CoStar Data and Forecasting Methods

CoStar™

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INTRODUCTION

Since its founding in 1987, the CoStar Group has assembled an unparalleled library of building-level and deal-level commercial and multifamily real estate information. Each day, CoStar researchers located in offices across the United States, Canada, the United Kingdom, and Europe collect tens of thousands of space listings, lease deals, and transactions, while field research teams systematically document and photograph every building and construction project using specialized cars and aircraft equipped with military-grade surveillance technology. Each day, millions of rent observations flow into CoStar datasets via the firm's marketplaces, including Apartments.com, ApartmentFinder.com, ForRent.com, and LoopNet. And STR, a CoStar Group company, collects high-frequency data for more than 60,000 hotels worldwide.

This comprehensive and up-to-the-minute dataset has become indispensable to those in the commercial real estate industry who use it for a variety of reasons, such as marketing or seeking space, identifying comparable properties, benchmarking performance purposes, and understanding the competitive threat from new projects underway.

CoStar's Quantitative Analytics team develops models and algorithms to extract the most accurate and timely account of these trends in vacancies, rents, prices, and cap rates, whether for an individual property, a custom set of properties, a submarket or market, or the entire nation.

The Quantitative Analytics team also produces forecasts of the key real estate variables. Where other firms provide their clients with market-level forecasts, CoStar offers a forecast for every building, freeing clients from the restrictions of geography and allowing them to view a forecast for any custom set of properties. Moreover, CoStar's forecasting models update in real time based on actual movements in the property, ensuring that clients will never need to rely on forecasts based on months-old data.

These property-level historical series and forecasts drive the CoStar Market Analytics service, by which CoStar clients can access full underwriting reports, rent comp reports, and market and submarket reports. These reports feature narratives written by dedicated market analysts who collectively represent the largest and most experienced team of commercial real estate experts in the industry. Taken together, CoStar's comprehensive datasets, real-time, property-level historical and forecasts series, and written analysis have transformed commercial real estate analytics and put local players on equal footing with the largest international institutional investors when it comes to market knowledge.

This document describes the underlying CoStar datasets, the models used to create property-level vacancy and rent series, the models used to estimate prices and cap rates, and the CoStar approach to forecasting and model validation.

1 Overview of CoStar's Data

Commercial real estate investors and financiers face unique challenges with obtaining the business data that they need. Unlike stocks or bonds, property prices and performance indicators are frequently not reported, nor do owners provide earnings guidance. To the contrary, owners and tenants generally keep these data private. Investors have had to rely on information they have on their own assets, broker advice and reports, and on NCREIF performance trends to arrive at a view of market trends and outlook. This approach has characterized commercial real estate research and analysis for decades. But with the typical institutional real estate deal trading above $100 million and the total market capitalization of the asset class now approaching $23 trillion, investors who seek a more objective and systematic approach can achieve superior returns.

The CoStar Group's mission is to provide transparency and efficiency to this notoriously opaque market. The firm has invested billions of dollars to create and maintain a research apparatus that can track availabilities, vacancies, asking rents, and transactions for 7 million properties in real time. This apparatus includes 2,100 researchers who, every day, contact market participants to inquire about the status of listings and properties; marketplaces such as Apartments.com, through which more than 1.3 million new rent data points each day flow into CoStar datasets, as well as LoopNet; STR, the trusted partner with which the world's hotels share their operating data; and sophisticated automated data collection technology to collect rents from community websites.

1.1 Commercial Data

CoStar's data provides the raw material for a comprehensive view of U.S. commercial real estate. As of June 2022, the CoStar database included approximately:

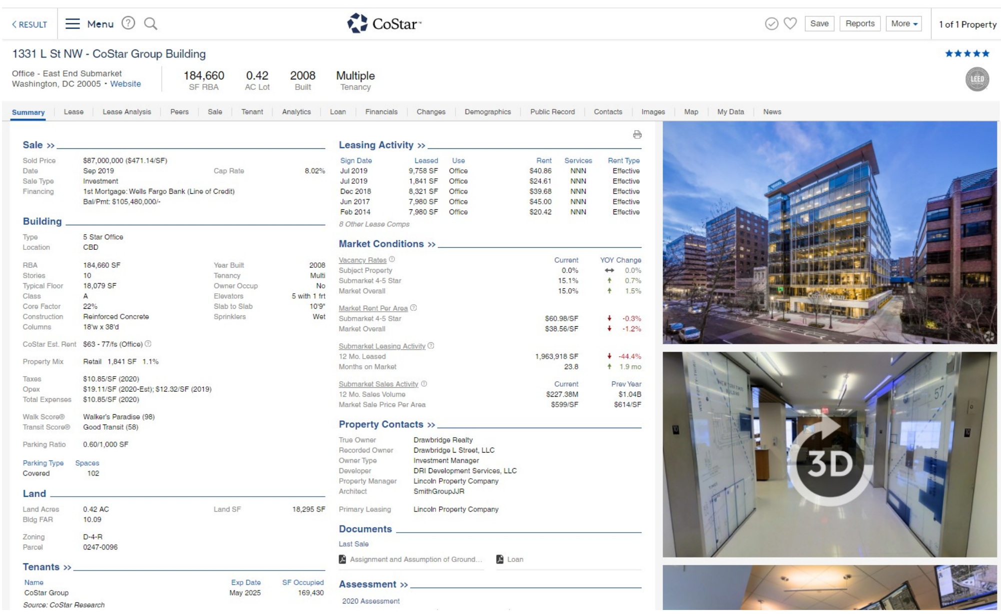
- 7 million total properties
- 868,000 sale and lease listings
- 7.3 billion square feet of sale and lease listings
- 8.1 million tenants
- 4.8 million sales transactions valued in the aggregate at approximately $13.0 trillion

This highly complex database contains hundreds of data fields, including:

- Location
- Mortgage details
- Deed information
- Site/zoning information
- For-sale information
- Building characteristics
- Income histories
- Expense histories
- Space availability
- Tenant names
- Tax assessments
- Lease expirations
- Ownership
- Contact information
- Sales and lease comps
- Historical trends
- Demographic information
- Retail sales per SF

This constitutes an effective census of the commercial real estate universe, as well as detailed pictures of individual assets. Exhibit 1.1 presents the landing page on the CoStar product for 1331 L St. in Washington, D.C., the headquarters location of the CoStar Group.

Exhibit 1.1: CoStar Data for 1331 L Street, Washington, D.C.



CoStar began collecting data in different markets at different times, so some markets have longer time series than others. For the office and industrial property types, most major markets have data back to at least 2000. Smaller markets and the retail property type typically begin in 2006. Exhibit 1.2 on the following page shows the analytic start date for fundamentals data for major markets by property type. Data for other markets begin in 2007. Same-store rent series (discussed in detail in Section 3) extend back to at least 2000 for all office, multifamily, and industrial markets, and to 2006 for all retail properties.

Exhibit 1.2: Data Collection Start Dates for Major Markets by Property Type

Market	Office Start	Industrial Start	Retail Start
Atlanta	1986Q4	1990Q1	2000Q1
Austin	2000Q4	2000Q4	2006Q1
Baltimore	1994Q1	1994Q1	2006Q1
Birmingham	2006Q1	2006Q1	2006Q1
Boston	1998Q1	1998Q1	2006Q1
Charlotte	2000Q1	2000Q1	2006Q1
Chicago	1996Q2	1996Q2	2006Q1
Cincinnati/Dayton	2000Q1	2000Q1	2006Q1
Cleveland	2000Q1	2000Q1	2006Q1
Columbus	2000Q1	2000Q1	2006Q1
Dallas/Ft Worth	1982Q1	1995Q1	2000Q1
Denver	1999Q4	1999Q4	2006Q1
Detroit	2000Q1	2000Q1	2006Q1
East Bay/Oakland	1997Q1	1997Q1	2006Q1
Greensboro/Winston-Salem	2006Q1	2006Q1	2006Q1
Greenville/Spartanburg	2006Q1	2006Q1	2006Q1
Hampton Roads	2005Q2	2005Q2	2005Q3
Hartford	2006Q1	2006Q1	2006Q1
Houston	1999Q1	1999Q1	2006Q1
Indianapolis	2000Q3	2000Q3	2006Q1
Inland Empire (California)	2000Q1	2000Q2	2006Q1
Jacksonville (Florida)	1999Q4	1999Q4	2006Q1
Kansas City	2000Q3	2000Q3	2006Q1
Las Vegas	2005Q3	2005Q3	2005Q3
Long Island (New York)	1996Q3	1996Q3	2006Q1
Los Angeles	1996Q2	2000Q4	2006Q1
Memphis	2000Q1	2000Q1	2000Q1
Milwaukee/Madison	2006Q1	2006Q1	2006Q1
Minneapolis/St Paul	2006Q1	2006Q1	2006Q1
Nashville	2000Q4	2000Q4	2000Q4
New York City	1994Q3	1994Q3	2006Q1
Northern New Jersey	1995Q2	1995Q2	2006Q1
Oklahoma City	2006Q1	2006Q1	2006Q1
Orange (California)	1996Q4	1996Q4	2006Q1
Orlando	1999Q3	1999Q3	2006Q1
Philadelphia	1997Q3	1997Q3	2006Q1
Phoenix	1999Q1	1999Q1	2006Q1
Pittsburgh	2000Q3	2000Q3	2006Q1
Portland	2003Q1	2003Q1	2006Q1
Providence	2006Q1	2006Q1	2006Q1
Raleigh/Durham	2000Q3	2000Q3	2006Q1
Richmond VA	2005Q2	2005Q2	2005Q2
Sacramento	1998Q4	1998Q4	2006Q1
Salt Lake City	2005Q4	2005Q4	2005Q4
San Antonio	2005Q3	2005Q3	2005Q3
San Diego	1999Q2	1999Q2	2006Q1
San Francisco	1997Q1	1997Q1	2006Q1
Seattle/Puget Sound	2000Q1	2000Q1	2006Q1
South Bay/San Jose	1997Q1	1997Q1	2006Q1
South Florida	1999Q3	1999Q3	2006Q1
Southwest Florida	2006Q1	2006Q1	2006Q1
St. Louis	2000Q1	2000Q1	2006Q1
Tampa/St Petersburg	1999Q3	1999Q3	2006Q1
Toledo	2006Q1	2006Q1	2006Q1
Tucson	2005Q3	2005Q3	2005Q3
Tulsa	2006Q1	2006Q1	2006Q1
Washington DC	1993Q1	1993Q1	2006Q1
Westchester/So Connecticut	1996Q3	1996Q3	2006Q1

Finally, the concept of a "slice" to group together similar properties is used. Slices are defined as shown in Exhibit 1.3.

Exhibit 1.3: Slice Definitions

Property Type	Slice	Includes
	Class A	4 & 5 Star properties
Office	Class B	3 Star properties
	Class C	1 & 2 Star properties
	Logistics	Warehouse & Distribution subtypes
Industrial	Specialized Industrial	All other Industrial subtypes
	Flex	All Flex properties
	Class A	4 & 5 Star properties
Multifamily	Class B	3 Star properties
	Class C	1 & 2 Star properties
	Malls	Malls
	Neighborhood Center	Neighborhood Centers
	Power Center	Power Centers
Retail	Strip Center	Strip Centers
	General Retail	Stand-alone retail locations
	Other	Other retail locations, including airport retail and retail in other public locations

1.2 Multifamily Data

CoStar began researching the multifamily space in 2013 and has amassed a dataset of 1.0 million apartment properties, totaling 19.2 million units, consistent with the firm's mission of recording every property. For comparison, the U.S. Census Bureau's American Housing Survey records total multifamily stock of fewer than ten million rental units in rental properties with at least 20 units as of 2019, in the latest available data.

The vast majority of CoStar's rent data comes via Apartments.com and the CoStar Group's other marketplaces. Each day, 1.3 million rent data points automatically flow into CoStar's datasets from 40 thousand properties.

This high-frequency data is augmented with data collected through more traditional methods. CoStar's multifamily research team calls about 12,500 properties per month to collect vacancy rates and rents. CoStar has also developed automated data collection technology to collect daily rent information from property websites. Finally, to extend the data's history, CoStar acquired RealFacts' apartment rent data set, which tracks some 12,000 properties back into the 1990s. Exhibit 1.4 shows the scale of CoStar's rent data.

The scale and quality of CoStar's rental data enables the creation of accurate, high-frequency analytic series that can show a market's reaction to events in near-real time. For example, Exhibit 1.5 shows CoStar's daily rent series for Houston during the COVID-19 outbreak in March 2020, showing rents falling as urban tenants fled to the suburbs.

Exhibit 1.4: CoStar Apartment Rent data, Neartown/River Oak Submarket in Houston

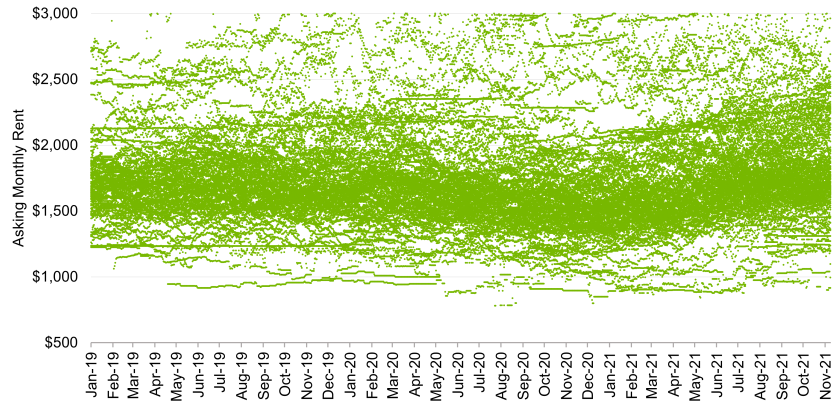
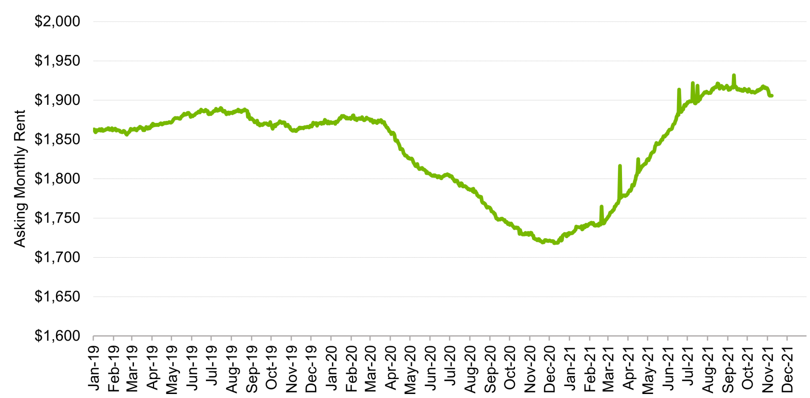


Exhibit 1.5: Daily Rent Series for Houston



1.3 Student Housing Data

Using similar research methods as other multifamily properties, CoStar collects data for roughly 8,300 student housing properties in the United States comprising 2.0 million beds. Efforts to provide the most accurate and up-to-date information were strengthened in June 2019 when Off Campus Partners, a leading online multifamily marketplace for student housing in the United States, joined the CoStar Group. Founded in Charlottesville, Virginia in 2000 by a University of Virginia student, Off Campus Partners enters into exclusive agreements with universities to provide an off-campus housing listing service for students.

Data for universities is collected from the National Center for Education Statistics, Integrated Postsecondary Education Data System (IPEDS). These data include student enrollment and admission counts, tuition costs, dormitory costs, financial aid statistics, and student demographics.

1.4 Hotel Data

CoStar's research teams have tracked hotel inventory and deals since the firm's inception, and CoStar's database includes 1.1 million hotel properties and 72,000 sales transactions. As with CoStar's data of other property types, the firm records physical building characteristics for hotel properties, and pricing information and market participants for hotel trades.

In September of 2019, STR joined the CoStar Group. Since its founding in 1985, STR has partnered with hotels around the world to serve as a clearinghouse for hotel operating and performance data—data that is relied upon by Wall Street, lenders, and investors to track the hospitality industry. As a service to hotel companies, STR uses the data it collects to benchmark individual hotel performance against peer sets. This analysis, reported weekly in the company's widely known STAR Report, has become an essential tool for hotel managers to measure their performance against competitors and to optimize pricing and occupancy. Virtually every branded hotel and a majority of non-branded properties contribute to STR's data. STR reports hotel trends on a monthly, weekly, and daily basis, which is the level of frequency of data that it collects from its clients.

STR's wealth of operating information for major hotel properties allows CoStar to report highly accurate trends in hotel occupancy, average daily rate (known as ADR) and revenue per available room (or RevPAR). However, the privileged nature of STR's data—collected directly from hotel operators and owners—also puts strict limitations on the use of this data. Specific hotel-level data is kept confidential, except to the contributing hotel in the content of the STAR report. Any analytics must meet STR's isolation and sufficiency requirements. Analytic data series must include a minimum number of properties and meet the following conditions:

- No single property can account for more than half of the total room supply in the peer set.
- No single brand (for example, Holiday Inn, Comfort Inn, Four Seasons) can account for more than half of the total room supply in the peer set.
- No single company (for example, Hilton Worldwide, Aimbridge Hospitality, Host Hotels & Resorts) can account for more than 70% of the total room supply in the peer set.

Checks are performed to ensure no individual property, brand, or parent company data can be isolated from one peer set to another.

STR assigns each hotel property a class, which is a categorization of chain-affiliated and independent hotels. The class for a chain-affiliated hotel is the same as its chain scale. An independent hotel is assigned a class based on its ADR relative to that of the chain hotels in its geographic proximity. The class segments are luxury, upper upscale, upscale, upper midscale, midscale, and economy. These six class segments collapse into three broad categories:

- Luxury and upper upscale
- Upscale and upper midscale
- Midscale and economy

STR also categorizes each hotel by its chain scale. Chain scale segments are grouped primarily according to actual average room rates. An independent hotel, regardless of its average room rate, is included as a separate chain scale category. The chain scale segments are luxury, upper upscale, upscale, upper midscale, midscale, economy, and independent. These segments collapse into four broad categories:

- Upscale chains – includes luxury, upper upscale, and upscale chains
- Midscale chains – includes upper midscale and midscale chains
- Economy chains – includes economy chains
- Independent – includes independent properties

To protect confidential property data, a weighted submarket methodology is used when aggregating and displaying property level data in Property Search. A user-selected set of properties will return results based on industry level data weighted to the size of the properties selected. In a user-selected set, each property is mapped to performance data for that property's submarket class aggregation. Should the submarket class data fail to meet STR sufficiency criteria, then the next lowest level of aggregation is used instead, continuing through the following hierarchy:

- Submarket class
- Submarket collapsed class
- Market class
- Market collapsed class
- Submarket
- Market

In this way, CoStar clients can arrive at high-quality performance analytics and trends for any selected set of hotel properties without viewing the actual property-specific information.

Beyond these restrictions, the STR data is stored in secure servers with limited access. CoStar does not and will not use STR data in any way that could inadvertently reveal performance data for an individual hotel, owner, or brand.

1.4.1 Weighted Submarket Methodology for a User Defined Selection Set

To protect and safeguard confidential proprietary data, property-level data is aggregated using a weighted-submarket methodology before being displayed in Property Search. When hotel properties are selected, the analytics are calculated using the following process.

- **Determine the Value for the Estimation Process**
  - For each time period (daily, weekly or monthly), the performance of the submarket class (Occupancy, ADR and RevPAR) is assigned to each property selected for the grouping based on the submarket class assigned to the property. If the submarket class is unavailable for that specific period, the value for the submarket collapsed class is calculated. This logic is continued through the following hierarchy until a sufficient value is found:
    - Submarket Class
    - Submarket Collapsed Class
    - Market Class
    - Market Collapsed Class
    - Submarket
    - Market

- **Determine the Weight of Each Property**
  - Once each property has been assigned a performance value for each time period in the selected range, the weight of each property is determined by calculating its room count percentage of the submarket class (the property's room count divided by the total room count for all properties in the set). If a property is closed during the time period being evaluated, there is no estimated data for that property/time period combination.
- **Apply Weights to Each Value**
  - Each value determined for a property in the first step is then multiplied by the calculated weight in the second step.
- **Sum Values for Aggregate Set**
  - For the aggregate set of properties, the weighted values for each property are aggregated by time period.
- **Calculate Raw Data for Aggregated Set**
  - For the set of properties, the aggregated values of Occupancy, ADR, and RevPAR are used to determine the following calculations:
    * Supply = Aggregated Set Room Count × Number of Days (daily=1, monthly=count of days in the month, yearly=365)
    * Demand = Aggregated Set Supply × Aggregated Set Occupancy
    * Revenue = Aggregated Set Supply × Aggregated Set RevPAR

1.5 Geographies

CoStar's data represents an effective census of commercial real estate, including 7 million properties. By offering data and forecasts at the individual property level, CoStar clients can aggregate the data in any way they choose. However, for the purposes of defining market coverage and for the convenience of clients, CoStar has established market and submarket definitions.

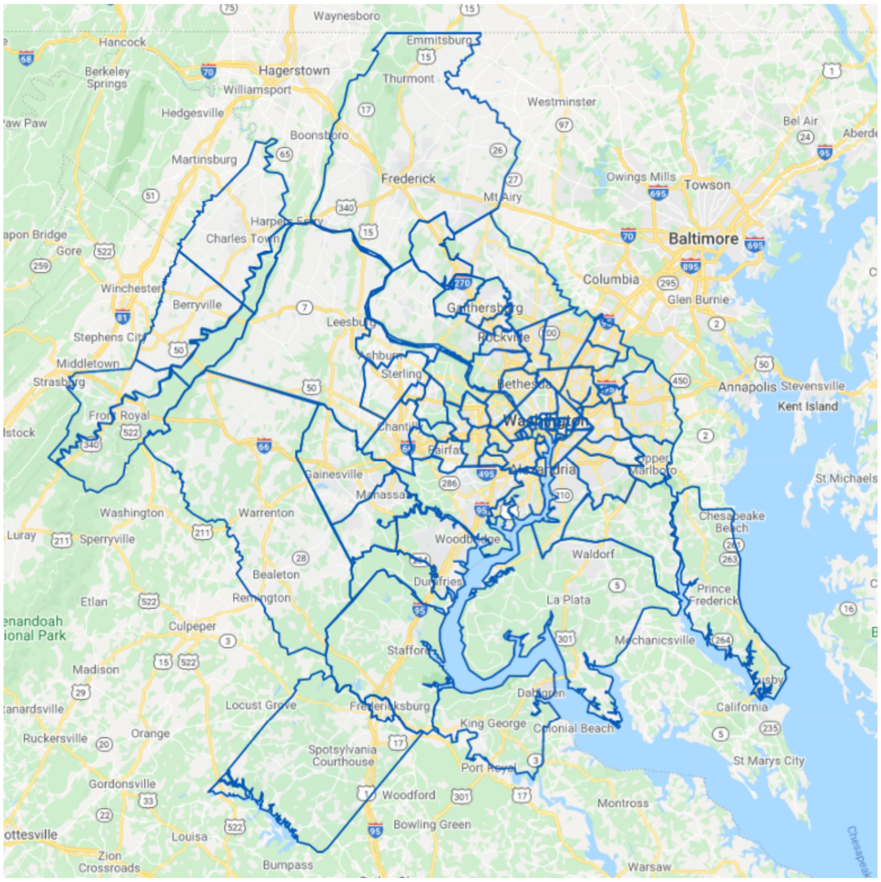
CoStar's market definitions for commercial and multifamily markets (which includes off-campus student housing) generally match Core Based Statistical Areas (or CBSAs), which include either Metropolitan Statistical Areas (MSAs) or Metropolitan Districts (MDs). Within each market, CoStar researchers and analysts, in consultation with local market participants, have drawn submarkets for each of the four main property types. On average, each major market contains 25 submarkets. As an example, Exhibit 1.6 shows the submarket map for the Washington-Northern Virginia-Maryland office market.

CoStar also reports data for submarket clusters, which represent aggregations of submarkets (as in New York Midtown or Downtown Washington).

Student housing geographies are based on proximity to universities. Apart from traditional student housing communities, CoStar includes market-rate multifamily properties that are within a 60-minute walk or 10-mile drive of a university in its analysis of student housing trends. In areas where there are multiple universities, properties are allocated to each respective university using geospatial analysis.

For the hotel sector, CoStar uses the markets defined by STR, which typically consist of an MSA, such as Atlanta, GA, a group of MSAs, such as South Central PA, or a group of postal codes, such as Texas North. Outside of the U.S., a market is defined as a city, region or country with at least 30 participating hotels. In total, CoStar tracks 166 markets in the United States and 654 submarkets defined by STR.

Exhibit 1.6: Washington, D.C. Office Submarket Map



2 Historical Fundamentals

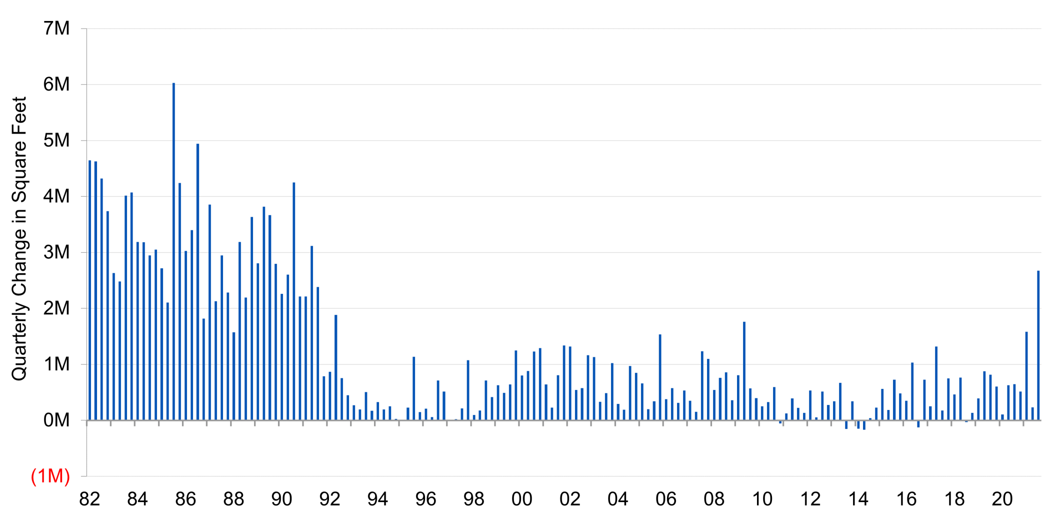
Commercial real estate analysis begins with the fundamentals: net deliveries, net absorption, and vacancy. CoStar's comprehensive property-level data on property size, date built, and tenancy makes these metrics easy to track. This chapter details the specific methodology by which CoStar creates full series at the submarket and market level for commercial, multifamily, and hotel fundamentals, starting with inventory.

2.1 Supply

Inventory is the total stock of commercial real estate space in a market, usually expressed in rentable building area (RBA) or units (for multifamily properties), beds (for student housing assets), or rooms (for hotels). The change in inventory in any given time period is referred to as net deliveries. Hence, net deliveries is defined as inventory that delivered during the period less inventory that was demolished.

CoStar tracks construction start and end dates for every property in its database and uses these to create full histories of net deliveries going back decades. Exhibit 2.1 presents net deliveries of office space for the Los Angeles market.

Exhibit 2.1: Los Angeles Office Net Deliveries Since 1982



Note that the accuracy of this measure falls over time, since properties that were demolished prior to the date that CoStar began tracking the market will not appear in the series.

For the hotel sector, supply refers to the number of available room nights, which is equal to the total number of rooms in operation multiplied by the number of nights in the selected time period. Thus, a market with 10,000 rooms will have a supply of 310,000 room-nights in March, per the equation below.

$$Supply = AggregatedSetRoomCount * NumberofDays$$

where *Number of Days* depends on the periodicity: for daily analytics, *Number of Days* is 1; for monthly, *Number of Days* is the count of days in the month; and for yearly, *Number of Days* is 365. In the hotel sector, the term “inventory” refers to the number of rooms in existence.

2.2 Commercial Vacancy and Demand

CoStar defines vacancy as space that is not physically occupied by a tenant. Thus:

$$VacancyRate = 1 - \left(\frac{OccupiedSpace}{Inventory}\right)$$

CoStar uses the term “availability” to denote space available for lease. A space can be available but not vacant if the landlord has begun marketing the space in anticipation of the current tenant moving out. CoStar has tracked the vacancy and availability of commercial real estate for over 30 years. At any given time, CoStar is tracking more than 640,000 individual spaces for lease, and at regular intervals contacts listing agents or landlords for updates on the status of each listing, including the current asking rent and whether a tenant is physically occupying the space. From these research efforts, CoStar can establish the vacancy rate for every commercial real estate asset at any point in the recent past, as well as when each space has leased. That allows CoStar to calculate the change in occupied space, referred to as net absorption, where:

$$NetAbsorption_t = OccupiedSpace_t - OccupiedSpace_{t-1}$$

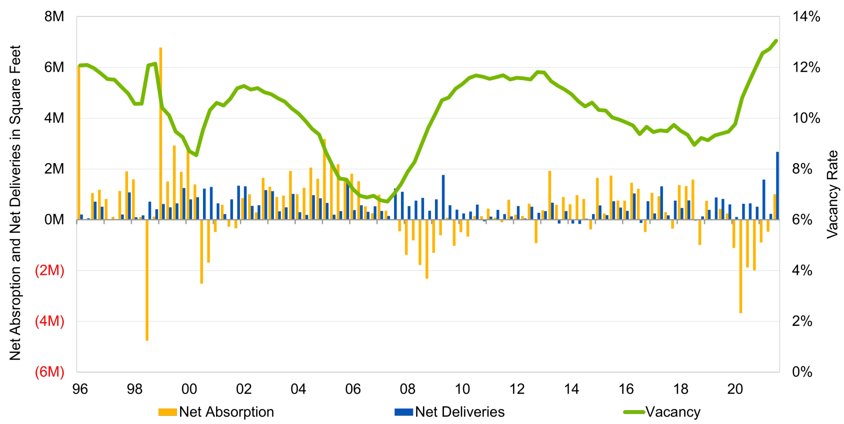
The building-level tenancy data is aggregated to arrive at submarket- and market-level vacant space. Vacancy rates are derived by combining this data with inventory figures. Exhibit 2.2 presents office net deliveries, net absorption, and vacancy for Los Angeles office.

CoStar’s building-level vacancy data begins around 2000 for most major metros, but a handful have longer histories, including Atlanta, Dallas-Fort Worth, Washington, New York, Chicago, Los Angeles, and Baltimore. Coverage for most of the smaller markets (and retail) began in 2006. Prior to these dates, CoStar backcasts major markets using broad market trends reported by brokerage firms since the early 1990s.

2.3 Multifamily and Student Housing Vacancy and Demand

Lease terms are shorter in multifamily and off-campus student housing properties than they are in commercial properties and have as many tenants as units (or more, as some tenants choose to live together as roommates), resulting in more turnover and more volatility in vacancy rates.

Exhibit 2.2: Office Fundamentals for Los Angeles Office



Because of this, CoStar tracks multifamily vacancy on a monthly cycle, rather than the quarterly cycle used for commercial properties.

In total, CoStar's vacancy data includes more than 4 million observations since 2015. This substantial research effort, however, falls short of collecting vacancy data every month for every configuration in every property—which would number more than 132 million data points in total. And it cannot be assumed that, in the absence of information, a multifamily property is fully leased. To fully populate the time series and provide a vacancy in every month for every configuration in every multifamily property, any missing data are estimated using quantitative methods as described below.

2.3.1 Filling in Missing Multifamily Data

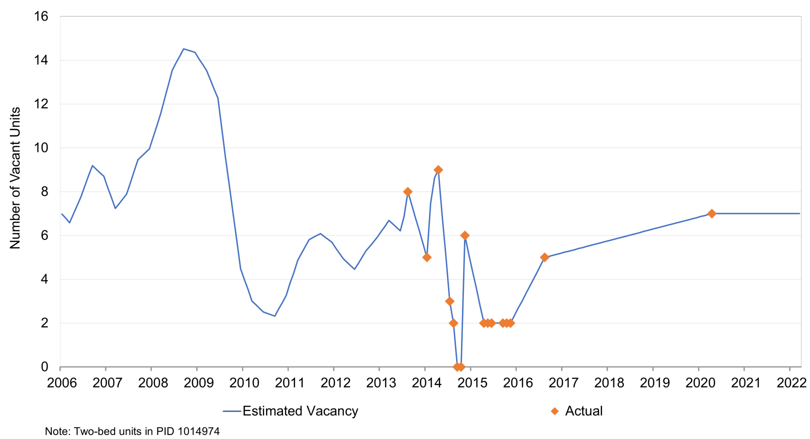
The process used to estimate missing multifamily vacancy data includes two steps: First, any missing data points in properties with vacancy data (about 175,000 properties out of the 670,000 total multifamily properties in the U.S., and in 100,000 out of 139,000 properties with at least 50 units) are filled in. Second, vacancy rates in the properties for which vacancy data have never been collected are estimated.

The first step—filling in missing data points—takes two forms. Any gap between two observations will be filled in by linear interpolation (i.e., a straight line between the two observed data points). Then to populate the data before the first observation and after the most recent observation, the trend of stabilized vacancy rates from the same bedroom type in the same submarket is used to extrapolate before the first observed data point and beyond the last observed data point. Exhibit 2.3 illustrates this process for an actual property.

The second step requires estimating the vacancy rate at each point in time for properties for which CoStar has never collected a vacancy observation, which number about 495,000. These properties tend to be quite small, and often do not have a leasing manager or landlord that a CoStar researcher could contact for updated information.

To estimate the vacancy in these properties, the average vacancy from other stabilized properties in the same submarket with similar characteristics is applied. Estimating these data points allows a full vacancy dataset to be compiled that aligns with supply, to allow the accurate estimation of aggregate demand.

Exhibit 2.3: Creating the Multifamily Vacancy Time Series



2.3.2 Estimating Multifamily Lease-Up

The methods outlined above apply to stabilized multifamily properties. Recently delivered properties exhibit different vacancy dynamics as they lease up. CoStar's research teams prioritize collecting data on recently delivered properties to ensure the most accurate trends in lease-up are captured. However, for the purposes of estimating lease-up in projects that delivered in the past and to fill in any missing data points in recent deliveries, an algorithm is deployed to estimate lease-up trends.

Exhibit 2.4: Multifamily Lease-Up Trends

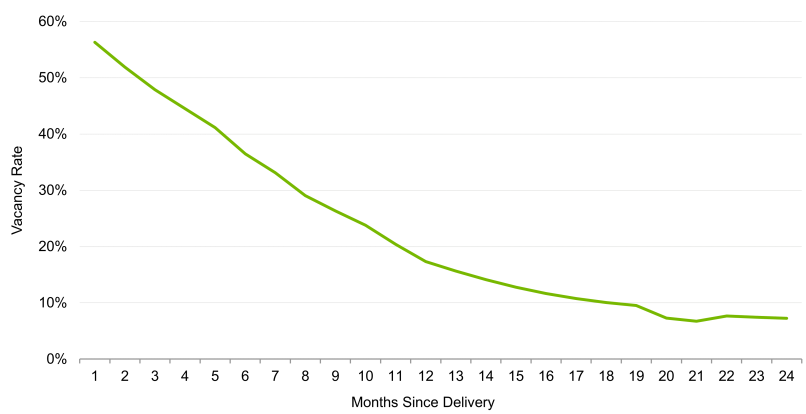


Exhibit 2.4 presents an analysis of vacancy observations for properties completed since 2014, where the x-axis indicates months since the delivery date. The data shows that the vacancy of a property upon delivery is related to the size and style of the property, but for all buildings, leasing

more or less follows an exponential curve from that initial vacancy, eventually approaching the market average. If the first observation for vacancy in a property is higher or lower than would be expected by the model, then the lease-up backcast is adjusted to correctly join up with that first data point. Vacancy is estimated to decline following the curve in Exhibit 2.4 over the next 18 months until converging to the market rate.

This algorithm is also applied to properties in lease-up that have some actual data points, filling in any gaps and trending the vacancy rates before the first observation and after the most recent observation.

2.3.3 Backcasting Multifamily Data

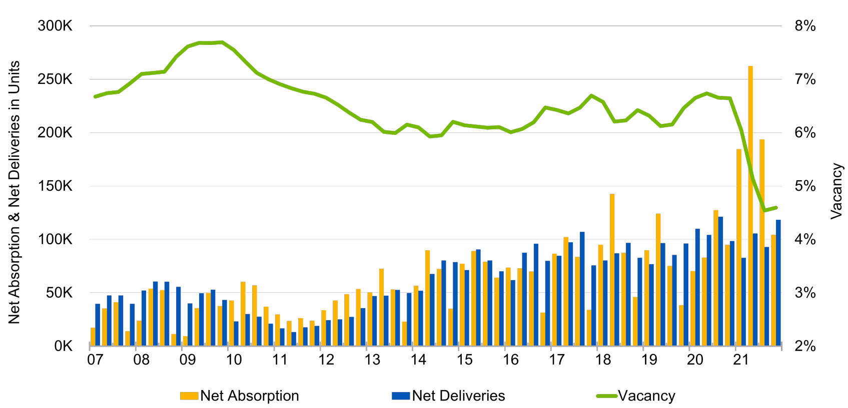
CoStar's collection of multifamily data began in 2012. In addition to filling in missing data, the vacancy series for multifamily properties are extended using trends based on data from the United States Census Bureau, which tracks rental vacancy rates for the 75 largest MSAs. CoStar also acquired the RealFacts dataset, which includes rent and vacancy data for approximately 12,000 properties with data extending back to the 1990s. These data are used to estimate longer time series. Finally, metro-level apartment rent trends reported by brokerage firms since the early 1990s are applied to each individual property to extend all multifamily series back to 2000.

2.3.4 National Multifamily Supply, Demand, and Vacancy

The algorithms described above allow the creation of full vacancy series for all 1.0 million multifamily properties in the CoStar database. These series use the millions of vacancy data points to estimate vacancy trends and levels, filling in gaps between observations and providing approximate vacancy levels for properties for which data has not been collected.

By aggregating the full time series for any set of properties, high-quality estimates of aggregate net deliveries and net absorption at a national, market or submarket level can be produced. Exhibit 2.5 presents CoStar's estimate of national multifamily net deliveries, net absorption, and vacancy based on all 1.0 million properties and 19.2 million units in the database.

Exhibit 2.5: National Multifamily Supply, Demand, and Vacancy



The increasing period-to-period volatility since 2012 illustrates the improving quality of CoStar's data. Prior to 2012, the series draws on broad, metro-level trends from the U.S. Census and legacy broker data. After 2012, the series is increasingly based on high-frequency, high-volume data collected by CoStar.

2.4 Hotel Occupancy and Demand

STR defines demand as the number of rooms sold in a specific period (excluding complimentary rooms). Whereas analyses of the commercial sector traditionally track the vacancy rate, the hotel industry tracks occupancy—or one minus the vacancy rate. For the hotel sector, the occupancy rate is equal to the demand (or total rooms sold in a period) divided by the total number of available room nights in that period, expressed mathematically as:

$$Occupancy = \frac{Demand}{Supply}$$

3 Rents: Methods and Estimations

Compared to supply, demand, and vacancy, rents pose a far greater analytic challenge. For commercial properties, CoStar collects asking rent data on spaces available for lease. Generally, only properties with availability report a rent, and that set of properties changes constantly. The changing mix of properties that report rents from period to period confounds analyses of rent trends, since the appearance of a new large block at a high or low rent relative to its peers can give the appearance of large swings in rents. To control for the effect of changing composition, and to ensure that every property has a rent in every period, CoStar constructs a “same-store” rent series, covered in section 3.1.

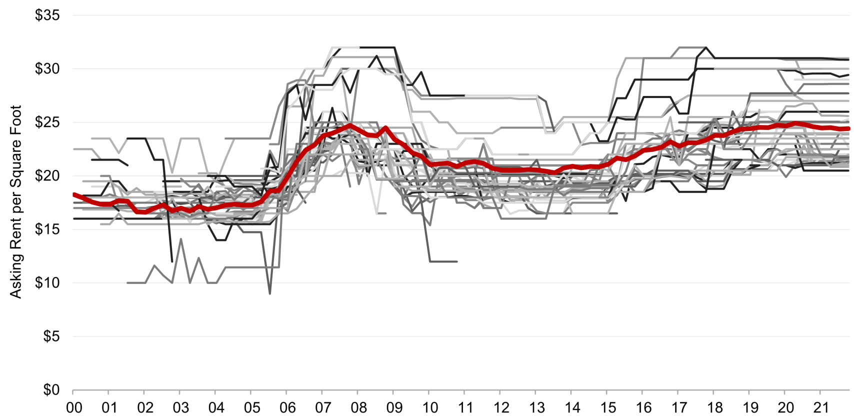
In contrast to commercial properties, most multifamily properties have some availability nearly all the time as leases expire and tenants move out. As a result, most multifamily properties are continually marketing availabilities and reporting asking rents. However, these suffer from the same sample bias that confounds commercial property rents. Apartments.com has become the primary marketing platform for the U.S. multifamily sector, and through Apartments.com and CoStar’s other marketplaces, CoStar collects more than 4 million apartment rent data points each day. This wealth of data enables CoStar to track multifamily asking rents on a daily basis with a high degree of accuracy. Section 3.2 details how CoStar creates rent series for multifamily that, similar to the “same-store” commercial rents, ensure that time series always include the same set of properties and units.

Whereas CoStar primarily collects asking rent information for the commercial and multifamily sectors, STR collects actual room revenue for the hotel sector. This is used to calculate the average daily rate (ADR) by dividing total room revenue by room demand in a given period. Section 3.3 details how CoStar uses hotel operating data to create market- and submarket-level trends for ADR.

3.1 Commercial Rents

As part of CoStar’s daily data gathering, researchers collect the asking rent for available spaces in commercial properties. As of June 2022, the database contained more than 6.6 million asking rent observations across industrial, office, and retail property types. Exhibit 3.1 illustrates the scale of CoStar’s commercial rent data for 4 & 5 Star office properties in Phoenix’s Midtown Submarket. Each gray line represents the asking rent for a particular space in a property.

Exhibit 3.1: Phoenix Midtown Submarket 4&5 Star Available Space-Weighted Rent

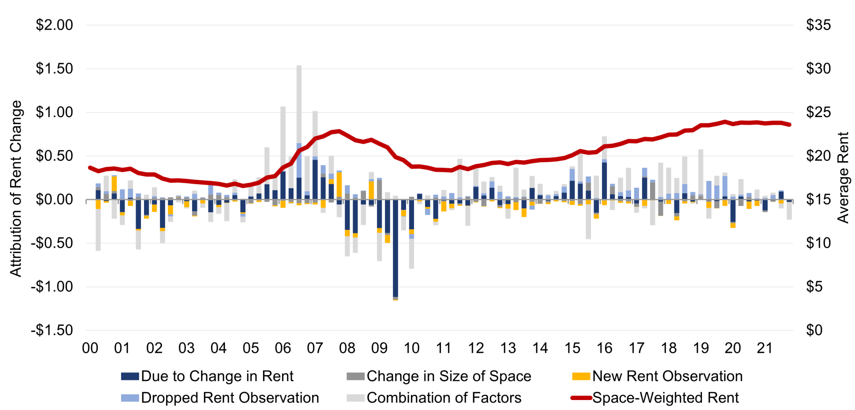


The red line shows the available space-weighted average rent of the submarket slide. This view essentially shows how much a tenant would pay per square foot to rent all the available space in the market in a particular quarter.

3.1.1 The Challenges of Commercial Rents

This view of the space market clearly has some flaws. While relatively stable from 2000 to 2007, thereafter the aggregate line exhibits fluctuations which are not representative of market trends. Rather, they result from changes in the composition of the set of spaces on the market. Exhibit 3.2 presents an attribution of movements in the aggregate series.

Exhibit 3.2: Attribution of Aggregate Rent Movements, Phoenix Midtown Submarket



The columns represent the reasons for the rent movements. The dark blue bars show movements in the aggregate rent directly attributable to observed changes in the underlying rent data. The decline in rents from 2001 to 2004, for example, resulted from observed cases where properties actually lowered asking rents on spaces that were available for lease.

Bars of the lighter blue color, on the other hand, represent movements in the aggregate rent that resulted from rents disappearing from the dataset due to spaces being leased or withdrawn, or to the listing manager no longer choosing to report a rent. In the first half of 2008, for example, rents fell by about 10% simply because the dataset included fewer high rents. This same dynamic explains the large swings in more recent years. Rents fall when expensive space comes off the market, and rents rise when cheaper space comes off the market.

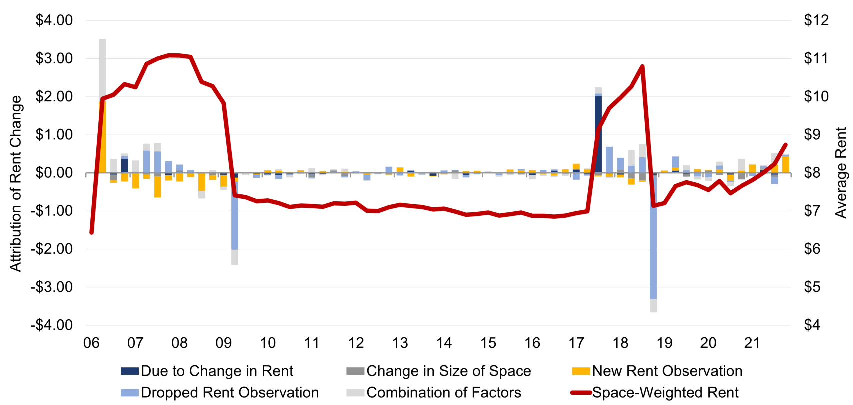
Dark gray bars demonstrate the effect of new rents entering the dataset, either due to new space on the market or to properties reporting a rent on an existing space which had previously been withheld. When higher rents enter the time series, as at the end of 2015, the aggregate rent series rises. On the other hand, if lower rents appear, as in 2017, the aggregate rent falls.

Orange bars show the effect of changes in the amount of space offered. For example, if a property with 100,000 SF for rent at $100 successfully leased 50,000 SF, then the weight on the $100 rent would fall by half, causing a decline in the aggregate rent.

The remaining effect, classified as "Combination of Factors," shows rent movements that cannot be attributed to a single cause. In these cases, both the size of the space and the asking rent have changed, making it impossible to attribute the movement in the aggregate rent to a single effect.

Scarce data in small markets (or submarkets in large markets) can produce series that can resemble a random walk, as in the example of the Scranton industrial market, shown in Exhibit 3.3.

Exhibit 3.3: Attribution of Aggregate Rent Movements, Scranton Industrial



These problems do not indicate any underlying deficiencies with the underlying data. Rather, the series shown above confirm that a more sophisticated approach is needed to use these data, one that can control for the changing composition of the set of properties reporting rents.

3.1.2 Standardizing Service Types

In the United States, an additional complication unique to office properties is that landlords report a myriad of different rent terms—triple net, full service, plus electric, and so on. To more accurately capture rent trends and levels, these various service types need to be normalized. Exhibit 3.4 presents the different categories, along with the frequency of each service type in the CoStar space-for-lease database as of mid-2022. Service types vary across the country, but also within markets, submarkets, and even properties, making accurate analyses of rent growth and levels difficult. One approach to normalizing rents would be to add estimates of the netted-out expenses to each asking rent–for example, adding an estimate of annual electric costs per square foot to all "plus electric" rents.

Exhibit 3.4: Office Rent Service Types as of June 2022

Service Type	Percentage
Full Service Gross	38.0%
Modified Gross	16.5%
Triple Net	15.3%
Negotiable	14.8%
Plus Electric	7.3%
Plus All Utilities	3.5%
Net	1.4%
Tenant Electric	1.1%
TBD	0.8%
+ Elec & Clean	0.5%
Plus Cleaning	0.4%

CoStar does not collect a statistically viable sample of expense data, both due to a relatively small sample size (especially at a market or submarket level) and to a geographic and quality bias, as existing expense data skews toward large, high-quality assets in major markets.

Hence, in addition to own sources, CoStar employs data from a number of other industry sources, including the Institute of Real Estate Management (IREM), the National Council of Real Estate Fiduciaries (NCREIF), and public CMBS data. CoStar has used these three data sources, as well as its own data, to estimate typical expenses by building quality and location.

The Institute of Real Estate Management's (IREM) Income/Expense data provides anonymized building-level financial data across a wide range of income and expense categories for more than 9,000 properties. CoStar has acquired this full dataset for use in estimating expenses.

NCREIF also provides income and expense data. Per NCREIF's policies, it requires a minimum number of properties to present aggregated data. Using its custom query tool, CoStar has downloaded the expense data at minimum aggregation levels that met those criteria.

CoStar also draws on publicly available financial data for the properties which serve as collateral in CMBS pools, a dataset of more than 200,000 properties. The CMBS data adds another dimension to CoStar's collection of expense information, as it includes mostly smaller assets located outside of major markets.

The information from these sources is used to estimate expenses across the relevant categories at a zip code level, a submarket level, a submarket-cluster level, a CBSA and CBD/suburban level, a state and CBD/suburban level, and a regional and CBD/suburban level. These aggregates are further sliced by quality, including 1 & 2 Star, 3 Star, and 4 & 5 Star. Each property is assigned the expense estimate from the lowest geographic level that meets statistical confidence tests. In general, properties in major markets use zip code or submarket level expense estimates, while properties located outside of major metros tend to use market, state, or region-level estimates.

These spot estimates of expenses are based on data as of 2013 and escalated to current dollars. To create time series of expenses, we apply same-store trends based on NCREIF data at a regional and CBD or suburban level for each expense category. Exhibit 3.5 shows CoStar's estimated expenses by category for all office properties in the New York market.

Other commercial property types report fewer service types and need less expense estimation. Most retail rents, for example, are triple net. Industrial rent service types can vary but not typically within a market. As such, CoStar does not estimate industrial or retail expenses.

Exhibit 3.5: New York Plaza District Office Expense Estimates as of June 2022

Market / Cluster	Utilities ($)	Cleaning ($)	Insurance ($)	Taxes ($)	Other ($)	Total ($)
New York	1.45	1.49	0.52	10.09	10.89	24.44
Bergen Central	0.82	1.50	0.19	4.39	7.00	13.90
Bergen East	1.12	1.58	0.25	5.09	6.94	14.98
Bergen North	0.82	1.51	0.19	3.49	6.82	12.83
Bronx	1.01	1.96	0.44	3.96	9.33	16.70
Brooklyn	0.92	1.21	0.43	8.39	7.16	18.11
Brunswick/Piscataway/I-287	0.73	1.47	0.31	4.39	6.93	13.83
Downtown	1.90	1.52	0.73	9.14	11.55	24.84
East I-287 Corridor	0.82	1.97	0.43	5.93	9.57	18.72
Hudson Waterfront	0.46	1.21	0.75	4.36	6.02	12.80
Meadowlands	0.50	0.58	0.71	5.34	8.31	15.44
Midtown	2.35	1.54	0.64	16.52	14.97	36.02
Midtown South	1.53	1.45	0.42	13.47	12.92	29.79
Monmouth East	0.81	1.42	0.32	6.70	6.68	15.93
Monmouth West	0.72	1.48	0.24	3.72	7.12	13.28
North	0.93	2.24	0.49	5.03	10.30	18.99
Northeast	0.80	1.92	0.42	2.56	9.43	15.13
Northwest	0.80	1.92	0.42	5.34	9.43	17.91
Ocean County	0.72	1.47	0.58	2.58	6.69	12.04
Orange/Rockland	0.73	1.50	0.34	4.75	7.08	14.40
Queens	0.98	1.32	0.44	7.69	7.74	18.17
Southeast	0.80	1.92	0.63	3.93	9.19	16.47
Southwest	0.80	1.92	0.42	3.71	9.43	16.28
Staten Island	0.81	1.10	0.37	4.04	6.86	13.18
Uptown	1.32	1.66	0.58	7.89	17.86	29.31
Wayne/Paterson	0.56	0.73	0.75	4.85	8.32	15.21
West I-287 Corridor	0.90	2.16	0.47	4.53	10.09	18.15
White Plains CBD	0.82	1.98	0.44	4.42	9.60	17.26
Woodbridge/Edison	0.69	1.43	0.23	5.21	6.94	14.50

Note: The category labeled “Other” includes management and administration, services, and miscellaneous expenditures. These estimated expenses are added to office rents according to the service type to “gross up” the various net rent categories, allowing rents to be compared across properties and markets on a full-service basis.

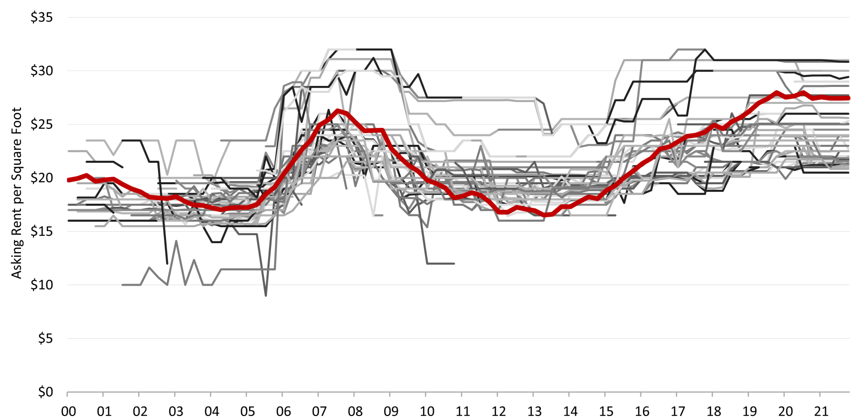
3.1.3 Commercial Same-Store Rents

Constructing same-store rent series for commercial properties involves creating a full time series for every property so they can be aggregated without regard to whether they have any rent observations or not. Creating full time series requires three types of estimations similar to those made for multifamily vacancy described in Section 2.3.1. First, any rent observations missing for time periods between actual observations must be estimated. Second, rent data points before the first known observation and after the most recent observation must be estimated. Finally, rents in properties for which CoStar has not collected any information must be estimated.

To estimate rents between, before, and after known rents, it is assumed that rents in the subject property would have followed the same trend as rents in nearby, similar properties. These trends are constructed from observed rent changes for individual peer properties. For office properties, comparable space would be on a similar floor level to prevent a rent in a more (or less) desirable floor being identified as an increase (or decrease) over the preceding period.

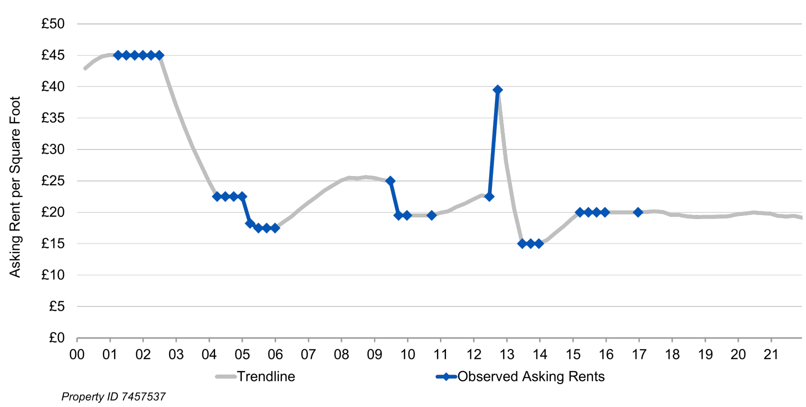
Exhibit 3.6 shows the raw asking rent data at the space level for 4 & 5 Star properties in the Phoenix Midtown submarket, along with the trend derived from these data. For the purposes of creating the trend, only observations that show a change (either positive or negative) are included to increase the volatility of the trend. The trend also includes changes between non-adjacent rent observations in the same property, assuming a constant growth rate between the non-adjacent observations.

Exhibit 3.6: Phoenix Midtown Submarket 4&5-Star Office Rents with Trendline



Once constructed, these trend lines are applied to individual properties. To fill in the gaps between rents for individual properties, the submarket trend line is pivoted by adding a constant equal to the quarterly difference in total growth between the trend line and the rents at the start and end of the gap. Rents before the first observation and after the last observation are extended by applying the rates of change from the trend line. Exhibit 3.7 illustrates how the trend is applied to create a full time series for a particular property.

Exhibit 3.7: Construction of Same-Store Rent Series for the London Office Market

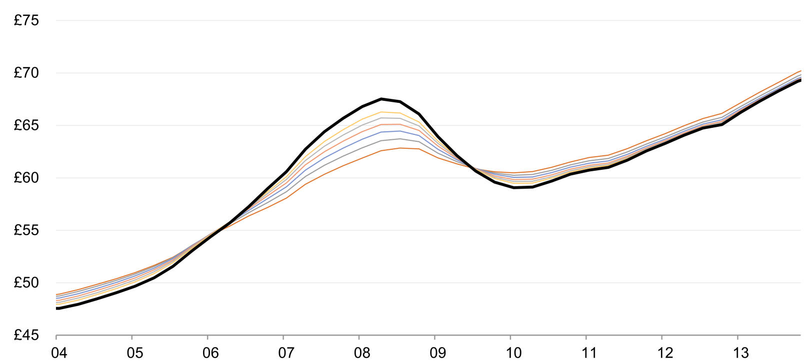


In this manner, every property for which CoStar has at least one rent observation will have a full same-store time series dating back to at least 2000 for office and industrial, and to at least 2006 for retail (the date at which CoStar began covering the retail sector). Markets for which CoStar collected data over a longer period will have earlier start dates.

The resulting aggregate series, however, understate the actual volatility in rents. As noted above, for the purpose of creating the trend lines, rent growth between non-adjacent rent observations is assumed to be constant over time. In fact, rent movements between these points would more likely have followed the market trend, which would not have been constant.

This problem is resolved by recreating new trend lines from the now-complete building level data. Whereas the initial trend line construction assumed a constant rate of growth between non-contiguous rent observations, this second iteration uses the shape of the trend line instead. This step produces somewhat more volatility, but not enough. By repeating the process, however, the results eventually converge to a true same-store view of the market based on the observed changes in real rents. Exhibit 3.8 illustrates how the trend line for London's Mayfair submarket changes with each additional iteration of the process, with the solid black line illustrating the final series.

Exhibit 3.8: Evolution of London Mayfair Trendline



Note: Time period selected to illustrate the impact during the Great Financial Crisis.

Each iteration applies an increasingly rounded trend line, enhancing the shape of the aggregate line and eventually converging to a line that most nearly approximates the movements in real rents. This process can be represented mathematically in the following manner:

First, growth rates are calculated as follows:

$$Growth_{0,t} = \frac{Rent_{B,t}}{Rent_{B,t-1}} - 1 \qquad where \ \ Rent_{B,t} \neq Rent_{B,t-1}$$

where $Growth_{0,t}$ denotes the initial calculation of growth, and $Rent_{B,t}$ denotes the rent in building B at time t. For the purposes of calculating growth, rents that do not change from period t-1 to period t are excluded to increase the volatility of the index.

Using growth rates $Growth_{0..n}$ an initial index $Index_{0,t}$ is created:

$$Index_{0,t} = 100 \prod_{0}^{t} (1 + Growth_{0,t})$$

This index is used to fill in missing points between rent observations for a given building B, where building B has an observed rent at times a and b but not at time c as follows:

$$EstRent_{B,c,1} = Rent_{B,a} \times \frac{Index_{0,c}}{Index_{0,a}} \left(\frac{Rent_{B,c}}{Rent_{B,a}} \times \frac{Index_{B,a}}{Index_{B,b}} \right)^{\frac{c-a}{b-a}}$$

where *$EstRent_{B,c,1}$* is the estimated rent in building *B* at time *c*, and where

$$a < c < b.$$

The process is repeated *n* times, where growth is based on both the actual rents and the estimated rents from the equation above, maintaining the condition that, for the purposes of creating a rent index, flat rents are excluded to maximize the volatility of the series:

$$Growth_{0,t} = \frac{Rent_{B,t,n}}{Rent_{B,t-1,n}} - 1 \quad where \;\; Rent_{B,t,n} \neq Rent_{B,t-1,n}$$

Then the index is recalculated as follows:

$$Index_{n,t} = 100 \prod_{n}^{t} (1 + Growth_{n,t})$$

And individual building rents are also re-estimated:

$$EstRent_{B,c,n} = Rent_{B,a} \times \frac{Index_{n-1,c}}{Index_{n-1,a}} \left(\frac{Rent_{B,c}}{Rent_{B,a}} \times \frac{Index_{B,a}}{Index_{B,b}} \right)^{\frac{c-a}{b-a}}$$

3.1.4 Estimating Rents in Properties Without Rent Information

More than half of all office properties in CoStar's database have at least one rent observation, and a complete same-store rent series is constructed using the methods described above. These tend to be larger, newer and higher-rated spaces than those without any rent observations, and therefore likely to be more expensive. Neglecting to account for sample properties without rents would overstate the true rent trend in a particular market.

To correct this bias, CoStar estimates rents in properties with no actual rent observations by assigning the average current rent by submarket, space type and quality to the subject property. In submarkets with limited data, a larger geography is used. Thereafter, the corresponding submarket trend line is applied to the estimate of current rent to create a full time series. Exhibit 3.9 presents the national series for properties with rents, those without, and the aggregate series.

The exhibit makes clear that properties for which CoStar does not have a rent observation have lower rent levels, such that reporting only the known rents would likely exaggerate the aggregate rent figures. This difference is more pronounced in some markets than in others. For example, office properties rent observations in Chicago are about $5 more expensive than properties that have never reported a rent to CoStar, as seen in Exhibit 3.10.

To summarize, CoStar creates a full time series for every property by filling in gaps between observations using market trends for properties with some actual rent information, and by estimating rent levels and applying the market trend for properties without any real rent information. Aggregating the property-level data produces series that fully control for the changing composition of the marketplace, as well as for the bias toward properties that report rents.

Exhibit 3.9: Aggregate Same-Store Office Rent Series Comparison

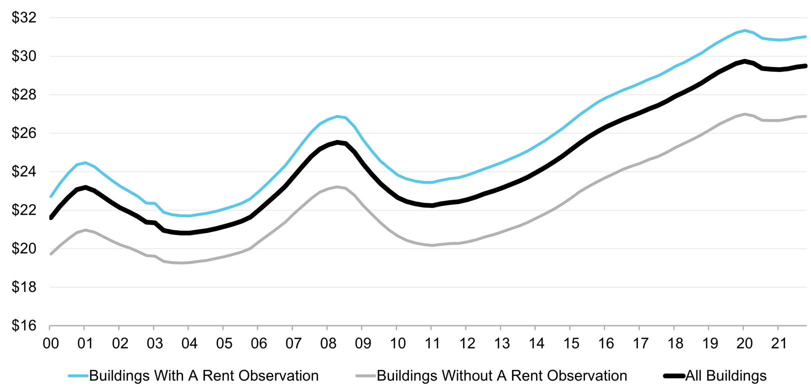
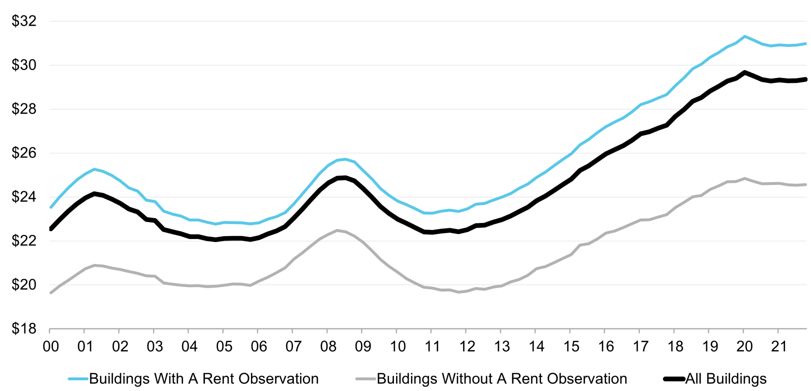


Exhibit 3.10: Aggregate Same-Store Chicago Office Rent Series Comparison



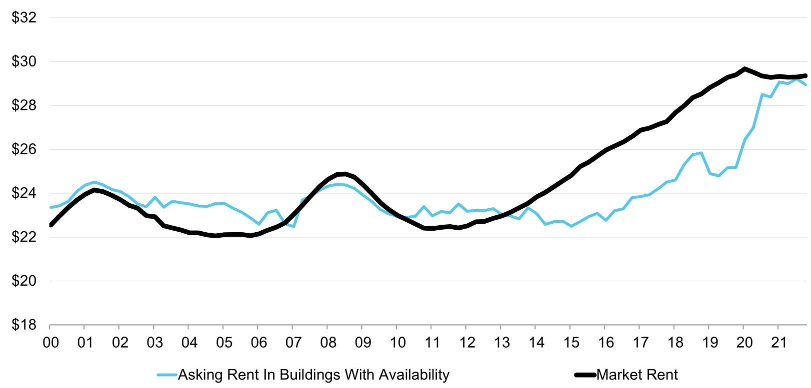
An example of the difference between the available space-weighted series shown in Exhibit 3.10 and the aggregate same-store series in Chicago is shown in Exhibit 3.11. The same-store approach smooths out the quarter-to-quarter volatility and produces a more well-behaved view of rent trends in the submarket.

3.2 Multifamily Rents

CoStar's multifamily rent data differs both in degree and kind from the commercial rent data. Whereas CoStar's dataset contains some 6.6 million asking rent observations for commercial properties, the multifamily rent dataset exceeds 2.6 billion data points, collected via various channels, including:

- CoStar's traditional research teams, who today focus on collecting vacancy and concession data, but historically have collected rent data since the inauguration of CoStar's apartment service in 2012.
- Direct feeds and user entered data from CoStar's marketplaces, including Apartments.com, ApartmentFinder.com, and ForRent.com.

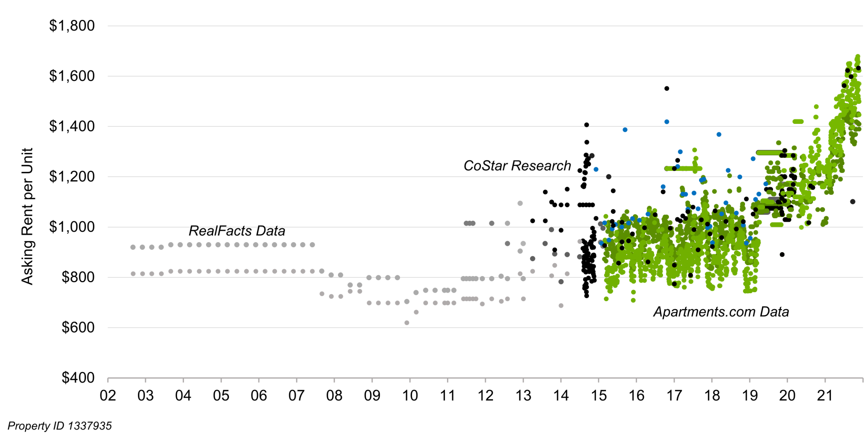
Exhibit 3.11: Same-Store v. Available Space-Weighted Rents in Chicago



- Automated data collection algorithms that collect data from property websites.
- The RealFacts dataset acquired by CoStar of building-level rent and vacancy data dating back to the mid-1990s for more than 12,000 properties. This data is used to estimate a longer time series back to 2000.

Exhibit 3.12 shows the rent data for one-bedroom units within a single property. The different shapes of the data points indicate the various data source, while the colors represent different one-bedroom models, varying by size and layout.

Exhibit 3.12: Multifamily Rent Data



The high frequency, detail, and abundance of CoStar's multifamily rent data provides all the information needed to present the most accurate and timely view of apartment rent trends.

However, the multifamily rent data also pose challenges. As seen in Exhibit 3.12, not all models have rent information at all points in time, as property managers seldom advertise units that are not available. Moreover, CoStar may collect rent observations for the same one-bedroom model at the same time from several different sources that may differ, with no guidance as to which is more accurate. Finally, there may be certain units within a community for which CoStar may have never collected rent data, such as a handful of four-bedroom units in a property that have never become available.

3.2.1 Same-Store Multifamily Rents

To solve these problems, CoStar creates a full time series back to 2000 for every unit model in any property for which a rent observation has been collected. Creating full time series for every property ensures that rent trends only reflect market-driven movements, rather than changes in the composition of properties and units available for rent.

Creating the multifamily same-store rent series involves three steps. First, the set of rents to use is selected from among the several sources available. Second, rents missing for time periods between actual observations are estimated, as are rent data points before the first known observation and after the most recent observation collected. Finally, rents for unit models for which CoStar has not collected any rent information are estimated.

For the headline asking rent series, preference is given to rent data supplied via Apartments.com direct feeds. These data match the rents advertised on CoStar's marketplaces, are updated frequently (typically daily), and comprise the majority of CoStar's rent data (numbering 2.6 billion observations as of June 2022). When data providers report a range of rents, the minimum rent is used. This is far more stable than the maximum rent, which can vary widely depending on the specific terms of the lease. For example, short-term furnished units can have very high rents that do not reflect the broad market. In general, the minimum rent reflects the typical 12-month lease. Another option, using the midpoint of the minimum and maximum, would still allow for half of the artificial volatility inherent in the maximum values to affect the series.

About 45,000 properties provide data via automated feeds. For the remaining 179,000 or so properties with rent data, preference is given first to data collected by CoStar researchers or analysts, then to user-entered rents on CoStar's marketplaces, and finally to rents collected via automated data collection. Should a model begin to receive data of a higher priority, the rent level is reset. Properties that had been on a feed will revert to lower-priority data sources if a feed update has not been received for at least three months. In these cases, the property is assumed to no longer be on a feed and the historical rent for all time is reset using the old feed history to inform the trend.

Missing rents between non-adjacent observations are estimated by linear interpolation—simply drawing a straight line between the two observations. Out-of-sample testing showed simple interpolation to be as good as or better than more sophisticated approaches, and because most gaps in the multifamily data are of short duration, the straight-line interpolation has little effect on broad trends.

Where data are missing prior to the first observation or after the most recent observation, it is assumed that rents would have followed the same trend as rents for other models in the same property. In the absence of other property-level data, rents are assumed to have followed the same trend as the submarket and quality slice.

In this manner, every property which has any rent information will have a full rent series. However, a small percentage of models in these properties do not have any rent data. Typically, these are larger three- or four-bedroom units that have never been available for rent.

Given the breadth and depth of the CoStar database, these rents can be estimated with a high degree of accuracy given the observed relationships between per-square-foot rents for various configurations. For example, the data may show that three-bedroom units rent for 25% less than one-bedroom units on a per square foot basis in a particular market or submarket. If the rent for a one-bedroom is observed, then it can be assumed that the rent of a three-bedroom unit in the same property will be 25% lower. Exhibit 3.13 shows the relationship between the per square foot rents of the units of such one configuration type at the national level.

Exhibit 3.13: National Rent Curve Matrix

Note: Includes top 12 bedroom-bath mix model types by unit-count in the U.S.

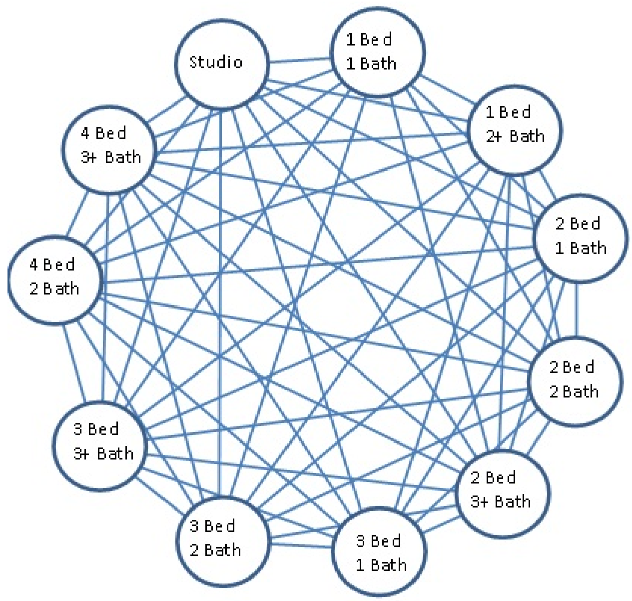
The underlying assumption of this approach is that rents in different units in the same building will move parallel to each other, all else equal. This is equivalent to saying that the ratio of rents between unit types will hold constant. If true, the rents of a given configuration for which CoStar does not have data can be estimated using the known rents for other configurations in the same building, submarket, or market. For example, as shown in Exhibit 3.13, studio apartments are about 20% more expensive per square foot than one-bedroom apartments on average for 3 Star-rated buildings across the nation. Therefore, when provided with rents for a one-bedroom unit in a given building, it could be assumed that the rents of studios within that same building are 20% higher.

In reality, the situation is more complex. The relationship between various configurations could be significantly different among metros, or even between different submarkets in the same metro. A building might have five, ten, or even more different layouts, and each layout might include a variety of rents related to the specific characteristics of each unit.

Moreover, some combinations occur more often than others, or not at all. For example, the ratio of studio to one-bedroom rents and the ratio of one-bedroom to two-bedroom rents might be observed, but the ratio of studios to two-bedroom rents might not because those data points do not appear in the database at the same time. Exhibit 3.14 presents a stylized view of all possible combinations.

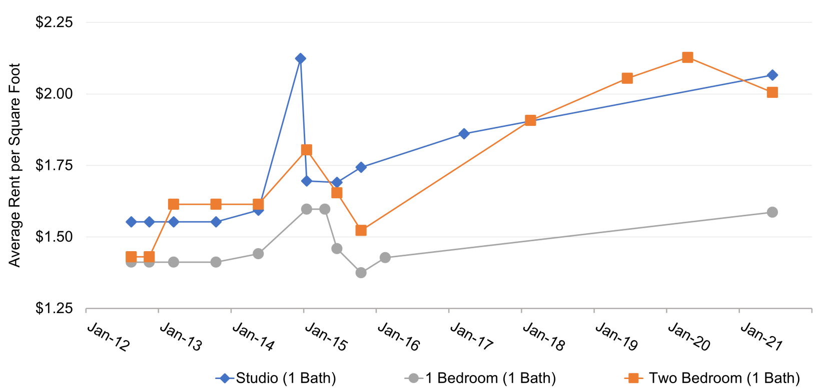
Furthermore, there is no guarantee that rents of various combinations are transitive. For example, in any building, the data may show that studios are 20% more expensive than one-bedroom units and that one-bedroom units are 5% more expensive than two-bedroom units, and at the same time show that studios are 40% more expensive than two-bedroom units. This may occur in the

Exhibit 3.14: Diagram of Possible Combinations of Configurations



data because the observations are from different time periods and across thousands of buildings. Exhibit 3.15 illustrates an example of this situation using an actual property in the dataset.

Exhibit 3.15: Rent Average in a Building with Changing Unit Type History



Note: PID 5728204. Rent observations shown with markers, lines are shown to demonstrate change between observations.

To resolve these complexities, the ratios of the rent observations in different configurations of each building in a geography are first calculated. Thereafter, the ratios from all buildings are combined into a single set of ratios against an average configuration, which is referenced as μ. Exhibit 3.16 illustrates the interactions between μ and various configurations.

Thus, via μ, the rent of any unit type can be related to any other unit type, and rents can be estimated for configurations with no rent observation in a building, as shown in Exhibit 3.17. In this example, the building has two-bedroom, three-bathroom units for which no rent observation has ever been collected. Using the relationships observed between two-bedroom, three-bathroom units and all other units across similar buildings, μ can be used to estimate any missing rents.

Exhibit 3.16: Illustration of Relationships Between Unit Types and μ

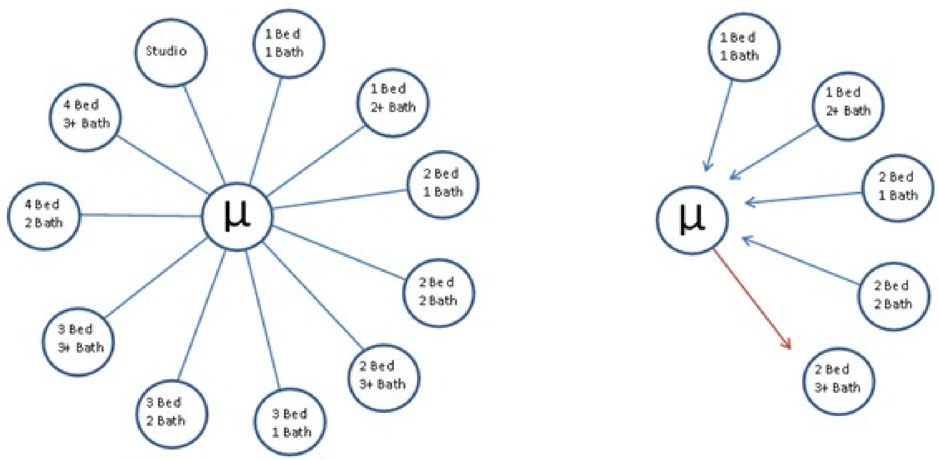
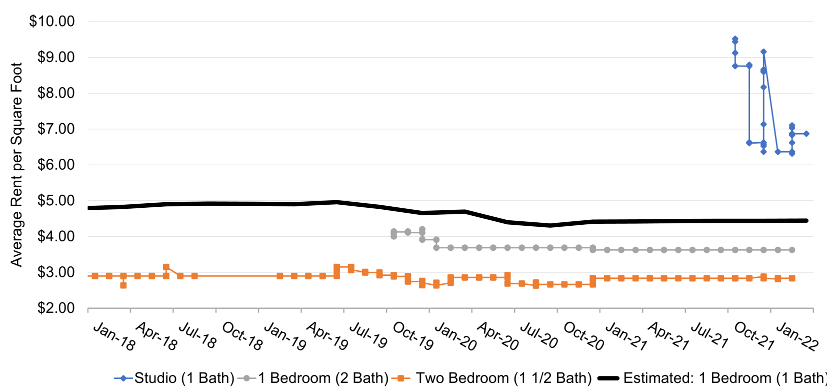


Exhibit 3.17: Rent Estimation Based on Other Unit Types



Note: PID 8020401

This method also makes it possible to compare rents for buildings with different unit mixes. For example, consider building A, which consists primarily of two-bedroom units with some three-bedroom units, and building B, primarily three-bedroom units with some two-bedroom units. Based on simple averages, building B would appear to have higher per-unit rents, while building A would have higher per-square-foot rents. But the differences are due to the mix of unit types rather than actual market forces. Here, μ can be used to estimate an equivalent rent, permitting direct comparisons between buildings (or markets) with systematically different unit mixes.

This innovative methodology, in the context of an online search tool, earned CoStar U.S. Patent No. 10789278, Database Search Engine Optimization (Filed 2017, Granted 2020).

3.2.2 Concessions and Effective Rents

The discussion above has considered only asking rents, but these do not necessarily reflect the actual rent paid by a new tenant. Properties frequently offer incentives and concessions to attract new renters, particularly in properties that are in initial lease-up. CoStar's multifamily research team focuses on collecting detailed information around various concessions offered by landlords, such as waived fees, gift cards, cash incentives, and months of free rent.

CoStar uses this rich dataset, which includes more than 20 million observations at the time of writing, to estimate concession rates for all properties over time. CoStar's definition of a concession includes free or reduced rent, as well as cash payouts and gift cards, but excludes waived fees, as the data suggest that many fees primarily exist for property managers to use in negotiations—offering to "waive" the fee in lieu of free rent or outright cash incentives. In general, fees represent a very small fraction of typical rent.

An estimate of concessions is applied to properties for which no concession data exists based on the age of the property and its vacancy rate. Newer and higher-vacancy properties will have higher estimated concessions, reflecting the tendency of newer properties, particularly those in initial lease-up, to offer concessions. The vast majority of properties, however, do not offer concessions. As a result, in the aggregate the effective rent series is very close to the asking rent series.

3.3 Hotel Room Rates and ADR

Whereas CoStar primarily tracks asking rents for commercial and multifamily properties, STR collects actual realized revenue information for hotel properties. The hotel sector uses the term "room rate" to define the asking price for a room, and "average daily rate" (ADR) as the measure of actual pricing. ADR is defined as total room revenue, based on the Uniform System of Accounts (12th edition), divided by total demand (or room nights sold). This equation is expressed mathematically as:

$$AverageDailyRate = \frac{Revenue}{Demand}$$

where *Revenue* is the total revenue generated from guestroom rentals or sales, and *Demand* is the number of rooms sold in a specific time period (excluding complimentary rooms).

As with all hotel data, CoStar does not reveal data for any individual hotel, and all aggregations of ADR data must meet STR's sufficiency criteria (outlined in section 1.4).

4 Developing Performance Metrics

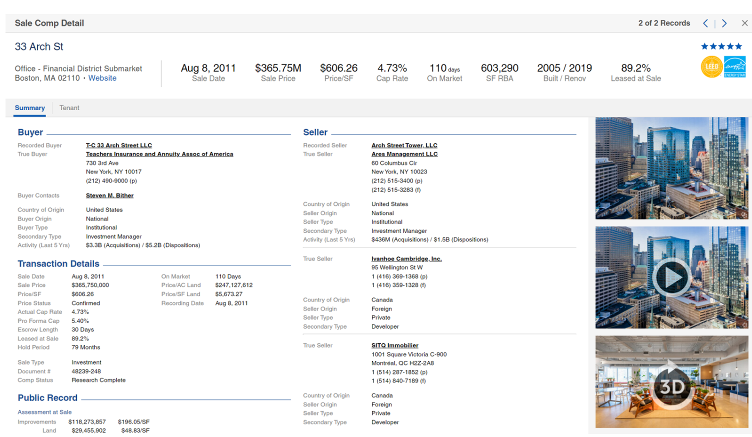
CoStar has amassed a database of more than 4.8 million commercial real estate sales transactions totaling more than $13 trillion and covering the entire universe from small offices selling for $10,000 to the largest portfolio deals. This vast collection of data, coupled with building-level information, offers unprecedented insight into the performance of commercial real estate investments.

What follows is a detailed description of CoStar's approach to estimate current and historical values and cap rates for the more than 7 million properties in the database, which can be aggregated to arrive at time series for a market, a submarket, the nation overall, or for any selected set of properties.

4.1 The CoStar Transaction Data

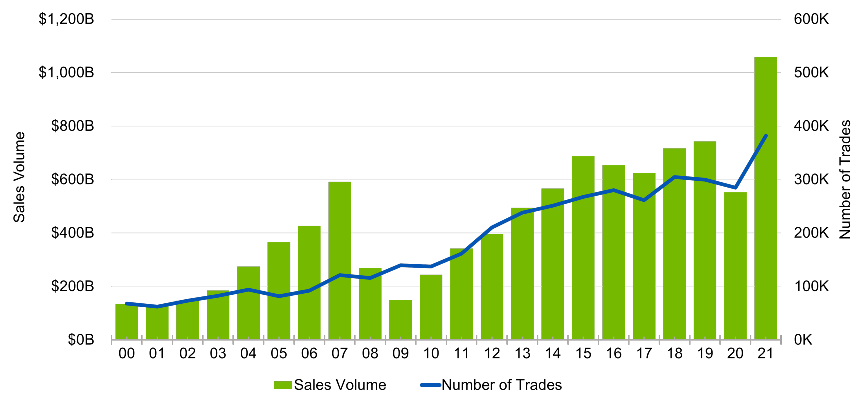
CoStar's comps team comprises the firm's most talented and experienced researchers, who are committed to collecting the highest quality information about every commercial real estate transaction that occurs, including the terms of each transaction, the reported and true buyer and seller, relevant sale conditions, and financing arrangements. Exhibit 4.1 presents the sales transaction information available on the CoStar platform for 33 Arch Street, CoStar's Boston office location.

Exhibit 4.1: CoStar Transaction Data for 33 Arch Street, Boston



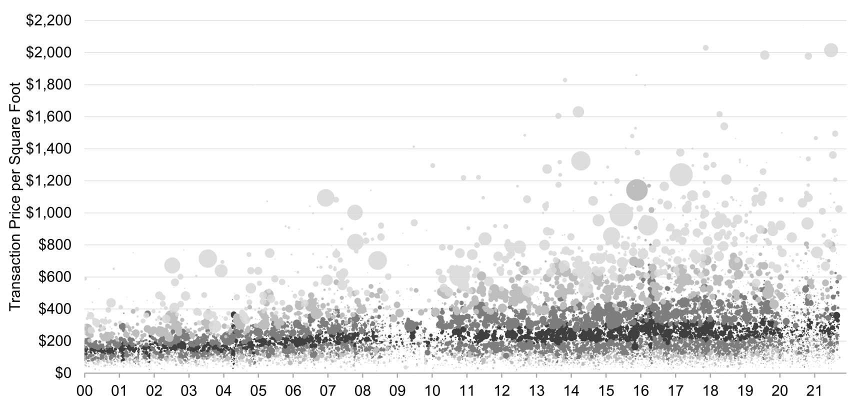
CoStar's comps researchers recorded more than 350,000 trades totaling more than $1 trillion in 2021. Exhibit 4.2 presents CoStar's comp data by year.

Exhibit 4.2: USD-Denominated Total Deal Volume, By Year



In addition to capturing a census of large trades, roughly 90% of the trades in CoStar's dataset are for less than $5 million. Exhibit 4.3 illustrates the scale of the CoStar data. Each dot represents a non-portfolio trade for an office asset in the United States of at least $1 million. The size of the dot represents the transaction value. Dots are shaded by their distance from the 180-day trailing average to highlight a general trend.

Exhibit 4.3: Office Trades in the United States



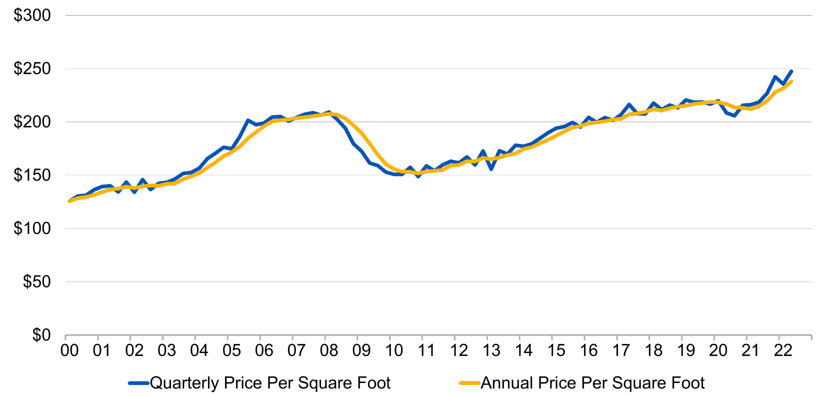
Prices are shaded by distance from trailing average to identify trend. Includes non-portfolio sales of offices, priced $1 million or above.

This vast dataset offers unmatched analytic potential for estimating commercial real estate pricing trends. Even a simple average of transaction prices offers a useful national series, as seen in Exhibit 4.4.

This simple approach works well enough in depicting broad, long-term trends at high levels of aggregation. However, even the national series exhibits more volatility at higher frequencies, as in the quarterly series shown in blue. These movements result from changes in the composition of properties and markets that trade from period to period.

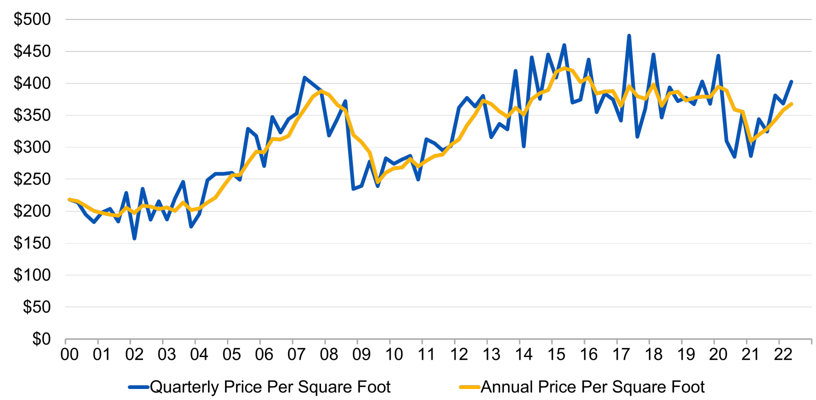
At lower levels of aggregation, these problems can make the series unusable for determining market trends. For example, Exhibit 4.5 shows the simple average transaction price for the heavily traded New York office market. While the annual series (shown in yellow) shows a well-behaved long-term trend, the quarterly series exhibits extreme period-to-period volatility.

Exhibit 4.4: Average Annual Office Price per Square Foot



Excludes portfolio sales, offices smaller than 1,000 SF, sales below $500,000, below $5 per SF, or more than $5,000 per SF.

Exhibit 4.5: Average Annual Office Price per Square Foot, New York

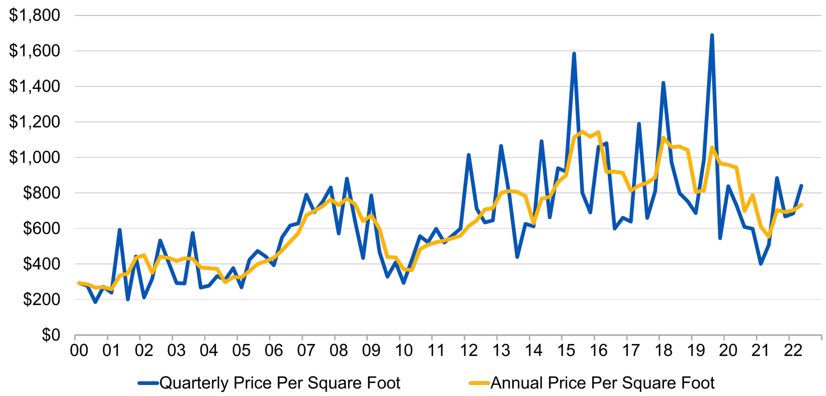


Excludes portfolio sales, offices smaller than 1,000 SF, sales below $500,000, below $5 per SF, or more than $5,000 per SF.

The simple averages shown in the exhibits above count each transaction the same regardless of the size of the property or of the deal. Value-weighting, an alternative method of averaging, weighs each transaction by the size of the deal or the size of the property. This method usually results in higher average prices, and also adds volatility since large trades outweigh the many smaller trades, rendering them irrelevant. Furthermore, periods in which "blockbuster" trades occur show much higher average prices than periods without a "blockbuster" trade. Exhibit 4.6 shows the value-weighted average transaction price for the New York office market. In this value-weighted series, even the annual trend becomes more volatile, while the spikes in the quarterly series illustrate the "blockbuster" trade problem.

Repeat-sale models offer a solution to the problem of the changing composition of the transactions over time. Repeat-sale models only include properties with multiple trades, thereby ascribing price movements to market forces rather than to changes in the sample. However, restricting the set of deals to include only repeat trade pairs reduces the number of eligible trade observations to about 10-20% of all transactions, and requires a minimum number of trades in each period to produce statistically meaningful price estimates. As a result, repeat-sale models only work at a national level and for large, heavily-traded markets.

Exhibit 4.6: Value-Weighted Average Annual Office Price per Square Foot, New York

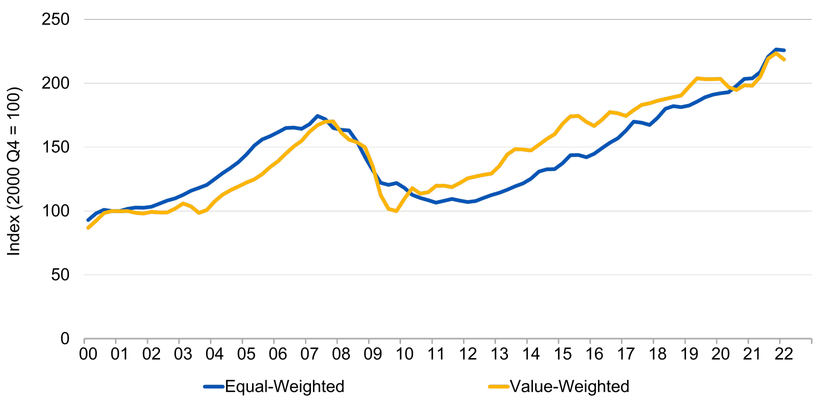


Excludes portfolio sales, offices smaller than 1,000 SF, sales below $500,000, below $5 per SF, or more than $5,000 per SF.

Repeat-sale models also require trades before and after each period to produce statistically valid results. The model will restate, often significantly, the current period (and the recent past) as researchers collect additional datapoints. Repeat-trades may also exhibit a bias, as data shows that properties that re-trade almost always do so at a profit. Owners may only sell the properties on which they can realize the highest returns and may choose to hold properties rather than incur a loss by selling. This bias affects the entire sample of transactions but may be more pronounced for repeat-trades.

These concerns notwithstanding, repeat-trade models offer a valid alternative to simple or weighted-average prices. In 2012, CoStar released the CoStar Commercial Repeat-Sales Indices (CCRSI), the first-large scale repeat-sales series for commercial real estate. The firm continues to report results each month, found at http://www.costargroup.com/costar-news/ccrsi. Exhibit 4.7 presents the national equal- and value-weighted composite repeat-sales indices through June 2022.

Exhibit 4.7: CoStar Office Repeat-Sales Indices



Only Includes offices that have sold multiple times.

Nevertheless, the vast CoStar transaction database can be used to produce reasonable and empirically testable estimates of prices and cap rates for every property over time. In doing so, the changing composition problem can be controlled by aggregating all the properties in a particular geography, rather than only those that traded. Moreover, including peer property trades in these estimates will capture high-frequency movements in the subject property's valuation. For example, if a property across the street trades at a higher price, the price of the subject property will surely rise.

Property-level price and cap rates series complete the set of variables needed to produce forecasts at the property level, as discussed in Chapter 5.

4.2 Estimating Property Values

Real estate assets trade infrequently, and the unique characteristics of any particular property make applying market average or comp trades problematic and estimating property values challenging.

The appraisal industry exists to answer this question, and to do so relies on a synthesis of three different approaches. The first approach is comps-based, where appraisers review and adjust nearby and recent comparable trades to arrive at the likely value of a subject property. A second approach uses a discounted cash flow (or DCF) analysis, where appraisers attempt to forecast future income and eventual sale proceeds discounted to present day. A third approach employs a replacement cost analysis, where appraisers attempt to estimate the cost of building the asset in question.

The latter two methods present unique limitations in terms of data availability and assumptions. A comps-based approach to value properties, on the other hand, maximizes the value of CoStar's unmatched comps dataset. Moreover, a comps-based approach arguably produces the most objective outcome, relying on market activity rather than forecasts or assumptions about costs of construction or capital.

For example, the value of a property on the day the property transacts is equal to the transaction price. Moving away from that transaction date, the value of the property becomes increasingly less certain and will vary based on the prices at which comparable properties trade, the local rent trends, and broad capital market conditions.

CoStar's approach to valuing properties that have traded differs from valuing those that have not, and large properties are handled differently than smaller properties. Testing results have shown that the comps-based approach performs much worse for smaller properties and that less sophisticated and more efficient results perform equally well. In this regard, small properties are defined as those that fall below the square footage cut-off at which no more than 35% of a ranked order of total RBA for the property type could be classified as "small." Exhibit 4.8 shows the specific cut-offs for each property type.

The subsections below describe how comp properties are identified, how comps are used to value large properties that have traded, how large properties that have not traded are valued, and how smaller properties are handled.

Exhibit 4.8: Cut-Offs For Large and Small Properties

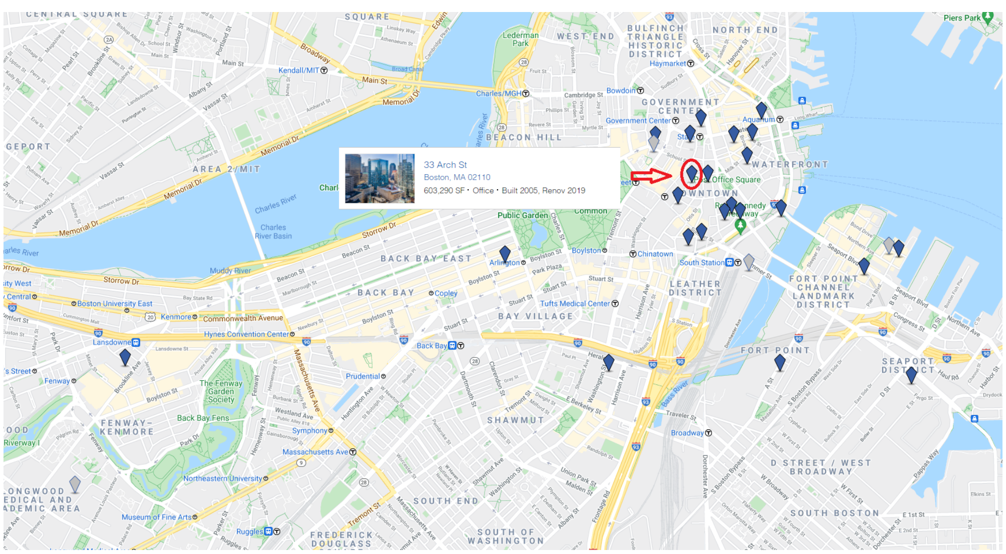
Property Type	Description
Office	37,000 SF
Industrial	50,000 SF
Multifamily	37,000 SF
Retail	12,000 SF

4.2.1 Identifying Comp Properties

To implement a pricing model based on comps, comp properties must first be identified. As an initial step, all properties within ten miles of the subject property with a market-rate trade (thus excluding all non-arms' length trades as well as condo, partial interest, portfolio, ground lease and other non-standard trades) are identified. Then a set of weights, each between 0 and 1, is calculated for each of the following: the distance to the subject property and the density of properties around it, the difference in sizes, the difference in the lot sizes, and the difference in the age of the comp property relative to the subject property. The product of these weights is used to judge the relevance of a particular property in valuing the subject property.

On average, each traded office property has about 50 comp properties. As expected, properties in large markets have many more comps, while more remote properties may have only a few comps, or even none at all. Exhibit 4.9 presents the comps for 33 Arch Street in Boston, CoStar's Boston office property.

Exhibit 4.9: Sale Comps for 33 Arch Street, Boston



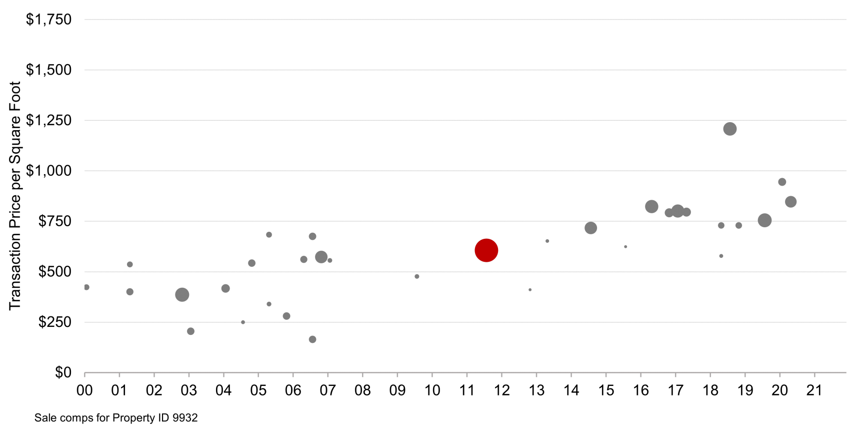
Properties in adjacent counties are not eligible to be used as sales comps in Boston, New York, Washington, and San Francisco. This prohibition ensures that, for example, trades in Oakland are not used as comps for San Francisco properties, or Queens for Manhattan, or Cambridge for Boston (and vice versa).

4.2.2 Estimating Values in Large Traded Properties

As noted above, the value of a property on the day that it trades is equal to the transaction price. Moving away from that date, estimated valuations will change based on three factors: (i) actual sales of peer properties (or the subject property), (ii) estimated trends in NOI, and (iii) broad national cap rate trends.

Sales of peer properties will affect the price estimate as follows. At each point in time after the subject property trades, the price estimate will equal the weighted average of the subject property's initial trade and the sale comps, where the weight of each comp (including the subject property) diminishes over time using an exponential decay function. Exhibit 4.10 displays the estimated value of 33 Arch Street based solely on comp trades. The size of each dot indicates the weight of that comp, with higher weights indicating a comp more similar in terms of proximity, size, lot size, and age.

Exhibit 4.10: Sale Comps for 33 Arch Street, Boston



The large red dot denotes the subject property trade. Assigning a weight to this trade poses a problem. By default, the weight on the subject property's trade would equal 1. However, in practice, a weight of 1 may not properly reflect the value of the information of the initial trade. A weight that is too low will decline too quickly over time or may be overwhelmed by comp trades in heavily-traded markets, such that the subject property trade ceases to matter almost immediately. In general, it would be preferable to assign the subject property a higher weight to ensure that its future estimated values do not deviate too far from the initial value.

To impose some permanence of the subject property's first trade, the weight of the subject property trade is set equal to a multiple of the sum of the all the time-adjusted weights on comp trades that have preceded the trade. This construct has the effect of giving the subject property a weight more or less proportional to the amount of trading activity in the market and ensures that comp trades do not overwhelm the initial value. Moreover, a large weight on the subject property helps maintain the premium or discount a particular property may have to its comps. For example, a property that trades at 20% above a large set of comps would be expected to maintain a 20% premium to the market going forward.

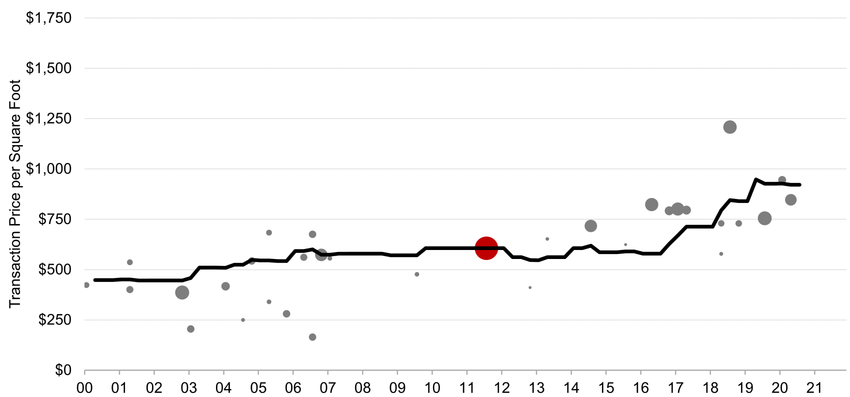
The function thus far for valuing properties based on comps is:

$$V_{p_t} = \frac{\Sigma_c V_c * W_{P,c} * e^{-(t-t_c)}}{\Sigma_c W_{P,c} * e^{-(t-t_c)}}$$

where V_{P_t} is the value of a given property p at time t, V_c is the value of comp c, $W_{P,c}$ is the time-invariant weight of comp c on property p, and $e^{-(t-t_c}$ is the time weight of comp c based on the difference between time t and the date of the trade of comp c at time t_c.

In simpler terms, the value of a property at a particular point in time equals the weighted average of all the comps since and including the subject property trade, where the weight of each trade depends on proximity, similarity in size and lot size, age, and time. Exhibit 4.11 adds a line as the estimate of pricing over time for the same office asset based solely on its comps.

Exhibit 4.11: Price Estimates for 33 Arch Street Using Comps



Sale comps for Property ID 9932

Adjustments to Comp Prices

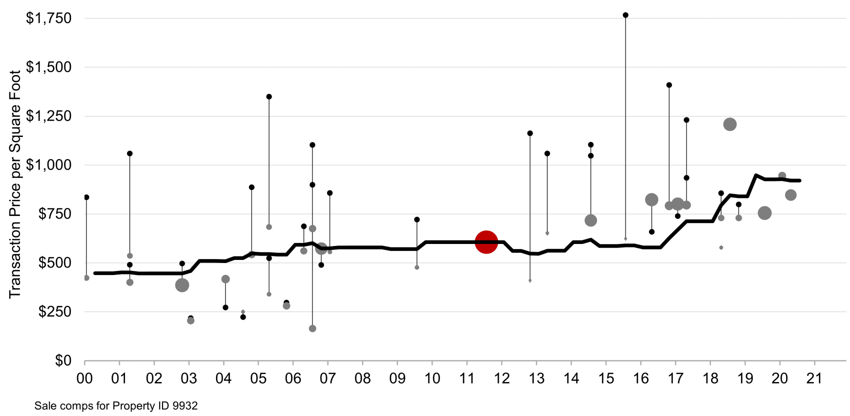
The weight assigned to each peer comp property reflects the relevance that the peer property value has in determining the subject property's value. However, the prices of peer properties may be misleading for estimating the valuation of the subject property. For example, the subject property may be far superior in all ways to the set of its peers, but the comp-based valuation will fall below its market value.

One approach to adjusting peer prices uses repeat trades of the peer properties. For example, consider a subject property that trades for $100 per square foot while an identified peer property trades for $200 per square foot. The subject property traded for half the price of the peer property. Five years later, the peer property trades again, this time for $400 per square foot. Using the ratio established by the initial trade, it can be assumed that the subject property has a value of $200 per square foot, half the value of the peer property in its more recent trade.

Repeat trades, however, happen infrequently. An alternate approach is to observe the price ratios between sets of traded properties across time and across properties to estimate ratios between any pair of properties, and assume that transaction values are transitive, i.e., that if the value of building A is twice the value of building B, and the value of building B is 1.5 times the value of building C, then the value of building A is three times the value of building C.

By this process, an adjustment factor is established for more than a third of all comps. The use of these adjustment factors significantly reduces the error around CoStar's estimates of the price per square foot in large, traded properties. Exhibit 4.12 presents the estimates for 33 Arch Street, incorporating the price adjustments. The darker dots indicate the adjusted prices for each comp.

Exhibit 4.12: Price Estimates for 33 Arch Street Using Adjusted Comps



The valuation function becomes:

$$V_{p_t} = \frac{\Sigma_c V_c * W_{P,c} * e^{-(t-t_c)} * ADJ_c}{\Sigma_c W_{P,c} * e^{-(t-t_c)}}$$

where ADJ_c is the adjustment factor for the comp in question.

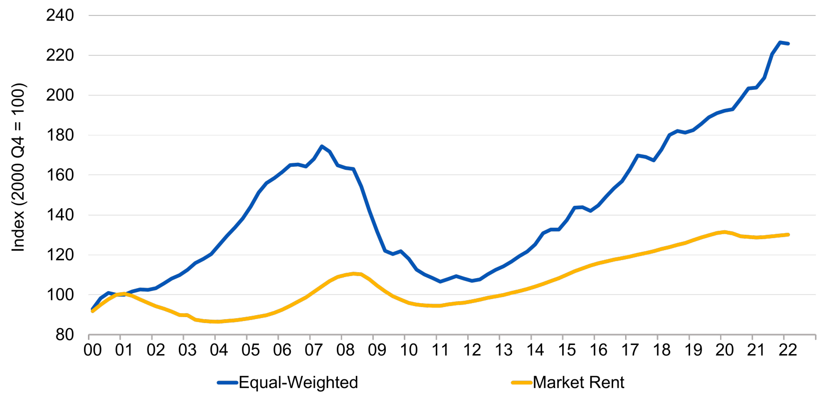
While the comps-based estimation includes the effect of new comps, it also includes all prior comps, including the subject property's initial trade, at their original prices. Rather than maintain these prices in nominal terms in the calculation moving forward, they are escalated (or deflated) using submarket rent and occupancy trends and broad national cap rate trends.

The Effect of Rent Movements on Price Estimates

All else equal, a property's price is assumed to change with trends in rents (using the same-store rent series) and occupancy at a submarket level. At a national level, a degree of correlation between the same-store rent series and the national repeat-sale series is observed, as shown in Exhibit 4.13.

At the property level, same-store rents can exhibit erratic changes or inertia, either of which could produce value trends out of step with the overall market, hence submarket rent trends are used. These create differentiation within a market while producing broadly consistent series for nearby properties.

Exhibit 4.13: Correlation Between Rents and Values



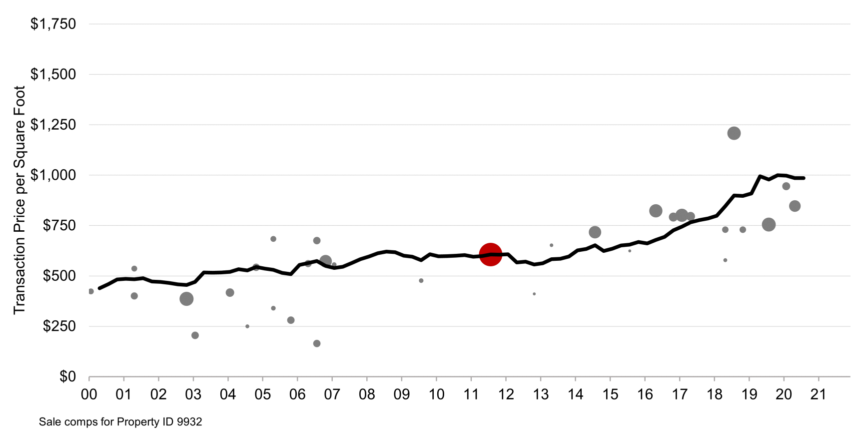
With the inclusion of the rent and occupancy data, the valuation function becomes:

$$V_{p_t} = \frac{\Sigma_c V_c * W_{P,c} * e^{-(t-t_c)} * ADJ_c * \Delta\,(RentOcc)_{ct}}{\Sigma_c W_{P,c} * e^{-(t-t_c)}}$$

where $\Delta (RentOcc)_{ct}$ is the percent change in rent times occupancy in comp c between time t_c (the date of the comp trade) to time t (the valuation date).

Testing results show that including submarket rent and occupancy trends decrease the error of property-level price estimates, as shown by the example of 33 Arch Street presented in Exhibit 4.14.

Exhibit 4.14: Price Estimates for 33 Arch Street Using Comps and Rent Trends

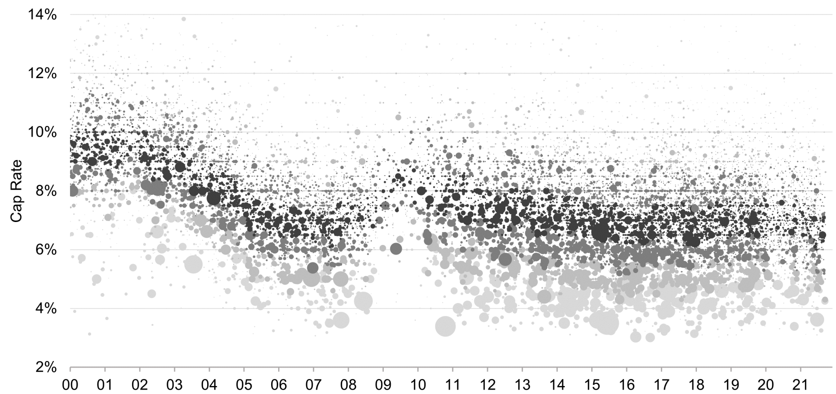


The Effect of National Cap Rate Trends on Price Estimates

Broad national cap rate trends serve as a proxy for the capital markets environment and overall pricing trends. Whereas rent and occupancy capture local trends in performance, the national cap rate trend ensures that, all else equal, property prices around the country will move together as they are all subject to the macro forces that allocate capital.

CoStar's database contains more than 640,000 cap rates. Not every transaction reports a cap rate, and cap rate definitions in the United States are not necessarily consistent—in some cases the seller reports the cap rate, in others the buyer. The reported cap rate may be based on stabilized, in-place NOI, or it may be based on pro forma cash flow expectations. Despite these inconsistencies, the breadth of CoStar's cap rate data allows the estimation of broad trends in cap rates. Exhibit 4.15 graphically depicts CoStar's cap rate data for 3 Star and higher quality office properties selling for at least $5 million. The size of each dot represents the size of the trade, and the shading indicates the trend. Cap rates nearer to the average show as black, and the lightest shading indicates outliers.

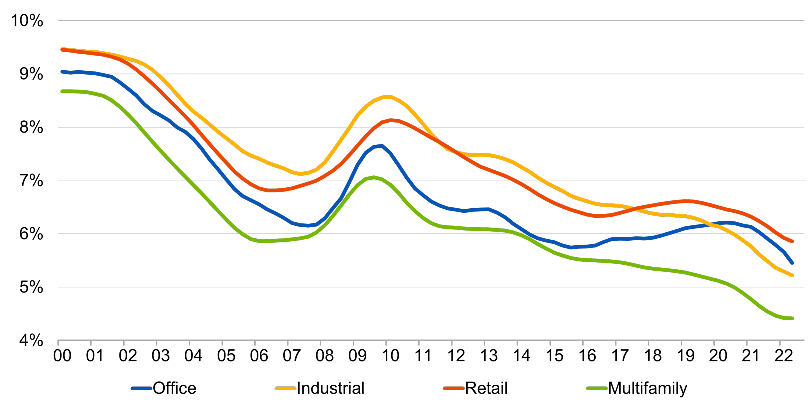
Exhibit 4.15: National Office Cap Rates



Prices are shaded by distance from trailing average to identify trend. Includes non-portfolio sales of offices, priced $1 million or above.

From this discrete transaction cap rate data, value-weighted average national series are derived to serve as the broad trend lines. These trends represent a center-smoothed value-weighted monthly average of the transaction cap rates. The center smoothing will result in some minor changes to history in the near term, but the extent of restatement has been minimized by assuming that cap rates will remain flat into the future. Exhibit 4.16 presents the resulting national cap rate trends for the four major property types.

Exhibit 4.16: National Cap Rate Trend Lines by Property Type



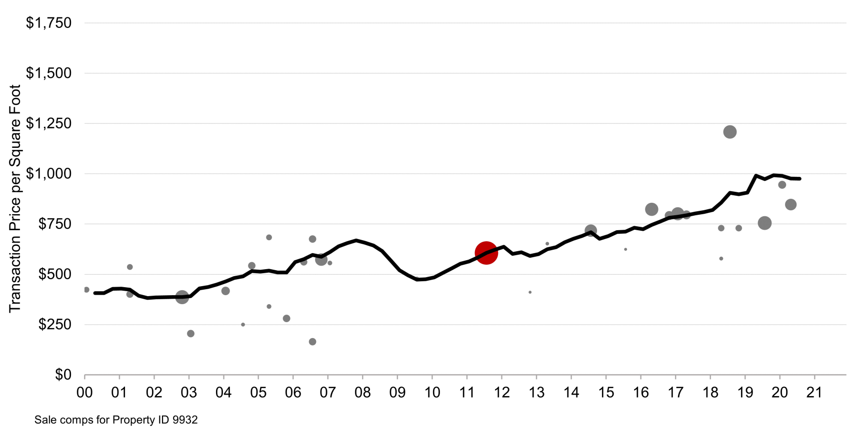
Prices are assumed to follow this national trend in cap rates, after adjusting the level of the national series to match the average cap rate level for each cluster. For example, the national series will be shifted lower in low cap rate markets, magnifying the percentage change in cap rates, while high cap rate markets will have less volatility due to cap rate movements. The final valuation function, with the inclusion of cap rate trends, is:

$$V_{p_t} = \frac{\Sigma_c V_c * W_{P,c} * e^{-(t-t_c)} * ADJ_c * \Delta\left(RentOcc\right)_{ct} * \frac{1}{\Delta(NatCap)_{ct}}}{\Sigma_c W_{P,c} * e^{-(t-t_c)}}$$

where $\Delta(NatCap)_{ct}$ is the percent change in the national cap rate series between time t_c (the date of the comp trade) to time t (the valuation date), where the national cap rate is shifted up or down by the difference between the typical cap rate in the cluster and the national average. This adjustment has the effect of increasing the volatility of price movements in low cap rate markets and vice versa.

Testing results show that including national cap rate trends decrease the error of property-level price estimates, as shown by the example of 33 Arch Street presented in Exhibit 4.17.

Exhibit 4.17: Price Estimates for 33 Arch Street Using Comps, Rents, and National Cap Rate Trends



The inclusion of the cap rate trends results in the expected decrease in values beginning in 2008, an effect not otherwise realized given the scarcity of comp rates and the slower reaction from rent trends.

4.2.3 Estimating Values in Large Untraded Properties

Approximately 20 percent of large properties have a recorded market-rate sale price from which a full time series can be extrapolated using the methodology described in the preceding section. For the remaining 80 percent, a similar approach can be used, with some adjustments to account for differences between the subject property and traded peer properties.

The set of peer properties once again depends on proximity, and similarities in age, size, and rent. These same differences in size, age, and rent are used to estimate an adjusted value for the peer properties, an approach commonly used by appraisers to adjust comp properties.

CoStar's adjustments are based on results of regressions by property type that seek to explain the differences in price based on differences in rent, building size, lot size, and age. The model specification is:

$$log\left(pricediff\right) = fn\left(log\left(sizediff\right), log\left(lotdiff\right), log\left(agediff\right), log\left(rentdiff\right)\right)$$

where *log* stands for the natural log and *pricediff* is the difference in price per square-foot (or price of units for multifamily assets) between two peer properties which traded within 12 months of each other in arms-length, market-rate trades. The independent variables are:

- *sizediff*, the difference in the physical size in square footage between the two assets.
- *lotdiff*, the difference in the lot size in square footage between the two assets.
- *agediff*, the difference in age between the two assets.
- *rentdiff*, the difference in rent between the two assets.

The specific equations and coefficients are presented for reference in Exhibit 4.18.

Exhibit 4.18: Peer Price Adjustment Regressions

Property Type	Constant	*rentdiff*	*agediff*	*rbadiff*	*lotdiff*	*storiesdiff*	*unitsdiff*
Industrial	-0.1300	0.3230	-0.4300	-0.1870	0.1460	NA	NA
Office	-0.0970	1.0020	-0.2180	NA	NA	NA	NA
Retail	-0.2150	0.6190	-0.4430	-0.3240	0.1240	NA	NA
Multifamily	-0.0021	0.8540	-0.3120	NA	0.0944	0.1450	-0.1370

These coefficients are used to systematically adjust the values of peer properties to make the peer valuations more applicable to a particular untraded asset. For example, the Inter-American Development Bank Building at 1300 New York Avenue NW in Washington, D.C. has many nearby peer properties, all built at different times and of varying sizes and rents. Exhibit 4.19 presents information for a set of nearby peer properties, and shows two measures of value for each peer asset—the unadjusted estimated value in the current period (second quarter at the time of writing) and the price adjusted by applying the coefficients above to the differences in size, lot size, age, and rent between the subject property and each peer property. For example, peer property 129241 (1001 Pennsylvania Avenue) is slightly newer (built in 1986) but has slightly lower rents. Applying the coefficients from above to these differences results in a $73 adjustment to the peer price for the purposes of estimating a value for the subject property.

The adjusted peer values are weighted by how similar each peer asset is to the subject property (measured by the size of the adjustment made), and the average of the weighted adjusted prices is used to derive an estimate of the subject property value. In this case, the subject asset is generally newer and charges higher rents than its peers, and as a result their values are revised higher.

In addition to the peer property prices, the subject property value estimate includes a geographic price average with a low weight. In heavily traded markets, this geographic average has no real impact on the estimate price, but in lightly traded markets, the price estimates depend heavily on the geographic average, proportional to the number of peer properties for which a price can be estimated based on an actual trade.

Exhibit 4.19: Adjusted and Unadjusted Peer Prices for 1300 New York Avenue, Washington

Peer ID	Distance	Rent Diff.	Age Diff.	Rent Adj. ($)	Age Adj. ($)	Constant Adj. ($)	Raw Peer Price ($)	Adj. Peer Price ($)
129241	0.34	-2.41	2.00	-21	-5	-50	540	467
129861	0.24	-12.91	11.00	-106	-33	-55	596	420
129855	0.56	0.21	7.00	2	-16	-43	463	408
753262	1.06	5.00	21.00	38	-49	-38	413	361
130089	1.36	8.22	7.00	99	-21	-57	617	628
130648	0.10	-2.62	19.00	-25	-62	-55	592	461
129386	1.17	12.79	-10.00	116	18	-39	426	513
129671	0.21	-0.65	-60.00	-6	116	-55	598	640
129118	0.76	7.69	-6.00	106	19	-66	717	766
478492	1.12	8.63	-15.00	75	27	-41	443	499
129089	0.68	-8.11	-12.00	-87	36	-67	730	612
9980272	1.30	9.49	36.00	106	-146	-52	559	446
129266	0.16	11.74	-56.00	110	82	-42	449	601
129110	0.87	11.65	-16.00	108	29	-41	444	505
129029	1.02	9.84	3.00	77	-5	-36	388	416
6389751	1.49	4.62	26.00	54	-101	-60	648	537
129210	0.13	-0.73	5.00	-7	-13	-50	539	472
129426	0.74	7.08	-11.00	60	20	-41	441	475
129720	0.37	18.57	17.00	237	-48	-49	525	629
129704	1.29	9.89	-55.00	107	97	-50	538	692
121296	0.52	7.08	0.00	73		-50	541	557
130483	0.33	3.82	16.00	33	-41	-45	483	428
1188918	1.91	8.62	27.00	86	-84	-47	511	453
129231	0.51	0.98	6.00	8	-14	-45	485	435
130011	0.27	4.46	17.00	57	-64	-65	706	629
129125	0.97	14.18	-15.00	131	26	-39	420	531
130293	1.31	14.33	26.00	137	-68	-40	432	435
129748	0.36	0.08	-62.00	1	174	-81	876	954
129211	0.13	2.99	5.00	28	-13	-49	535	499
817883	0.22	-17.81	22.00	-214	-116	-86	928	567

4.2.4 Estimating Values for Small Properties

Applying the comps-based approach described above to smaller properties results in relatively poor estimates. Error measures are much higher for small properties, for which the idiosyncrasies of a particular trade represent a larger share of the trade price. For example, trades can include business value, land, furniture or furnishings, or any other non-real estate value. Moreover, deals for smaller properties often involve non-institutional investors who may have different motivations for acquiring properties beyond earning a return.

Complicating matters further, small properties represent more than 80% of all trades, and a corresponding demand on data storage and computation time. Thus, the comps-based valuation algorithm would spend most of its computational resources making relatively poor estimates for small properties, the peers of which comprise a significant portion of the very large peer property dataset.

As an alternative, CoStar's approach to estimating values for small properties uses a gross rent multiplier, which is estimated for each quality cut as the average sale price divided by the rent for trades involving smaller properties. This is then trended using the reference cap rate series and an income trend based on lagged rents and vacancies for the local market. The gross rent multiplier approach assumes that values relate directly to rents, according to the quality of the asset. As every commercial property in the dataset has a rent, albeit estimated in many cases, an estimate of value can be easily derived by applying a rent multiplier. This value estimate will change with the property's rents, and with modulations in the gross rent multiplier.

4.2.5 Estimating Values for Hotel Properties

Due to the relatively low volume of hotel trades, the gross rent multiplier approach outlined above is employed to value hotels. The process starts with the estimation of a smooth national cap rate trend based on observed transaction cap rates. The national cap trend creates the shape of the gross rent multiplier trend.

For each hotel trade, a gross rent multiplier is computed based on a trailing 3-year average of the property's estimated 12-month ADR (average daily rate), multiplied by the market's trailing average occupancy. Hotel property valuations are derived by applying the gross rent multiplier to the property's own ADR and occupancy.

4.2.6 Accuracy of Value Estimates

The quality of CoStar's building-level price model ultimately depends on how accurately a property's trade value is predicted. Minimizing the estimate errors will result in the best depiction of aggregate prices and trends.

A variety of testing methods are used to measure errors. For repeat trades, the error is calculated as the difference between the repeat trade price and the estimated price in the preceding quarter (which will incorporate information from the first trade). For first-time trades, the trade price is compared to the estimated price based on peer properties and the geographic averages.

Exhibits 4.20 through 4.23 below present the median absolute error by property type for all trades, a property's first trade, and a property's repeat trades. The overall error is lowest for apartment properties and highest for retail properties. In general, the error is lower for higher-value trades than for lower-value trades. The higher error is believed to result from the inherent idiosyncrasies of small trades, which may include business value, land value, other non-real estate assets, or unusual relationships between buyers and sellers. The error on repeat trades is also significantly lower than the error on first trades, reflecting the large amount of information contained in a property's prior trades, an effect especially apparent for retail properties.

Exhibit 4.20: Office Price Estimate Median Absolute Error

Value	Total Observations	Total	First Trade	Repeat Trades
Total	199,802	0.30	0.32	0.21
$100,000 to $999,999	122,382	0.32	0.34	0.22
$1,000,000 to $9,999,999	63,576	0.29	0.31	0.22
$10,000,000 to $49,999,999	10,488	0.22	0.23	0.16
$50,000,000 to $99,999,999	1,823	0.18	0.21	0.12
$100,000,000 to $249,999,999	1,148	0.19	0.22	0.12
$250,000,000 to $499,999,999	295	0.18	0.20	0.11
$500,000,000+	82	0.21	0.22	0.15

Exhibit 4.21: Apartment Price Estimate Median Absolute Error

Value	Total Observations	Total	First Trade	Repeat Trades
Total	220,912	0.26	0.31	0.19
$100,000 to $999,999	92,621	0.34	0.40	0.22
$1,000,000 to $9,999,999	105,104	0.24	0.29	0.19
$10,000,000 to $49,999,999	17,780	0.15	0.15	0.15
$50,000,000 to $99,999,999	4,263	0.12	0.13	0.12
$100,000,000 to $249,999,999	1,066	0.14	0.14	0.12
$250,000,000 to $499,999,999	55	0.15	0.14	0.18
$500,000,000+	2	0.46	0.46	-

Exhibit 4.22: Industrial Price Estimate Median Absolute Error

Value	Total Observations	Total	First Trade	Repeat Trades
Total	236,933	0.29	0.31	0.21
$100,000 to $999,999	128,981	0.34	0.36	0.22
$1,000,000 to $9,999,999	99,725	0.25	0.27	0.20
$10,000,000 to $49,999,999	7,564	0.24	0.24	0.21
$50,000,000 to $99,999,999	527	0.27	0.28	0.26
$100,000,000 to $249,999,999	115	0.26	0.25	0.42
$250,000,000 to $499,999,999	6	0.39	0.38	4.39
$500,000,000+	1	0.77	0.77	-

Exhibit 4.23: Retail Price Estimate Median Absolute Error

Value	Total Observations	Total	First Trade	Repeat Trades
Total	358,430	0.41	0.46	0.22
$100,000 to $999,999	216,713	0.51	0.59	0.24
$1,000,000 to $9,999,999	136,519	0.33	0.35	0.21
$10,000,000 to $49,999,999	4,950	0.33	0.36	0.14
$50,000,000 to $99,999,999	148	0.39	0.45	0.12
$100,000,000 to $249,999,999	41	0.47	0.50	0.08
$250,000,000 to $499,999,999	4	0.51	0.51	-
$500,000,000+	1	0.82	0.82	-

4.3 Estimating Property Cap Rates

Cap rates represent another important pricing metric for commercial real estate. In keeping with CoStar's philosophy of providing property-level data across all key commercial real estate metrics, current and historical cap rates are estimated for all properties in the CoStar database. As with prices, it is believed that accurate property-level cap rate estimates will also result in the most accurate portrayal of aggregate trends. Additionally, property-level cap rate estimates allow clients to define their own custom sets of properties and view cap rate series most applicable to their investments. This section outlines CoStar's approach to estimating property-level cap rates and presents the aggregate national series.

4.3.1 Spot Cap Rate Estimates

Before building cap rate series for each property, spot cap rates at a point in time are estimated. For the 130,000 or so traded properties that report a cap rate, this transaction cap rate is used as of the date of the trade. For all properties for which CoStar has not collected a cap rate, a cap rate as of 2015Q1 is estimated using a regression of actual observed yields between 2011 and 2017 on the natural logs of estimated price per square foot, total deal size and cap rates on peer trades (over the same 2011 to 2017 time period, and weighted by similarity to the subject property as well as proximity). The specific equations and coefficients used to estimate cap rates are presented below for reference.

- **Office Cap Rate Model:**
  $log\left(CapRate\right) = 1.492 - 0.124log\left(ppsf\right) - 0.0889log\left(price\right) + 0.636log\left(peercaprate\right)$
- **Industrial Cap Rate Model:**
  $log\left(CapRate\right) = 1.016 - 0.0723log\left(ppsf\right) - 0.0268log\left(price\right) + 0.845log\left(peercaprate\right)$
- **Retail Cap Rate Model:**
  $log\left(CapRate\right) = 1.601 - 0.137log\left(ppsf\right) - 0.0120log\left(price\right) + 0.624log\left(peercaprate\right)$
- **Apartment Cap Rate Model:**
  $log\left(CapRate\right) = 1.806 - 0.142log\left(ppsf\right) - 0.0266log\left(price\right) + 0.598log\left(peercaprate\right)$
- **Hotel Cap Rate Model:**
  $log\left(CapRate\right) = 2.807 - 0.067log\left(ppsf\right) - 0.0264log\left(price\right) + 0.242log\left(peercaprate\right)$

4.3.2 Cap Rate Trends

To create full cap rate time series back to 2000 for every property, the national cap rate series is modulated based on the cap rate level for the particular property and the price performance of that property relative to the national trend. Properties that have outperformed the national price series will see cap rates compress by more than the national cap rate series, and vice versa, based on the equation presented below:

$$CapRate_t = CapRate_{t-1} * \frac{NatCapRate_t}{NatCapRate_{t-1}} * \sqrt{\frac{\left(\frac{NatPrice_t}{NatPrice_{t-1}}\right)}{\left(\frac{PropPrice_t}{PropPrice_{t-1}}\right)}}$$

where *CapRate*$_t$ is the estimate of the property cap rate at time *t*, *NatCapRate* is the national cap rate, *PropPrice* is the estimate price per square foot for the property, and *NatPrice* is the national price per square foot.

4.4 Hotel Performance Data

The hotel sector uses industry-specific metrics to track performance. These metrics are occupancy, average daily rate (ADR), and revenue per available room (RevPAR), described as follows.

Occupancy is equal to the percentage of available rooms (supply) that were sold (demand) during a specific time period, or:

$$Occupancy = \frac{Demand}{Supply}$$

Average daily rate (ADR) measures the average rate paid for the rooms sold, and is equal to total room revenue divided by the total rooms sold (demand), or:

$$AverageDailyRate = \frac{Revenue}{Demand}$$

Finally, revenue per available room (RevPAR) is equal to total rooms revenue divided by the total rooms available (supply), or:

$$RevPAR = \frac{Revenue}{Supply}$$

Algebraically, RevPAR is also equal to ADR multiplied by occupancy.

STR collects data directly from hotel operators and does not, under any condition, publish information for any individual hotel, brand, owner, parent, or manager. All aggregations of hotel data must include a minimum number of properties and meet the following conditions:

- No single property can account for more than half of the total room supply in the aggregated set.
- No single brand, such as, for example, Holiday Inn or Comfort Inn, can account for more than half of the total room supply in the set.
- No single company, such as, for example, Hilton Worldwide or Interstate Hotels & Resorts, or Host Hotels & Resorts, can account for more than 70% of the total room supply in the set.

Checks are performed to ensure no individual property, brand, or parent company data can be isolated from set to set.

5 Forecasting Approach and Methods

The commercial real estate sector's particular interest in forecasts likely relates to the widespread use of DCF models to underwrite and evaluate deals. These models require a forecast of rents and occupancies, cash flows, and exit cap rates. Forecasts help investors allocate capital by providing metrics to rank markets. More recently, lenders have employed statistical models to evaluate loans that rely on forecasts of the performance of the underlying collateral. And Wall Street investment firms believe they can gain an edge in trading commercial real estate assets like REITs or CMBS pools by tying the underlying assets to a forecast and generating an aggregate expected return.

Traditionally, commercial real estate forecasters have only had market-level data at their disposal, either from brokerage firms or industry organizations like NCREIF. Consequently, they have produced market-level forecasts of the key variables of supply, demand, vacancy, rent, NOI, cap rates, and price change. With the increasing availability of submarket-level fundamentals and rent data, forecasters have developed share-down models to produce submarket forecasts. CoStar brings forecasts to individual properties at scale. The processes and methods laid out in the preceding sections to create same-store rents and price and cap rate estimates for every property not only produce the most accurate view of historical trends, but also provide the necessary inputs for creating building-level forecasts for every commercial and multifamily property that CoStar tracks.

Property-level forecasts confer many benefits. No longer limited to market or submarket forecasts, clients may view a forecast for any set of properties—their own portfolio, a REIT, or a CMBS pool. Property-level forecasts also allow real-time forecasting. As CoStar researchers update data for a property, the forecast will update in real time as well to reflect the new information. A property-level model provides a structure for handling specific types of properties differently, such as, for example, affordable-rate housing, or owner-occupied office properties.

These nuances produce rich, textured forecasts that can consider many more variables than traditional market-level models. Finally, and most obviously, property-level forecasts mean that analysts and underwriters can use a forecast for the subject property in question, rather than relying on a market- or submarket-level forecast that may or may not capture the individual characteristics of the asset.

This chapter describes how CoStar produces property-level forecasts, starting with the exogenous economic and capital markets inputs. Next, the market model is described, which produces the guidelines that individual properties will follow. Finally, the model that creates the property-level forecasts is explained. The final section presents an overview of CoStar's backtesting and model validation work around the forecasting models.

5.1 Economic and Capital Markets Data

Commercial real estate forecasts start with exogenous economic and capital markets inputs. Traditionally, demand models have used job growth, often specific to the particular property type, as the primary independent variable in the demand model on the theory that jobs translate into real estate demand. Capital markets inputs like interest rates and risk spreads drive price and cap rate models.

CoStar's forecasting systems have been designed to run a wide range of scenarios, potentially including custom economic forecasts. This section discusses the economic and capital markets inputs used, as well as the economic scenarios that CoStar runs each quarter.

5.1.1 Economic and Capital Markets Inputs

CoStar's forecasting models operate at a metro (or regional) level, and as such require metro-level economic inputs. CoStar receives these inputs from Oxford Economics. Headquartered in London with offices around the world, and long regarded as the industry leader in city, regional and other sub-national economic forecasting globally, Oxford Economics recently expanded its US forecasting coverage to include more than 3,500 sub-national economies, spanning all 50 states, 382 metros and 3,142 counties.

In the hotel sector, market geographies do not necessarily match the CBSA or MSA division and can in some cases span vast areas. In cases where hotel market geographies do not match the definition used in the economic data, county-level economic data is aggregated to create economic inputs that align with the hotel markets.

5.1.2 Forecast Scenarios

Oxford Economics produces a range of economic forecast scenarios, including a Baseline scenario, Moderate Upside and Downside scenarios, and a Severe Downside case. In addition, CoStar developed an Interest Rate Shock scenario, which is similar to the Moderate Downside scenario but applies a shock to the corporate bond yield, a proxy for a sudden and unexpected increase in risk.

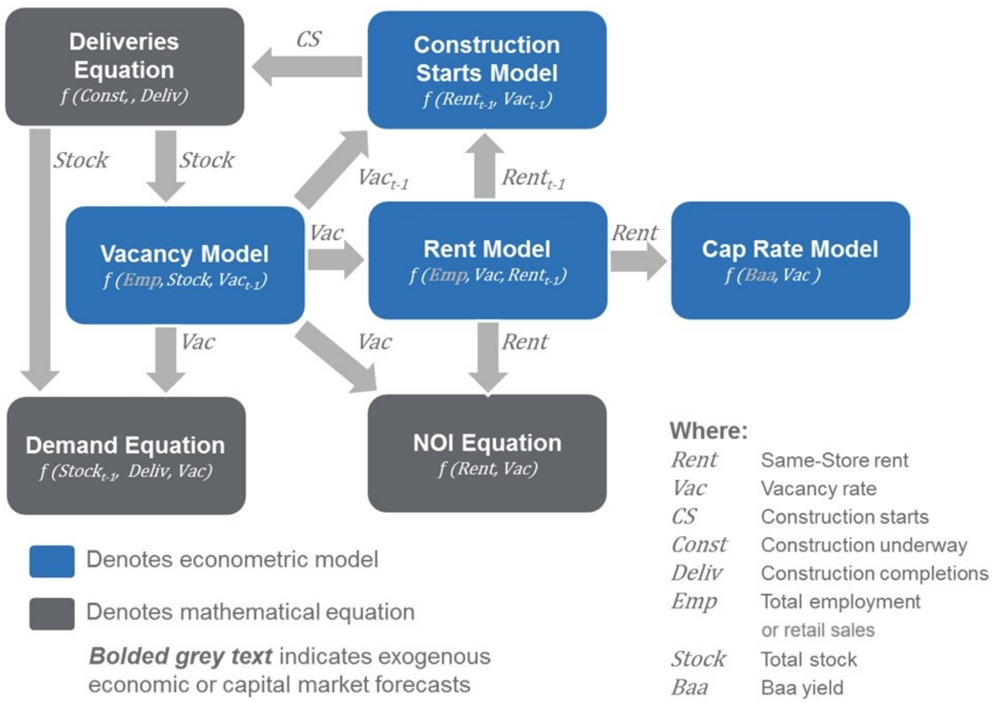
CoStar also developed an in-house Trend Growth scenario. In this scenario, it is assumed that the labor force in each metro will continue to grow at the average rate of the past three years, and that the unemployment rate in each metro will revert to the post-2000 average over the next five years, leveling off thereafter. Under these assumptions, this scenario depicts conditions in which recent trends largely persist.

5.2 Forecast Guidelines: The Market Models

CoStar's market-level forecasting models, described in detail below, differ from other forecasting approaches in that they do not produce the final forecast results. Rather, the outputs of the market models provide guidelines that, all else equal, all properties in the market will follow.

The market models employ a series of interlinked regression models addressing supply, vacancy, rent, and cap rates. From the results of these models, demand, NOI, and price change are mathematically derived. Exhibit 5.1 presents the market-level forecasting process.

Exhibit 5.1: Market Guideline Forecasting System



These regression models are run for the 54 largest metros. At the same time, panel regressions are run using all the metros. The panel models serve as back-up models in situations where the metro model does not produce useful results, either due to incorrect relationships between variables, low statistical significance, or poor r-squared measures.

The remaining, smaller metros are grouped together into regional sets and the regions themselves are forecast. These regional forecasts serve as the guidelines for the properties in these smaller, lower-tier metros. The sections below discuss each model in turn.

5.2.1 The Supply Model

The market-level forecasting process begins with a forecast of supply, defined as the change in total stock. The supply model is comprised of two steps: (i) an estimate of construction starts, and (ii) a translation of those starts into completions. These steps correspond to the Construction Starts Model and the Deliveries Equation in Exhibit 5.1.

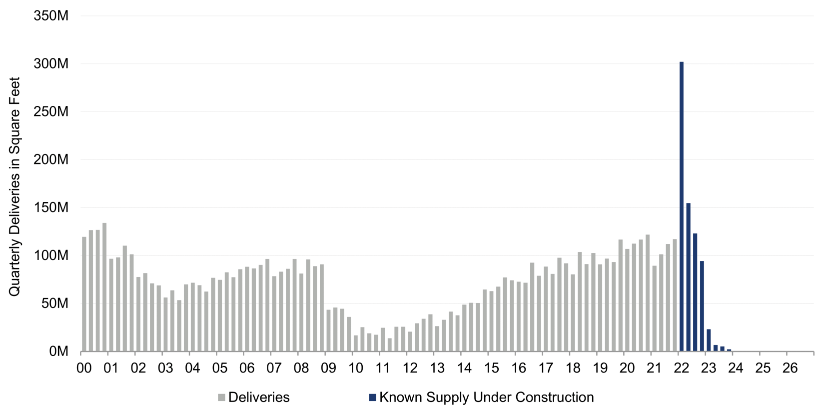
Since buildings take some time to complete—many years for urban towers—the near-term supply forecast can rely on known projects already underway, but a longer-term supply forecast will rely on estimates. Thus, the supply forecast consists of two types of supply: known supply —which includes the properties currently underway and for which research has collected a completion date, and the econometrically-generated modeled supply.

Known Supply

As of June 2022, CoStar was tracking some 26,900 properties that are under construction for which the size and expected completion date are known. CoStar's research teams regularly review under-construction projects as to their status and the likelihood of meeting the delivery date.

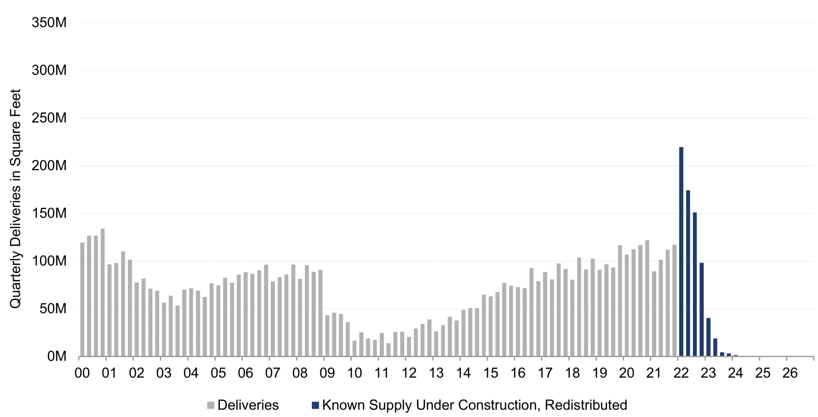
This information is used directly to produce the near- and medium-term supply forecasts. However, in reality, aggregate supply can appear optimistic in the near term. Exhibit 5.2 shows industrial deliveries for the United States back to 2000 and the supply currently underway. Based on the expected completion dates, the next quarter would see a significant supply shock relative to the recent past. However, that near-term spike is due to completion delays of properties with delivery dates in the past. As they failed to deliver as expected, their delivery date was pushed into the following quarter.

Exhibit 5.2: U.S. Industrial Construction, Historical and Expected



In actuality, some of these projects will be further delayed. The likelihood of that happening is captured by moving forward by one month the completion dates for every property currently under construction. Since the forecast uses a quarterly periodicity, the one-month shift has the effect of moving roughly one-third of the supply into the following quarter. Exhibit 5.3 illustrates the effect of this shift on the industrial supply outlook.

Exhibit 5.3: U.S. Industrial Construction, Historical and Expected With Date Shift

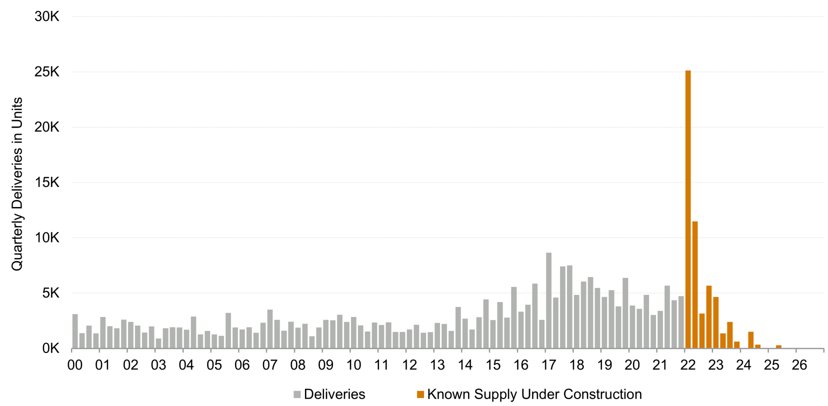


The shift brings near-term deliveries more in line with historical norms and removes the unlikely supply spike in the next quarter, resulting in a more accurate outlook.

Multifamily Supply

At the time of writing in June 2022, a large number of multifamily projects are underway, and a large number of these projects are expected to deliver in the next quarter, as shown in Exhibit 5.4.

Exhibit 5.4: New York Market Multifamily Construction, Historical and Expected



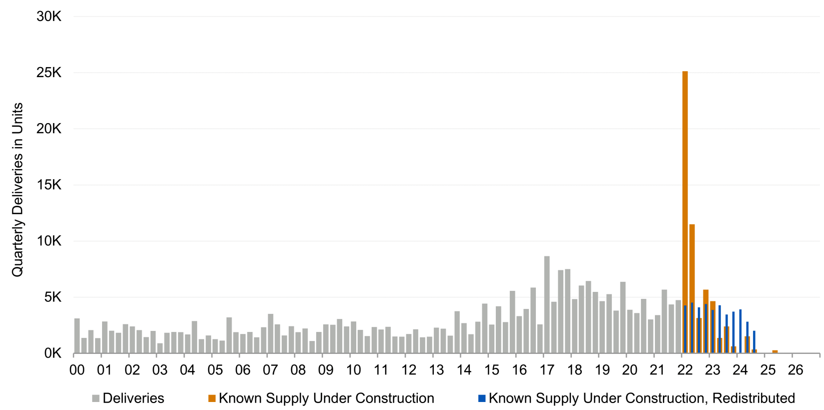
As shown, the expected deliveries for next quarter, based on researched and curated delivery dates, represent about four times the typical quarterly deliveries. This "wall of supply" has increased every quarter during this period of heightened multifamily construction. Over-optimistic developers, delays of nearly completed projects, and the reality that some percentage of delivery dates, however accurate on an individual basis, will slip, account for this unrealistic outlook.

History has shown that only a fraction of these scheduled deliveries completes in the next quarter as anticipated. Those that do not deliver are then assumed to deliver in the following quarter, exacerbating the supply spike.

The one-month shift applied to commercial property completion dates does not alleviate the multifamily supply problem, as it only spreads the "wall" over two quarters. An alternative solution would spread the deliveries out over the next year or even longer. To effect such a distribution, all scheduled deliveries are ranked into a queue for each market (or region, for smaller markets), ordered by size, scheduled delivery date, and by time under construction in descending order.

It is then assumed that these deliveries will follow the shape produced by the supply model described in the section above, which estimates quarterly deliveries as a share of the space underway. Given the large amount of construction currently underway, the model produces a jump in modeled deliveries in the near-term. But the model assumes that only a share —typically about one eighth —of the supply underway will deliver each quarter. The queued properties are allocated across this distribution such that the last property allocated to each quarter causes the total space to exceed the modeled deliveries. Exhibit 5.5 illustrates this dynamic for the New York apartment market, where the orange bars show the scheduled deliveries, and the blue bars show the redistributed supply.

Exhibit 5.5: New York Market Adjusted Multifamily Construction



Modeled Supply

A supply forecast that relies only on known supply will systematically understate total new supply, since over the course of the next several years developers will plan for, propose, start, and ultimately complete new projects. Thus, an accurate forecast of supply must include estimates of how much new space will deliver beyond the projects tracked by CoStar research.

Traditionally, supply models have used completions of new supply as the dependent variable, since most datasets for commercial real estate track completions. These models typically use real estate performance metrics like rent growth, vacancy, or price change, and capital market variables as independent variables. However, such models must necessarily include lags in the independent variables to account for the construction time between the decision to start a new project and when the project delivers. These lags in the independent variables result in problematic models, for several reasons. First, imprecision around construction times—and as a result the length of the lag between completions and the independent variables—lowers the statistical power of the model. Second, the defined lag can create breaks and jumps in the data. For example, if deliveries today depend on interest rates two years ago, and interest rates jumped in that quarter and then returned to normal levels in the following quarter, then the modeled supply forecast today would show a corresponding movement. Finally, the build time in different markets, or for different property types, and in different time periods, can vary widely, and models of completions fail to account for such variation.

CoStar's property-level data includes not only the completion date for every property, but also the start date for most. Therefore, CoStar can directly model the decision to start construction projects using contemporaneous variables instead of multi-year lags, resulting in much stronger models. The starts model includes lagged change in rent and the lagged natural log of the vacancy, represented as:

$$Equation 1: \qquad Starts_t = f\left(\Delta Rent_{t-1}, \ln Vac_{t-1}\right)$$

where $Starts_t$ is construction starts, $\Delta Rent_{t-1}$ is the percentage change in rents, and Vac_{t-1} is the lagged natural log of the vacancy rate. The model is restricted to the period since 2008 to capture the trends during the most recent expansion.

The amount of construction underway can then be modeled by starting with the space underway today (the last historical date) and adding modeled starts and subtracting modeled deliveries, as in:

$$Equation2: \quad Const_t = Const_{t-1} + Starts_t - Deliv_t$$

where $Const_t$ is the amount of space underway at time t, $Const_{t-1}$ is the amount of space underway in the prior period, $Starts_t$ is construction starts (from Equation 1), and $Deliv_t$ is modeled deliveries.

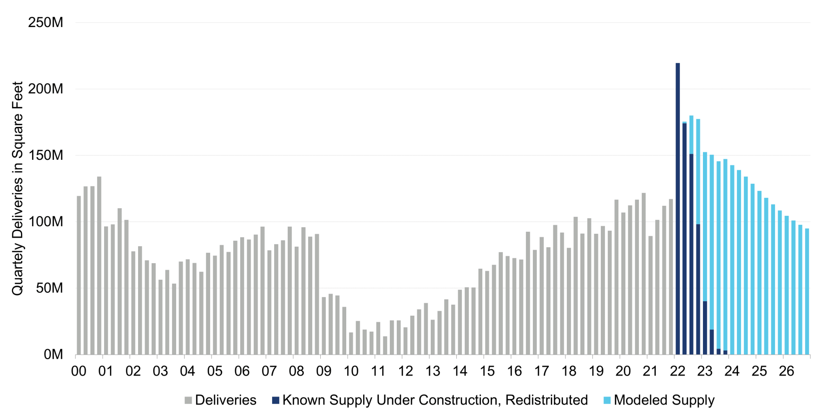
Deliveries are estimated by applying the historical average of deliveries as a share of space underway in each market, as in:

$$Equation3: \qquad Deliv_t = Const_t \frac{1}{n}\left(\sum_{h=0}^{n} \frac{Deliv_h}{Const_h}\right)$$

where $Deliv_t$ is the deliveries of new space at time t, $Const_t$ is the amount of space underway at time t, and h denotes historical time periods.

The final supply forecast includes both the known and modeled supply. Exhibit 5.6 presents the supply outlook for U.S. industrial, showing both the known supply and modeled supply. Typically, the forecast calls for very little modeled supply in the first few quarters of the forecast. In the case of industrial, the very short build times common to the sector result in some modeled supply even in the first forecast quarter.

Exhibit 5.6: U.S. Industrial Construction, Historical and Forecast, Including Modeled Supply



As a final note, the supply model separately forecasts demolitions based on the average amount of space demolished each quarter.

5.2.2 The Vacancy Model

Rather than forecasting demand, which is defined as the net change in occupied space, CoStar models the vacancy rate directly and derives demand.

The vacancy model begins with establishing a long-term steady-state vacancy rate, using a regression of the vacancy level against demand driver growth in the market (or region, for smaller markets). This steady-state forecast will serve as an independent variable in the second step of the vacancy forecast. Mathematically, this model is represented as:

$$Equation1: \qquad Vac_t = f\left(DD_t\right)$$

where Vac_t is log vacancy and DD_t is demand driver growth. Demand driver is employment for office, employment and real personal income for multifamily, and real retail sales for industrial and retail.

The second step of the vacancy forecast model estimates the quarterly change in the log vacancy rate as a function of the trailing four-quarter demand driver level relative to a trailing 20-quarter median, the change in stock, and the lagged predicted residual from Equation 1 above, as denoted below:

$$Equation2: \quad \Delta Vac_t = f\left(\Delta DD_t, \Delta Stock_{t-1}, \hat{\nu}_{t-1}\right)$$

where ΔVac_t is the first difference in log vacancy, ΔDD_t is the ratio of the trailing four-quarter average demand driver to the trailing 20-quarter median demand driver level, $\Delta Stock_{t-1}$ is the lagged first difference of log stock, and $\hat{\nu}_{t-1}$ is the lagged predicted residual from Equation 1. Demand driver is employment for office, employment and real personal income for multifamily, and real retail sales for industrial and retail.

The use of the trailing median in the vacancy model arises from the COVID-19 period, when the second quarter of 2020 recorded job losses of 15 million —the worst since the end of the Second World War. The use of a trailing median in the denominator effectively removes such outliers from the trend, while the use of a trailing four-quarter average in the numerator smooths out, delays, and extends the effect of such outliers on vacancy.

The model specifications have been tested and results find these variables to produce low model error across all markets while also having high-quality backtesting results. The lagged predicted residual from Equation 1 ensures that the long-term forecast reverts to the steady-state vacancy rate established by Equation 1. This error-correction step also improves backtesting results.

To arrive at the demand forecast, the forecast supply is simply multiplied by the forecast occupancy rate, which is equal to 1 minus the vacancy rate.

5.2.3 The Rent Model

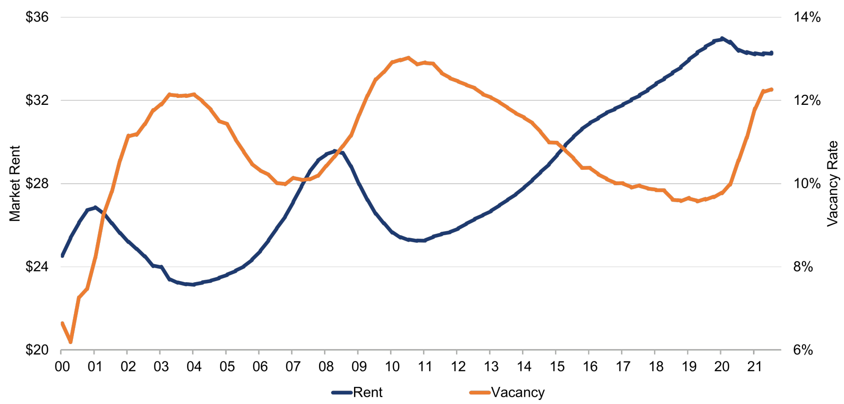
Rents tend to be negatively correlated to vacancies, as illustrated in Exhibit 5.7 which presents the office same-store rent and the vacancy rate for the National Index of the 54 largest markets in the United States.

Consequently, forecasters typically model rent change as a function of vacancy. Such models tend to produce good results. Refinements include adding the recent trajectory of vacancy rates to capture momentum, and lagged rent levels such that rent growth slows as rents reach higher levels (and vice versa).

As with vacancies, CoStar first establishes a long-term rent trend forecast by estimating the rent level as a function of the occupancy rate and rent driver, denoted as

$$Equation1: \qquad Rent_t = f\left(Occ_{t-1}, RD_t\right)$$

Exhibit 5.7: U.S. Office Same-Store Rent and Vacancy



where $Rent_t$ is log rent, Occ_{t-1} is lagged log occupancy, and RD_t is log rent driver. Rent driver is employment for office and multifamily and nominal retail sales for industrial and retail.

The rent change forecast includes this steady-state rent level from Equation 1, along with the first difference of log occupancy and rent driver change, denoted as:

$$Equation2: \qquad \Delta Rent_t = f\left(\Delta Occ_{t-1}, \Delta RD_t, \hat{r}_{t-1}\right)$$

where $\Delta Rent_t$ is the first difference in log rent, ΔOcc_{t-1} is the first difference in lagged log occupancy, ΔRD_t is the current rent driver level relative to either the prior peak in recessionary periods or to the rent driver level four quarters prior in expansionary periods, and $\Delta\hat{r}_{t-1}$ is the lagged predicted residual from Equation 1. Rent driver is employment for office and multifamily and nominal retail sales for industrial and retail.

At this time, CoStar's rent change model does not address inflation. Many models estimate the change in real rents and then add an inflation forecast to the outlook. Past analysis has shown that models trained on nominal rents have higher goodness-of-fit measures and have produced better backtesting results since 2000.

5.2.4 Performance Models: NOI, Cap Rates, and Prices

CoStar also develops forecasts of market- and regional-level guidelines for the three real estate performance variables: net operating income (NOI), cap rates, and prices. These variables form the essential commercial real estate return equation,

$$Yield = \frac{NOI}{Value}$$

where *Yield* is the initial yield, *NOI* is income, and *Value* is the estimated value of an asset.

Based on this framework, two of the variables, NOI and cap rates, will be modeled while price will be mathematically derived.

NOI Model

Net operating income refers to the cash flows generated by a property before taxes and depreciation, or, in other words, potential rental income less vacancy and fixed and variable operating expenses. A typical multi-tenant asset will house occupiers who have signed leases at various points in the cycle at different rents. The rental income will depend on when these leases were signed and at what rent levels, while the growth in income will depend on scheduled escalations on in-place leases and on the rate at which existing leases expire and new leases are signed at higher rents.

Similar to CoStar's historical price estimates, NOI is estimated as the trailing four-quarter average rent multiplied by current occupancy, for all property types. This consistency across sectors is to ensure that all property types would produce the same price change given the same rent, vacancy, and cap rate trends.

The Cap Rate Model

Cap rates are modeled as a function of secular capital market conditions and metro-level vacancy change. The model specification for the cap rate model is:

$$CapRate_t = f\left(B_t, \Delta Vac_t\right)$$

where B_t is the BBB corporate bond yield rate at time t and ΔVac_t is the change in vacancy rate at time t.

The use of the BBB yield performs particularly well at capturing the rise in long term interest rates that began in 2022.

5.2.5 Interventions to Market Models

CoStar does not make any direct interventions in the market- and regional-level Algorithmic models, either by altering input variables, entering add factors, or by adjusting constants or model coefficients. CoStar does, however, produce Houseview forecasts, where manual interventions are made to the forecasts to account for structural and cyclical impacts in CRE markets that may not be adequately reflected in macroeconomic forecasts. These interventions result in forecasts better aligned with the professional views of CoStar's property sector specialists.

Should the models begin to produce results that do not appear reasonable, the company's position may change and adjustments to model specifications or parameters may be applied to produce results more in line with expectations. For example, during the COVID-19 period in Spring 2020, extreme economic data resulting from the cessation of economic activity during the lockdown produced unreasonable CRE forecasts. In response, several changes were made that were communicated to clients via regular email updates and are now incorporated into the methodology narrative herein.

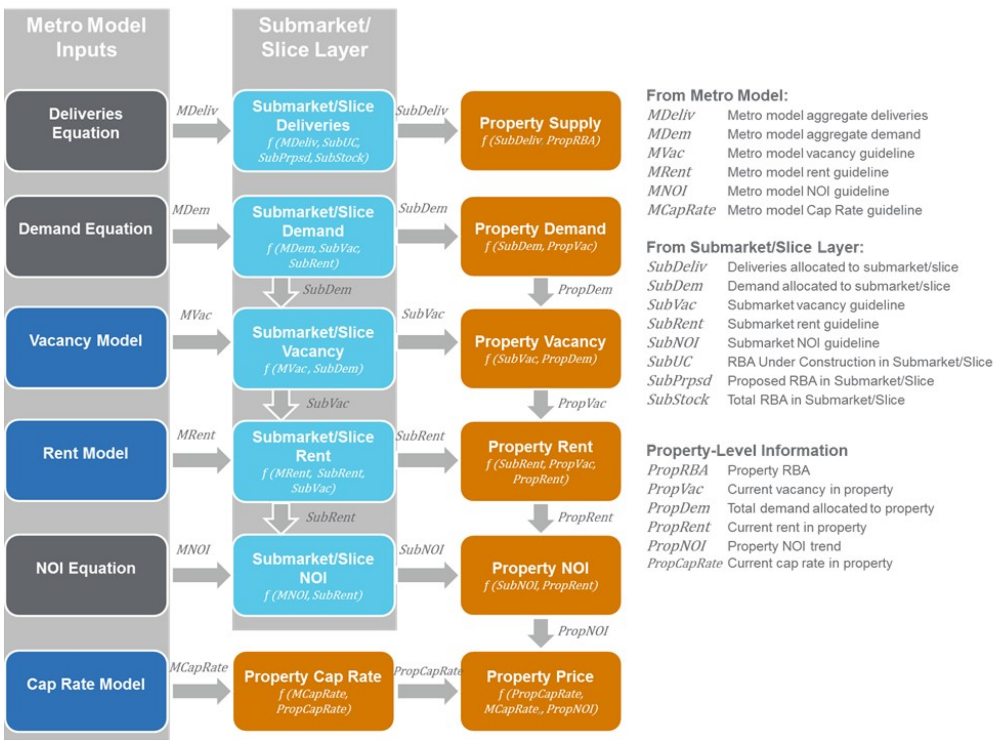
5.3 The Property-Level Forecast Model

Commercial real estate forecasters have traditionally provided forecasts for markets or submarkets. With CoStar's wealth of data, more granular levels of analysis are possible. Today, CoStar forecasts key real estate variables for all properties in its database across the apartment, office, industrial, flex, and retail property types. These property-level forecasts can be used by CoStar clients to underwrite deals, value collateral, or manage portfolios, among other analytic activities. Clients may produce forecasts for any set of properties by aggregating the individual properties into, for example, submarket slices, custom grouping of submarkets or of any selected set of properties.

CoStar's property-level forecasting process is illustrated in Exhibit 5.8. The process begins with the market guidelines (or, for smaller markets, regional guidelines) produced by the market models, denoted by the gray and blue boxes in the leftmost column that correspond to the metro models shown in Exhibit 5.1. These guidelines include forecasts for supply (both known and modeled), aggregate demand, rent, NOI, and cap rate.

The property-level forecast process then shares the guidelines down to the submarket slice level (denoted as the blue boxes in the center column), and finally to the individual properties (denoted by the orange boxes in the rightmost column). The multiple layers ensure that all properties in a particular geography broadly follow the same trend.

Exhibit 5.8: The Property-Level Forecasting Process



5.3.1 Property-Level Supply Forecasts

The market-level model provides a forecast of aggregate modeled supply, which is allocated across the submarket slices and then to individual properties. Allocating the supply across submarkets uses two factors: (i) the amount of space currently under construction plus deliveries over the past two years, and (ii) the amount of proposed space in each submarket slice, where proposed space is calculated to be one-tenth of the under-construction space.

This has the effect of putting the modeled supply into submarkets with significant recent construction and/or construction underway, with a secondary effect from proposed space. All new space is assumed to be 4 & 5 Star.

In the rare market with no construction underway, no recent deliveries, and nothing proposed, the modeled supply is distributed proportional to the amount of existing stock in each submarket slice.

Allocating the modeled supply to individual properties is done by adding a small amount of modeled supply to each property in each forecast quarter, in proportion to each property's share of the submarket slice total stock. This distributes the modeled supply across the submarket in relation to the current distribution of 4 & 5 Star properties.

The model also allocates the pool of demolitions across submarkets. It is assumed that only lower-quality properties are demolished, and that demolitions tend to occur in submarkets with the highest levels of construction.

5.3.2 Allocating Demand Across Buildings

As with supply, the market-level model returns a forecast of aggregate demand for the market. This is allocated to properties in the same geographical cascade: first to submarket cluster slices, then to submarket slices, and finally to individual properties.

The first allocation of demand goes to new construction, both projects currently underway and the modeled supply later in the forecast. A standard lease-up pattern is assumed based on analysis of CoStar's historical data in the first two years of a property's life.

Existing properties can not only receive new demand, they can also lose their current occupancy. To capture the possibility of a property losing occupancy, a small percentage of its occupancy is deducted from every property and added to the aggregate pool of demand as "churn." The churn percentage varies by slice to recognize the relative inelasticity of some occupancy (for example, in high-quality or owner-occupied offices).

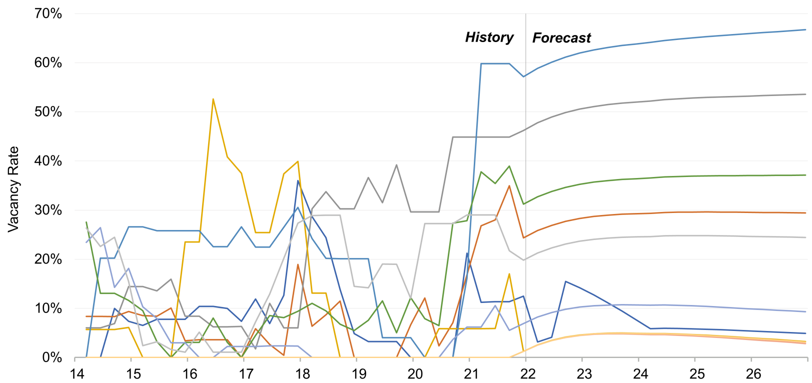
Each existing property receives an allocation of the aggregate demand (including the churn) based on its vacancy rate and its rent relative to its peers. All else equal, higher vacancy properties receive more demand, as will lower rent properties. Properties that receive less demand than their churn will see vacancies rise. Exhibit 5.9 illustrates an example of vacancy trajectories for the ten 3 Star office properties in San Francisco's Financial District.

Generally, higher-vacancy properties receive more demand, while lower-vacancy or completely rented properties lose some demand, depending on the rent in the property and its location within the market.

5.3.3 Property-Level Rent Forecasts

The rent forecast for a particular building is derived from the following five factors: (i) the metro rent guideline, shared down to the submarket slice for the property's location; (ii) the property's vacancy forecast; (iii) the property's rent level relative to its peers; (iv) the recent momentum in rent growth; and (v) the property's relative performance over the past two years.

Exhibit 5.9: Property-Level Vacancy Forecast Example

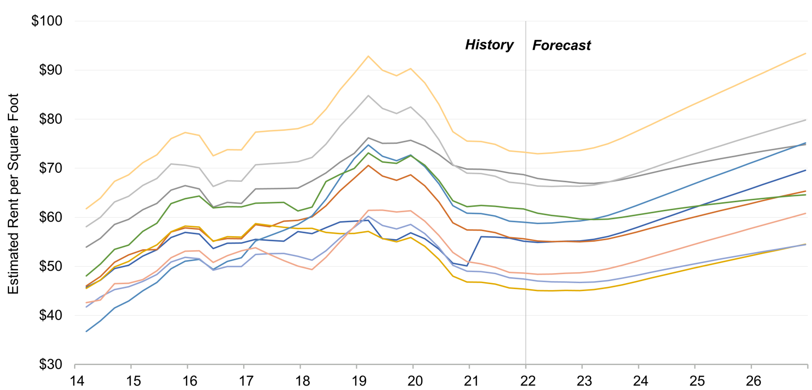


Note: 10 Largest 3-Star Offices in San Francisco's Financial District Submarket

Vacancy is assumed to affect the rent forecast in the expected way—properties with higher vacancy will experience slower rent growth and vice-versa. Similarly, properties with higher rent levels than the submarket slice average are assumed to have slower rent growth.

The final two factors consider the property's recent history. It is assumed that momentum maintains the recent performance, such that properties with rising rents will see rents continue to rise in the near-term. It is further assumed that relative performance has the opposite effect. Rent growth in properties that have outperformed the submarket slice average over the past two years will experience slowing rent growth in the outer years of the forecast. Exhibit 5.10 presents rent forecasts for the same set of San Francisco office properties as above, illustrating the divergence in rent growth across properties dependent on each property's vacancy, rent level, and recent performance.

Exhibit 5.10: Property-Level Rent Forecast Example



Note: Ten of the largest 3-Star Offices in San Francisco's Financial District Submarket

5.3.4 Hotel Sector Forecasts

Hotel occupancy and revenue forecasts are shared down from either a market or a national guideline. National guidelines are shared down to smaller markets, then those, plus the larger markets which have their own guidelines, are shared down to the submarket/quality combinations, which are then shared down to the properties.

To allocate demand across buildings, occupancy is first assigned to new construction based on the historical behavior of new construction in the submarket/quality slice. Typically, a new hotel delivers with fairly low occupancy, but it rises to the level of its comps within nine or ten months. Once demand has been assigned to new construction, any remaining demand is assigned to stabilized buildings. A regression determines how rapidly a submarket will revert to its historical premium above or below the market, and how much a recent premium that is different from history is likely to continue. For instance, if a submarket has historically had occupancy of 3% higher than the market, but for the last two years it has been 6% higher than the market, occupancy would be expected to come down to 4% or 5% above the market. Once the submarket lines are calculated, the buildings are calculated from them in exactly the same way.

The forecast of ADR is similar to the forecast for occupancy. The submarket ADR premium is predicted by a regression on lagged ADR premium in the same month, historical average ADR premium in that month, and contemporaneous occupancy.

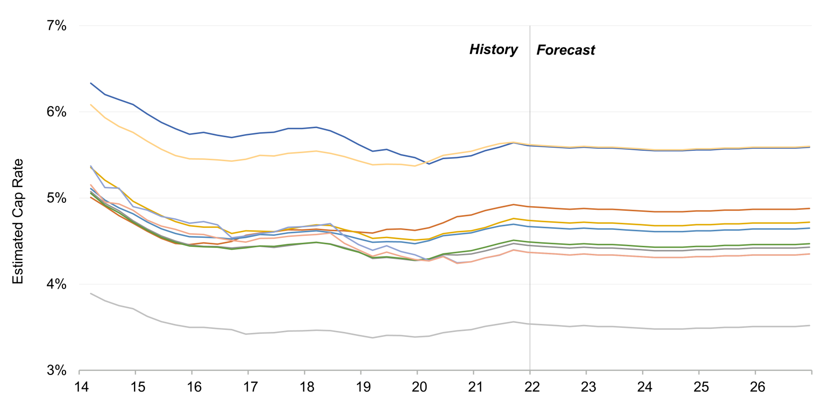
5.3.5 Property-Level Performance

Property-level forecasts of NOI, price, and cap rate offer a variety of useful purposes, including assisting underwriters, investors and lenders in valuation estimates for a single building, loan pool, portfolio, or REIT.

To create a property-level NOI forecast, the market NOI guideline is modulated by the building's rent forecast relative to the guideline. By doing so, a property with a rent forecast that outperforms the guideline by 1% will also have an NOI forecast that outperforms the market by 1%.

Similarly, property-level cap rates are derived by attaching the market guideline trend to each property by adjusting the level. This has the effect of producing different rates of percentage change in cap rates depending on the cap rate level of the property. For example, properties with lower cap rates will experience large percentage changes, on average, and properties with higher cap rates will have lower volatility. This dynamic is consistent with historical performance trends suggesting that lower cap rate properties show more volatility, both on the downside and especially on the upside. Exhibit 5.11 presents cap rate forecasts for the same set of San Francisco office properties as used above.

Exhibit 5.11: Property-Level Cap Rate Forecasts



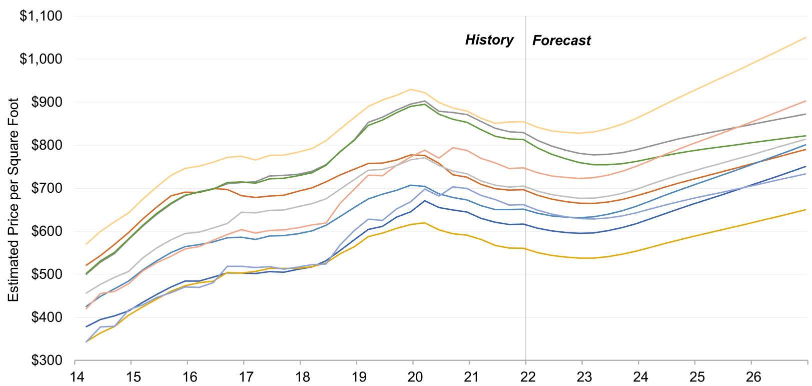
Note: Ten of the largest 3-Star Offices in San Francisco's Financial District Submarket

With property-level NOI and cap rate forecasts in hand, property-level price forecasts are derived by the essential commercial real estate equation:

$$\Delta Yield = \frac{\Delta NOI}{\Delta Value}$$

By modulating individual property NOI series based on rent, and arriving at different percentage changes in cap rates by adjusting the level of the market guideline, broadly similar outlooks in prices are created with enough variation to produce interesting results. Exhibit 5.12 presents the price forecasts for the same set of office properties in San Francisco.

Exhibit 5.12: Property-Level Price Forecasts



Note: Ten of the largest 3-Star Offices in San Francisco's Financial District Submarket

5.3.6 Interventions to Property-Level Forecasts

By design, the ability to apply adjustments to specific commercial and multifamily properties has not been implemented. As noted, all known move-ins and move-outs are incorporated into the property-level forecasts.

There is, however, the capability to make adjustments in the models using add factors to cluster or submarket forecasts. This capability was added to make interventions when future events are expected to occur that the CoStar data cannot reflect. These events could include known future demolitions or conversions (such as the former U.S. embassy in Grosvenor Square in London); the anticipated arrival of a large new tenant where the specific property has not yet been identified (for example, Amazon's HQ2, before a location was determined), or natural disasters or weather events, such as hurricanes or wildfires. All such interventions are fully documented and systematically reviewed.

For hotel forecasts, interventions are deployed for non-repeating events. Large events in a market that occur the same time each year behave like seasonality and should be accounted for in the model simply by looking at past behavior in that month. Large events that are not always at the same time or place must be handled manually. For example, the Super Bowl has a dramatic impact on occupancy and ADR which cannot be predicted just from a market's own real estate history or the economic inputs, so CoStar analysts manually adjust the ADR and occupancy in the forecast for the city hosting the Super Bowl each year. CoStar maintains an events database that is manually reviewed periodically to keep it current.