The Commercial Real Estate Eco-System

Ralph S.J. Koijen[1]
Neel Shah[2]
Stijn Van Nieuwerburgh[2]

[1]Chicago Booth
[2]Columbia Business School

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Context: The Great Rotation

- The past 25 years have seen a large migration of risk from public to private markets
  - Publicly listed stocks: 8,000 in 1997 down to 4,000 in 2023
  - Private AUM: $13 trillion in 2023, 2x since 2013, 2x over 2023–29
  - Recent increase in private credit amplify this trend

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- Pension funds allocate 25-30% to private and real assets, rotated out of public equity and fixed income

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- Pension funds allocate 25-30% to private and real assets, rotated out of public equity and fixed income
- Private and real assets are special
  1. Traded infrequently, often in bilateral search and matching markets
     $\Rightarrow$ no frequent prices, only cash flows
     $\Rightarrow$ challenging for risk management; scope for "volatility laundering"
  2. Lumpy
  3. Unique features (e.g., location); hence heterogeneity across assets
  4. Ecosystem of heterogeneous, specialized investors

Context: The Great Rotation

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- Pension funds allocate 25-30% to private and real assets, rotated out of public equity and fixed income
- Private and real assets are special
- **Next frontier for asset pricing!**
  - Goetmann, Spaenjers, and Van Nieuwerburgh (RFS 2021)

Commercial Real Estate Ecosystem: Overview

- Develop a **valuation** and **matching** model for private assets that recognizes the unique features of private and real assets
  - Micro founded by a portfolio choice model featuring lumpy real assets
- Empirically, we find that
  - Accounting for nonlinearities in a **rich set of building characteristics and macro variables** is important to explain valuations
  - **Investor composition** significantly impacts the pricing of private assets
- Uncover the **structure of trade**: who transacts what with whom?
- In context of **commercial real estate** markets, a $39 trillion asset class in the U.S. (Flow of Funds), and more than 2x globally

Literature

- Valuing private assets Kaplan and Schoar (2005); Korteweg and Sørensen (2010); Driessen et al. (2012); Korteweg and Nagel (2016); Ang et al. (2018); Gupta and Van Nieuwerburgh (2021); Gupta et al. (2025)
  - This paper: Starts from a valuation model at the investor level, no reference to public market SDF
- Linear hedonic valuation model Lancaster (1966); Griliches (1971); Rosen (1974); Witte et al. (1979); Wallace (1996)
  - This paper: large improvements from non-linearities, interactions, and investor characteristics
- Demand-system asset pricing Koijen and Yogo (2019); Koijen et al. (2024)
  - This paper: model transaction of entire property in bilateral exchange
- Risk and return in CRE Plazzi et al. (2008, 2010); Van Nieuwerburgh et al. (2015); Peng (2016); Van Nieuwerburgh (2019); Sagi (2021)
  - This paper: large sample, not just REITs, new model
- Role of investor characteristics in CRE Ghent (2021); Cvijanović et al. (2022); Badarinza and Ramadorai (2018); Badrinza et al. (2022)
  - This paper: systematic approach to sources of heterogeneity, potential price distribution provides complementary liquidity risk measure

Outline

- Model: Valuation and transactions
- Estimation procedure: Inspiration from NLP modeling
- Data
- Results valuation model
- Results listing and matching model
- Counterfactuals

Model

Model

- Build a model of the demand system adapted to private assets
- Model features
  - Investor heterogeneity z_{it}
  - Asset heterogeneity x_{nt}

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- Model features
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  - Asset heterogeneity x_{nt}
- Model has two blocks:
  1. Valuation model
  2. Listing and matching model

Valuation Model

- Buyer b and seller s have private valuation for each asset n, $V_{it}(n)$:

$$v_{it}(n) \equiv \ln V_{it}(n) = h\left(z_{it}, x_{nt}; \gamma_t\right) + \epsilon_{it}(n),$$

- Valuation residual $\epsilon_{it}(n) \sim \mathcal{N}(0, \sigma_t^2)$ captures liquidity or funding constraints, belief heterogeneity, unobserved quality
- Allow flexible functional form for $h(\cdot)$
- Special case: heterogeneous valuation for characteristics

$$\begin{aligned} h_{it}(n) &= \beta'_{x,i} x_{n,t} + \gamma_t, \\ \beta_{x,i} &= \beta_x z_{i,t}, \end{aligned}$$

- $x_{n,t}$ and $z_{i,t}$ each contain a constant so effects enter separately + $N_x \times N_z$ interactions ⏩ Micro Foundation

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- Price determined by bargaining with equal weights

$$p_t(n) = \frac{1}{2} v_{bt}(n) + \frac{1}{2} v_{st}(n)$$

Listing, Meeting, and Transacting

- Search and matching model between seller s and buyer b
- Transaction happens w.p. $\pi_{bs} = \pi^{\ell} \cdot \pi^{m}_{bs} \cdot \pi^{\tau}_{bs}$

Listing, Meeting, and Transacting

- Search and matching model between seller s and buyer b
- Transaction happens w.p. $\pi_{bs} = \pi^{\ell} \cdot \pi_{bs}^{m} \cdot \pi_{bs}^{\tau}$
- Seller with listing s meets buyer $b \neq s$ with probability π_{bs}^{m}

$$\pi_{bs}^{m} = \frac{\exp\left(\lambda_1 S_b + \lambda_2 \Delta S_{b,s}^{-1} + \lambda_3' \delta_{b,s} + \lambda_4 N_b\right)}{\sum_{c \neq s} \exp\left(\lambda_1 S_c + \lambda_2 \Delta S_{c,s}^{-1} + \lambda_3' \delta_{c,s} + \lambda_4 N_c\right)},$$

- Meeting more likely if
  1. $\lambda_1 > 0$: buyer is larger in terms of portfolio size
  2. $\lambda_2 > 0$: buyers and sellers have similar size
  3. $\lambda_3 > 0$: Asset is similar to buyer's consideration set $\delta_{b,s}$ in terms of:
     (i) asset size
     (ii) asset location (geography, market)
     (iii) sector expertise
     (iv) quality (measured based on local rents)
  4. $\lambda_4 > 0$: Buyer owns more than 2 assets

Listing, Meeting, and Transacting

- Search and matching model between seller s and buyer b
- Transaction happens w.p. $\pi_{bs} = \pi^{\ell} \cdot \pi_{bs}^{m} \cdot \pi_{bs}^{\tau}$
- Seller with listing s meets buyer $b \neq s$ with probability π_{bs}^{m}
- Conditional on meeting, transact with probability π_{bs}^{τ}

$$\pi_{bs}^{\tau} = P\left(V_b > V_s\right) = P\left(h_b - h_s > \epsilon_s - \epsilon_b\right)$$

If $\epsilon_i \sim N(0, \sigma^2)$ then $\pi_{bs}^{\tau} = \Phi\left(\frac{h_b - h_s}{\sqrt{2}\sigma}\right)$

Listing, Meeting, and Transacting

- Search and matching model between seller s and buyer b
- Transaction happens w.p. $\pi_{bs} = \pi^{\ell} \cdot \pi^{m}_{bs} \cdot \pi^{\tau}_{bs}$
- Seller with listing s meets buyer $b \neq s$ with probability π^{m}_{bs}
- Conditional on meeting, transact with probability π^{τ}_{bs}
- Owner lists building for sale with probability π^{ℓ}
  - Chosen to match $\#$ transactions T_t in each year-sector:

$$\sum_{s} \pi^{\ell}_{t} \sum_{b} \pi^{m}_{bs} \pi^{\tau}_{bs} = T_t,$$

Listing, Meeting, and Transacting

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- Seller with listing s meets buyer $b \neq s$ with probability π^{m}_{bs}
- Conditional on meeting, transact with probability π^{τ}_{bs}
- Owner lists building for sale with probability π^{ℓ}
- The probability that a building does not transact:

$$\pi_{no}(s) = (1 - \pi^{\ell}) + \pi^{\ell} \sum_{b} \pi^{m}_{bs}(1 - \pi^{\tau}_{bs}).$$

Estimation

Estimating Valuation Model

- Log price given by

$$p_t(n) \quad = \quad \frac{1}{2}(h_{bt}(n) + h_{st}(n)) + \frac{1}{2}(\epsilon_{bt}(n) + \epsilon_{st}(n)).$$

- Price only observed when $v_b > v_s$, or $h_b - h_s > \epsilon_b - \epsilon_s$
- But, $\mathbb{E}\left[\epsilon_b + \epsilon_s \mid \epsilon_b - \epsilon_s\right] = 0$ under normality, hence no bias

Estimating Valuation Model

- Log price given by

$$p_t(n) \quad = \quad \frac{1}{2}(h_{bt}(n) + h_{st}(n)) + \frac{1}{2}(\epsilon_{bt}(n) + \epsilon_{st}(n)).$$

- Flexibly capture $h(\cdot)$ using **Light Gradient Boosted Machine**
  - Here: $\dim(x) + \dim(z)$ + time + market predictors
  - Tree-based model: non-linearities and interactions
  - Handles large datasets and categorical variables
  - LGBM faster to train than XGBoost; built-in regularization

Estimating Valuation Model

- Log price given by

$$p_t(n) \quad = \quad \frac{1}{2}(h_{bt}(n) + h_{st}(n)) + \frac{1}{2}(\epsilon_{bt}(n) + \epsilon_{st}(n)).$$

- Flexibly capture $h(\cdot)$ using **Light Gradient Boosted Machine**

- Custom LGBM implementation: Recursive gradient-descent on $h_b(x_n, z_b)$ given h_s and on $h_s(x_n, z_s)$ given h_b to enforce $p_t(n) = \frac{1}{2}(h_{bt}(n) + h_{st}(n)) + \frac{1}{2}(\epsilon_{bt}(n) + \epsilon_{st}(n))$

Estimating Meeting Model: An Intractable Problem?

- Maximize the log likelihood $\sum_s \mathcal{L}(s)$ where

$$\mathcal{L}_s = \sum_{b=1}^{B} y_{b,s} \ln \pi(b,s) + \left(1 - \sum_{b=1}^{B} y_{b,s}\right) \ln \pi_{no}(s),$$

  where $y_{b,s} = 1$ when a transaction take place, 0 otherwise
- For every building, need to compute the likelihood $\mathcal{L}(s)$ with every potential buyer: $N \times B$ possibilities, where $N \approx 120,000$ buildings per sector, $I = 350,000$ possible buyers, and do this for every function valuation when estimating the parameters.
- Computationally expensive!

Consistent Estimator

- Use **ideas from the NLP literature**'s word embedding problem (Mikolov et al, 2013a, 2013b, Ma and Collins, 2018)
  - Maximize similarity of words that belong in the same sentence with a target word and minimize the similarity of words that do not belong together (e.g., dog, bark, banana)

Consistent Estimator

- Use **ideas from the NLP literature**'s word embedding problem (Mikolov et al, 2013a, 2013b, Ma and Collins, 2018)
- For each transaction (s), consider the actual buyer b and small number $K-1$ of non-buyers $k \in \mathcal{N}_s$ with $\#(\mathcal{N}_s) = K-1$.
- Likelihood that b is the buyer out of these K potential buyers

$$\pi_r(b,s) = \frac{\xi_{b,s}}{\xi_{b,s} + \sum_{k \in \mathcal{N}_s} \xi_{k,s}},$$

where $\xi_{b,s} = \exp\left(\lambda_1 S_b + \lambda_2 \Delta S_{b,s}^{-1} + \lambda_3' \delta_{b,s} + \lambda_4 N_b\right) \pi_\tau(b,s)$

Consistent Estimator

- Use **ideas from the NLP literature**'s word embedding problem (Mikolov et al, 2013a, 2013b, Ma and Collins, 2018)
- For each transaction (s), consider the actual buyer b and small number $K-1$ of non-buyers $k \in \mathcal{N}_s$ with $\#(\mathcal{N}_s) = K-1$.
- Minimize loss function over observed transactions: $-\sum_s \ln \pi_r(b,s)$
- *Ranking estimator* is consistent for $K>1$, asymptotically normal, and converges to MLE as $K \to \infty$

Price Distribution and Counterfactuals

- Algorithm for computing distribution of potential transaction prices
  - For some asset that trades, compute $\widehat{\epsilon}_{st} = \mathbb{E}[\epsilon_{st} \mid \frac{1}{2}(\epsilon_{st} + \epsilon_{bt})]$
  - Form $v_{st} = h_{st} + \widehat{\epsilon}_{st}$
  - Form meeting probabilities for every candidate buyer b': $\pi^m_{b's}$
  - Draw C candidate buyers with replacement $\propto \pi^m_{b's}$
  - For each candidate buyer in resulting sample, draw $\epsilon_{bt} \sim N(0, \sigma^2_t)$
  - Form h_{bt}, $v_{bt} = h_{bt} + \epsilon_{bt}$
  - For each candidate buyer, check that $v_{bt} > v_{st}$.
  - If yes, record the price $p_t = \frac{1}{2}(v_{bt} + v_{st})$. If not, set price to missing.
  - Report mean and IQR of the distribution of non-missing prices

Price Distribution and Counterfactuals

- Algorithm for computing distribution of potential transaction prices
- Potential transaction price distribution useful for:
  - Comparing to observed price (low price: seller drew unlucky v_b)
  - Pricing strategy when trading asset next
  - Performance of seller's or buyer's broker
  - Risk management: IQR on valuation

Price Distribution and Counterfactuals

- Algorithm for computing distribution of potential transaction prices
- Potential transaction price distribution useful for:
- Counterfactuals: role of investor composition
  - Remove one group of buyers from algorithm (type, size group, etc.)
  - Resolve for potential transaction price distribution
  - Show new mean, IQR
  - Repeat for each group of investors
  - Helps understand which investors matter most for prices

Data

Data

- **Micro Data**: Universe of institutional CRE transactions from MSCI Real Capital Analytics (RCA) between 2001 and 2023
  - *Sectors*: Apartments, Office, Industrial, Retail
  - **Asset characteristics** x_{nt}
    - *Asset*: log size, log age, log renovation-adj age, floors, subtype, CBD flag, superstar city flag
    - *Deal type*: regular sale, entity sale, distressed sale
    - *Location*: 60 markets
  - **Investor characteristics** z_{it}
    - Investor type
    - Portfolio size: log dollar value of portfolio (built from transactions)
    - Portfolio composition: % of portf in superstar cities, % of portf in same market, % of portf in same sector
    - JV flag
    - Relative size of buyer to seller portfolio (log ratio)
  - RCA has unraveled the **identity of the buyers and sellers**!

Data

- **Micro Data**: Universe of institutional CRE transactions from MSCI Real Capital Analytics (RCA) between 2001 and 2023
- **Macro Data**: At the market level (60 markets)
  - Market size: population (A) or employment (O, I, R) from BEA,
  - Purchasing power: personal income per capita from BEA,
  - Occupancy rate from NCREIF,
  - NOI growth rate from NCREIF,
  - Neighborhood quality: Net Effective Rent per sqft (O, I, R) from Compstak or NOI per unit (A) from Fannie Mae **at the block level**

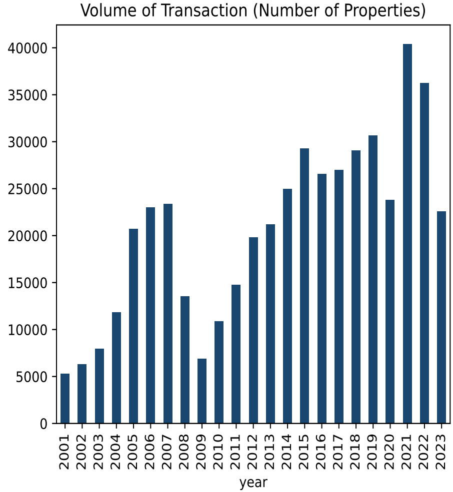
Data

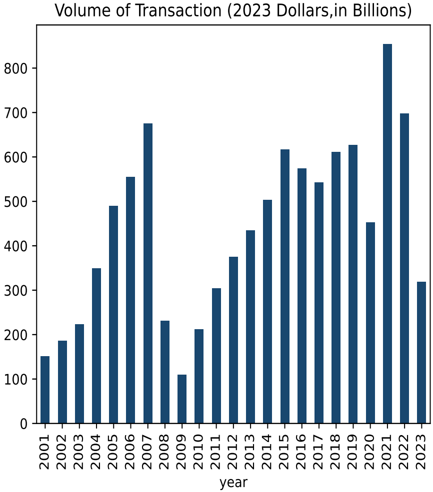
- **Micro Data**: Universe of institutional CRE transactions from MSCI Real Capital Analytics (RCA) between 2001 and 2023
- **Macro Data**: At the market level (60 markets)
- **Summary Statistics**
  - 476,000 property transactions
  - $10 trillion aggregate transaction volume
  - 325,000 unique investors
  - $8.6 trillion in asset value at end 2023

Data

- **Micro Data**: Universe of institutional CRE transactions from MSCI Real Capital Analytics (RCA) between 2001 and 2023
- **Macro Data**: At the market level (60 markets)
- **Summary Statistics**
- Our focus is on U.S., but data exist to do this internationally

Transaction Volume





Transaction Volume by Asset Location

	# Trans	% Trans	$ Vol	% Vol	%A	%I	%O	%R
Manhattan	12,617	2.65	733.41	7.27	26.15	0.85	63.82	9.18
Los Angeles	30,892	6.49	578.30	5.73	29.03	20.25	33.95	16.77
Dallas	18,720	3.93	448.09	4.44	44.79	18.30	24.20	12.72
Chicago	19,060	4.00	405.98	4.02	21.55	24.14	36.34	17.97
Atlanta	15,828	3.33	372.71	3.69	43.72	17.27	24.37	14.64
Houston	12,937	2.72	303.41	3.01	42.57	14.15	28.35	14.92
Boston	8,268	1.74	303.20	3.00	20.36	12.95	57.92	8.78
Seattle	10,744	2.26	279.32	2.77	34.78	14.64	39.27	11.30
Phoenix	13,512	2.84	277.81	2.75	46.14	16.21	22.14	15.51
San Francisco	7,561	1.59	242.48	2.40	21.18	8.48	60.49	9.85
DC VA burbs	5,051	1.06	236.12	2.34	36.26	10.96	42.38	10.40
Northern NJ	10,114	2.12	205.36	2.03	24.83	28.42	32.81	13.94
San Diego	9,332	1.96	199.01	1.97	31.34	19.69	33.75	15.22
San Jose	6,280	1.32	197.36	1.96	17.02	23.26	50.56	9.15
Washington DC	2,395	0.50	147.88	1.47	16.20	1.18	78.14	4.48
Miami	7,239	1.52	142.94	1.42	30.99	19.78	27.49	21.74
All Others	285,472	59.97	5,019.61	49.73	36.85	20.13	21.08	21.94

- We define 60 markets (geographies)
- 16 are superstar cities (11 of these in bold)

Transaction Volume by Asset Size

	# Trans	% Trans	Cum. % Trans	$ Vol	% Vol	Cum. % Vol
Above 1 Bil	269	0.06	0.06	327	3.24	3.24
500 Mil - 1 Bil	701	0.15	0.20	374	3.71	6.95
250-500 Mil	2,368	0.50	0.70	704	6.97	13.92
100-250 Mil	12,525	2.63	3.33	1,726	17.10	31.02
75-100 Mil	9,301	1.95	5.29	772	7.65	38.68
50-75 Mil	19,926	4.19	9.47	1,181	11.71	50.38
25-50 Mil	52,693	11.07	20.54	1,814	17.97	68.35
20-25 Mil	22,517	4.73	25.27	496	4.91	73.26
15-20 Mil	33,779	7.10	32.37	578	5.72	78.99
10-15 Mil	57,414	12.06	44.43	695	6.89	85.87
5-10 Mil	135,100	28.38	72.81	951	9.42	95.30
Below 5 Mil	129,429	27.19	100.00	474	4.70	100.00

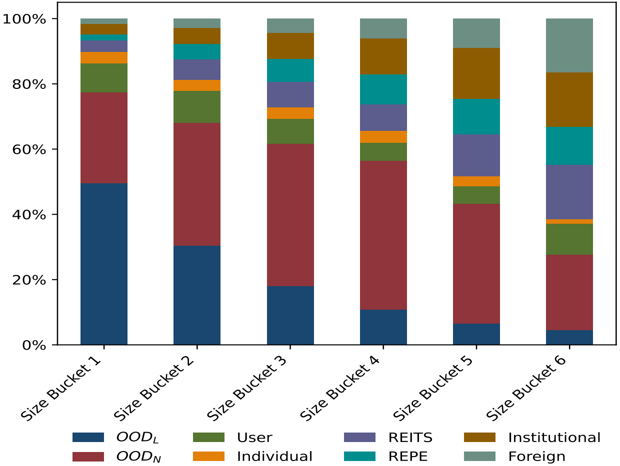
- About equal volume in 6 size groups: $>$\$250M, \$100-250M, \$50-100M, \$25-50M, \$10-25M, $<$ \$10M

Investor Composition: Investor Types

	Buyer (#Trans)	Buyer ($ Vol)	Buyer (% Vol)	Seller (#Trans)	Seller ($ Vol)	Seller (% Vol)	Unique Investors
REPE	28,853	1241	12.30	22,058	1031	10.22	596
Institutional	38,066	1479	14.66	38,148	1371	13.59	3,435
OOD_L	147,030	1316	13.05	161,967	1656	16.41	238,140
OOD_N	150,678	3083	30.56	131,966	3081	30.54	25,385
Individual	19,453	406	4.02	19,399	285	2.82	15,811
REITS	33,518	1182	11.72	35,135	1254	12.43	389
Foreign	17,606	844	8.37	13,055	616	6.11	2,782
User	28,771	418	4.14	33,663	554	5.49	29,845
Unknown	12,044	119	1.18	20,627	241	2.39	7,802
Total	476,018	10,088	100	476,018	10,088	100	324,185

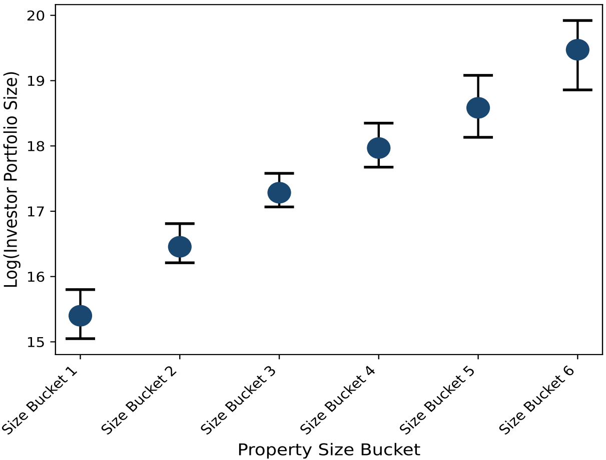
- Institutional: Pension fund, Endowment, Open-ended fund, Bank, Finance, Insurance, Investment Manager, CMBS
- User: Corporate, Government, Non-profit, Educational, Religious, Cooperative
- Individual: High net worth, non-traded REIT
- Foreign: Sovereign wealth fund, foreign OOD + all other foreign

Who Owns What? Investor Type By Asset Size

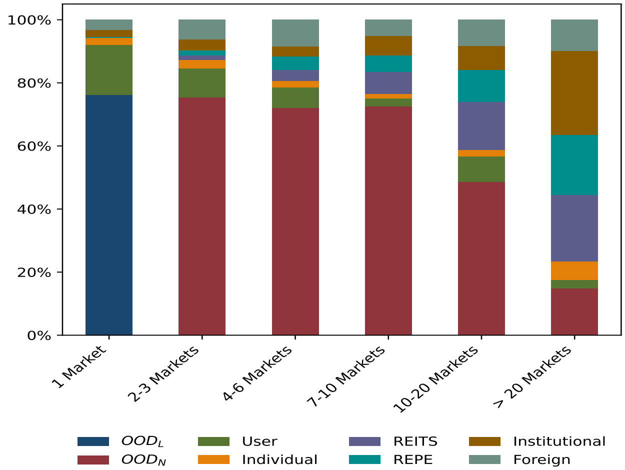


▸▸ investor size distribution

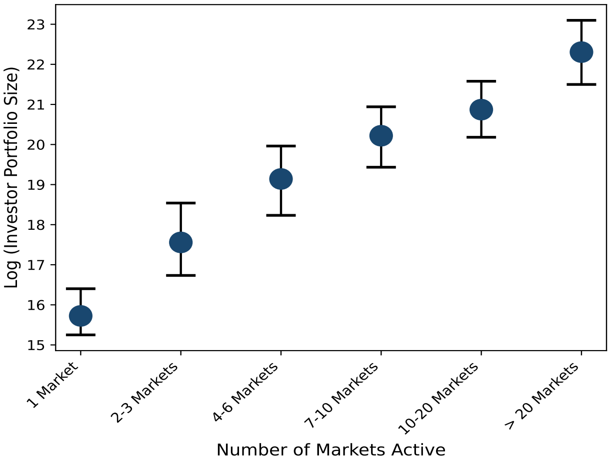
Who Owns What? Investor Size By Asset Size



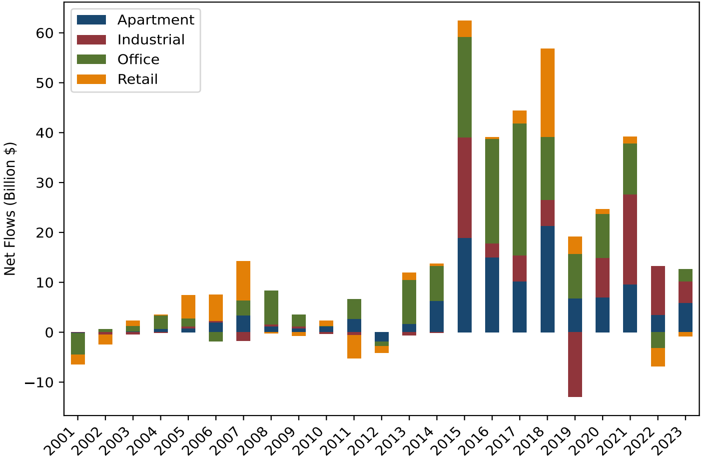
Who Owns What? Investor Type By Number of Markets



Who Owns What? Investor Size By Number of Markets



Investor Flows: Foreign Net Purchases



Results: Valuation Model

Benchmark: Linear Hedonic Model

	Apartment	Industrial	Office	Retail
CBD Indicator	0.153*	0.288***	0.095	0.269***
	(0.057)	(0.059)	(0.049)	(0.052)
Age	-0.075***	0.001	-0.036***	-0.006
	(0.010)	(0.007)	(0.008)	(0.006)
Renovation Adj Age	-0.032***	-0.093***	-0.081***	-0.105***
	(0.007)	(0.010)	(0.011)	(0.009)
Property Size	-0.091***	-0.269***	-0.226***	-0.373***
	(0.020)	(0.014)	(0.022)	(0.014)
Property Subtype	0.137***	0.129***		0.050*
	(0.026)	(0.020)		(0.025)
No. of Floors	0.116***	0.024	0.087***	0.055*
	(0.016)	(0.021)	(0.010)	(0.020)
Entity Sale	0.207*	0.117	0.152	0.050
	(0.090)	(0.093)	(0.093)	(0.110)
Transfer	-0.233***	-0.228***	-0.316***	-0.292***
	(0.028)	(0.032)	(0.032)	(0.040)
Market Occupancy	0.294	-0.082	0.404***	0.075
	(0.364)	(0.093)	(0.096)	(0.100)
NOI growth	0.078	0.010	0.035	-0.069
	(0.090)	(0.047)	(0.036)	(0.043)
Personal Income	0.568***	0.284***	0.352***	0.433***
	(0.072)	(0.066)	(0.054)	(0.031)
Population/Employment	0.022	0.019	-0.030*	0.038***
	(0.013)	(0.013)	(0.012)	(0.006)
NER	0.130***	0.230***	0.461***	0.164***
	(0.026)	(0.037)	(0.070)	(0.033)
Year FE	✓	✓	✓	✓
Market FE	✓	✓	✓	✓
Observations	141,135	116,737	96,139	114,223
Adj. R^2	59.94	58.46	46.35	57.96
Adj. R^2 (Excluding NER)	58.48	57.54	43.26	57.20

Results: Main Valuation Model with LGBM

Sector	Apartment		Industrial		Office		Retail	
	R^2	R2C	R^2	R2C	R^2	R2C	R^2	R2C
Hedonic Model	53.36		53.39		46.99		61.93	
+ Macro Vars	73.95		68.95		64.53		70.39	
+ Year Fixed Effects	76.31		70.39		67.32		71.52	
+ Market Fixed Effects	80.45		73.76		67.25		73.98	
+ Investor Types	81.93	7.57***	79.20	20.73***	71.87	14.11***	79.39	20.79***
+ Portfolio Vars	89.76	47.62***	89.89	61.47***	87.20	60.92***	90.70	64.26***

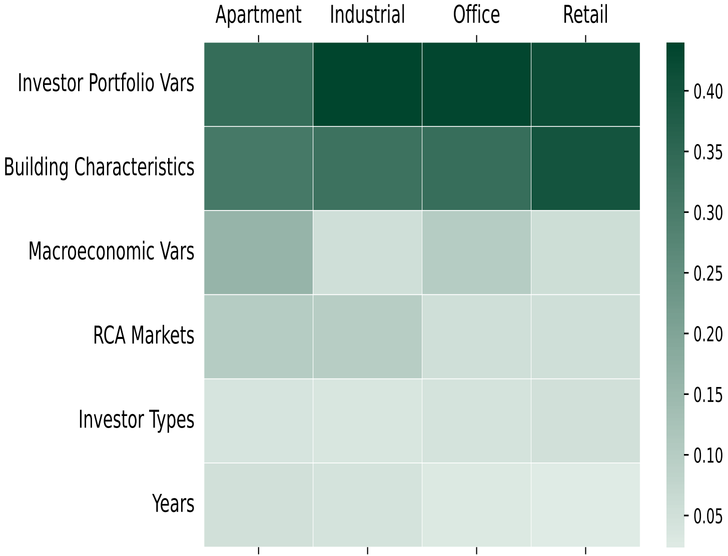
- Linear hedonic $\rightarrow$ LGBM model: adds 20%, 15%, 21%, 16% points in R^2 due to **non-linearities** and **interaction effects**

Results: Main Valuation Model with LGBM

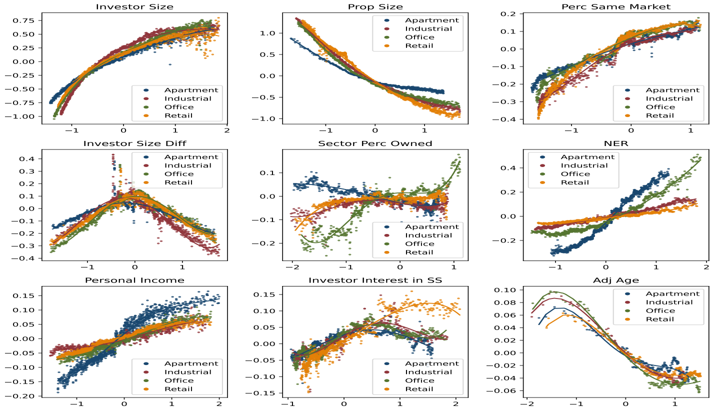
Sector	Apartment		Industrial		Office		Retail	
	R^2	R2C	R^2	R2C	R^2	R2C	R^2	R2C
Hedonic Model	53.36		53.39		46.99		61.93	
+ Macro Vars	73.95		68.95		64.53		70.39	
+ Year Fixed Effects	76.31		70.39		67.32		71.52	
+ Market Fixed Effects	80.45		73.76		67.25		73.98	
+ Investor Types	81.93	7.57***	79.20	20.73***	71.87	14.11***	79.39	20.79***
+ Portfolio Vars	89.76	47.62***	89.89	61.47***	87.20	60.92***	90.70	64.26***

- LGBM model without $\rightarrow$ with **investor characteristics**: adds 9%, 16%, 20%, 17% points in R^2
- Reduces unexplained variation $R2C$ by 48-64%.

Feature Importance in Valuation Model

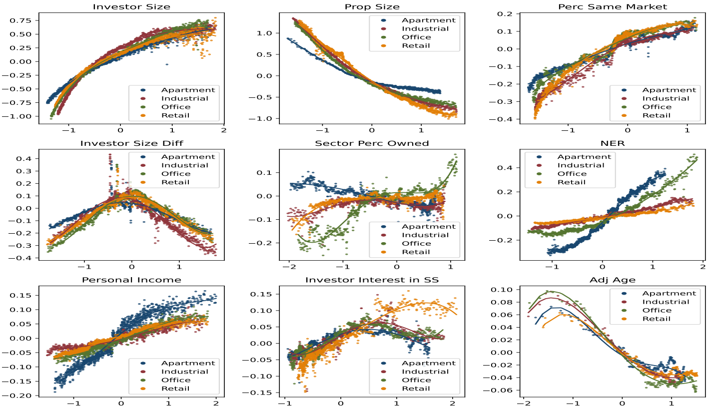


Feature Importance: Non-linearities



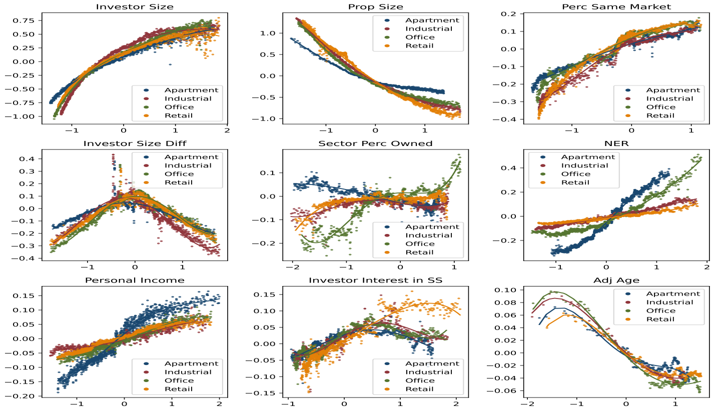
- Shows importance of a feature (SHAP) for transaction prices at different percentiles of that feature

Feature Importance: Non-linearities



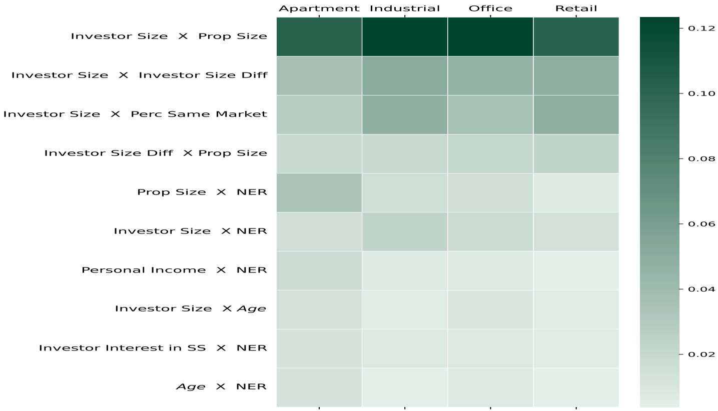
- Importance of investor size is increasing and concave, that of property size decreasing and convex, and size imbalances lower valuations

Feature Importance: Non-linearities



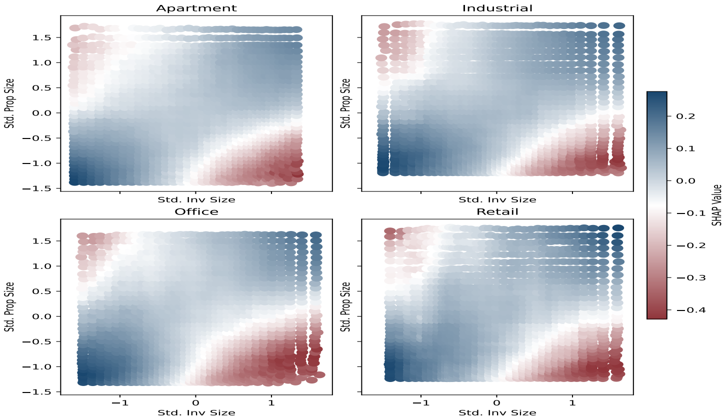
- Geographic specialization increases valuations, sector specialization does not (except high Office concentration)

Feature Importance: Interactions



- Investor size interacts with property characteristics and other investor characteristics

Feature Interaction of Investor and Property Sizes



- Large investors have lower valuations for small properties; small investors have lower valuations for large properties

Results: Matching Model

Table: Meeting Model Calibrations

	λ_1	λ_2	$\lambda_{3,1}$	$\lambda_{3,2}$	$\lambda_{3,3}$	$\lambda_{3,4}$	λ_4
Apartment	1.55	2.69	8.27	5.58	4.12	7.31	2.21
	(0.03)	(0.17)	(0.25)	(0.14)	(0.15)	(0.33)	(0.08)
Industrial	1.66	3.01	8.53	5.83	4.02	9.71	2.13
	(0.04)	(0.19)	(0.32)	(0.17)	(0.15)	(0.50)	(0.10)
Office	1.58	2.76	8.13	5.66	3.30	10.35	2.37
	(0.04)	(0.19)	(0.3)	(0.17)	(0.16)	(0.54)	(0.09)
Retail	1.54	2.76	8.22	5.54	3.85	7.6	2.19
	(0.04)	(0.18)	(0.29)	(0.17)	(0.14)	(0.38)	(0.09)

- Negative set $K = 1,000$ active investors (bought property in last 5 years), bootstrap standard errors

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- $\lambda_1 > 0$: 1% larger investors have 1.5-1.7% higher transaction likelihood; $\lambda_4 > 0$: buyers with > 2 assets 2.2% more likely to trade

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- $\lambda_2 > 0$: more similar-sized buyers and sellers more likely to trade (positive assortative matching)

Results: Matching Model

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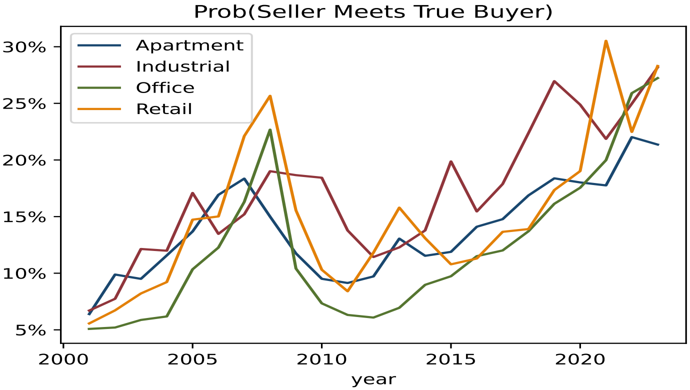
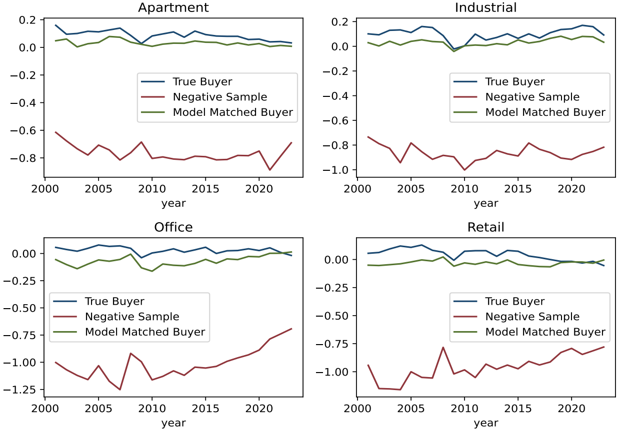
- $\lambda_3 > 0$: similarity of asset to existing portfolio (size, location, sector, neighborhood quality) all very important

Matching Model Works



- Model discriminates btw actual buyer and negative sample well, with dip in the GFC; compare to random matching: 0.1%

Matching Model Works



- Positive sample has higher valuation gap than negative sample

Results: Listing Probabilities

- Reconciles the model-implied transaction probabilities with observed transaction volumes for each sector-year

Results: Listing Probabilities

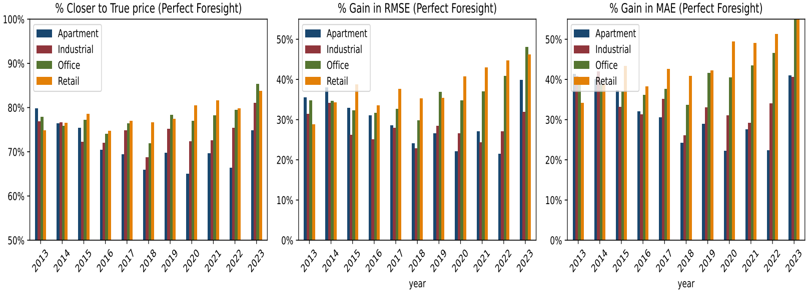
- Nicely captures boom-bust volume dynamics in data

Results: Listing Probabilities

- Can be further micro-founded by reference dependence and loss aversion (Genesove and Mayer, 2001; Andersen et al., 2022)

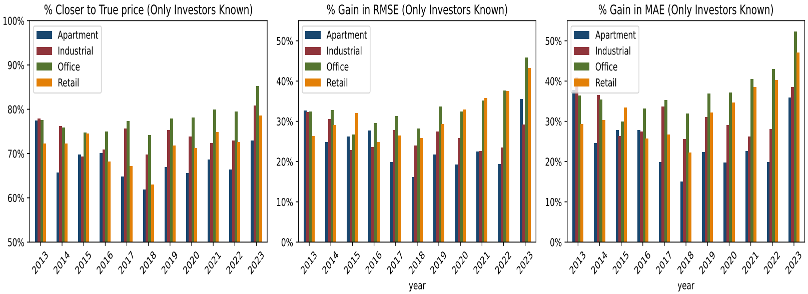
Applications:
Predictions and Counterfactuals

Out-of-Sample Transaction Price Prediction



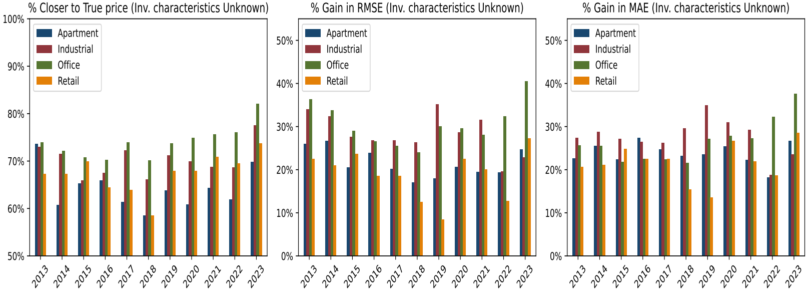
- Model is estimated with data up until time t
- Step 1: assume (x_{t+1}, z_{t+1}) known
- LGBM closer to true price than LHM in 70-80% of transactions, average pricing error is 30-40% lower

Out-of-Sample Transaction Price Prediction



- Step 2: assume z_{t+1} known, but predict $\mathbb{E}[x_{t+1}] = x_t$
- Results similar

Out-of-Sample Transaction Price Prediction



- Step 3: predict $\mathbb{E}[x_{t+1}] = x_t$,
  predict z_{t+1} using meeting model: draw 1,000 potential buyers $\propto \pi^{\tau}_{bs}$,
  take average of *potential price distribution*
- LGBM closer to true price than LHM in 60-70% of transactions, pricing error is 20-30% lower

Counterfactual: Price Impact from Changed Buyer Pool

Model	Trans. %	ppsf $	Major Buyers (% Buy Volume)
Truth	100.0	208.3	[REPE: 41.7, Instit.: 19.9, :OOD_N 17.4, REITS: 9.9]
Benchmark	78.2	194.1	[REPE: 24.0, Instit.: 19.4, OOD_N: 17.1, REITS: 16.4]
Excl. REPE/Instit.	67.3	168.1	[OOD_N: 31.9, REITS: 27.4, OOD_L: 20.4]
Excl. REPE/Institut. & REITS	62.4	149.5	[OOD_N: 41.9, OOD_L: 27.0]

- REITS sold a lot of office assets to REPE funds in 2007; REPE had strong fundraising (buying pressure)
- Experiment: Remove REPE from the buyer pool, recompute counterfactual *potential price distribution*

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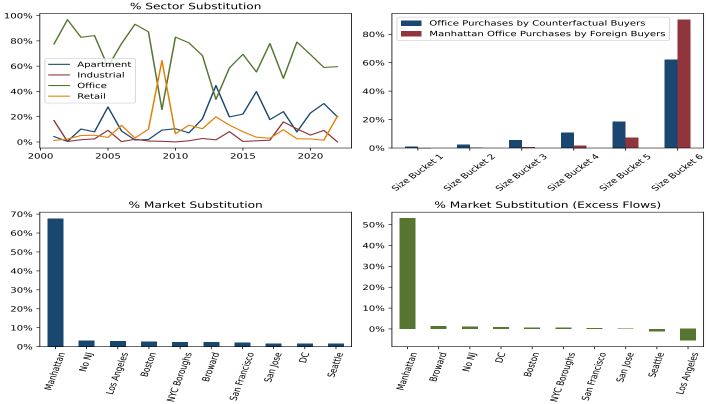
- Office prices would have been 13% lower and volume 11% lower
- Reason: REPE funds had a higher valuation for offices in 2007 than other investors such as OODs
- Without REIT buyers as well, office prices would have been 23% lower

Counterfactual: Substitution Patterns

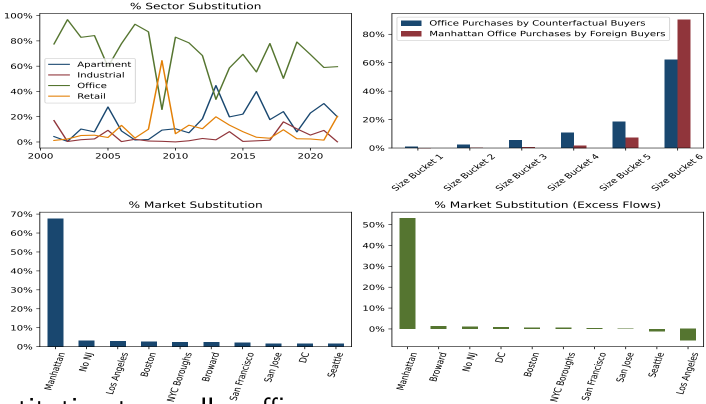
- Foreign buyers were important in 2015-18 and 2021, e.g., Middle East sovereign wealth funds and Canadian pension plans ⏩ graph
- Strong preference for large, high-end properties in superstar cities
- Sample **alternative buyers** for Manhattan Offices bought by foreign buyers; recompute counterfactual *potential price distribution*
- Removing foreign buyers lowers average Manhattan office prices by 4.7% over 2001–2023, and by **7.5% over 2013–2022** ⏩ graph

Counterfactual: Substitution Patterns



- Substitution: What assets did those alternative buyers actually buy?

Counterfactual: Substitution Patterns



- Substitution to smaller offices
- Limited spatial crowd-out: 65% of alternative purchases are in Manhattan
- But foreigners crowded out Manhattan office specialists

Conclusion

- Develop a new asset pricing framework for private and real assets
  - **Investor characteristics** are important new hedonics
  - Recognizes bilateral nature of trade, uniqueness of each asset
- Composition of investor base matters for expected price and *price risk*
- Increasingly important as size of private and real asset market grows

Conclusion

- Develop a new asset pricing framework for private and real assets
  - **Investor characteristics** are important new hedonics
  - Recognizes bilateral nature of trade, uniqueness of each asset
- Composition of investor base matters for expected price and *price risk*
- Increasingly important as size of private and real asset market grows
- Next steps:
  - Endogenize the listing probability model: lagged volume, reference dependence and loss aversion, market and asset size dependence
  - Explore more counterfactuals ⏩ list

Thank you!

Micro foundation of the private valuation model

- A two-period model, $t = 0, 1$.
  - Period $t = 0$, investor i considers buying a building with cash C_{0i}
  - Period $t = 1$, investor receives the net cash flow and resale value of the building N_{1i}
- The building may be part of a broader property portfolio.
- Without the new building, the broader portfolio generates a payoff D_{1i} and investor's wealth at $t = 1$ is $A_{1i} = D_{1i} + C_{0i}$.
- Investors have heterogeneous beliefs about future payoffs: $(D_{1i}, N_{1i}) \sim N(\mu_i, \Sigma_i)$.
- If i adds the building to her portfolio, period $t = 1$ wealth equals $A^P_{1i} = D_{1i} + C_{0i} - P_0 + N_{1i}$, where P_0 is the purchase price of the property.

Micro foundation of the private valuation model

- Investor has mean-variance preferences over terminal wealth:

$$\mathbb{E}_i[A_{1i}] - \gamma_i \mathrm{Var}_i(A_{1i}),$$

where γ_i is risk aversion.

- This valuation then solves the following equation:

$$\mathbb{E}_i[D_{1i}+C_{0i}]-\gamma_i \mathrm{Var}_i(D_{1i}) = \mathbb{E}_i[D_{1i}+C_{0i}-V_{0i}+N_{1i}]-\gamma_i \mathrm{Var}_i(D_{1i}+N_{1i})$$

- This gives investor's private valuation:

$$V_{0i} = \mathbb{E}_i[N_{1i}] - \gamma_i \mathrm{Var}_i(N_{1i}) - 2\gamma_i \mathrm{Cov}_i(D_{1i}, N_{1i}),$$

depends on: the expected payoff, $\mathbb{E}_i[N_{1i}]$, discount for its variance, $\mathrm{Var}_i(N_{1i})$, and further discount or premium depending on property's covariance with other assets in investor's portfolio, $\mathrm{Cov}_i(D_{1i}, N_{1i})$.

Micro foundation of the private valuation model

To obtain a characteristics-based model of investors' private valuations, we follow Koijen and Yogo (2019) and model the moments as functions of characteristics with investor-specific coefficients that reflect differences in beliefs:

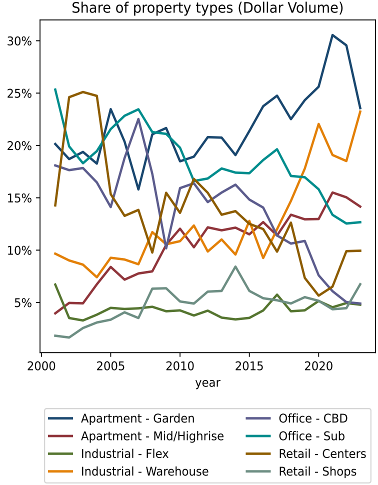
$$\begin{aligned} \mathbb{E}_i[N_{1i}] &= \beta_{i0}' x_n, \\ \gamma_i \mathrm{Var}_i(N_{1i}) &= \beta_{i1}' x_n, \\ \gamma_i \mathrm{Cov}_i(D_{1i}, N_{1i}) &= \beta_{2i}' x_n. \end{aligned}$$

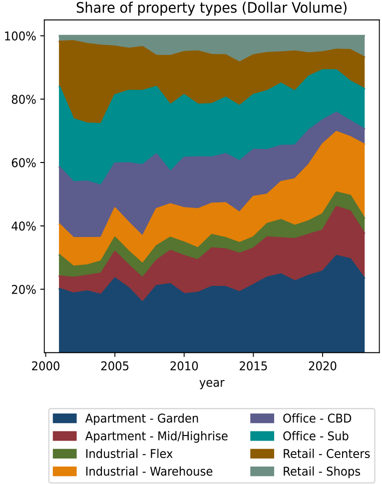
Risk aversion, beliefs, and D_{1i} are heterogeneous across investors.
Model heterogeneity across investors as function of size of investor portfolio, investor type, etc.:

$$\beta_{ki} = \beta_k' z_i, \quad \forall k = \{0, 1, 2\}.$$

back

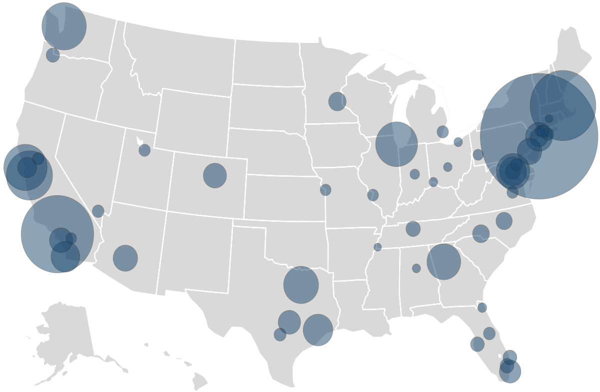
Transaction Volume by Asset Type



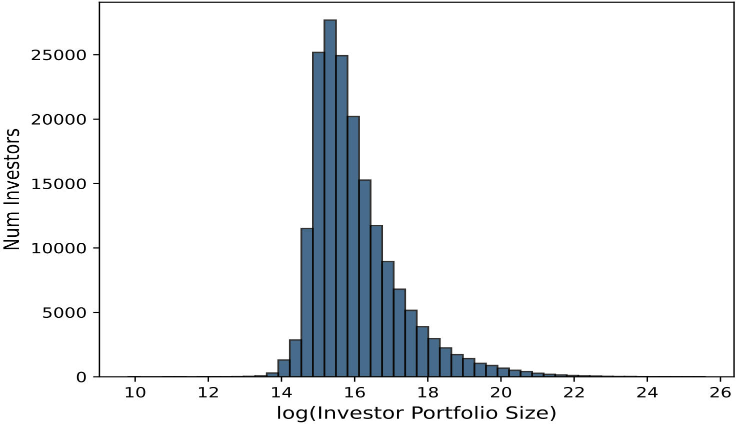


Transaction Volume by Asset Location

Office Properties: Market Sizes in 2023



Investor Size Distribution



- 16.2 = \$10 mi, 17.7 = \$50 mi, 20.7 = \$1 bi

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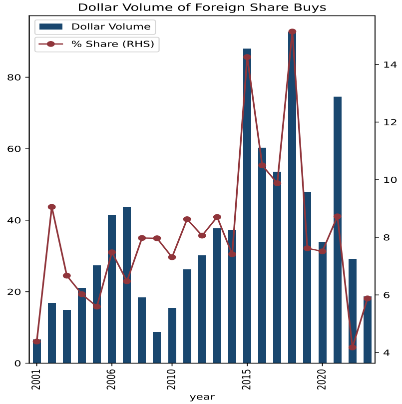
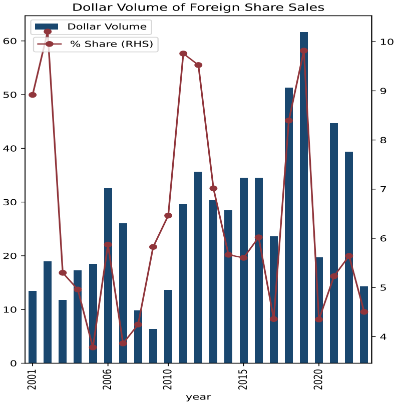
Foreign Investment Activity

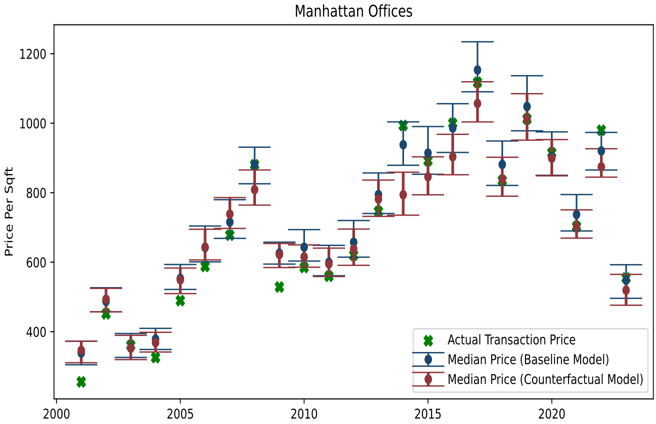




back to data
back to counterfactuals

Counterfactual: Price Impact of Foreigners

back



- Blue: with foreign buyers
- Red: without foreign buyers

Counterfactuals on Investor Composition

- What would have happened to CRE prices and trading volumes if...
  - REPE funds had not experienced as much selling pressure $\sim$10 years after large fundraising vintage (e.g., 2005-07, 2014-17)
  - REITs had not been unable to buy assets when $P < NAV$
  - Foreign investors did not have such a strong preference for green buildings
  - Pension funds had not searched for yield in CRE
  - Local rent regulation reform in apartment sector had not occurred in CA, OR, NYC
  - Work-from-home shock had not hit office as hard in cities with large tech sector
  - The Fed had not hiked interest rates as much as they did in 2022-23 (mon pol shock affecting investors differently through financing)

back

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