## **Estimating Commercial Property Fundamentals from REIT data**

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#### Overview

- We propose a new methodology for the estimation of fundamental property-level investment real estate time series performance and operating data using real estate investment trust (REIT) data.
- We show that it can be used to estimate, e.g., time series of property values, net operating income, cap rates, operating expenses and capital expenditures, etc. per square foot of building area, by property type (sector) at a quarterly frequency for multiple specific geographic markets.
- Current methodology is an extension of the "PureProperty®" method published & produced by FTSE/NAREIT 2012-2019.
- Our method doesn't need any data source other than REIT data and is able to estimate actual
  quantity levels rather than just longitudinal relative values (index numbers).
- We also introduce additive (hierarchical) and Bayesian (structured time series) framework that allows the estimation of reliable time series even in small markets.

### **Data**

- Sample consists of all U.S. equity REITs during 2004-2018.
- Financial data from S&P Global SNL REIT Financial database merged & asset holding data from S&P Global Real Estate Properties database.
- Study REITs holdings by property type (office, apartments, retail, industrial, and other) as well as location wise (top 15 MSAs by population, and other)
- Main variables used to create fundamental time series:
  - Enterprise value/Sq Ft
  - NOI/EV
  - CAPEX/EV
  - OPEX/EV

### Averages of Main Variables per Year

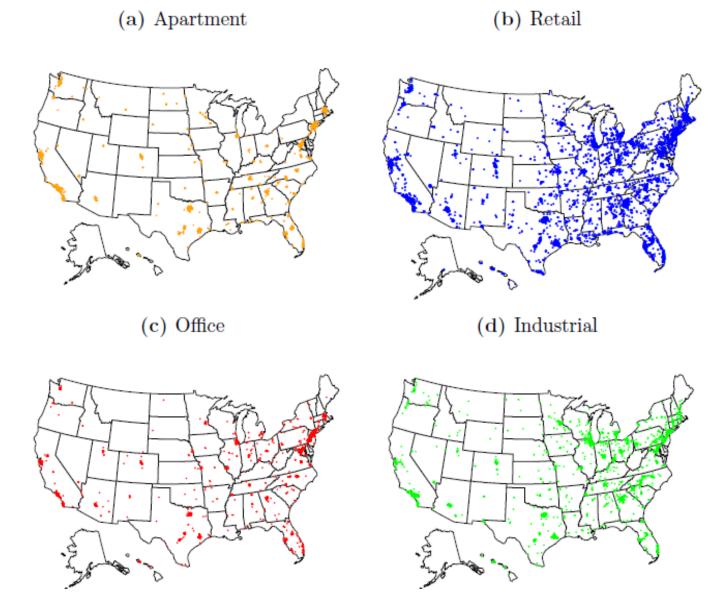
year	N	$\mathbf{EV}$	NOI	CAPEX	OPEX	age
2004	365	\$ 158.42	6.44%	0.93%	3.27%	21
2005	391	\$ 161.55	6.46%	0.65%	3.20%	19
2006	371	\$ 194.64	5.72%	0.57%	2.90%	20
2007	345	\$ 209.05	5.72%	0.43%	2.83%	21
2008	375	\$ 190.15	6.81%	0.51%	3.34%	21
2009	395	\$ 161.83	7.86%	0.57%	4.04%	23
2010	396	\$ 190.37	6.68%	0.67%	3.54%	23
2011	432	\$ 204.88	6.49%	0.72%	3.41%	24
2012	456	\$ 253.09	6.37%	0.68%	3.20%	24
2013	471	\$ 272.81	6.14%	0.71%	3.06%	24
2014	499	\$ 307.61	6.11%	0.65%	3.02%	25
2015	520	\$ 355.17	6.11%	0.59%	2.96%	26
2016	525	\$ 387.52	5.82%	0.53%	2.65%	26
2017	526	\$ 405.98	5.78%	0.54%	2.60%	27
2018	518	\$ 384.22	6.14%	0.61%	2.81%	27
N	6,585	4,067	5,628	3,966	5,606	6,066

### **Descriptive Statistics of Control Variables**

REITs holdings are more diversified by geographical location than property type.

Panel A: Property Types										
	mean	$\operatorname{sd}$		mean	$\operatorname{sd}$					
Office	0.264	0.381	Apartment	0.112	0.296					
Industrial	0.133	0.289	Other	0.199	0.284					
Retail	0.293	0.421								
HHI			0.901							
Panel B: Metropolitan Statistical Areas										
	mean	$\operatorname{sd}$		mean	$\operatorname{sd}$					
New York-Newark-Jersey City	0.087	0.209	Atlanta-Sandy Springs-Alpharetta	0.041	0.105					
Los Angeles-Long Beach-Anaheim	0.048	0.138	Boston-Cambridge-Newton	0.020	0.067					
Chicago-Naperville-Elgin	0.041	0.110	San Francisco-Oakland-Berkeley	0.024	0.068					
Dallas-Fort Worth-Arlington	0.037	0.085	Phoenix-Mesa-Chandler	0.020	0.055					
Houston-The Woodlands-Sugar Land	0.036	0.100	Riverside-San Bernardino-Ontario	0.009	0.042					
Philadelphia-Camden-Wilmington	0.031	0.096	Detroit-Warren-Dearborn	0.013	0.069					
Washington-Arlington-Alexandria		0.165	Seattle-Tacoma-Bellevue	0.013	0.045					
Miami-Fort Lauderdale-Pompano Beach		0.087	Other	0.484	0.299					
ННІ			0.516							

# Location of REITs' Assets after Filters are Applied in 2018 for the main four Property Types



## Methodology: GK Model

PureProperty® was based fundamentally on Geltner and Kluger (1998): regression used to produce "pure" sector level price indexes using REIT data. Solves problems of REITs holding diverse portfolios, extracts "pure" property market segment data...

$$r_{kt} = \sum_{i}^{I} \beta_{it} \times x_{ikt} + \epsilon_{ikt}, \tag{1}$$

where;

 $r_{kt}$  = de-leveraged return of REIT "k" in year "t"  $x_{ikt}$  = REIT k's value share in sector "i" and year "t";

The estimated  $\beta_{it}$  coefficients are the estimates of the returns in period "t" to sector "i"

Note that the value share in above equation is obtained by multiplying the square feet a REIT has in every sector with the average square foot price in said sector, and subsequently dividing this by the sum of the value of all the REIT's properties combined. This involves price/SF coming from a third-party data source based on private property transaction prices or appraised values (e.g. RCA or NCREIF).

Eq. (1) can be estimated period-by-period with OLS and  $\beta_{it}$  coefficients can be chain-linked to produce a longitudinal investment performance index.

### Limitations of the GK Model

- Can only produce indexes.
- Requires private property market valuation data (e.g. transaction price based indexes such as RCA CPPI, CoStar CCRSI or appraisal based indexes such as NCREIF or MSCI/IPD) in addition to the REIT data. Using additional data potentially introduce noise and bias.
- Only Interactive model (single cluster).
- Requires bond market data for the de-leveraging process
- Only OLS model

### **Our Contribution**

- Methodology proposed in the current paper:
  - Can produce both levels of fundamentals as well as indexes
  - Requires only the REIT data
  - Allows for fixed effects and multiple-cluster additive specifications which are more parsimonious
  - We avoid any de-leveraging by using the firm's enterprise value
  - We use both OLS as well as Bayesian estimation, which helps to estimate reliable time-series even in small markets, more index granularity

## Methodology:

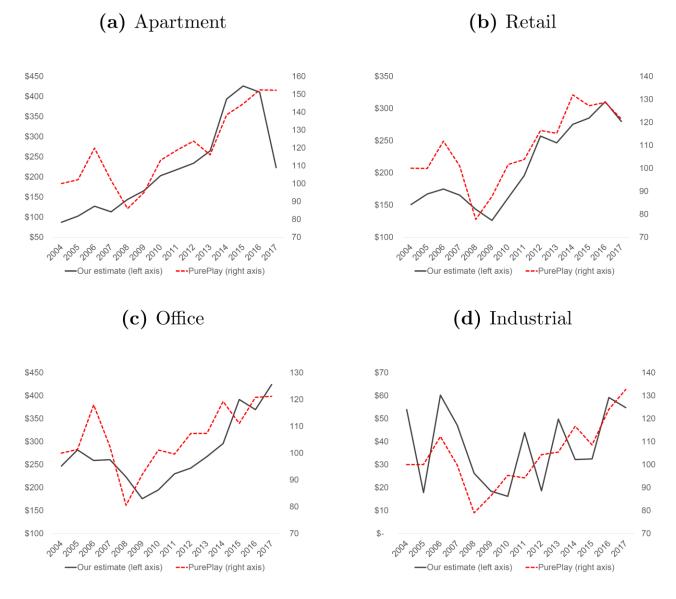
### Creating time-series in levels

• Example:

$$EV_k = \sum_{i}^{I} \text{Price per square foot}_i \times \text{Square foot}_{ik} + \epsilon_k,$$
 (2)

- EV<sub>k</sub>: Enterprise value of REIT "k"
- Price per Square foot<sub>i</sub> = square foot prices in sector "i",
- Square foot<sub>ik</sub> = Square feet invested by REIT "k" in sector "i"
- The estimated coefficients on the RHS variable (the square foot holdings) would provide the average (across the REITs) real estate values per square foot of built space for year "t" in each market or sector "i"
- We can either trace out the history of the square foot values over time, or we could normalize to an inception year and create a value change index across time for each sector i.
- Note: the Y variable in eq. (2) can be replaced with NOI/EV, CAPEX/EV, OPEX/EV, etc. to obtain other fundamental time series

# Enterprise Value per Square Foot using Levels Specification



# Normalization Per Square Foot & the Additive Model

- Eq. (2) in previous slide is limited to single cluster and cannot have an additive structure of geographical locations and property types (i.e. double cluster).
- Therefore, we next propose a general approach by dividing the enterprise value (or any other relevant variable) by square feet (Sqft) per REIT per year

$$y_{kt} = \frac{\text{EV}_{kt}}{\text{Sqft}_{kt}} = \mu_t D_{kt}^T + \delta_i D_{kt}^I + \gamma_m D_{kt}^M + \beta X_{kt} + \epsilon_{kt}, \tag{3}$$

- D<sup>T</sup> indicates the time period
- D<sup>I</sup> contains the square footage the REIT has invested in property type "i"
- D<sup>M</sup> contains the square footage the REIT has invested in location "m"
- Covariate X contains any other explanatory variables that might impact the y variable e.g. age of the property

# Normalization Per Square Foot & the Additive Model

- Parameter  $\mu_t$  traces out the common trend across time in all of the sector values, in money values per square foot
- In above specification, covariates do not have to be limited to the square footage % (e.g. age)
- Another advantage: we conserve degrees of freedom (specification has (T + I + M) instead of (T x I x M) variables) → hence would result in less volatile indexes.
- However, plotting the indexes is not straightforward, specification (3) constrains all the property types and locations to move in lock-step.
- Therefore, we consider 4 different specifications, ranging from pure additive to pure interactive, with two hybrid specifications in between.

# Normalization Per Square Foot & the Additive Model

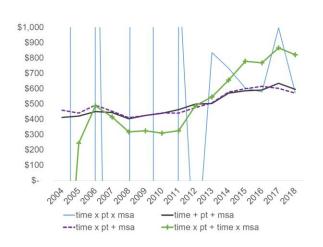
time + pt + loc: 
$$y_{kt} = \mu_t D_{kt}^T + \delta_i D_{kt}^I + \gamma_m D_{kt}^M + \beta X_{kt} + \epsilon_{kt};$$
time x pt + loc: 
$$y_{kt} = \mu_{it} (D_{kt}^T \times D_{kt}^I) + \gamma_m D_{kt}^M + \beta X_{kt} + \epsilon_{kt};$$
time x pt + time x loc: 
$$y_{kt} = \mu_{it} (D_{kt}^T \times D_{kt}^I) + \mu_{mt} (D_{kt}^T \times D_{kt}^M) + \beta X_{kt} + \epsilon_{kt};$$
time x pt x loc: 
$$y_{kt} = \mu_{imt} (D_{kt}^T \times D_{kt}^I) + \beta X_{kt} + \epsilon_{kt}.$$

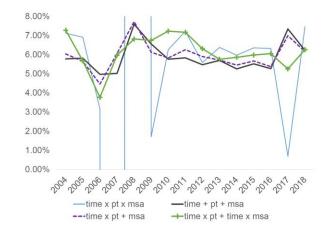
- Going from first specification to last specification, we loose degrees of freedom with the advantage of gaining more flexible/unique trends. Note that, less degrees of freedom would likely give noisy indexes (Geltenr and Ling, 2006).
- We retrieve pure price series by fitting the representative property as the average property held by all the REITs over the entire 2004-2018 sample period.

## Results for Offices in Los Angeles using OLS Methods

(a) Enterprise Value / SF

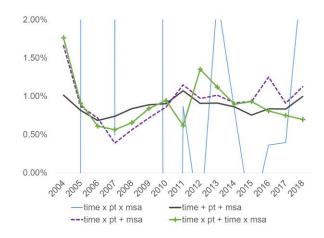


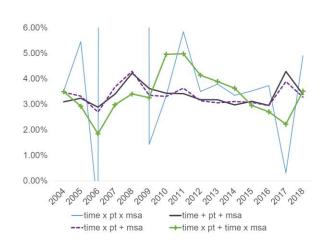




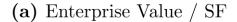
(c) Capex / EV

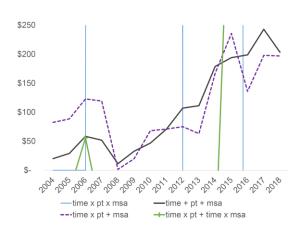
(d) Opex / EV



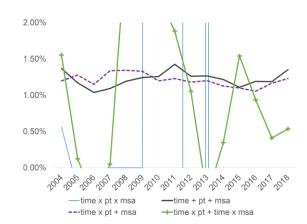


### Results for Apartments in Atlanta using OLS Methods

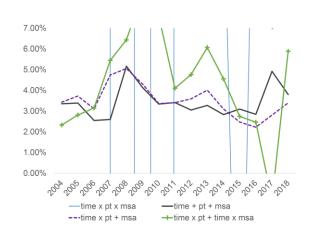




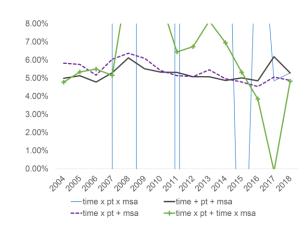
(c) Capex / EV



**(b)** NOI / EV



(d) Opex / EV



### A Bayesian Extension for Subtrends

Given the commercial property space markets are highly segmented, it is more useful to study specific market segment, i.e. a granular level analysis is needed.

However, market segments tend to be small in size with only limited properties, the OLS specifications in previous slides are likely to give excessively noisy results

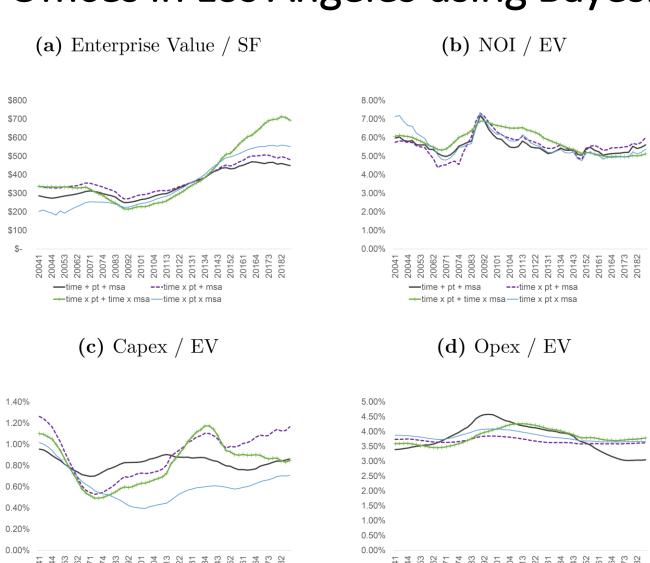
Therefore, we extend eq. (3) using Bayesian approach by adding a common trend ( $\kappa$ ) in the following Bayesian models

time + pt + loc: 
$$y_{kt} = \kappa_t D_{kt}^T + \delta_i D_{kt}^I + \gamma_m D_{kt}^M + \beta X_{kt} + \epsilon_{kt};$$
time x pt + loc: 
$$y_{kt} = \kappa_t + \mu_{it} (D_{kt}^T \times D_{kt}^I) + \gamma_m D_{kt}^M + \beta X_{kt} + \epsilon_{kt};$$
time x pt + time x loc: 
$$y_{kt} = \kappa_t + \mu_{it} (D_{kt}^T \times D_{kt}^I) + \mu_{mt} (D_{kt}^T \times D_{kt}^M) + \beta X_{kt} + \epsilon_{kt};$$
time x pt x loc: 
$$y_{kt} = \kappa_t + \mu_{imt} (D_{kt}^T \times D_{kt}^I \times D_{kt}^M) + \beta X_{kt} + \epsilon_{kt};$$

$$\Delta \kappa_t \sim \mathcal{N}(0, \sigma_{\kappa}^2);$$

$$\Delta \mu_t \sim \mathcal{N}(0, \sigma_{\mu}^2).$$

### Results for Offices in Los Angeles using Bayesian Approach



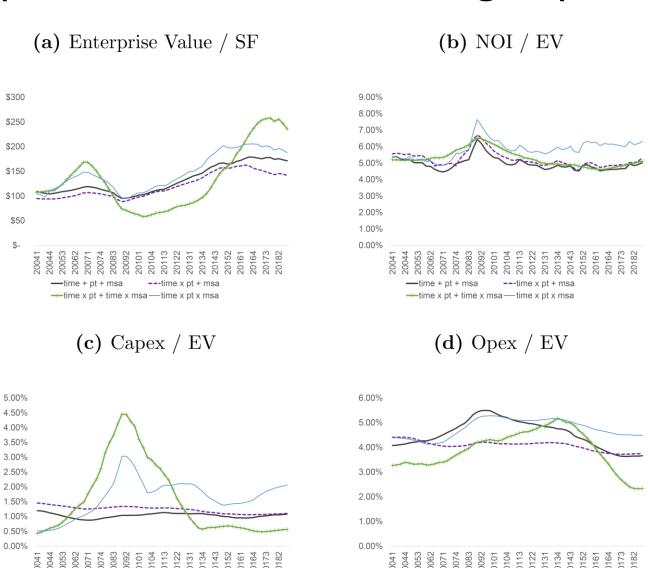
—time x pt + time x msa — time x pt x msa

time x pt + time x msa — time x pt x msa

time x pt x msa

time x pt x msa

### Results for Apartments in Atlanta using Bayesian Approach



-time x pt + time x msa -time x pt x msa

-time x pt + time x msa -time x pt x msa

### **Concluding Remarks**

- We propose a new methodology that allows the estimation of fundamental real estate time series and provide insights about asset performance.
  - Our method allows us to estimate money-valued levels of the fundamentals in addition to generating indexes.
  - The main time series estimated are: property values, cap rates, operating expenses and capital expenditures, per square foot of building area, by property type (sector) at a quarterly frequency for specific geographic markets.
  - However, one may estimate several other time series as well
- Current methodology does not need any additional data sources besides the REIT data itself.
  - Given that REITs holdings are not 100% pure play, our methodology enable construction of "pure" fundamental time series for a specific property type and/or geographical location.
- In addition to interactive (single-cluster) specifications, our model also allows for fixed effects and multiple-cluster additive specifications.
- We introduce a Bayesian estimation framework that allows us to produce reliable time series even in smaller markets.
- Overall, the methodological contribution of the paper enable us to generate both operating and investment related time series, which enrich our understanding of commercial property productivity and investment performance.