Chapters 23 & 25:

Dealing with Problems in Real Estate Periodic Returns Data

"Macro-level Valuation":

Valuing aggregates of many properties at once (e.g., portfolios, indexes, entities like REITs or partnerships).

Most basic macro-level valuation problem is valuing *static portfolios*…

"Static Portfolio":

A portfolio consisting of a constant fixed set of properties (the same properties over time).

"Static Portfolio Valuation":

The value of the portfolio is the *sum of the values* of all the individual properties in the portfolio (i.e., simple cross-sectional *aggregation* of values, across the properties in the portfolio).

Sounds simple: we know how to value individual properties (Chs.10-12), and we know how to add…

But in fact some additional considerations become important at the macro-level.

Most fundamentally, you must understand:

The *trade-off* that exists between:

VALUATION PRECISION

(minimizing random error)

VS.

VALUATION "CURRENTNESS"

(minimizing temporal lag bias)

To begin, let's go back to some basics at the micro-level of individual property valuation…

Chapter 12 Appendix:
Noise & Values in Private R.E. Asset Mkts:
Basic Valuation Theory…

Understand the difference between:

- ***Inherent Value***
- ***Investment Value***
- ***Market Value***
- ***Reservation Price***
- ***Transaction Price.***

Inherent Value: **Maximum value a *given user* would be willing (and able) to pay for the subject property, *if they had to pay that much for it* (or, for a user who already owns the property, the *minimum* they would be willing to sell it for), *in the absence of any consideration of the market value ("exchange value") of the property*. – Based on usage value of the property.**

Investment Value: **Inherent value for a non-user owner (a "landlord"), i.e., for an *investor*.**

Market Value: **Most likely or expected sale price of the subject property (*mean of the ex ante transaction price probability distribution*).**

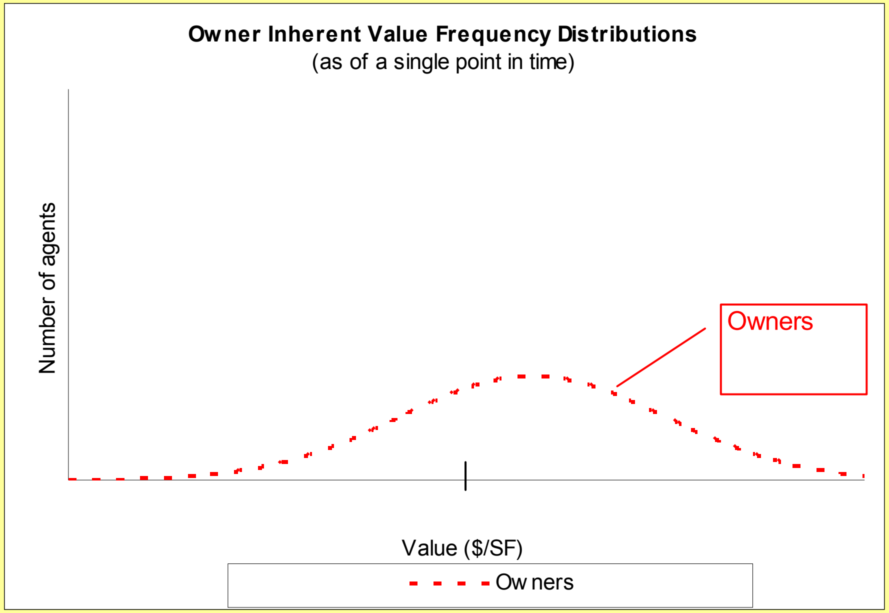
Reservation Price: **Price at which a market participant will stop searching and stop negotiating for a better deal and will close the transaction.**

Transaction Price: **Actual price at which the property trades in a given transaction.**

Only the last of these is directly empirically observable.

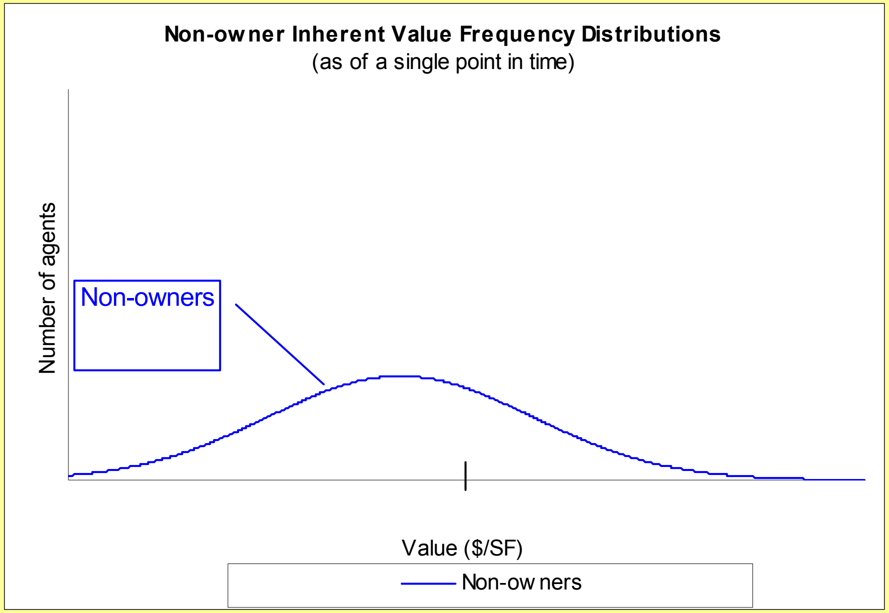
Consider a certain type of property…

- **There are many individual properties, examples of the type,**
- **With many different owners.**
- **Because the owners are heterogeneous, there will be a wide dispersion of *"inherent values"* that the owners place on the properties (e.g., like *"investment value"*) because IV differs across investors.**
- **We can represent this dispersion by a frequency distribution over the inherent values. . .**



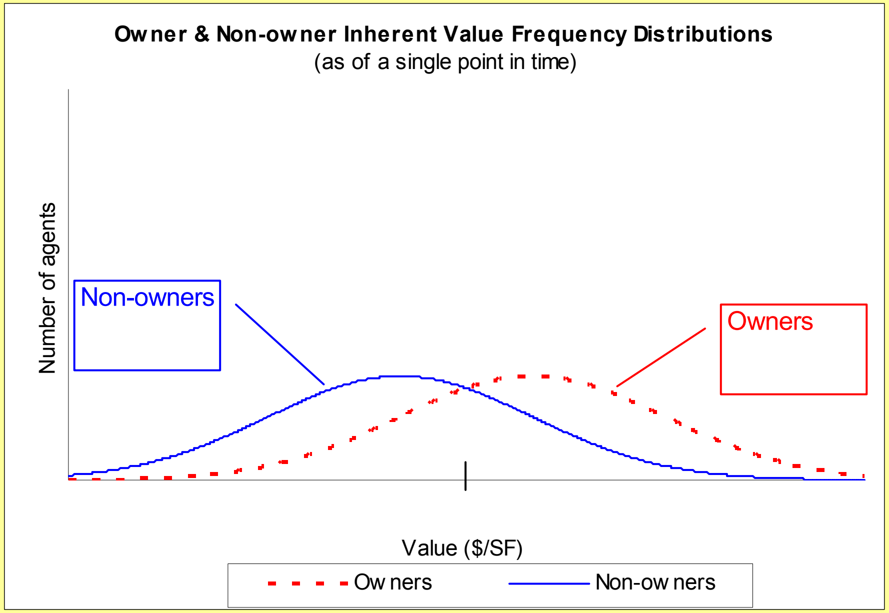
Consider a certain type of property…

- There are also many non-owners of this type of property,
- Potential investors.
- Because these non-owners are also heterogeneous, there will be a wide dispersion of their IV values for this type of property as well.
- Another frequency distribution over the inherent values . . .



Consider a certain type of property…

• There will usually be *overlap* between the two distributions. . .

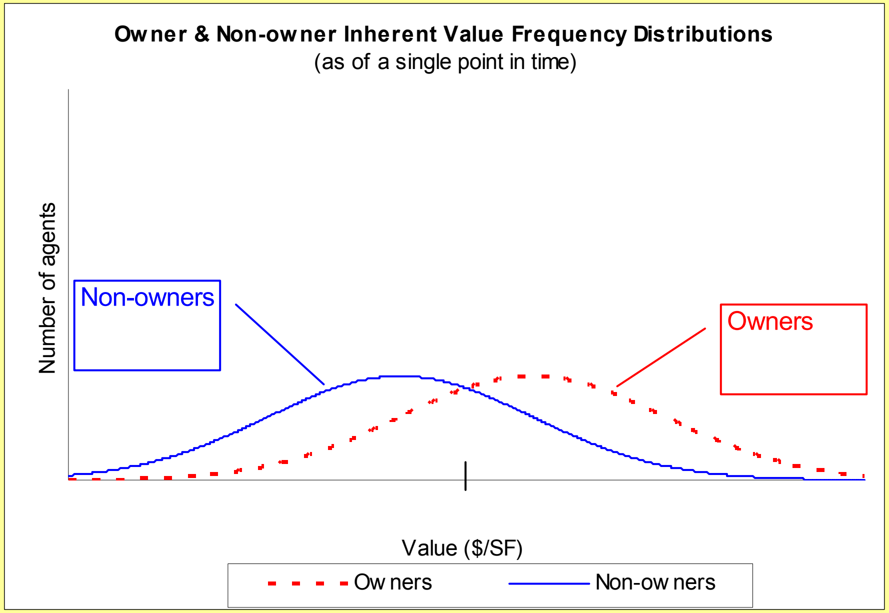


• It makes sense for the ***owners' distribution*** to be centered to the *right* of the ***non-owners' distribution***, because of past selection:

• Those who have placed higher values on the type of property in question are more likely to already own some of it.

Because there is *overlap*, there is scope for ***trading*** of assets.

(Recall from Ch.7 how investor ***heterogeneity*** *underlies the investment industry.)*



There is a mutual benefit from some non-owners whose IV values exceed those of some owners getting together and trading:

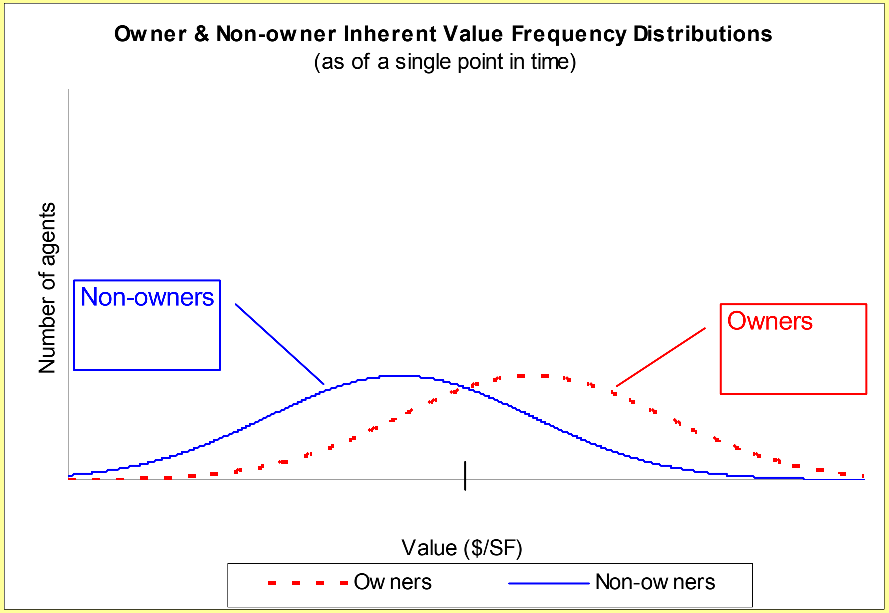
- ***A price (P) can be found such that:***

IV(owner) < P < IV(non-owner).

$$\mathbf{NPV_{IV}(non\text{-}owner) = IV(non\text{-}owner) - P > 0}$$

$$\mathbf{NPV_{IV}(owner) = P - IV(owner) > 0}$$

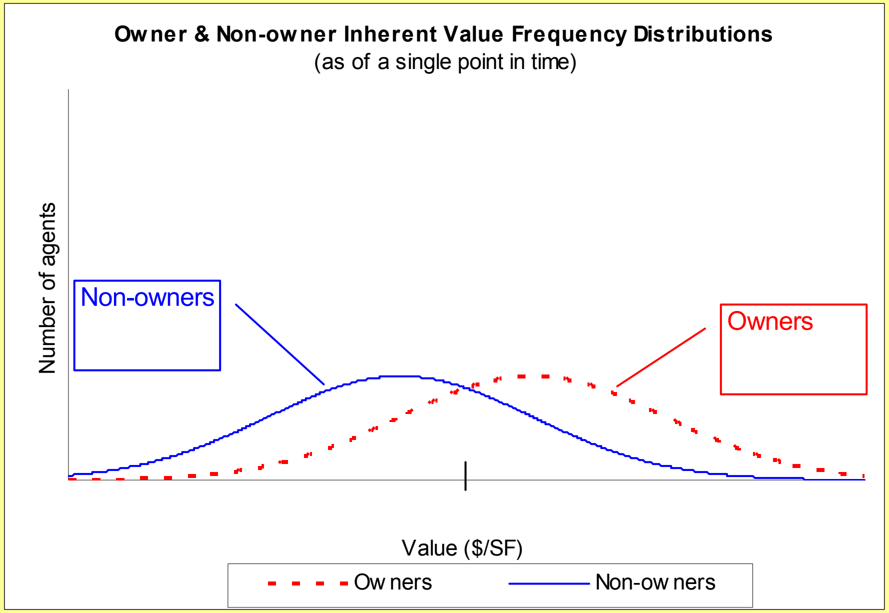
Because there is *overlap*, there is scope for ***trading*** of assets.



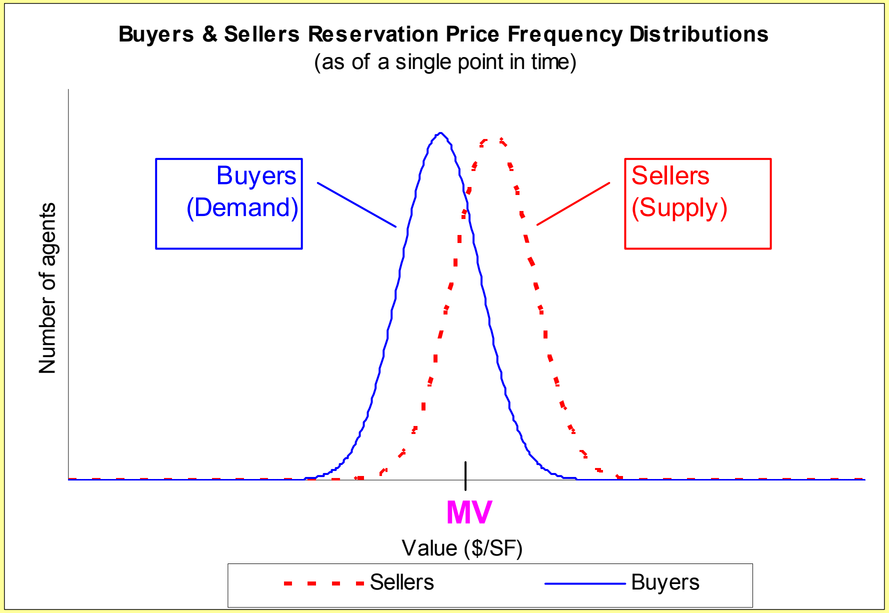
The number of non-owners willing to trade equals the *area* under the non-owner distribution *<u>to the right</u>* of the trading price.

The number of owners willing to trade equals the *area* under the owner distribution *<u>to the left</u>* of the trading price.

If permitted in the society, a real estate *<u>asset market</u>* will form and begin operation . . .

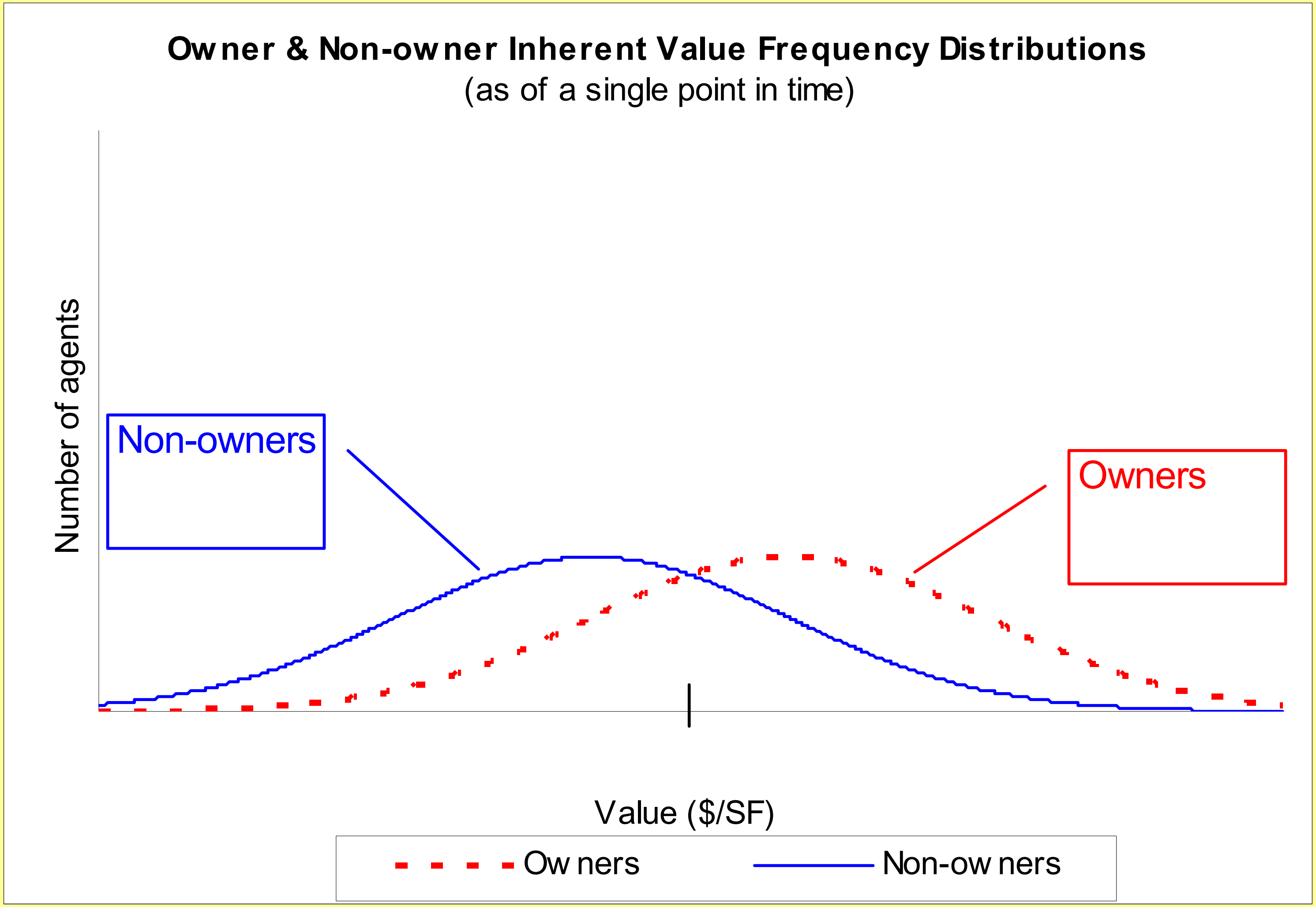


Inherent values tend to be widely dispersed, reflecting investor heterogeneity.

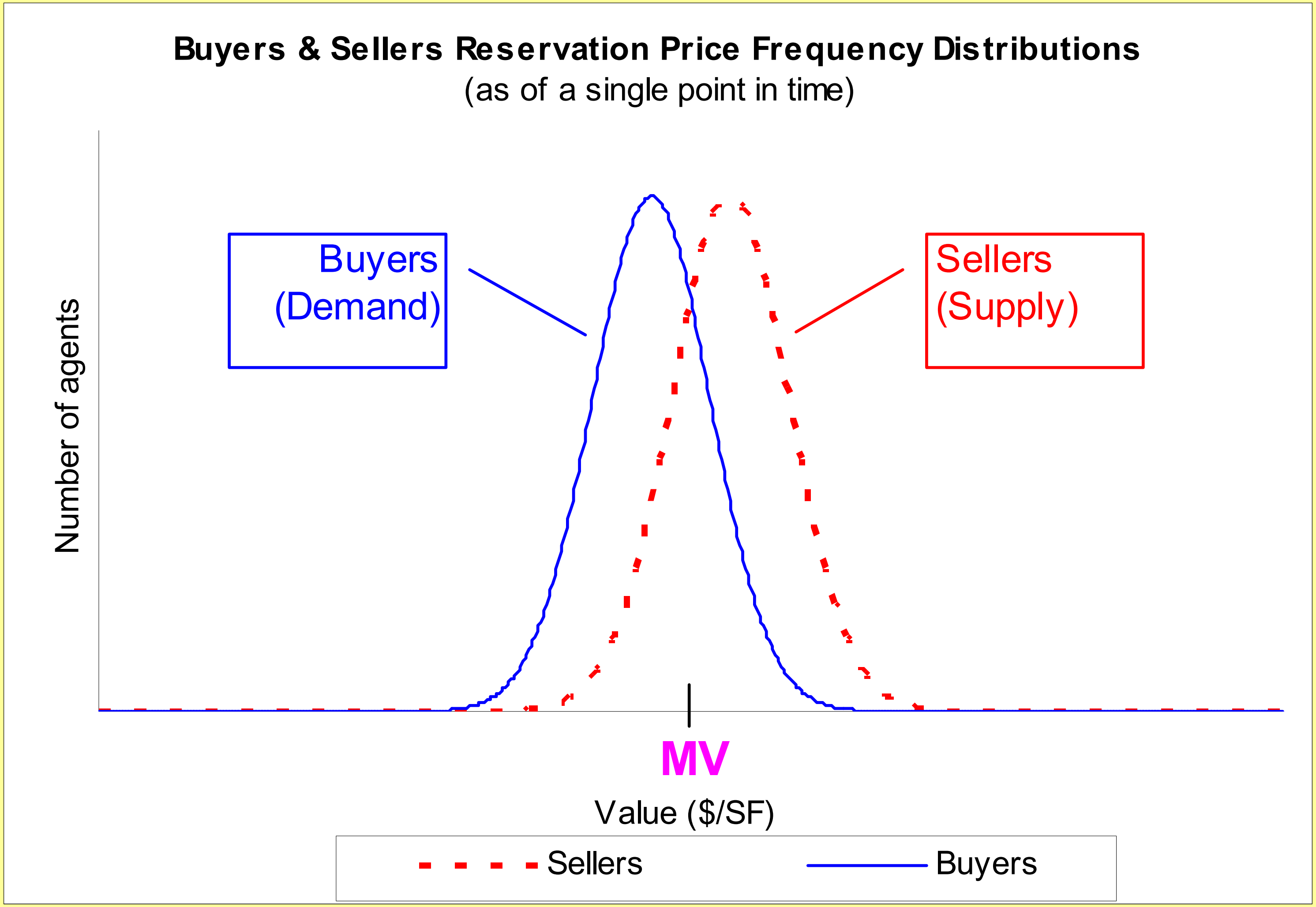


The operation of the asset mkt creates *"price discovery"* & *"information aggregation"*, which causes agents' *"reservation prices"* (the price at which they will stop searching or negotiating and trade) to collapse around the midpoint of the overlap, the *"mkt clearing price"* (MV). (Less interested owners & non-owners effectively drop out of the distributions.)

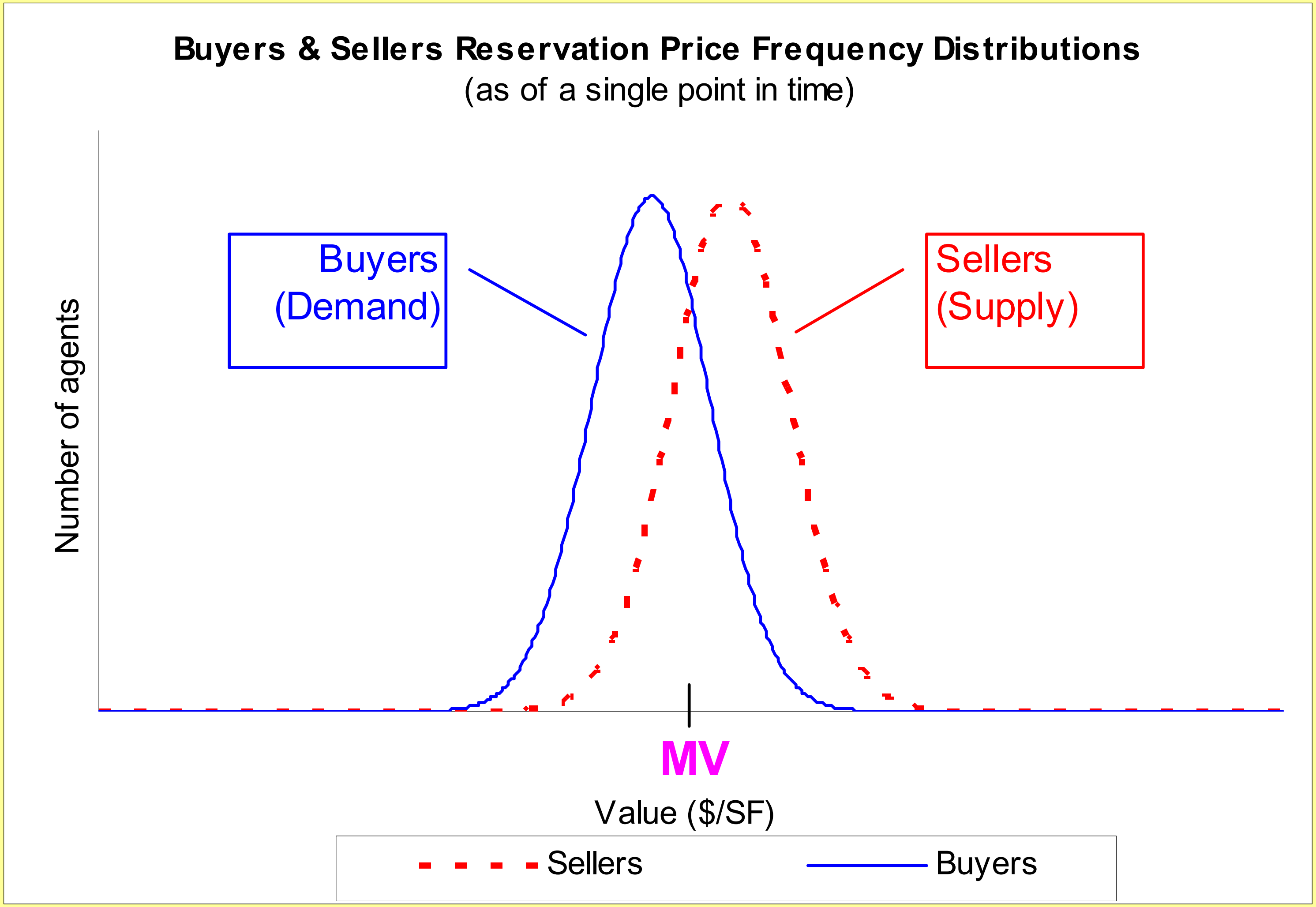
Inherent Values



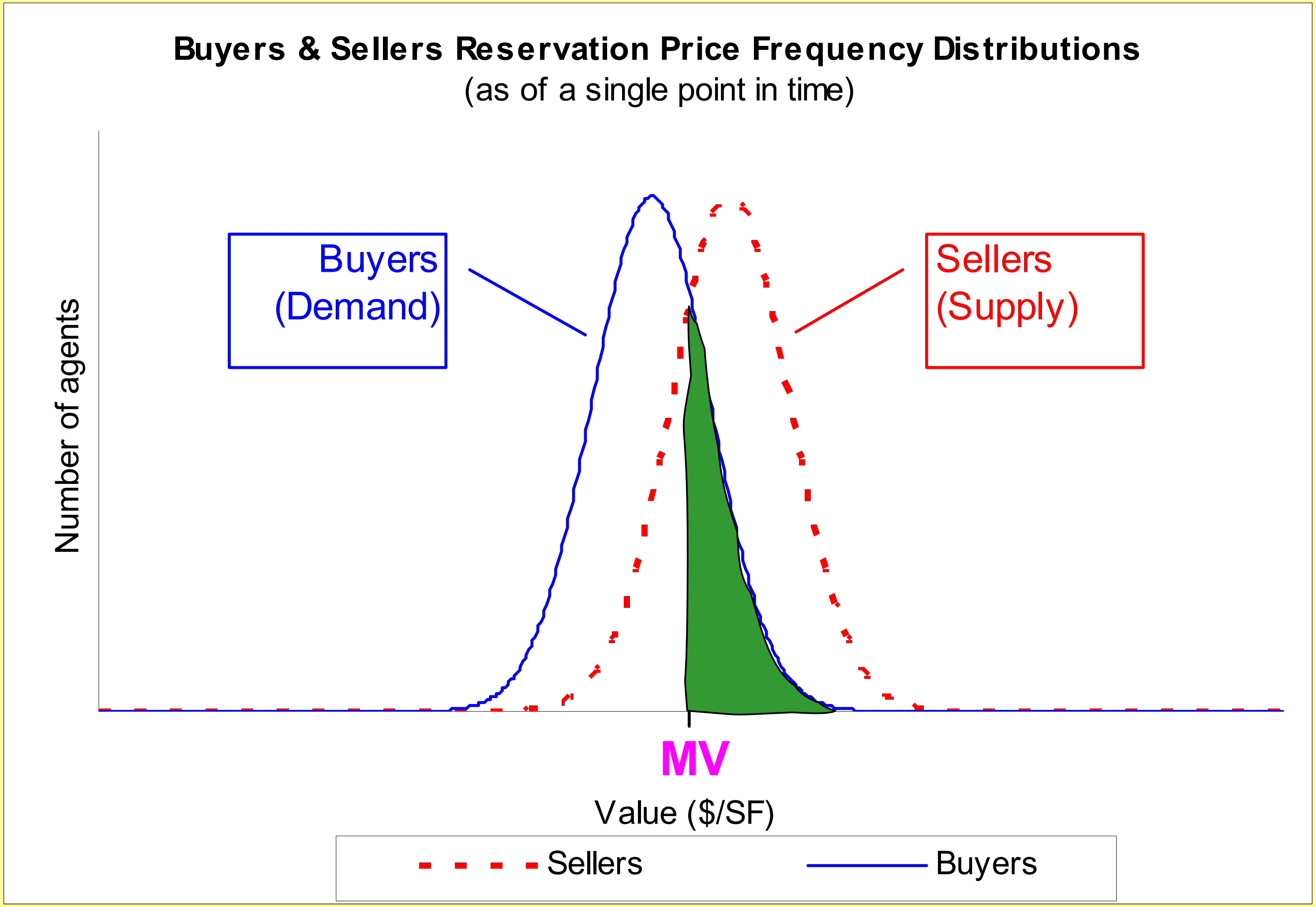
Reservation Prices



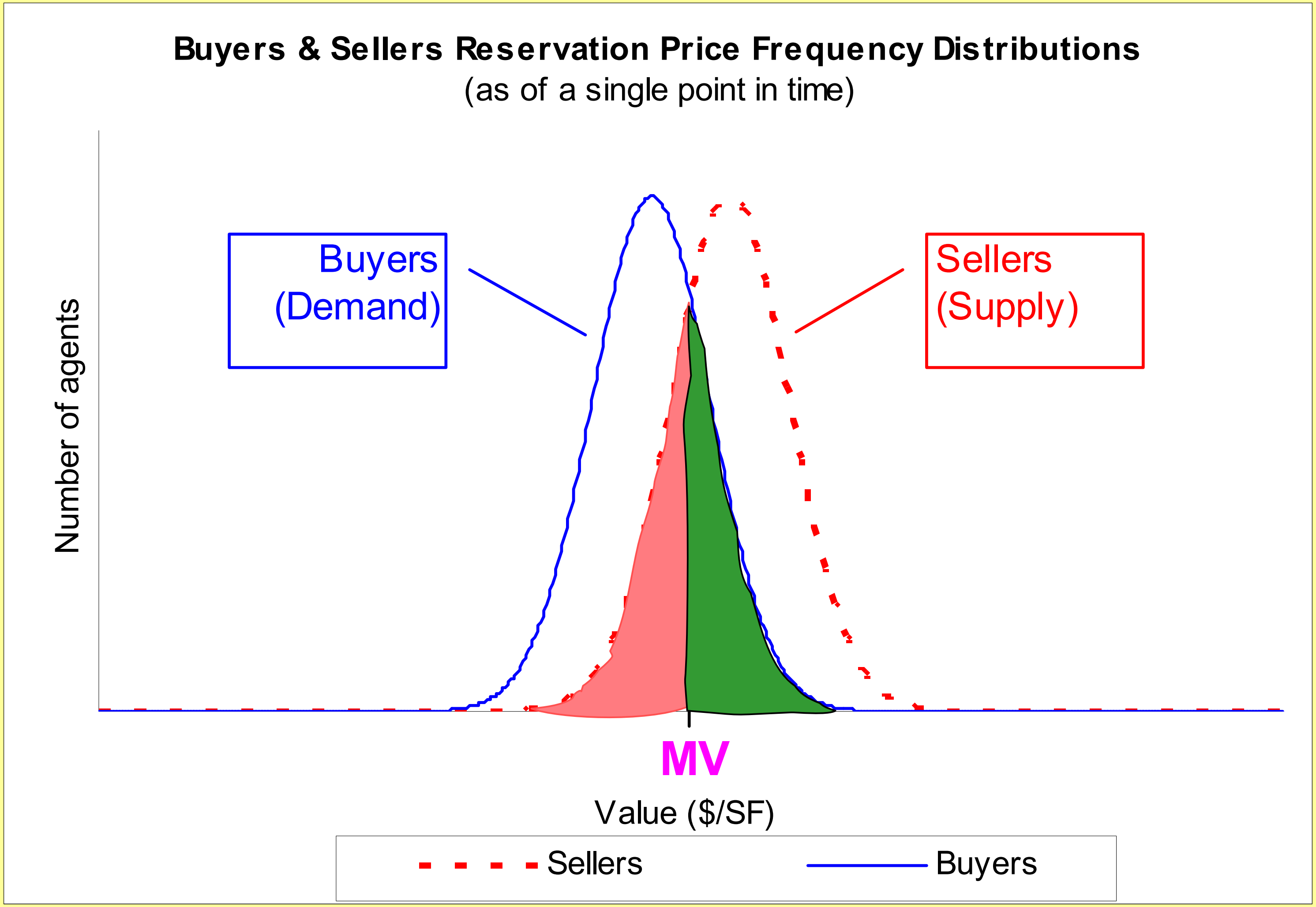
Reservation Prices



Reservation Prices are influenced not only by agents' inherent values and perceptions of the market value, but also by agents' search costs and degree of certainty about their value perceptions.



Market Value **equals *market clearing price*, at which number of buyers (to *right* of price under *buyer* distribution) . . .**

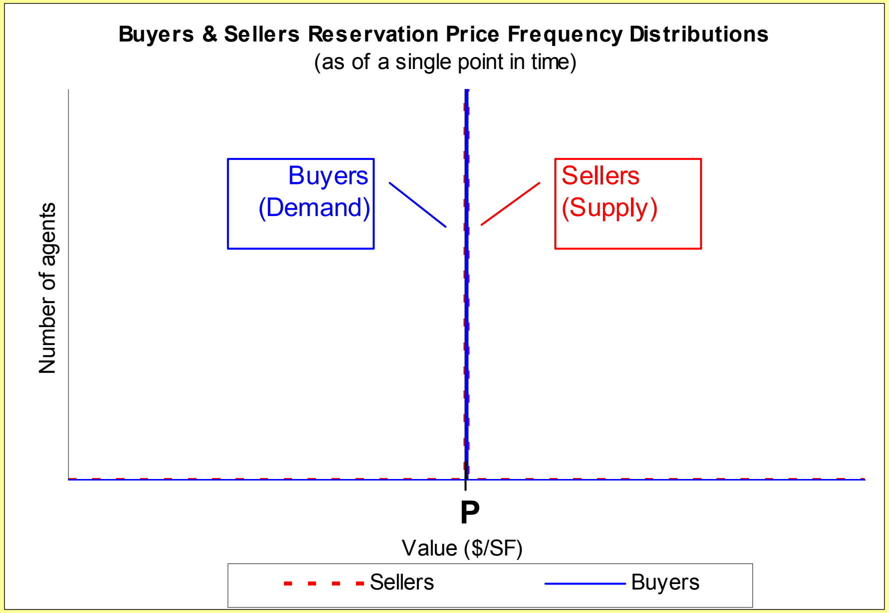


Market Value **equals** ***market clearing price*****, at which number of buyers (to** ***right*** **of price under** ***buyer*** **distribution) equals number of sellers (to** ***left*** **of price under** ***seller*** **distribution).**

The more *"informationally efficient"* is the asset market, the more effective is the *price discovery* and the *information aggregation*.

The market *learns from itself* (about the value of the type of asset being traded in the market).

In the extreme, the distributions on both sides of the market (the buyers and the sellers) will collapse onto the single, market-clearing price, at which the number of buyers equals the number of sellers:

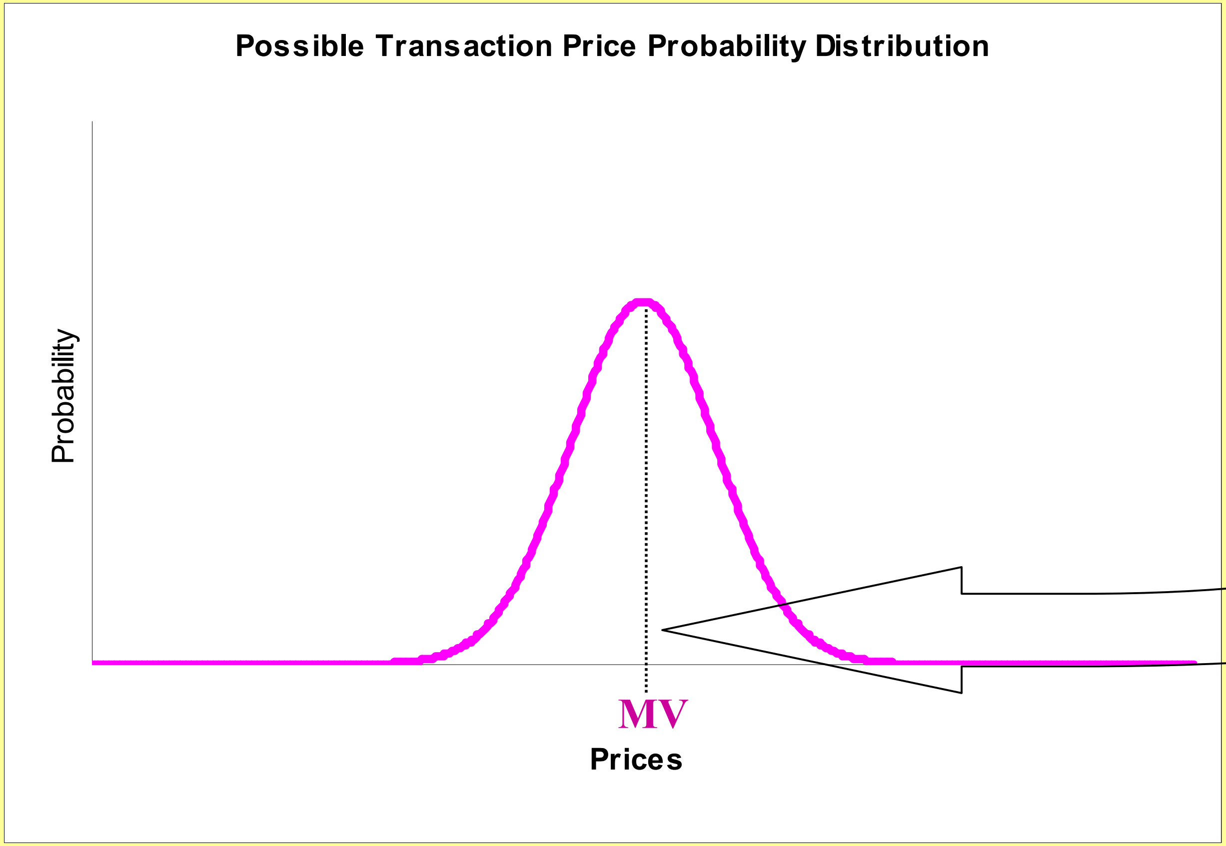


Hence, observed prices exactly equal market values.

This is approximately what happens in the stock market.

Real estate markets are not that informationally efficient.

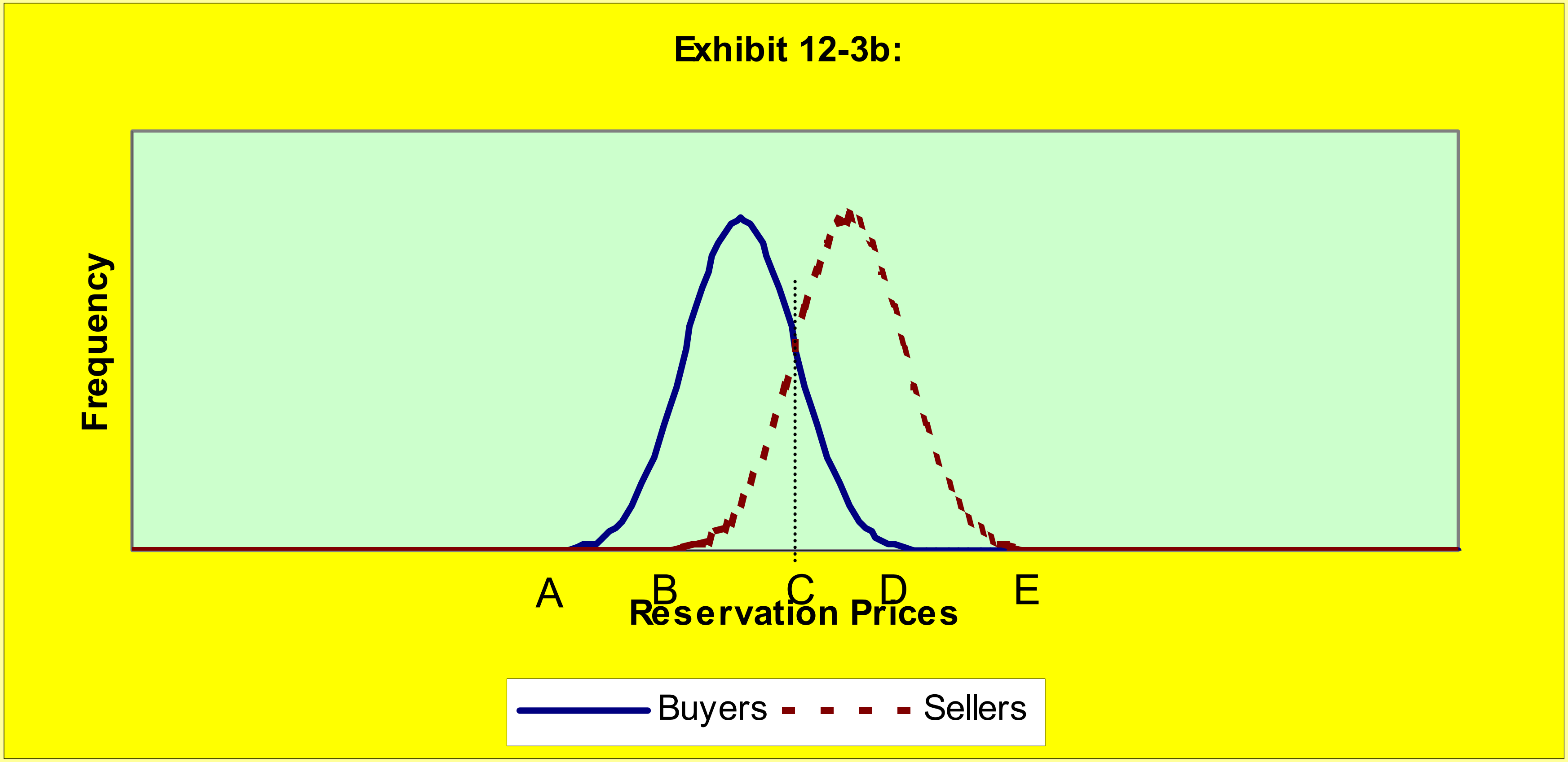
There is *price dispersion*.



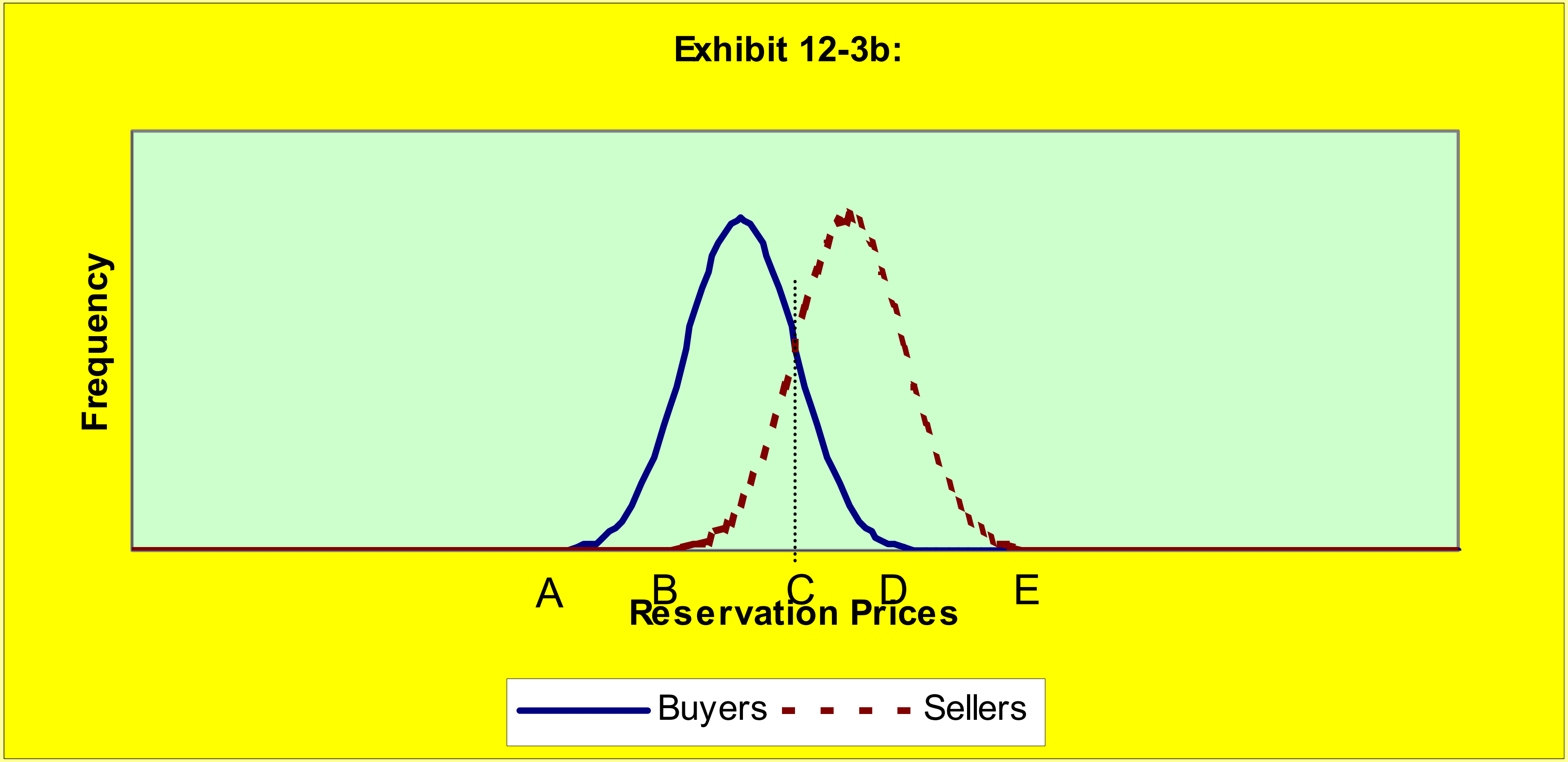
The *mean* of this distribution ("*expected price*") is the *market value* (MV)

Observed *transaction prices* are distributed around the *market value*.

Consider the "reservation prices" of market participants…



e.g., All buyers would be willing to pay at least A, no buyer would be willing to pay more than D. No owner would sell for less than B, all would sell for E.



At any one point in time, for a given type of property:

B = Min possible transaction price

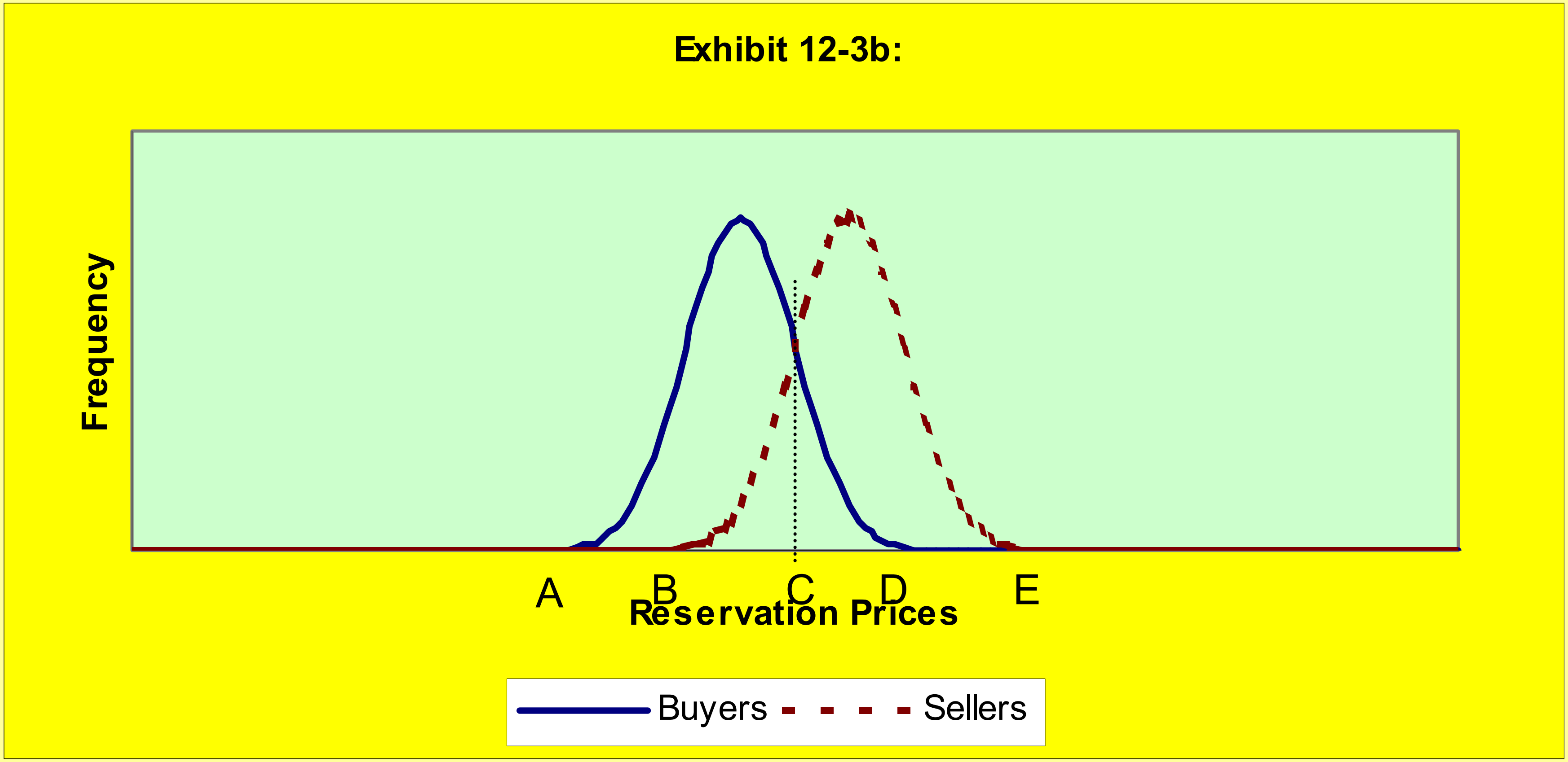
D = Max possible transaction price

C = Expected transaction price (ex ante)

C = Market clearing price (# willing buyers = # willing sellers)

C = Price at which ALL transactions would take place in a very liquid double-auction market like the stock market.

C = **"Market value"** of an asset of this type, at this point in time.



As it is, in the real estate asset market we may observe transactions anywhere between B and D:

$$\mathbf{V^T_{it} = V_{it} + \varepsilon_{it}}$$

V^T_{it} = observed transaction price for property "i"as of time "t"

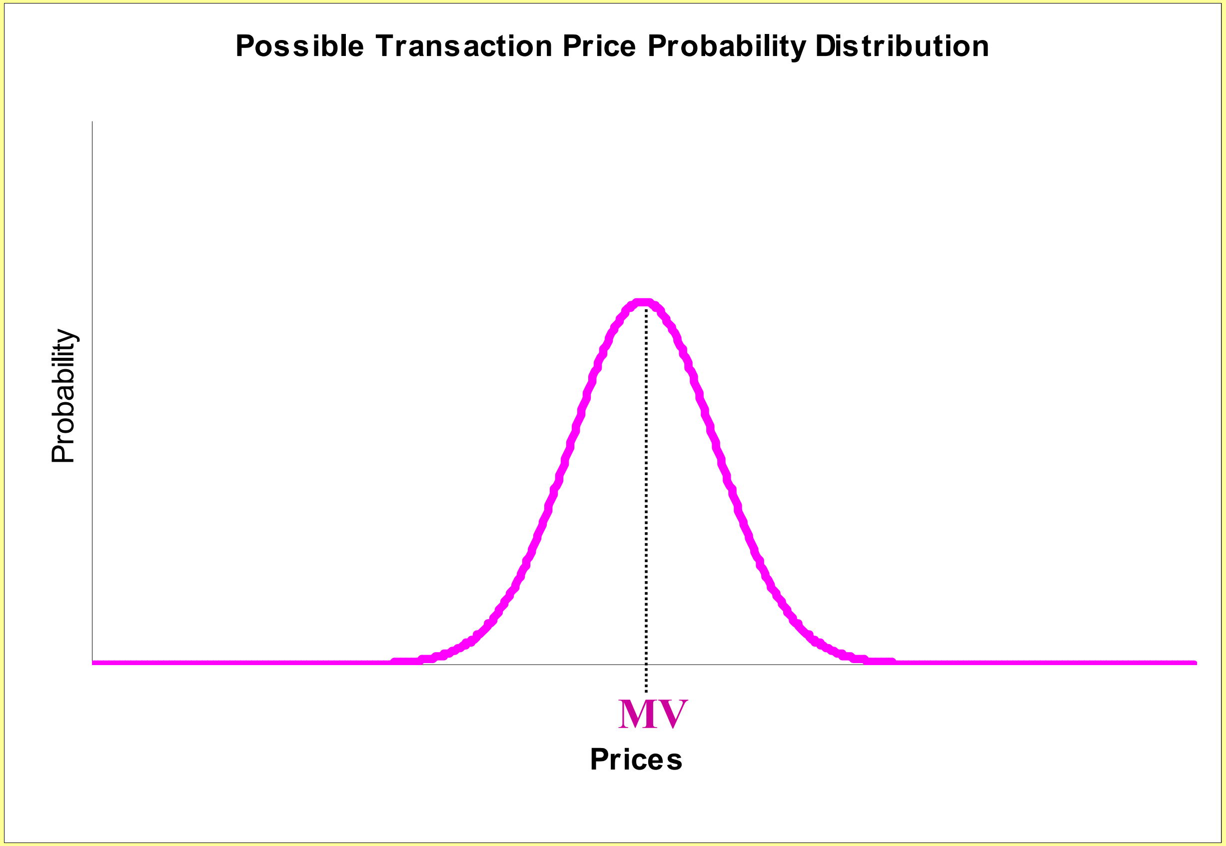
V_{it} = unobservable "true" mkt val (MV) of prop. "i" as of time "t" (= **C**)

ε_{it} = unobservable random "error" or "noise".

(E.g., suppose the seller happened to be a particularly good negotiator and/or the buyer happened to be a particularly eager purchaser, then ε_{it} would be positive.)

It is impossible to know exactly what is the market value of any property at any point in time. Observed *prices* are *"noisy"* indications of value.

MV can be *estimated* by observing the distribution of transaction prices, using *statistical* or *appraisal* techniques.



MV can be estimated more accurately:

- **The larger the number of transactions (more frequent trading, *"denser market"*), &**
- **The more *homogeneous* the assets traded in the mkt.**
- **Nevertheless . . .**

***All* estimates of MV (whether appraisal or statistical) contain *"error"*.**

Summarizing . . .

$$NPV_{IV}(buyer) = IV(buyer) - P$$

$$NPV_{IV}(seller) = P - IV(seller)$$

$$P = MV + \varepsilon$$

$$M\hat{V} = MV + u$$

$$M\hat{V} = P - e = MV + \varepsilon - e$$

$where:$

$IV = Investment\ Value\ (Inherent\ Value\ for\ an\ Investor)$

$P = Observed\ Transaction\ Price$

$MV = True\ (unobservable)\ Market\ Value$

$M\hat{V} = Estimate\ (appraisal\ or\ statistical)\ of\ Mkt\ Val$

$\varepsilon = Transaction\ Price\ "Noise"\ (randomly\ distributed)$

$u = Estimation\ Error\ (may\ or\ may\ not\ be\ random)$

$e = Regression\ "Residual"\ (random)$

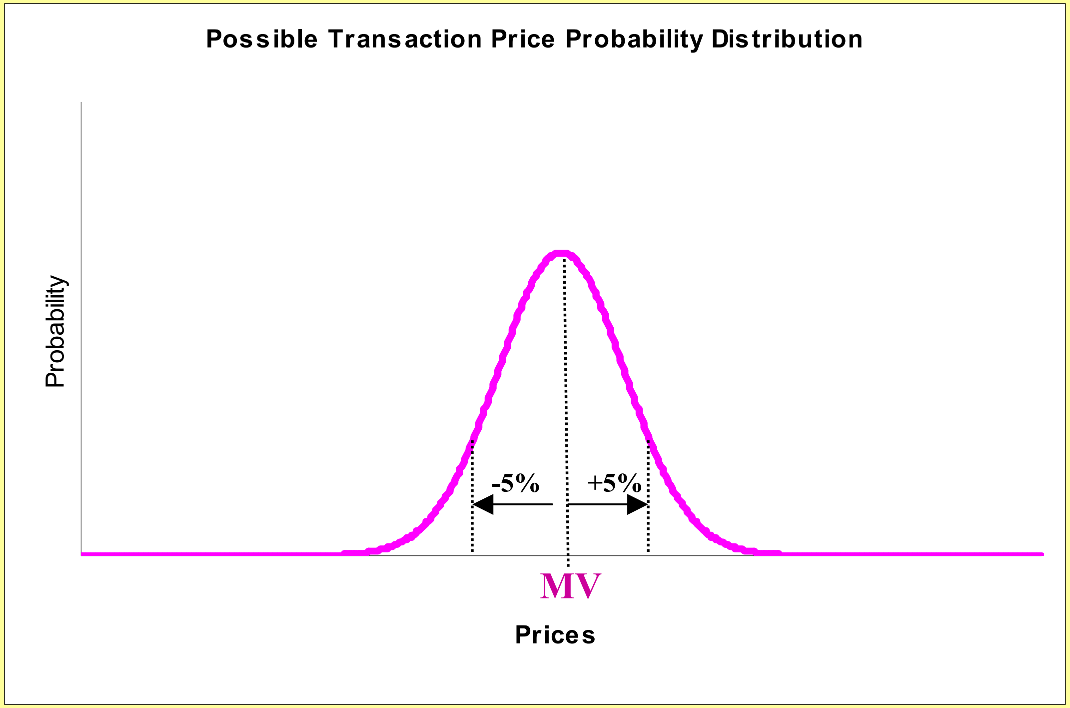
How big is random noise or error in real estate prices and value estimates? . . .

There is some statistical and clinical evidence that for typical properties such noise or error has a magnitude of around 5% to 10% of the property value.

That is: Std.Dev.[ε] = 5% to 10% (price dispersion)

Std.Dev.[u] = 5% to 10% (appraisal dispersion)

Probably larger for more unique properties.



Appraisal error differs from transaction noise, but is similar in nature. (Ch.23)

For example, suppose we hire an appraiser to estimate the market value of property "i" as of point "t" in time (and the appraiser does not know the transaction price). The appraised value can be represented as follows:

$$V^*_{it} = V_{it} + u_{it}$$

V^*_{it} = appraised value of poperty "i" as of time "t",

V_{it} = unobservable "true" market value,

u_{it} = random unobservable appraisal error.

The two "errors", the transaction noise ε_{it} and the appraisal error u_{it}, are different random numbers, probably independent of one another.

Thus, if we compare an appraised value with a transaction price of the same property as of the same point in time, we are observing the difference between two random errors. The transaction price is not more "right" in any fundamental sense than the appraised value:

$$V^*_{it} - V^T_{it} \quad = \quad u_{it} - \varepsilon_{it} \quad \neq \quad u_{it}$$

Fundamental problem is that in private real estate markets:

- ***unique, whole assets*** **are traded**
- ***infrequently and irregularly*** **through time,**
- **in deals that are privately negotiated between *one buyer and one seller*.**

(All three of these characteristics differ from securities mkts.)

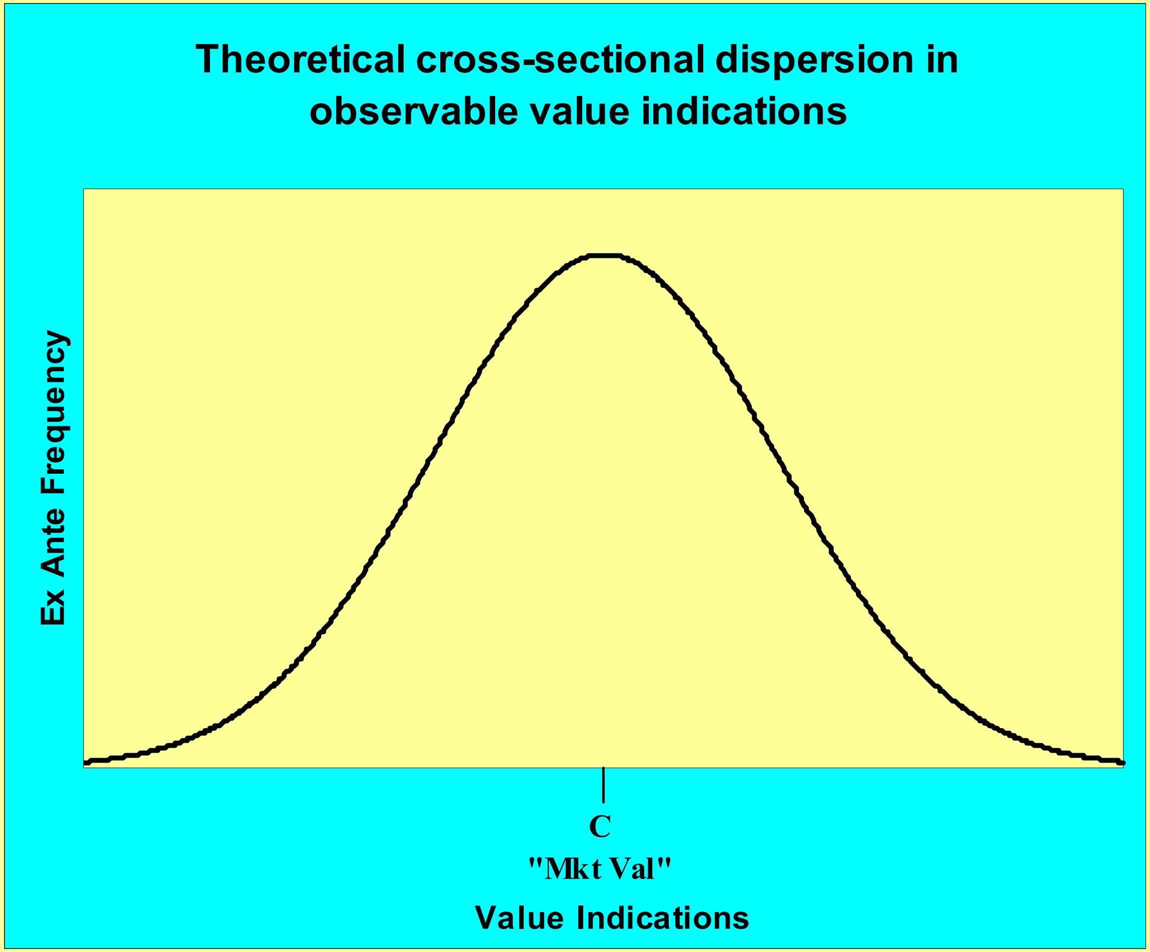
Implication of these differences from securities is that:

Real estate asset values are measured with *error*.

This is true for *both* major types of empirical value data:

- **Transaction prices;**
- **Appraised values.**

Valuation Methodology: Transactions or Appraisals? . . .



Transaction price error = Obs.Price – True Val: $\varepsilon_t = \overline{V}_t - C_t$

Appraisal error = Estd.Val. – True Val: $u_t = \hat{V}_t - C_t$

Transaction prices are distributed around contemporaneous market value: "*market value*" = mean of potential (*ex ante*) transaction price distribution (actual transaction prices are like random drawings from this distribution).

Contemporaneous transaction prices thus contain *purely random error* (aka "*noise*"), but *no temporal lag bias*.

Noise reduces the accuracy with which values or periodic returns can be estimated or quantified empirically.

But noise alone does not induce a temporal lag bias into such data.

Noise is diminished according to the "*Square Root of N Rule*":

The STD[ε] is proportional to the inverse of the square root of the number of transaction observations used in the value estimate.

Appraisals also contain noise (random value estimation error).

But appraisers try to minimize noise, i.e., they try to maximize the accuracy of their value estimates.

In effect, they do this by using the *Square Root of N Rule*: They use as many "*comps*" (as much transaction price evidence) as possible.

This requires that appraisers go *back* in time (transaction evidence is observable only across historical time).

This results in an additional type of error in appraisals, not present in purely contemporaneous transaction prices:

***Temporal lag bias* error tends to exist in appraisals.**

The effect of aggregation across individual property valuations:

The "Square Root of N" Rule applies to *random* "error" in estimating V_{it} (based on observations of V^T): $\sigma = \sigma_\varepsilon / \sqrt{N}$ where: σ is Std.Dev of "Population" (Distn betw "B" & "D").

Thus, when numerous individual property valuations made by numerous independent appraisers are averaged (or aggregated) together (across properties), the *random* valuation errors (or "noise") tends to diversify away.

But *systematic* errors (types of errors that are common across all appraisals) remain in the aggregate. *Temporal lag bias* is systematic, and so remains in the aggregate valuation.

Example 1:

Percentage "**error**" (deviation from true market value) will tend to be:

1/2 AS LARGE WHEN AN APPRAISER USES:

8 COMPS INSTEAD OF 2, OR

32 COMPS INSTEAD OF 8…

(N = 4 times, $N^{1/2}$ = 2 times)

Each appraisal might use only a few comps, but in an index aggregated from hundreds of appraisals or transactions each period, random error tends to get pretty small (in percentage terms).

Bottom Line: ➔ At <u>aggregate</u> level (index or large portfolio of properties) purely random error component is often not very important.

Example 2:

Suppose in a certain market one property sells each month, and appraisers simply take the average of the prices of all the comps they use to estimate a subject property's value, starting with the current sale:

- **"Type A" Appraisers use 2 comps, and therefore have only ½ month of average lag in their valuation estimates (½ weight on the current sale, plus ½ weight on the previous month's sale), but their valuations contain a large amount of purely random error (standard deviation of their value estimate around the unobservable true value).**
- **"Type B" Appraisers use 8 comps, and therefore have only half (1/SQRT(8/2)) the random error of Type A Appraisers, but they have an average lag of 3½ months.**

Note: If we averaged the valuations of a large number of either type of appraisers' valuations, the random error would diminish, but the lag would not diminish.

The *NOISE vs. LAG TRADE-OFF*

Example:

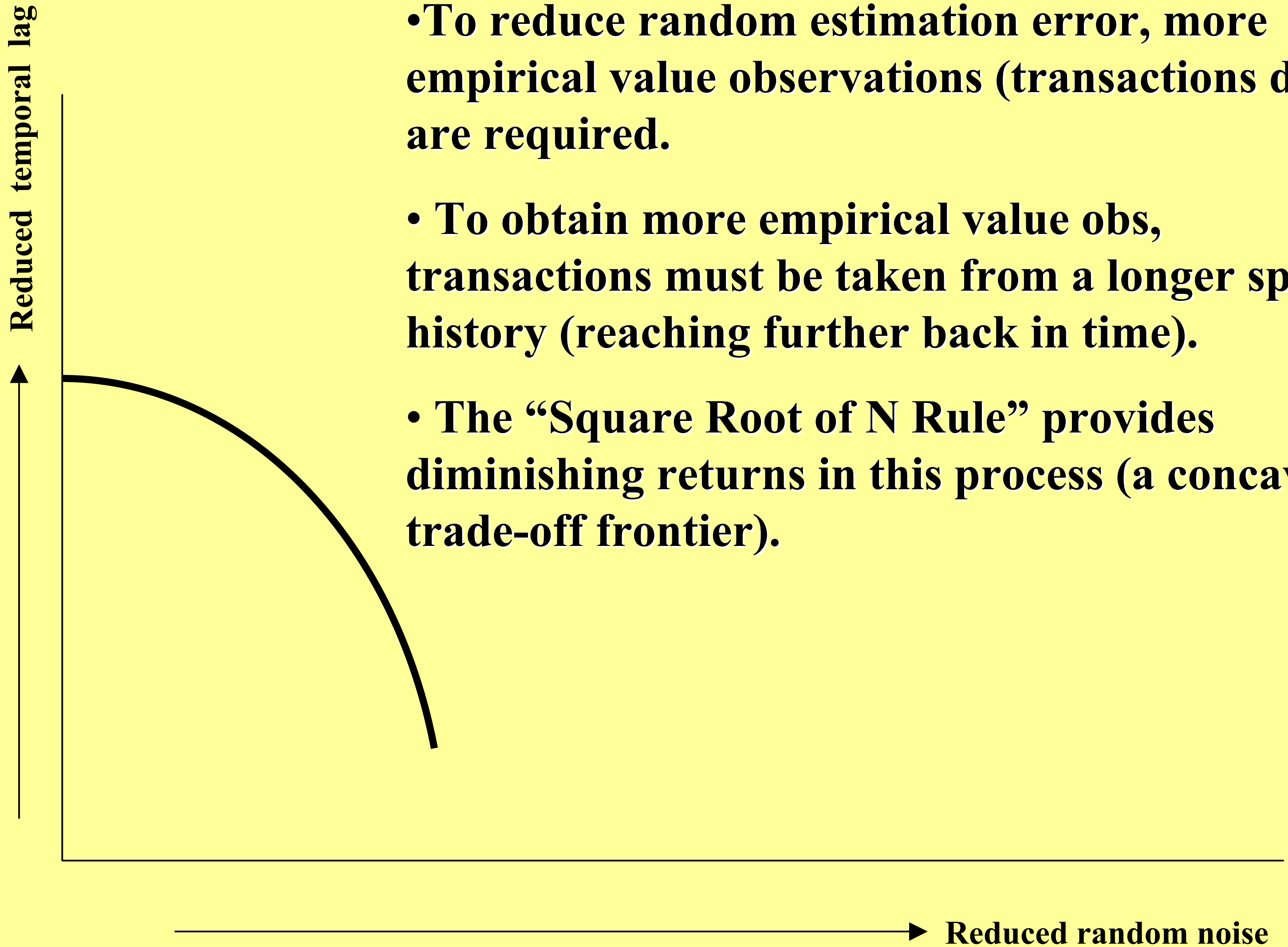
You own a property. Would you rather have an estimate of value that is accurate to within ± 10% with no lag bias, or to within ± 2% but whose most likely value is what the property was worth 6 months ago?…

Your answer probably depends on how you are going to use the appraisal:

- ***Are you just interested in the value of that one property?***
- ***Or will you be combining that property's valuation with many others to arrive at the value of an entire portfolio or index?***

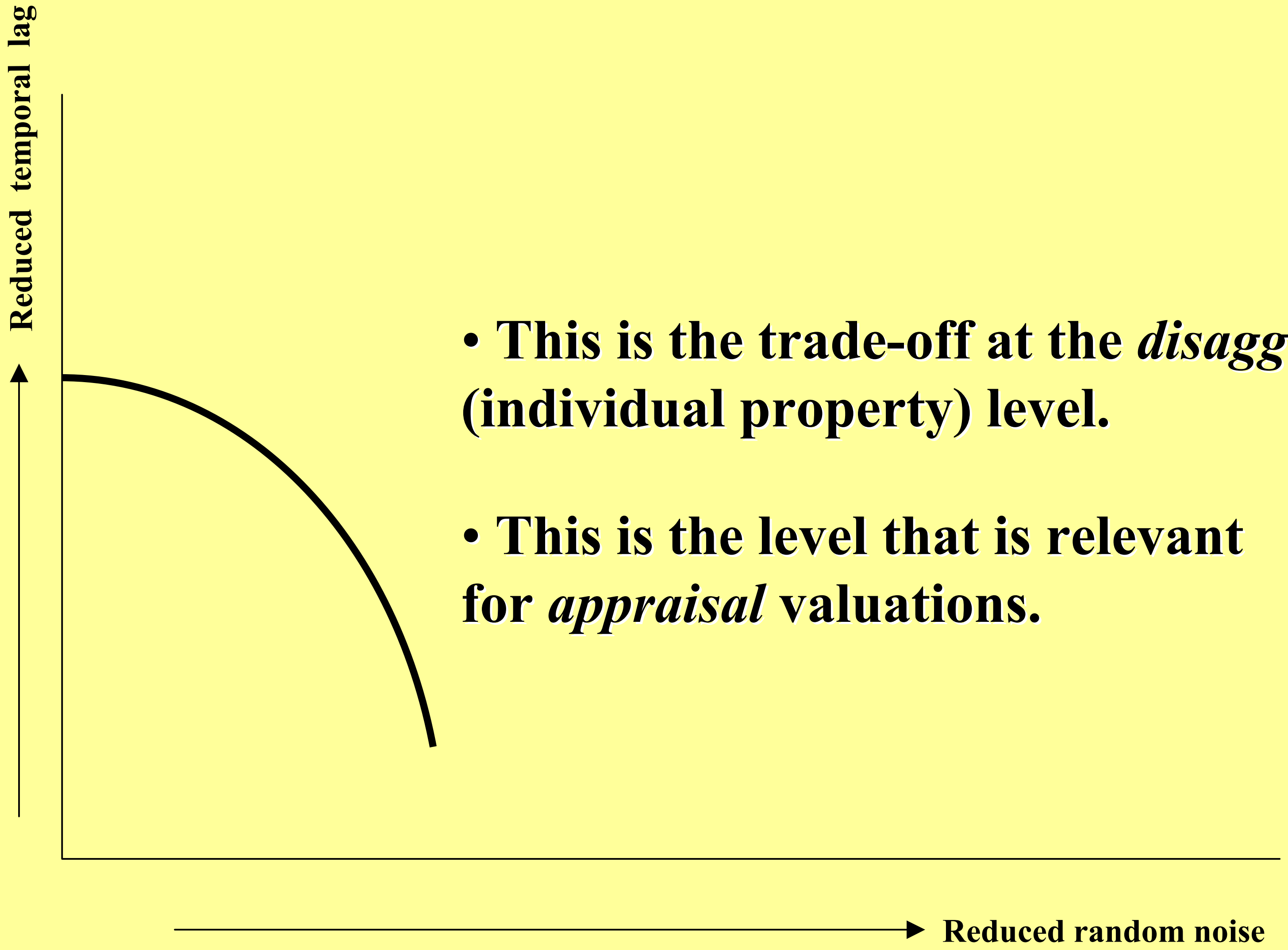
In the latter case, the purely random error in the property valuation estimate will tend to cancel out with other errors and diversify away, but the temporal lag bias will not go away.

The Noise vs Lag Trade-off (Ch.23) . . .



- To reduce random estimation error, more empirical value observations (transactions data) are required.
- To obtain more empirical value obs, transactions must be taken from a longer span of history (reaching further back in time).
- The "Square Root of N Rule" provides diminishing returns in this process (a concave trade-off frontier).

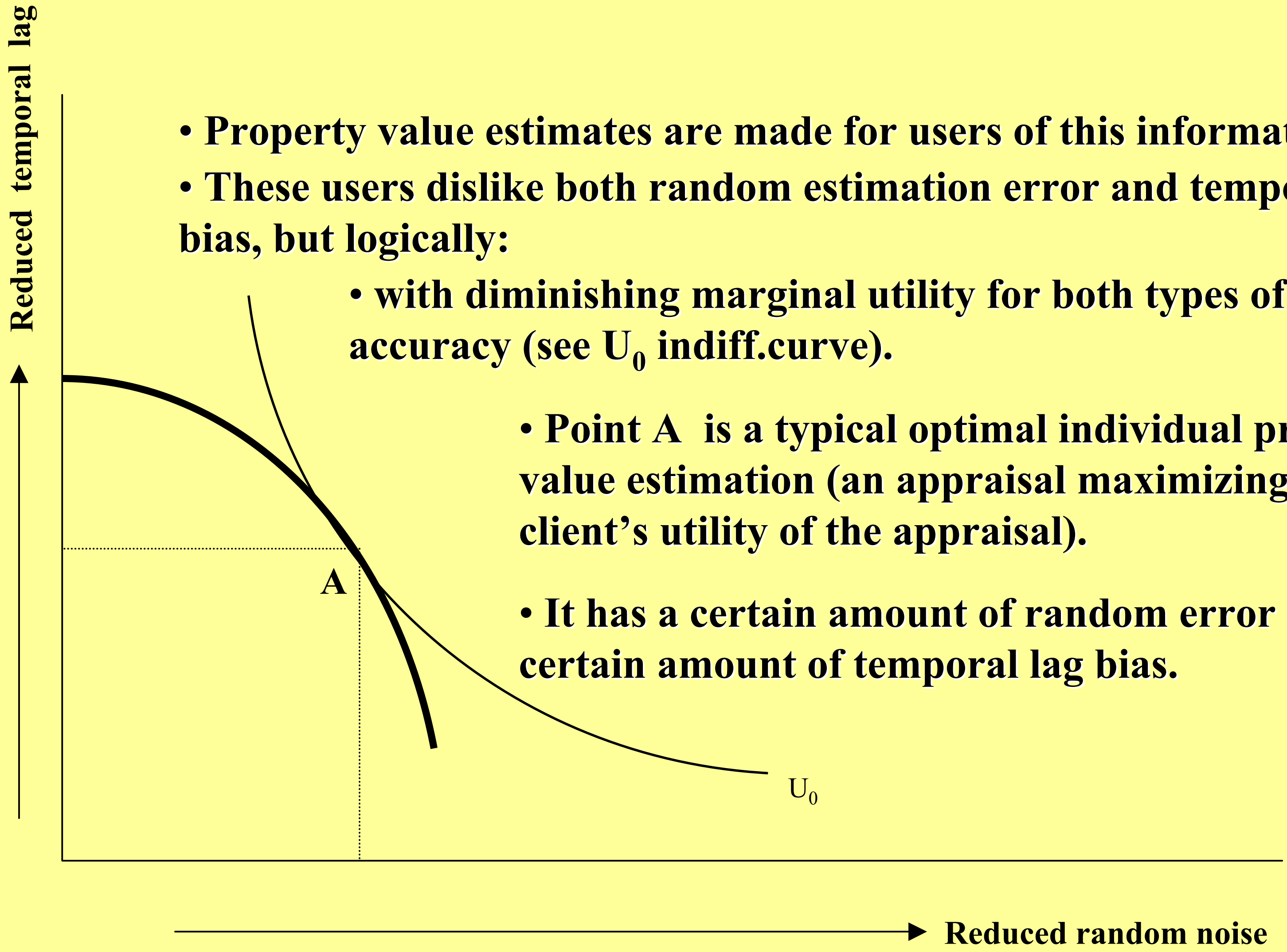
The Noise vs Lag Trade-off (Ch.23) . . .



• **This is the trade-off at the *disaggregate* (individual property) level.**

• **This is the level that is relevant for *appraisal* valuations.**

The Noise vs Lag Trade-off (Ch.23) . . .



- **Property value estimates are made for users of this information.**
- **These users dislike both random estimation error and temporal lag bias, but logically:**
  - **with diminishing marginal utility for both types of accuracy (see U_0 indiff.curve).**
- **Point A is a typical optimal individual property value estimation (an appraisal maximizing the client's utility of the appraisal).**
- **It has a certain amount of random error and a certain amount of temporal lag bias.**

The Noise vs Lag Trade-off (Ch.23) . . .

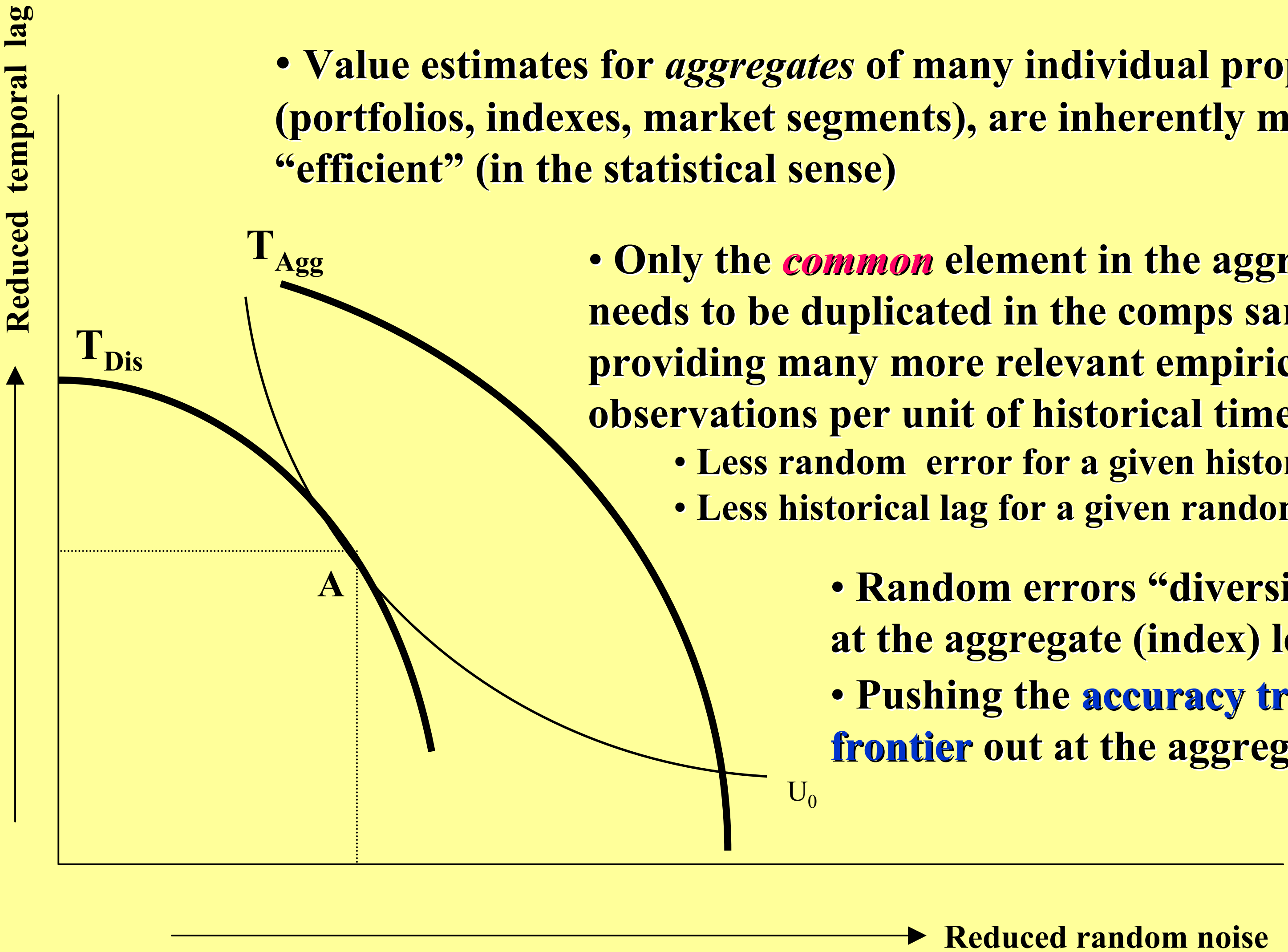
• Value estimates for *aggregates* of many individual properties (portfolios, indexes, market segments), are inherently more "efficient" (in the statistical sense)

• Only the ***common*** element in the aggregate needs to be duplicated in the comps sample, providing many more relevant empirical value observations per unit of historical time:

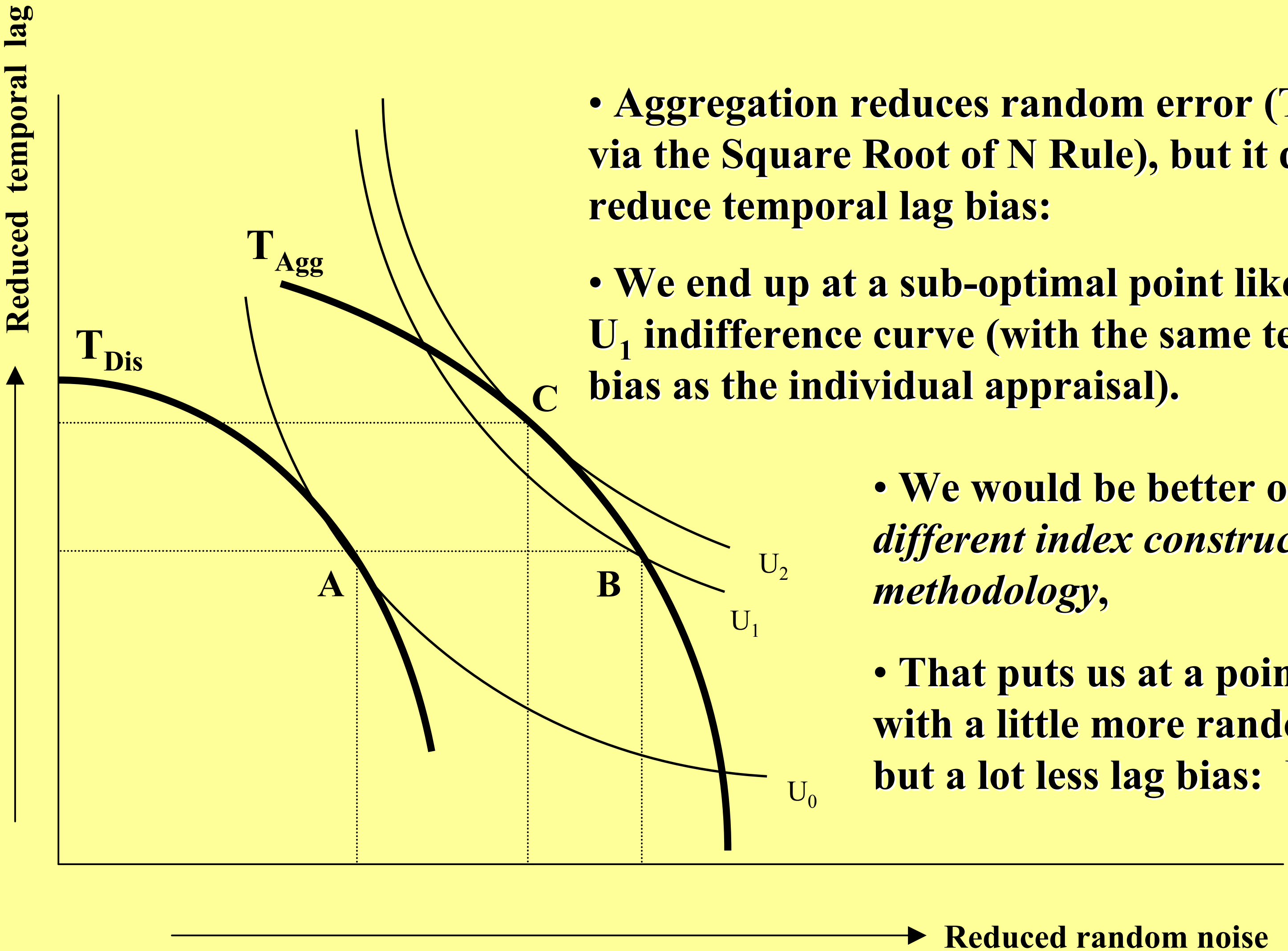
- Less random error for a given historical lag;
- Less historical lag for a given random error.

• Random errors "diversify out" at the aggregate (index) level.

• Pushing the **accuracy trade-off frontier** out at the aggregate level.



The Noise vs Lag Trade-off (Ch.23) . . .



- **Aggregation reduces random error ($T_{Agg} > T_{Dis}$ via the Square Root of N Rule), but it does not reduce temporal lag bias:**
- **We end up at a sub-optimal point like B, on the U_1 indifference curve (with the same temporal lag bias as the individual appraisal).**
- **We would be better off with a *different index construction methodology*,**
- **That puts us at a point like C, with a little more random error, but a lot less lag bias: U2 > U1.**

- **Simple aggregation of value estimates that were optimized at the disaggregate individual property level will not produce an estimate of value that is optimal at the aggregate index or portfolio level…**

II. Problems in real estate periodic returns data…(Ch.25)

Background: From values to returns…

Recall the definition of the periodic return:

$$r_t = \frac{V_t - V_{t-1} + CF_t}{V_{t-1}} = \frac{V_t - V_{t-1}}{V_{t-1}} + \frac{CF_t}{V_{t-1}} = g_t + y_t$$

We need:

V_t = True value of asset ***as of the end of period "t" in time***.

V_{t-1} = True value of asset ***as of the end of period "t-1" in time***.

OK for publicly-traded securities (at quarterly frequency).

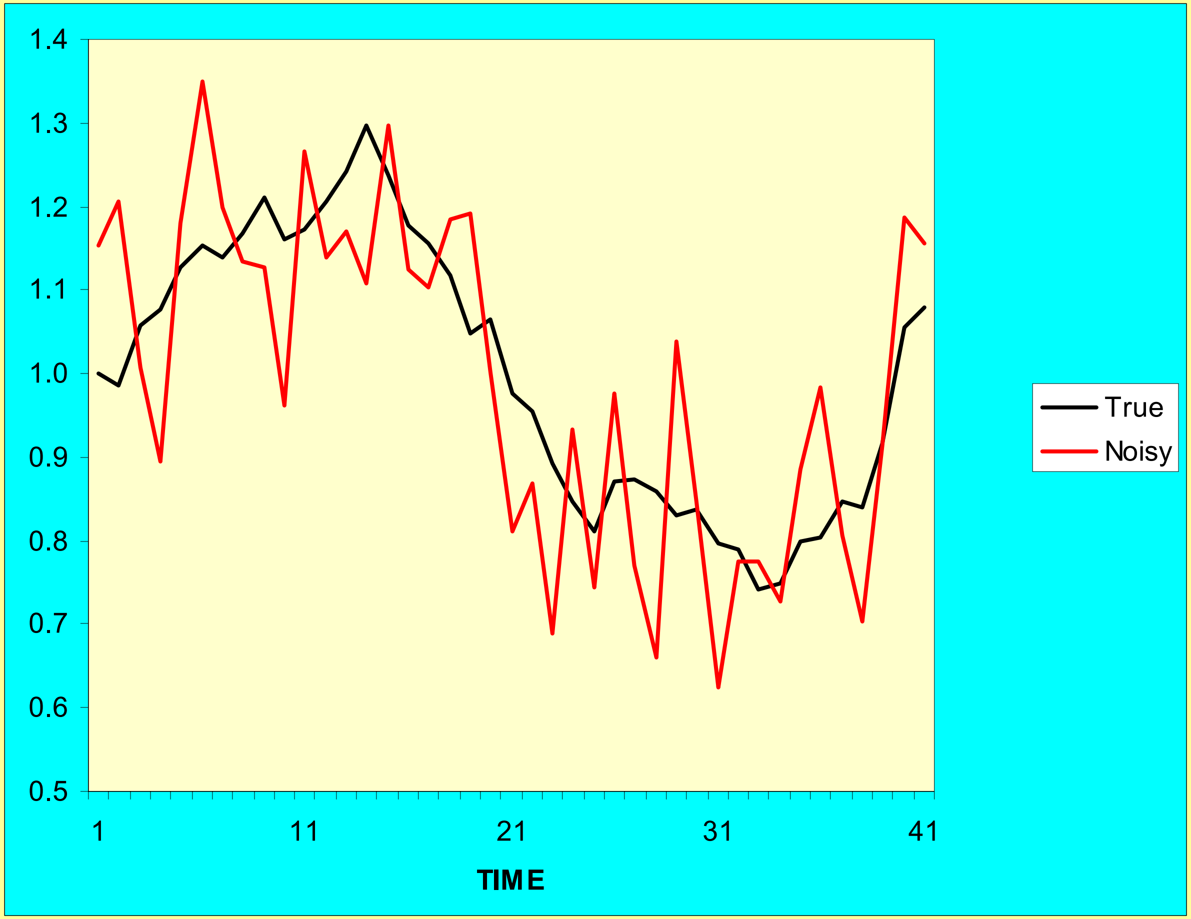
But for private real estate, "we have a problem"…

In fact, we have ***two*** problems:

➔ Observed value of V_t is measured with ***random error***, exhibits ***"noise"***.

➔ Observed value of V_t exhibits ***"temporal lag bias"***, as if computed from a ***trailing moving average*** across time.

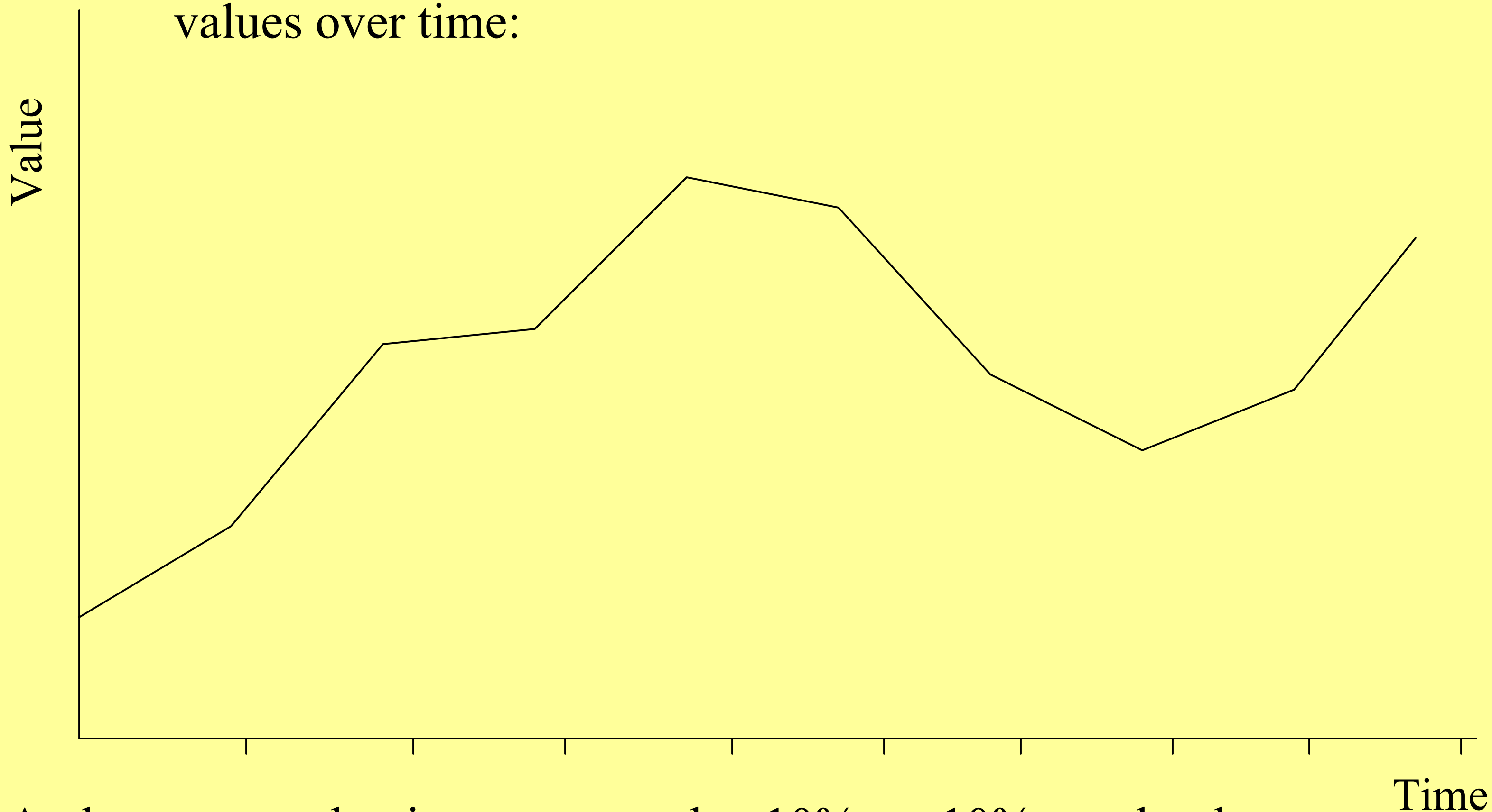
Here is a picture of the typical pure effect of **noise** (alone) on an index of cumulative asset or portfolio value levels:



How does this *"sawtooth"* effect result from random noise? . . .

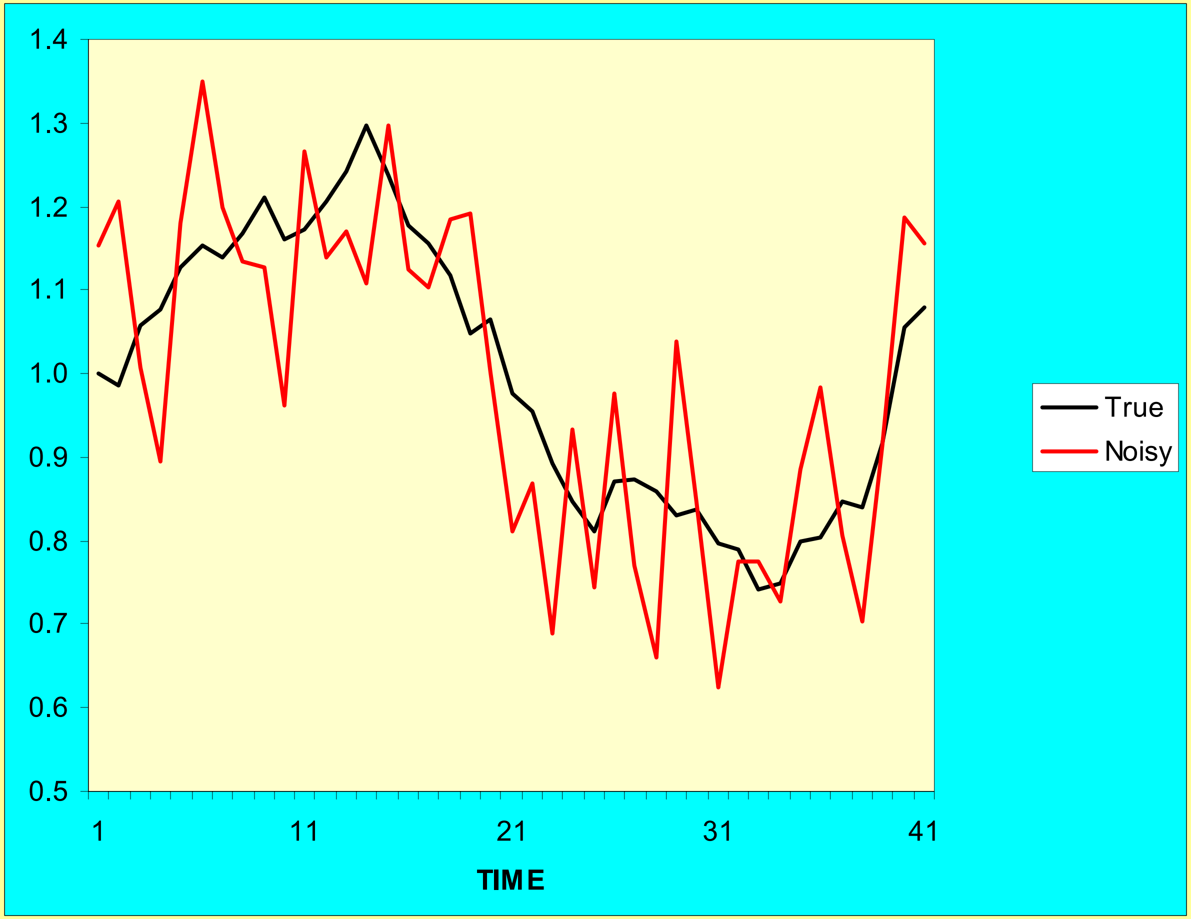
Aside: How does this *"sawtooth"* effect result from random noise? . . .

Suppose this is the true (unobservable) history of real estate values over time:



And suppose valuation error equals +10% or -10%, randomly over time (independent errors), as if from the flips of a coin…

Random valuation error adds excess apparent volatility, that is transient *("mean-reverts")* over time:

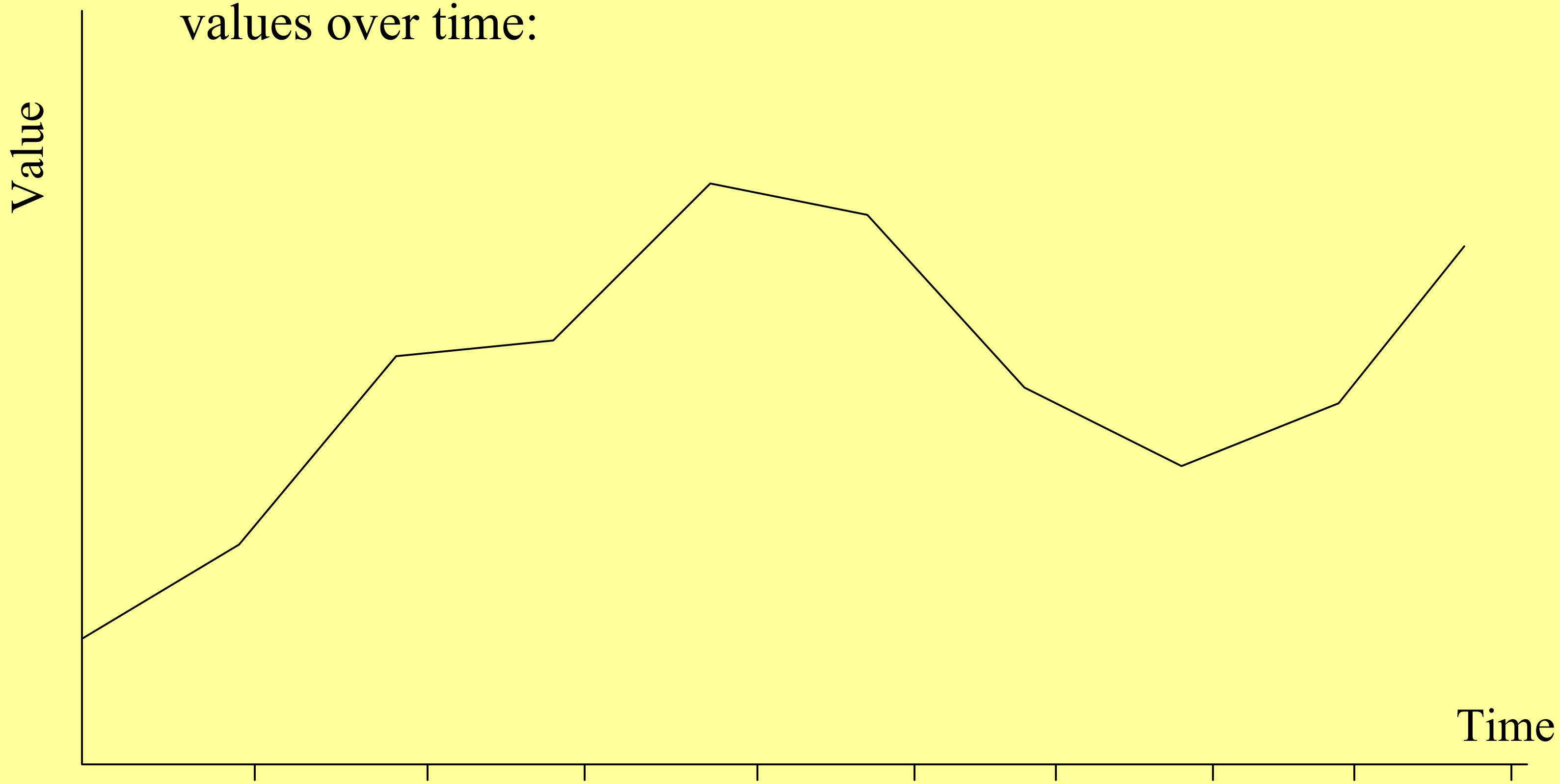


Here is a picture of the typical pure effect of temporal lag bias (alone) on an index of cumulative asset or portfolio value levels:

How does this lag effect result from historical temporal aggregation?

Aside: How does the lag effect result from historical temporal aggregation? . . .

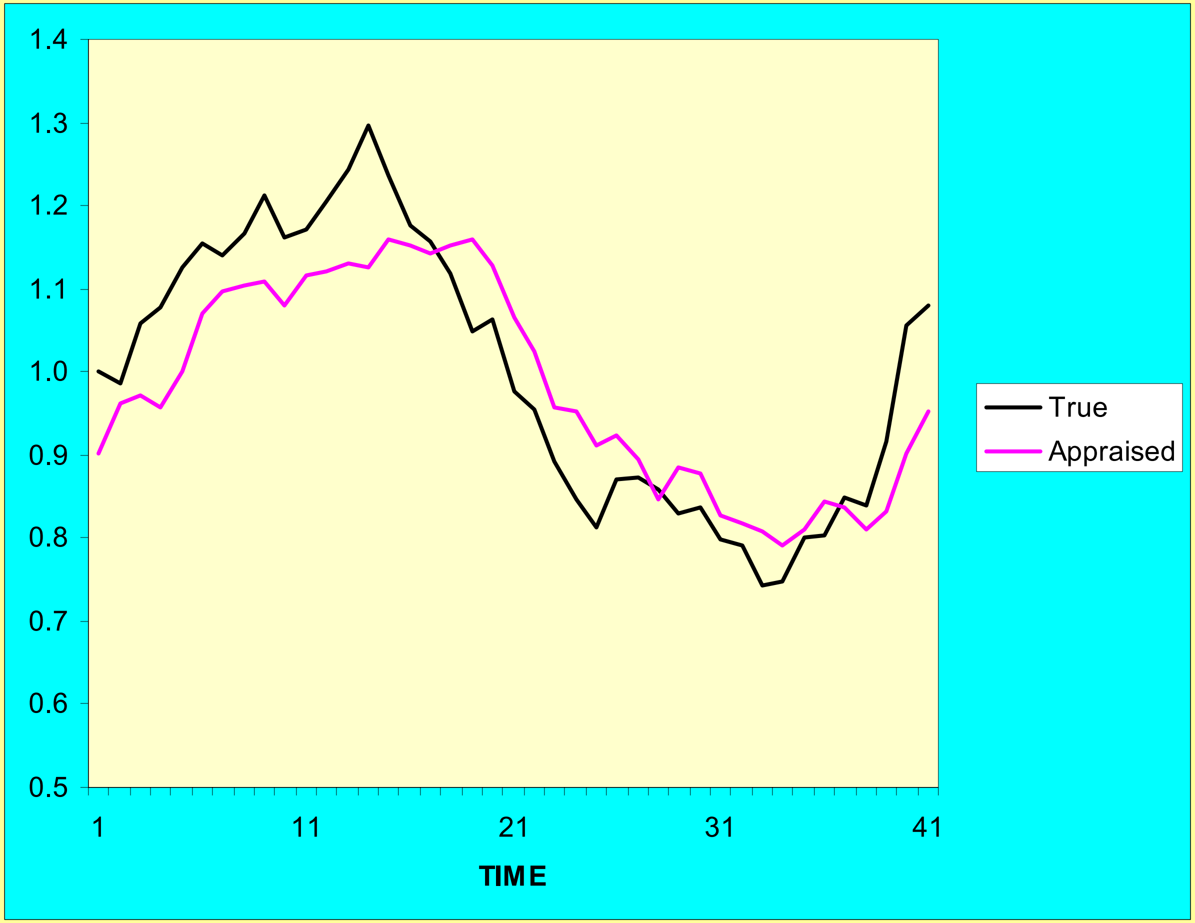
Suppose this is the true (unobservable) history of real estate values over time:



And suppose appraisers use two comps which they weight equally to estimate the current period's value, one comp is current, the other from the previous period (& ignore random error to focus on the pure temporal aggregation effect).

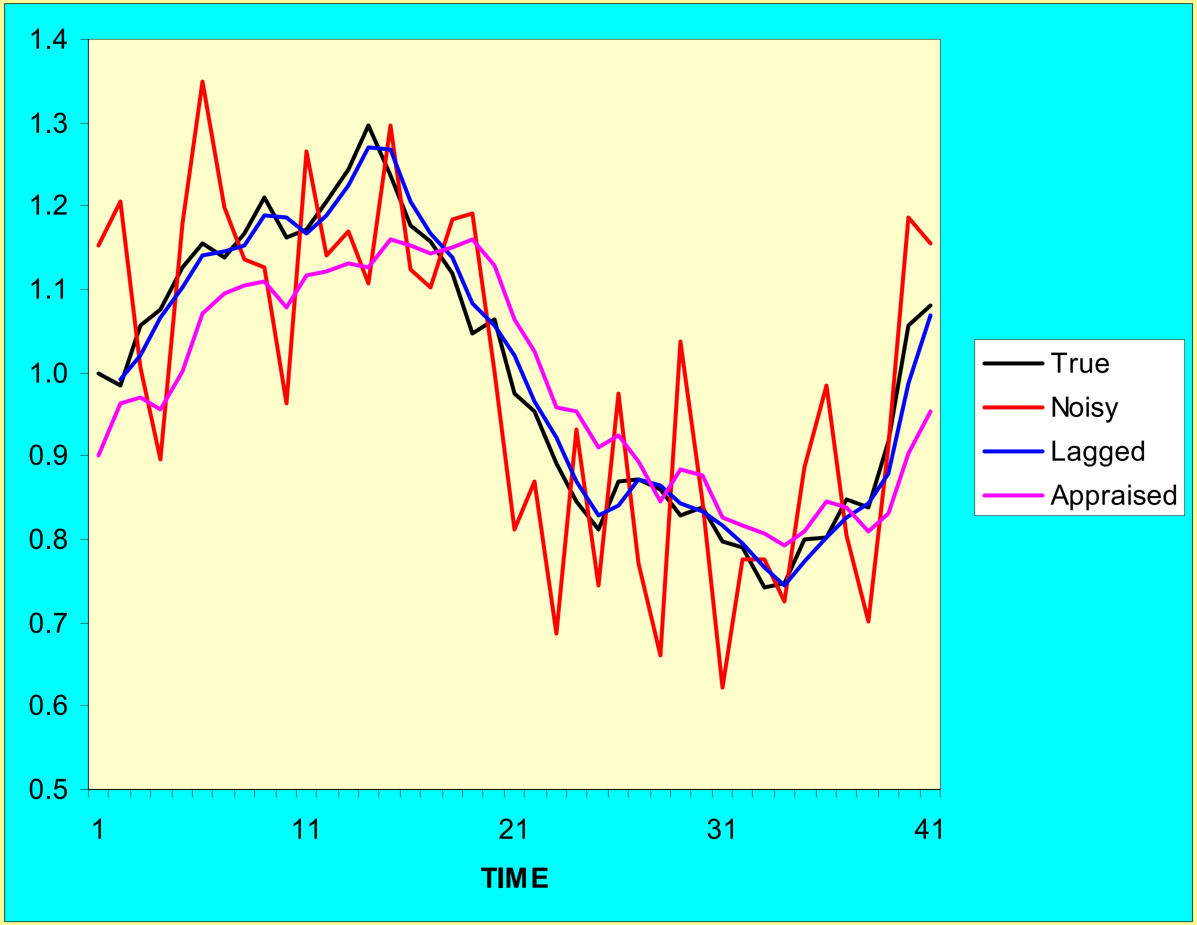
Temporal aggregation results in an apparent index that is both lagged and smoothed (less volatile) compared to the true values:

Here is a picture of the typical appraisal-based index, which includes both random noise & temporal lag:



How much of each type of error depends on how many properties (appraisals) are included in the portfolio or index, and on how much lagging the appraisers had to do at the individual property (disaggregate) valuation level.

The two pure effects and appraisals . . .



Of course, the "*true*" value index would be unobservable in the real world.

These types of valuation errors can cause a number of *problems*:

- ➔ "Apples vs oranges" comparison betw R.E. and securities returns
- ➔ Misleading estimates of R.E. ex post investment performance
- ➔ Misleading estimates of R.E. risk and co-movement:
    - (e.g., R.E. covariance or β is underestimated.)
- ➔ Out-of-date information about property mkts:
    - (e.g, have mkts "peaked", or are they still "rising"?)

How to understand, recognise, and deal with the returns data problem (Ch.25)…

III. *The temporal pattern of aggregate real estate returns data…*(25.2)

Suppose publicly-observable "news" arrives at a *point* "t" in time. This news is relevant to the value of real estate assets. What will happen?

1st) REIT share prices quickly and fully respond to the news, changing to the newly appropriate level almost immediately (probably within a day or two). We can represent this as:

$V^{*REIT}_t = V^{REIT}_t$

V^{*REIT}_t = Observed REIT value, as of end of period "t".

V^{REIT}_t = True REIT value, as of end of period "t".

(Maybe a little "overreaction", then correction?…)

(Maybe some "spurious" movements: things REIT investors care about that property investors don't care about?…)

(But at least they move quickly and in the right direction in response to relevant news.)

2nd) Property market liquid asset values respond more gradually to the news:

$$V_t = \beta_0 V^{REIT}_t + \beta_1 V^{REIT}_{t-1} + \ldots, \textit{ where } 0<\beta_t<1, \textit{ and } \Sigma\beta_t=1$$

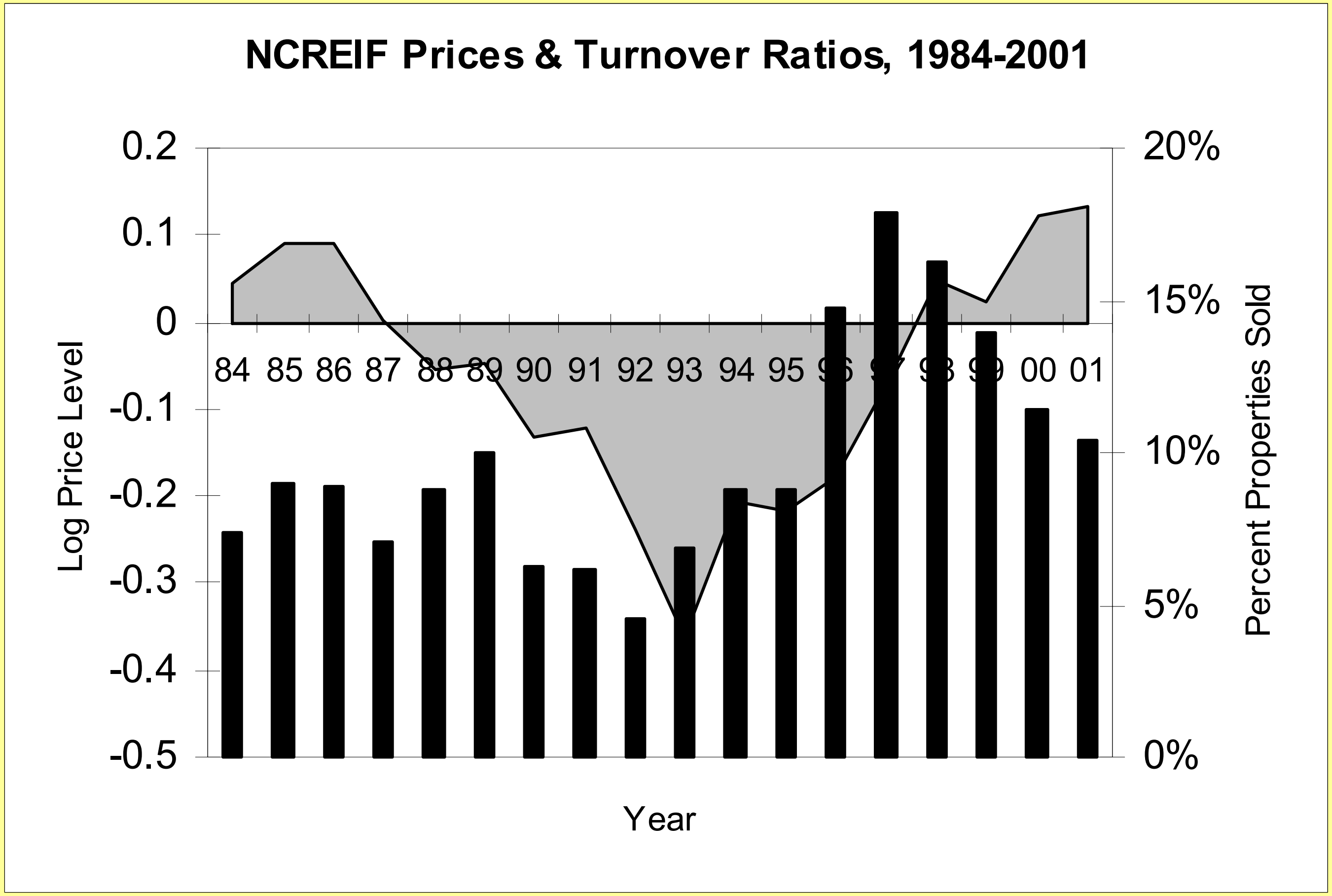
V_t = Property market value *("liquid" value, "bid price")* as of end of "t".

V^{REIT}_t = Full-information value *(as if it were a REIT)* in that same market.

Note: $V_t \neq V^T_t \ldots$

Transaction prices *(V^T_t)observed in the property asset market at time "t" are* ***not*** *generally the same as* ***fully liquid*** *market prices (especially in a down-market). This is because liquidity is in fact not constant across time in property markets, as many property owners do not require constant liquidity in their real estate holdings, so they tend to hold properties off the market during "down markets" and to sell more properties during "up markets".*

Here is what pro-cyclical variable liquidity looks like in the NCREIF Index:



3rd) Empirically observable transaction prices in the property market will even more gradually reflect the news (at least during down-markets, when prices are falling):

$$\bar{V}_t = \beta_0 V_t + \beta_1 V_{t-1} + \beta_2 V_{t-2} + \ldots, \quad \sum \beta = 1$$

where: $\bar{V}_t$ = Cross-sectnl avg transaction price in period t;

V_t = Cross-sectnl avg liquid value (bid price) in period t.

4th) Appraised values of properties will respond even more gradually *(Appraisers tending to be more **"backward-looking"**, dependent on transaction price observations, than property market participants who make or lose money depending on how well they can be "forward-looking".)*

We can represent this as:

$$V^*_t = \alpha\overline{V}_t + (1-\alpha)V^*_{t-1}$$

$0<a<1$,

a = "Confidence Factor",

$(1-\alpha)$=Smoothing factor.

where V^*_t is property appraised value as of the end of quarter "t" and $\overline{V}_t$ is the average empirically observable transaction price during quarter "t".

5th) Indexes of appraisal-based returns may respond even more slowly to the news, if all properties in the index are not reappraised every period, yet they are included in the index at their last appraised valuation.

➔ Problem of "stale" valuations in the index, e.g.:

$$V^{**}_t = (1/4)V^{*}_t + (1/4)V^{*}_{t-1} + (1/4)V^{*}_{t-2} + (1/4)V^{*}_{t-3}$$

where V^{**}_t is the index value in quarter t.

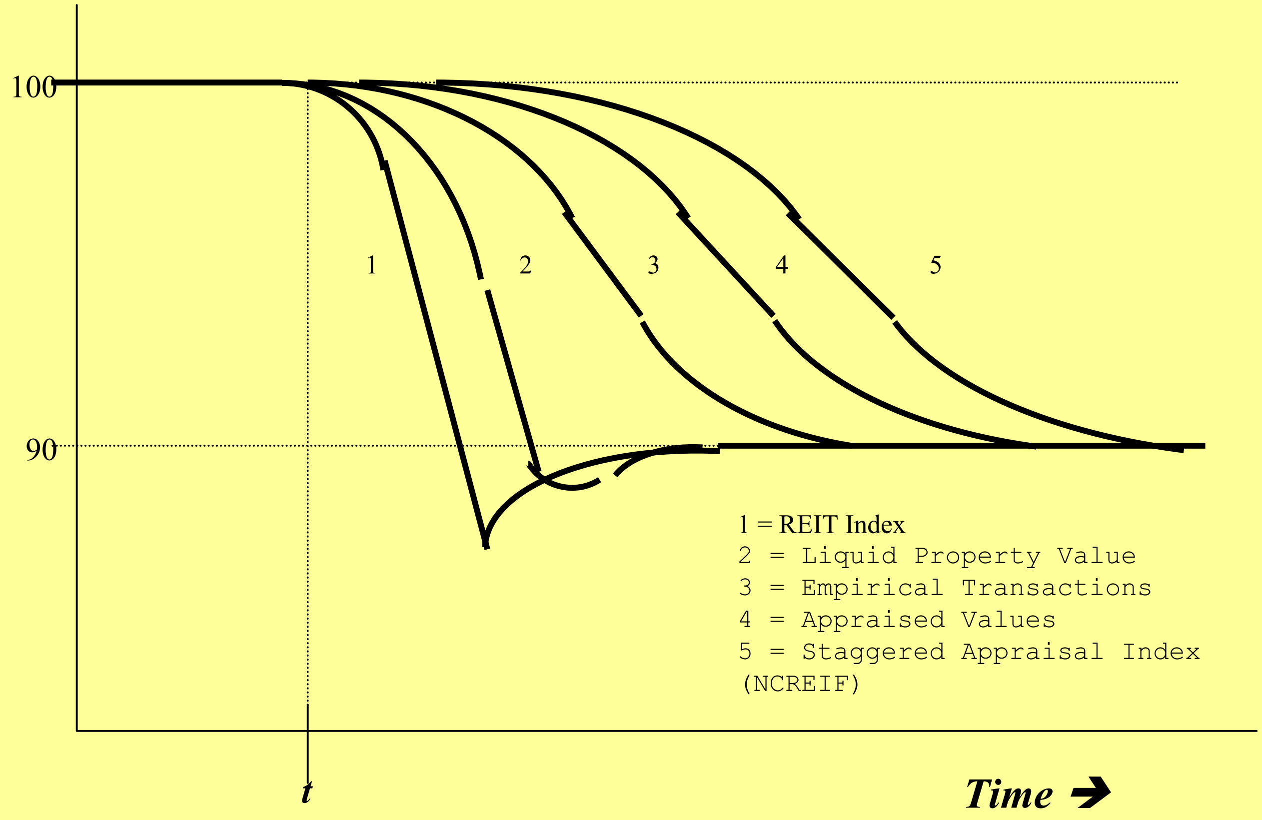
If more of the properties are reappraised in the fourth calendar quarter (as with the NCREIF Index), then something like the following model might well represent the index in the 4th quarter of every year:

$$V^{**}_t = (1/2)V^{*}_t + (1/6)V^{*}_{t-1} + (1/6)V^{*}_{t-2} + (1/6)V^{*}_{t-3}$$

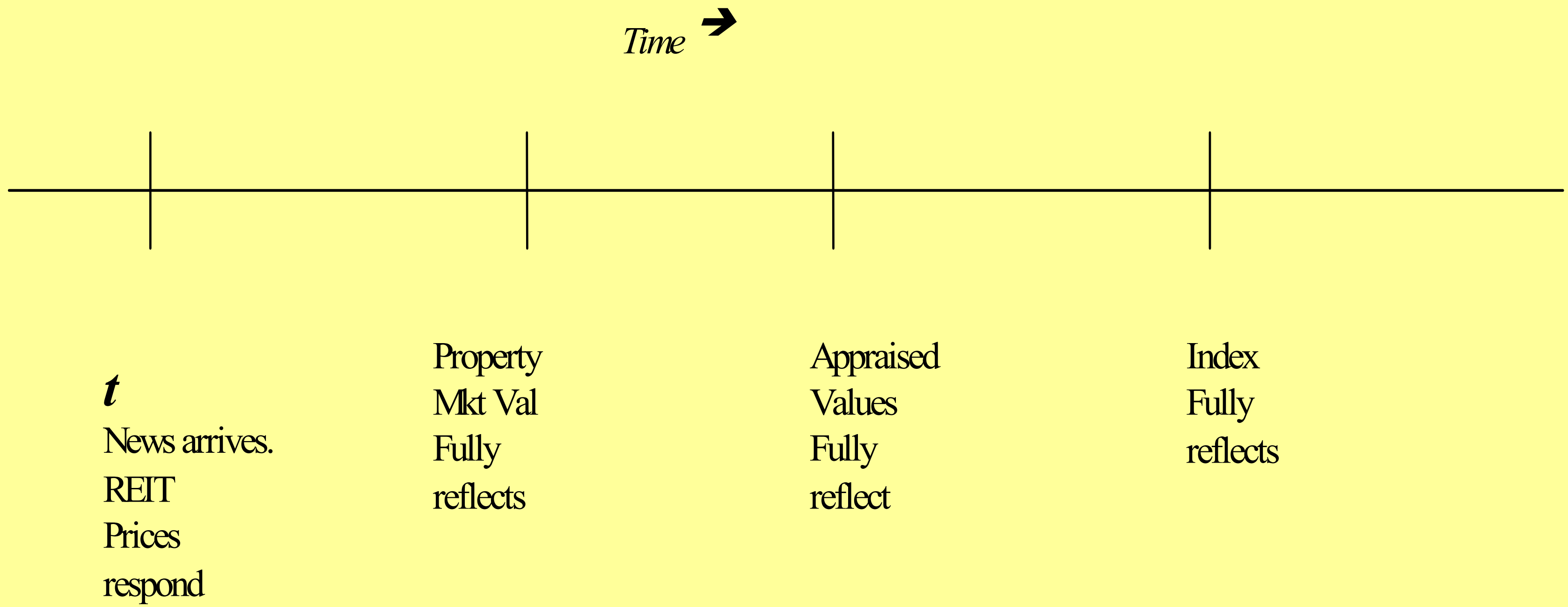
This will make the index more "up-to-date" at the end of the 4th quarters than it is in the other quarters, and it will impart ***"seasonality"*** into the quarterly index returns.

Here is a schematic picture of how this **time-line of *price discovery*** might play out in response to the arrival of a single piece of (bad) news…

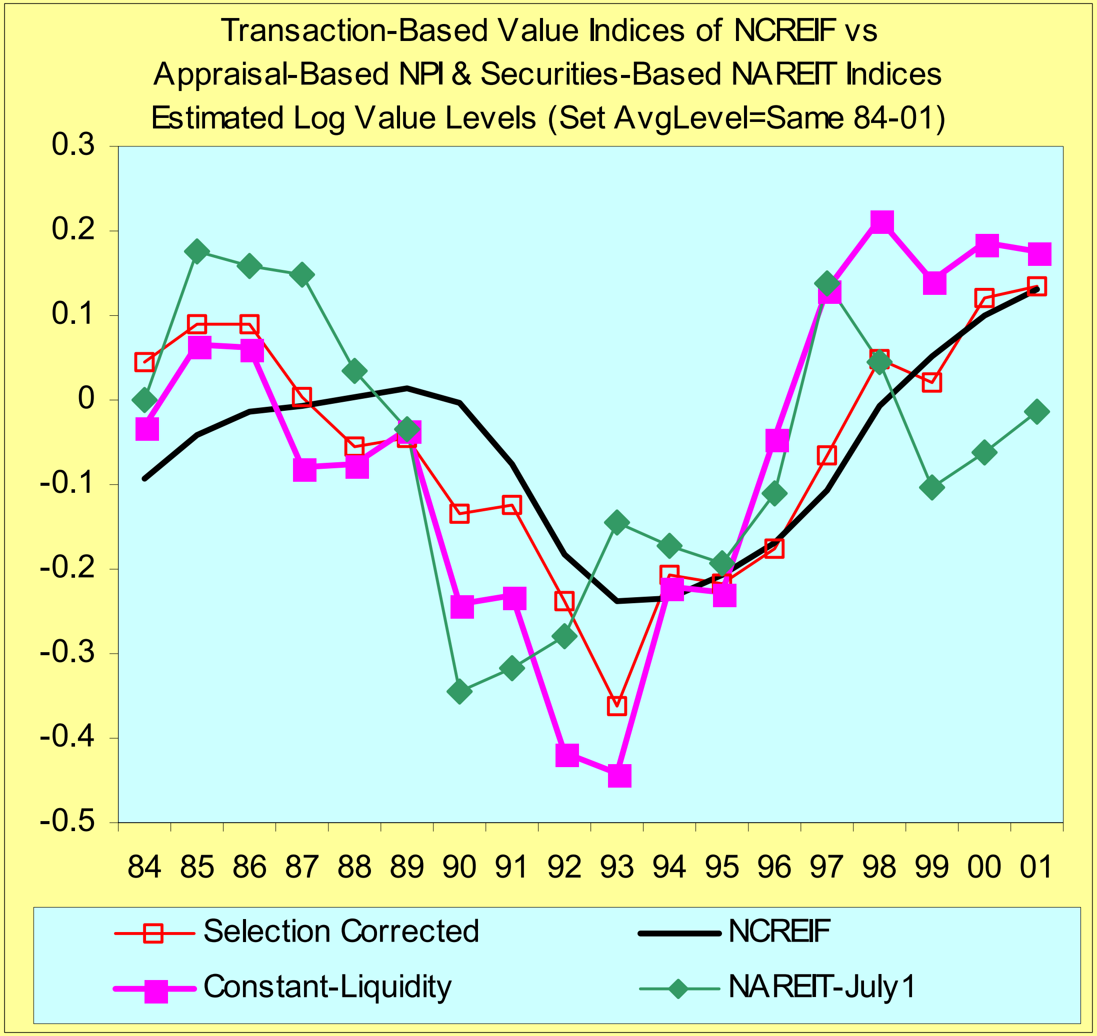
Exhibit 25-4 (page 670)



Summary of lagged incorporation of “news” into values:



What this looks like in the real world:
The time line of real estate price discovery…
Public ➔ Const.Liq ➔ Var.Liq. ➔ Appraisal:



Return Statistics (continuously compounded annual capital returns), 1984-2001:

	NCREIF	VariableLiq	ConstLiq	NAREIT
Mean	1.32%	0.52%	1.22%	-0.08%
Std.Dev	5.22%	8.33%	12.07%	12.99%
AutoCorr	80.06%	6.56%	8.83%	10.16%
CrossCorr:				
NCREIF	1	63.07%	49.52%	2.43%
Variable-Liquidity Transactions		1	83.85%	25.97%
Constant-Liquidity			1	50.17%
NAREIT				1
Cycle Amplitude & Turning Points:				
Fall:				
Period	89-93	85-93	85-93	85-90
Magnitude	25%	45%	51%	52%
Rise:				
Period	93-01	93-01	93-98	90-97
Magnitude	37%	50%	66%	48%

IV. *Correcting the lag problem: "Unsmoothing" real estate data…* (Sect. 25.3)

When do you need to "unsmooth"?

Not always.

Unsmoothing most important in:

- Doing portfolio analyses across asset classes,
- Comparing risk and returns between private property and REITs,
- Identifying the exact timing of peaks and troughs in property value cycles,
- Quantifying property investment performance just after major turning points in the property market.

Note: Smoothing is a phenomenon of <u>*aggregate*</u> level index and portfolio returns. Disaggregate level returns series (returns to one or a small number of properties) have additional problems: random “errors”. This makes disaggregate returns appear artificially volatile or “choppy”, and this obfuscates the smoothing, making it impossible to correct it at the disaggregate level.

How to “unsmooth” appraisal-based indices of direct private property market values or returns (such as the NCREIF Index)…

Three major types of techniques:

1. Zero-autocorrelation techniques;
2. Reverse-engineering techniques;
3. Transaction price-based regression techniques.

Method 1: ***"Zero Autocorrelation"*** Unsmoothing…

The basic idea: Statistically remove the autocorrelation from the appraisal-based returns series.

The oldest unsmoothing technique.

➔ *Still widely used in academic research.*

The reasoning behind the zero-autocorrelation approach:

Consider the basic present value model of asset value:

$$V_t = \frac{E_t[CF_{t+1}]}{(1+r_t)} + \frac{E_t[CF_{t+2}]}{(1+r_t)^2} + \ldots$$

Market values of assets change over time (or deviate from their long-term trend) either because:

- Expectation of Future Cash Flows Changes or
- Required Return (discount rate) Changes

i.e., because of the arrival of **"news"** (new information):

About the Rental Market: $(\text{Rental Mkt})_t \Rightarrow CF_t$

About the Capital Market: $(\text{Capital Mkt})_t \Rightarrow r_t$

"NEWS", BY DEFINITION, IS ***UNPREDICTABLE***:
➔ IN A LIQUID, INFORMATIONALLY EFFICIENT MARKET, ASSET RETURNS (ESSENTIALLY: CHANGES IN VALUES) WILL BE *"UNCORRELATED"* ACROSS TIME: **"ZERO AUTOCORRELATION"**.

***Aside:** How can real estate asset market returns be unpredictable when property earnings (rents) are very predictable?…*

Consider “Property X”. Suppose everybody knows for sure Property X will generate net cash flow of \$100 next year, followed by a bad year of only \$50, followed by a final good third year of \$150, and then the property will be flooded forever by the “10 Gorgeous Gorges Dam”. The opportunity cost of capital is 10% per year. The value of Property X will be:

At the beginning of Year 1: PV = $100/1.1 + 50/(1.1)^2 + 150/(1.1)^3$ = \$245.
At the beginning of Year 2: PV = $50/1.1 + 150/(1.1)^2$ = \$169.
At the beginning of Year 3: PV = $150/1.1$ = \$136.

The periodic total returns to an investor in Property X will be:
During Year 1: $r_1 = (100 + 169 – 245) / 245 = 24/245 = 10\%$.
During Year 2: $r_2 = (50 + 136 – 169) / 169 = 17/169 = 10\%$.
During Year 3: $r_3 = (150 + 0 – 136) / 136 = 14/136 = 10\%$.

The investor’s periodic returns will be constant, even though the property’s cash flows are quite variable.

This is because the variability in the cash flow was entirely predictable, and the opportunity cost of capital was constant.

The periodic returns would change only in response to changes in cash flows that <u>were not predictable in advance</u> (or to changes in the opportunity cost of capital). In other words, periodic returns change over time primarily only in response to <u>news</u> (either about cash flows or capital cost).

BACK TO THE UNSMOOTHING MODEL . . .

RATIONALE:

IF REAL ESTATE RETURNS WERE LIQUID, FULL-INFORMATION VALUE BASED RETURNS, THEY WOULD HAVE NO "AUTOCORRELATION".

TECHNIQUE:

1) REMOVE AUTOCORRELATION FROM THE OBSERVED, APPRAISAL-BASED REAL ESTATE RETURNS, BY TAKING *RESIDUALS* FROM A UNIVARIATE TIME-SERIES REGRESSION OF THE OBSERVED RETURNS. (THIS CORRECTS THE LAG, BUT NOT THE VOLATILITY.)

2) ADJUST THESE RESIDUALS BY MULTIPLYING BY A CONSTANT FACTOR, AND ADDING A CONSTANT TERM, TO PRODUCE THE MEAN & VOLATILITY WHICH SEEMS REASONABLE BASED ON *A PRIORI* INFORMATION & JUDGEMENT, OR ON OTHER ASSUMPTIONS.

ZERO-AUTOCORRELATION UNSMOOTHING PROCEDURE DETAILS:

TYPE OF REGRESSION:

•ANNUAL RETURNS:

➔ 1st-ORDER AUTOREGRESSION USUALLY SUFFICIENT.

•QUARTERLY RETURNS:

➔ USE 1st- & 4th-ORDER AUTOREGRESSION.

TYPICAL MEAN ASSUMPTION:

USE UNADJUSTED APPRAISAL-BASED MEAN

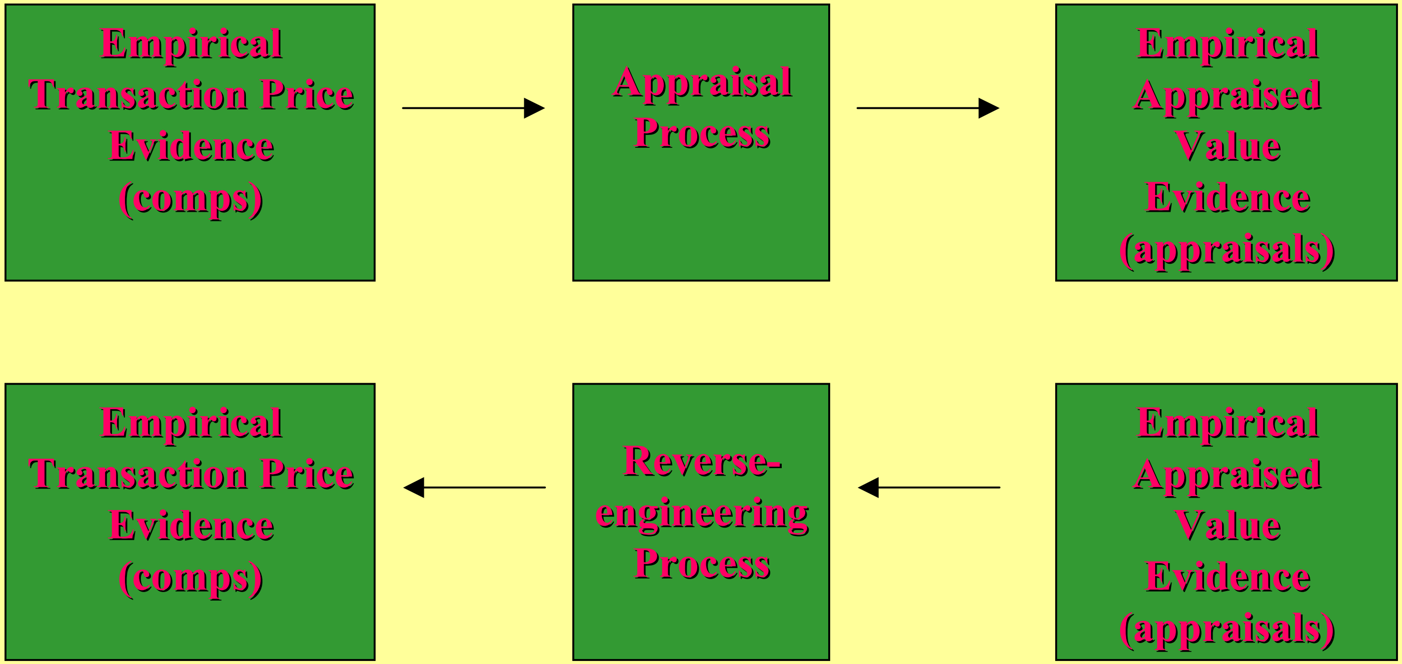
TYPICAL VOLATILITY ASSUMPTIONS:

1) A-PRIORI ASSUMPTION (E.G., 10% PER YEAR);

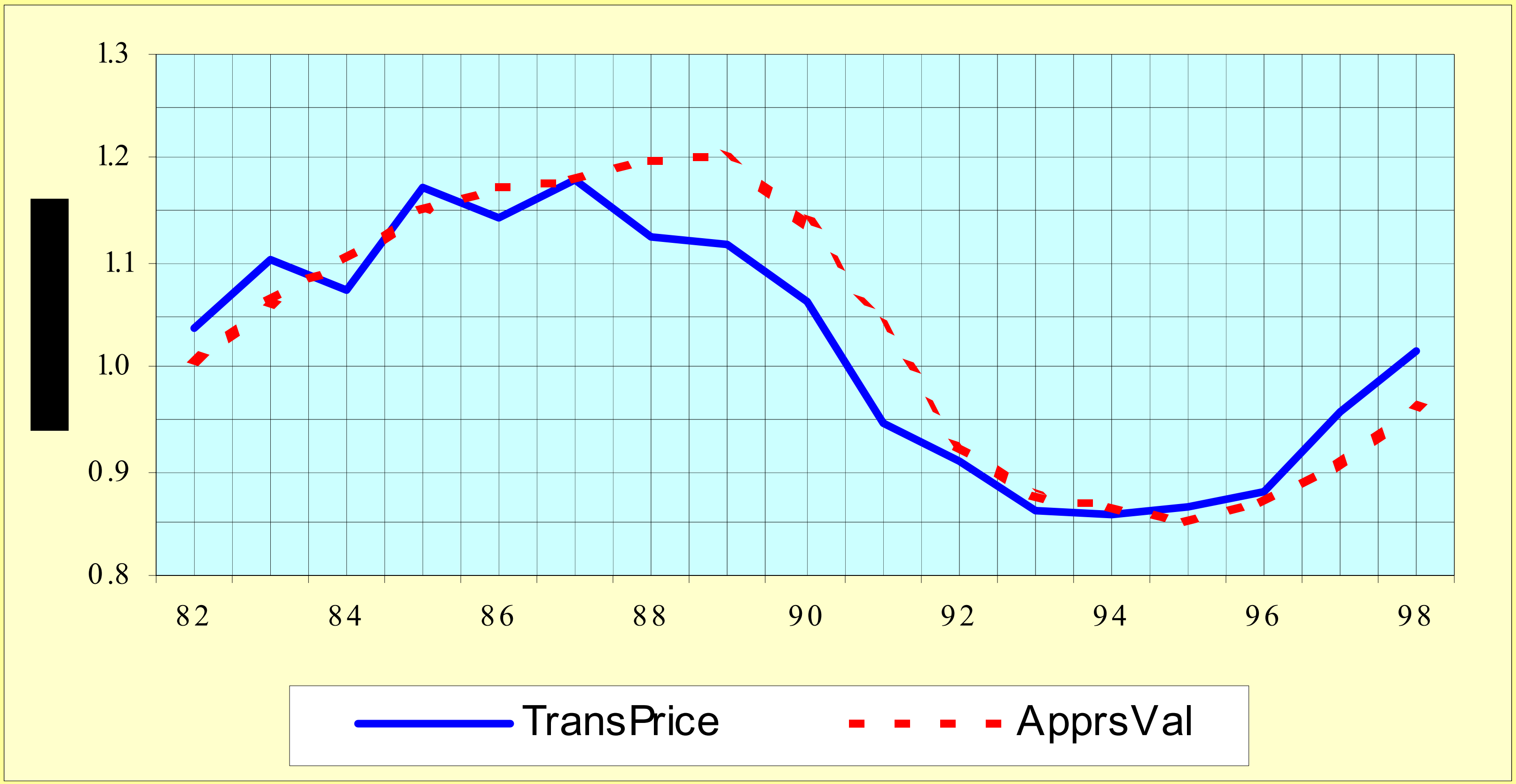
OR

2) BACK OUT IMPLIED VOLATILITY FROM ASSUMPTION OF EQUALITY IN ASYMPTOTIC MEANS CONSTRAINT *(See Ch.25 Appendix)*.

Method 2: "***Reverse Engineering***" Techniques…



Calibrate the reverse-engineered index (REI) by comparing NCREIF Index turning points with transaction price index turning points, measuring the average temporal lag from transaction prices to NCREIF appreciation values…



Lag is horizontal gap from transaction price level to appraisal-based index value level.

General reverse-engineering (de-lagging) formula:

(simple exponential smoothing)

$$\hat{g}_t = (K+1)g^*_t - Kg^*_{t-1}$$

$$= \frac{g^*_t - \left(K/(K+1)\right)g^*_{t-1}}{1/(K+1)}$$

where: $\hat{g}_t$ = Reverse-engineered appreciation return period *t*.

*g** = Appraisal-based appreciation return year *t*.

K = Average number of periods lag of appraisal valuations behind contemporaneous market values.

Example:

If periods (t) are quarters, then:

$$\hat{g}_t = 5g^*_t - 4g^*_{t-1}$$

implies average lag of four quarters (1 yr)…

If periods (t) are years, then:

$$\hat{g}_t = 2g^*_t - g^*_{t-1}$$

implies same average lag of 1 year (4 quarters).

1) Annual 1-step reverse-engineering formula:

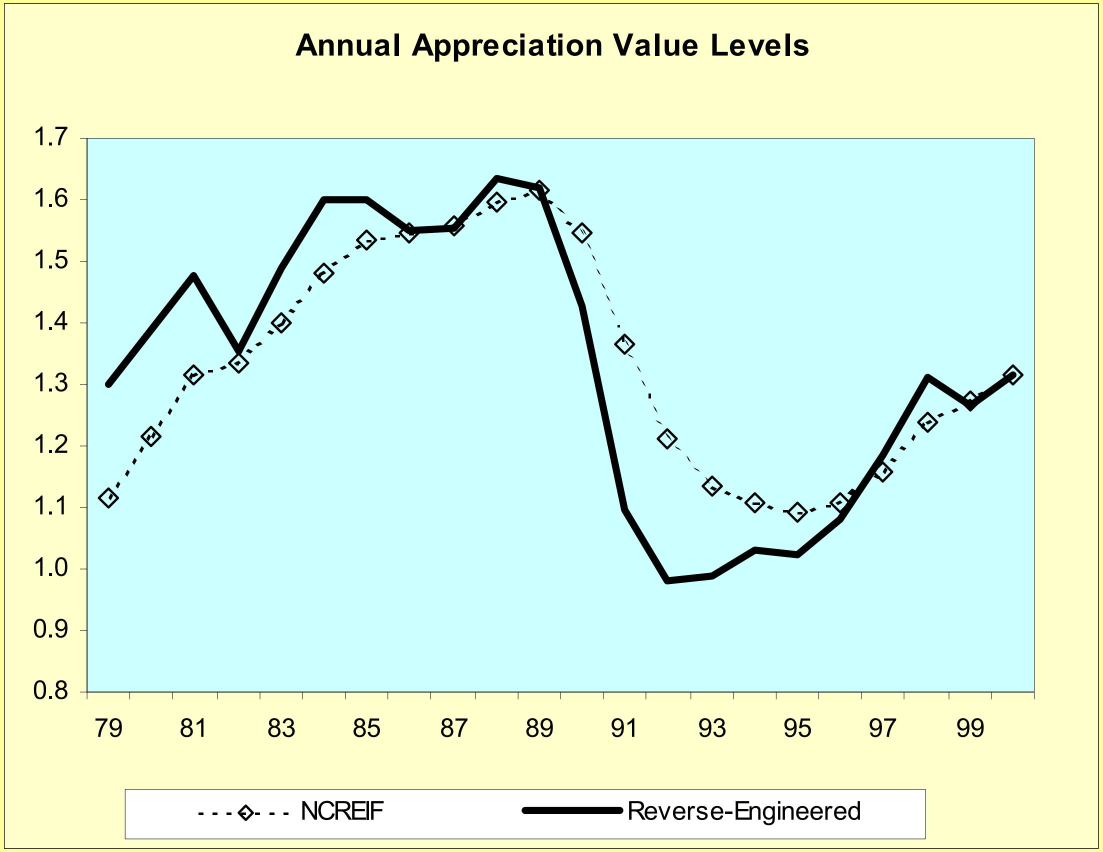
- Simplest reverse-engineering procedure
- Applicable directly to official NCREIF Property Index
- Applicable only to end-of-calendar-year (4th qtr) annual appreciation returns
- Following formula seems to work pretty well in this context:

$$\hat{g}_t = 2.5gNPI_t - 1.5gNPI_{t-1}$$

where: $\hat{g}_t$ = Reverse-engineered appreciation return year t.

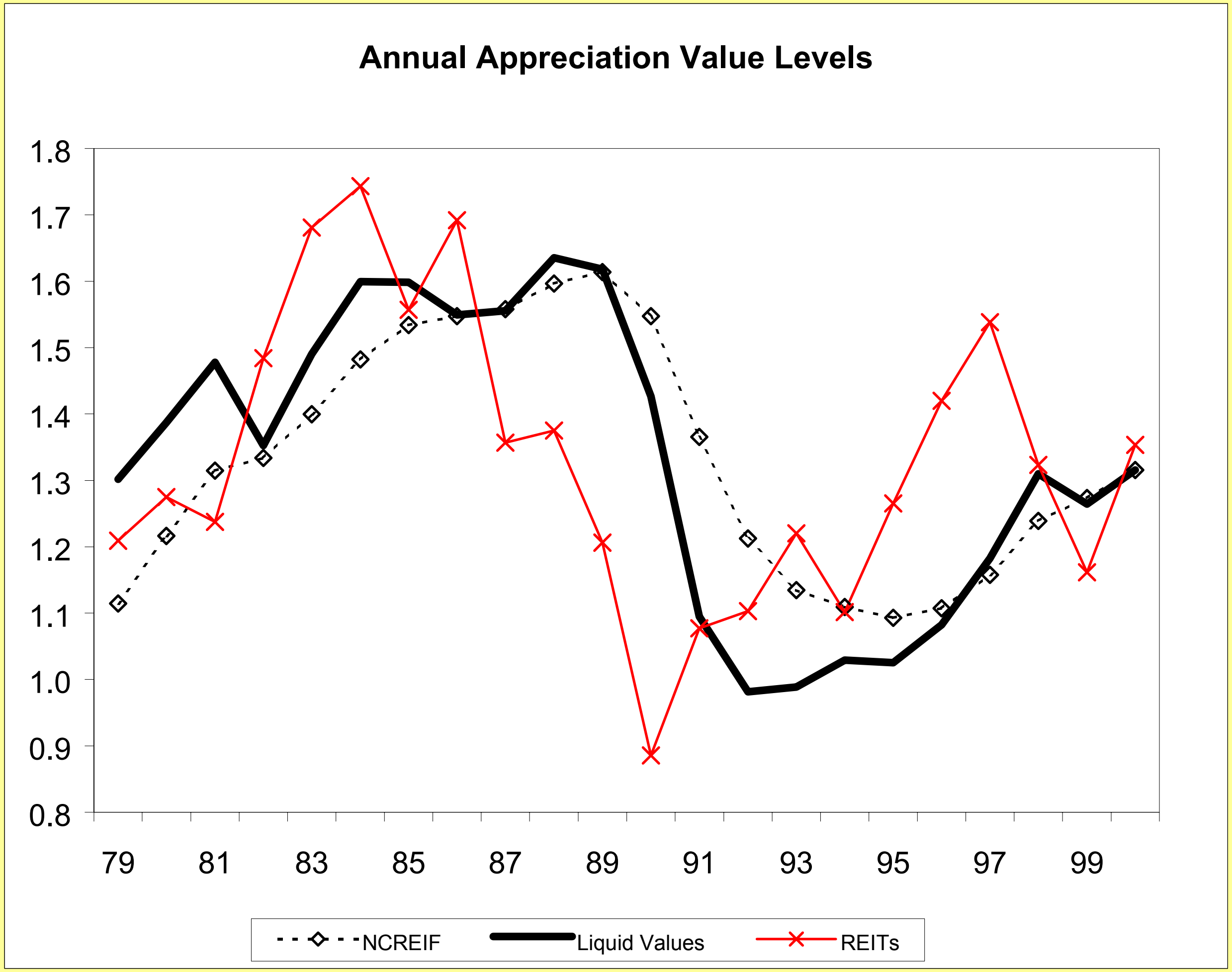
$gNPI$ = Official NCREIF appreciation return year t.

Here is a picture of the simple 1-step annual de-lagged NCREIF appreciation value levels (based on), compared to the official NPI…



Note: Due to technical problems caused by "stale appraisal" effect in NCREIF Index (seasonality and non-stationarity)*, simple 1-step procedure cannot be applied at the quarterly frequency.

Adding REITs to the picture:



Recall the temporal pattern:

REITs 1st, then property market, then appraisals.

2) Quarterly reverse-engineering model for NCREIF *(aka "TVI"):*

Step 1: Get rid of "stale appraisal" (seasonality) in NCREIF Index using repeated-measures regression (RMR) construction (currently published by NCREIF as the "Current Value Indicator" – CVI).

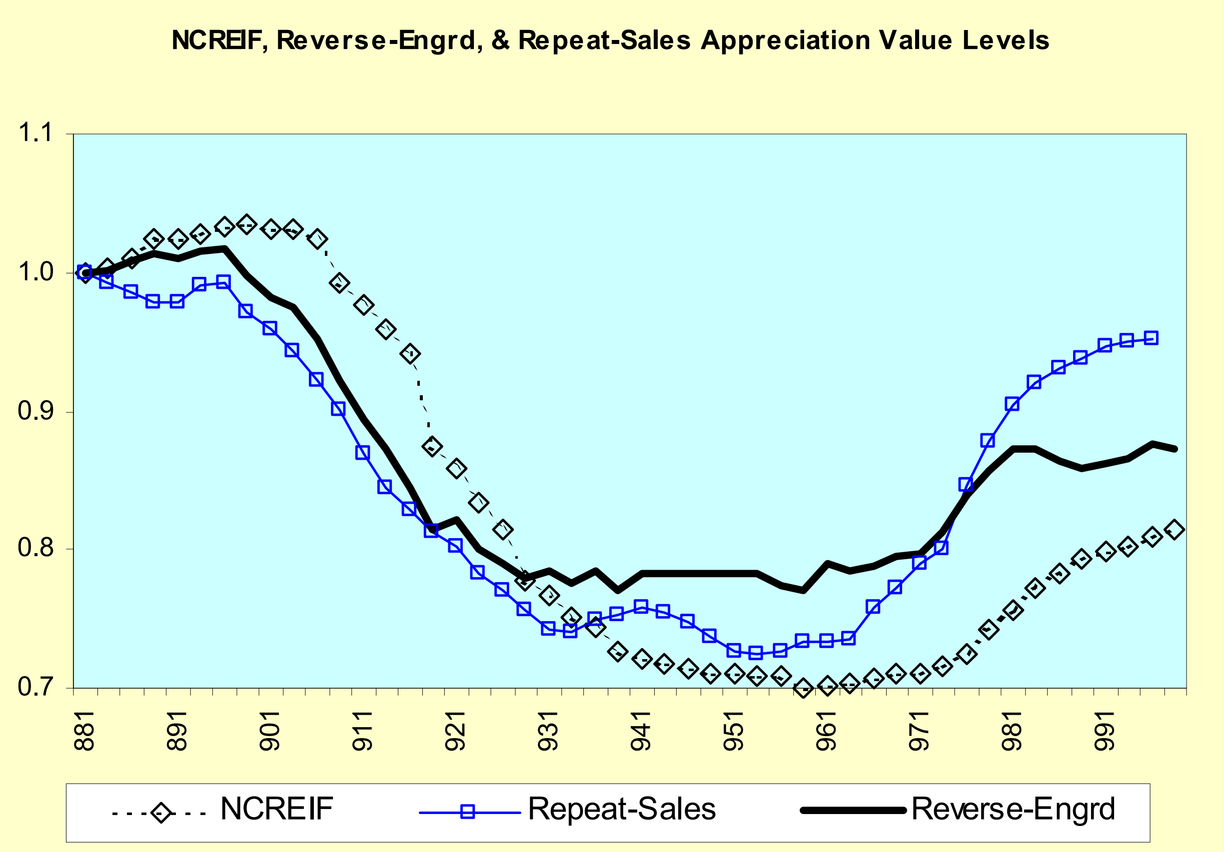
Step 2: Apply quarterly-frequency reverse-engineering formula to CVI (augmented by Bayesian ridge regression noise filter). 1-year lag seems to work well in this context…

$$\hat{g}_t = 5gCVI_t - 4gCVI_{t-1}$$

where: $\hat{g}_t$ = Reverse-engineered index appreciation in qtr *t*.

$gCVI_t$ = NCREIF RMR-based appreciation in qtr *t*.

Here is a picture of the quarterly de-lagged NCREIF appreciation value levels based on the above reverse-engineering formula, and also based on a transaction-based "repeat-sales" index constructed from properties sold from the NCREIF Index, both compared against the official NPI….

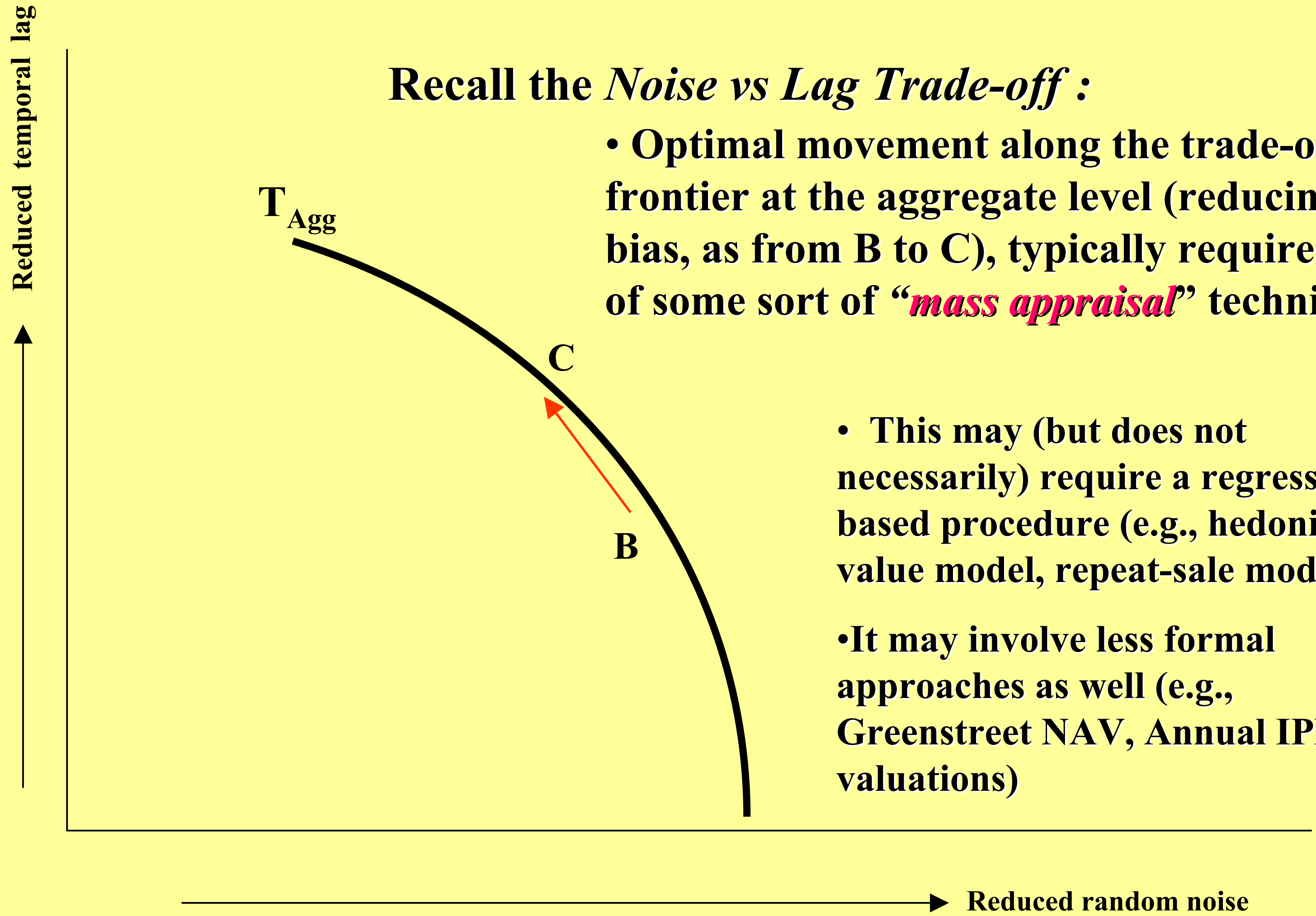


Method 3: Direct ***Transaction Price*** Indices Based on Regression:

(Probably the most important method in the future.)

Recall the *Noise vs Lag Trade-off* :

- **Optimal movement along the trade-off frontier at the aggregate level (reducing lag bias, as from B to C), typically requires use of some sort of "*mass appraisal*" technique.**



- **This may (but does not necessarily) require a regression-based procedure (e.g., hedonic value model, repeat-sale model).**

- **It may involve less formal approaches as well (e.g., Greenstreet NAV, Annual IPD valuations)**

But regression-based procedures have been the focus of academic development…

Basic problem: scarce valuation observations.

- Each individual R.E. asset is unique, different.
- ➔ "Apples vs oranges" problem in averaging or comparing prices of different assets at the same point in time.
- Each individual asset transacts only rarely and irregularly in time.

So how can we observe "apples vs apples" $V_t - V_{t-1}$?

Two statistical methodologies are most widely used…

1) The “Hedonic Regression” (HR). This is based on the hedonic value model (property value is a function of property characteristics...):

$$V_{it} = f\left(X_{1it}, \ldots, X_{nit}\right)$$

V_{it} = Value of property “i” at time “t”
X_{jit} = Value of hedonic (property quality characteristic) variable “j” for property “i” as of time “t.

Thus, HR controls for differences across individual properties by modeling the value effects of those differences.

Re-estimate model every period to produce index of periodic returns.

Problem: requires enough transactions every period. There is never this much data for commercial property.

Solution: Court-Griliches intertemporal price model...

$$\ln P_{it} = \sum_{j=1}^{J} \beta_j \ln X_{jit} + \sum_{t=1}^{T} c_t D_{it} + e_{it}$$

where: P_{it} = Transaction price of house "i" at time "t"
$X_{j\,it}$ = Value of jth hedonic characteristic
D_{it} = Time dummy (=1 if sale “I” occurred in period “t”, 0 o.w.)
c_t = Price index (log level)

2) The “repeated measures regression” (RMR) or “repeat-sales regression” (RSR).

➔ Use only properties for which we have valuation observations at least twice.

The periodic returns are then estimated only from the percentage changes in the valuation observations across time within the same assets.

Thus, differences across assets are controlled for by only using price-change information from assets that are the same assets.

Aside: A simple way to understand the repeat-sales regression model (Specification for value-wtd arithmetic average price index…)

1) Definition of the price-change or capital component of the simple "holding period return" (HPR):

$$1+g_{t+1}=\frac{V_{t+1}}{V_t}$$

where: g_{t+1} = Price appreciation in period "t+1"
V_t = Price of asset at end of period "t".

2) Expand the definition mathematically (just simple algebra):

$$V_t=\frac{V_{t+1}}{(1+g_{t+1})}=\frac{V_{t+2}/(1+g_{t+2})}{(1+g_{t+1})}=\frac{V_{t+2}}{(1+g_{t+1})(1+g_{t+2})}=\cdots$$

Therefore:

$$0=-V_t+\left(\frac{1}{1+g_{t+1}}\right)(0)+\left(\frac{1}{1+g_{t+1}}\right)\left(\frac{1}{1+g_{t+2}}\right)(0)+\cdots+\left(\frac{1}{1+g_{t+1}}\right)\cdots\left(\frac{1}{1+g_{t+N}}\right)(V_{t+N})$$

Note:➔ N periods of time
⇨ Asset value observed only twice:
⇨ at t, & at t+N

Suggests regression with 0 on LHS and time dummies on RHS equal to $-V_t$ (price in 1st sale) for dummy corresponding to time of 1st sale (here "t"), equal to V_{t+N} (price in 2nd sale) for dummy corresponding to time of 2nd sale (here "t+N"), and zero otherwise (before, after, and between sale times). . .

3) The above equation is linear in the inverse of the cumulative levels of the price index. So it can be estimated using classical regression...

Each observation "i" is pair of consecutive sales of same property:
First sale at time "f",
second sale at time "s". . .

Regression is:

$$V_i = \sum_{t=1}^{T} \beta_t D_{i,t} + \varepsilon_i = \beta_1 D_{i,1} + \beta_2 D_{i,2} + \ldots$$

where:

$$V_i = \begin{cases} V_f, \; if \; "f" = 0, \; where \; "f" \; is \; period \, of \; 1st \; sale \; of \, obs. "i" \\ 0, \; otherwise \end{cases}$$

$$D_{i,t} = \begin{cases} -V_f, \; if \; "t" = "f", \; period \; of \; 1st \; sale \; of \; obs. "i" \\ V_s, \; if \; "t" = "s", \; period \; of \; 2nd \; sale \; of \; obs. "i" \\ 0, \; otherwise \end{cases}$$

Then the regression estimates the values of the parameters β_t, the inverse cumulative total return levels index.

Estimated level of price index in period t is:

$$1/\hat{\beta}_t = (1+\hat{g}_1)(1+\hat{g}_2)\cdots(1+\hat{g}_t)$$

where Index=1 at time 0.

A numerical example:

EXAMPLE PRICE DATA FOR FOUR PROPERTIES
1994-1997

Property:	1994	1995	1996	1997
Property #1	$1,000,000	NA	NA	$1,157,205
Property #2	$2,299,000	$2,413,950	NA	NA
Property #3	$695,466	NA	$752,146	NA
Property #4	NA	$1,738,425	$1,790,578	NA

Note: All transactions occurred at the end of the calendar year.

Actual periodic price change relatives are:

1995: 5%
1996: 3%
1997: 7%

As seen below:

```
Prop.#1:   1,000,000*1.05*1.03*1.07  = 1,157,205
Prop.#2:   2,299,000*1.05            = 2,413,950
Prop.#3:   695,466*1.05*1.03         = 752,146
Prop.#4:   1,738,425*1.03            = 1,790,578
```

But suppose we did not know these returns . . .

Prop.#1: $1,000,000*(1+r_{95})*(1+r_{96})*(1+r_{97}) = 1,157,205$
Prop.#2: $2,299,000*(1+r_{95}) = 2,413,950$
Prop.#3: $695,466*(1+r_{95})*(1+r_{96}) = 752,146$
Prop.#4: $1,738,425*(1+r_{96}) = 1,790,578$

Therefore:

$$\text{Prop.\#1: } 1{,}157{,}205 / 1{,}000{,}000 = (1+r_{95})*(1+r_{96})*(1+r_{97})$$
$$\text{Prop.\#2: } 2{,}413{,}950 / 2{,}299{,}000 = (1+r_{95})$$
$$\text{Prop.\#3: } 752{,}146 / 695{,}466 = (1+r_{95})*(1+r_{96})$$
$$\text{Prop.\#4: } 1{,}790{,}578 / 1{,}738{,}425 = (1+r_{96})$$

Linearize

*(using the fact that: LN(a*b)=LN(a)+LN(b), LN(a/b)=LN(a)-LN(b)*:

$$\text{Prop.\#1: } LN(1157205/1000000) = LN(1+r_{95})+LN(1+r_{96})+LN(1+r_{97})$$
$$\text{Prop.\#2: } LN(2413950/2299000) = LN(1+r_{95})$$
$$\text{Prop.\#3: } LN(752146/695466) = LN(1+r_{95})+LN(1+r_{96})$$
$$\text{Prop.\#4: } LN(1790578/1738425) = LN(1+r_{96})$$

This is the same as:

$$LN(1157205/1000000) = LN(1+r_{95})*1 + LN(1+r_{96})*1 + LN(1+r_{97})*1$$
$$LN(2413950/2299000) = LN(1+r_{95})*1 + LN(1+r_{96})*0 + LN(1+r_{97})*0$$
$$LN(752146/695466) = LN(1+r_{95})*1 + LN(1+r_{96})*1 + LN(1+r_{97})*0$$
$$LN(1790578/1738425) = LN(1+r_{95})*0 + LN(1+r_{96})*1 + LN(1+r_{97})*0$$

Which is equivalent to the above-noted RSR specification only in returns (log differences) instead of levels. This RSR specification is:

$Y = D\beta + \varepsilon$

where: Y = Log price relative ($Y_i \equiv LN(P_{is}/P_{if})$)

D = Time dummy (=1 *between* 2 sales)

β = Index of log price increments (capital returns)

$Y = D\beta + \varepsilon$

where: Y = Log price relative ($Y_i \equiv LN(P_{is}/P_{if})$)

D = Time dummy (=1 *between* 2 sales)

β = Index of log price increments (capital returns)

IN OUR NUMERICAL EXAMPLE:

LHS data:	RHS dummy variable data:
$LN(1{,}157{,}205 / 1{,}000{,}000) = 0.1460 =$	$\hat{\beta}_{95}*1 + \hat{\beta}_{96}*1 + \hat{\beta}_{97}*1 + u_1$
$LN(2{,}413{,}950 / 2{,}299{,}000) = 0.0488 =$	$\hat{\beta}_{95}*1 + \hat{\beta}_{96}*0 + \hat{\beta}_{97}*0 + u_2$
$LN(752{,}146 / 695{,}466) = 0.0783 =$	$\hat{\beta}_{95}*1 + \hat{\beta}_{96}*1 + \hat{\beta}_{97}*0 + u_3$
$LN(1{,}790{,}578 / 1{,}738{,}425) = 0.0296 =$	$\hat{\beta}_{95}*0 + \hat{\beta}_{96}*1 + \hat{\beta}_{97}*0 + u_4$

Which is solved by:

$\hat{\beta}_{95} = 0.0488 = LN(1.05)$

$\hat{\beta}_{96} = 0.0296 = LN(1.03)$

$\hat{\beta}_{97} = 0.0677 = LN(1.07)$

with no noise in this case, so that: $u_1=u_2=u_3=u_4=0$.
More generally, Ordinary Least Squares (OLS) regression procedure finds solution that minimizes the sum of squared errors: $\min(SSE)=\min(\Sigma u^2)$.

Comparing the HR and RSR:

HR problems are with RHS variables:

- ➔ Specification errors in the model,
- ➔ Omitted variables,
- ➔ Measurement error in the variables,

These problems are especially severe for commercial property.

The result is that all HR price indexes estimated so far for commercial property have been rather "noisy", that is, lots of spurious random volatility.

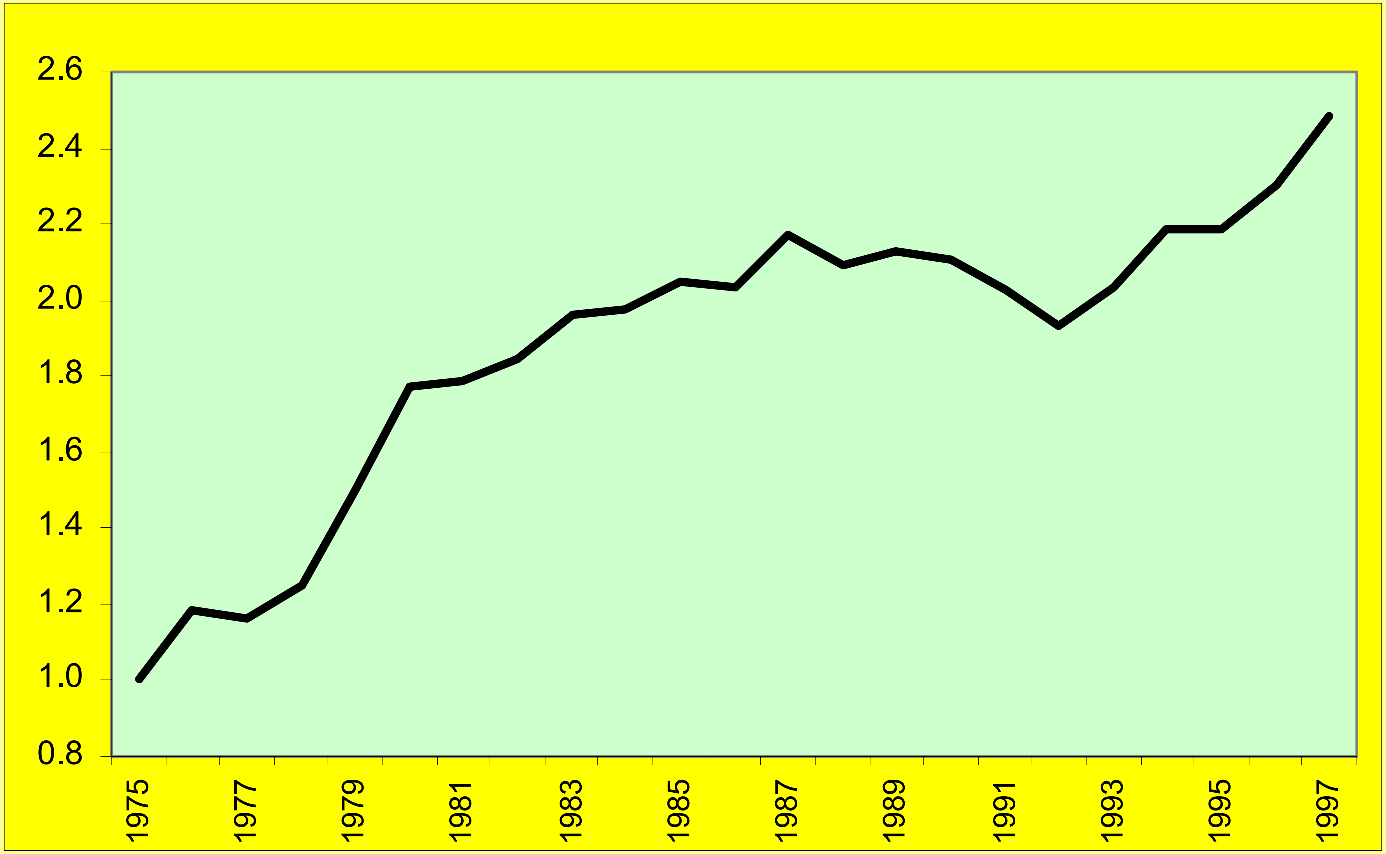
RSR problems:

- ➔ Data availability,
- ➔ Sample selection bias

Data problem is most severe for commercial property, because there are fewer commercial properties to begin with.

Example of a regression-based transaction price index for commercial property . . .

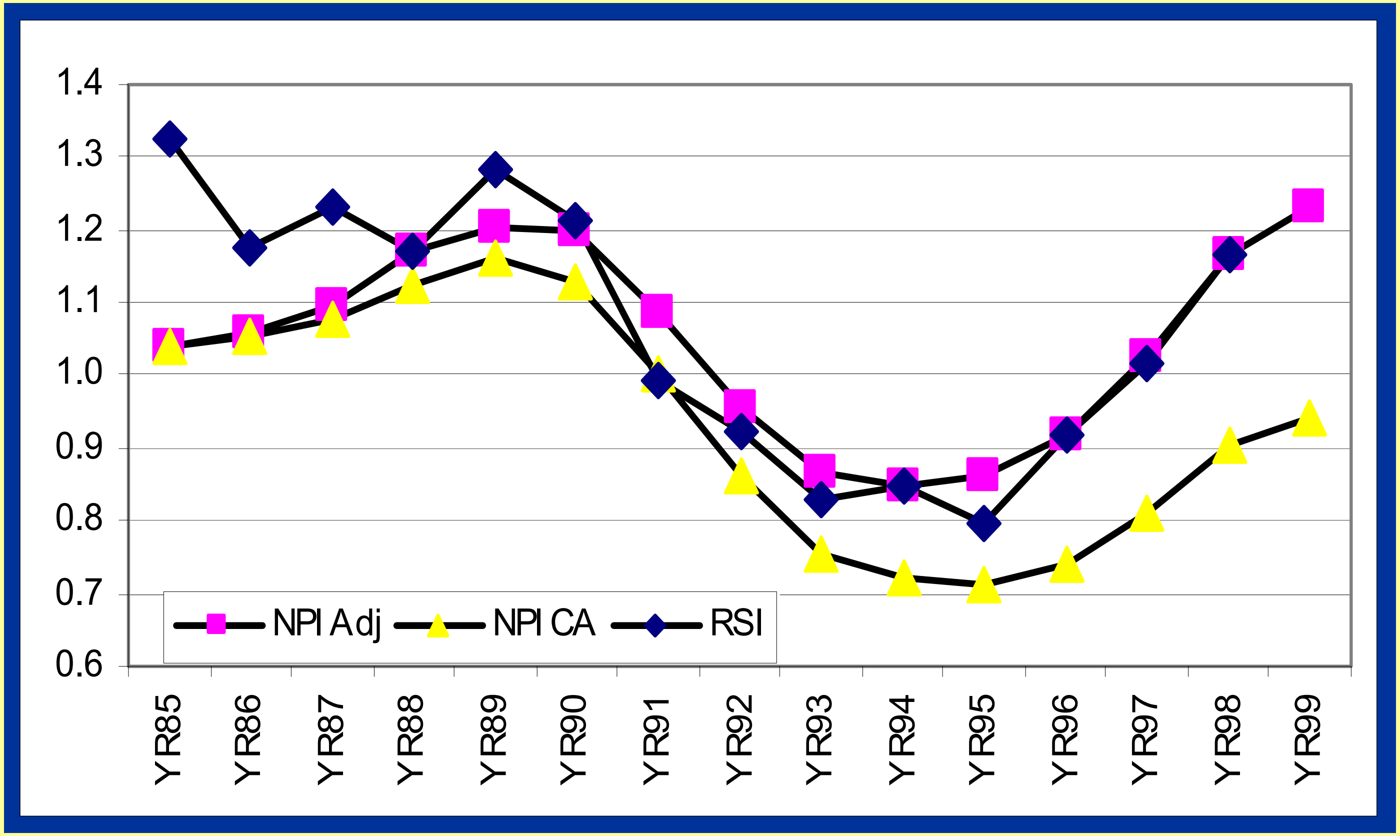
Florida Commercial Property Repeat-Sale Price Index:



- **Based on state property tax transaction price records of all (125,000) commercial properties in Florida.** ***(Gatzlaff-Geltner, REF, Spring 98)***

Example of a regression-based transaction price index for commercial property . . .

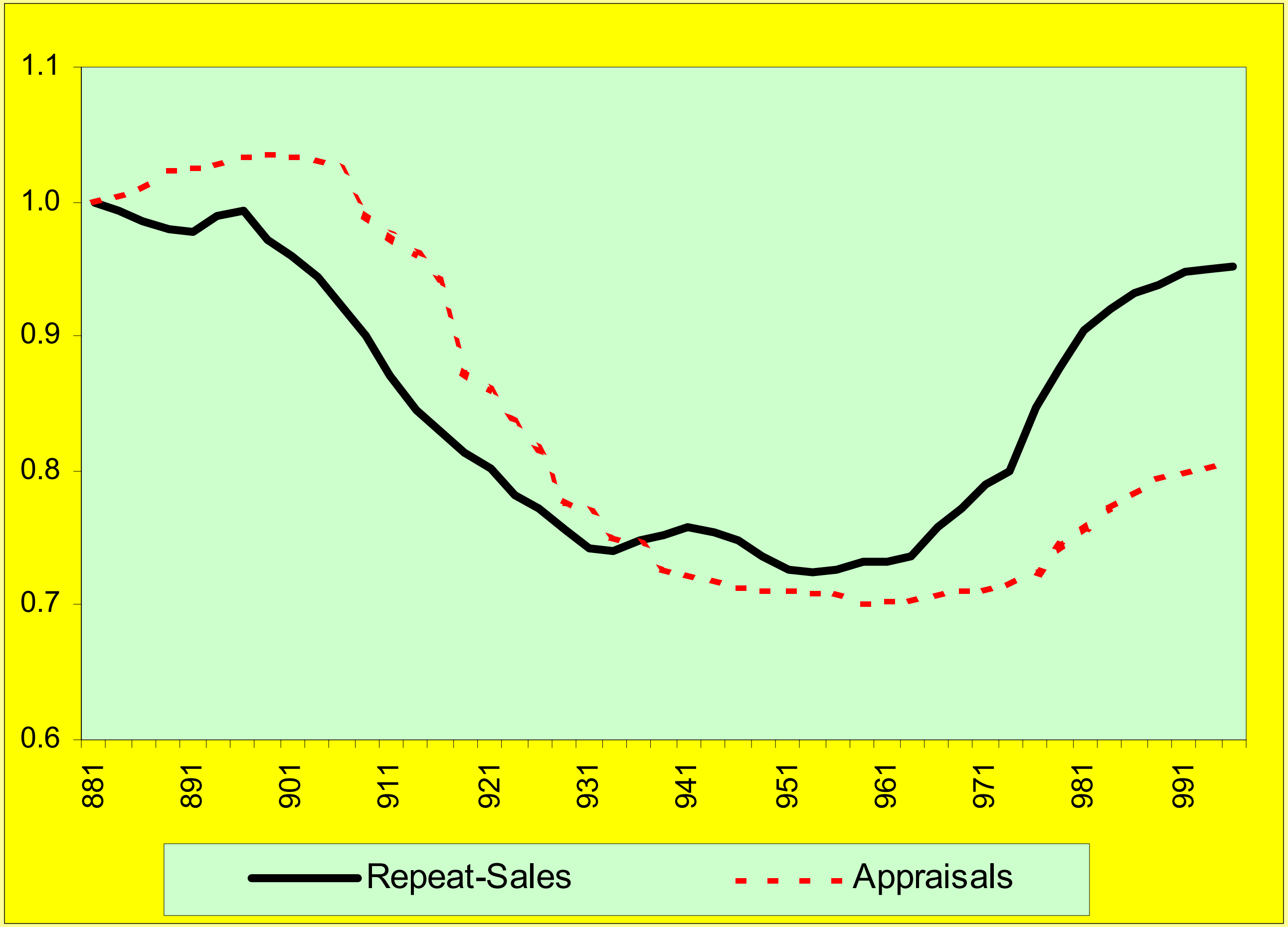
California Large Property Repeat-Sale Price Index:



- **Based on all CoStar transaction price records of California properties >$10 million value.** ***(Chai ARES Wkg Paper, April 2000)***

Example of a regression-based transaction price index for commercial property . . .

NCREIF Repeat-Sale Price Index:



- **Quarterly index based on 3000 properties sold from the NCREIF database. *(Fisher-Geltner, REF, Spring 2000)***