Daily Valuation of Private Commercial Real Estate

A New Mixed Frequency Approach

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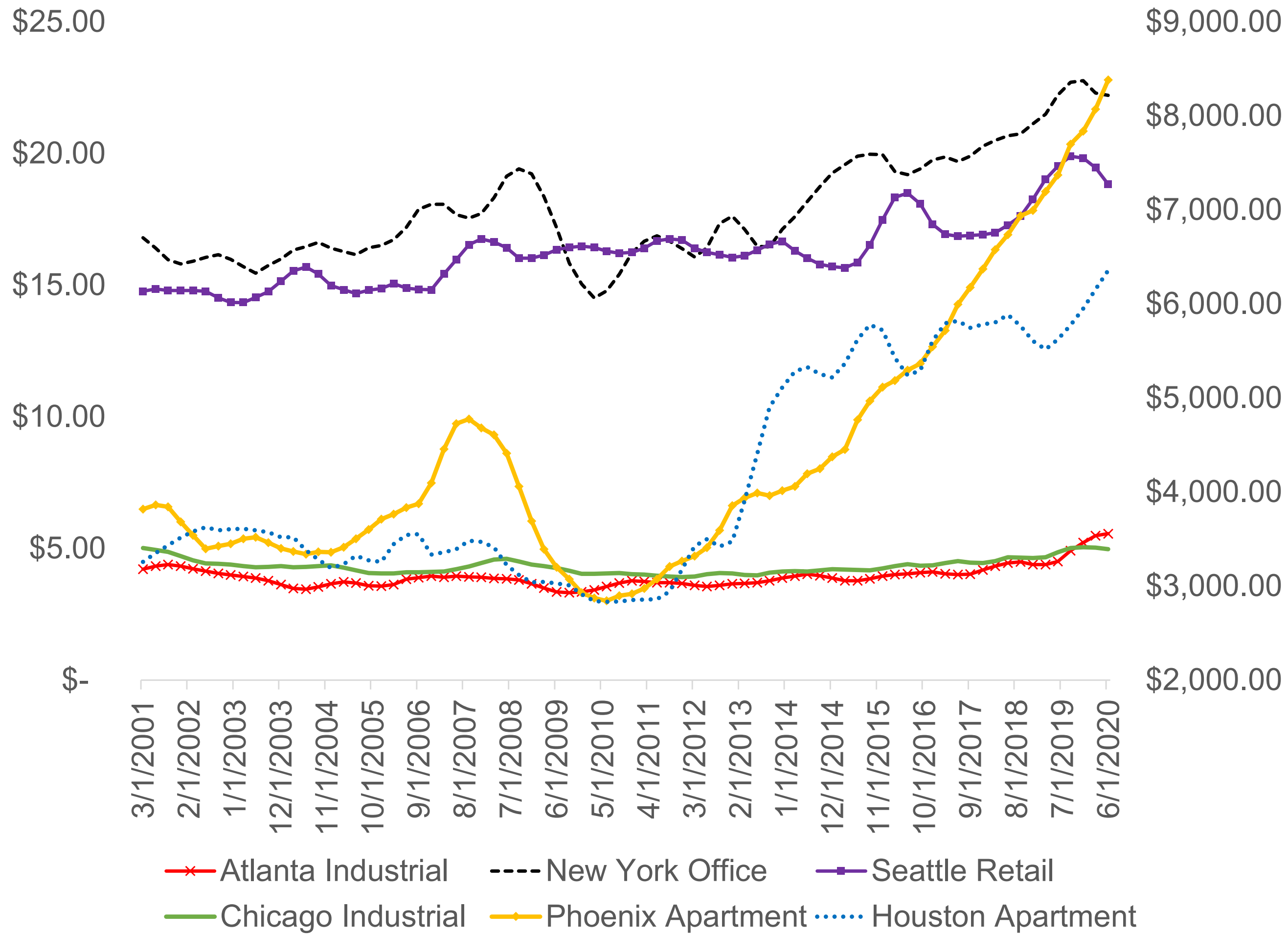
Introduction

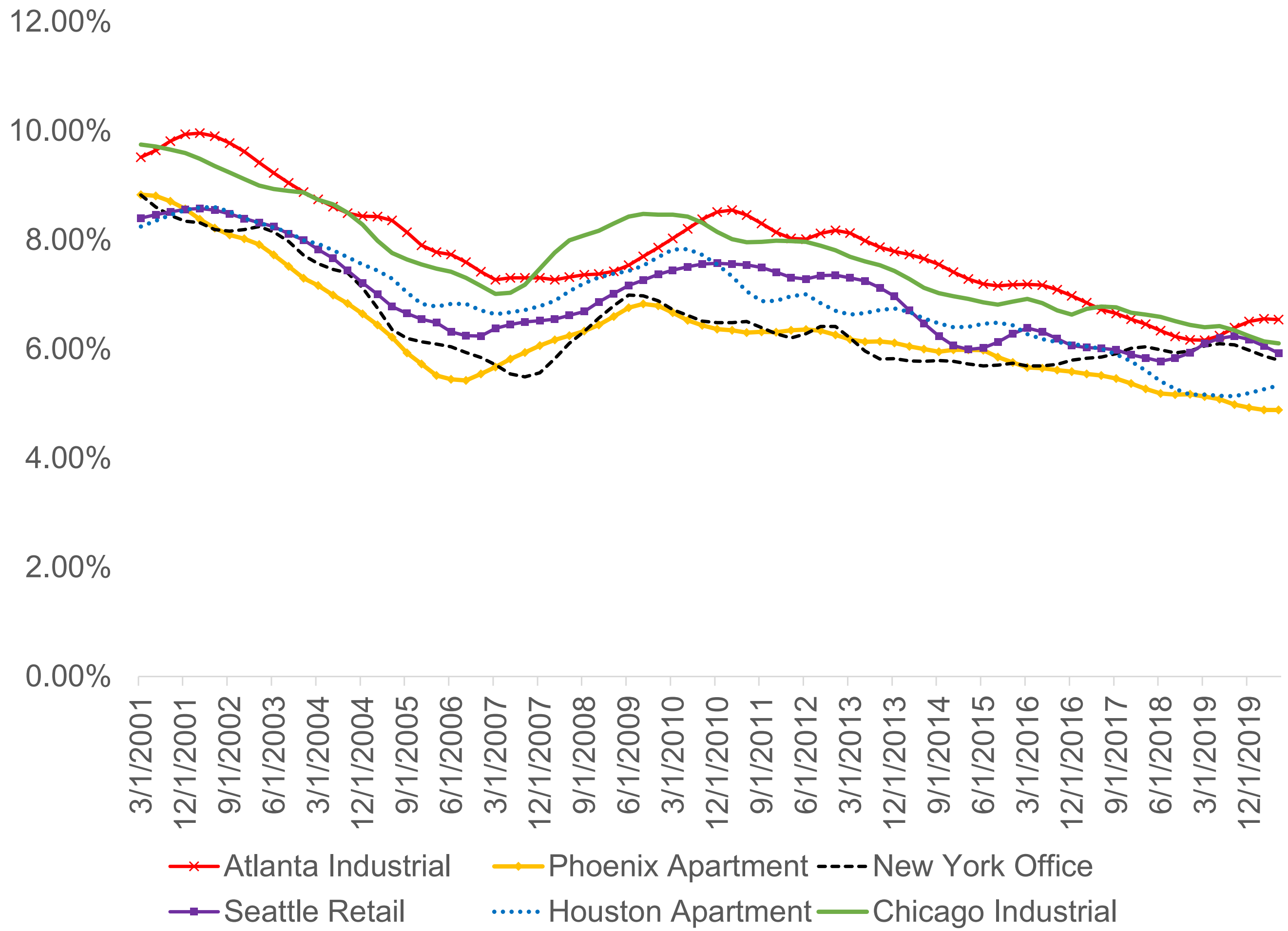
Why do we want daily indexes?

- In the US, commercial real estate is among the largest asset classes;
  - Total value is estimated to be $18 Trillion in 2018 (Zillow & NAREIT).
  - Total value of "investable" commercial real estate is estimated to be $5 Trillion, of which $1 Trillion is owned by REITs (Real Capital Analytics).
  - By comparison, single family housing is valued at $23 Trillion in 2019 (Zillow).
- Having daily indexes can therefore help banks, and policy makers to identify bubbles and crashes in a more timely manner.
- Also, roughly the same group of investors that fall under the NCREIF (National Council of Real Estate Investment Fiduciaries) family are **mandated** to provide daily valuations of their AUM.
  - These include pension funds and insurance funds that operate under a defined contribution plan, or 401(k).
  - Pension/Insurance funds have around $ 250 Billion in real estate AUM (own calculations), about half of that falls under defined contribution.

- In this research we provide a new methodology that allows us to give daily valuations of **real estate portfolios**.
- The only input we need is a daily change in Net-Operating-Income. The change in portfolio value due a changes in P/E ratios (plus something else, more on that later) comes from our model;
  - The **monthly returns** of a repeat sales model (with underlying data from Real Capital Analytics), are modeled explicitly as a function of **daily returns** realized by REITs. More specifically, we use changes in stock values (so levered) of an aggregate of REITs provided to us by NAREIT.
  - To reduce some of the “stock market noise” we apply a weekly moving average on our daily returns. However, the “purely” daily results, and even monthly and quarterly MA smoothed results, are readily available if someone is interested. (I left it out to conserve space.)
- Specifically for this seminar we also prepared a 6 month forecast using our model.

US space markets. NOI per square foot (per unit for apartment, right axis.)

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12/1/2013
9/1/2014
6/1/2015
3/1/2016
12/1/2016
9/1/2017
6/1/2018
3/1/2019
12/1/2019
Atlanta Industrial
Phoenix Apartment
New York Office
Seattle Retail
Houston Apartment
Chicago Industrial

Connection with previous literature

- **Daily pricing** for single family housing has already been researched, see;
  - Bollerslev, Patton, and Wang, 2016, JAE.
  - However, this has not been the case for commercial real estate;
    - Lack of transactions.
    - Lack of characteristics.
    - Large amount of heterogeneity.
- **Structural time series repeat sales models.** See for example;
  - Francke, 2010; Francke and van de Minne, 2017; van de Minne et al., forthcoming, JREFE.
- **Mixed frequency** modelling and temporal aggregation. See for example;
  - Ghysels, Sinko, and Valkanov, 2007, ER and Proietti, 2006, EJ
- The **relationship between public and private real estate**. See for example;
  - Barkham and Geltner, 1995; Geltner and Kluger, 1998, REE

Methodology

Repeat Sales Model (1/2)

- First of all, our private real estate data is a cross sectional dataset of real estate transactions.
- To estimate our time series (capital gains), we use a repeat sales framework.
- Normal hedonic Equation is given by;

$$\ln P_{it} = \mu_t + X_{it}\beta + Z_{it}\alpha + \epsilon_{it}, \tag{1}$$

- with;
  - μ being time dummies at time t.
  - X being the **observed** characteristics of property i, with corresponding vector of coefficients β.
  - Z being the **unobserved** characteristics of property i, with corresponding vector of coefficients ζ.
  - The residuals are given by ϵ which is assumed to be normally distributed; $\epsilon \sim N(0, \sigma_\epsilon^2)$.

Repeat Sales Model (2/2)

- With repeat sales model, we replace all observed (and hopefully unobserved) characteristics with property level dummies;

$$\ln P_{it} = \mu_t + \delta_i + \epsilon_{it}, \tag{2}$$

- with δ_i being the property fixed effect.
- Things become even more tractable when modelling the returns, as the property fixed effect cancels;

$$\ln P_{it} - \ln P_{is} = \mu_t - \mu_s + \epsilon_{it} - \epsilon_{is}, \tag{3}$$

- where s is time of buy, and t is time of sell.
- Finally, we add the change in Net Operating Income (NOI) to our repeat sales model, as this is an important input (on a daily basis) to explain changes in prices. This gives us **measurement Eq**;

$$\ln P_{it} - \ln P_{is} = \mu_t - \mu_s + \omega(\ln \text{NOI}_{it} - \ln \text{NOI}_{is}) + \epsilon_{it} - \epsilon_{is}. \tag{4}$$

- There are two issues with the repeat sales model for our application;
  - Estimates of index can be “noisy” due to limited observations and heterogeneity.
  - Our (private) real estate data is on a monthly frequency.
- To kill two birds with one stone, we use a structural time series approach, in which we model our monthly returns as a function of higher frequency REIT prices.
- For the **state Eq.** we therefore get;

$$\Delta\mu_t \sim \left(\sum_{j=0}^{l} \lambda_j \Delta\bar{x}^{(k)}_{mt-j}, \sigma_\mu\right). \tag{5}$$

- If τ is the higher frequency k (say days), then the REIT returns (Δx_τ) are observed at $\tau = (t-1)m+1, \ldots, tm$.
- Note that there are two inputs; the **frequency** and the **amount of lags**.

- As a quick example, say we estimate a monthly index (μ).
- The REIT returns are averages over a week, meaning that $m = 4$. (In other words there are always 4 weeks in 1 month.)
- We take up two months worth of lags of REITS, or 4 weeks $\times$ 2 months = 8 coefficients in vector λ.
- We get;

$$\begin{bmatrix} \Delta\mu_2 \\ \vdots \\ \Delta\mu_T \end{bmatrix} = \begin{bmatrix} \Delta x_8 & \cdots & \Delta x_1 \\ \vdots & \vdots & \vdots \\ \Delta x_{4T} & \cdots & \Delta x_{4T-7} \end{bmatrix} \begin{bmatrix} \lambda_1 \\ \vdots \\ \lambda_8 \end{bmatrix} + \begin{bmatrix} \eta_2 \\ \vdots \\ \eta_T \end{bmatrix}. \tag{6}$$

- If μ_t would be simple univariate time series data, this model could be estimated by means of OLS.

- We found the most interesting results (but not per se the best fit) if fix our lags, so they always add up to 1 years worth of lags.
- This also means the we potentially have a **lot** of coefficients in vector λ.
- The most widely used method in literature is the so-called Almon transformation, like quadratic or exponential Almon functions. However, we found that this did terribly in our application.
- In stead, we use a random walk on the parameter;

$$\Delta\lambda_j \sim N(0, \sigma_\lambda), \tag{7}$$

$$\lambda_1 \sim N(0, 1). \tag{8}$$

- We have experimented with different frequency for τ.
- The model is estimated using the No-U-Turn Sampler (which is proper MCMC, akin to HMC).
- We denote our model the **Mixed (K) Frequency** repeat sales model (*MKF*).

Data

- We utitlize two sources;
  - **Real Capital Analytics (RCA).** Repeat sales transaction data of CRE between 2006 - 2020, including NOI.
  - **NAREIT.** Composite index of stock prices of listed REITs, both all and for only apartments.

RCA data for **all properties**;

	mean	**sd**	**1Qrt**	**3Qrt**
Price	\$ 45,619,870	\$100,052,553	\$7,050,209	\$ 45,000,000
- return	0.172	0.380	-0.021	0.402
- return (YoY)	0.053	0.109	-0.004	0.102
NOI	\$ 2,574,722	\$ 5,055,628	\$ 441,771	\$ 2,677,553
- return	0.105	0.349	-0.085	0.288
- return (YoY)	0.032	0.106	-0.016	0.065
Year of sale	2013	4	2009	2016
N		10,482		

- We utitlize two sources;
  - **Real Capital Analytics (RCA).** Repeat sales transaction data of CRE between 2006 - 2020, including NOI.
  - **NAREIT.** Composite index of stock prices of listed REITs, both all and for only apartments.

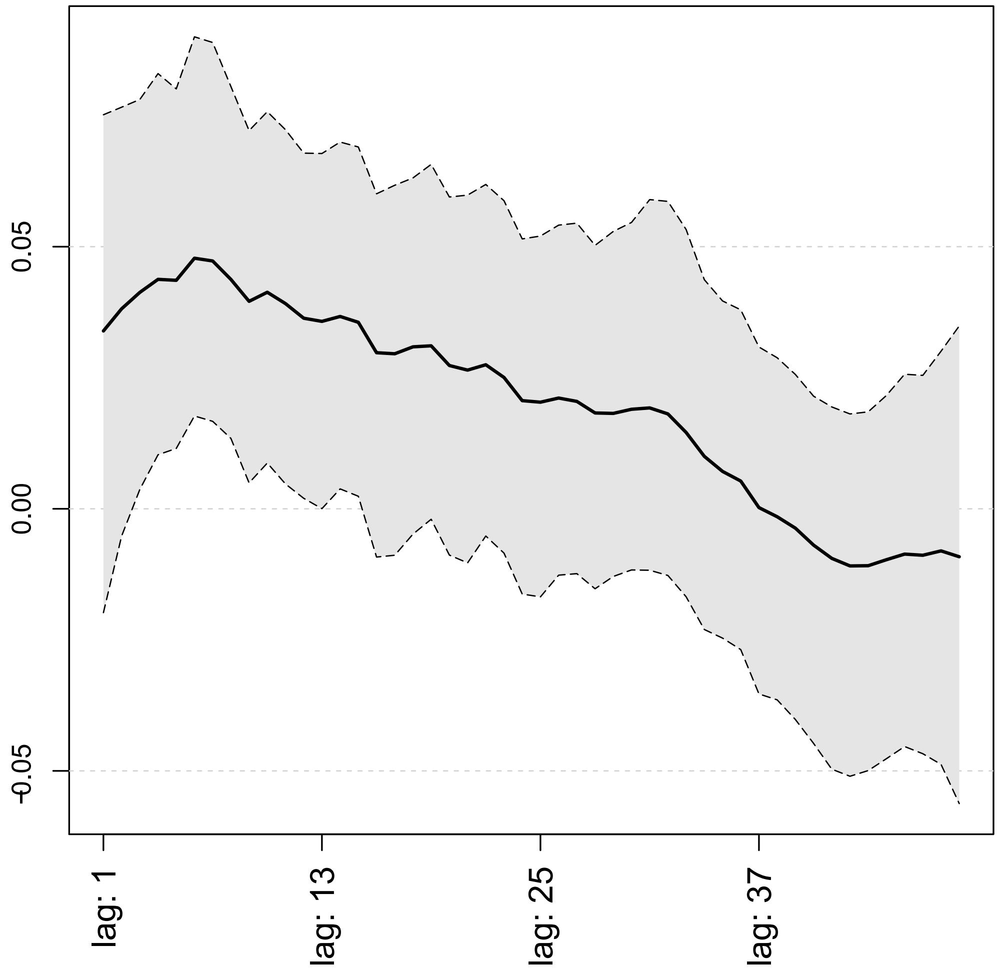
RCA data for **Apartments**;

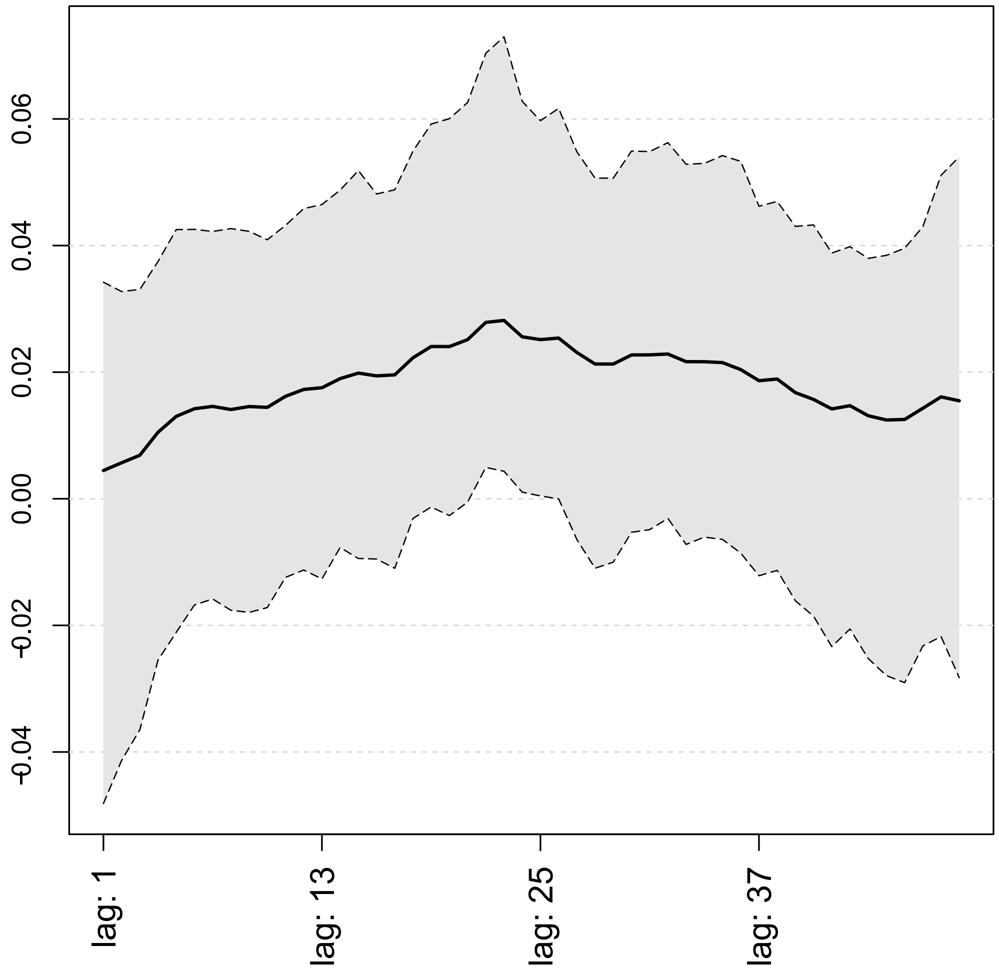
	mean	sd	1Qrt	3Qrt
Price	$ 22,891,264	$ 27,319,159	5,400,000	$31,300,000
- return	0.319	0.338	0.134	0.507
- return (YoY)	0.083	0.100	0.026	0.131
NOI	$ 1,262,857	$ 1,382,152	$ 314,558	1,801,016
- return	0.243	0.340	0.049	0.427
- return (YoY)	0.064	0.113	0.010	0.098
Year of sale	2013	4	2010	2017
N		3,804		


600.00
500.00
400.00
300.00
200.00
100.00
0.00
03-Jan-06
03-Jan-07
03-Jan-08
03-Jan-09
03-Jan-10
03-Jan-11
03-Jan-12
03-Jan-13
03-Jan-14
03-Jan-15
03-Jan-16
03-Jan-17
03-Jan-18
03-Jan-19
03-Jan-20
All
Apartment

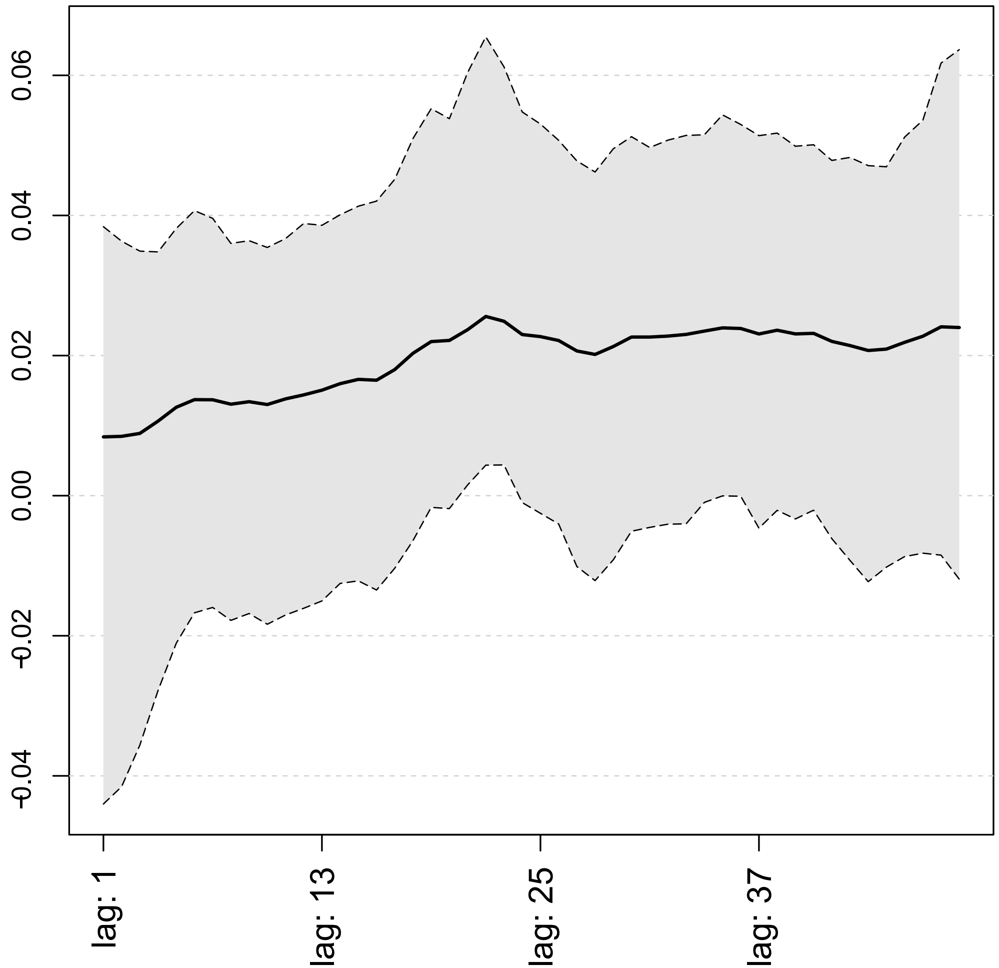
Results - Estimates on λ

All property types



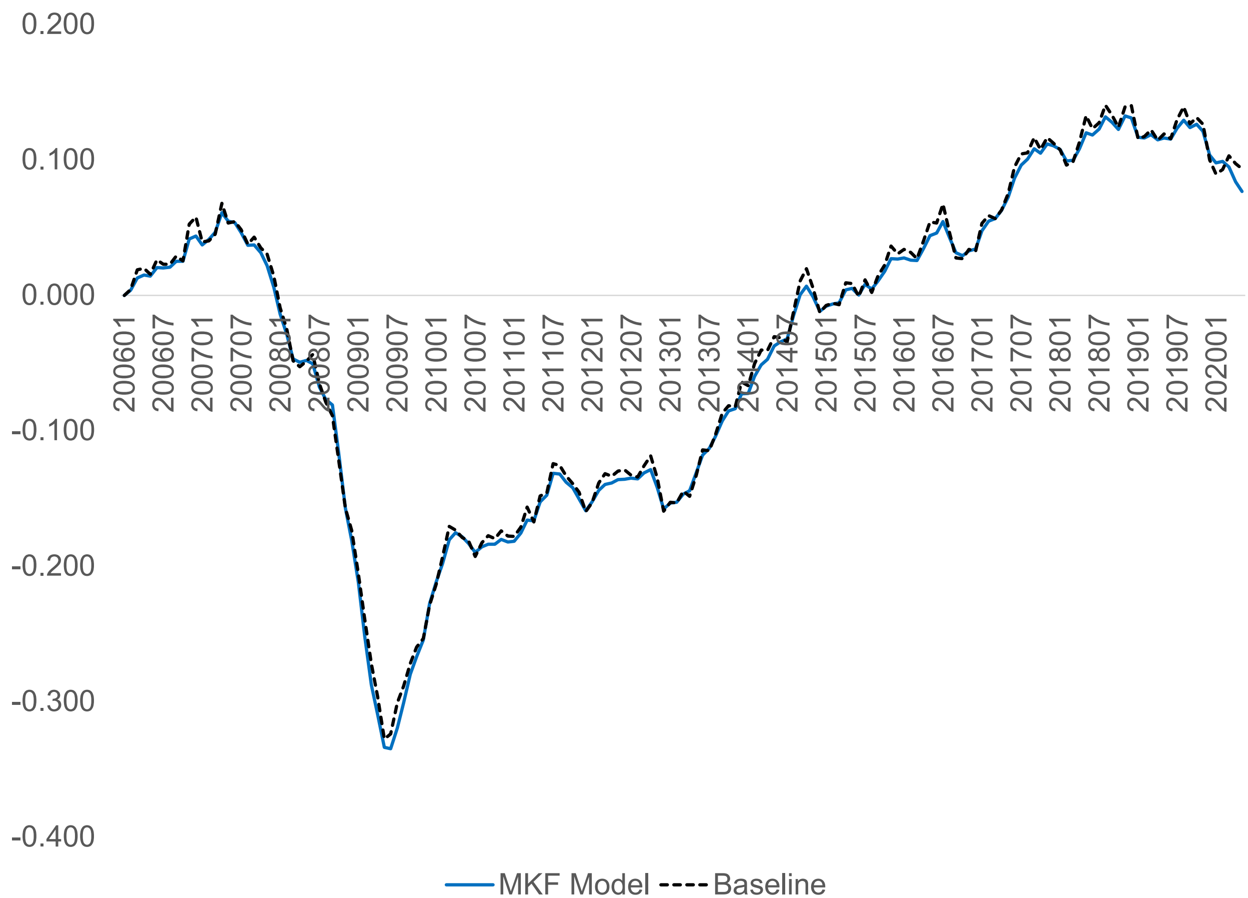

0.06
0.04
0.02
0.00
−0.02
−0.04
lag: 1
lag: 13
lag: 25
lag: 37

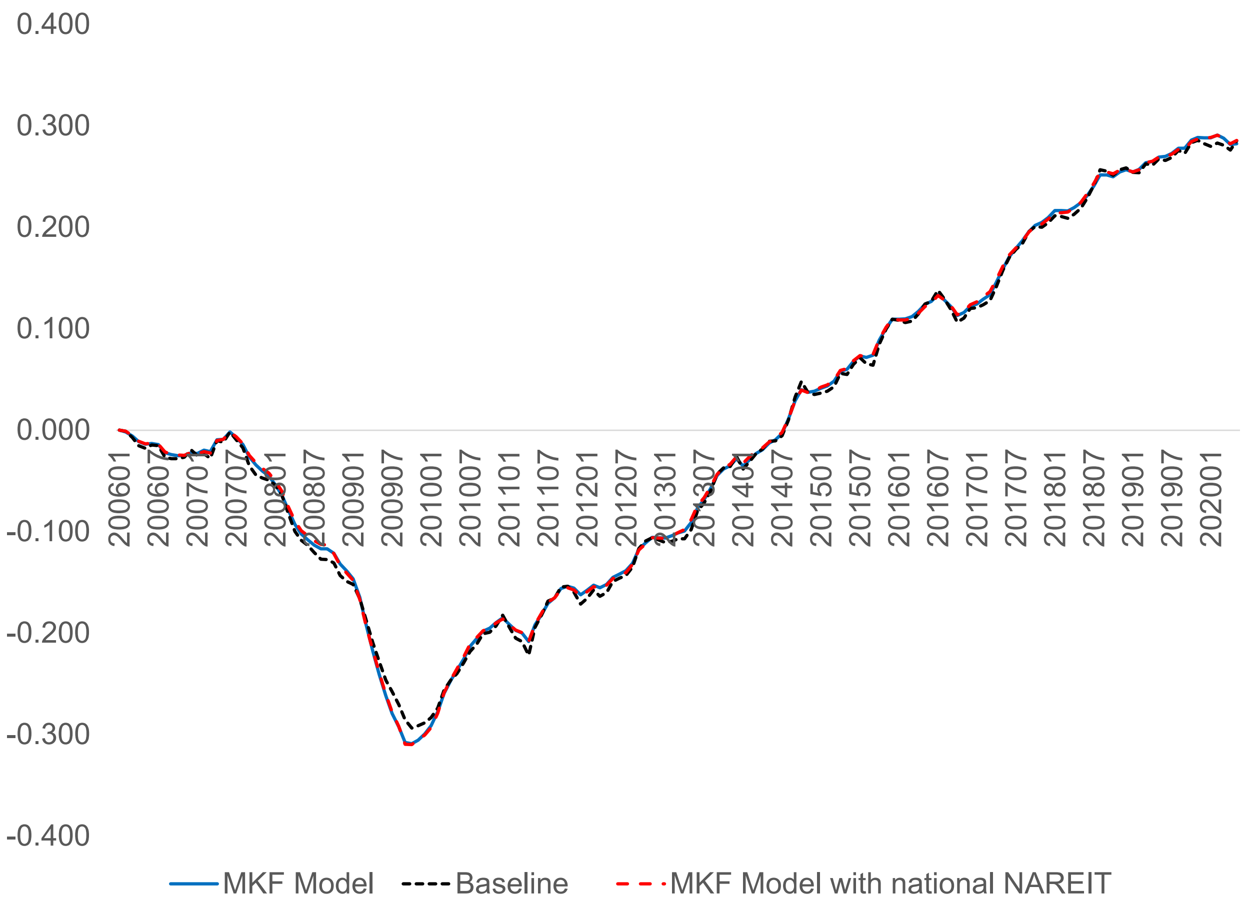
Apartment with all types NAREIT returns



Results - Indexes

Indexes - all types





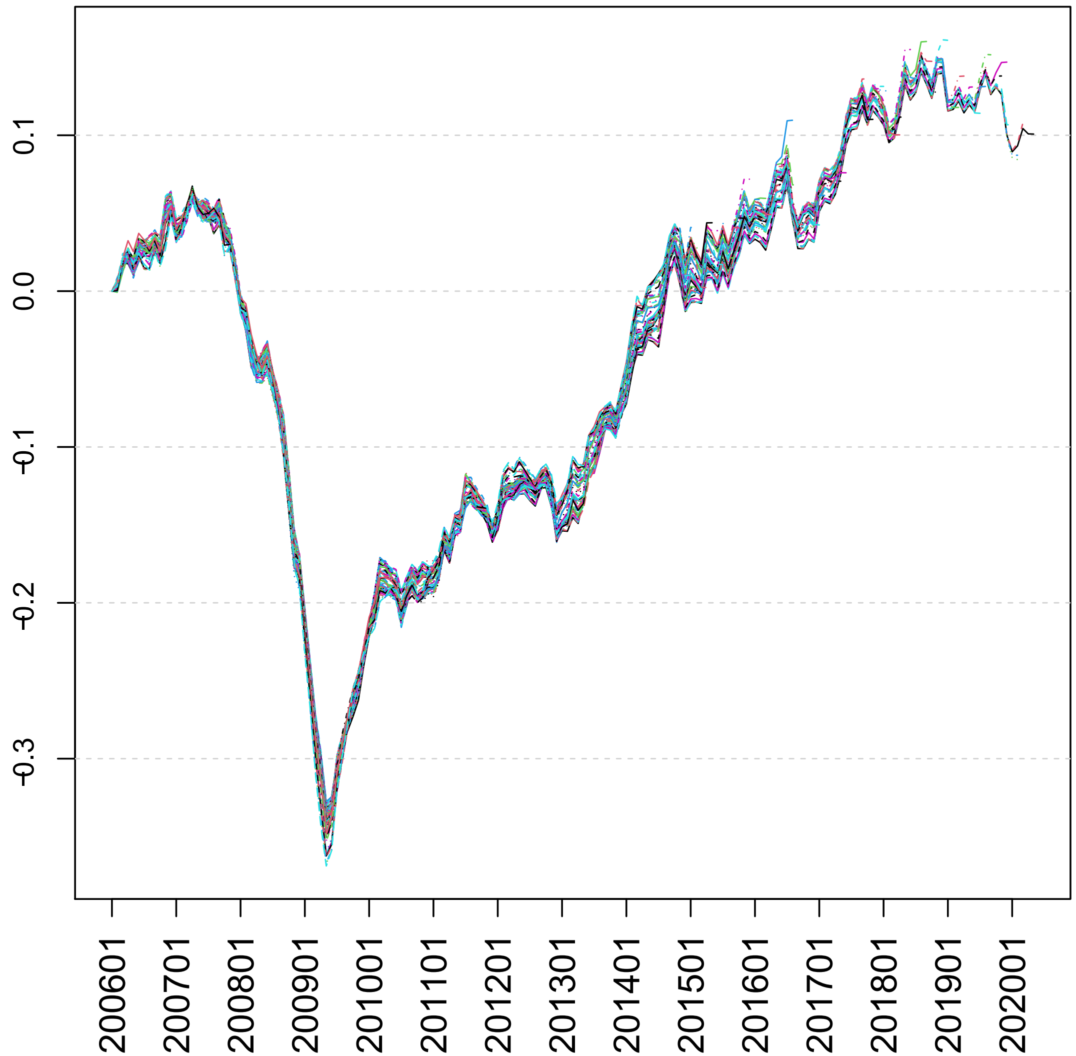
0.400
0.300
0.200
0.100
0.000
-0.100
-0.200
-0.300
-0.400
200601
200607
200701
200707
200801
200807
200901
200907
201001
201007
201101
201107
201201
201207
201301
201307
201401
201407
201501
201507
201601
201607
201701
201707
201801
201807
201901
201907
202001
MKF Model
Baseline
MKF Model with national NAREIT

	All types		*Apartments*		
	Baseline	**MKF**	**Baseline**	**MKF**	**MKF - Robust**
	Return Statistics				
mean (YoY)	0.007	0.005	0.020	0.020	0.020
sd	0.013	0.011	0.009	0.008	0.008
min	-0.035	-0.041	-0.022	-0.027	-0.026
max	0.027	0.027	0.027	0.018	0.020
	Parameter Estimates				
ω	0.751	0.751	0.614	0.614	0.614
σ_ϵ	0.227	0.228	0.182	0.182	0.182
σ_μ	0.020	0.013	0.018	0.013	0.012
σ_λ	-	0.011	-	0.008	0.007

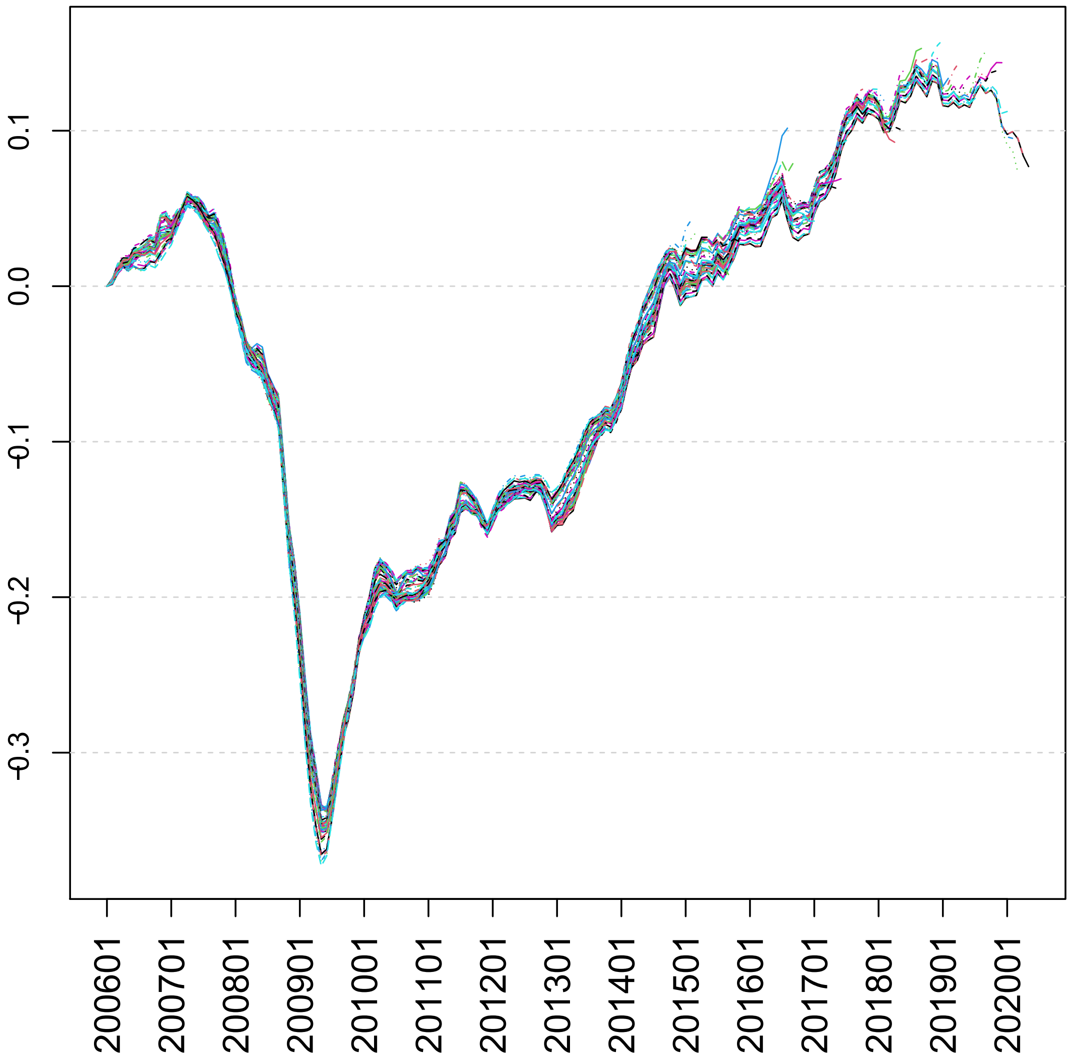
Fit

- Measuring model fit of indexes is challenging, because standard fit statistics are all based on cross-sectional residuals.
- In order to measure fit, we will do a revision analysis.
  - First we run the model using data only up to jan 2015.
  - We subsequently estimate the model using only data up to feb 2015, all the way to the end of our sample, which is jun 2020.
  - This gives us 65 different indexes.
  - We subsequently compute the statistics on the following returns;
    1. We forecast 1 month out and and compare the forecast error with the actual return.
    2. We compare the final period's revisions. (I.e. the "embarrassing revision".)
    3. We compute statistics on all revisions, not just the final period(s).

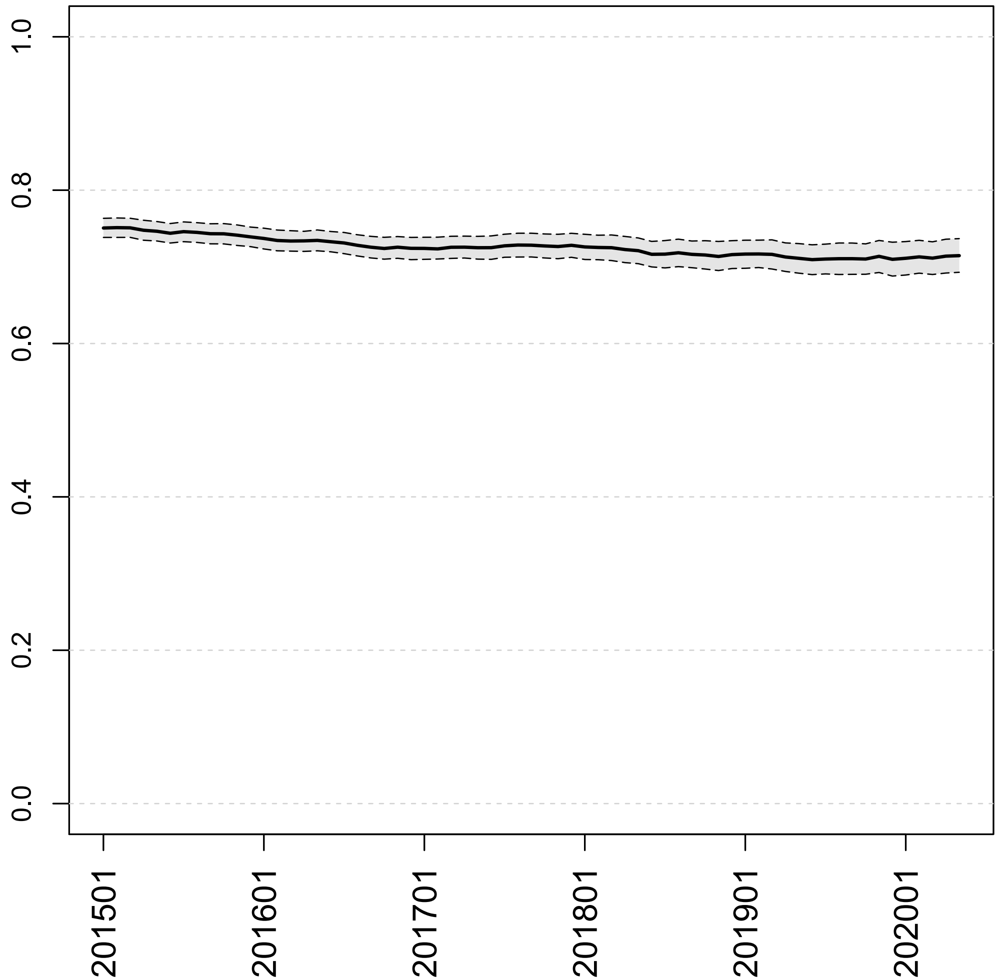
Index revisions (all types) of Baseline model - including forecast.



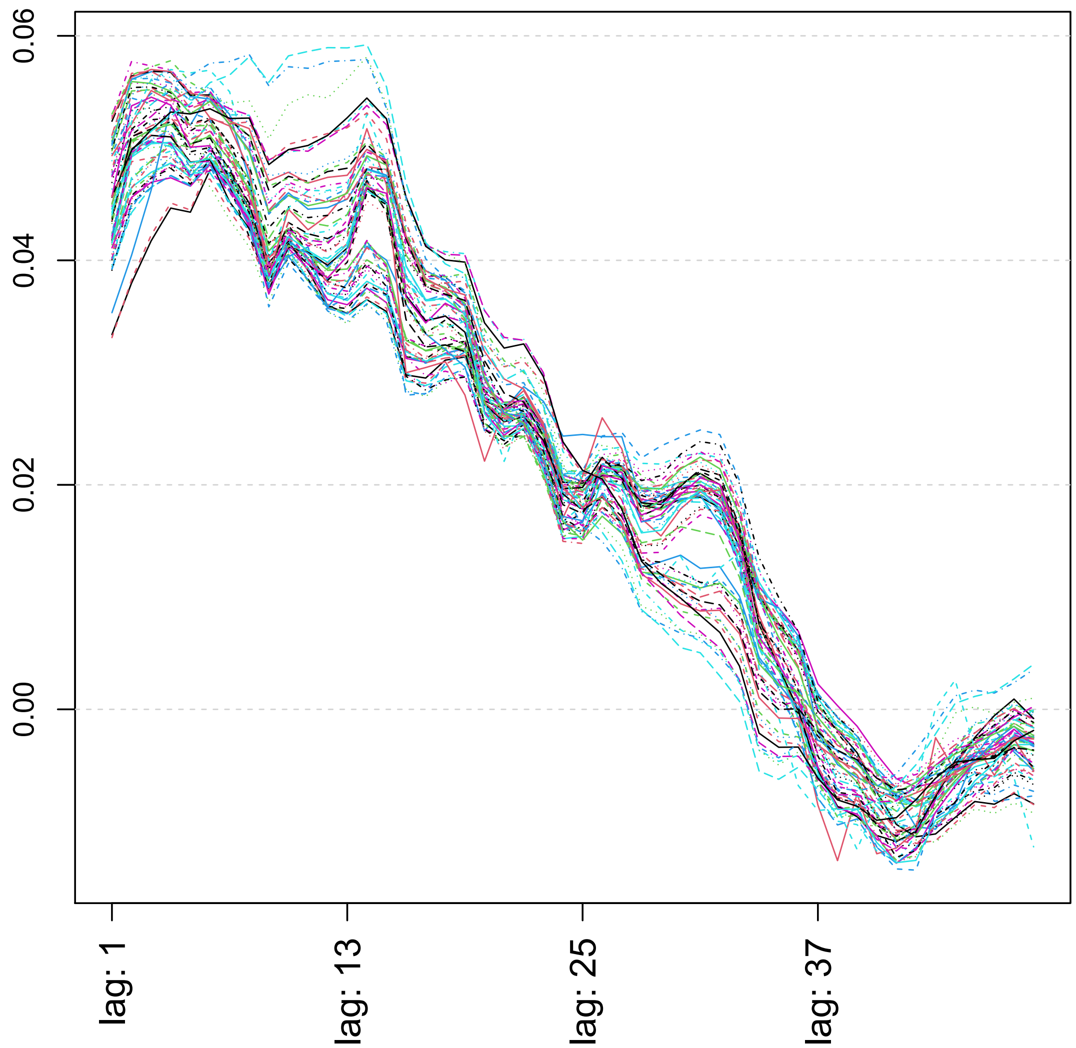
Index revisions (all types) of the MKF model - including forecast.



Revision of parameters (1/2); Net-Operating-Income (ω)



Revision of parameters (2/2); REIT returns (λ)



MAPE Statistics - all types.

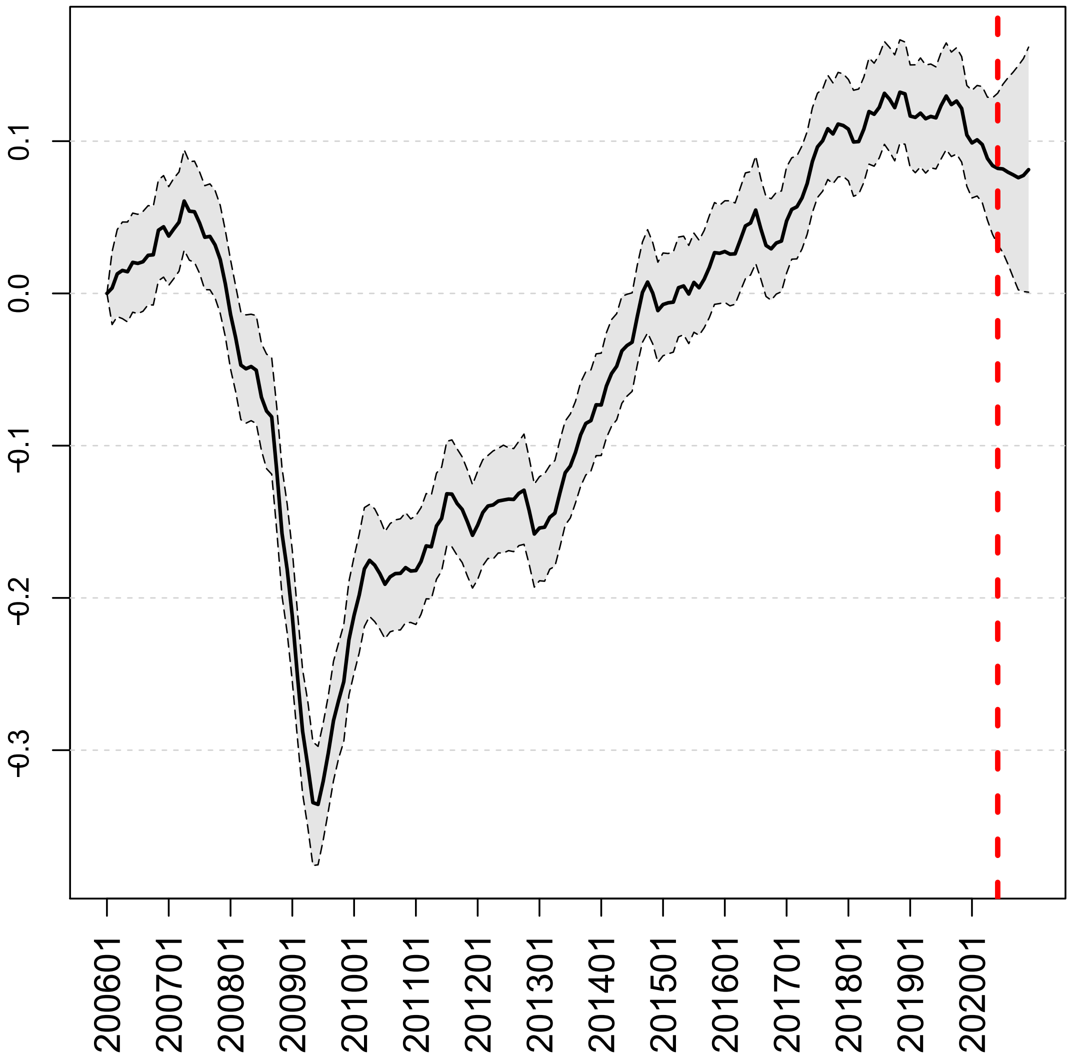
	mean	mape	sd	min	max
			Baseline		
forecast	-0.00122	0.01072	0.01285	-0.02693	0.02751
final period	-0.00027	0.00396	0.00471	-0.01045	0.01070
all	-0.00001	0.00012	0.00015	-0.00037	0.00033
			MKF repeat sales model		
forecast	-0.00005	0.00525	0.00662	-0.01595	0.01892
final period	-0.00003	0.00288	0.00363	-0.00918	0.00775
all	0.00000	0.00008	0.00010	-0.00024	0.00023

MAPE Statistics - Apartments.

	mean	**mape**	**sd**	**min**	**max**
		Baseline			
forecast	-0.00175	0.00555	0.00663	-0.01827	0.01106
final period	-0.00085	0.00295	0.00355	-0.00862	0.00740
all	-0.00003	0.00009	0.00010	-0.00029	0.00019
		MKF repeat sales model			
forecast	-0.00047	0.00361	0.00446	-0.01348	0.00821
final period	-0.00026	0.00224	0.00281	-0.00805	0.00610
all	-0.00001	0.00007	0.00009	-0.00019	0.00018
		MKF repeat sales model - robust			
forecast	-0.00061	0.00351	0.00424	-0.01205	0.00819
final period	-0.00059	0.00218	0.00261	-0.00721	0.00607
all	-0.00001	0.00007	0.00008	-0.00017	0.00014

December 2020 forecast and the GFC

Forecast


0.1
0.0
-0.1
-0.2
-0.3
200601
200701
200801
200901
201001
201101
201201
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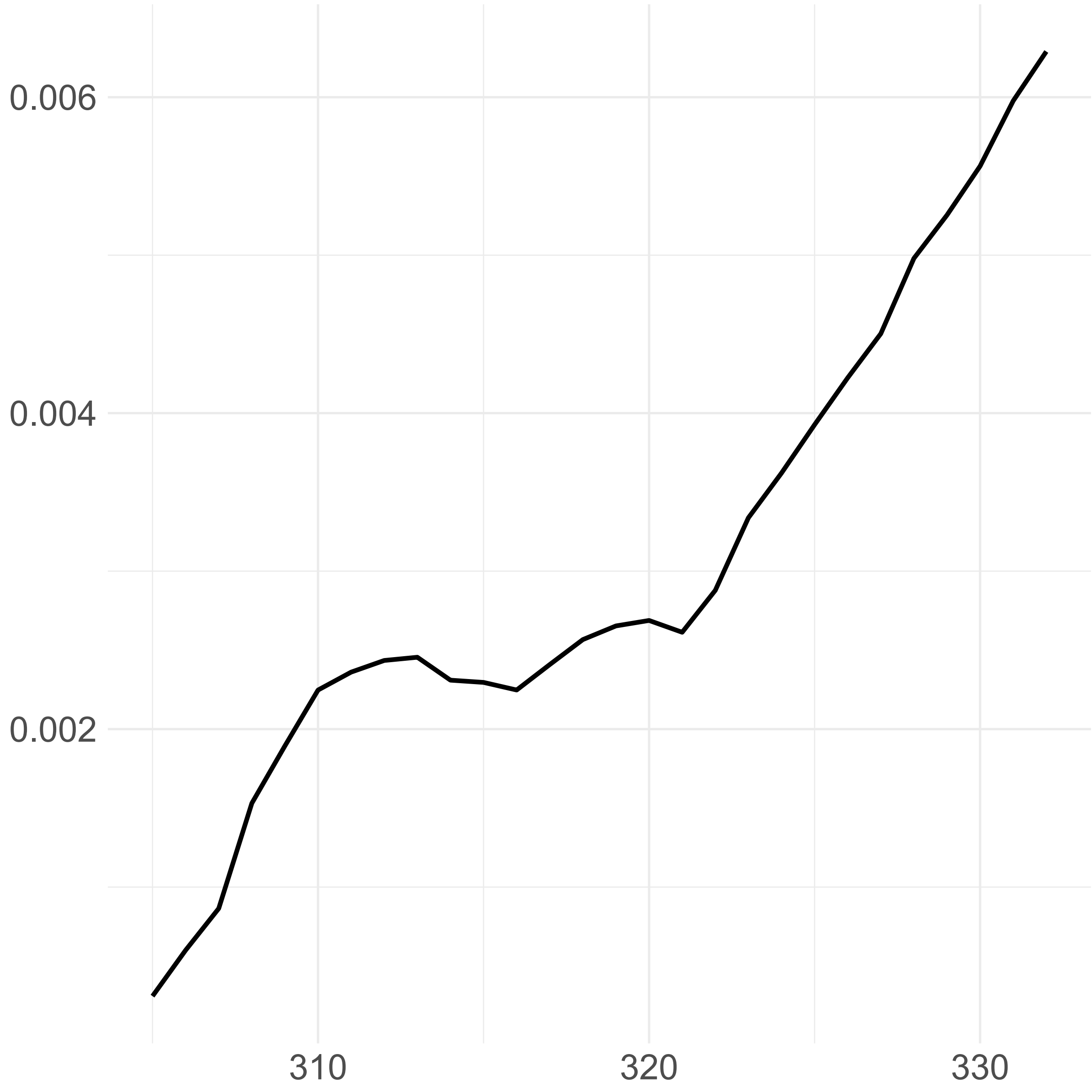
201701
201801
201901
202001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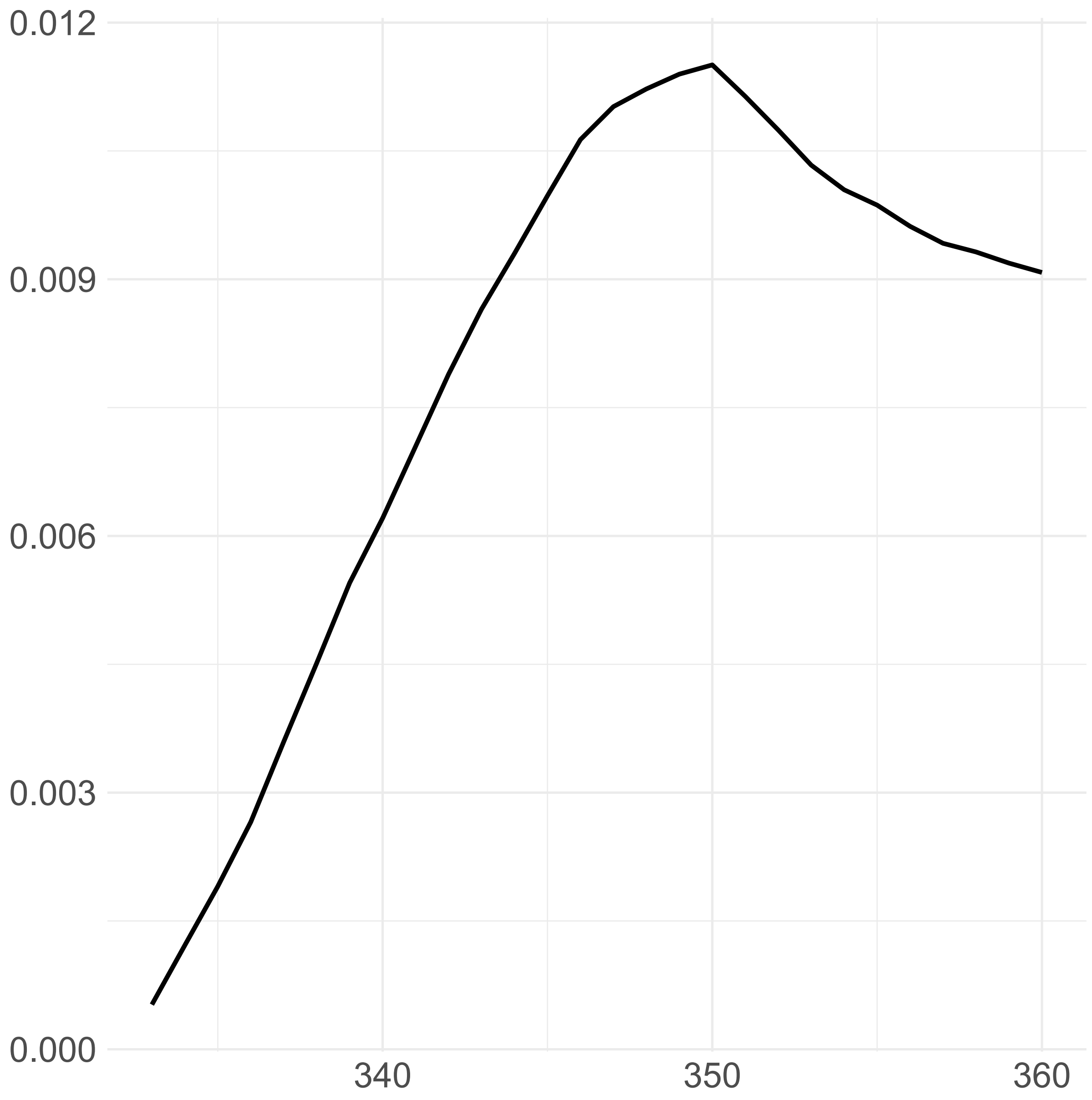
0.004
0.002
310
320
330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0.006
0.003
0.000
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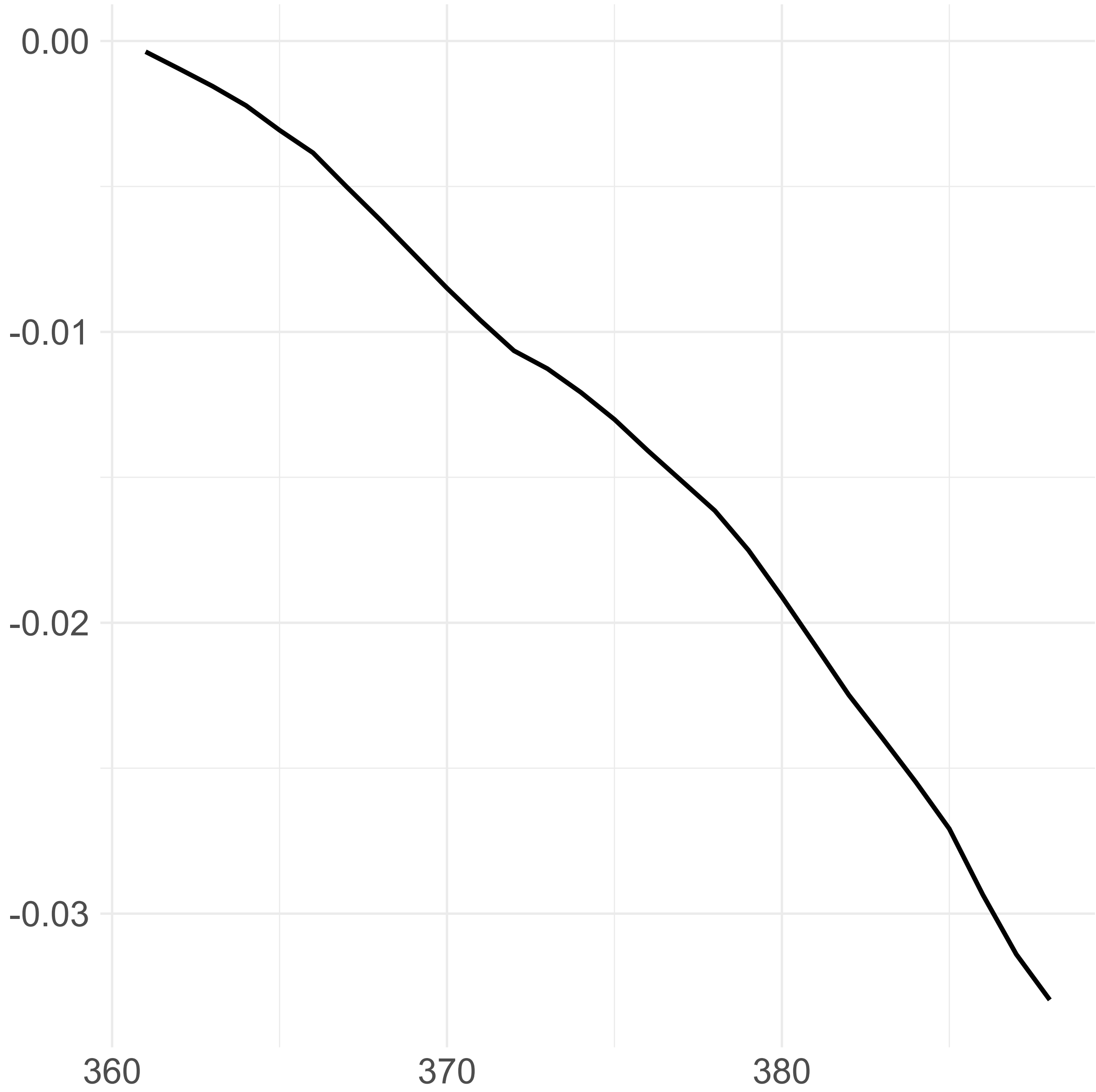
350
360


0.00
-0.01
-0.02
-0.03
360
370
380