Analytical Tools & Recent Findings: Selected Research Projects of the MIT Real Estate Price Dynamics Platform
(Sponsored by Real Capital Analytics Inc)
(Dr. Alex van de Minne, Head)

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Projects to Date of the Price Dynamics Platform:

1. Price Point Indexes of US Commercial Property (quantile regression, *JPM* published).*
2. Using revisions as a measure of price index quality in repeat-sales models.*
3. HBU indexes (riskiness of RE dvlpt).*
4. Price indexes & value of retrofit “green” office properties (risk & return).*
5. Supply & Demand Indexes (“constant liquidity prices”) granular US property markets.*
6. Rent indexes for Indian office properties (data from Propstack).*
7. Synthetic total return transaction-based indexes for granular US property markets.
10. Clustering Commercial Real Estate by Property Level Systematic Risk (“beta” clusters at the property level).

*Available on SSRN.com.
Brief Summary Today of These Four (*time permitting*):

1. **Price Point Indexes of US Commercial Property** (quantile regression, *JPM* published).*
2. Using revisions as a measure of price index quality in repeat-sales models.*
3. **HBU indexes** (riskiness of RE dvlpt).*
4. Price indexes & value of retrofit “green” office properties (risk & return).*
5. **Supply & Demand Indexes** (“constant liquidity prices”) granular US property markets.*
6. Rent indexes for Indian office properties (data from Propstack).*
7. **Synthetic total return transaction-based indexes** for granular US property markets.
8. **Forecasting US commercial property prices** using Dynamic Factor Modeling.*
10. **Clustering Commercial Real Estate** by Property Level Systematic Risk (“beta” clusters at the property level).

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Price-Point Indexes of US Commercial Property Investment Performance...

- Quantile Regression Based Indexes of Price Dynamics by Price-Point
- Based on Transaction Prices (Chained Hedonic Models)
- Constant-Quantity “Pure Price” Indexes
- Similar Models, Quantile Indexes Constructed for Cap Rate (Income Yield)
- Combine Price & Income for Total Investment Performance Quantile Indexes
- Compare “Treynor Ratios” of Risk-Adjusted Investment Performance By Price-Point
- Find Lower Price-Points Seem to Perform Better
- “Arbitrage” Opportunity? (Maybe not.)
Different types of investors, clienteles, at different price-points…

Properties > $16.5M <=> Mostly Institutions & REITs
Properties < $3.5M <=> Mostly Private & Owner-Occupiers
Price-point index tracks same price quantile across time.

Chained (imputed) hedonic model (de Haan & Diewert 2011) re-estimates attribute coefficients ("shadow prices") based on all property transaction prices in each year. Quantile regression produces entire distribution of coefficients each year. Applied to constant "representative property" (constant attributes), gives constant-quality price distribution each year.
Price quantile indexes (pure price change, constant-quantity/quality). “q=0.25” (25%ile of prices) is low price-point index. “q=0.95” (95%ile of prices) is high price-point index…

High-price properties have more volatility and cycle amplitude, and slightly higher average price growth (capital return). Low-price properties lag behind in time.
Quantile Cap Rate Indexes: High-price properties have lower cap rates, except at bottom of the Financial Crisis...

Combine Quantile Cap Rate Indexes with Quantile Price Indexes to produce Quantile Total Return ("Investment Performance") Indexes: Risk & Return by Price-Point...
“Treynor Ratio” (Risk-adjusted Return) as a Function of Price-Point Quantile: High Price-Point Properties Display Much Lower Risk-Adjusted Return…

Violates “Law of One Price” (==⇒ “Arbitrage”?...)

“Treynor Ratio” (Risk-adjusted Return) = (Avg Return – Riskfree Rate) / “Risk”.

“Risk” defined as annual volatility, or as Peak-to-Trough Cycle Amplitude.

Reflects segmented market, barriers to trading, or other issues (Liquidity?, Info Quality?, Uncertainty?...)
Results persist at more granular level across most metro markets and property sectors…

Conclusion: Invest in small properties?...
Would similar market segmentation and results occur in Japan?...
Repeat-Sales Based Supply & Demand Reservation Price Indexes (including “Constant-Liquidity Price Indexes”) at Granular Level…

- Assume Transaction Price = Halfway Between Buyer’s & Seller’s Reservation Prices.
- Assume Trading Volume (Propensity of Sale: Probit Model) = Essentially a function of Buyers’ Reservation Prices Minus Sellers’ Reservation Prices.
- Model Price Changes (Repeat-sale index).
- Model Sale Probability (Probit).
- Assume Property “Universe” is all properties that ever sold (at least once) in historical database.
- Derive Sale Propensity from Repeat-Sales within that database.
- Combine these two models to invert and derive Index of Sellers’ Reservation Prices (Supply Index) & Index of Buyers’ Reservation Prices (Demand Index, “Constant Liquidity Price” Index).
- Methodology developed by Dorinth van Dijk & Alex van de Minne.
- With various econometrics enhancements, can be applied at “granular” level of individual metro markets.

Soon to be a quarterly updated “product” produced & published by the Price Dynamics Platform.
Frequency (Density) of Buyers’ and Sellers’ Reservation Prices
Average Market...
Frequency (Density) of Buyers’ and Sellers’ Reservation Prices
“Up” Market…
Frequency (Density) of Buyers’ and Sellers’ Reservation Prices
“Down” Market…
Cumulative Reservation Price Functions are Demand & Supply Schedules…
Demand and supply

Price or Value

\[ P^* \]

\[ Q^* \]

Quantity (or rate) of Transactions (per unit of time)

\[ Q^* = \text{“Normal” Trans.Volume.} \]
Price change at constant volume \( Q^* \) from \( P_1 \) based on \( D_1 \) to \( V^b \) based on \( D_2 \) is “Constant Liquidity” Price Index.
New York Metro Area

As is typical, Demand tends to lead Supply in major turning points.

Supply (property owner) Reservation Prices tend to be “sticky”

Difference: Demand – Supply = Market “Liquidity”
Phoenix Metro Area

As is typical, Demand tends to lead Supply in major turning points. Supply (property owner) Reservation Prices tend to be “sticky”

Difference: Demand – Supply = Market “Liquidity”
Synthetic total return transaction-based indexes for granular US property markets...

- Combine granular markets RCA CPPIs (repeat-sales transaction based) USA price indexes, with...
- RCA granular markets cap rate data (of same markets), and...
- Hedonic model of capital expenditure fraction of property value (based on NCREIF property-level data)
- To produce synthetic Total Return (“Investment Performance”) Indexes, Transaction Based & Granular Markets...

\[ r_{kt}^{\text{Total}} = r_{kt}^{\text{Capital}} + r_{kt}^{\text{Income}} - c_k \]

For Market “k” & Quarter “t”
28 RCA CPPI Markets: Cumulative Price Change (Repeat-Sales):
Same 28 RCA Markets: Average Cap Rate of Sold Properties

“Cap Rate” not net of capital expenditures (“capex”).
Same 28 RCA Markets: Cumulative Synthetic Total Returns

Average Time-Wtd Total Returns 2002-17
8% to 12% per annum

Quarterly 2002 - 2017
Treynor Ratio (TR) Defining “Risk” as Qtrly Volatility

$$TR_k = \frac{R_k - R_f}{Risk_k}$$

Big range in risk-adjusted investment performance

28 RCA CPPI Markets: 2002-2017
Treynor Ratio (TR) Defining “Risk” as GFI Cycle Amplitude

\[ TR_k = \frac{R_k - R_f}{\text{Risk}_k} \]

Big range in risk-adjusted investment performance

28 RCA CPPI Markets: 2002-2017
### Table B.6: Total return statistics per market (quarterly frequency)

<table>
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<tr>
<th>Location</th>
<th>Property Type</th>
<th>mean</th>
<th>sd</th>
<th>crisis</th>
<th>min</th>
<th>max</th>
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<th>TR (crisis)</th>
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</table>

LA = Los Angeles Metro, NY = New York Metro, SF = San Francisco Metro.

sd = standard deviation and crisis is the crash magnitude during the crisis (In difference in index levels between 2010Q1 and 2008Q2).

TR = Treynor ratio. This is calculated by $TR_k = \frac{R_k - R_{r}}{\sigma_k}$, where $R$ is the average return per market $k$. The riskfree rate ($R_f$) is the average 30-days treasury bill during our analyzed period, or 1.2%. Risk is measured by volatility of the index returns (sd) or by the crash magnitude (crisis).
Forecasting US commercial property prices using Dynamic Factor Modeling (DFM)…

- DFM$s are structural time series models that reduce a large number of related time series into a few common factors.
- Good for out-of-sample forecasting when many series are related (too many for VAR): Efficiently uses information across the related time series.
- We apply DFM to 80 non-overlapping RCA CPPI granular investment property markets: 40 metros (each Commercial & Apartments). Test 1, 2, 3, 4 common factors.
- Build Auto-Regressive models to forecast the common factors. Test various lags.
- Build Auto-Regressive Distributed lag (ARDL) Models of Price Indexes.
- Combine ARDL with factor forecasts to forecast 80 markets prices. Demo typical results on Boston Apts & Dallas Comm by comparing to tradl AR benchmark…
8-qtr Out-of-Sample Forecast at time of Crash: Boston Apts

Test up to 4 factors $\times$ up to 8 lags (same lags in univariate factor forecast & in ARDL price forecast) and 3 variance covariance structures $\implies 4 \times 8 \times 3 = 96$ ARDL models.

Judge based on out-of-sample residuals, 8-qtr prediction, both periods (crash & recovery).

Three DFM methods: Avg all 96 (“mean”), Ex post optimal (“best”), Avg of best 10 specifications across all mkts (“top 10”). “Benchmark” is **best** univariate AR.

“Good average” DFM-based ARDL predicts turning point out-of-sample; Traditional univariate AR does not.
8-qtr Out-of-Sample Forecast at time of **Recovery**: Boston Apts

- Test up to 4 factors X up to 8 lags (same lags in univariate factor forecast & in ARDL price forecast) $\Rightarrow 4 \times 8 = 32$ ARDL models.
- Judge based on out-of-sample residuals, 8-qtr prediction, both periods (crash & recovery).
- Three DFM methods: Avg all 32 ("mean"), Ex post optimal ("best"), Avg of best 10 specifications across all mkts ("top 10"). "Benchmark" is **best** univariate AR.

“Good average” DFM-based ARDL predicts turning point out-of-sample; Traditional univariate AR does not.
8-qtr Out-of-Sample Forecast at time of Crash: Dallas Comm

- Test up to 4 factors X up to 8 lags (same lags in univariate factor forecast & in ARDL price forecast) ==> 4 X 8 = 32 ARDL models.
- Judge based on out-of-sample residuals, 8-qtr prediction, both periods (crash & recovery).
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