style and type and amount of bathrooms. Summary statistics for these

[9]However, once a property is in the database RCA will keep tracking it, even if subsequent sales are below that threshold.

dummies are available upon request, but not shown here for the sake of brevity.

[Place Table I about here]

The average purchase price for commercial real estate in the US is $40mn with a standard deviation of $83mn (Panel A Table I). Some of the smallest transactions are of a value of around $3mn and some of the largest ones of $50mn. On average, prices where higher during at the time of sale, relative to purchase. This is also reflected in the (log) returns between sales, which is 0.172 on average. Note that the (log) return is our dependent variable in the regression models. The standard deviation of the (log) returns is quite high with 0.378, meaning there is a lot of heterogeneity in returns. The average year-over-year (log) return is 5.5%, with a standard deviation of 10.1%. The 25th percentile most profitable deals had an annual return of more than 10.6%. More than 10% of the deals had a negative average annual return. The average holding period is close to 6 years with a standard deviation of 3.4 years. Some of the longest holdings periods, 90th quantile, take 11 years. In total we observe over 14,566 repeat sales, or approximately 30 thousand individual transactions. The average Net Operating Income at the time of purchase (sale) was $2.4mn ($2.6mn), indicating an average cap rate of 6% (5.5%). The change in Net Operating Income during our analyzed period was less (9.1%) compared to asset value changes (17.2%), meaning price increases were driven by both changes in the space, and asset markets.

Industrial properties are sold for about half the price on average compared to the national average (Panel B, Table I). More specifically, the average price at the time of purchase (sale) is $22mn ($25.7mn). The (log) return is 0.130 on average for this property type. Net Operating Income is $1.6mn approximately both at time of the time of purchase and the time of sale. Note that we only observe 1,133 industrial repeat sales (or 2,266 transactions).[10]

[10]We lose many observations, specifically for industrial properties, because we miss NOI at *either* buy or sale. This is less the case with other property types.

In panel C we show some descriptive statistics of our subset of retail properties in Phoenix (AZ). We have too few observations to construct a repeat sales model for this market (only 133, not shown in the table), which necessitates the use of the hedonic form of our model specification. The average sales price is \$10mn, with an average Net Operating Income per square foot of \$18. Other variables we observe; total square footage of structure, walk score (going from 0 to 100), Q score (a proprietary measure of building quality given to us by the data provider), age of the building, and some dummies on distressed sales, properties that are up for either renovation or redevelopment and a dummy for strip malls (as opposed to other types of retail). We observe 829 transactions in our data that includes all these covariates.

For single family houses in West Hartford (CT) the time period is too short to construct repeat sales data (2017 – 2021). Most properties are single family houses (87%), indicating 13% of the observations are condominiums sales. The average sales price is \$350K for 2,174 square foot of building (average of \$160 per square foot). Properties in West Hartford are relatively old compared to the US average with 67, while the lots are on the small side as well with 0.3 acres. (Note that condominiums have 0 acres of land in the MLS data.)

In our state Equation we include both an autoregressive component and an aggregate price index to help improve forecasting accuracy (Van de Minne et al., 2019). For commercial real estate we simply use an composite index of (levered) REITs. More specifically, we use the Wilshire US Real Estate Investment Trust Price Index (WILLREITPR), available on the website of the Federal Reserve of St. Louis (Fred). Note that we use the same REIT index for all our commercial property markets, including industrial and retail properties in Phoenix. For our housing data in West Hartford (CT) we use the returns of the Case and Shiller (1987) index for the greater Hartford area. This data is also readily available on Fred. Both returns series a provided in Figure 1. Note that we show the data of the Case and Shiller (1987) index all the way from 2000 through 2021, even though we will only use this data between 2017 and 2021.

[Place Figure 1 about here]

IV. Results

A. Main Results

Table II shows the posteriors and fit of our main model, which is the repeat sale model for the entire US. We see that all variables in our model converge with a Rhat value below 1.1. All variables are significant in the sense that the confidence intervals of 2.5% and 97.5% lie outside the zero line. The average value of the signal is 0.33 and the average value of noise is 0.098. The interpretation of these variables is not straightforward. A higher value means that both signal and noise can change faster on a period-by-period basis. The average value of the posterior for the NOI is 0.724. This indicates that historically, NOI (or in general rents and space markets) was not the only driver of prices, but that capital markets also played a role, which was assumed ex-ante (Shiller, 1981; Geltner et al., 2013). As expected, we have a positive and significant loading (at 1%) on holding period on noise. For every log 1 year the holding period of the property extends, noise increases by 0.261.

Looking at our state equation which predicts price returns, we find that REIT index returns only predict private market returns at the 10% confidence level (and not 5% as shown in Table II). A 1% increase in REIT index returns one quarter ago, predicts an increase in private market returns of 0.06%. Note that the effect of REIT returns on private market returns was expected to be lower than 1, because REITs are levered, whereas our data is unlevered. In line with previous research, we do find a relatively big and significant coefficient on autocorrelation. A return of 1% in the previous quarter, translates in a 0.56% return in the concurrent quarter.

[Place Table II about here]

Figure 2 shows the two types of a uncertainty indices – signal and noise, together with a "price index" (μ_t) we construct using this novel methodology.

We can see that signal peaks in 2008 which is associated with the GFC. In 2008 it reached the highest level it has even been for the sample period between 2000 and 2021. The volatility goes from as low as 0.01 to as high as 0.04. The volatility is also elevated during the dot-com bubble in 2001. The volatility has reached historically low levels since 2011 and has remained low until the end of 2019. We also observe that signal quickly insreases between 2007 and 2008 followed by a quick drop in 2010-2011. It shows that our model is able to control for the stickiness of the real estate market and can do a good job in measuring real uncertainty in illiquid markets beyond simply observing changes in general prices on markets, which are much more slowly to see through.

The noise instead is much more volatile and less related to macroeconomic or market events. This is understandable because the noise captures the residual risk associated with the individual buildings in each market. An increase in the noise in a given location, i.e. the market becoming "noisier" is associated with less informed traders, thin trading, illiquidity and less efficient price discovery. We can see that the noise is not following a random walk but rather has a trend, similar to an index. We see the noise also goes up around 2008 associated with the GFC. It then gradually falls, however, much more slowly and steadily than the signal. At the end of 2019 it starts to gradually go up reaching similar levels in 2021 to those during the GFC. We also see that the noise risk is lowest in 2001 and 2002. A similar spread between the lowest and highest value of the noise risk index is observed to the signal. The lowest value is at 0.04 and the highest is around 0.07, which gives a maximum spread of 0.03.[11]

[Place Figure 2 about here]

[11] Note that the estimated values of noise represents the noise for properties with 0 years of holding period due to the setup of the model. To get a more realistic market average, one would have to multiply the estimated values with the log of the average holding period (approximately 6 years).

B. Dynamic Responses to Our Uncertainty Measures

Before we provide the results of our model on more granular markets, we want to compare our national unicertainty measures to other uncertainty measures that are readily available as the later are only available nationally. First we estimate temporal causality of our uncertainty indices to different dependent variables (x) using the following equation:

$$x_t = \beta_0 + \mu_t + \sum_{j=1}^{J} \alpha_j x_{t-j} + \sum_{j=1}^{J} \beta_j Uncertainty_{t-j} + \varepsilon_t, \tag{8}$$

where x_t includes {CRE prices, CRE investor activity, NBER crisis dummy}. CRE prices are measured by the Van de Minne et al. (2019) repeat sales model, and data is provided to us by RCA/MSCI. Investor activity is the total transaction volume per quarter as measured by RCA. *Uncertainty* denotes our two (longitudinal signal and idiosyncratic noise) uncertainty measures as estimated in Section IV.A. All variables (except the NBER crisis dummy) are first-differenced to adjust for the presence of unit roots and results are presented in Table VI.

We then test for each uncertainty index whether (1) it has a long-run significant impact on the dependent variables (prices and volumes); (2) the coefficients of the uncertainty indices are jointly significant (i.e., Granger causal) in explaining the dependent variables.[12] The results can be found in Table III. We see that the direction is from uncertainty towards prices/volumes. Signal Granger causes prices and volumes significantly but not the other way around. In the same way, noise Granger causes prices and volumes but not the other way around. Price levels do not affect the uncertainty indices which makes them suitable for forecasting prices and volumes.

[Place Table III about here]

Next, we estimate a VAR model to understand the dynamic relationships

[12]We use Newey–West standard errors which are robust to heteroskedasticity and autocorrelation in all estimations.

between uncertainty indices and real estate prices and volumes. In this way, we account for the simultaneity between uncertainty, prices, volumes and other macroeconomic variables. We follow existing research on VAR and include the Federal Funds rate (FFR) to account for US monetary policy shocks. We include the 10-year Treasury rate (10-year T-rate) to account for unexpected shocks to the yield curve. This is important as real estate investments have long horizon periods of 10 years or more. Those expectations affect the discount rates when valuing property and hence the pricing. We also include the S&P 500 stock market index to capture unexpected shocks to valuations on stock markets and the overall sentiment in the US economy. We also include industrial production (IP) as a measure of unexpected shocks to output, which can affect the demand and supply of new and existing real estate. The last four variables are our real estate market variables. We include our own uncertainty indices – signal and noise, and the self-constructed real estate price and volume indices. We consider that unexpected shocks to volume are associated with a change in real estate investor activity, which is a proxy for the supply of existing real estate. In turn, shocks to prices capture unexpected changes to the demand for real estate. Signal and noise are metrics from out uncertainty model, which feed as inputs into the VAR. The main macroeconomic variables used in the analysis are obtained from the website of the Federal Reserve of St. Louis (Fred).

Before we estimate the VAR, we test if the above variables have a unit root. If they do, they have to be transformed in first differences in order to satisfy the stationarity requirement. We use an Augmented Dickey Fuller (ADF) test to test for unit roots. Table III shows the results. As expected, all variables except the FFR have a unit root in the levels and therefore we take the first differences before we estimate the VAR. This means that the model consists in volume growth, price growth, S&P500 return, and IP growth. Hence, it is important to note that following the state of the art VAR models, these variables represent quarterly growth rates/returns and as such are not expressed in levels.

[Place Table VI about here]

Before we show the impulse responses (IRs) of the effect of shocks to some of the variables in the model, we first need to impose an identification structure. This is based on assumptions of how the variables are economically related to each other and assumptions on endogeneity. Given that the focus of this paper is not the VAR model, but on providing a novel way to measure uncertainty in illiquid markets, the VAR model and results are only for providing some applications. We therefore follow the standard approach and use a Choleski decomposition to identify the various economic relationships within the VAR. For a Choleski decomposition, the identification is achieved by ordering the variables in a recursive structure, in which the first variable affects the second, the second the third, and so one, but it is assumed that there is no immediate feedback. The variables at the top of the VAR matrix are the ones that are least dependent on other economic factors, i.e. are the most exogenous. The variables which are ordered at the bottom of the Choleski matrix are influenced by all other variables in the model. The VAR is hence ordered as follows: FFR, 10-year 10-y T-rate, IP, signal, noise, real estate prices, real estate investor activity.

$$\begin{pmatrix} \text{federal funds rate} \\ \text{10-year treasury rate} \\ \text{S\&P 500} \\ \text{industrial production} \\ \text{signal} \\ \text{noise} \\ \text{prices} \\ \text{investor activity} \end{pmatrix}$$

Since there is no specific theory on the ordering of the uncertainty indices in a VAR set-up, we follow Bloom (2014) who suggests that volatility represents both exogenous and endogenous components: volatility immediately increases after exogenous events, e.g., 9/11, oil price jumps and also endogenously increases during recessions. Furthermore, from Table III we know that the uncertainty indices Granger cause prices and volumes but not the other way around. Therefore, we order the uncertainty indices before the real estate variables but after the macroeconomic variables, to allow uncertainty to be endogenous to the real estate market but exogenous the the macro variables. This means that uncertainty indices are affected by interest rates, the yield curve and output but are not affected by real estate prices or volumes.

Figure 3 reports the VAR IR results. We only present the key IRs – the shocks to volatility indices on prices and volume. The effect of an unexpected shock to either signal or noise leads to a drop in real estate prices, however the effect is not significant. In turn, both uncertainty variables lead to a significant drop in transaction volume. The drop in volume as a result of an unexpected shock to signal lasts for about five years after the shock. One standard deviation increase in signal leads to 10% drop in volumes after three quarters and remains at that level. An unexpected shock to noise leads to an instantaneous drop in volumes by as much as 8% after three quarters. After that volume recovers. The effect of a noise shock is short lived but strong. The effect of a signal shock is more persistent and even becomes significant again after 3 years.

[Place Figure 3 about here]

Figure 4 shows the IRs of a shock to prices and volumes on each other. We can see that an unexpected shock to prices significantly affects volume. A one standard deviation increase in price growth leads to up to 10% increase in volume growth three quarters after the shock. The effect of prices on volumes is quick with prices immediately responding to changes in volumes. It lasts about three years. We also find an effect of a shock to volume on prices, however it takes longer to materialize. Only after three years do we find a positive effect of volume on prices.It remains significant up to 7 years after the shock.

[Place Figure 4 about here]

A positive price-volume correlation is a well established phenomena in commercial real estate (van Dijk, Geltner, and Van de Minne, 2020). Since it is difficult to gauge actual real estate values, buyers tend to move the market. Technically speaking, in a hot (cold) market, potential buyers will increase (decrease) their reservation prices. Existing owners are not immediately aware of this adjustment, because reservation prices are private and not easily observed. As a result, in a hot market, liquidity increases (due to the higher overlap of reservation prices), and average transaction prices will increase as well. This can also help explain why a change in uncertainty translates more in investor activity, i.e. volume, compared to pricing. It might be that a shock to uncertainty affects prices through the volume channel. In uncertain times, investors become more conservative. In other words, the reservation prices of buyers decrease, whereas the reservation prices of sellers increase. In such an environment, the average transaction price (*if a transaction even takes place*) remains relatively similar, but the amount of possible matches between buyers and sellers declines.

Figure 6 shows to what extent the use of different measures of uncertainty within the VAR model play a role within the variance decomposition of the real estate price growth. In addition to our own uncertainty measures – noise and signal taken together as ''own uncertainty indices" – we substitute those with a more conventional measure of uncertainty – the VIX. We also use the Macro Uncertainty (MU) measure of Jurado et al. (2015). We re-estimate our VAR model with VIX and MU separately to compute the variance decomposition and subsequent explanatory power. A graphical representation of all four measures (signal/noise/VIX/MU) is given in Figure 5.

[Place Figure 5 about here]

We see that out of all those measures of uncertainty, the strongest explanatory power is delivered by our own real estate uncertainty indices, but all three of them roughly follow a similar pattern. The CRE uncertainty measures have the fastest and strongest effect on prices. The volatility of prices increases sharply within the fist five quarters. It also remains high for the next 20 quarters. This means that prices do not stabilise after a sudden increase in volatility. The prices are explained to 11% by shocks to our uncertainty indices taken together. After five quarters, up to 4% of the volatility in prices is explained by the VIX and only about 1% by MU. MU increases its explanatory power to reach up to 9% by quarter 10. The VIX explains up to 8% as of quarter 7.

[Place Figure 6 about here]

Figure 7 shows even more striking results for the variance decomposition of transaction volumes. Unlike for prices, here, our real estate uncertainty measure clearly dominates VIX and MU. It explains around 30% of the entire variation in volumes and that effect persists for the next five years. In turn, VIX and MU explain less than 10% of the variation in volumes. The effect of our own uncertainty indices is immediate and strong, within the first two quarters. This means that investor activity is immediately and strongly affected by shocks to volatility and investors do not change their behavior for a long period of time.

[Place Figure 7 about here]

V. Robustness

In this Section, we discuss three potential applications on measuring real estate uncertainty for: industrial real estate across the US, retail properties in Phoenix (AZ) and for housing in West Hartford (CT).

A. Uncertainty measures for individual property types

In this subsestion we discuss the results of estimating our model on more granular markets. We begin by looking at industrial properties in the US in Figure 8 and Table IV.

[Place Figure 8 about here]

[Place Table IV about here]

Compared to our risk measures for the US in general, the estimation on industrial property type renders different results. The "index" (μ_t) outperformed the national average, but the correlation is quite high (not shown here but available upon request). Prices (while controlling for NOI) increased before the GFC, dropped significantly during the GFC, and showed a steady recovery since then. However, unlike the US national, stochastic conditional volatility time series, or signal, for industrial real estate has its peak at the end of the Covid period. Industrial real estate have seen a change in status in recent years, due to it becoming more focused on transportation, compared to manufacturing in the past. As a result, predicting the direction of prices has became more challenging according to our forecasting model. It is worth to note that noise is also close the the all-time peak in recent periods, although the peak in noise for industrial properties was not during the GFC (as was the case for the national average), but around 2013. What is also interesting, is that the autoregressive (AR) component of the state equation is now insignificant, whereas it was large and significant for the US national average. However, past REIT returns have a larger explanatory power compared to the national average.

B. Application to property-type location specific markets: hedonic approach

Figure 9 gives the uncertainty indices for retail properties in Phoenix (AZ), which are estimated using the hedonic framework.

Panel A in Table V provides the estimates on the covariates.

[Place Figure 9 about here]

[Place Table V about here]

The signal behaves relatively similar to the national average. It peaked during the GFC, and remained relatively low since then. Although we do see a small uptick during Covid, and the signal had a pre-peak before the GFC around 2006. The time-varying noise is relatively volatile, as was the case with the national average. The estimates of the state equation reveal both a heavy AR-component (close to 1) and REIT returns also positively impacting the direct real estate returns. Such predictability is expected in a smaller and well defined market like retail in Phoenix, as not many transactions happen periodically, and therefore there is not enough information for efficient price discovery. The other estimates in the measurement equation have expected signs and posterior means. One exception is the effect of age on prices which is negligible and/or insignificant. Usually, properties depreciate as they age, resulting in lower prices (Francke and van de Minne, 2017). However, note that we include NOI per square foot in our model. As shown in Bokhari and Geltner (2018), most (if not all) depreciation goes through NOI.

Finally, we use our model on MLS data for housing transactions (mostly single family) in West Hartford (CT). A graphical representation of the uncertainty measures can be found in Figure 10. The estimates are given in Panel B of Table V. In this case we were only provided with a relatively short time period, namely 2017 – 2021. As a result we cannot construct repeat sales, and have to resort to using the hedonic specification, as we did in case of retail properties in Phoenix (AZ)..

[Place Figure 10 about here]

Given that we do not control for NOI for the housing properties, the μ coefficients (red line in Figure 10) can be more easily interpreted as a constant quality price index. Prices increase by 20% since the outbreak of Covid. Covid also impacted both signal and noise, but they do not reach pre-Covid peaks. Panel B of Table V shows that neither the AR-component, nor the Case and Shiller (1987) repeat sales price return of the greater Hartford (CS Hartford) area have any explanatory power in predicting price growth. One possible explanation is that housing markets are more efficient due to the larger homogeneity and transaction volume.

Although we cannot completely rule out other patterns as the time series is too short for our model to train on. All other estimates have the expected sign and size.

Taken together, the results presented in this Section highlight that our methodology for measuring real estate uncertainty is easy to extend to different functional forms (i.e. hedonic in addition to repeated sales model), and to specific property types (i.e. industrial or retail) or locations (i.e. Phoenix (AZ)).

VI. Concluding Remarks

In this paper, we provide a new way to measure uncertainty in illiquid markets. We produce real estate uncertainty indices that are as free as possible from the structure of specific theoretical models.

Employing a generalized Hamiltonian Monte Carlo Bayesian procedure we provide a novel way to measure uncertainty in commercial real estate (CRE) market. Our measure of uncertainty explicitly encapsulates conditional stochastic volatility and noise. When applied to real estate markets, results of VAR analyses indicate that our measures outperforms conventional measures of volatility in predicting CRE price growth and transaction volume. Our novel measure explains up to 11% or CRE price growth, and around 30% of the overall transaction volume. Taken together, these results suggest that our novel measure of real estate uncertainty has superior properties when it comes to measuring volatility of illiquid assets characterized by low trading frequency.

In this study we have intentionally taken an approach that is not based on any specific theoretical model, in order to provide a model-free index of real estate uncertainty that can be tracked over time. Such an index can be of significant use to policy makers, industry practitioners and real estate investors. We show how our framework can be applied to create property type and location subindices. Given the nature of our model, it can be easily applied to measuring uncertainty of a more broad set of illiquid assets, such as: art, collectibles, municipal bonds, among others.

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Tables

Table I. Descriptive statistics of our main variables. Note: Pct(25)/Pct(75) = 25 (75) percentile of target variable. Ann = annualized, that is, the returns are divided by the holding period in years. Returns are in log differences. Note that each repeat sale pair consists of two transactions (observations). The price and net operating income variable both include the buy and sell of a property. Data are provided by Real Capital Analytics (RCA) Inc. For the dummy variables (*Dummy*), the reference categories are: conventional sale (for distressed sale), no intent to either renovate or redevelop, other sub property types (for strip malls), and apartments (for single family houses).

Statistic	N	Mean	St. Dev.	Pctl(25)	Pctl(75)
		Panel A: All properties, repeat sales			
Price (first sale)	14,566	\$ 39,558,205	\$ 83,096,911	\$ 7,604,584	\$ 39,705,733
Price (second sale)	14,566	\$ 46,994,308	\$ 95,990,273	\$ 9,000,000	\$ 48,000,000
return	14,566	0.172	0.378	−0.009	0.391
return (ann)	14,566	0.055	0.101	−0.001	0.106
Net Operating Income (first sale)	14,566	\$ 2,427,193	\$ 4,499,742	\$ 522,629	\$ 2,514,084
Net Operating Income (second sale)	14,566	\$ 2,613,708	\$ 4,800,036	\$ 571,200	\$ 2,761,626
- return	14,566	0.091	0.341	−0.079	0.268
- return (ann)	14,566	0.030	0.101	−0.014	0.063
holding period in years	14,566	5.618	3.429	3	8
		Panel B: Industrial Properties, repeat sales			
Price (first sale)	1,133	\$ 22,163,189	\$ 25,493,844	\$ 7,508,928	\$ 25,894,512
Price (second sale)	1,133	\$ 25,775,283	\$ 30,994,086	\$ 8,600,000	\$ 30,859,330
- return	1,133	0.130	0.382	−0.051	0.368
- return (ann)	1,133	0.038	0.105	−0.009	0.087
Net Operating Income (first sale)	1,133	\$ 1,564,461	\$ 1,655,714	\$ 587,760	\$ 1,899,827
Net Operating Income (second sale)	1,133	\$ 1,612,255	\$ 1,793,674	\$ 603,385	\$ 1,955,213
- return	1,133	0.021	0.316	−0.135	0.186
- return (ann)	1,133	0.012	0.083	−0.022	0.040
holding period in years	1,133	5.951	3.537	3	8
		Panel C: Phoenix Retail, hedonic			
Price	829	\$ 10,318,994	\$ 17,128,670	\$ 3,675,000	\$ 10,600,000
Square Footage	829	54,126	89,185	14,000	69,622
Net Operating Income (p. sqf)	829	\$ 18.382	\$ 11.836	\$ 10.488	\$ 22.945
Walk score	829	50.398	14.367	41	60
Q Score	829	0.573	0.271	0.350	0.810
Age	829	13.259	12.151	4	20
Distressed Sale (*Dummy*)	829	0.051	0.219	0	0
Intent to renovate (*Dummy*)	829	0.012			
Intent to redevelop (*Dummy*)	829	0.011			
Strip mall (*Dummy*)	829	0.642			
		Panel D: Single Family, West Hartford (CT), hedonic			
Price	2,996	\$ 350,197	\$ 163,052	\$ 244,675	\$ 416,089
Square Footage	2,996	2,174.294	1,059.406	1,494	2,558.8
Acres	2,996	0.300	0.335	0.2	0.3
Age	2,996	67.026	24.696	59	82
Single Family (*Dummy*)	2,996	0.870			

Table II. Posteriors and fit of our main model, repeat sales all of the US. Mean is the average of the posterior, 2.5% and 97.5% present the 5% credible intervals of the posterior. The Rhat gives a measure of convergence, with values under 1.1 indicating convergence. SD(Noise) / SD(Signal) gives the hyperparameter of the noise ($\sigma_{\epsilon,t}$) / signal parameter ($\sigma_{\mu,t}$). WA-IC is the Watanabe Information Criterium (Watanabe, 2010), and LOO-IC gives the Leave-One-Out IC (Vehtari et al., 2017).

Variable:	**Mean**	**2.5% credible**	**97.5% credible**	**Rhat**
		Measurement Equation		
Net-Operating Income	0.724	0.713	0.735	0.999
SD(Noise)	0.098	0.068	0.132	1.002
Holding period	0.261	0.242	0.280	1.000
		State Equation		
AR-component	0.555	0.211	0.865	1.009
REIT	0.063	-0.011	0.141	1.005
SD(Signal)	0.331	0.028	0.928	1.018
		Fit-statistics		
WA-IC	1,311			
LOO-IC	-2,621			
nr. repeat sales	14,566			

Table III. Granger Causality tests between a selection of variables. F-statistic is given with corresponding significance levels. *** = significant at the 1%-level, ** = significant at the 5%-level. Both prices and volume are provided to us by Real Capital Analytics / MSCI. *NBER* = recession dummy as published by the National Bureau of Economic Research. Following previous literature (Nguyen Thanh et al., 2020), we fix the lag length at 3 quarters.

(A)	**(B)**	**(A) $\rightarrow$ (B)**	**(B) $\rightarrow$ (A)**
	Impact of signal		
Signal	Prices	4.2787***	2.6511
Signal	Volume	7.8435***	0.7723
Signal	NBER	4.1671***	1.0986
	Impact of noise		
Noise	Prices	6.8734***	0.0832
Noise	Volume	3.6960**	0.9340
Noise	NBER	4.0499**	0.5253

Table IV. Posteriors and fit of our main model, repeat sales Industrial Properties. Mean is the average of the posterior, 2.5% and 97.5% present the 5% credible intervals of the posterior. The Rhat gives a measure of convergence, with values under 1.1 indicating convergence. SD(Noise) / SD(Signal) gives the hyperparameter of the noise ($\sigma_{\epsilon,t}$) / signal parameter ($\sigma_{\mu,t}$). WA-IC is the Watanabe Information Criterium (Watanabe, 2010), and LOO-IC gives the Leave-One-Out IC (Vehtari et al., 2017).

Variable:	**Mean**	**2.5% credible**	**97.5% credible**	**Rhat**
		Measurement Equation		
Net-Operating Income	0.802	0.760	0.845	1.000
SD(Noise)	0.063	0.010	0.141	1.001
Holding period	0.217	0.149	0.285	1.001
		State Equation		
AR-component	0.213	-0.168	0.546	1.002
REIT	0.148	0.023	0.266	1.002
SD(Signal)	0.104	0.003	0.396	1.009
		Fit-statistics		
WA-IC	128			
LOO-IC	-255			
nr. repeat sales	1,133			

Table V. Summary of posteriors of our hedonic models. *Mean:* gives the mean of the posterior, *2.50% (97.50%)* give the 2.5% (97.50%) percentile of posterior. *REIT* denotes the log returns of the Wilshire US Real Estate Investment Trust Price Index (WILLREITPR). *CS Hartford* are the log returns of the Case and Shiller (1987) index for the greater Hartford area. This index is used for our example on single-family homes in West Hartford, CT.

	mean	**2.50% credible**	**97.50% credible**
Panel A: Phoenix Retail			
State			
AR-component	0.871	0.733	0.937
REIT	0.105	0.057	0.154
SD(Signal)	0.461	0.038	1.321
Measurement			
Constant	3.366	3.186	3.536
ln Net Operating Income	0.307	0.254	0.360
ln Square footage	0.996	0.988	1.004
ln(Walk score + 1)	0.017	-0.004	0.039
ln(Q score + 1)	2.297	2.137	2.448
Age	0.000	-0.002	0.001
Age^2	0.000	0.000	0.000
Strip mall	-0.020	-0.034	-0.005
SD(Noise)	0.505	0.355	0.682
Panel B: Housing West Hartford			
State			
AR-component	0.077	-0.660	0.551
CS Hartford	-0.215	-0.888	0.614
SD(Signal)	1.092	0.135	3.101
Measurement			
Constant	7.633	7.374	7.891
Square Footage	0.631	0.596	0.666
Acres	0.037	0.007	0.066
Single Family	0.119	0.077	0.160
Age	-0.003	-0.004	-0.003
Age^2	0.000	0.000	0.000
SD(Noise)	0.256	0.108	0.489

Table VI. Augmented Dickey Fuller test for unit roots for our variables. The critical values (MacKinnon, 1991) are: -2.60 (1pct), -1.95 (5pct), and -1.61 (10pct). Note that we cannot take the log first difference of the 10 year treasury because of some negative values in said time series. Lag length is determined based on the Akaike Information Criterium (AIC).

Variables		**F-statistic**	**sig.**
Volume	Log level	0.7464	
	Log difference	-7.1309	***
Prices (RCA)	Log level	0.1037	
	Log difference	-2.2477	**
S&P500	Log level	1.5692	
	Log difference	-5.5867	***
Fed Fund Rate	Level	-1.8816	*
	Log difference	-4.9781	***
10 year treasury	Level	-1.3572	
	Log difference	NA	
Industrial Production	Log level	0.4790	
	Log difference	-5.7480	***

Figures

Figure 1. Variables used in our state equation. *REIT* denotes the Wilshire US Real Estate Investment Trust Price Index (WILLREITPR) available on Fred. This series is used for all our commercial real estate examples. *CS Hartford* is the Case and Shiller (1987) index for the greater Hartford area. This index is used for our example on single-family homes in West Hartford, CT. The y-axis gives the standardized returns of the corresponding time series. The x-axis give the time quarters (YYYYQ). Grey bars indicated NBER recession periods.

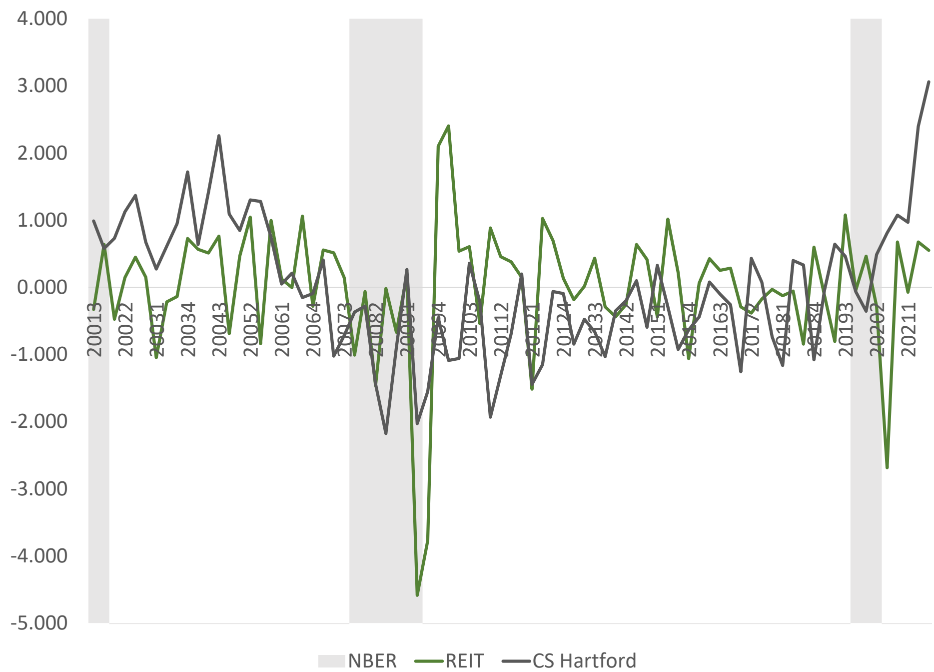

Figure 2. Estimated uncertainty indices for signal and noise, and a price index, using the repeat sales model. The y-axis gives the log values. The x-axis give the time in quarters (YYYYQ). Data starts in 2001Q1 and ends in 2021Q3. Index stays for a self-constructed price index further explained in the text.

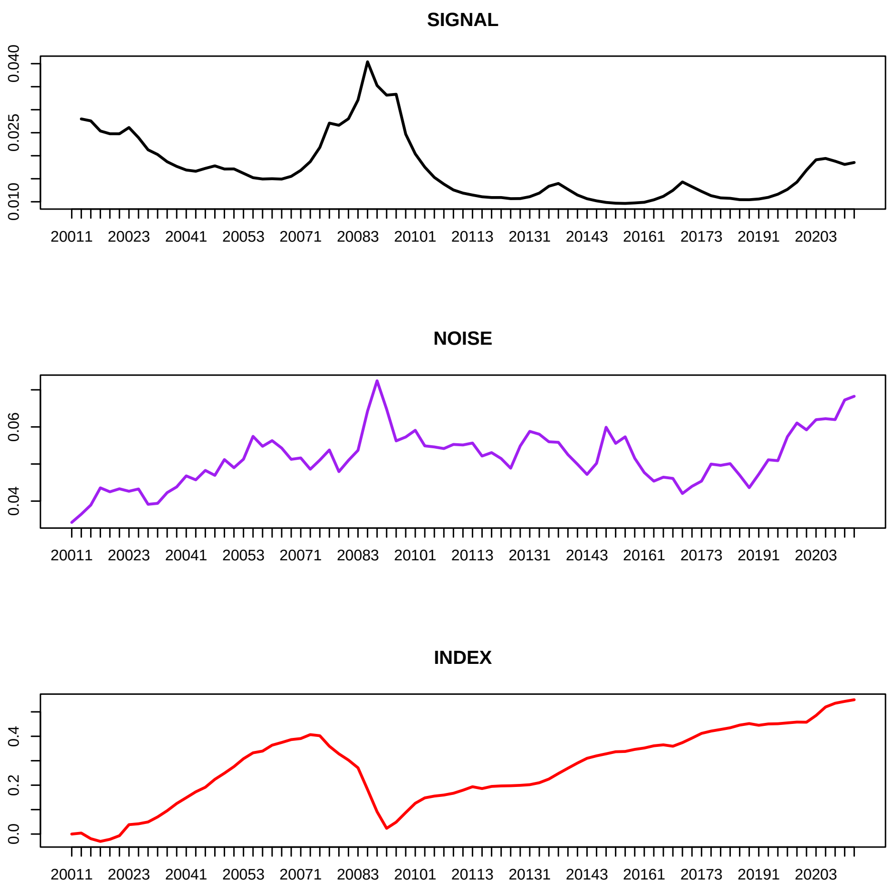

Figure 3. Impulse responses of CRE prices and volume to a shock in the uncertainty indices. Prices are given by the RCA / MSCI CPPI (Commercial Property Price Index). Volume is the change in the sum of transaction prices of all investable commercial property. The y-axis gives the cumulative change over time after shock. The x-axis give the quarters since the shock. Data starts in 2001Q1 and ends in 2021Q3. Blue area represents the 95% confidence bounds.

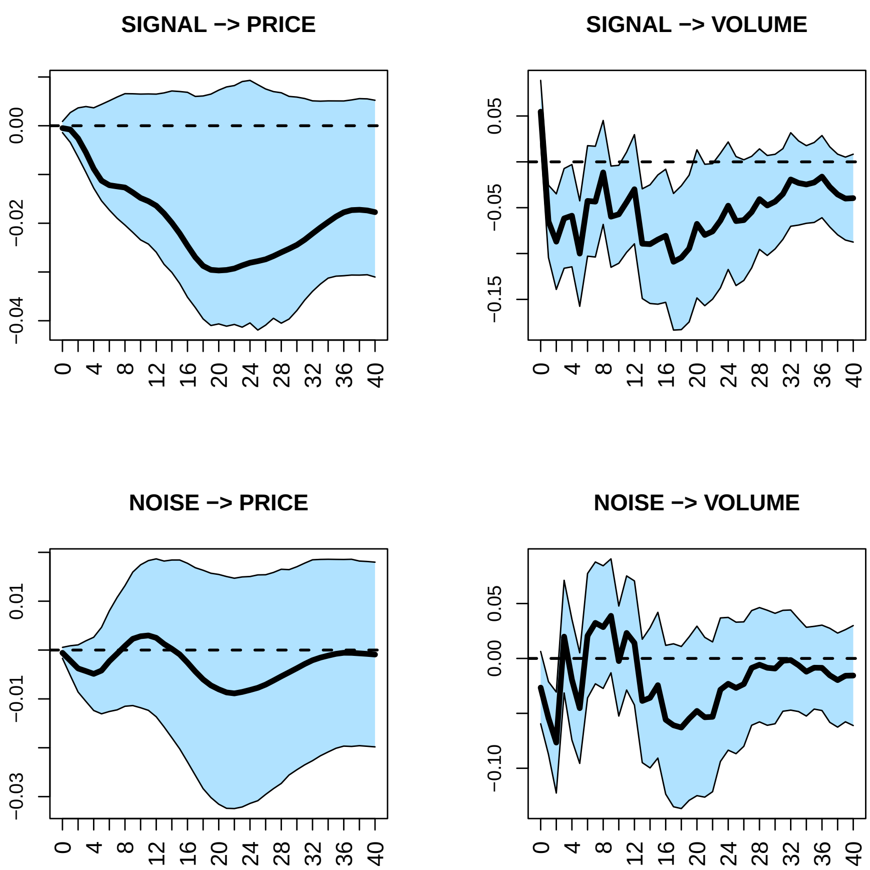

Figure 4. Impulse responses of prices and volume to shocks in prices and volume. Prices are given by the RCA / MSCI CPPI (Commercial Property Price Index). Volume is the change in the sum of transaction prices of all investable commercial property. The y-axis gives the cumulative change over time after shock. The x-axis give the quarters since the shock. Data starts in 2001Q1 and ends in 2021Q3. Blue area represents the 95% confidence bounds.

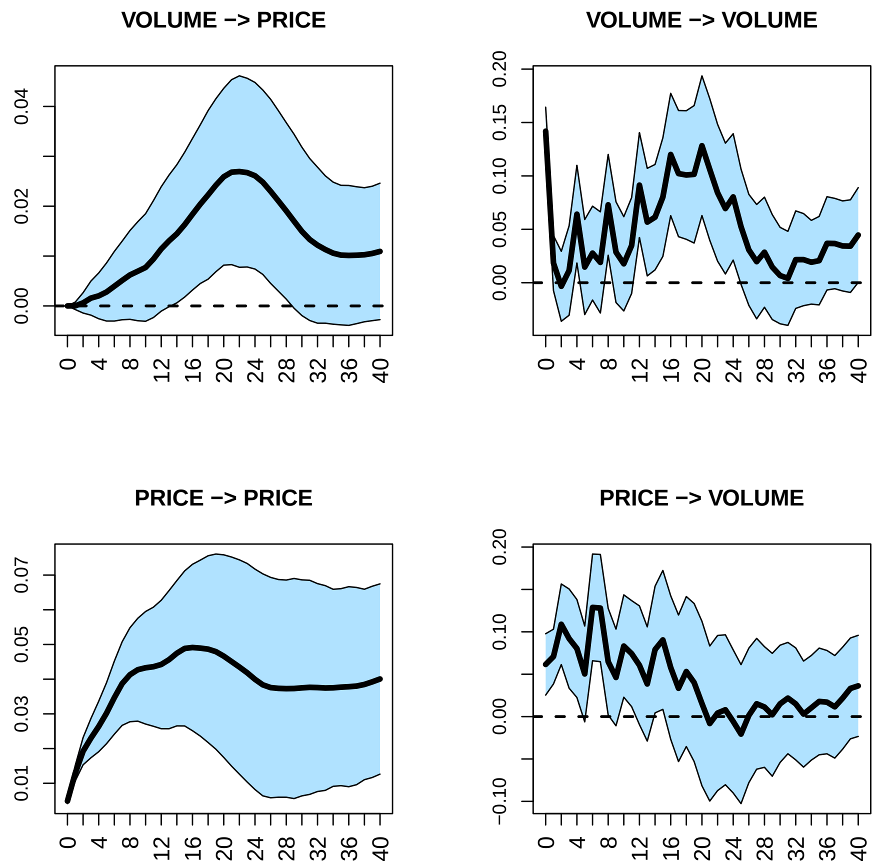

Figure 5. Own uncertainty measures (signal and noise) , macro uncertainty (MU) and financial uncertainty (VIX). Signal and noise are our estimated uncertainty indices. MU(1) is the macro uncertainty measure as proposed by Jurado et al. (2015), and VIX is the CBOE Volatility Index. Grey bars represent the NBER recession periods. All time series are scaled for comparability.

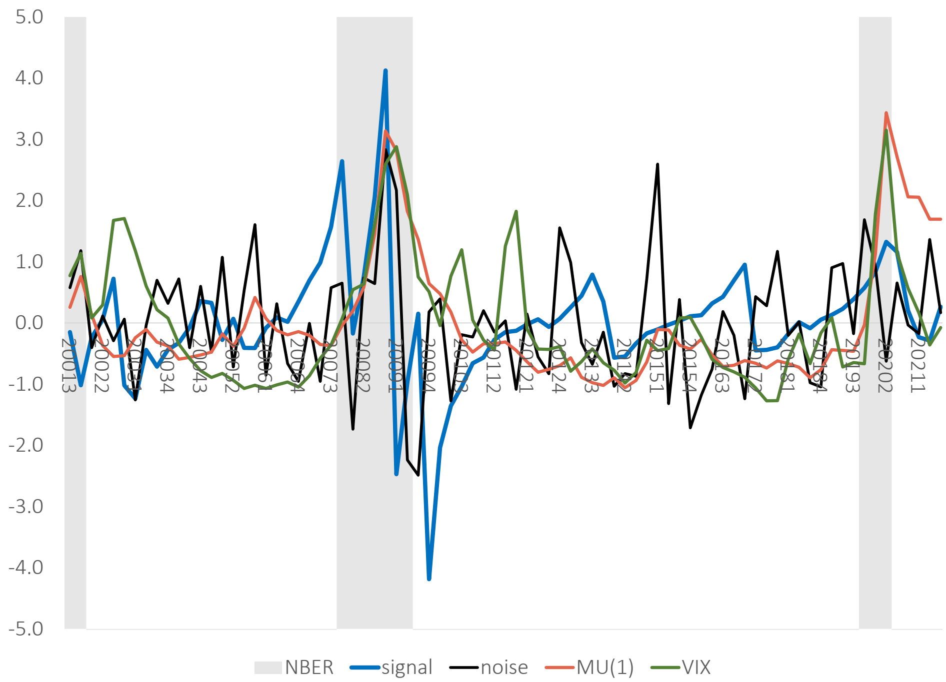

Figure 6. Variance decomposition of CRE prices by various uncertainty variables. *Uncertainty:* indicates the joint effect of the signal and noise indices, which are estimated using our uncertainty model. MU(1) is the macro uncertainty measure as proposed by Jurado et al. (2015), and VIX is the CBOE Volatility Index. x-axis is in quarters.

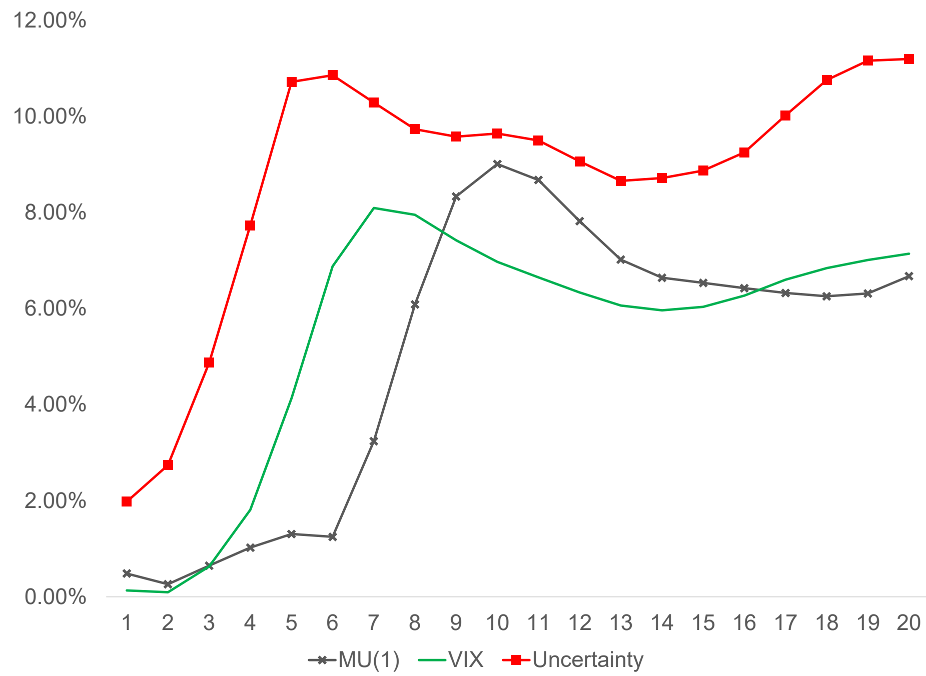

Figure 7. Variance decomposition of CRE transaction volume by various uncertainty variables. *Uncertainty:* indicates the joint effect of the signal and noise indices, which are estimated using our uncertainty model. MU(1) is the macro uncertainty measure as proposed by Jurado et al. (2015), and VIX is the CBOE Volatility Index. x-axis is in quarters.

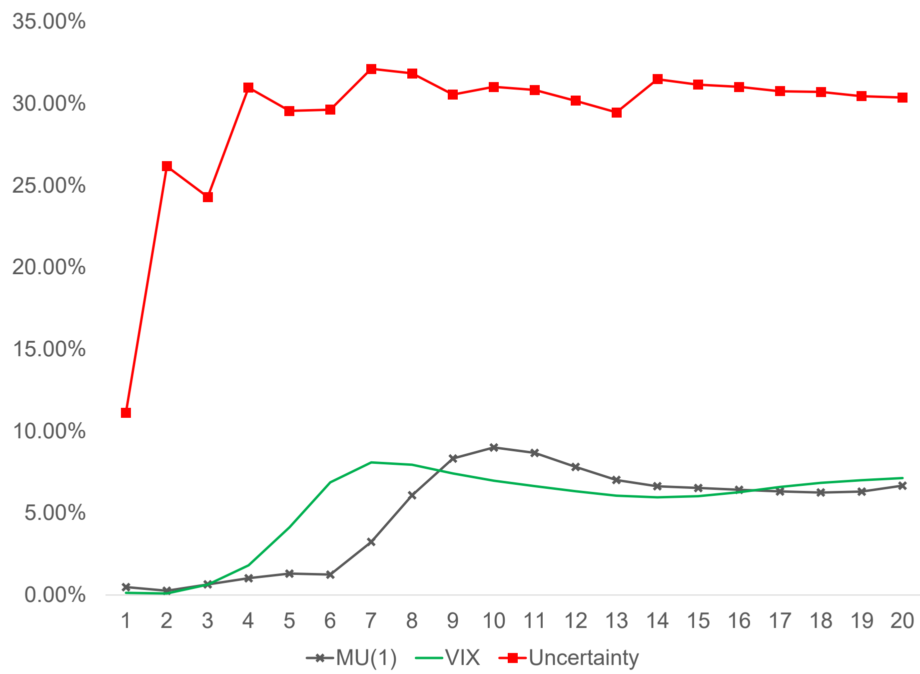

Figure 8. Estimated uncertainty indices for signal and noise, and the remaining trend index, using the repeat sales model for industrial properties in the US. The y-axis gives the log values. The x-axis give the time quarters (YYYYQ). Data starts in 2001Q1 and ends in 2021Q3. *Index:* gives the estimates of μ_t.

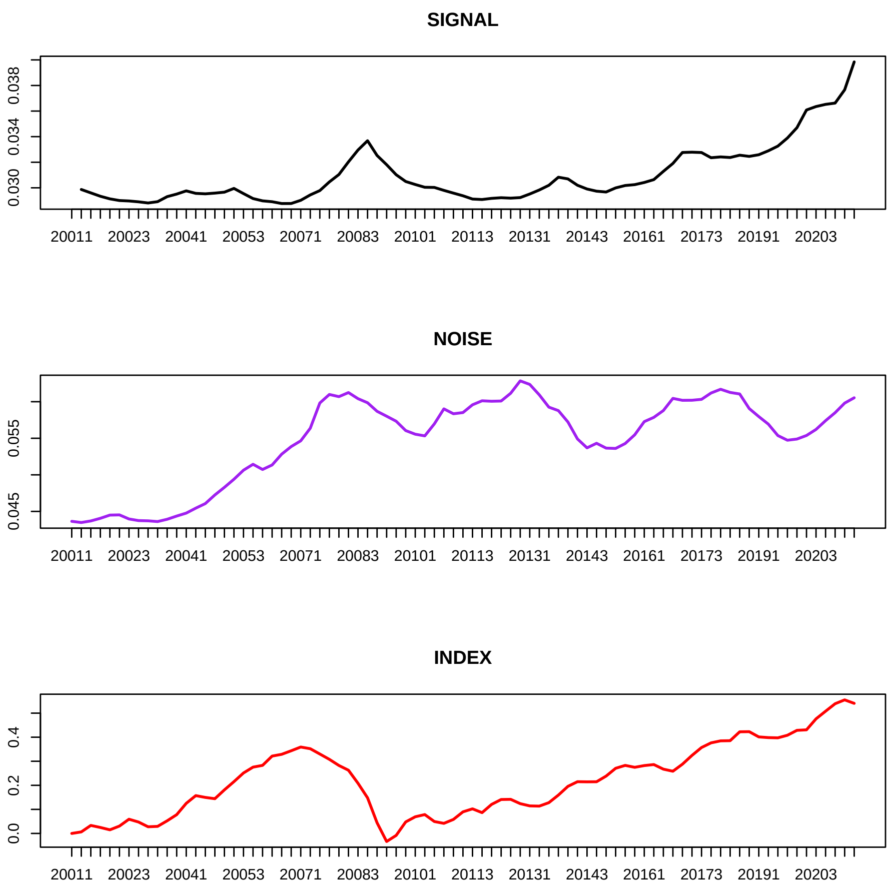

Figure 9. Estimated uncertainty indices for signal and noise, and the remaining trend index, using the hedonic model for Phoenix (AZ) retail. The y-axis gives the log values. The x-axis give the time quarters (YYYYQ). Data starts in 2001Q1 and ends in 2021Q3. *Index:* gives the estimates of μ_t.

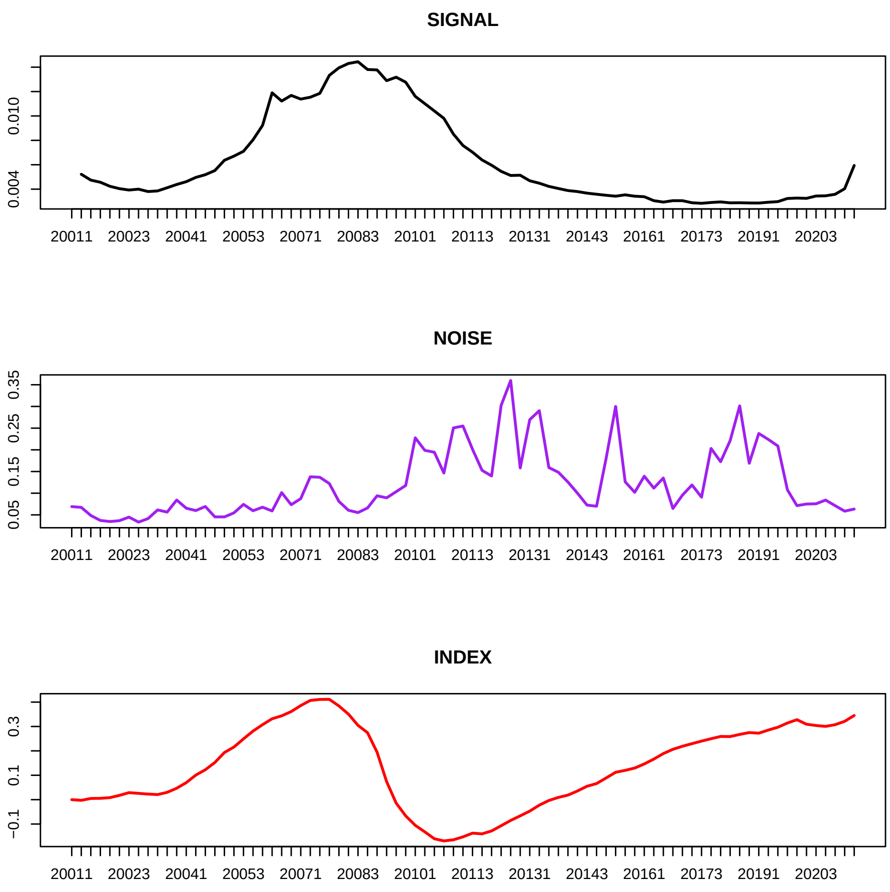

Figure 10. Estimated uncertainty indices for signal and noise, and the remaining trend index, using the hedonic model for single family houses in West Hartford (CT). ***Index:*** **gives the estimates of μ_t.** The y-axis gives the log values. The x-axis give the time quarters (YYYYQ). Data starts in 2001Q1 and ends in 2021Q3.