Work-From-Home, COVID-19, and Online Retail Effects on Commercial Real Estate Prices*

John V. Duca
Danforth-Lewis Professor of Economics, Oberlin College
Emeritus Economist, Federal Reserve Bank of Dallas
jduca@oberlin.edu

David C. Ling
McGurn Professor of Real Estate, Hough Graduate School of Business,
University of Florida
ling@ufl.edu

December 31, 2024

Abstract

This study decomposes the effects of changes in required rates of return and expected rent growth on average national prices for the four major types of commercial property. Results imply that work-from-home (WFH) has raised capitalization rates (essentially, earnings-price ratios) for top-end commercial offices by enough to lower equilibrium prices by 25 percent. While the rise of online shopping appears to have lowered warehouse cap rates enough to boost prices by 20%, we do not find a discernible effect on apartments or retail power centers. We also find that capitalization rates react quickly to changes in required rates of return; however, the latter tends to respond with a lag to factors affecting risk premia. Finally, accounting for shifts in expected rent growth and risk premia (which incorporate WFH and online retailing effects) as well long-term interest rates, we find that prime offices and apartments remained overvalued by 5 and 30 percent, respectively, in late 2024. The potential degree of apartment overvaluation is noteworthy but may reflect a shift in fundamentals that we did not track. In contrast, prices for top quality warehouses and retail power centers appear little below current long-run fundamentals.

Key Words: Commercial real estate, office, retail, work from home, COVID, online retailing

JEL Codes: R33, E44

*****The views expressed are those of the authors and are not necessarily those of the Federal Reserve Bank of Dallas or the Federal Reserve System. We thank Jason Damm and participants at the 2024 Boca Raton Conference on Finance and Real Estate for helpful comments and suggestions. This study has benefited from long-lasting intellectual debts to our dissertation advisors Pat Hendershott and the late Dwight Jaffee, and also to Wayne Archer, John Muellbauer, Susan Wachter, and Bill Wheaton.

After being buoyed by low interest early in the pandemic, commercial real estate (CRE) prices have fallen notably since late 2021 across each of the four major property types, as shown in Figure 1. Indeed, for commercial offices and apartments the declines are of the same magnitude seen during the subprime and CRE bust of the late 2000s. While much of the common downshifts across the four property types reflect the sharp rise in long-term interest rates, there has been a notable divergence in the relative price trends across the property types since the mid-2010s. Much of this divergence reflects structural factors that have induced relative changes in valuations.

In particular, shifts in the way we shop and work, which were accelerated by the COVID-19 pandemic, have disrupted CRE markets. This is also evident in a widening dispersion of acquisition capitalization ("cap") rates across major types of CRE properties, with higher cap rates (or earnings-price ratios) seen for retail power centers and office buildings located in central business districts (CBDs), that have plausibly been hurt by COVID-induced effects, and lower cap rates for industrial warehouses that have benefited (Figure 2).[1]

Consistent with asset pricing theory, these swings align with movements in required rates of return and expected rates of net rent growth (all tax adjusted). Figure 3 shows how the pandemic, via spurring online shopping in place of brick-and-mortar store sales, altered cap rates by raising risk premiums and lowering expected rent growth on most retail properties and lowering risk premiums on most warehouse properties. [2] A similar portrayal of the channels of pandemic effects can be made for offices. The relative movements in cap rates across the major property types are paralleled by relative shifts in risk premia and expected rent growth (Figures 4 and 5, respectively).

[1]A power center is an outdoor shopping center dominated by multiple "big-box" retailers, including discount department stores, off-price stores, and wholesale clubs, but may include other businesses. Power centers are usually located in suburbs due to land costs and space restrictions. The U.S. has about 2,200 power centers (www.icsc.com).

[2] Required rates of return minus Aa-corporate bond yield. The latter is more highly correlated with required returns than are the 10-year or 20-year Treasury bond yields and the A- and Baa-rated corporate bond yields.

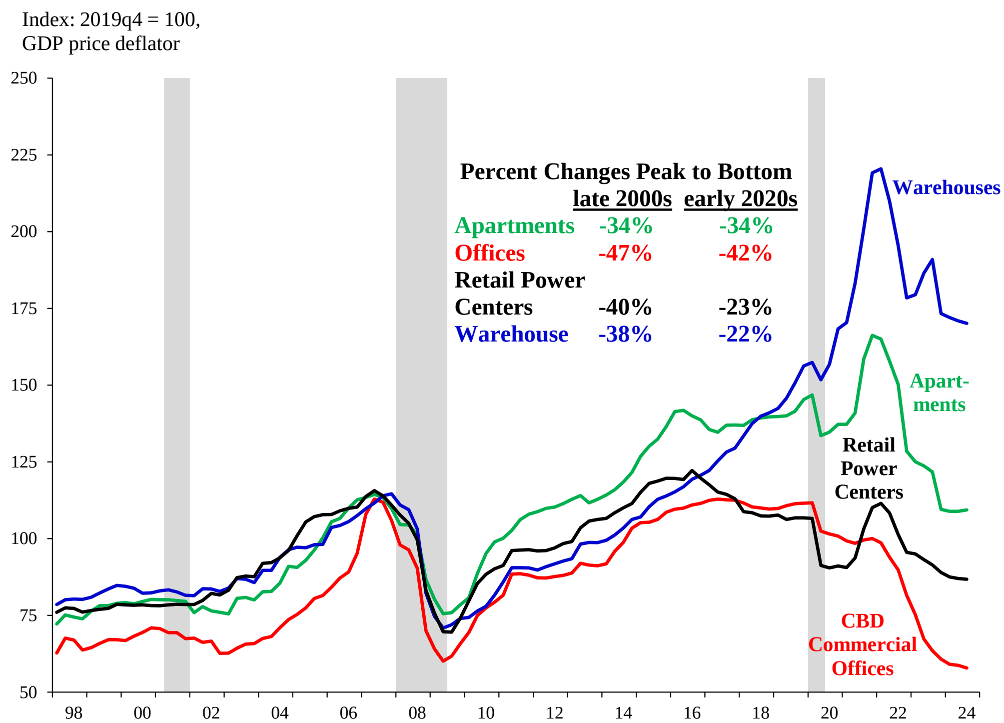

Figure 1: Real Commercial Real Estate Prices Have Swung Dramatically Lower, and Have Diverged More Since the Mid-2010s or Since COVID
(Source: SitmusAMC, BEA, and authors' calculations)

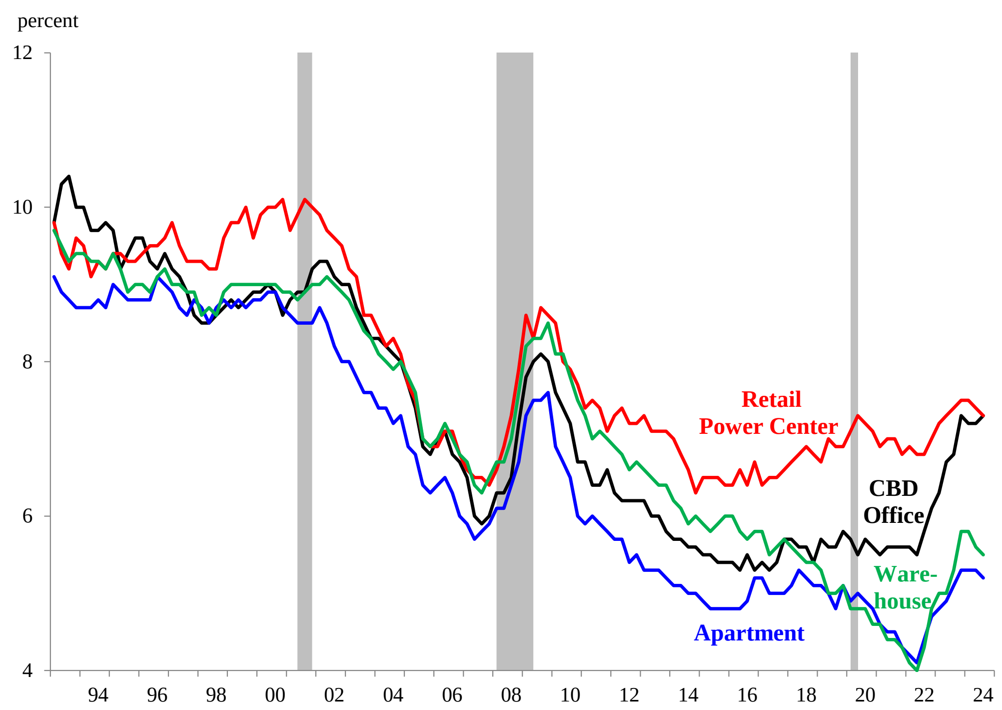

Figure 2: Capitalization Rates for CRE Property Types Have Diverged More Since COVID
(Source: SitmusAMC)

Two responses to the pandemic have had disparate effects on CRE valuations. First, as stressed by the work of Barrero, et al. (2021, 2023), a noteworthy shift to working from home (WFH) has had large negative effects on the use and valuations of commercial office space, which some real estate economists have likened to an apocalypse (Gupta, et al., 2022). In our study, we consider four indicators of WFH, each of which we aggregate from annual and monthly data provided by Barrero, et al. (2021, 2023). As discussed later, each differs in whether it tracks the overall percentage of time that employees work from home (*WFHTotal*) or is based on the share of workers who primarily work from home (*WFHPrime*) and *WFHPrimeAdj*). As shown in Figure 6, the two series jump during the early pandemic reflecting government restrictions and early pandemic caution. Although these increases have partly subsided, a prolonged upshift in WFH is visible in both series.

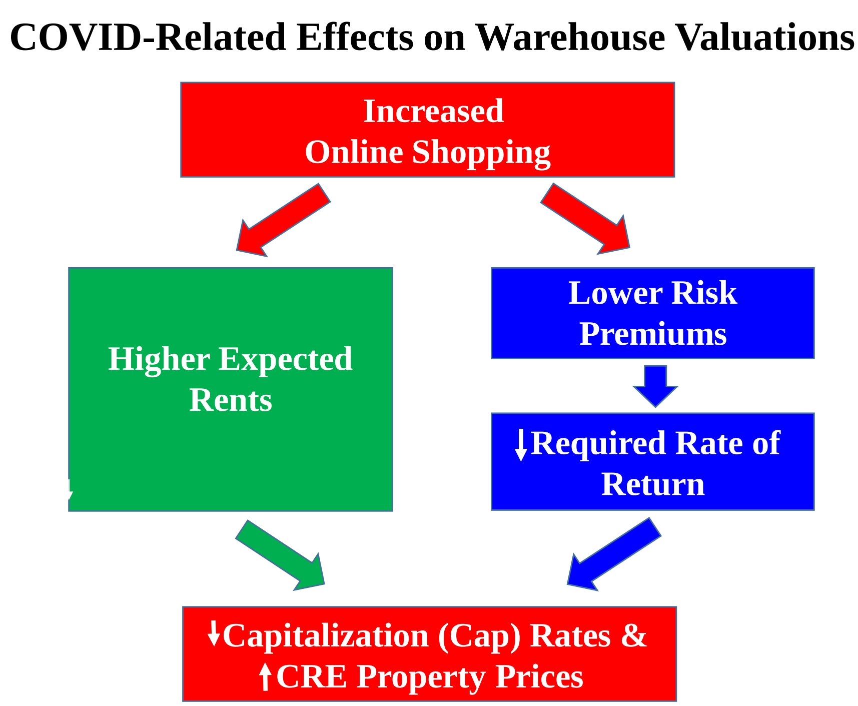

Figure 3: Via Bolstering Online Shopping, the Pandemic Plausibly Lowered Warehouse Cap Rates by Lowering Risk Premiums and Raising Expected Rent Growth

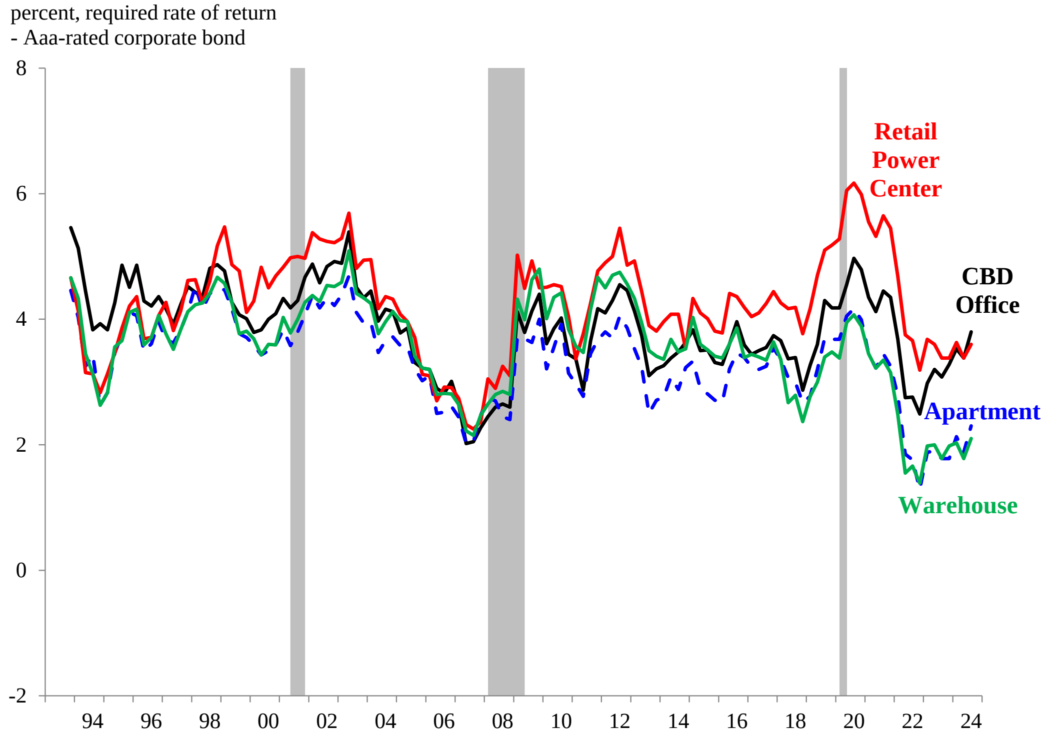

Figure 4: Risk Premia for CRE Property Types Have Diverged More Since COVID
(Sources: SitmusAMC, Federal Reserve, and authors' calculations)

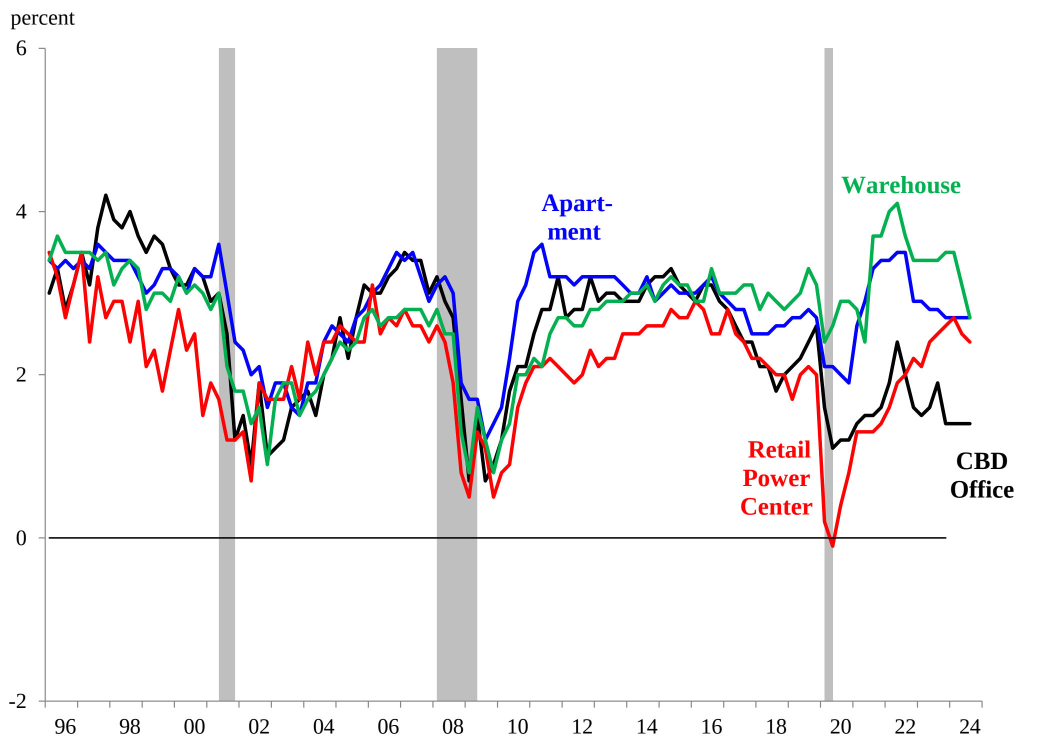

Figure 5: Expected Rent Growth for CRE Property Types Have Diverged Since COVID
(Source: SitmusAMC)

The second major response to the pandemic has been an acceleration in online retailing (OLR) tracked by the share of retail sales conducted online or via mail-order (Figure 7).[3] The rise of OLR appears to have helped push up prices of many warehouse properties. Nevertheless, much of the rapid acceleration in OLR in the early pandemic was temporary, as reactions to the pandemic induced a shift in consumer spending from services to goods that later unwound.

It is less clear whether COVID-related effects have induced a permanent upshift in OLR. For example, according to a simple cubic time trend estimated using data from 2000-19, the OLR share is about 1.5 to 2 percent above its pre-COVID trend, whereas a cubic trend estimated over 2010-19 suggests that the online share has returned to its pre-COVID path (Figure 7). It is reassuring that coefficient estimates of the long-run impact of online shopping on the risk premiums of warehouses—shown later—have the expected negative effect. Moreover, the estimated negative effects are similar in magnitude when estimated with pre-COVID or full sample data. This pattern suggests that COVID-related effects on risk premia for warehouses are well-tracked by the online share of retail sales.

Interestingly, there is not much evidence of a strong link between the share of online retail sales and the implied risk premium on investments in retail power centers. This fits with the view that OLR did not have much of an impact on (grocery-anchored) neighborhood shopping centers because people still needed the goods and services provided by grocery stores, take out restaurants, hair salons, etc…Instead, the implied risk premiums for retail power centers tended to move with the severity of government imposed COVID restrictions and vaccinations, with premiums rising early in the pandemic and then abating as government restrictions eased and as vaccination rates rose (inducing more in-person shopping).

[3] As noted in Duca (2018), the combined share of online and mail order sales internalizes shifts between them, and better tracks the net impact of the rise of online retailing on industrial warehouses needed to support such sales.

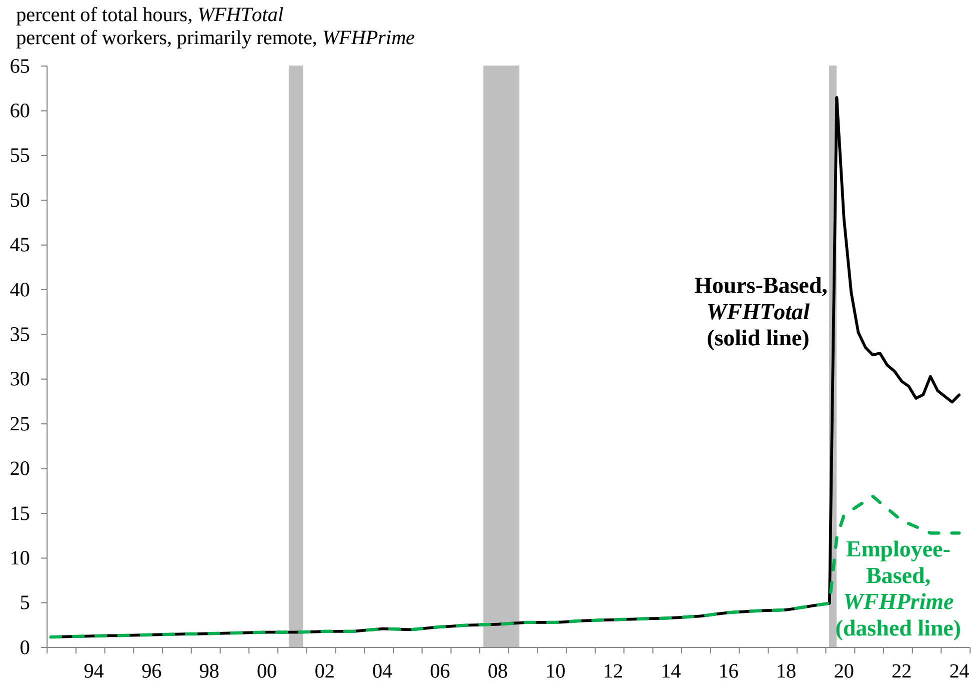

Figure 6: Work From Home Jumps During the Early Pandemic, Later Ebbs Some, and Remains Above Pre-Pandemic Trends
(Sources: Census, Barrero, et al. (2021, 2023), and authors' calculations)

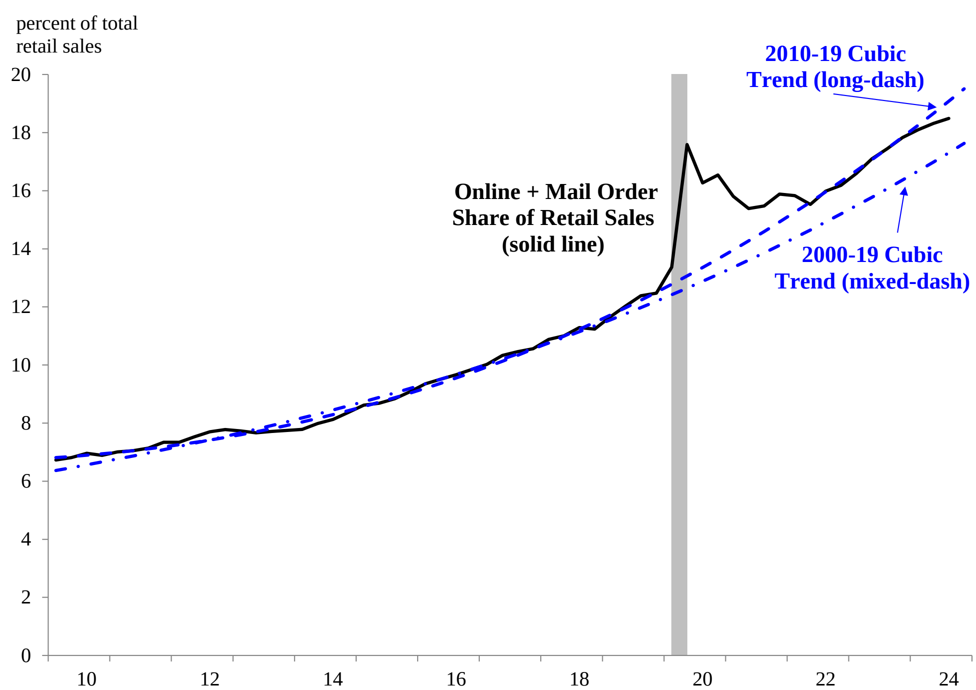

Figure 7: The Online Share of Retail Sales Jumped Above Its Pre-Pandemic Upward Trend Early in the Pandemic Before Later Subsiding
(Sources: Census and authors' calculations)

In addition to its effects on the valuations of commercial office, retail power centers, and warehouses, COVID initially reduced demand to live in center cities while raising it in outer, less dense suburbs, giving rise to a "donut effect" on residential property valuations (see Ramani and Bloom, 2022; Rosenthal et al., 2021). While this effect has likely bolstered the demand for, and prices of, owner-occupied housing (Duca, et al., 2021; and Murphy, Duca, and Muellbauer, 2024), the impact on apartment prices may be more nuanced initially reflecting the countervailing effects of a decrease in demand for less socially-distanced multifamily housing units (see Duca, et al., 2021) and higher WFH-related demand for larger sized residences (see Mondragon and Wieland, 2022).

Although a large literature investigates the effects of the COVID pandemic, WFH, and OLR on CRE markets, these studies tend to use short times series and local data. Our study complements this literature by providing a more macro and long-run assessment of these important events and trends that is useful for three important reasons. First, because the COVID Recession prompted a sharp drop in long-term interest rates that rapidly reversed in the economic recovery, the swings in CRE prices reflect the effects of cyclical and new secular influences. For this reason, it is important to gauge when CRE valuations are likely to hit bottom. By incorporating key features from our required rate of return models into long-run error correction models, we separate the role of traditional factors on CRE valuations (e.g., interest rates) from the effects of WFH, OLR, and other aspects of the pandemic. This is important because the initial, negative effects of COVID on retail and office prices may have been partially offset by the support to prices that emanated from conventional and unconventional monetary policy that lowered long-term interest rates, as well as by the support to individuals and firms from unconventional fiscal policies.[4]

[4] Temporary policy changes during the pandemic, stimulated the economy. The CARES Act authorized payments of $1,200 per adult plus $500 per child for individuals and couples making up to $75,000 and $150,000, respectively.

A second useful aspect of our study is that it sheds light on CRE pricing that has ramifications for construction and development. The large transactions costs, heterogeneity across properties, and illiquidity that characterizes CRE transactions generate significant lags in adjustments to shocks (see, *inter alia*, Wheaton and Torto, 1990) that manifest in long swings in construction and development activity.

These implications and the aggregative focus of our study make our findings relevant in a third way. CRE lenders on existing properties are primarily banks and holders of CMBS (see Faria-e-Castro and Jordan-Wood, 2023). CRE comprises about 20 percent of commercial bank assets. CRE equity investors tend to hold property portfolios for asset diversification purposes, and as such the price behavior of property classes is more relevant than subsets or individual properties. Large bank exposures to CRE have threatened financial stability in the past. For example, the collapse of an overbuilt office market damaged many commercial banks in the 1990s and CRE loan losses triggered credit crunches then and in the Great Recession (Meeks, 2008). Indeed, Antoniades (2015) shows that CRE losses drove more bank failures in the Great Recession than residential real estate losses, while CRE losses triggered the failures of both Bear Stearns and Lehman Brothers that contributed directly to the Global Financial Crisis (see Duca, et al., 2021, p. 779, footnotes 7 and 10).

Our study analyzes the impact of trends in WFH and OLR, as well as the effect of past government restrictions, on CRE risk premia and capitalization rates. To establish our findings, Section 2 briefly reviews the literature on the effects of WFH, COVID-19, and OLR on CRE. Section 3 presents our baseline- and modified dynamic models, and Section 4 discusses the data we use. Results regarding cap rates and risk premia are presented in Sections 5 and 6, respectively, while the conclusion provides perspective on our findings.

2. Overview of Related Literature and Findings

The COVID19 public health shock produced immediate declines in listed CRE prices (e.g., Ling et al., 2020) and a reorganization of the spatial relationship between where we live and where we work (Ghosh et al., 2022). However, the COVID 19 pandemic was also accompanied by rapid improvements in, and adoption of, information and communication technologies. Many office workers have forcefully expressed a desire to work from home for at least a part of the work week. The percentage of days worked from home stabilized at 30 percent in the immediate aftermath of the pandemic (Barrero et al., 2021) and office occupancy remains low in the largest U.S. cities. Whether workers are more productive when they work from home or other remote locations is still being debated (Bloom et al., 2015, Morikawa, 2022, Gibbs et al. 2023). Nevertheless, work from home has quickly become widespread among "skilled" workers, at least for some of the work week (Dingel and Neiman, 2020; Adams-Prassl et al., 2022; and Kawaguchi and Motegi, 2021).

WFH, or teleworking, is profoundly affecting real estate markets. As noted above, the "lockdowns" that resulted from the onset of the COVID19 pandemic emptied office buildings and crippled the economies of most urban areas. This urban flight increased the demand for non-urban apartments and single-family homes, often leading to increased prices in suburbs and increased household demand for more living space to accommodate WFH (Liu and Su, 2021; Gokan et al., 2022; Brueckner et al., 2023; and Van Nieuwerburgh, 2023). Although evidence suggests that natural disasters tend to have only transitory effects on city structure (Davis and Weinstein, 2002; Ouazad, 2021), factors that alter worker productivity, such as information and communication technology, tend to have more permanent effects. The model developed by Davis et al. (2024) predicts that the COVID-induced shock to the productivity of working from home will have long-lasting effects on the structure of cities, which is consistent with the findings of Ouazad (2021).

Many office users are paying for space that is notably underutilized, and most are expected to downsize substantially when their leases expire (Gupta et al., 2022) if they do not default before then. These developments have put downward pressure of office valuations, although evidence suggests that “prime” office space is weathering the downturn better than older, less well-located properties. However, the lack of sale transactions since the Federal Reserve started aggressively raising interest rates in early 2022 has made price discovery difficult. Although much uncertainty exists, declining office values and mortgage rates that have at least doubled since early 2022 will make the refinancing of maturing CRE loans difficult, and it is estimated that more than $2 trillion of CRE mortgage debt will come due by 2027. Most CRE debt is held by small and medium size banks, which has raised concerns about the stability of the U.S. banking system.

The estimates of future CRE rental rates and prices needed to value CRE assets must also factor in supply responses. Although the supply of new retail and office properties has slowed to a near stop in most markets, a large excess supply of office buildings currently exists. This has led to the adaptive reuse of some office properties, with a focus on conversions to rental apartments. The extent to which such conversions can absorb the oversupply of office buildings will depend on may factors, including the magnitude of office valuations in a local market, the extent to which it is physically feasible to convert these properties into rental apartments, and the degree to which local planners and land use codes adapt to changes in the relative demand for different land uses.

Telecommuting has received increasing attention in the management and psychology literature (Behrens et al., 2024),[5] while theoretical work on the effects of WFH on real estate markets is in a nascent stage, spurred on by the onset of COVID19. Brueckner et al. (2023) and Brueckner and Sayantani (2023) consider how WFH affects the relative size of two cities in which

[5] Allen et al. (2015) provides a survey of this literature that contains several hundred citations.

workers can move between cities but commuting within cities is not considered. In contrast, Gokan et al. (2022), Kyriakopoulou and Picard (2023) and Monte et al. (2023) model the effects of WFH on the structure of cites. Behrens et al. (2024) develop a general equilibrium model with skilled and unskilled workers, the latter of which cannot work from home. In their model, endogenous work arrangements determine worker productivity, salaries, and demand for office buildings and apartments. They find that firms “outsource” workers to their homes to reduce costs, especially in high-cost markets. This finding contrasts with the popular notion that office workers are resisting employer pressure to return to the office and with new evidence that face-to-face communication remains more efficient than communicating through information and communication technologies (Battiston et al., 2021 and Davis et al.,2024). Delventhal et al. (2022) and Kyriakopoulou and Picard (2023) find that WFH induces spatially concentrated jobs and monocentric cities, respectively, with clear consequences for urban and suburban land uses and relative prices.

Due to the complexities of modeling the effects of WFH on productivity, wages, land uses, and real estate prices, it is not surprising that most of the recent literature on WFH is empirical. Moreover, much of this literature focuses on residential housing. The COVID19-induced urban-to-suburban migration of households has lowered demand, and therefore rents and prices, in urban areas, while increasing demand and prices in the suburbs of these markets, which resulted in the flattening of the price gradients that is more pronounced in MSAs with larger proportions of skilled workers who can work remotely (Ghosh et a., 2022, Gupta et al., 2022). Haslag and Weagley (2024), Liu and Su (2021), and Ramani and Bloom (2022) also document an increased tendency toward suburbanization in the immediate aftermath of the COVID19 pandemic; Biljanovska and Dell’Ariccia (2024) find that the pattern of increasing suburban house prices relative to urban centers produced by the pandemic continues to be observed in the largest 30 U.S. MSAs.[6] In addition, cities that more heavily regulate land use and building codes, as well as local housing markets that are supply inelastic for other reasons, have displayed more pronounced flattening of the residential price gradient (Gupta et al., 2022). Finally, Ramani and Bloom (2021) find that city size also appears to be related to the degree of suburbanization of housing demand post COVID19.

Given the tendency of some industries to cluster in space, the long-run pricing effects of WFH on the demand and supply of real estate are likely to be unevenly distributed across real estate markets (Ghosh et al., 2022). Nevertheless, understanding the short- and long-run effects of WFH on CRE markets entails macroeconomic analysis of COVID19 and WFH on CRE required equity rates of return and pricing. One reason is that frictions in CRE markets give rise to lagged adjustment to shocks and long property cycles. Another is that because the recent CRE downturn reflects both an interest rate cycle and new secular trends, its severity and eventual end will reflect both macroeconomic as well as property specific secular shifts. Finally, because CRE assets are illiquid and have long down cycles, it is difficult to resolve CRE losses, which coupled with portfolio exposures to CRE, can threaten financial stability and induce credit crunches (Duca, et al., 2021).

E-Commerce, including on-line shopping, has received much attention in many literatures, including Transportation (Hsiao, 2009), Marketing (Kim et al., 2007), Urban Studies (Kim et al., 2005), Information Systems (Koo et al, 2010), and Psychology (Peterson et al., 2003). As on-line shopping began to expand in the 1990s, many researchers, such as Graham and Marvin (2002), also began to explore the effects of e-commerce on CRE markets, especially retail properties (e.g., Zhang et al., 2016; Worzala et al., 2002; Sing, 2005; and McClatchey et at., 2007. Although most

[6] Biljanovska and Dell'Ariccia (2024) also report find Denmark, France, and the United Kingdom did not experience a trend toward increased suburbanization or flattening of the residential price gradient.

“bricks and mortar” retail shopping was hard-hit by COVID19 shutdowns, online retail sales surged during the COVID-19 pandemic, although this change in behavior was an acceleration of an existing trend. The online share of retail sales has subsided to its pre-COVID19 trend (Figure 7); however, the continued rise in OLR has broad implications for the demand for physical retail space and the warehouse space needed to store these to-be-delivered retail goods. In particular, the future success of both retail and warehouse properties within and across cities will require the appropriate balance of traditional retail properties and warehouse space (Balemi et al., 2021).

Similar to the effects of WFH, the expected effects of OLR on CRE will vary by property type and across and within cites. However, in addition to these “micro” effects, we seek to understand the broad implications of OLR on the pricing of four CRE property types. This, in turn, requires analyzing how much OLR affects the expected level and riskiness of future rents and property prices, as well as its effects on the rates of return required by equity investors, while controlling for the general level of interest rates and other macroeconomic variables.

3. Baseline and Modified Empirical Models

We estimate structural models based on theoretical cap rate models following several studies [Chervachidze and Wheaton, 2013, Sivitanides, Torto and Wheaton (2001), Hendershott and MacGregor (2005), Plazzi, et al., (2010), Sivitanidou and Sivitanides (1999), and Duca and Ling (2020)]. We find that cap rates move one-for-one with the tax-adjusted difference between the pre-tax required rate of return minus the expected growth rate of rents. This difference is often referred to as the “user cost of capital.” Digging deeper, we develop long- and short-run models of the required rate of return on properties by adding proxy variables for the implicit time-varying risk premium which is added to a time-varying, long-term private bond yield. We use an error-correction framework, which allows required rates of return to adjust with a lag to new information. As stressed by Duca and Ling (2020), partial adjustment in CRE risk premia reflect illiquidity and market inefficiencies, “such as high transaction costs, lengthy decision making and due-diligence periods, informational inefficiencies, and significant limits to arbitrage (short-selling).”

3a. Baseline Pre-COVID Long-Run Cap Rate Relationships:

We estimate the equilibrium cap rate using a discounted cash flow model for valuing commercial property. Following Duca, Hendershott, and Ling (2017), if a property’s net operating income (*NOI*) grows at a constant rate (g_t,) over the relevant investment horizon and the net selling price of a property is expected to remain a constant multiple of *NOI*, the equilibrium price P_t^e of an all equity-financed investment, adjusted for the present value of tax depreciation *(taxdep*), equals:

$$(1 - taxdep)\, P_t^e = \frac{NOI_1}{r_t - g_t} \tag{1}$$

where *r* is the unlevered equity discount rate and time (t) is measured in quarters. By implication, the equilibrium cap rate (NOI/P^e) is:

$$CapRate^e{}_t = (r_t - g_t)(1 - taxdep_t) \equiv Usercost, \tag{2}$$

where $(r_t\text{-}g_t)(1 - taxdep_t)$ can be interpreted as the after-tax user cost of capital rate (*Usercost*). *r* and *g* are directly measured in the SitmusAMC survey (discussed below) and *taxdep* is calculated as in Duca, Hendershott, and Ling (2017). A simple long-run equilibrium cap rate ($CapRate^e$) relationship can be estimated:

$$CapRate^e{}_t = \beta_o + \beta_1\, Usercost_t + \varepsilon_t\,, \tag{3a}$$

where $\beta_1 \approx 1$ and ε_t is an i.i.d. residual. Using Johansen’s (1995) approach, the long run relationships in eq. (3a) can be jointly estimated with a model for short-run changes in the cap rate:

$$\Delta CapRate_{jt} = \alpha_0 + \alpha_1 EC_{t\text{-}1} + \sum\beta_i\Delta(CapRate_j)_{t\text{-}i} + \sum\theta_i\Delta(UserCost)_{t\text{-}i} + \delta S\text{-}runVar_t + \varepsilon_t \quad (3b)$$

where changes in time *t* help close the time *t*-1 gap between the actual and estimated equilibrium cap rate (EC_{t-1}). Cap rate changes are also driven by prior short-run changes in the long-run variables and short-run exogenous factors (*S-runVar*). As discussed later, reflecting that Sitmus-AMC user costs and cap rates move very closely together for each of the major property types, we find that $\beta_1 \approx 1$; that is, the adjustment of cap rates to user costs conforms to theory.[7]

3b. Baseline Pre-COVID Long-Run and Short-Run Models of the Required Rate of Return:

The discount rate or required rate of return (*r*) in eq. (2) can be modeled as the benchmark bond yield (*benchmarkyield*) plus an additional risk premium, $r^{prem}{}_t$:

$$rrr_t{}^* \equiv benchmarkyield_t + r^{prem}{}_t \qquad \text{(pre-COVID baseline)} \qquad (4)$$

There are several possible benchmark yields for CRE assets. While a long-term Treasury yield is often used, for an asset that trades in an illiquid private market, such as CRE, the more relevant benchmark and substitutable asset is a highly rated corporate bond. Indeed, we find that the Aaa-rated corporate bond yield (*Aaa*, Moody's) is more correlated with required equity returns on CRE than are the 10- or 20-year Treasury bond yields and the Aa-, A- and Baa-rated corporate bond yields. Using the Aaa corporate yield, eq. (4) becomes:

$$rrr_t{}^* \equiv Aaa_t + r^{prem}{}_t \qquad \text{(pre-COVID baseline)} \qquad (5)$$

implying that the required rate of return on CRE includes the liquidity and default risk premiums of an Aaa-rated bond plus an additional CRE risk premium, r^{prem}.[8]

We find two time series proxy variables to be very useful in tracking pre-COVID time variation in CRE risk premiums. The first draws from Duca and Ling (2020) and is the effective

[7] Since the AMC-Sitmus data track required rates of return we avoid using proxy variables for them that introduces error and results in cap rates partially adjusting to imperfect measures of user costs (as in Duca, et al., 2017).
[8] In a related, but different framework Duca and Ling (2020) impose the 10-year Treasury yield as a benchmark and use the Baa-Treasury spread to track business cycle risk.

required capital ratio (*CapReq*) for holding or issuing commercial mortgage-backed securities (CMBS). The greater the regulatory capital that banks are required to hold on commercial mortgages or CMBSs, and on CMBS that they have issued but no longer hold (under Basel III, aka the Dodd-Frank Act), the more downside tail risk they bear for which they charge higher borrowing costs. Because these regulations apply to all commercial mortgages and CMBS, *CapReq* plausibly affects the equity risk premium on each property type.

To control for short-run time variation in risk premia we include among our short-run variables *GLEI*, the two-quarter percent change in the Index of Leading Economic Indicators (Conference Board), which is often used as an indicator of future real GDP growth. The higher is *GLEI*, the better is the economic outlook and the lower may be the cyclical risk that affects ex ante risk premia. However, because *GLEI* is stationary and to avoid simulatneity, we include its t-1 lag among the short-run variables used to model the change in the required rate of return. To some extent, the spread of Aaa-rated corporate bonds over long-term Treasury yields reflects variation in macroeconomic or business cycle risk (see Jaffee, 1975). However, including *GLEI* as a proxy for time variation in risk premia in eq. (5) can capture variation in equity risk premiums for property types that are more vulnerable to business cycle risk than Aaa-rated corporations.

Substituting *CapReq* plus a constant for r^{prem} into an estimable version of eq. (5) yields:

$$rrr_t^* \equiv \alpha_0 + \alpha_1 Aaa_t + \alpha_2 CapReq_t + \varepsilon_t \qquad (6)$$

which is the long-run pre-COVID baseline relationship for each property type, and $\alpha_2 > 0$. If the risk of an equity investment in property is roughly the risk of investing in Aaa-rated bonds, $\alpha_1 \approx 1$.

Required rates of return may take time to reach their long-run equilibrium levels, as suggested by Figure 8 in which the required rates for warehouses and CBD office tend to lag slightly behind the Aaa corporate bond yield. In an error-correction framework, the change in the

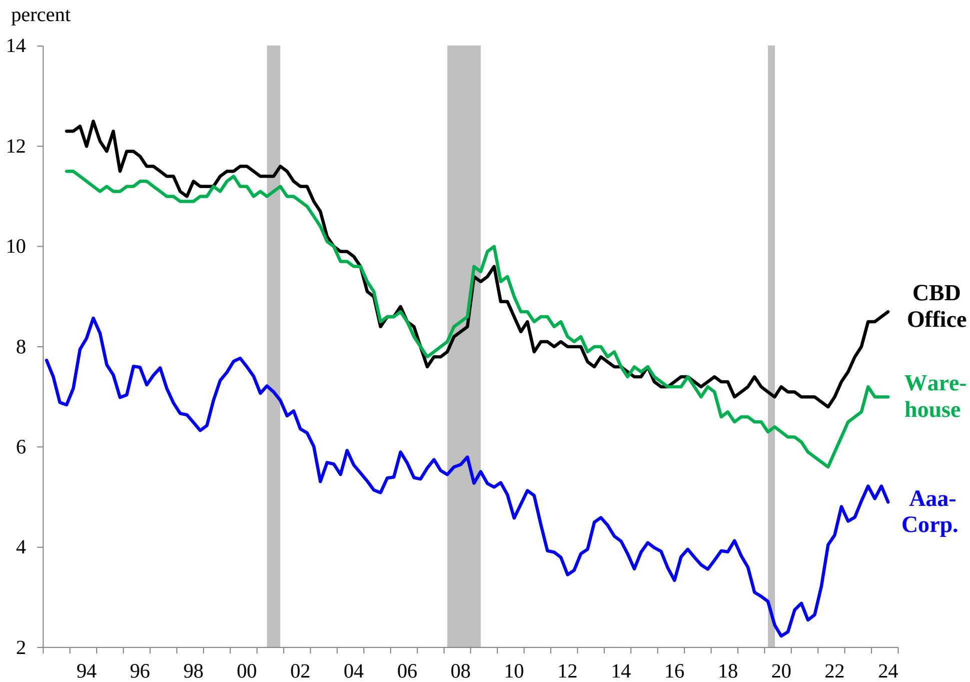

Figure 8: Required Rates of Return on CRE Properties Tend to Lag Slightly Behind the Aaa Corporate Bond Yield
(Source: SitmusAMC)

required rate of return reacts to the *t*-1 gap between the actual and estimated equilibrium required rates of return (EC_{t-1}), to prior short-run changes in the long-run variables, and to short-run exogenous factors (*S-runVar*, e.g., $GLEI_{t-1}$):

$$\Delta rrr_{jt} = \alpha_0 + \alpha_1 EC_{t-1} + \sum\beta_i\Delta(rrr_j)_{t-I} + \sum\theta_i\Delta(CapReq)_{t-i} + \delta S\text{-}runVar_t + \varepsilon_t \qquad (7)$$

where $EC \equiv rrr$–- rrr^*_j, eq. (7) is the short-run equation corresponding to the long-run eq. (6); Jointly estimating eqs. (6) and (7) using Johansen's (1995) method yields estimates of the long-run coefficients on the determinants of required rates of returns and estimates of how short-run changes reflect error-correction toward long-run equilibrium.

In addition to $GLEI_{t-1}$, we included several exogenous shock variables in the short-run (but not long-run) models of the change in required rates of return to control for unusual and large temporary shocks to risk premia whose effects as outliers could obscure long-run relationships or induce second-degree autocorrelation in errors by causing a sudden jump followed by a drop in required rates of return. Three shocks pertain to the subprime and global financial crisis of the mid- to late 2000s. The first variable, *DSubPrFail* is a dummy for possible portfolio substitution toward CRE and away from subprime investments when investors reacted to 25 failures of subprime institutions in mid-February through March of 2007 that portended and foreshadowed the subprime bust. Reflecting the occurrence late in 2007q1, *DSubPrFail* equals 0.5 and 1 in 2007q1 and 2007q2, respectively, and 0 otherwise. The second dummy, *DLehman* (= 1 in 2009q1, 0 otherwise) controls for the unusual jump in required rates of return on all four property types in 2009q1 following the collapse of Lehman Brothers. The third, *DEuroCrisis* (=1 in 2009q4, and 0 otherwise), controls for a sudden jump in required rates of return in 2009q4 when the onset of the European debt crisis was viewed a potential global economic threat (akin to a second Lehman Brother's failure). This effect on the required rates of return is evident for office, apartment, and warehouse properties but not for retail power centers. The expected signs on *DLehman* and *DEuroCrisis*, are positive, while that on *DSubPrFail* is negative.

A fourth shock variable is only included in the short-run model of required rates of return for warehouses, rrr^{ware}. The t-1 lag of this variable, Δ*TaxOppZone* (=1 in 2018q1, 0 otherwise) controls for a large drop in rrr^{ware} in 2018q2, when investors became aware of provisions in the 2017 Tax Cuts and Job Act (TCJA) that greatly expanded tax breaks for opening facilities in opportunity zones, some of which were very suitable for warehouses.[9] These provisions allowed investors to avoid taxes on 10%, 15%, and 100% of a capital gain if the investment is held for at least 5, 7, and 10 years, respectively. This provision plausibly lowered rrr^{ware}. As an alternative, we also tested a level shift dummy *TaxOppZone* (=1 since 2018q1, 0 before) that enters the long-

[9] Warehouses are particularly suitable for this tax advantage as they are relatively generic buildings and the use of robotics reduces the need for recruiting a sizable workforce. Also favoring warehouses over other CRE types is the appeal of locating warehouses supporting online sales near metro areas and using lower cost land in opportunity zones. Indeed, Amazon was very aggressive in locating new warehouses in such zones (Zakrzewski, 2021).

run relationship.

A fifth short-run shock variable is included in the short-run model for retail power centers. This variable, *D2014q4* (=1 in 2014q4, and 0 otherwise) controls for a negative outlier in 2014q4, when surveyed required rates of return oddly dipped 50 basis points while Aaa corporate yields continued to rise. Its coefficient is expected to be negative. Including the short-run shock variables either eliminates serial correlation in the residuals for the short-run equations or slightly strengthens the significance of long-run relationships without resulting in any noticeable change in the estimated long-run coefficients. These considerations, plus the unusual nature of the shocks underlying these variables, make them reasonable to include as exogenous short-run shocks. Finally, for the retail power center models we include *DY2K* = 1 in 1999q4 at height of the Internet stock boom, -1 in 2000q2 at the start of Internet stock bust and 0 otherwise. This variable tracks fears that software glitches would aid brick and mortar sales at the expense of online sales when the century date change posed potential disruptions to information technology that supported online shopping. The temporary drop in required rates of return on retail power centers reversed in the quarter after century date change (2000q2) when those fears proved unfounded. Accordingly, *DY2K* expected to have negative effect on rrr^{ret}.

3b. Post-COVID Long-Run Cap Rate Relationships:

In principle, agents' estimates of future rent growth (g), net of operating expenses and capital expenditures, would reflect the expected short- and long-run impact of the COVID pandemic-related effects on expected net rents. Moreover, uncertainty about the effect of the pandemic on net rents and future sale prices should be reflected in the risk premia embedded in required rates of return. For this reason, adding work-from-home (*WFH*) or online retail sales (*OLR*) variables to our cap rate equation (6) should not add marginal information beyond that already embedded in expected net rent growth and the risk premia—and their inclusion may result in some multi-collinearity. Nevertheless, we estimate the following long-run cap rate equation:

$$CapRate^{e}_{t} = \beta_{o} + \beta_{1}\, Usercost_{t} + \beta_{2}\, [WFHTotal_{t} \text{ or } WFHPrime_{t} \text{ or } OLR_{t}] + \varepsilon_{t}\,, \qquad (8)$$

where ε is an i.i.d. residual and the null hypotheses are that $\beta_2 = 0$ and, as before, $\beta_1 \approx 1$. However, β_2 and β_i may not equal 0 if some SitusAMC survey respondents report near-term rather than long-term assessments of future rent growth or do not incorporate an implicit risk premium that fully reflects COVID-related effects in their estimate of the required rate of return.

3c. Post-COVID Long- and Short-Run Effects on Required Rates of Return

It may be more plausible that the pandemic has affected cap rates by altering the expected growth rate of rents (tracked by readings on *g* from SitusAMC) and/or the risk premia embedded in required rates of return from that survey. Accordingly, our empirical approach is to assess the effects of COVID, work-from-home, and online retail sales on CRE valuations.

Because WFH and OLR reflect large and potentially long-run changes in the demand for Space, and both are I(0) variables, it is appropriate to test their effects by including them in the long- and short-run equations for the required rates of return for warehouses, offices, and apartments.

In analyzing required rates of return and cap rates for samples extending into 2024, we find that adding the online share of retail sales to the factors affecting the required rate of return for warehouses yields a well-behaved full sample model:

$$rrr^{*ware} = \alpha_0 + \alpha_1\, Aaa_{t} + \alpha_2\, CapReq_{\,t} + \alpha_3\, OLR_{\,t} \qquad (9)$$

where the subscript *ware* denotes warehouses. The null hypothesis is that $\alpha_3 > 0$. Appropriate adjustments are made to the corresponding short-run model of changes in *rrr*.

For offices, instead of adding *OLR* as an explanatory variable, we assess the marginal importance of COVID-related effects by including several *WFH* variables:

$$rrr^{*off} = \alpha_0 + \alpha_1 \, Aaa_t + \alpha_2 \, CapReq_t + \alpha_3 \, WFH_t \qquad (10)$$

where superscript *off* denotes CBD offices. The null hypothesis is that $\alpha_3 > 0$. This results in a well-behaved cointegration model for the full-sample period. Appropriate adjustments are made to the corresponding short-run model of changes in *rrr* for apartments.

Because most rental apartments are less easy to adapt for working at home than are detached homes, it is unclear a priori, whether WFH should affect risk premia on apartments. We test for possible effects by adding *WFH* to the long-run, required rate of return model (eq. (6)):

$$rrr^{*apt} = \alpha_0 + \alpha_1 \, Aa_t + \alpha_2 \, CapReq_t + \alpha_3 \, WFH_t \, . \qquad (11)$$

where the superscript *apt* denotes apartments, the null hypothesis is that $\alpha_3 < 0$, and appropriate adjustments are made to the corresponding short-run model of changes in *rrr*.

3d. Post-COVID Effects on Required Rates of Return for Retail Power Centers

As discussed earlier, patterns of required rates of return and expected net rent growth suggest that the largest effects of the pandemic on aggregate variation in retail power center valuations may be more temporary than those affecting other property types. Neither significant nor sensible estimates arise when we add the online share of retail sales to the long- and short-run equations for the required rate of returns for retail power centers (tre^{at}). Instead, the time variation in the combination of government-imposed restrictions and the mitigating effects of vaccinations on household willingness to shop in person are plausible factors affecting the valuation of retail power centers.

Following Bordo and Duca (forthcoming), we add the Oxford Blavatnik Center's index of government-imposed COVID restrictions (*GRest*) to our models, which is adjusted for the share of fully vaccinated adults (*Vax*, in decimals) by multiplying *GRest* by (1-*Vax(t-1)*). Because the resulting variable, *GRestVax* (see Figure 9), reflects temporary and largely exogenous influences, we include it only in the short-run equation (eq. (8)) when estimating eqs. (7) and (8) jointly. We later draw out the cumulated effects of a series of positive observations of these variables by using the speed of error correction to gauge how the effects wear out. This allows us to track these medium-run effects of COVID on the required rates of return for power centers over 2020-23.

4. Data and Variables

Some of the data series that we use are discussed above. These include the online share of retail sales (*OLR*) from Duca's (2018) calculations based on underlying Census data and measures of government imposed COVID restrictions and their interaction with vaccination rates (*GRest*, and *GRestVax*) from Bordo and Duca (forthcoming). Important details on the primary real estate and work-from-home variables are reviewed in this section.

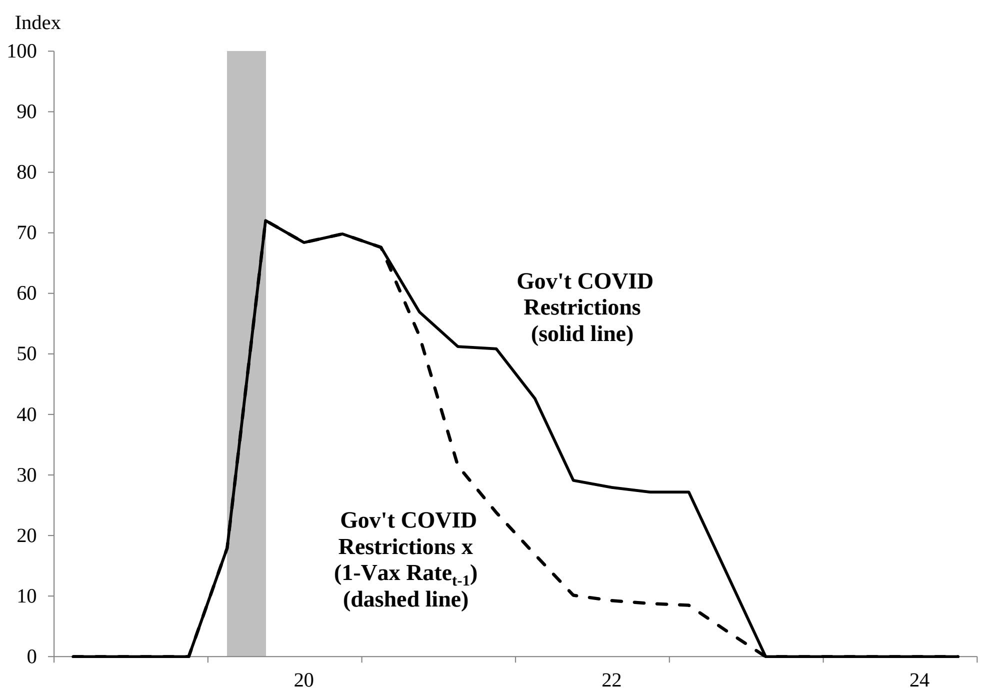

Figure 9: Variables Tracking Government-Imposed COVID Restrictions and Vaccinations
(Sources: Oxford Blavatnik Center, *OurWorldinData*, and authors' calculations)

4a. Core Real Estate Data

We follow Duca and Ling (2020) by drawing most of our key CRE variables from the quarterly *Real Estate Investment Survey* published by SitmusAMC. This report produces the results of a survey of U.S. CRE investors, lenders, fee appraisers, and managers about acquisition cap rates, unlevered required rates of return on equity, and expected rental growth rates for institutional grade properties owned and financed by institutional investors, such as life insurance companies, pensions, endowments, private equity funds, investment banks, and real estate investment trusts. The survey data track mean reported cap rates and required rates of return (*rrr*) in the market for notional, stabilized, institutional grade properties of constant quality, and thus avoids the noise in data series that abstract cap rates from the transaction prices of a sample of heterogeneous properties that happen to be sold in a particular quarter. To avoid readings that lag actual changes in required cap rates and discount rates, the survey specifically asks respondents to indicate what cap rates and required rates of return they are observing in the current survey quarter on transactions of a standard (hypothetical) property.[10,11]

A second advantage of the SitmusAMC data is that it provides data on required unlevered rates of return and expected rent growth that can be used to sort out the effects of traditional drivers of CRE valuations (e.g., interest rates and risk factors) from those of emerging WFH and OLR trends that alter risk in unusual ways. A third advantage is that all of these key variables are from the same data source, which avoids distortions that may arise from using multiple data sources.

4b. Tracking Work-From-Home (WFH)

We use two indicators of WFH. For each, quarterly readings before 2020:q2 are

[10] For example, cap rate data from the American Council of Life Insurers (ACLI) that track aspects of the CRE mortgages bought by life insurers, can be distorted by a handful of heterogeneous sales in some quarters.
[11] For more details, see https://store.rerc.com/collections/real-estate-report.

interpolated from several spliced annual series, including irregularly spaced annual readings from the American Heritage Time Use Study (AHTUS) through 1998, annual readings from the American Time Use Survey (ATUS) from 2003 to 2019, and 2019-2020 Census data on workers who primarily are home-based from Gumber and Burrows (2023).[12,13] *WFHTotal* splices quarterly interpolations of the break-adjusted, smoothed annual share of jobs that are primarily conducted from home over 1975-2020q1 with the quarterly share since 2020q2 of the percent of employee work-time that was worked from home (primarily or secondarily), aggregated from monthly data provided by Barrero, et al. (2021, 2023).[14]

A second measure, *WFHPrime*, linearly interpolates annual Census readings of employees who primarily work from home into a quarterly series. This measure displays much less of a rise in 2020 and a fallback in 2021. Its advantage is that it focuses on employees who primarily work from home. Such workers should affect the demand for office space more than those who partially work from home, but primarily work at their employers' offices. *A priori*, it is unclear whether the hours-based (*WFHTotal*) or worker-based (*WFHPrime*) measures of WFH are more informative for modeling required rates of return. *Table 1* contains a list of all regression variables and their definitions.

[12] The AHTUS data displayed slow and fairly smooth upward trend before 1998 that extended nicely through the 2003 reading from the AHUS. Hence, splicing and interpolating the AHTUS and AHUS readings is not problematic.

[13] There is a break in the annual series from 1975-2019 that we account for in all four series. The original methodology used to create ATUS readings until 2019 caused survey bias for 2020. Gumber and Burrows (2023) of the U.S. Census recalculated the 2019 and 2020 data to eliminate the bias, revising WFH to 4.7 % from the original 5.7%. We adjust pre-2019 WFH rates by multiplying the original data by the ratio (4.7/5.7) before splicing them onto 2019-2022 data. Owing to evidence of a jump in WFH in May 2020, we use the slight upward trend in annual data from 2018 to 2019 to interpolate a 2020q1 reading for all series. The two series differ in how they are constructed since 2020q2.

[14] Each series temporarily spikes in 2020q2 and partly unwinds in 2020q3 owing to the government shutdown of the economy in 2020q2 followed by a reopening in 2020q3. We tested alternative measures for *WFHTotal* and *WFHPrime* that replaced the 2020q2 and 2020q3 readings of each with the 2020q4 reading. The unadjusted WFH series outperformed their adjusted alternatives in both the long- and short-run models of required rates of return.

4c. Statistical Properties of Key Variables

Table 2 provides summary statistics for our key variables, with superscripts denoting the property type for commercial offices (^{off}), apartments (^{apt}), retail power centers (^{ret}), and industrial warehouses (^{ware}). Each series displays at least some serial correlation in short-run changes, with changes in required rates of return displaying less correlation and changes in expected rents exhibiting some negative short-run serial correlation. Cap rates and required rates of return for each of the four property types vary notably over time, are nonstationary in levels, but are stationary in first differences, thus exhibiting a unit root as reported in Tables 2b-2c. The same is true for other long-run regression variables, including yields on Aaa-rated corporate bonds[15] and the marginal effective capital requirements on CRE mortgages (*CapReg*) from Duca and Ling (2020) that account for regulations on CRE loans held in portfolio or securitized by banks. These variables also exhibit unit roots over the sample.

5. The Long-Run Relationship Between Cap Rates and the User Cost of Capital

This section presents results for estimating the long-run portion of the baseline cap rate model (eq. (3)). For each property type, we define the user cost using the SitmusAMC data on the required rate of return and the expected rate of future rent growth and use the appropriate present value of tax depreciation for nonresidential or residential CRE property extended from Duca, Ling, and Hendershott (2017). We do not report results from the estimation of our short-run error correction models because the cap rates and the user costs derived from the SitmusAMC data move contemporaneously with each other. This is illustrated in Figure 10 for apartments, where the gap between survey cap rates and user costs (required returns minus rent growth) roughly equals the constant in the long-run relationship between the two that is reported in Table 3. The estimated

[15] Alternative benchmark long-term yields, such as those on 10- and 20-year Treasury yields and those on A- and Baa-rated corporate bonds, also have unit roots, but those test statistics are omitted from Table 2 to conserve space.

coefficients on the long-run user cost terms are used later to assess how changes in expected rent growth since 2019, together with COVID-related effects (e.g., WFH and OLR), have so far affected user costs of capital, and thereby cap rates and property values.

Estimates of the long-run cap rate relationships for each of the four property types are reported in *Table 3* for pre-COVID and full sample periods ending in 2019q4 and 2024q3, respectively. In each case, subject to being long enough to eliminate serial correlation in the short-run model residuals, the lag length (reported in the tables) minimized the Akaike Information Criterion. Several short-run shock variables (discussed above) are included in the short-run portion of the models to prevent unusual shocks from the Global Financial and European Debt Crises from imparting serial correlation on the residuals. In all cases, a significant and unique cointegrating vector was identified. Interestingly, the estimated coefficient on the user cost is statistically indistinguishable from unity for apartments and offices, and reasonably close to unity for retail

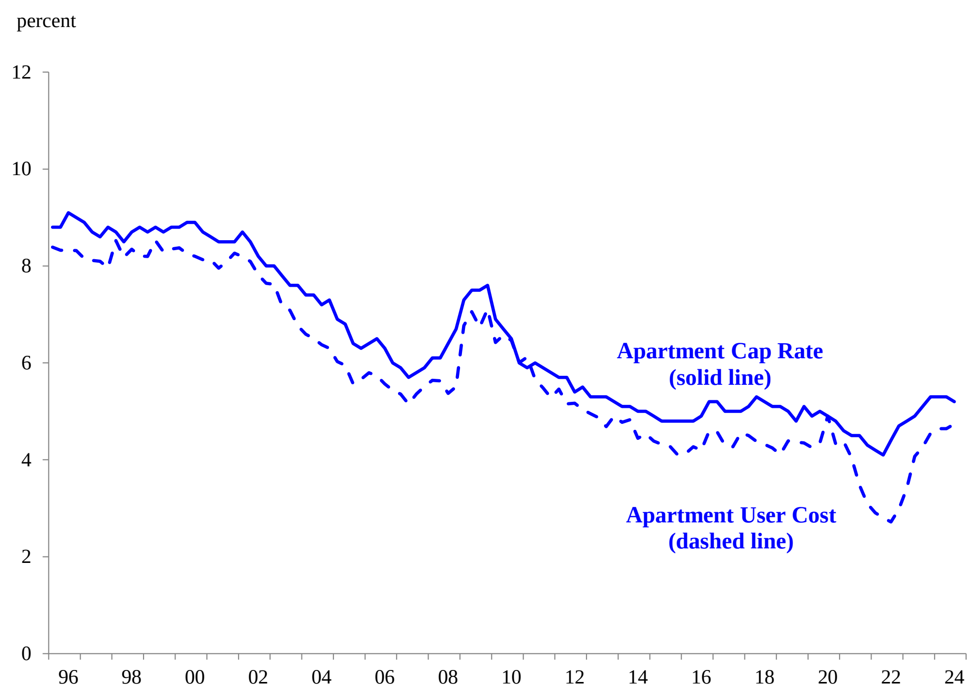

Figure 10: Apartment User Costs and Cap Rates Move Parallel to One Another Centers
(Sources: SitmusAMC, Federal Reserve, Moody’s, and authors’ calculations)

power centers and industrial warehouses. This is consistent with the perception that of the various property types, institutional and other important investors were more apt to include apartments and offices in their portfolios than other property types, though the advent of WFH has diminished the appeal of offices and the rise of online shopping has made warehouse properties somewhat more attractive.

6. Estimation Results for Required Rates of Return

This section presents estimation results for the baseline and modified models of the required rates of return for the four CRE property types. Later, Section 7 combines estimated COVID-related effects on required rates of return with post-COVID changes in expected rent growth to gauge the effects of COVID on cap rates and property valuations.

6A. Results for Required Rates of Return on Central Business District (CBD) Offices

Results from our required rate of return models for offices are in *Table 4*. Models 1 and 2 are baseline models (eqs. (7) and (9)) estimated over the pre-COVID (1995-2019) and COVID-inclusive (1996q2-2024q3) sample periods, respectively. Models 3 and 4 are the corresponding WFH-modified models that use *WFHTotal*, which tracks the hours worked at home. Models 5 and 6 use *WFHPrime*, which tracks the share of workers who primarily work from home.

There are several important patterns among the long-run model estimates reported in the upper panel of *Table 4* with uncorrelated (clean) residuals that set lag lengths to minimize the AIC criterion. First, a unique and significant long-run (cointegrating) relationship is identified for the baseline models estimated over the full and pre-COVID samples and for the full sample WFH model that uses *WFHTotal*, but not *WFHPrime*. In those models, the estimated long-run coefficients on the Aaa-yield and capital requirements have the expected positive signs, with the coefficient on the Aaa-rated bond yield indistinguishable from unity--as theory would suggest for a benchmark rate.

In Model 4, the long-term WFH variable is significant with the expected positive sign, implying that the rise of WFH is associated with higher risk premia embedded in required rates of return. The inability to identify a unique and significant cointegrating vector in Model 3 also characterized Model 5, which is estimated over the pre-COVID sample but uses *WFHPrime*. Overall, these findings suggest there is not enough variation in WFH before 2020 to identify a link between required rates of return on CBD office properties and WFH.

Results from estimating the change in required office returns are presented in the lower panel of Table 4. It is noteworthy that the error-correction coefficient is significant across the models. The estimated magnitude is similar in the full sample baseline Model 2 and the full sample *WFHTotal* (Model 4), indicating that 17 to 19 percent of the prior quarter's gap between the actual and equilibrium return is, on average, closed by changes in the following period, respectively. Overall, among the full sample models, Model 4, which uses a WFH measure based on the overall share of hours worked (*WFHTotal*) remotely, has the best fit and overall performance.

6B. Results for Required Rates of Return on Apartments

Table 5 reports estimates from our corresponding apartment models. A unique and significant cointegrating vector could be identified in all cases, with significant and positive coefficients on *CapReg* and *Aaa*, with the latter indistinguishable from unity (as expected). Both WFH variables are insignificant in the pre-COVID sample. In the full sample models, *WFHTotal* is marginally significant while *WFHPrime* is significant at the 95 percent level. The last finding suggests that the household demand for work space at home is more sensitive to whether one's employment can primarily be done at home rather than on less intensive hybrid models with one or two days worked at home.

While the long-run *WFH* coefficient is significant in all full sample models, the baseline model (Model 2) outperforms the Model 4 and Model 6 in modeling changes in required rates of return, as shown in the adjusted R^2 and standard errors in the bottom panel of Table 5. This implies that the identified WFH link in the long-run relationship does not improve upon the superior fit of the baseline model. This, coupled with instability in estimated WFH effects across the pre-COVID and full samples casts doubt on the existence of a reliable and sensible link between WFH and apartment valuations. This is in line with the weakness or ambiguity of theoretical reasons to undergird a relationship between WFH and the required rates of return for apartments.

6C. Results for Required Rates of Return on Industrial Warehouses

Table 6 reports our findings for required rates of return on warehouses. Models 1 and 2 are baseline models (eqs. (7) and (8)) estimated over the pre-COVID and full sample periods, respectively. Models 3 and 4 are *OLR*-modified models (eq. (11)) estimated over corresponding samples. Model 5 replaces levels and changes in *OLR* with the tax level shift variable *TaxOppZone*. Note that Models 1-4 include the *t*-1 first difference of this variable. As shown in the upper-panel of *Table 6*, a unique and significant cointegrating vector can only be found for the OLR models (Models 3 and 4).

We also find positive and significant long-run coefficients on *CapReg* and *Aa* (whose coefficient is close to 1). However, we could not identify a significant and unique long-run relationship (cointegrating vector) for the baseline model over either the pre-COVID or full samples, nor for the *TaxOppZone* model estimated over the full sample period. In the full sample, the fit of the short-run OLR model is higher than that of the baseline model and the estimated speed of error correction is twice as fast in the OLR-modified model. Nevertheless, one drawback of the full sample OLR model is that the estimated coefficient on the Aaa corporate bond yield is below one in magnitude. In the pre-COVID sample, however, the baseline model has a better fit and a significant speed of adjustment, whereas the OLR model has an insignificant error correction speed. Together, these findings imply that higher online shopping appears to bolstered the expected long-run demand for warehouses among tenants to the point of lowering required risk premiums. Nevertheless, the OLR models do not (yet) appear robust and it may take more time to estimate OLR effects with reasonable confidence.

6D. Results for Required Rates of Return on Retail Power Centers

Table 7 reports findings for required rates of return on retail power centers. Models 1 and 2 are baseline models estimated over the pre-2020 and full sample periods, respectively. Because the COVID-era controls are stationary, the modified models add the levels of these terms to the short-run model that estimates changes in required rates of return. By the nature of these variables, the pre-2020 models are identical to the baseline model 1. Models 3 and 4 add $GRest_t$ and $GRestVax_t$, respectively, to the short-run part of the baseline model. Owing to the nature of the pandemic, this timing reflects the exogenous nature of the restrictions and vaccinations.

As shown in the upper-panel of *Table 7*, we find unique and statistically significant long-run (cointegrating) relationships, with sensible and expected positive signs on *Aaa* and *CapReg*. The short-run model results in the lower panel are also sensible, with speeds of adjustment varying between 21 and 27 percent per quarter. *GRest* is statistically significant, while *GRestVax* is only marginally significant. Adding *GRest* improves the adjusted R^2 by nearly 1 percent over the baseline, with a smaller, nearly ½ percentage point improvement from adding *GRestVax* instead. These findings indicate that COVID had a short- to medium-term effect on the required rates of return for retail power centers. This is consistent with the widening of the gap between required rates of return on retail power centers versus apartments during the pandemic and the subsequent narrowing of that gap to its pre-COVID level. Note that attempts to include OLR in the retail power center models failed and are not reported to conserve space.

7. Implications for CRE Current Valuations

This section addresses two issues. First, to what extent are recent CRE prices under- or overvalued? Second how much have increased work from home and online shopping affected CRE valuations via affected expected rent growth and risk premia in required rates of return?

7A) By How Much are 2023q4 CRE Prices Over- or Under-Valued?

As shown in Table 8, we use several steps to assess whether the CRE valuations implied by the SitmusAMC survey are above or below long-run equilibrium prices in 2024q3. First, as shown in line (1), assuming that user costs are in equilibrium in 2024q3, we use the estimated long-run equilibrium from the relevant full sample cap rate model in *Table 3* to measure the degree to which cap rates for each property type deviate from equilibrium. Next, line (2) uses the preferred full sample model from the appropriate table (from *Tables 4-7*) to gauge to what extent actual required rates of return exceed equilibrium rates of return. Line (3) provides the product of (1-*taxdep*) and the coefficient on the user cost from the preferred cap rate model in *Table 3*. Line (4) multiplies lines (2) and (3). This product indicates by how much the cap rate deviates from its equilibrium because the required rate of return is out of line with its fundamentals. Line (5) adds lines (1) and (4) to gauge how much cap rates deviate from their equilibrium levels. Line (7) then uses the ratio of line (5) to the 2024q3 cap rate in line (6) to gauge the extent to which CRE prices at the national level were over- or under-valued in late 2024.

Based on these calculations, retail power center prices were close to the equilibrium level in 2024q3 and warehouses were about 6 percent undervalued. In contrast, office and apartment properties were overvalued by 5 and 30 percent, respectively. For apartment properties, the overvaluation is attributable to required rates of return being notably below their equilibrium levels. Nevertheless, it should be stressed that these calculations are based on historical benchmarks that may no longer be accurate. In particular, the large, calculated overvaluation for apartments could arguably reflect a shift in long-run fundamentals for this asset class. For example, the relative decline in the appeal of office properties coupled with a perceived long-lasting shortage of housing and a decline in the price elasticity of housing could have led investors to demand a lower risk premium for apartment properties.

7B. How Have COVID-Related Developments Affected Expected Rent Growth and CRE Prices?

As mentioned earlier, COVID-related shifts in WFH, OLR, and government COVID-restrictions may affect user costs of capital by altering expected net rent growth and/or the risk premia embedded in required rates of return. To gauge these effects, line (1) of Table 9 lists the change in the expected rate of rent growth between 2019q4 and 2024q3, which varies by property type. Likely depressed by increased WFH, expected annual office rent growth, averaged across all U.S. markets, slowed by a notable 1.2 percentage points over this period, whereas expected rent growth for warehouses increased by 0.4 percentage points, plausibly owing to higher expected demand for space associated with the rise in online shopping. Expected rent growth was flat for retail power centers between 2019 and 2023, but then dipped 0.4 percent in 2024. In line with weak or ambiguous theoretical reasons for WFH to have much of a net effect on apartment demand, there was no change in the expected growth rate of net apartment rents comparing 2019q4 with 2023q4 or 2024q3. Likely reflecting the increased demand for warehouse space linked to the rise of online shopping, the expected growth rate of warehouse rents also increased 0.40 percentage points between year-ends 2019 and 2023.

Line (2) is the product of (1-*taxdep*) times the long-run user cost coefficient from the full sample Model 2 of cap rates in Table 3. The product of lines (1) and (2) is the implied effect on cap rates in row 3. Dividing line 3 by the 2024q3 cap rate in line 4 converts the cap rate impact into the percentage price change induced by changes in expected rent between 2019 and 2024q3 on CRE prices that is reported in line 5. The implied price effects appear sensible.

7C. How Have COVID-Related Developments Affected Required Rates of Return?

This subsection uses coefficient estimates from models in Section 6 to gauge how COVID-related developments have affected required rates of return for offices, retail power centers, and warehouses. (An analysis of effects on required rates of return for apartments is omitted because these estimated effects were doubtful.) In turn, the near 1-1 long-run link between cap rates and user costs can be used to gauge how the effects on user costs translate into effects on CRE prices.

The impact of government restrictions on the level of the required unlevered equity return for retail power centers can be inferred from the estimated coefficients on *GRest* (β_{GR}) and the error correction coefficient (β_{ECM}) from the short-run model. The effect of the contemporaneous reading of *GRest* on the time *t* level of *rrr* equals $\beta_{GR}\, GRest_t$. The time *t* impact of $GRest_{t-k}$, reflects that the original effect in time t-k wears off each subsequent quarter by the quarterly speed of adjustment, which equals β_{ECM}, The effect of current and past readings of *GRest* on the time *t* level of *rrr* equals the sum of $\beta_{GR}\, GRest_t$ plus the cumulated impact of prior readings of *GRest*, which can be expressed as:

$$\sum_{k=0}^{12} [1- \beta_{ECM}]^k \text{ x } \beta_{GR} GRest_{t-k} \qquad (13)$$

where the time limit on k reflects 13 quarters of restrictions. Since the restrictions were lifted in May 2023, we trace their effects out of the next few years. As shown in Figure 11, these effects are sizable and plausible, having pushed up required rates of return for several quarters, peaking near 60 basis points before abating to 5 basis points at year-end 2024 and eventually to zero.

Figure 12 plots the equilibrium effects of *WFHTotal* and *OLR* on the required rates of return for offices and warehouses from Model 4 in Tables 5 and 6, respectively. Because levels of WFH and OLR are not expected to fall back to their 2019 levels, their effects will be more persistent than those from the temporary government COVID restrictions. For 2024q3, the estimated WFH effects are a plausible boost in the required return of 65 basis points, while the OLR effect lowers warehouse required returns by 280 basis points, which seems large. On the other hand, since 2019, the *change* in online shopping has lowered equilibrium warehouse cap rates by about 92 basis points, which seems in line with the relative decline in observed warehouse cap rates in recent years.

By comparing data from 2019q4 and 2024q3, the lower panel of Table 9 gauges the implied effects of COVID-related developments on required rates of return, user costs, and CRE prices. To begin, line (6) displays how much the levels of *WFHTotal* (for offices) and *OLR* (for warehouses) have changed between 2019q4 and 2024q3. Line (7) then provides the long-run coefficients on these variables in the full sample using the Model 4 results from the corresponding Tables 4 and 5. Line (8) provides the product of (1-*taxdep*) and the long-run coefficient on user costs from the preferred cap rate model in Table 3. The net effect on the required rate of return is in line (9), which, for offices and warehouses, is the product of lines (7) and (8). Line (9) for apartments is zero owing to the lack of credible WFH effects on the required rate of return for apartments. In contrast, those for retail power centers are equal to the product of the 5-basis point effect on the cap rate for 2024q3 (Table 8) multiplied by line (8). Line (10) then multiplies lines (8) and (9) to provide an implied estimate of how changes in COVID-related developments translate into changes in equilibrium cap rates. Next, line (10) provides the 2024q3 level of cap rates. Line (11) then uses the ratio of lines (9) and (10) to calculate by how much equilibrium CRE

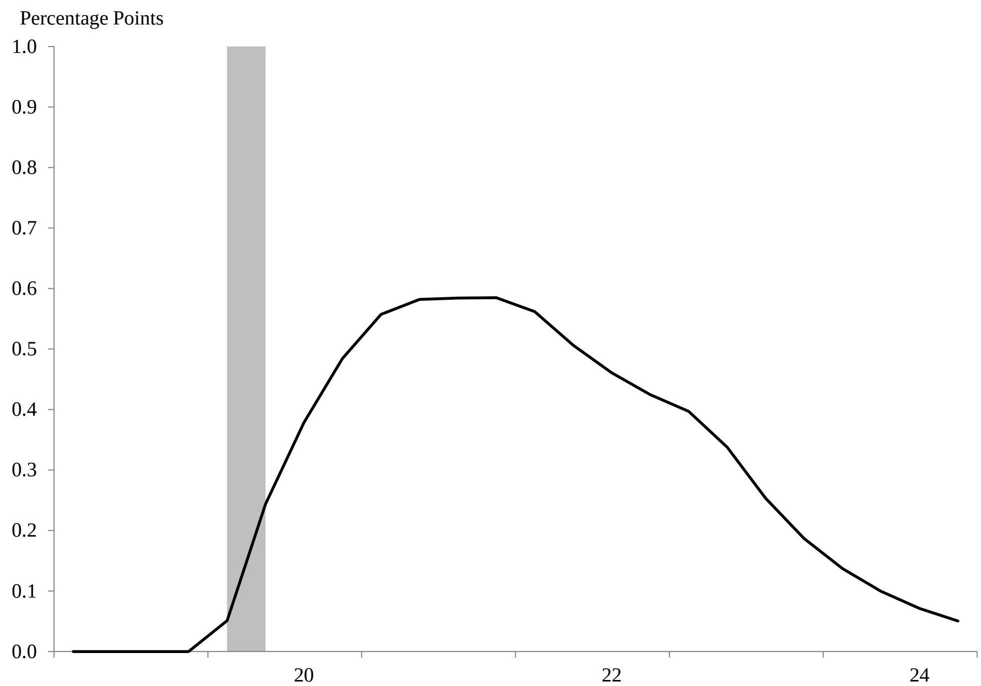

Figure 11: Cumulative Impact of Government COVID Restrictions on Required Rates of Return on Retail Power Centers
(Sources: SitmusAMC, Federal Reserve, Moody's, and authors' calculations)

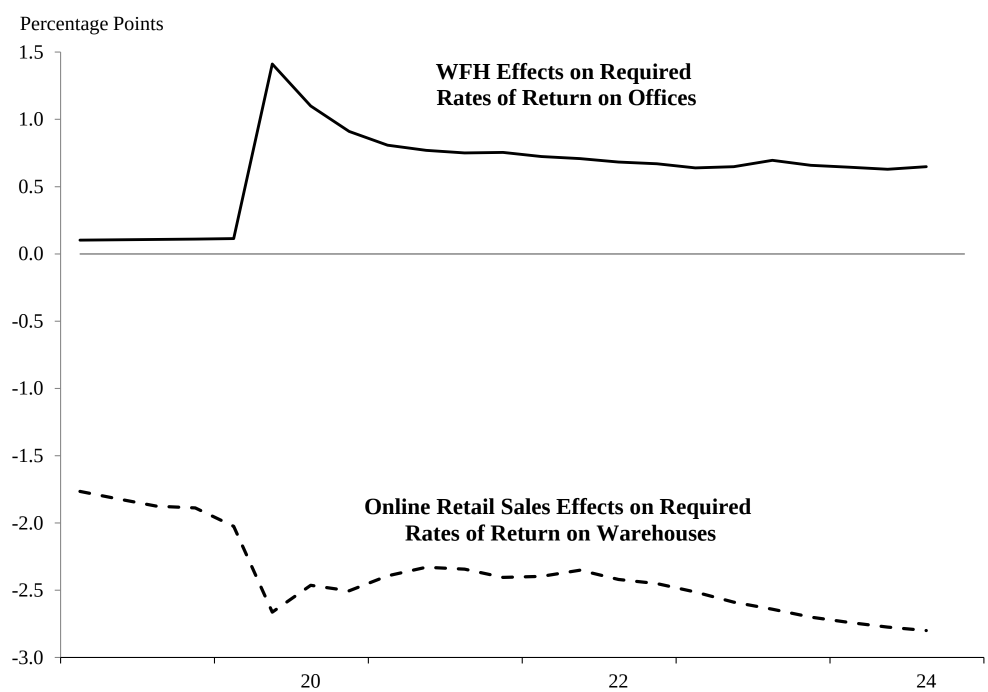

Figure 12: Equilibrium Effects of WFH and OLE on the Required Rates of Return on Offices and Warehouses, Respectively
(Sources: SitmusAMC, Federal Reserve, Moody's, and authors' calculations)

prices were affected by COVID-related developments via their effects on risk premia and the required rate of return.

7D. Combined Rent and Risk-Premia Effects of COVID-Related Developments on CRE Prices

The combined effects of changes in expected rent growth and required rates of return are listed in line (12) of Table 9. There are negligible effects on retail power center cap rates because the estimated effects of government COVID restrictions have largely unwound with the lifting of these requirements. For apartments, the zero overall implied effect stems from the lack of apparent effects of WFH on expected rent growth and required rates of return. In contrast, there is a sizable, implied effect of WFH on the equilibrium cap rates for CBD offices stemming the combination of slower expected rent growth and higher risk premia embedded in the required rate of return.

Finally, estimates indicate that warehouse cap rates have declined because of somewhat faster expected rent growth and lower risk premiums linked to higher demand for warehouse space stemming from the notable rise in online shopping. The ramifications for equilibrium CRE prices are calculated in the bottom row of Table 9 and indicate that work-from-home effects on expected rent growth and office risk premiums have lowered equilibrium prices for CBD offices by about 25 percent and raised those for industrial warehouses by about 20 percent based on current fundamentals. Interestingly, most of the calculated impact on CBD offices stems from the WFH effect on expected rents, whereas most of the estimated effect on warehouse prices emanates from changes in the risk premium. The latter estimate (a 14 pp. effect) may be overstated as it implicitly assumes that all of the rise in online shopping since 2019q4 was COVID induced. Reflecting negligible effects on long-run cap rates for apartments and retail power centers, the direct effects on prices for these types of property appear minimal.

8. Concluding Comments

This study decomposes the effects of changes in required rates of return and expected rent growth on average national-level prices for four major types of commercial property. Results imply that work-from-home has raised cap rates for top-end commercial offices enough to lower equilibrium prices by 25 percent. This figure is close to the middle of the range of Gupta et al.'s (p. 43, Figure 13, 2022) estimated WFH effects on NY City Class A+ offices at the end of 2023. That we come to such similar magnitudes while using different data and different approaches (their study is a calibration exercise and ours a time series analysis) for this upper end segment of offices is notable and enhances the credibility of the WFH estimates from both studies.

While we estimate that the rise of online shopping appears to have lowered prime warehouse cap rates enough to boost prices by up to 20%, we do not find a discernible long-run effect on apartments or retail power centers. In the case of the latter, the impact of the pandemic was more related to government restrictions and the ameliorating effects of vaccines that plausibly affected in-person shopping, which will further wear off.

With respect to whether CRE prices are over- or under-valued, we find that while notional cap rates move quickly with respect to required rates of return, the latter can respond with a lag to factors affecting risk premia. For prime CBD offices, sizable price declines have pushed prices close to their calculated equilibrium level, the degree of overvaluation near 5 percent in late 2024. The prices for top quality warehouses and retail power centers were also not far from their calculated long-run equilibrium levels. However, in the case of apartments, we find that despite sizable declines in real prices since 2021, this property type is overvalued by 30 percent using our historically based approach. This degree of overvaluation is plausibly overstated because the perceived long-run risk of investing in apartments may have downshifted for reasons not measured by our approach. Moreover, these estimated degrees of overvaluation apply at the national level; certainly, the degree of overvaluation varies by local market and by the quality of the property. For example, prime office space in some highly desirable locations has not experienced the price declines observed for many older, less well located, office properties. Said differently, the modest degree of overvaluation we estimate for the upper tier of CBD offices tracked by Situs AMC is not necessarily inconsistent with larger estimates for a broader spectrum of quality tiers in the office market.

A second additional qualification is that we use data from Sitmus-AMC and Green Street, data whose price and fundamentals are measured in a more contemporaneous way that avoids the tendency of many other CRE price indexes to lag market conditions. As a result, the correction of real CRE prices seen since 2021 reflects our use of more timely readings from SitusAMC compared to other indexes whose declines will likely lag behind those in the SitusAMC readings. A further caveat is that, given the tendency for CRE markets to partially adjust in the short-run, our estimates for the higher quality segments of CRE markets are based on fundamental economic factors at the most recent point in time and thus are subject to uncertainties about how interest rates, shopping patterns, work habits, rents, and regulation evolve.

With these qualifications in mind, we find that apartment prices at the national level likely exceed equilibrium levels despite recent real declines. As risk premiums continue to adjust upward toward equilibrium levels, multifamily prices are likely to experience more downward pressure unless underlying fundamentals further change. From a broader perspective, CRE prices have been greatly affected by swings in long-term interest rates and by post-pandemic structural changes reflected in the rise of work-from home and online retailing.

References

Antoniades, Adonis. 2015. "Commercial Bank Failures During the Great Recession: the Real (Estate) Story." BIS Working Paper 530, Bank for International Settlements.

Barrero, Jose Maria, Nicholas Bloom, and Steven J. Davis, 2021. "Why Working from Home Will Stick," National Bureau of Economic Research Working Paper 28731.

Barrero, José María Nicholas Bloom, and Steven J. Davis. 2023. "The Evolution of Work from Home." *Journal of Economic Perspectives* 37(4): 23-40.

Blundell-Wignall, Adrian and Paul E. Atkinson. 2008. "The Sub-prime Crisis: Causal Distortions and Regulatory Reform," in P. Bloxham and C. Kent (Eds.), *Lessons from the Financial Turmoil of 2007 and 2008,* Reserve Bank of Australia.

Bordo, Michael D. and John V. Duca. Forthcoming. "Money Matters: Broad Divisia Money and the Recovery of U.S. Nominal GDP from the COVID-19 Recession." *Journal of Forecasting.*

Chaney, Thomas, Sraer, David, and Thesmar, David. 2012. "The Collateral Channel: How Real Estate Shocks Affect Corporate Investment," *American Economic Review* 102: 2381-2409.

Chen, Lian, Yueran Ma, and Carmen Wang, 2019. "Low Interest Rates and Risk-Taking: Evidence from Individual Investment Decisions." *Review of Financial Studies* 32(6), 2107-2148.

Chervachidze, Serguei, Costello, James, and William Wheaton. 2009. "The Secular and Cyclical Determinants of Capitalization Rates: The Role of Property Fundamentals, Macroeconomic Factors, and 'Structural Changes'." *Journal of Portfolio Management* 35: 50-69.

Chervachidze, Serguei and William Wheaton. 2013. "What Determined the Great Cap Rate Compression of 2000-2007, and the Dramatic Reversal During the 2008-2009 Financial Crisis?" *Journal of Real Estate Finance and Economics* 46: 208-231.

Chu, Yongqiang. 2014. "Banking Deregulation, Credit Constraints, and Asset Prices: Evidence from Commercial Real Estate." manuscript, University of South Carolina.

CMSA (Commercial Mortgage Securities Association). 2007. "The Commercial Mortgage-Backed Securities Industry Factual Background." July. <http://www.crefc.org/uploadedFiles/CMSA_Site_Home/About_CMSA/Frequently_Asked_Questions/CMBS_Overview_jul07.pdf >.

Davis, Morris, Andra Ghent and Jesse Gregory. 2024. "The Work-From-Home Technology Boon and its Consequences." *Review of Economic Studies* 91(6): 3362-3401.

Dell'Ariccia, Giovanni, Luc Laeven, and Robert Marquez. 2014. "Real Interest Rates, Leverage, and Bank Risk-Taking." *Journal of Economic Theory* 149(0), 65 – 99.

Dell-Ariccia, Giovanni, Luc Laeven, and Gustavo A. Suarez. 2017. "Bank Leverage and Monetary Policy's Risk-Taking Channel: Evidence from the United States." *Journal of Finance* 72(2): 613-54.

Duca, John V. 2018. "Inflation and the Gig Economy: Have the Rise of Online Retailing and Self-Employment Disrupted the Phillips Curve?" Federal Reserve Bank of Dallas Working Paper 1814.

Duca, John V., Patric H. Hendershott, and David C. Ling. 2017. "How Taxes and Required Returns Drove Commercial Real Estate Valuations over the Past Four Decades." *National Tax Journal* 70 (3): 549–84.

Duca, John V. and David C. Ling. 2020. "The Other (Commercial) Real Estate Boom and Bust: The Effects of Risk Premia and Regulatory Capital Arbitrage." *Journal of Banking and Finance* 112(C): 1-16.

Duca, John V., Martin Hoesli, and Joaquim Montezuma. 2021. "The Resilience and Realignment of House Prices in the Era of Covid-19." *Journal of European Real Estate Research* 14(3): 421-431.

Duca, John V., Muellbauer, John, and Murphy, Anthony. 2016. "How Mortgage Finance Reform Could Affect Housing," *American Economic Review* 106(3): 620-24.

Duca, John V., John Muellbauer, and Anthony Murphy. 2021. "What Drives House Price Cycles? International Experience and Policy Issues." *Journal of Economic Literature* 59(3): 773-864.

The Economist. 2012. "An Uber-Review of the Crisis: The Lo Down." Jan. 14, 2012. http://www.economist.com/node/21542781

Faria-e-Castro, Miguel and Samuel Jordan-Wood. 2023. "Commercial Real Estate: Where Are the Financial Risks?" St. Louis Fed *On the Economy*, November 17. Available at: https://www.stlouisfed.org/on-the-economy/2023/nov/commercial-real-estate-where-are-the-financial-risks

Geltner, David M., Norm G. Miller, James Clayton, and Piet Eichholtz. 2007. *Commercial Real Estate Analysis and Investments*, 2nd edition, South-Western Publishing, Cincinnati, OH.

Geltner, David M., Norm G. Miller, James Clayton, and Piet Eichholtz. 2014. *Commercial Real Estate Analysis and Investments*, 3rd edition, OnCourse Learning, Mason, OH.

Geltner, David. 2015. "Real Estate Price Indices and Price Dynamics: An Overview from an Institutional Perspective." *Annual Review of Financial Economics* 7: 615-33.

Ghosh, Chinmoy, Lyndsey Rolheiser, Alex Van de Minne, and Xiaofeng Wang. 2022." The Price of Work-from-Home: Commercial Real Estate in the City and the Suburbs." (November 16, 2022). Available at SSRN: https://ssrn.com/abstract=4279019 or http://dx.doi.org/10.2139/ssrn.4279019

Gorton, Gary B. and Andrew Metrick. 2012. "Securitized Lending and the Run on the Repo," *Journal of Financial Economics* 104: 425-51.

Gumber, Clayton and Michael Burrows. 2023. "Home Based Workers 2019–2021." Current Population Reports, P70BR-184, U.S. Census Bureau, Washington, DC, 2023"

Gupta, Arpit, Vrinda Mittal, and Stijn Van Nieuwerburgh. 2022. "Work From Home and the Office Real Estate Apocalypse." NBER Working Paper 30526.

Hamilton, James D. 1994. *Time Series Analysis*, Princeton University Press, Princeton.

Hendershott, Patric H. and Bryan MacGregor. 2005. "Investor Rationality: Evidence from U.K. Property Capitalization Rates." *Real Estate Economics* 26: 299-322.

Hendershott, Patric H. and Kevin Villani. 2012. "What Made the Financial Crisis Systemic?" Cato Institute Policy Analysis, no 693, http://www.cato.org/publications/policy-analysis/what-made-financial-crisis-systemic

Johansen, Soren. 1995. *Likelihood-Based Inference in Cointegrated Vector Autoregressive Models* (New York: Oxford University Press).

Levitin, Adam J. and Susan M. Wachter. 2013. "The Commercial Real Estate Bubble." *Harvard Business Law Review* 3: 83 -118.

Ling, David C., Andy Naranjo, and Benjamin Scheick. 2016. "Credit Availability and Asset Pricing Dynamics in Illiquid Markets: Evidence from Commercial Real Estate Markets." *Journal of Money, Credit, and Banking* 28(7): 1321-62.

Ling, David. C., Chongyu Wang, and Tingyu Zhou. 2020. "A First Look at the Impact of COVID19 on Commercial Real Estate Prices: Asset Level Evidence." *Review of Asset Pricing Studies* 10(4): 669-704.

Meeks, Roland. 2008. "Financial Crisis Casts Shadow Over Commercial Real Estate." Federal Reserve Bank of Dallas *Economic Letter* 3(12): 1-8.

Mondragon, John and Johannes Wieland. 2022. "Housing Demand and Remote Work." Available at: https://johanneswieland.github.io/Papers/house_prices_rw_draft.pdf.

Moore, Heidi N. 2007. "The Accidental CMBS Recovery." *Fortune*, July 13, <http://archive.fortune.com/2010/07/13/news/economy/CMBS_accidental_recovery.fortune/index.htm>.

Murphy, Anthony, John V. Duca, and John Muellbauer. 2024. "A Tale of Two U.S. Housing Booms." Unpublished manuscript, March 2024.

Pennacchi, George G. 1988. "Loan Sales and the Cost of Bank Capital." *Journal of Finance* 43 (2): 375-96.

Plazzi, Alberto, Walter M. Torous, and Rossen Valkanov. 2010. "Expected Returns and Expected Growth in Rents of Commercial Real Estate." *Review of Financial Studies* 23: 3469-3519.

Ramani, Arjun and Nicholas Bloom. 2022. "The Donut effect of COVID-19 on Cities." NBER Working Paper 28876.

Rosenthal, S.S., Strange, W.C., Urrego, J.A., 2021. "Are city centers losing their appeal? Commercial real estate, urban spatial structure, and COVID-19. *Journal of Urban Economics-Insights*, 103381.

Sing, Tien Foo. 2005. "Impact of Information and Communications Technology on Real Estate Space: Perspective of Office Occupiers." *Journal of Property Investment and Finance* 23(6) 494-505.

Sivitanides, Petros, Southard, Jon, Torto, Raymond, and William Wheaton. 2001. "The Determinants of Appraisal-based Capitalization Rates." MIT Working Paper.

Sivitanidou, Rena, and Petros Sivitanides. 1999. "Office Capitalization Rates: Real Estate and Capital Market Influences." *Journal of Real Estate Finance and Economics* 18(3), 297-322.

Stanton, Richard and Nancy Wallace. 2012. "CMBS Subordination, Ratings Inflation, and Regulatory-Capital Arbitrage." manuscript, University of California-Berkeley.

Van Nieuwerburgh, Stijn. 2023. "The Remote Work Revolution: Impact on Real Estate Values and the Urban Environment." *Real Estate Economics* 51(1): 7-48.

Wheaton, William C. and Raymond G. Torto. 1990. "An Investment Model of the Demand and Supply for Industrial Real Estate." *Real Estate Economics* 18(4): 530-54.

Wilcox, James A. 2012. "Commercial Real Estate: Underwriting, Mortgages, and Prices." SSRN working paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2024176

Zakrzewski, Cat. 2021. "Amazon is Building Warehouses in 'Opportunity Zones' that Provide Tax Breaks and Secrecy." *Washington Post* Dec. 23, 2021. https://www.washingtonpost.com/technology/2021/12/23/amazon-opportunity-zone-tax-breaks/

Table 1: List of Variables

Aaa = Average yield on Aaa-rated corporate bonds. Source: Moody's.

Caprate$_j$ = caprate on prime (A+) CRE property type. Source; SitmusAMC survey. This notional cap rate is unaffected by changes in the quality of properties sold

CapReq = capital requirement on holding investment-grade, private-label CMBS through 2010 or for issuing CMBS sinceDodd-Frank. Source: Duca & Ling, 2020.

rrr = required pre-tax gross rate of return on a property type. Source: SitmusAMC.

OLR = share of non-auto retail sales conducted online or via mail order. Including the latter internalizes some of the shift from mail order to online sales that would not much affect retail power centers. Sources: Census and authors' calculations.

GLEI = The two-quarter percent change in the Index of Leading Economic Indicators. Source: Conference Board. This is a proxy for short-run cyclical effects on CRE risk premia and is expected to have a negative effect on Δ*rrr* in the short run.

UserCost = user cost of capital = the product of the gap between required rate of return and the long-run expected growth rate of rents and one minus the tax-adjusted rate of depreciation. Sources: SitmusAMC, Federal Reserve, authors' calculations.

WFHPrime = share of U.S. workers primarily working from home (Census and authors' annual interpolations and break adjustments).

WFHTotal = share of hours worked by U.S. workers from home (Barrero, et al. (2023), Census and authors' annual interpolations and break adjustments).

DSubPrFail = 0.5 in 2007q1, 1 in 2007q2, and 0 otherwise. Dummy for the failures of 25 subprime financial institutions in late 2007q1 that induced a portfolio shift toward CRE investments, lowering required rates of return.

Lehman = impact dummy equal to 1 2009q1 and 0 otherwise. It controls for the unusual effects of the failure of Lehman Brothers and the global financial crisis.

DEuroCrisis = dummy = 1 in 2009q4 (European Debt Crisis hit financial markets), = 0 otherwise.

DY2K = 1 in 1999q4 before century date change, -1 in 2000q2 quarter after century date change tracks fears that software glitches would aid brick and mortar sales at expense of online sales. Reverses in quarter after century date change.

D2014q4 = 1in 2014q4 for a temporary outlier plunge that reversed in 2015q1.

TaxOppZone = 1 in 2018q2 for TCJA tax break for opportunity zones that favored warehouses.

Table 2A: Summary Statistics

Cap Rate Variables, 1993q2-2024q3; Risk Premium Variables, 1994q1-2024q3

Variable	Mean	St. Dev.	Min.	Median	Max.
Cap Rate Variables					
$Caprate^{off}$	7.3056	1.5666	5.3000	6.8500	10.400
$Caprate^{apt}$	6.6750	1.6431	4.1000	6.3500	9.1000
$Caprate^{ret}$	7.9806	1.2575	6.3000	7.4000	10.100
$Caprate^{ware}$	7.2282	1.6267	4.0000	7.0500	9.7000
$UserCost^{off}$	6.5712	1.6998	3.7308	5.9141	9.3076
$UserCost^{apt}$	6.0116	1.7019	2.7183	5.6408	8.5247
$UserCost^{ret}$	6.9641	1.4467	4.6178	6.4761	9.7230
$UserCost^{ware}$	6.3377	1.7381	2.5614	6.2001	8.7412
WFHPrime	4.0133	4.1965	1.1925	2.6000	16.900
WFHTotal	6.1791	10.0506	1.1925	2.6000	39.700
OLR	7.1313	4.4520	2.0033	5.8097	17.714
Other Required Rate Of Return Variables					
rrr^{off}	9.1298	1.8451	6.8000	8.4000	12.5000
rrr^{apt}	8.6347	1.8491	5.9000	8.2000	11.6000
rrr^{ret}	9.5339	1.5517	7.4000	8.8000	12.6000
rrr^{ware}	8.8653	1.8370	5.6000	8.6000	11.5000
Aaa	5.5238	1.6092	2.3832	5.5621	8.7200
CapReq	5.4342	2.3246	1.6000	5.0000	8.0000
GLEI	0.0066	0.0345	-0.1383	0.0161	0.0631

Notes: Sample periods for caprate variables cover 1993:q2-2024:q3, reflects use of up to t-3 first difference of these variables in the estimation of the models over 1993:q3-2024q3. Sample periods for risk premium variables cover 1994:q1-2024:q3, reflects use of up to t-3 first difference of these variables in the estimation of the models over 1994:q4-2024q3. Dummy variables are omitted from the Table as they are discrete variables with values of either 0 or 1.

Table 2B: Unit Root Tests, Phillips-Perron
(Cap Rates 1992q3-2024q3; Usercost 1993q4-2024q3;
Required Rate of Return Data 1994q1-2024q3)

Unit Root?		*PP*	Band-width.		*PP*	Band-width.
	Cap Rate Variables					
Yes**	$Caprate^{off}$	-0.911	5	Δ $Caprate^{off}$	-7.731**	2
Yes**	$Caprate^{apt}$	-1.964	5	Δ $Caprate^{apt}$	-8.875**	3
Yes**	$Caprate^{ret}$	-1.848	6	Δ $Caprate^{ret}$	-10.352**	5
Yes**	$Caprate^{ware}$	-2.494	6	Δ $Caprate^{ware}$	-8.051**	5
Yes**	$UserCost^{off}$	-2.164	6	Δ $UserCost^{off}$	-10.350**	5
Yes**	$UserCost^{apt}$	-2.762	5	Δ $UserCost^{apt}$	-7.929**	3
Yes**	$UserCost^{ret}$	-2.642	5	Δ $UserCost^{ret}$	-11.885**	4
Yes**	$UserCost^{ware}$	-2.839	5	Δ $UserCost^{ware}$	-10.425**	4
Yes**	*WFHPrime*	-1.490	5	Δ *WFHPrime*	-7.733**	2
Yes**	*WFHTotal*	-2.130	3	Δ *WFHTotal*	-11.086**	8
Yes**	*OLR*	-0.614	10	Δ *OLR*	-13.807**	13
	Other Required Rate of Return Variables					
Yes**	rrr^{off}	-0.227	1	Δ rrr^{off}	-11.996**	3
Yes**	rrr^{apt}	-2.707	3	Δ rrr^{apt}	- 9.081**	5
Yes**	rrr^{ret}	-1.953	7	Δ rrr^{ret}	-9.003**	2
Yes**	rrr^{ware}	-2.125	4	Δ rrr^{ware}	-10.081**	2
Yes**	*Aaa*	-1.549	1	Δ *Aaa*	-8.346**	7
Yes**	*CapReq*	-1.760	2	Δ *CapReq*	-10.992**	0
No**	*GLEI*	-3.692**	5	Δ *GLEI*	7.418**	15

Notes: * and ** denote 95% and 99% significance levels, respectively. PP stationarity tests employ a Bartlett kernel spectral estimation method using a Newey-West bandwidth selector. The combination of an insignificant PP test statistic on the level of a variable (rejecting that it is stationary) and a significant test statistic on its first difference (accepting it is stationary) is evidence against trend stationarity. Unit root tests include a time trend. The sample for the unit root tests cover 1993:q2-2024:q3 for the cap rate estimation variables to match the time span of the data used for estimation that include lags of the first differences of the variables in the cointegrating vector. The sample for the unit root tests covering the required rate of return variables covers 1994-2024q3 to match the time span of the data used in the required rate of return regressions.

Table 2C: Unit Root Tests DF-GLS

(Cap Rates 1992q3-2024q3; UserCost 1993q4-2024q3; Risk Premium Data 1994q1-2024q3)

Unit Root		*DF-GLS*	lag len.		*DF-GLS*	lag len.
Yes**	$Caprate^{off}$	-1.455	1	Δ $Caprate^{off}$	-7.184**	1
Yes**	$Caprate^{apt}$	-2.387	2	Δ $Caprate^{apt}$	-4.600**	1
Yes**	$Caprate^{ret}$	-1.970	2	Δ $Caprate^{ret}$	4.820**	1
Yes**	$Caprate^{ware}$	-2.381	1	Δ $Caprate^{ware}$	-7.457**	0
Yes**	$UserCost^{off}$	-1.672	0	Δ $UserCost^{off}$	-5.430**	1
Yes**	$UserCost^{apt}$	-2.098	0	Δ $UserCost^{apt}$	-10.077**	0
Yes**	$UserCost^{ret}$	-2.197	0	Δ $UserCost^{ret}$	-11.883**	0
Yes**	$UserCost^{ware}$	-2.091	0	Δ $UserCost^{ware}$	-9.787**	0
Yes**	*WFHPrime*	-1.590	1	Δ *WFHPrime*	-7.796**	0
Yes**	*WFHTotal*	-1.992	0	Δ *WFHTotal*	-10.973**	0
Yes**	*OLR*	-0.795	0	Δ *OLR*	-12.456**	0
Yes**	rrr^{off}	-0.823	4	Δ rrr^{off}	-4.750**	3
Yes**	rrr^{apt}	-2.289	6	Δ rrr^{apt}	-6.542**	1
Yes**	rrr^{ret}	-2.160	4	Δ rrr^{ret}	-6.797**	1
Yes**	rrr^{ware}	2.746	1	Δ rrr^{ware}	7.830**	0
Yes**	*Aaa*	-2.459	0	Δ *Aaa*	-8.437**	0
Yes**	*CapReq*	-1.728	0	Δ *CapReq*	-4.439**	5
No**	*GLEI*	-3.684**	4	Δ *GLEI*	-6.960**	3

Notes: * and ** denote 95% and 99% significance levels, respectively. The Schwartz Information Criterion (SIC) is used to select lag lengths. The combination of an insignificant DF-GLS test statistic on the level of a variable (rejecting that it is stationary) and a significant test statistic on its first difference (accepting it is stationary) is evidence against trend stationarity. Unit root tests include a time trend. The sample for the unit root tests cover 1993:q2-2024:q3 for the cap rate estimation variables to match the time span of the data used for estimation that include lags of the first differences of the variables in the cointegrating vector. The sample for the unit root tests covering the required rate of return variables covers 1994-2024q3 to match the time span of the data used in the required rate of return regressions.

Table 3: Cap Rates and User Costs

Long-Run Relationship: *Caprate* = $\beta_0 + \beta_1$*UserCost* + ε_t

UserCost ≡ (*Req Rate of Rtn – Expected Rent Growth*) x (*1-taxdep*)

	Apartments		Office (CBD)	
Sample:	97q1-19q4	96q3-24q3	97q4-19q4	97q4-24q3
	Model 1	**Model 2**	**Model 3**	**Model 4**
Constant	0.965	1.110	1.706	1.379
UserCost$_t$	1.009**	0.994**	0.867**	0.906**
	(0.07)	(0.07)	(0.07)	(0.08)
TraceCorr (1v.)	20.39*	18.24*	17.26*	16.86*
TraceCorr (2v.)	2.28	2.46	1.34	2.77
Unique Coint-	Yes*	Yes*	Yes*	Yes**
Lag Length	3	1	6	6

	Retail Power Center		Industrial Warehouse	
Sample:	96q3-19q4	96q4-24q3	97q2-19q4	99q1-24q3
	Model 5	**Model 6**	**Model 7**	**Model 8**
Constant	2.471	1.891	2.460	2.342
UserCost$_t$	0.763**	0.838**	0.781**	0.795**
	(0.06)	(0.09)	(0.05)	(0.03)
TraceCorr (1v.)	17.57*	15.93*	22.22**	32.79**
TraceCorr (2v.)	0.92	3.02	1.08	2.98
Unique Coint-	Yes*	Yes*	Yes**	Yes**
Lag Length	1	2	3	11

Notes: Data used in the estimation cover 1996:q1-2024q3. To address serial correlation in residuals, all models include a 0-1 dummy for the quarter (2008:q3) for the collapse of Lehman Brothers and the two following quarters (2008:q4 and 2009:q1) and the warehouse models also included a dummy for 2009:q4 marking the onset of the European Debt Crisis. "v." denotes vector. ** and *** denote 95% and 99% significance. Standard errors are in parentheses. Estimates allow for a linear trend in the VAR and a constant and no trend in cointegrating vector.

Table 4: Quarterly Models: Required Rate of Return on Central Business District Offices

Long-Run Relationship: $rrr^{prem}_t = \beta_0 + \beta_1 Aa_t + \beta_2 CapReq_t + \beta_3 WFH_t$

	Baseline Models		*WFHTotal*		*WFHPrime*	
Sample:	96q1-19q4	96q1-24q3	96q1-19q4	96q1-24q3	96q1-24q3	96q1-24q3
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Constant	2.577	2.826	2.759	2.306	2.759	2.076
Aaa_t	1.050**	0.964**	0.972**	1.082**	0.972**	1.107**
	(19.66)	(20.22)	(7.63)	(16.56)	(7.63)	(17.51)
CapReq	0.184**	0.223**	0.209**	0.175**	0.209**	0.176**
	(5.90)	(6.68)	(7.95)	(4.67)	(7.95)	(5.21)
WFH			0.042	0.023**	0.042	0.061*
			(0.21)	(2.70)	(0.21)	(2.41)
TraceCorr (1v.)	30.21*	38.01**	65.16**	50.28**	65.16**	94.87**
TraceCorr (2v.)	3.70	8.19	29.86*	20.02	29.86*	47.60
Unique Coint-	Yes*	Yes**	No[1]	Yes**	No[1]	No[2]
Lag Length	5	5	5	4	5	8

Short-Run: $\Delta rrr_{jt} = \alpha_0 + \alpha_1 EC_{t-1} + \sum\beta_i\Delta(rrr)_{t-i} + \sum\theta_i\Delta(Aa)_{t-i} + \sum\theta_i\Delta(CapReq)_{t-i} + \sum\theta_i\Delta(WFH)_{t-i} + \delta S\text{-}runVar_t + \varepsilon_t$

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Constant	-0.046*	-0.014	-0.033	-0.022	-0.033	-0.031^{+}
	(2.40)	(0.94)	(0.90)	(1.47)	(0.90)	(1.87)
EC_{t-1}	-0.222**	-0.169*	-0.207**	-0.188**	-0.207**	-0.229**
	(3.70)	(3.61)	(3.16)	(4.44)	(3.16)	(3.15)
Δrrr_{t-1}	-0.004	-0.045	-0.061	-0.064	-0.061	-0.014
	(0.04)	(0.53)	(0.36)	(0.80)	(0.36)	(0.15)
ΔAaa_{t-1}	-0.064	-0.002	-0.030	-0.040	-0.030	-0.061
	(0.79)	(0.03)	(1.04)	(0.62)	(1.04)	(0.62)
$\Delta CapReq_{t-1}$	-0.044^{+}	-0.035	-0.047^{+}	-0.026	-0.047^{+}	-0.045^{+}
	(1.70)	(1.43)	(1.69)	(1.16)	(1.69)	(1.72)
ΔWFH_{t-1}			0.225	0.000	0.225	0.021
			(0.23)	(0.13)	(0.23)	(0.89)
$GLEI_{t-1}$	-0.963	-1.622**	-1.361^{+}	-1.200^{+}	-1.361^{+*}	-1.153^{+}
	(1.35)	(2.81)	(1.92)	(1.90)	(1.92)	(1.73)
$DSubPrFail_{t-1}$	-0.547**	-0.546**	-0.478**	-0.563**	-0.478**	-0.714**
	(3.66)	(3.71)	(3.01)	(3.92)	(3.01)	(4.73)
$DLehman_{t-1}$	0.797**	0.751**	0.765**	0.794**	0.756**	0.641**
	(4.54)	(4.49)	(4.28)	(4.81)	(4.28)	(3.84)
$DEuroCrisis_{t-1}$	0.432**	0.403**	0.388**	0.404**	0.388**	0.335*
	(3.27)	(3.14)	(2.86)	(3.28)	(2.86)	(2.66)
Adjusted R^2	.551	.539	.541	.560	.541	.593
S.E.	0.153	0.152	0.155	0.149	0.155	0.143
VECLM(1)	6.55	7.94	14.38	20.49	14.38	8.40
VECLM(4)	9.27	10.38	15.80	24.18	15.80	10.26

Notes: Data used in the estimation cover 1993q4-2024q3. “v.” denotes vector. ** and *** denote 95% and 99% significance. Absolute t-statistics are in parentheses. Estimates allow for a linear trend in the VAR and a constant and no trend in cointegrating vector. The significance of VECLM statistics accounts for vector size. Lagged first differences beyond lag t-1 are omitted to conserve space. [1] No lag resulted in a unique and statistically significant vector. [1]This lag length minimized the AIC. [2]This lag length resulted in clean residuals.

Table 5: Quarterly Models of the Required Rate of Return on Apartments

Long-Run Relationship: $rrr^{prem}_t = \beta_0 + \beta_1 Aaa_t + \beta_2 CapReq_t + \beta_3 WFH_t$

	Baseline Models		*WFHTotal*		*WFHPrime*	
Sample:	95q2-19q4	95q3-23q4	95q2-19q4	95q3-23q4	95q3-23q4	95q3-23q4
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Constant	2.205	2.046	1.933	2.288	2.201	2.610
Aaa_t	1.099**	1.107**	1.141**	1.088**	1.111**	1.055**
	(19.62)	(19.27)	(5.83)	(15.74)	(5.67)	(16.89)
CapReq	0.135**	0.141**	0.161**	0.138**	0.163**	0.139**
	(4.09)	(3.50)	(4.16)	(3.45)	(4.21)	(4.15)
WFH			-0.047	-0.017+	-0.082	-0.070**
			(1.16)	(1.90)	(0.27)	(3.13)
TraceCorr (1v.)	29.98*	34.08*	61.47**	56.21**	56.31**	58.87
TraceCorr (2v.)	3.66	6.84	28.67	21.43	28.13	18.49
Unique Coint-	Yes*	Yes*	Yes**	Yes**	Yes**	Yes**
Lag Length	5	5	5	6	5	5

Short-Run: $\Delta rrr_{jt} = \alpha_0 + \alpha_1 EC_{t-1} + \sum\beta_i\Delta(rrr)_{t-i} + \sum\theta_i\Delta(Aaa)_{t-i} + \sum\theta_i\Delta(CapReq)_{t-i} + \sum\theta_i\Delta(WFH)_{t-i} + \delta S\text{-}runVar_t + \varepsilon_t$

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Constant	-0.047*	-0.033*	-0.107**	-0.029+	-0.111*	-0.027+
	(2.39)	(2.18)	(3.26)	(1.83)	(3.31)	(1.74)
EC_{t-1}	-0.185**	-0.141*	-0.146**	-0.118**	-0.158**	-0.117**
	(3.22)	(3.70)	(3.26)	(2.96)	(3.20)	(2.76)
Δrrr_{t-1}	0.089	0.053	0.021	0.029	0.050	0.013
	(0.84)	(0.58)	(0.21)	(0.31)	(0.48)	(0.14)
ΔAaa_{t-1}	-0.041	0.009	0.034	0.045	0.026	0.057
	(0.51)	(0.15)	(0.46)	(0.74)	(0.34)	(0.97)
$\Delta CapReq_{t-1}$	-0.056*	-0.049*	-0.050*	-0.046*	-0.051*	-0.046*
	(2.32)	(2.27)	(2.04)	(2.06)	(2.06)	(2.06)
ΔWFH_{t-1}			-0.271	0.000	-0.321	0.012
			(0.30)	(0.09)	(0.36)	(0.52)
$GLEI_{t-1}$	-0.748	-0.753	-0.987	-1.090+	-0.876	-1.358*
	(1.13)	(1.43)	(1.59)	(1.85)	(1.38)	(2.41)
$DSubPrFail_{t-1}$	-0.304*	-0.306*	-0.367*	-0.326*	-0.368*	-0.330*
	(2.04)	(2.23)	(2.44)	(2.25)	(2.43)	(2.33)
$DLehman_{t-1}$	0.600**	0.639**	0.618**	0.588**	0.635**	0.548**
	(3.31)	(3.97)	(3.98)	(3.46)	(3.58)	(3.24)
$DEuroCrisis_{t-1}$	0.577**	0.560**	0.615**	0.564**	0.586**	0.571**
	(3.95)	(4.30)	(3.76)	(4.16)	(4.04)	(4.35)
Adjusted R^2	.432	.471	.457	.428	.466	.422
S.E.	0.154	0.143	0.149	0.149	0.150	0.148
VECLM(1)	2.58	2.43	14.51	8.74	12.70	12.53
VECLM(2)	10.82	8.00	20.57	13.89	22.53	13.28

Notes: Data used in the estimation cover 1993q4-2024q3. "v." denotes vector. ** and *** denote 95% and 99% significance. Absolute t-statistics are in parentheses. Estimates allow for a linear trend in the VAR and a constant and no trend in cointegrating vector. The significance of VECLM statistics accounts for vector size. Lagged first differences beyond lag t-1 are omitted to conserve space. [1] No lag resulted in a unique and statistically significant vector.

Table 6: Quarterly Models: Required Rate of Return on Industrial Warehouses

Long-Run Relationship: $rrr^{prem}_t = \beta_0 + \beta_1 Aaa_t + \beta_2 CapReq_t + \beta_3 OLR_t$

	Baseline Models		*Online Retail Sales (OLR)*		*TaxOppZone*
Sample:	96q1-19q4	96q1-24q3	96q1-19q4	96q1-24q43	96q1-24q3
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Constant	2.950	2.185	0.967	4.054	3.328
Aaa_t	1.040^{**}	1.153^{**}	1.382^{**}	0.623^{**}	0.928^{**}
	(11.86)	(12.03)	(4.03)	(6.00)	(10.66)
CapReq	0.109^{*}	0.196^{**}	0.036	0.162^{**}	0.156^{**}
	(2.17)	(4.24)	(0.48)	(4.49)	(3.25)
OLR (mod. 3,4)			-0.404^{*}	-0.151^{**}	-0.929^{**}
TaxOppZone (mod. 5)			(2.23)	(4.41)	(3.21)
TraceCorr (1v.)	26.28	25.83	53.84^{*}	57.11^{**}	38.97
TraceCorr (2v.)	3.65	6.66	27.87	21.92	13.67
Unique Coint-	No	No	Yes^{*}	Yes^{**}	No
Lag Length	5	5	4	5	5

Short-Run: $\Delta rrr_{jt} = \alpha_0 + \alpha_1 EC_{t-1} + \sum\beta_i\Delta(rrr)_{t-i} + \sum\theta_i\Delta(Aaa)_{t-i} + \sum\theta_i\Delta(CapReq)_{t-i} + \sum\theta_i\Delta(OLR)_{t-i} + \delta S\text{-}runVar_t + \varepsilon_t$

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Constant	-0.039^{*}	-0.030^{*}	-0.025	-0.014	-0.029^{*}
	(2.53)	(2.17)	(0.75)	(0.83)	(2.09)
EC_{t-1}	-0.118^{**}	-0.085^{*}	-0.024	-0.157^{**}	-0.127^{**}
	(3.53)	(3.27)	(1.07)	(4.11)	(3.65)
Δrrr_{t-1}	-0.073	-0.098	-0.161^{+}	-0.065	-0.069
	(0.80)	(1.13)	(1.83)	(0.73)	(0.75)
ΔAaa_{t-1}	0.032	0.071	0.124^{+}	0.068	0.059
	(0.53)	(1.33)	(1.99)	(1.33)	(1.07)
$\Delta CapReq_{t-1}$	-0.050^{*}	-0.041^{*}	-0.033^{+}	-0.053^{**}	-0.049^{*}
	(2.62)	(2.10)	(1.69)	(2.71)	(2.44)
ΔOLR_{t-1} (mod. 2,3)			-0.065	-0.007	-0.445^{**}
$\Delta TaxOppZone_{t-1}$ (mod. 5)			(0.38)	(0.22)	(3.17)
$GLEI_{t-1}$	-1.297^{*}	-1.470^{**}	-1.873^{**}	-1.742^{**}	-1.493^{**}
	(2.12)	(2.66)	(2.86)	(3.07)	(2.74)
$DSubPrFail_{t-1}$	-0.245^{*}	-0.233^{+}	-0.197	-0.285^{*}	-0.248^{+}
	(2.04)	(1.81)	(1.48)	(2.23)	(1.91)
$DLehman_{t-1}$	0.773^{**}	0.788^{**}	0.729^{**}	0.709^{**}	0.761^{**}
	(5.28)	(5.35)	(4.40)	(4.84)	(5.16)
$DEuroCrisis_{t-1}$	0.346^{**}	0.302^{**}	0.350^{**}	0.304^{**}	0.304^{*}
	(3.12)	(2.68)	(2.95)	(2.73)	(2.62)
$TaxOppZone_{-1}$	-0.546^{**}	-0.505^{**}	-0.479^{**}	-0.526^{**}	
	(4.10)	(3.65)	(3.21)	(3.83)	

Adjusted R^2	.654	.612	.603	.625	.609
S.E.	0.125	0.132	0.134	0.130	0.132
VECLM(1)	7.36	6.51	14.44	16.38	8.16
VECLM(2)	9.11	12.82	21.21	13.73	14.06

Notes: Data used in the estimation cover 1993q4-2024q3. "v." denotes vector. ** and *** denote 95% and 99% significance. Absolute t-statistics are in parentheses. Estimates allow for a linear trend in the VAR and a constant and no trend in cointegrating vector. The significance of VECLM statistics accounts for vector size. Lagged first differences beyond lag t-1 are omitted to conserve space. [1] No lag resulted in a unique and statistically significant vector. [1]This lag length resulted in clean residuals and minimized the AIC; no lag resulted in a significant and unique cointegrating vector.

Table 7: Quarterly Models of the Required Rate of Return on Retail Power Centers

Long-Run Relationship: $rrr_t = \beta_0 + \beta_1 Aaa_t + \beta_2 CapReq_t$

	Baseline Models		COVID Controls	
Sample:	94q2-19q4	94q3-24q3	96q1-24q3	96q1-24q3
	Model 1	**Model 2**	**Model 3**	**Model 4**
Constant	4.060	4.218	3.370	3.973
Aaa	0.775**	0.731**	0.812**	0.808**
	(10.84)	(11.61)	(12.02)	(12.16)
CapReq	0.265**	0.278**	0.246**	0.250**
	(6.25)	(6.27)	(6.13)	(6.16)
TraceCorr (1v.)	41.88**	45.05**	49.75**	49.55**
TraceCorr (2v.)	3.34	7.15	8.49	8.01
Unique Coint-	Yes**	Yes**	Yes**	Yes**
Lag Length	5	5	5	5

Short-Run: $\Delta rrr_t = \alpha_0 + \alpha_1 EC_{t-1} + \sum\beta_i\Delta(rrr)_{t-i} + \sum\theta_i\Delta(Aaa)_{t-i} + \sum\theta_i\Delta(CapReq)_{t-i} + \delta S\text{-}runVar_t + \varepsilon_t$

	Model 1	**Model 2**	**Model 3**	**Model 4**
Constant	-0.010	-0.012	-0.029	-0.024
	(0.43)	(0.60)	(1.41)	(1.19)
EC_{t-1}	-0.268**	-0.214**	-0.247**	-0.236**
	(5.56)	(5.43)	(5.71)	(5.60)
Δrrr_{t-1}	0.190*	-0.196*	0.174*	-0.183*
	(2.22)	(2.49)	(2.20)	(2.32)
ΔAaa_{t-1}	-0.045	-0.017	-0.056	-0.038
	(0.51)	(0.24)	(0.78)	(0.54)
$\Delta CapReq_{t-1}$	-0.061+	-0.050+	-0.051+	-0.049+
	(1.93)	(1.69)	(1.73)	(1.66)
$GRest_t$, m.3 x100			0.286*	0.284+
$GRestVax_t$, m.4 x100			(2.24)	(1.95)
$GLEI_{t-1}$	-1.511**	-2.031**	-1.675*	-1.729*
	(2.94)	(2.98)	(2.44)	(2.51)
$DSubPrFail_{t-1}$	-0.439*	-0.380*	-0.420*	-0.417*
	(2.24)	(2.08)	(2.31)	(2.28)
$DLehman_{t-1}$	0.918**	1.006**	1.028**	1.027**
	(3.89)	(4.66)	(4.78)	(4.75)
$DY2K_t$	-0.592**	-0.145	-0.591**	-0.588**
	(3.93)	(0.87)	(4.19)	(4.15)
$D2014Q4_t$	-0.767**	-0.761**	-0.763**	-0.762**
	(3.60)	(3.79)	(3.84)	(3.81)
Adjusted R^2	.563	.543	.552	.547
S.E.	0.204	0.194	0.192	0.193

VECLM(1)	6.51	7.51	6.72	7.01
VECLM(2)	8.12	8.73	7.26	8.11

Notes: Data used in the estimation cover 1993q4-2024q3. "v." denotes vector. ** and *** denote 95% and 99% significance. Absolute t-statistics are in parentheses. Estimates allow for a linear trend in the VAR and a constant and no trend in cointegrating vector. The significance of VECLM statistics accounts for vector size. Lagged first differences beyond lag t-1 are omitted to conserve space.

	CBD Office	Apartment	Retail Power Center	Warehouse
(1) Extent Cap Rate Below Equilibrium[1]	-0.04	-0.29	-0.82	-0.40
(2) Extent Required Rate of Return is Below Equilibrium[2]	0.43	1.89	0.68	0.12
(3) (1-*taxdep*) x user cost coefficient	0.9097	0.9918	0.8494	0.7871
(4) *rrr* implication for Cap Rate = (2) x (3)	0.39	1.87	0.58	0.09
(5) Total Extent Cap Rate Below Equilibrium = (1) + (4)	0.39	1.58	-0.24	-0.31
(6) 2024q3 Cap Rate	7.30	5.20	7.30	5.50
(7) Implied overvaluation[3] = (5) / (6)	5% Overvalued	30% Overvalued	3% Undervalued	6% Undervalued

Notes:

1) Extent 2024q3 equilibrium is above the actual level, using even numbered full sample Cap Rate Models from *Table* 4. Implies overvaluation.
2) Extent 2024q3 equilibrium is above the actual level, using the full sample Model 4 from the appropriate Table among *Tables 4-7*. For retail power centers this adds in the temporary cumulated effect of government-imposed COVID restrictions of 0.18 to l-run equilibrium level.
3) Extent equilibrium cap rate is above the actual divided by the actual.

Table 8: Estimated Extent to Which Commercial Real Estate Prices Are Over- or Under-Valued

(Source: authors' calculations)

	CBD Office	Apartment	Retail Power Center	Warehouse
Effects of Changes in Expected Rent Growth				
(1) Change in Expected Rent Growth from 2019q4 to 2024q3	-1.20	0	-0.40	+0.40
(2) (1-*taxdep*) x user cost coefficient	0.9097	0.9918	0.8494	0.7871
(3) implied effect on User Costs = (1) x (2)	1.31	0	0.34	-0.31
(4) 2019q4 Cap Rate	5.8	5.1	6.9	5.1
(5) Implied price effect = (3) / (4)	-23%	0%	-4.9%	+6%
Effects of Changes in Risk Premia or Rates of Return				
(6) Change in WFH or OLR from 2019q4 to 2024q3	+8.0			+6.0
(7) Coefficient from long-run required rate of return model	0.023			-0.151
(8) (1-*taxdep*) x user cost coefficient	0.9097	0.9918	0.8494	0.7871
(9) Implied Cap Rate Effect = (6) x (7) x (8)	0.17	0	0.04[1]	-0.71
(10) 2019q4 Cap Rate	5.8	5.1	6.9	5.1
(11) Implied price effect = (-9)/(10)	-2%	0%	-0.1%	+14%
(12) Total price effect (5) + (11)	-25%	0%	-5%	+20%

Table 9: Estimated Effects of COVID Restrictions, Work-From-Home, and Online Shopping on Commercial Real Estate Prices
(Source: authors' calculations)

Notes:
1) Equals cumulated short-run effects of COVID on the 2024q3 equilibrium cap rate level (=+0.05) multiplied by line (8).