Synthetic cap rate indices (1991-Covid era)

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Abstract

We introduce a method that combines Euclidean distancing and OLS techniques to project synthetic capitalization rate indices ('SCXs') for metropolitan statistical areas in the US. SCXs are projected independently of market prices, asset specific characteristics and geographic location (ex-ante). In contrast to market cap rates, driven by geographic proximity and market comparables, our new method is driven by economic proximity. We find SCXs provide better forward guidance than market cap rates for commercial real estate ('CRE') defaults and CRE values before and during the Covid pandemic. Our method establishes CRE benchmark cap rate indices across property types that explicitly connect CRE valuation at the MSA level to macroeconomic indicators through economic proximity.

Key Words: Credit Risk, Fair value, Indexing, Information content, Macroeconomics, Real estate
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Introduction

'Location, location, location' is an often heard phrase commonly used in the commercial real estate ('CRE') industry to emphasize the notion that the central defining characteristic of property value is linked inextricably to its geographic location. This paper calls into question the validity of this phrase and common perspective. Our research suggests that the term location, as used in common practice, is too coarse a measure for model driven, market price independent 'fair value' estimation. Instead, we find our technique based on economic proximity, not geographic proximity, generates better insights into CRE risk and better insights into the future direction of CRE values. We formalize this perspective through the introduction of a simple model which combines elements of Euclidean distancing and ordinary least squares ('OLS') estimation. Our technique yields the production of synthetic capitalization rate indices ('SCXs') across all property types at the MSA level. Our model makes explicit the influence of key macroeconomic indicators onto 'fair' investor expectations of CRE in the channel of the cap rate with SCXs. Since SCXs appear to provide better insights than market cap rates into value and risk of properties in our study, we claim they can be interpreted as a new set of benchmark indexed measures of CRE health in the US. This is new to the literature.

Recall, CRE property is an income producing asset class whose income is derived from revenue paid by tenants for the use of the property's space. In standard CRE valuation practice, a property's current net operating income ('NOI') interacts with a property's capitalization rate ('cap rate') in the CRE valuation identity, $V = \frac{\text{NOI}}{\text{cap rate}}$, as noted in Brueggeman and Fisher (2019). This identity is an adaptation of the model for dividend paying stocks introduced in Gordon and Shapiro (1956) and is frequently used in static and proforma CRE valuation. Asset characteristics such as building structure, divisions of rentable space, rents, lease terms, and occupancy rates all influence the channel of NOI. In contrast to the property NOI (numerator), the cap rate (denominator) in the CRE valuation identity is inherently less tethered to the property specific characteristics, and less directly observable. Apart from instances with an observed CRE value, V, and disclosed NOI at the point of sale or financing, cap rates are not as readily observed as property specific characteristics.

Additionally, cap rates based on market comparables from recent sales in a local submarket are often used as benchmarks to impute a similar CRE property value, V, given an observed (or even estimated) NOI. These benchmarks may be geographically and temporally proximate to the subject property, and may implicitly reflect similar financial characteristics, at the time of the financial event at the local level. Additionally, cap rates are also revealed ex-post, following observation of a CRE property sale or refinancing, with NOI reported. As such, a revealed market cap rate for a property may by its nature obscure more elemental drivers of CRE risk hidden by the market's valuation process which itself may suffer from delays in reporting, delays in appraisals, and infrequent comparable sales data.

Repeat sales indices and hedonic price indices for CRE are two generally accepted methods for estimating benchmark values for CRE as noted in Geltner (2015). Both methods are exposed to a variety of data driven challenges such as reporting delays. On the one hand, cap rates by their nature must contemplate the future prospects for a property. On the other hand, cap rates may be more market and incentive driven as reflected in observed sales. It is also not necessarily binary, as the cap rate may contemplate both future prospects for CRE value as well market driven incentives from actors such as lenders, appraisers and property investors. Parsing issues between repeat sales and hedonic index construction is not the focus of this paper. Instead, we propose a novel quantitative method for cap rate construction that utilizes signals of economic similarity, statistically, to project SCXs as quantitative fair value estimates of CRE value independent of market price.

In this paper, we find geographically disparate macroeconomic signals, projected by our method into MSA level SCXs, to statistically provide insights into subject property risk at the MSA level. The process for projection that we introduce accomplishes both: (i.) production of replicable, transparent, and statistically significant benchmark valuation indices for CRE (the SCXs), and (ii.) discloses the application of SCX benchmarks to be better at risk and fair value estimation of CRE than actual market cap rates.

We first construct sixty multivariate OLS with the dependent variables observable cap rates at National, State and Regional levels (together, 'supralocations') reported by the National Council of Real Estate Investment Fiduciaries ('NCREIF') from 1991 thru 2015 and the independent variables five macroeconomic variables (house price indices ('HPI'), unemployment rates ('UE'), the corporate bond credit slope (equal to the difference in yields to maturity for Baa and Aaa rated corporate bonds), the Freddie Mac ('FHLMC') conforming 30-year mortgage rate, and the CRE chargeoff rate. Next, we apply Euclidean distancing techniques to formulate the new measure of *economic proximity*, $\text{dist}(k,\, j)_t$, which includes house price indices and unemployment rates, both of which are observable at both MSA and supralocations. We then formulate 402 MSA level cap rates using OLS selecting period by period the constants and coefficients on the right hand side corresponding to the minimizing economic proximity and then interacting those selected coefficients with observable MSA-level and National-level macroeconomic data. This produces a projected time series of MSA level SCXs for 402 MSAs over the period 1991 thru 2015. We perform a battery of robustness tests of our methodology which demonstrate very good fit and high explanatory power for macroeconomic variables distilled into SCXs. The tests suggest no need to alter our method. Finally, we construct statistically significant linear estimates of the projected SCXs from 2015 thru 2022 to establish 1-year forward estimated out of sample SCXs before and during the Covid pandemic period when NCREIF data was not made available to us. Our study yields three main results.

First, we create SCXs at the MSA level which do not exist in nature. We validate the SCX model with tests of a.) multicollinearity, b.) Shannon Entropy scoring (introduced by Shannon (1948)), c.) leave one out cross validation, and d.) pairwise supralocation similarity. We find our distancing methodology to be stable across geographically disparate supralocations in the US that are used to create SCXs and thus confirm the methodological soundness of our SCX projection method and the values produced.

Second, SCXs provide greater insights into lifetime CRE default risks than actual cap rates observed for properties at origination. This claim is supported by logistic regressions applied to 25101 CRE mortgages totaling $700 billion over the period 2000-2015. We find SCXs to be highly significant predictors of CRE default, and comparatively more so than actual cap rates. This is especially the case for the lifetime risks of CRE default in regions outside of central business districts ('CBDs') where the majority of CRE loans in the US are underwritten. This supports our view that market cap rates obscure CRE risks, while elements of the macroeconomy, distilled into SCXs, disclose CRE risks more accurately. We find substantial differences in valuations based upon SCXs compared with those based on actual cap rates totaling about $77 billion (about 11% of market value of properties) with SCXs exhibiting more conservative and more accurate property value assessments than actual cap rates even divorced from property specific characteristics.

Third, using a linear estimate of SCXs we provide a reliable benchmark for CRE values in 1-year forecasts before and during the Covid pandemic. By computing out of sample projections for the MSA level SCXs, we are able to secure insights into CRE values reflective of emerging macroeconomic data during the pandemic. We find considerable variation in this period between the top 25 MSAs, which have 50% of the total eligible workforce, compared with the rest of the country. The exodus away from urban centers (in the top 25 MSAs) during Covid, as noted in Whitaker (2021), appear to prompt a more severe compression in CRE values (increases in SCXs) compared with remainder of the country. More recent reversals in migration (return to cities) is also captured by our method, resulting in projected increases in CRE values (decreases in SCXs) through June 2022. Our projected benchmarks of CRE values during the Covid era are in line with some other projections in the literature. They provide a novel, and transparent, reconciliation between macroeconomic effects and CRE valuation. The stability of SCX estimations, precision in default and valuation estimation, and observable differences in CRE valuation historically, support these forward projections during the Covid pandemic, though further research can be conducted.

Our paper makes at least four contributions to the literature. First, our approach makes explicit the benefit of using disparate macroeconomic indicators for CRE valuations independent of market prices. This refinement in CRE valuation contributes to the fair value literature. Second, the findings of our study suggest that the geospatial term 'location' is, in the economic terms determined by our model, actually a statistical aggregation of macroeconomic influences which are not bounded to geographic location of the property, ex-ante. This represents a contribution to the field of urban economics using a cross-disciplinary and unique quantitative approach applied to risk based pricing of CRE. Third, SCXs which do not exist in nature represent a new, reliable, readily-producible, set of benchmark indices of CRE health and valuation. As such our paper also contributes to the literature on indexing providing a readily observable measure which may be used for benchmark pricing within MSAs in the current period estimates representing forecasts out one year. Finally, fourth, we claim that the information content contained in SCXs represent a new set of 'hard information', in the sense of Liberti and Peterson (2018), for the CRE market. Given the corroboration of our projections with stated claims of changes in property values in the midst of the Covid pandemic, such hard information holds promise for further research, use and policy for CRE with SCXs a useful indicator for property valuation at the MSA, State and National level. In conjunction, the large research question as to whether 'Does location matter for CRE?' is addressed in this paper with the validated response of 'Not the way you might commonly think.'

The remainder of this article is organized as follows. Section 1 provides a short literature review. Section 2 discusses the data used in our study. Section 3 describes the methodology for SCXs. Section 4 discusses the validation of our model. Section 5 validates the use of SCXs in valuation and lifetime default estimation of CRE loans. Section 6 provides application of SCXs during the Covid pandemic. Section 7 summarizes with suggestions for future research. An Online Appendix is available upon request providing extensive supplementary robustness checks, discussions, and long form tables documenting findings into SCX creation and implications of testing results at the MSA level.

1 Literature Review

People live (Multifamily) and work (Office), shop (Retail), relax and travel (Hotel), and are served indirectly by (Industrial) CRE in most aspects of their daily lives in the US. As noted in Fuller (2020), even excluding new construction activity, existing US CRE stock of 49.6 billion square feet supported 4.5 million American jobs, generating a total economic contribution to US GDP of $464.4 billion in salaries and wages. Additionally, recent estimates of the total value of US CRE property range between $14.4 and $17.0 trillion (NAREIT (2020)), with total US CRE debt outstanding equal to $4.7 trillion (Federal Reserve (2020) and ARES (2020)).

In capital markets, about $1.9 trillion in US CRE securities are found in the investment portfolios of insurance companies, pension funds, investment managers, hedge funds, and individuals in the US. This aggregate consists of Real Estate Investment Trusts, ('REITs'), which have a market capitalization of about $1.3 trillion with average daily trading volume ('ADV') of $8.7 billion while and commercial mortgage backed securities, ('CMBS'), which have an outstanding principal balances of about $600 billion in the US exhibited ADVs of $0.84 billion. These figures are dwarfed, for example, by the agency residential mortgage backed securities market with $9.9 trillion outstanding and ADV of $289.8 billion.[1]

Given the size of CRE across multiple facets, it is surprising that it remains relatively opaque as an asset class in terms of valuation.

Measures to track CRE pricing may suffer due to the heterogeneity of the CRE assets and infrequency of their trading, relative to say publicly traded securities, as noted in Geltner (2015). A compounding effect of opaque valuation may translate into asset illiquidity observed in related debt and equity instruments. There we observe muted frequency of securities trading compared with in other more liquid markets. For example, the US Census and US Energy Information Administration, report that residential properties outnumber CRE properties by at least a factor of 14x in the US. Additionally, the average securitized CRE mortgage size is 30-40x the average size of US residential mortgages.

In the absence of frequent transactions, which often reveal prices, CRE asset values remain inherently opaque. There is no secondary market for building assets; they are not traded on public exchanges and they exhibit infrequent transactions which contribute to their highly illiquid profile. When comparing the issuance volumes of residential and CRE securities as described in Killian and Cox (2016), as well as their relative trading frequency, as seen in He and Mizrach (2017), we see substantially lower quantities of observable transaction information for CRE securities investors than are seen in the residential sector. These discrepancies in market driven information content are further confirmed in Marcato and Nanda (2016) who find the residential sector to be significantly more responsive to changes in investor sentiment as captured in prices, compared with the non-residential sector. At the loan level, Titman, Tompaidis and Tsyplakov (2005) find a considerable portion of CRE loan risk premia may be associated with illiquidity of the securing asset and a lack of integration

[1] See NAREIT (2020) and SIFMA (2021).

between real estate and more developed corporate credit markets. While the recording of trading in CRE securitizations is improving the information content flow to enhance liquidity as discussed in Hollifield, Neklyudov and Spatt (2017), information deficits within such revealed prices in CRE transactions may still confound transparency and underscore opacity in the CRE market for hard building assets.

Findings of such CRE market opacity are also supported in the literature on the equity side focusing on a disconnect between investor expectations and REIT portfolio valuations as discussed in Pavlov, Steiner and Wachter (2018). This aggregation effect is also noted by Bond and Mitchell (2011) on the debt side of the capital structure for U.K. real estate derivatives. Misspecification of underlying risks also affects the liquidity of instruments as found Christopoulos (2017) who suggests a possible aggregation effect CMBS index prices ('CMBX'). Similarly, Christopoulos and Jarrow (2018) provide evidence of market mispricing of CRE debt in securitizations, which may also suggest imprecise CRE risk assessment. Recently, Griffin and Priest (2020) claim CRE values may be influenced by systemic use of inflated NOI in CMBS lending practice which may have lead to overvaluation of CRE.

Cap rates which play a central role in valuation of CRE, are necessarily imbued with the market's expectations of future real estate growth. However, the expectations of such future growth may be misspecified as noted in Sivitanides, Southard, Torto and Wheaton (2001). Recent cap rate studies by Chervachidze, Costello and Wheaton (2009), Liang (2013), and Seagraves and Wiley (2016) provide innovations into cap rate risk composition. While these works advance the literature in querying into implications of cap rate use in valuation and risk components of cap rates, none of these studies project cap rate indices independent of market pricing which is of central importance to our paper.

Our methodology clarifies the relationship between some macroeconomic variables and CRE valuation. SCXs are created from macroeconomic factors, independent of market pricing and in this way are a model or 'fair value' estimate. Our approach differs from the motivating indexing literature of Bailey, Muth and Nourse (1963), Case and Shiller (1987) and Fisher (2000) who do not use distancing techniques for indexing. Our methodology is not, ex ante, geographically restricted. If an MSA and supralocation pair are geographically distant from one another (e.g. the MSA of Tallahassee, FL compared with the supralocation of the State of Alaska) but, nevertheless, exhibit similar variation in their macroeconomic signals, we claim that such similarities should have similar influences on CRE property valuation, regardless of geographic distance. This insight is central to our method. Matches based upon economic proximity, which is temporal and data driven, may vary considerably from period to period. Indeed the richness of our approach is established through our ability to methodically scan the nation for signals of economic similarity between MSAs and supralocations and to then project MSA level SCXs based upon that similarity.

In so doing, our approach inherently challenges the primacy of property geographic location at the MSA level in valuation as discussed in Grissom, Hartzell and Liu (1987) and Wheaton and Nechayev (2005). Our results suggest that location at the MSA, State and National level in the traditional sense matters much less than is commonly thought. Instead, we claim that macroeconomic influences appear to matter much more than previously considered in CRE property valuation in indexed form at the MSA, State and National levels across all property types as demonstrated by our work. Earlier work in the real estate literature does not fully disentangle the geographic influence from the economic influence in CRE valuation. Hartzell, Shulman and Wurtzebach (1987) and Mueller (1993) identify economic diversification through reclassification of geographic regions based on industry representation. However, those reclassifications are inherently geographic and do not partition economic proximity from geographic proximity. In contrast, our work does disentangle these influences. Additionally, recent work by Chegut, Eichholtz and Rodrigues (2015), Hyun and Milcheva (2018) and Silver (2016) suggest geographic proximity is driving the idiosyncrasy in valuation of CRE assets. Our approach utilizes geographic distinctions with a freer economic configuration that supersedes geographic proximity.

2 Data

This section discusses the data we use in our study to project SCXs. To project these measures we use both public and private information. Both sets of data are broadly utilized by market actors. Wherever possible we preserve the integrity of the data in its raw form consistent with the way in which it is absorbed in common practice.

2.1 Public data

The public data we use to capture macroeconomic influences on CRE are: HPI, UE, the corporate bond credit slope, the FHLMC conforming 30-year mortgage rate, and the CRE chargeoff rate. HPI are reported by the FHFA. UE and able workforce are reported by the Bureau of Labor Statistics ('BLS'). The credit slope, mortgage rate and CRE chargeoff rate are reported by the Federal Reserve Board as captured in the FRED Economic Database of the St. Louis Federal Reserve[2]. The selection of these specific data is purposeful. First, capturing public data influences on market actors decision-making requires that such information be readily observable and in the form in which it is transmitted. Each of the variables we have selected satisfy this criteria. Second, we want prior continuity with the literature[3] that utilize macroeconomic variables to describe the impact debt instruments. Third, for our distancing technique to be implemented, we require that the macroeconomic variables be readily observable at both the supralocational levels and the MSA levels and used by market actors. HPI and UE satisfy those criteria and thus are selected for the distancing procedures described in Section 3.

We capture all public data from 1990-2021 on a quarterly basis. HPI and UE are reported at National, State, and 402 MSA levels of granularity, while the credit slope, mortgage rate and CRE chargeoff rate are reported only at the National level. HPI values are converted into simple nominal returns. UE and CRE chargeoff rates are expressed as annual percentages. The credit slope between Baa and Aaa rated corporate bond yields to maturity is converted to basis points ('bps'). The mortgage rate is expressed as an annualized percent rate of interest. We also use quarterly observations of the Dow Jones Industrial Average ('DJIA') which were captured from Yahoo! Finance. We also utilize the VIX volatility index as reported by the Chicago Board Options Exchange.

[2]See https://fred.stlouisfed.org/

[3]See Yan, Xie, Shi and Wu (2008), Liang (2013) and Figlewski, Frydman and Liang (2012).

2.2 Private data

There are two types of private data: NCREIF and Intex. They are used in a variety of ways in projecting and validating SCXs as described in the text.[4]

The NCREIF sample spans 1991-2015. Since 1977, NCREIF has provided quarterly CRE asset valuation data reported by member institutional fiduciaries with property value estimations lagging by 1 quarter (3-months). NCREIF's regular reporting reflects institutional valuations on more than 35000 CRE properties totaling several trillions of US dollars.[5] The data is reported quarterly and reflects actual sale prices and marked-to-market valuations by the largest commercial real estate property holders in the United States including: pension funds, commercial banks, investment banks, and life insurance companies. NCREIF indices have been widely used in academic studies for more than twenty-years, as described in Diehl (1993) and others. However, problems with NCREIF's frequency of reporting and smoothing of such data as noted in Clayton, Geltner and Hamilton (2001) partially motivates our work. NCREIF returns are captured at the State and National levels for each of 8 mutually exclusive and exhaustive Regional partitions of the US: East North Central, Mideast, Mountain, Northeast, Pacific, Southeast, Southwest, and West North[6] and 6 property types: Industrial, Lodging, Multifamily, Office, Retail and Other.

[Insert Table 1 about here]

The Intex reporting period spans 2007-2015. This includes reported loan level information (Table 1) from Intex for loans with origination dates spanning 2000-2015 on 25101 properties whose mortgages serve as collateral for 175 CMBS transactions. We use these data in comparative default and valuations assessments. The total balance of the private loan data at origination was $389 billion with property values at the point of origination totaling approximately $700 billion. The average loan size at origination was about $15mm. This sample represents 1/3 of the CMBS universe and 10% of all CRE properties in the US. Of these loans, 1013 totaling about $15 billion, defaulted over the period of 2007 to 2015. Defaults in our study are defined as instances where loan payments are terminated and

[4] Private data was provided by an anonymous institutional investor with ~$0.7 trillion AUM.

[5] See https://www.ncreif.org/.

[6] The partitioning of US states is shown in Section 1 of the Online Appendix (available on request).

where a liquidation of the securing property occurred as indicated by a State of Real Estate Owned/Foreclosure. The private loan level data includes zip code level information and property cap rates at origination allowing for grouping by CBD and non-CBD location classification. Table 2 summarizes some statistics corresponding to the 1013 defaulted loans from Intex and juxtaposes those data with their corresponding cap rates SCXs.[7]

[Insert Table 2 about here]

3 The Model

This section presents the methodology to project SCXs at the MSA level using a technique that utilizes OLS and selection based on economic proximity.

3.1 Background: Capitalization rates

Cap rates are applied throughout the CRE industry to determine a benchmark estimate of the value of a property, and ex-post to record the relationship between current[8] NOI and property value following a sale transaction and in ongoing monitoring of the value of the property through time. It is well known in the literature and practice, as noted by Titman (2014) and Brueggeman and Fisher (2019), that cap rates may be interpreted as an application of the Gordon Growth model for dividend paying stocks, introduced by Gordon and Shapiro (1956). In the Gordon Growth framework, the observable price, P_0, of a dividend paying stock may be expressed as, $P_0 = \frac{D_0}{r-g}$ with D_0 the current dividend, r the rate of return on the stock and g the growth rate of dividends. In the CRE context NOI, O_0, is substituted for the dividend D_0 and the property value, V_0, is substituted for the stock price P_0. Following Brueggeman and Fisher (2019), the investor's rate of return on the property, r, and the expected growth rate of NOI, g, allows us to express the cap rate $C_0 = r - g$, such that

$$V_0 = \frac{O_0}{C_0} \therefore C_0 = \frac{O_0}{V_0} \tag{1}$$

[7]For greater detail these default data are organized by CBDs and non-CBDs as found in Section 1 of the Online Appendix (available on request).

[8]In proforma analyses, growth rates may be applied to current NOI, affecting NOI levels projected into the future and these too may be asset specific.

Cap rates and both expected rates of return r and implied NOI growth rates, g, are subject to investor interpretation at any given time t. In this work, we do not investigate into the components of the cap rate, r and g which is left to other work and not our focus. Rather, we introduce a new method resulting in the projection of CRE valuation benchmark indices as 'all-in' cap rates at the MSA level. In particular, we project the cap rate (C_0, the left-hand side of Eq. (1)) independent of the right-hand side $\frac{O_0}{V_0}$. The approach is statistical and the projected cap rates represent benchmark health indices for CRE (consistent with NCREIF reporting).

3.2 Step 1: Computing NCREIF cap rates

We begin by computing the NCREIF cap rate indices, using the NCREIF data across all property types which is also done and published by NCREIF in many studies. We use values for O and V as for all loans in the fiduciary portfolios for each time t. These aggregates are partitioned by supralocation, property-type and time in the sample data. Consistent with NCREIF (and others), we too compute an *all property-type* cap rate index. We adjust Eq. (1) with the following notation. Let $j \in \begin{cases} 1...51 & = \text{Fifty-one (51) total State regions} \\ 52 & = \text{One (1) total US National region} \\ 53...60 & = \text{Eight (8) total NCREIF regions} \end{cases}$ represent distinct geographic *supralocations*; $t \in [1, 95]$ the consecutive quarters from Q4 1991 to Q2 2015; and $p \in \begin{cases} 1 = & \text{Industrial (IN)} \\ 2 = & \text{Lodging/Hotel (LO)} \\ 3 = & \text{Multifamily (MF)} \\ 4 = & \text{Office (OF)} \\ 5 = & \text{Other (OT)} \\ 6 = & \text{Retail (RT)} \end{cases}$ the distinct CRE property types. For each location j, at each time t, across *all* property types p, each NCREIF indexed NOI, O, is given by

$$O_{j,t} = \sum_{p=1}^{6} O_{j,t,p} \tag{2}$$

and each observed NCREIF indexed property value, V, is given by

$$V_{j,t} = \sum_{p=1}^{6} V_{j,t,p} \tag{3}$$

giving the NCREIF indexed cap rate for the time t, j-th supralocation as

$$C_{j,t} = \frac{O_{j,t}}{V_{j,t}} \tag{4}$$

We compute $C_{j,t}$ for each $j \in [1, 60]$ geographic supralocation for all times t resulting in 60 distinct NCREIF cap rate time series.

[Insert Figure 1 about here]

Figure 1 depicts 4 of 60 NCREIF cap rate time series from Eq. (4) for: $j = 35$ (State of New York), $j = 44$ (State of Texas), $j = 52$ (US-Nation), and $j = 55$ (NCREIF Region of Northeast).[9] We use these 60 series of NCREIF cap rates, $C_{j,t}$, as dependent variables in the OLS in Section 3.3.

Finally, note that for stabilized properties with existing history of NOI and tenancy, the Office of the Comptroller of the Currency ('OCC') as noted in OCC (2017) advise the use of current NOIs instead of forecasted NOIs. Since the entirety of our sample from both NCREIF and Intex are based on stabilized properties, we follow the recommendation of the OCC, and the CREFC (2018), and Trepp (2018) and use *current* NOIs in Eq. (1) to calculate NCREIF indexed cap rates as well as the property specific cap rates from the Intex data. We will use these computed cap rates compare to our SCX cap rate measures in the valuation and default analyses in Section 5.

3.3 Step 2: Selecting lead time of covariates

It is well known that the macroeconomy leads CRE (or, equivalently, CRE lags the macroeconomy) as noted for example in NAR (2006), Warren (2010), Geltner (2015) and Hill and Steurer (2020), among others. The lag of CRE values may reflect property specific issues related to lease structures for tenants which may result in below or above market NOIs. Additionally, reporting lags from price indices due to lags in appraisals and the time to execute them properly may also contribute to delay in valuation estimates of CRE. Finally, the heterogeneity

[9] Section 1 of the Online Appendix (available on request) provides summary statistics for all 60 NCREIF actual cap rate time organized by their supralocations.

of the assets and infrequency of observed prices as found in securities markets make extrapolation from comparable assets challenging and obscure confident valuation in the absence of transactions in current periods.

We have to make a modeling choice that reflects economic intuition while also capturing a reasonable lead time. Consider the following regression for the US.

$$\begin{aligned} C_{US,\,t+n} = \quad & \alpha_j + \beta_{1,US}\mathrm{HPI}_{US,\,t} + \beta_{2,US}\mathrm{UE}_{US,\,t} + \beta_{3,US}\mathrm{CreditSlope}_{US,t} \\ & +\beta_{4,US}\mathrm{MtgRate}_{US,t} + \beta_{5,US}\mathrm{CREchgoff}_{US,t} + \epsilon_{US,t} \end{aligned} \tag{5}$$

Since the forecast literature recommends no more than 12 months forward, we consider the results of five regressions in Eq (5) computed with cap rate leads of $n \in [0, 4]$ quarters[10]. The summary results of the five regressions are provided in Table 3.

[Insert Table 3 about here]

The F-tests indicate statistical significance for all regressions, and the regressions exhibit similar signs across covariates with similar Adjusted R-squared values ranging from 0.78 to 0.80. The signs of the covariates are also economically intuitive. Higher cap rates correspond to lower house prices, higher unemployment, lower mortgage rates, and lower commercial real estate chargeoff rates. The creditslope, which is only significant in the 4 quarter lag of the independent variable compared with the dependent variable is more variable in sign. But in the 4 quarter lag case it corresponds to intuition with higher cap rates corresponding to a steeper credit curve.

Since the statistical significance of covariates are somewhat better for 4 quarter lags for the macroeconomy, and the Adjusted R-squared of 0.80 is highest for that lag, we make the modeling choice to determine our SCXs for any time, t, with 1-year lagging macrovariables, $t - 4$. We will also exploit these lead/lag relationships between CRE and macroeconomic variables in the construction of SCXs in a variety of ways throughout the paper.

[10] This could be written equivalently, with the same results fastening t for the dependent variable and varying lags for the macroeconomic variables $n \in [0, 4]$ resulting in subscripts of $t - n$ subscripts for the macroeconomic variables. This is discussed further in Section 5.4.

3.4 Step 3: Supralocation ordinary least squares ('OLS')

There are 60 distinct geographic supralocations. The OLS is thus given by

$$\begin{aligned} C_{j,t} = \; & \alpha_j + \beta_{1,j}\mathrm{HPI}_{j,t-4} + \beta_{2,j}\mathrm{UE}_{j,t-4} + \beta_{3,j}\mathrm{CreditSlope}_{j=52,t-4} \\ & + \beta_{4,j}\mathrm{MtgRate}_{j=52,t-4} + \beta_{5,j}\mathrm{CREchgoff}_{j=52,t-4} + \epsilon_{j,t} \end{aligned} \tag{6}$$

with $j \in \begin{cases} 1...51 & = \text{Fifty-one (51) total State regions} \\ 52 & = \text{One (1) total US National region} \\ 53...60 & = \text{Eight (8) total NCREIF regions} \end{cases}$. Where $j{=}52{=}US$ is but one of the 60 supralocations.

Since we compute observable NCREIF cap rates, $C_{j,t}$, for all $j \in [1, 60]$ geographic supralocations with Eq. (4) from the NCREIF data, we thus are able to compute 60 total OLS with $C_{j,t}$ as the observed dependent variable.

We note that in Eq. (6) we restrict the index for credit slope, 30 year mortgage rate and CRE chargeoff rates to $j = 52$ which corresponds to the National (US) supralocation, because those three variables are only reported at the National level, while HPI and UE are available for all $j \in [1, 60]$ supralocations. We compute Eq. (6) for all supralocations $j \in [1, 60]$. As we are determining a different set of coefficients for each Region, the α, β and ϵ values must also carry the index associated with the j-th supralocation. The indexed estimated constants and coefficients are used in the projection of SCXs.

[Insert Table 4 about here]

Table 4 provides reports summary results for the 60 OLS regressions at the supralocation level. We report the regression results corrected for serial correlation in the residuals with Newey-West standard errors. All regressions were significant as evidenced by the F-test. Adjusted R-squared values range from 0.25 to 0.98. The results are generally consistent across for most of the supralocations. The independent variables of commercial real estate charge-off rates ('crechargeoff') and credit slope ('creditslope') are generally highly significant and with negative sign. The independent variables of house price indices ('hpi'), the 30-year FHLMC mortgage rate ('mortgagerate') and unemployment rate ('ue') were mixed in sign but, generally, highly significant.

Figure 2 summarizes the statistical profile graphically across all 60 supralocations. Figure 2a (on the left) shows the composition of significance for each of the independent variables within all OLS regressions. For example, HPI and UE exhibit varying levels of significance in about 40% of the cases while CRE chargeoffs are significant in virtually all cases. Figure 2b (on the right) shows the adjusted R-squared values for all OLS regressions.

[Insert Figure 2 about here]

3.4.1 Robustness checks - Supralocational OLS

We perform many standard robustness tests on the OLS model at National, Regional and State levels corresponding to the OLS models described in Eq. (6) detailed the Online Appendix (available on request). They include discussion and results for: i.) Omitted variables; ii.) Multicollinearity amongst the explanatory variables; iii.) Serial correlation; iv.) Endogeneity between the model regressors and the error term; and v.) the insignificance of cap rate deltas as explanatory variables. In conjunction the tests do not require us to alter the OLS in Eq. (6). The results are purely supplementary to the results presented in the main text of this paper and may be provided to the interested reader.

3.5 Step 4: Economic proximity to relate MSAs with Supralocations

Distance matrices are a well established tool used in scientific research. Fields such as genomics, chemistry, economics, and financial risk management apply distance matrices to evaluate differences between object pairs based on some common characteristic.[11] In biology, for example, Jiang, Oron, Clark, Bankapur, D'Andrea, Lepore and Funk et al (2016), use similarity matrices derived from nucleotide sequences and structural similarity between genes in different organisms to assign putative biological functions to genes for which no experimental functional validation is available. The particular application of economic distancing we develop in this paper is new to the literature focusing on CRE. Economic parameters of observed HPI and UE create a reasonable backdrop for characterization of economic health. Since publicly available time series of cap rate indices at the MSA level

[11] See Dokmanic, Parhizkar, Ranieri and Vetterli (2015).

do not exist to our knowledge, we resolve to project them as follows. For each time t, we define the economic proximity, $\text{dist}(k,\, j)_t$, between each of the 402 MSA levels and the 60 supralocational levels as

$$\text{dist}(k,\, j)_t = \sqrt{(\text{HPI}_k - \text{HPI}_j)^2 + (\text{UE}_k - \text{UE}_j)^2} \tag{7}$$

with $k = [1,\, 402]$ MSAs and $j = [1,\, 60]$ supralocational levels of granularity above the MSA level. FHFA's HPIs and BLS's UEs are reported at the MSA level which allows us to use Euclidean distancing to determine the SCXs from these observable primitives. We exclude CRE chargeoff rate, credit slope, and mortgage rate variables from Eq. (7) since they are reported only at the National level. We normalize HPI and UE at each time t by the range of their values in the sample to ensure neither value dominates the other in the distancing.

3.6 Step 5: Capturing economic similarity

For each of $t \in [1,\, 95]$ consecutive quarters from Q4 1991 to Q2 2015 a matrix with dimensions 402 rows (corresponding to the $k \in [1,\, 402]$ MSAs) and 60 columns (corresponding to the $j \in [1,\, 60]$ geographic supralocations of Nation, Region and State) is formed with the distances calculated in Eq. (7). These distances are elements of the matrix $D_{k,\, j,\, t}$ where

$$D_{k,\, j,\, t} = \begin{bmatrix} \text{dist}(1,\, 1)_t & \text{dist}(1,\, 2)_t & \cdots & \text{dist}(1,\, 60)_t \\ \text{dist}(2,\, 1)_t & \text{dist}(2,\, 2)_t & \cdots & \text{dist}(2,\, 60)_t \\ \vdots & \vdots & \vdots & \vdots \\ \text{dist}(401,\, 1)_t & \text{dist}(401,\, 2)_t & \cdots & \text{dist}(401,\, 60)_t \\ \text{dist}(402,\, 1)_t & \text{dist}(402,\, 2)_t & \cdots & \text{dist}(402,\, 60)_t \end{bmatrix},\ \forall\ t \in [1,\, 95] \tag{8}$$

There are 95 such matrices, one corresponding to each quarterly date, t. Figure 3, a heatmap, depicts one such matrix, $D_{k,\, j,\, t=93}$, corresponding to *one* time, $t = 93$.

[Insert Figure 3 about here]

The elements of each matrix consist of 24120 economic proximities $\text{dist}(k,\, j)_{t=93}$ as defined in Eq. (7). These economic proximities, differ from quarter to quarter and are used to calculate the SCXs.

We are 'searching' for the supralocation that is most economically similar to the MSA by using the HPI and UE dimensions in each period t. Thus, for a given time period t, the supralocation that is most economically similar to the MSA will be the one corresponding to the smallest value for the economic proximity, $\text{dist}(k,\, j)_t$ as defined in Eq. (7). For each time t and on each row k, the minimum economic proximity is calculated as

$$d^*_{k,t} = \min_j \left[D_{k,\,j,\,t}\right] \tag{9}$$

In other words, $d^*_{k,t}$ is the distance between k-th MSA and the j-th nearest neighboring supralocation among the 60 supralocations at time t. These minimizing values, $d^*_{k,t}$, will reflect the closest (most similar) economic proximity values between the k-th MSA and the minimizing j-th supralocation. Necessarily, we must also capture, for any time t, the corresponding j-th supralocation for the k-th MSA to be a function of the minimization search expressed in Eq. (9), such that

$$j^*_{k,t} = \operatorname*{argmin}_j \left[D_{k,\,j,\,t}\right] \tag{10}$$

where $j^*_{k,t}$ is the index of the supralocation nearest to MSA k at time t. The best economic proximity value at time t will have the smallest value $d^*_{k,t}$ as determined in Eq. (9) and its corresponding supralocation, $j^*_{k,t}$, as determined in Eq. (10).

3.7 Step 6: Projecting the SCXs

Since we do not observe public MSA level cap rate indices for all property types in nature, we project them with the following selection method. The minimum economic proximity, $d^*_{k,t}$, is calculated, and the corresponding $j^*_{k,t}$ supralocation for the k-th MSA is recorded. We then select the constants (α_j's) and coefficients (β_j's) from the regressions estimated in Eq. (6), where all such selections must correspond to the recorded $j^*_{k,t}$ minimum economic proximity supralocation for the k-th MSA as noted in Eq. (10).

Using data for each of the independent variables observed at any time t we then interact the data with the j-th selected OLS constants (α_j's) and coefficients (β_j's) as described above to compute $k \in [1, 402]$ MSA level SCXs, $\tilde{\mathrm{C}}_{k,t}$, defined as

$$\begin{aligned}\tilde{\mathrm{C}}_{k,t} = \quad & \alpha_j + \beta_{1,j}\mathrm{HPI}_{k,\,t-4} + \beta_{2,j}\mathrm{UE}_{k,\,t-4} + \beta_{3,j}\mathrm{CreditSlope}_{j=52,\,t-4} \\ & +\beta_{4,j}\mathrm{MtgRate}_{j=52,\,t-4} + \beta_{5,j}\mathrm{CREchgoff}_{j=52,\,t-4}\end{aligned} \tag{11}$$

As previously noted in the description for Eq. (6), Eq. (11) also restricts the index for the values of the CreditSlope, MtgRate, and CREchgoff to $j = 52$ which corresponds to the National (US) supralocation, while HPI and UE correspond to the $k \in [1, 402]$ MSAs. We emphasize that the left hand side values in Eq. (11) are not observed in nature. Rather, they are projected by us by our method combining OLS at the supralocation levels in Eq. (6) and selection of those corresponding supralocation constants and coefficient based on the method described above in Eqs. (7, 8, 9, and 10). Since Eq. (11) is a straight projection of $\tilde{\mathrm{C}}_{k,t}$ from estimated (and selected) constants and coefficients by our method described, it is not itself an OLS, no error term, ϵ, is included.

We project 38190 values for the left-hand side $\left(\tilde{\mathrm{C}}_{k,t}\right)$ of Eq. (11) with selected values on the right-hand side of Eq. (11) corresponding to all MSAs $k \in [1, 402]$ for all times $t \in [1, 95]$ shown in Figure 4. Figure 4 shows SCXs for 4 of the 402 total MSAs as specified in Eq. (11) governed by the distance equation Eq. (7) and the selection procedure as previously described. The procedure yields a total of 402 separate quarterly time series of SCXs from Q4 1991 to Q2 2015.[12]

[Insert Figure 4 about here]

Because SCXs are constructed from macroeconomic variables, and not CRE prices, they provide a reflection on the impact of broader macroeconomic trends on CRE property risk, independent of market price sentiments.

3.8 Discussion

When predictive models perform well, there is some suggestion that the variables under consideration are important as in our model choices. Our approach is more subtle. We believe the effects of HPI and UE are different under different regimes, and thus we apply

[12]The Online Appendix provides long form table summary statistics for all 402 SCXs.

different effects to those and all other variables relative to each other based on the most similar observable regime. HPI and UE will be prominent in some regime models, less so in others, and we will choose the model that is observably closest to the property in question based on all available information in the model. All models consider HPI and UE in addition to all the global variables. The selection of a model supralocation is as dependent on HPI as it is on UE, since both values are normalized prior to calculation of the distance measurement. Thus both have the same variance, and over all time periods and locations will have the same aggregate impact on choice of the nearest model. Only the selection of the model parameterization is determined by economic distance. The minimizing distance measure governs the selection of the j-th supralocation level coefficients used in Eq. (11) to calculate the SCX at each time t. In this way the economic distancing selects coefficients based upon economic similarity without regard to geographic proximity, ex-ante. SCXs thus differ from existing index methods which, through use of repeat sales indices or appraisal based indices, as described in Bailey, Muth and Nourse (1963), Case and Shiller (1987), and Pagliari, Lieblich, Schaner and Webb (2001), all take information on underlying valuations as a given. SCXs in contrast do not. Instead we create projections of implied cap rates which may be thought of as commercial real estate health indices distilled from disparate information that is bound together through our methodology.

Importantly, the values $\tilde{\mathrm{C}}_{k,t}$ have neither ex ante geographic restrictions nor information directly identifying industry concentration, population density, construction, or other local factors. In our approach, economic conditions are captured solely in the parameters HPI and UE which govern the MSA level to supralocational level economic proximity used for coefficient selection in each period for each MSA. As such, the j-th minimizing supralocations determined in each time t for each of the $k \in [1, 402]$ MSAs are often different for different times t. This is purposeful. Table 5 shows the economic proximities for MSA $k = 1$ for two periods: period $1 = Q41991$ and period $80 = Q42011$. In period $t = 1$, the minimal value of $d_{k,t} = d^*_{1,1} = 0.3876$ which corresponds to supralocation $j_{k,t} = j^*_{1,1} = 21$, the US State of Hawaii. In period $t = 80$, the minimal value of $d_{k,t} = d^*_{1,80} = 0.1911$ which corresponds to supralocation $j_{k,t} = j^*_{1,80} = 17$, the US State of Delaware.

[Insert Table 5 about here]

4 Model validation

This section provides the validation of the model using standard validation methods and drawing on prior work from Shannon (1948) and Kohavi (1995).

4.1 Multicollinearity analysis

The SCX model should produce cap rate values that are intrinsically stable. Because we use OLS, there may be some instability in the coefficients exclusively between the National, Regional, and Statewide variables and MSAs due to multicollinearity. However, this is a straight result of interactions between those National, Regional, and Statewide variable averages which are by their nature multicollinear. The initial regressions from which the coefficients are 'farmed' for SCX projection do not exhibit multicollinearity in testing. The estimations therefore should remain the same regardless of shifts amongst National, Regional, and Statewide coefficient weights.

While explanatory variables may exhibit multicollinearity it will not reduce the predictive power of the model. We are 'switching' from one set of coefficients to another based upon the distance $d^*_{k,t}$ in each period. As such, concerns related to instability of coefficient estimation for small changes in data should be muted. To investigate, we note that the economic distance, $d^*_{k,t}$, in our model will not necessarily produce the same $\tilde{\mathrm{C}}_{k,t}$ for a given period even if the aggregated values $\mathrm{dist}(k,\, j)_t$ for two or more different k locations are equal. Only in cases where HPI and UE from two different locations are identical to one another will the model produce identical $\tilde{\mathrm{C}}_{k,t}$ values for the period. However, in this study where we calculate 38190 SCX values between 1991 and 2015, our method produces only 110 instances of non-unique (identical) values (or 0.288% of all calculated SCXs). This bolsters our claims as to the precision and stability of SCXs determined using our methodology, especially given the geographic and historical breadth of the study. If we simply found MSA x supralocation pairs that were consistently reliable proxies from period to period, one would question the contribution of our approach.

4.2 Shannon Entropy scoring analysis

While it is tempting to look at the variation of nearest neighboring regions over the 95 quarters in terms of the variance in their indices in the [1, 60] domain (i.e., $E\left[{(x-\mu)^2}/{\sigma^2}\right]$) it is important to recognize that any such variance estimate is strongly dependent on the arbitrary choice of order of the index. Thus there is no non-arbitrary measure of the variance of a non-ordinal categorical variable. However, there is a clear difference between a categorical variable which is typically observed to take on only a small subset of its possible values, and one that is observed to take on all of its possible values at similar rates. The corresponding measure of variance of such a non-ordinal variable is its Shannon Entropy[13] which, like the scalar variance, takes into account the number and frequency of different values it takes on, without the scalar's requirement of a mean, which is meaningless to categoricals. We compute Shannon's Entropy score, $H_j(x_k)$, where

$$H_j(x_k) = -\sum_{x_k} p(x_k) log_2 p(x_k) \tag{12}$$

which is the negative logarithm of base 2 of the probability mass function for categorical variables. In this context, the categorical variables are the MSAs and supralocations and $p(x_k)$ represents the percentage of quarters of the j-th MSA in the k-th supralocation observed over 95 quarters. Shannon's Entropy scores which span from 0 (certain) to infinity provide an additive measure of uncertainty for categorical variables. Computing $H_j(x_k)$, allows us to create a single value reflecting the stability of the distancing procedure for each MSA determined from the set of supralocations. The score allows us to then rank order based on supralocation selection variability as depicted in Figure 6. Figure 5 summarizes the Shannon Entropy score analysis.

[Insert Figure 5 about here]

Figure 5a shows the scatterplot of the Shannon Entropy scores for MSAs which range from 2.6763 to 5.2524. Figure 5b groups the scores in partitions with increments of 0.25, with most scores falling between 4.75 and 5.00 and mean and median of 4.7 and 4.8, respectively.

[13] As introduced in Shannon (1948).

Table 6 provides a long form table of Shannon Entropy scores for all 402 MSA locations in support of the model validation.

[Insert Table 6 about here]

The Shannon Entropy scores we calculate support the perspective that our distancing procedure, while utilizing many supralocations across the US, appears to be consistent across most MSAs. The scoring results do not suggest serious uncertainty based on the additivity principle, nor does the scoring indicate levels of certainty as might be seen in perfect substitutes. The distancing measure appears to be sensitive to changes in the HPI and UE drivers across the nation and reasonably stable with respect to selection uncertainty across MSAs.

4.3 Leave one out cross-validation ('LOOCV') analysis

A standard quantitative method to validate the model methodological approach is to implement the standard leave one out cross-validation ('LOOCV') approach described in Kohavi (1995). Briefly, for each supralocation $j \in [1, 60]$ we assume that a supralocation k is our target MSA, and that our pool of supralocations now consists of the remaining 59. Then, reproducing our methodology with this change, for each of $t \in [1, 95]$ consecutive quarters from Q4 1991 to Q2 2015 a matrix of dimensions 60 rows (corresponding to each of the artificially 'missing' $k \in [1, 60]$ supralocations of Nation, Region and State) and 59 columns (corresponding to the $j \in [1, 59]$ geographic locations of existing Nation, Region and State) is formed with the distances, $\mathrm{dist}(k, j)_t$ representing the elements of the matrix $D_{k,j,t}$. There are 95 such k x j matrices, one corresponding to each quarterly date, t. For each row, k, the minimum distance, $d^*_{k,t} = \min_j [D_{k,j,t}]$, is calculated giving 60 such distances, one for each supralocation substitute for MSA. We compare the 60 time series comparing for each time t, the actual cap rates at the supralocations, $C_{j,t}$, to the 60 LOOCV projected cap rates, $\widehat{C}_{j,t}$ by calculating their mean square errors ('MSEs') as

$$MSE = \frac{1}{T} \sum_{t=1}^{T=95} \left(C_{j,t} - \widehat{C}_{j,t} \right)^2 \tag{13}$$

The results are summarized in Table 7 and are quite good. The overall MSE for all observations was 5.30% which compares well with the accuracy found in credit ratings literature as described in Kramer and Guttler (2008) and others. Of the 60 supralocations, 50 exhibited MSEs $< 9\%$ with the remaining 10 exhibiting MSEs$> 11\%$. The MSE for the US (4.65%) was close to the overall MSE of 5.30%. Good results in NCREIF Northeast Region, NY and Rhode Island with MSEs of less than 0.70% were offset by extreme MSEs in NJ of more than 30%. Poor MSEs in TX and NCREIF Mideast Region were offset by excellent performance in other NCREIF Regional composites, NY, and CA. In conjunction, these results suggest that the SCX values are stable and fully utilizing the geographic breadth of the Nation through economic proximity.

[Insert Table 7 about here]

4.4 Supralocational pairing analysis

To get a visual sense for different levels of the stability corresponding to different MSAs across time we note that the variables of interest are the MSAs and the supralocations across time. The matrix $J_{k,t}$ with 402 rows (corresponding to the $k \in [1, 402]$ MSAs) and 95 columns (corresponding to the $t \in [1, 95]$ successive quarters) has as its elements the collection of 38190 supralocations, $j^*_{k,t}$, determined from Eq. (10) such that

$$J_{k,\,t} = \begin{bmatrix} j^*_{1,1} & j^*_{1,2} & \cdots & j^*_{1,95} \\ j^*_{2,1} & j^*_{2,2} & \cdots & j^*_{2,95} \\ \vdots & \vdots & \vdots & \vdots \\ j^*_{401,1} & j^*_{401,2} & \cdots & j^*_{401,95} \\ j^*_{402,1} & j^*_{402,2} & \cdots & j^*_{402,95} \end{bmatrix} \tag{14}$$

Figure 6, a heatmap, corresponding to Eq. (14) reveals the distribution of all 38190 supralocation selections (with values 1 thru 60, as indicated in the legend) for all 402 MSAs across all 95 quarters in the sample period.

[Insert Figure 6 about here]

We see the selection procedure of mapping coefficients from the supralocation level to the MSA level varies geographically over time. There are instances of lighter and darker clusterings corresponding to supralocation selection for given dates. There does not appear to be a regular pattern. This suggests that the procedure is 'using' the entire Nation divided amongst the supralocations to find the best economic proximity for a given period and MSA.

4.5 Discussion

In this section, we used standard validation tests of multicollinearity, Shannon Entropy scoring and LOOCV as well as an innovative visual representation of supralocational pairing across time to validate our model. All techniques are appropriate for validation of this class of models and support our claim of a novel and valid approach to our SCX method.

This section corresponds to our *first main result*: we validate the soundness of our method by confirming the stability, and levels, of SCXs produced by our method.

5 Model implications: Valuation and default analysis

In this section we investigate SCX contribution to CRE risk assessment with comparisons between SCXs and actual cap rates. We conduct distributional, probabilistic, valuation and default estimation analyses. In all analyses, we consider 25101 CRE properties underlying 125 CMBS transactions in our sample.

5.1 Distributions and probabilistic analysis

Each of the properties in the private loan data described in Section 2 are independent of properties included in the NCREIF portfolio and have an origination date, and corresponding property value, NOI, and cap rate information at origination. The cap rates associated with such properties are also independent of NCREIF cap rates. This allows us to conduct an out of sample comparative analysis between SCXs and values $\kappa_{\iota,t}$ representing the actual cap rate for the ι-th property with $\iota \in [1, 25101]$. For each property we find the SCX, $\tilde{\mathrm{C}}_{k,t}$, that corresponds to the MSA identifier of the property at the loan origination date. We split the sample between all properties and only those properties that defaulted on their loan obligation secured by the property. In Figure 7a and 7b we plot cumulative cap rate distributions for the non-defaulted and defaulted subsets. While actual cap rates and SCXs exhibit differentiating capabilities between safer and more risky assets, the assessment of such risks made with SCXs appears to be more conservative than were made by actual cap rates. SCXs are higher than actual cap rates and differences between defaulted and non-defaulted cumulative distributions are wider for SCXs than for actual cap rates.

[Insert Figure 7 about here]

We conducted t-tests summarized in Table 8 for paired samples for non-defaulted and defaulted subsets. These results allow us to reject the null hypothesis that the means of the differences between the sample are zero at the 1% level of significance.

[Insert Table 8 about here]

We quantify the relative propensity to lend at or below cap rate upper bounds in probabilistic terms. The probability of lending at, or below, a given cap rate C is given by

$$F(\mathrm{C}) - F(0) = \Pr(0 < X \leq \mathrm{C}) = \int_0^{\mathrm{C}} f(x)\,dx \tag{15}$$

Table 9 provides the cumulative normal probability distributions corresponding to the mean and variances previously provided in Table 8.

[Insert Table 9 about here]

Looking at the top row for all loans, the probability of lending on a property at or below a 7% cap rate is 49.87% using the lending practices associated with the actual cap rate history. In contrast, using SCXs for all loans, the probability of lending at or below 7% (on the same properties) is 31.67%. The economic interpretation is that lending according to actual practices is about 57% more likely to result in a loan at a cap rate at or below 7%, evidencing a more conservative CRE valuation with SCXs, $\tilde{\mathrm{C}}_{k,t}$, than with actual cap rates.[14]

[14]With NOI, $O_{\iota,t}$, held constant at origination date t, for $\kappa_{\iota,t} < \tilde{\mathrm{C}}_{k,t}$, $V_{\iota,t,\kappa} = \frac{O_{\iota,t}}{\kappa_{\iota,t}} > V_{\iota,t,\tilde{\mathrm{C}}} = \frac{O_{\iota,t}}{\tilde{\mathrm{C}}_{k,t}}$.

This relationship increases non-linearly. The effect is most pronounced in the default sub-sample. Loans that ultimately defaulted with values at origination corresponding to actual cap rates were about 3x as likely to occur (0.4588/0.1439) at or below the 7% upper bound than for evaluations informed by SCXs.

5.2 Valuation analysis

Table 10 provides summary statistics conducting property valuation with SCXs and comparing to actual values reported.

[Insert Table 10 about here]

The actual underwritten valuation of all properties (25083) in the sample was $706.1 billion of which $685.9 billion (24071) did not not default, while $20.2 billion (1012) did default on loan obligations over the sample period. For this sample, we then computed the implied valuation of the property (V) using the NOI (O) at origination and the corresponding SCX (C) corresponding to the quarter in which the loan was originated and within the MSA in which the loan's collateralizing property zip code is found. We then use that SCX (C) in the CRE valuation identity, Eq. (1). We find aggregate property valuations determined by SCXs to be lower than actual property values determined with actual cap rates by about 11% overall. Further, importantly SCXs produced property valuations lower by about 13% for those loans that defaulted suggesting a more conservative approach to CRE valuation with SCXs than with actual market cap rates.

[Insert Figure 8 about here]

Figure 8, for example, shows the geographic distribution of 1013 defaulted loans in our sample at the US (Figure 8a); approximate geographic center of the continental US (Figure 8b); and neighborhood in Wichita, KS (Figure 8c).This granular parsing allows us to observe for example, a defaulted $5.4mm loan on a $6.9mm property carried with it a SCX in the corresponding MSA at origination of 0.087, while the corresponding actual cap rate at origination of 0.070 was 187 bps tighter. Thus, for this one loan, the underwritten CRE valuation was substantially higher than would have been the case with a CRE property valuation conducted with the MSA level SCX. However, conservative does not mean categorically lower CRE valuations with SCXs. There are many instances the CRE valuations were considerably higher than indicated at the point of origination as indicated in the nominal maximum ratios in Table 10.

This valuation analysis could be refined further with simulated sensitivity analysis of upper and lower bounds over a confidence interval for SCXs, but that is left to future research, Overall, the valuation statistics are consistent with the distribution and probabilistic analysis above. These analyses do support questioning as to whether lending practices and corresponding CRE valuations associated with actual cap rates were overly optimistic (or pessimistic) relative to underlying credit risks. In short, do SCXs provide a more accurate estimate of CRE risk and value than actual cap rates? We investigate this further with logistic regressions next.

5.3 Default estimation analysis

Because we have actual cap rates at origination, and corresponding matched SCXs, we may investigate into the comparative strengths of actual cap rates compared with corresponding SCXs in the estimation of lifetime default likelihoods. As such, we implicitly test market expectations of future real estate values with a fair value measure, which necessarily must be independent of market prices.

To quantify whether lending practices which used actual cap rates (vs SCXs) accurately reflected the impounding of macroeconomic influences contained in SCXs we use the standard method of multivariate logistic regression of the form

$$Pr(\text{Def}) = F(x) = \frac{1}{1 + e^{-\beta_0 + \sum_{i=1}^{n} \beta_i x_i}} \tag{16}$$

where $F(x)$ represents the probability of default. The dependent variable is the default indicator variable equal to 1 if the loan defaulted at any point over the sample period and 0, otherwise. The parameter estimates, β_i, are determined numerically with maximum likelihood estimation.

Our actual (market) cap rates in this analysis are not NCREIF cap rate estimates. Rather we use the actual cap rates from Intex data determined using Eq. (1) at the point of loan origination. Specifically, in the logistic regression testing of SCXs we use the 'going-in' market cap rates, $C_{t,i\in[1,\,25101]}$ for the 25101 loans from Intex and compare them to the SCX, $\tilde{\mathrm{C}}_{k,t}$, defined in Eq. (11) for the loan in the quarter in which the loan was originated and within the MSA in which the loan's collateralizing property zip code is found..

5.3.1 *First Treatment*

In the first treatment we consider only one explanatory variable, $x_1=$ cap rate (actual or synthetic), to evaluate differences between defaults that took place in CBDs compared with those in non-CBDs. The results are summarized in Table 11.

[Insert Table 11 about here]

The significance of the estimates is indicated by the z-values produced by the Wald test. The significance of the regression overall is determined with Chi-squared test and we use McFadden's adjusted pseudo R-squared which measures 1 minus the ratio of the estimated log likelihood for the model with parameters (adjusted for the number of parameters) with that of the null model. The results show higher cap rates are associated with higher probability of default at the 1% significance level with better Chi-Squared and Adjusted Pseudo-R-squared statistics. Interestingly, the results show that SCXs have greater sensitivity to lifetime default risk than actual cap rates for the entire sample and in each of the CBD and non-CBD sub-samples. These disparities in sensitivity are most pronounced for loans categorized as non-CBD loans where SCXs are highly significant and actual cap rates are insignificantly different from zero. This result supports claims of misspecification of CRE risk when lending outside of CBDs.

5.3.2 *Second Treatment*

In the second treatment we consider five independent variables $x_1=$ cap rate (actual or synthetic); $x_2=$ occupancy rate; $x_3=$ property age; $x_4=$ CBD dummy with 1 indicating property location within a CBD and 0 indicating property location outside of a CBD; and

x_5= property type fixed effects which exclude the 1009 mixed-use/other properties (OT). The results in Table 12 are in-line with Table 11.

[Insert Table 12 about here]

Occupancy rate and property age are highly significant as expected. Higher likelihoods of default are associated with lower occupancy rates at origination and older properties (possibly due to more stable tenancy and usage). Presence within CBDs is highly significant and positive suggesting higher likelihoods of default in CBDs. Property fixed effects are insignificant. Consistent with the first treatment, SCXs are highly significant predictors of default across all groupings. In particular, non-CBD results again indicate that actual cap rates provide no statistically significant insights into the lifetime risk of CRE default. This contrasts with the significant assessment of CRE risk articulated by SCXs.

5.3.3 *Third Treatment*

The purpose of SCXs is to isolate the time-agnostic aspect of the model. As such, in the third treatment, we control for distinct lending regime time fixed effects with an additional independent variable x_6. We divide the sample into origination sub-periods corresponding to: i.) pre-911 (34 loans originated prior to September 2001); ii.) pre-crisis (11192 loans originated between October 2001 and December 2006); iii.) crisis (8736 loans originated between January 2007 and December 2009); and iv.) recovery (5139 loans originated between January 2010 and December 2014). The mean loan-to-value ratios ('LTVs') of 58%, 68%, 74%, and 63% corresponding to these regimes map to intuition. Following the September 11th terrorist attack, lending restrictions in the US eased (higher LTVs than pre-911). Lending became freer still in the crisis (with higher leverage) in carry over funding obligations until origination ceased in mid-2009. In the recovery period, when lending resumed in 2011, a new lending paradigm characterized by lower leverage took hold with lower LTVs than observed in both pre-crisis and crisis periods. Because of distinct phase shifts in lending regimes, we project our time fixed effect with dummies from pre-911, pre-crisis, and recovery periods, 'bookending' the crisis period. Additionally, we consider the publicly observable VIX volatility index as another covariate, x_7, to capture exogenous market volatility. We map end of day closing values for VIX values to corresponding origination dates for each loan in our sample. The results found Table 13 echo key observations from the two prior treatments. Property fixed effects are insignificant while occupancy, property age, and CBD location remain highly significant. The lending regime time fixed-effects and VIX exhibit significance with little distinction between sub-samples. The main results persist from the earlier treatments persist: SCXs exhibit more significant assessment of lifetime property default risk than actual cap rates outside of CBDs, with equivalent assessments within CBDs.

[Insert Table 13 about here]

5.4 SCXs as natural 1-year forecasts

It is important to note that the method we introduce provides a wealth of insights across current and forward states of the economy with meaning for CRE. Introducing some simplifying notation to keep reporting tractable, let $G_{k,t-q}$ represent the right hand side composite of selected constants, coefficients and macroeconomic data in Eq. (11), for the k-th MSA location and lagged dates SCX, observed at time $t-q$ quarterly lags with $q \in [0, 4]$. So we may write $\tilde{\mathrm{C}}_{k,t} = G_{k,t-4}$ as a shorthand equivalent to Eq. (11). $\tilde{\mathrm{C}}_{k,t}$ is correctly interpreted as the *current* SCX based on 4 quarter lagged macro variables supported by the discussion Section 3.3.

However, at any time t there are *five* SCXs that are projected by our method[15] for any MSA varying by the time index of the right hand macroeconomic data and correct selection of coefficients and constants. Specifically, by shifting the time index and matching the data and estimates in periods correctly, we produce: (i.)$\tilde{\mathrm{C}}_{k,t} = G_{k,t-4}$, (ii.)$\tilde{\mathrm{C}}_{k,t+1} = G_{k,t-3}$, (iii.) $\tilde{\mathrm{C}}_{k,t+2} = G_{k,t-2}$, (iv.) $\tilde{\mathrm{C}}_{k,t+3} = G_{k,t-1}$, and (v.)$\tilde{\mathrm{C}}_{k,t+4} = G_{k,t}$. Therefore, just as (i.)$\tilde{\mathrm{C}}_{k,t} = G_{k,t-4}$ is correctly interpreted as the *current SCX* based on 4 quarter lagged macroeconomic variables, it is also true that (v.)$\tilde{\mathrm{C}}_{k,t+4} = G_{k,t}$ is correctly interpreted as a *natural 1-year forecast SCX* based on current (time t) macroeconomic variables, which, in expanded form is written as:

[15] As described in Eqs. (6, 7, 8, 9, and 10).

$$
\begin{aligned}
\tilde{\mathrm{C}}_{k,t+4} = \quad & \alpha_j + \beta_{1,j}\mathrm{HPI}_{k,\,t} + \beta_{2,j}\mathrm{UE}_{k,\,t} + \beta_{3,j}\mathrm{CreditSlope}_{j=52,\,t} \\
& + \beta_{4,j}\mathrm{MtgRate}_{j=52,\,t} + \beta_{5,j}\mathrm{CREchgoff}_{j=52,\,t}
\end{aligned}
\tag{17}
$$

Figure 9 shows the predicted National cap rate (SCX at the National level) compared with the actual NCREIF cap rate index at the National level. As is evident, the time series for the SCX projects forward an additional 1-year. Specifically, the 1-year natural forecast SCXs, $\tilde{\mathrm{C}}_{k,t+4}$, distilled from macroeconomic variables projected onto CRE valuation provide current and forward looking insights into CRE health at the MSA level.

[Insert Figure 9 about here]

5.5 Discussion

A robustness check of Treatments 1, 2 and 3 was conducted comparing natural '1-year forecast SCXs', $\tilde{\mathrm{C}}_{k,t+4}$ in Eq. (17) to going-in actual loan level market cap rates $C_{t,i\in[1,\,25101]}$ where time t origination time corresponds to time t calculation time of SCXs. Those results are reported in the Online Appendix and are consistent with main findings, if a bit better, than the three treatments above. We leverage this and the natural forecast capability of SCXs in the next section.

This section reports our *second main result*: SCXs provide better insights into lifetime CRE default risks than actual cap rates and different real estate valuations than market driven cap rates.

6 Linear estimates of SCXs during Covid

In this section we provide a treatment of linear estimates of SCXs during the Covid pandemic. SCXs are particularly well suited to make statements about forward CRE valuation in the midst of the Covid pandemic as macroeconomic trends from policy begin to emerge and as policy changes are implemented. The natural 1-year forecast SCXs are used in this Section and we will leverage, statistically, the inherent forward looking nature of SCXs to add to the information content for the CRE industry.

6.1 Background: Covid, CRE, and SCXs

During the Covid pandemic CRE experienced a very serious economic shock. At a high level, in an effort to contain sickness and fatalities associated with the Covid-19 virus, government mandated restrictions on the use of space emerged. Social distancing policies, travel restrictions, work from home options combined to have a dampening effect on CRE activity with deterioration in common patterns of human gathering and use of CRE space. As a result many property types such as hotels and retail were unable to generate revenues to support debt service. Additionally, migration out of urban centers, as noted by Whitaker (2021), that were especially hard hit by Covid, compressed apartment building rents. Finally, rethinking of longer term and more permanent use of at least partial work from home options began to emerge as commonplace and weighed on terms for existing office leases and terms for lease renewals. These changes in the frequency and intensity of human engagement with CRE property had negative impacts on NOI for many properties and gave rise to a broader perception of a deterioration in CRE values. These perception of stresses to CRE values manifested clearly in capital markets. Broad based declines in 2020 in REIT and CMBS prices occurred in the opening stages of the Covid pandemic when vaccinations and inoculation was still not yet a certainty. These perception of stresses in capital markets were then followed by increases in delinquency and default rates on CRE debt as described in Buhayar, Gittlesohn and Gu (2020).

While the Covid pandemic has been a global tragedy, a healthy banking system and judicious use of credit post Great Financial Crisis ('GFC') allowed lenders to engage with a coordinated response to Covid and gyrations over perceived value declines observed in capital markets. Tools such as forbearance, loan extensions, and Federal support from emergency loan and grant subsidization in the form of paycheck protection program ('PPP') loans to a variety of businesses that lease space from CRE property owners[16] have combined to bring delinquency, default and charge off rates to substantially lower levels during the first 18 months of Covid[17], though this may change in the future due increases in borrowing rates

[16] See Jones (2021).

[17] As described in DeSanctis (2021), Duski and Che (2021) and Federal Reserve Board of Governors (2021), among others.

emerging from tighter monetary policy as noted in Wheeler (2022). While efforts to stave off the emergence of bad loan chargeoffs and corresponding liquidity pressures (as seen in the GFC) have been reasonably successful to date, these efforts say nothing directly about the benchmark valuation of CRE directly reflective of the policies themselves.

By providing an assessment of CRE with benchmark SCXs at MSA levels, we capture the relationship between the macroeconomic variables and the implication of value one year forward for CRE. This is a well suited exercise during the Covid era when CRE exhibited considerable dislocation.

6.2 Isolating estimates for SCXs at the MSA level

Since we projected validated SCXs at the MSA level in Section 3, we consider the statistical significance and direction of the independent variables for $k \in [1, 402]$ MSAs on the right-hand side of those now *newly created* SCXs, $\tilde{\mathrm{C}}_{k,t}$ on the left hand side of Eq. (11). To do this, we carefully revisit (and re-note) the initial model parameters and re-estimate the constants and coefficients for the model computing 402 new OLS for $k \in [1, 402]$ MSAs, of the form

$$\begin{aligned}\tilde{\mathrm{C}}_{k,t} = \;& \alpha_k + \beta_{1,k}\mathrm{HPI}_{k,\,t-4} + \beta_{2,k}\mathrm{UE}_{k,\,t-4} + \beta_{3,k}\mathrm{CreditSlope}_{j=52,\,t-4} \\ & + \beta_{4,k}\mathrm{MtgRate}_{j=52,\,t-4} + \beta_{5,k}\mathrm{CREchgoff}_{j=52,\,t-4} + \epsilon_{k,t}\end{aligned} \tag{18}$$

Figure 10 summarizes the statistical results.[18]

[Insert Figure 10 about here]

As before, all regressions were significant as evidenced by the F-test. The figure on the left shows the composition of significance for each of the independent variables across all regressions while the figure on the right shows their adjusted R-squareds. HPI and UE at the MSA level exhibit some level of significance in 40% to 50% of the cases with the mortgage rate statistically significant for all MSAs. The adjusted R-squared values are somewhat improved compared with the original supralocation results produced from Eq. (6).

The results are quite good over a long period of time. They indicate over the long term the relationship among the macroeconomic drivers governing the cap rate indices at the

[18] The long form table with estimates for all 402 MSAs is available in the Online Appendix.

MSA level. Importantly, these estimates at the MSA level may now be used to generate linear estimates of SCXs directly from the macroeconomic variables without going through the entire procedure of Section 3. Since the NCREIF data was not made available to the authors after 2015 reporting dates, this is quite convenient and allows us to perform an out of sample analysis at the MSA level during the Covid era.

6.3 Computing linear estimates of SCXs

We leverage the 1-year forecast capability described in Section 5.4 and Eq. (17) and the new MSA level estimates described in Section 6.2 generated from Eq. (18) and summarized in Figure 10 to produce linear estimates of SCXs 1-year forward, $\check{C}_{k,t+4}$, defined as

$$\begin{aligned} \check{C}_{k,t+4} = \quad & \alpha_k + \beta_{1,k}\mathrm{HPI}_{k,\,t} + \beta_{2,k}\mathrm{UE}_{k,\,t} + \beta_{3,k}\mathrm{CreditSlope}_{j=52,\,t} \\ & +\beta_{4,k}\mathrm{MtgRate}_{j=52,\,t} + \beta_{5,k}\mathrm{CREchgoff}_{j=52,\,t} \end{aligned} \tag{19}$$

directly from the MSA level linear estimates α_k, $\beta_{1,k}$, $\beta_{2,k}$, $\beta_{3,k}$, $\beta_{4,k}$, and $\beta_{5,k}$ determined in Eq. (18) and the current (time t) macroeconomic variables $\mathrm{HPI}_{k,\,t}$, $\mathrm{UE}_{k,\,t}$, $\mathrm{CreditSlope}_{j=52,\,t}$, $\mathrm{MtgRate}_{j=52,\,t}$, and $\mathrm{CREchgoff}_{j=52,\,t}$.[19] In other words, we compute the left hand side (projected 1-year linear estimated SCX) from the right hand side (historical estimates and data). This allows us to consider, out of sample, the formation of SCXs during the Covid era.

6.4 National average SCX from linear estimates of MSA SCXs

Consider the period 2014 through 2021, quarterly, with the latest update the June 2021 reporting period. For each reporting period t, the variable estimate interaction produces 1-year forecast SCXs as discussed in Section 3 and reiterated in Section 6.2. So, for example, data provided as of June 2021 correspond to 1-year SCX forecasts for June 2022.

[Insert Figure 11 about here]

Figure 11.a shows the simple unweighted National average SCX, $\check{C}_{US,t+4}$, defined as

[19] As previously discussed in Section 3, HPI and UE are specified at the $k-th$ MSA level while CreditSlope, MtgRate and CREchgoff are specified at the $j = 52$ (National) supralocational level.

$$\check{C}_{US,t+4} = \frac{\sum_{k=1}^{402} \check{C}_{k,t+4}}{402} \quad (20)$$

quarterly, formed from the linear estimates of MSA level SCXs in Eq. (19). The figure captures the average 1-year forward projections for each quarter for December 2015 through June 2022. The lines plot the time series of the National average SCX and the minimum and maximum MSA level SCX found in each period. These values correspond to the intervals on the left y-axis. The bars show the standard deviation across all MSAs for the period which are reported on the right y-axis. The vertical line in March 2021, separates the pre-Covid period from the current-intra-Covid period. Not surprisingly the SCX forecasts peaked in June 2021 at 6.78% nationally, reflecting peaks in Covid infection rates and high societal uncertainty reported in the June 2020 period, 1 year prior. At that time the maximum SCXs forecast was 12.34% with the minimum SCX value forecast to about 2.99%. Interestingly, for the US overall, while there was an uptick in SCXs for June 2021, forecasts out to June 2022 show persistent declines tending towards 5.5%. This would suggest that at the National level, broader macroeconomic trends emerging in the Covid era hold future promise for CRE property values.[20]

6.5 Differences across linear estimated MSA level SCXs by workforce

While the future projections generated in June 2021 forward to June 2022 hold promise, at the same time, the use of CRE is not evenly distributed. Indeed from BLS we note that 50.9% of the able workforce reside in just 25 MSAs. Additionally, we note, that while intensity of use may be larger for MSAs with dense workforce populations, they still only account for the minority of CRE loans originated in the US as previously discussed. Finally, there have been developments both in the popular press and in academic inquiry into the phenomenon of large scale movement or so-called urban flight or exodus in response to Covid. If this sentiment is true, then SCXs for the largest MSAs which contain the large urban centers in the US, should underperform SCXs in the smaller MSAs with fewer able workforce citizens.

[20] A separate vector autoregression and impulse-response function analysis of SCXs found in Christopoulos, Barratt and Ilut (2022b) at the National level.

We consider this by looking at differences in linear estimated SCXs determined by Eq. (19) at the MSA level by the workforce population as captured by BLS. We divide the MSAs into two sets representing approximately 50% each of the working population living the MSA. From BLS data, 50.9% of the able workforce population in the US reside in 25 MSAs. Figure 11.b captures the weighted average SCXs at the National level and for the top 50% and bottom 50% MSA cohorts by workforce population. What we find is evidence that the top 50% cohort, pre-Covid, exhibited persistently lower cap rates (as measured by SCXs), than the bottom 50% cohort. However, when the Covid shock hit that relationship reversed in sympathy with higher levels of UE and more dramatic compression in HPIs in the top 50% cohort compared with the bottom 50% cohort. Consistent with Figure 11.a, the forecast trends of SCXs for both the top 50% and bottom 50% cohorts are expected to decline out to June 2022.

Finally, Table 14 summarizes the quarterly data for each of those MSAs in the top 50% cohort from December 2019 to June 2022. In the last two columns we also calculate the simple change (in bps) between December 2019 and June 2021 and then the change from June 2021 to June 2022. The table is presented sorting the final column from smallest to largest values. What we observe is that, as expected, many MSAs exhibited substantial SCX increases from December 2019 to June 2021 as shown by positive values in the second to last column. This would be consistent with the implied decline in CRE property values nationwide during Covid indicated. For example, SCXs for the MSA which contains New York City increased from 6.63% in December 2018 to 7.67% in June 2021, for a widening of 103.97 bps as shown in the second to last column. At the same time, New York City also appears to be poised for a significant improvement of a decline of 156.40 bps by June 2022, corresponding to a SCX benchmark level of 6.11%. The SCXs in MSAs that increased the most from December 2019 to June 2021 such as Detroit, Los Angeles and Orlando also are forecast to have the greatest tightening by June 2022. Interestingly, for those MSAs where SCXs narrowed during the pandemic such as Austin, TX and San Francisco, CA the remaining improvement (suggested by forecast tightening through June 2022) appears quite muted.

[Insert Table 14 about here]

6.5.1 Corroborating anecdotal support

Anecdotal support for these trends (forecast in June 2021 for June 2022) do appear to be surfacing in the current popular press as of the date of this writing. Consistent with an eclipse in the Austin, TX tightening of cap rates forecast by us at the MSA level for all properties in June 2021 (in Table 14) consider The Real Deal (2022) published one year later calling for a ‘bursting’ of the housing bubble in Austin which precede compression in CRE values (increase in SCX values) by our method. In contrast, consider calls for further tightening in cap rates in New York office in Wong (2022) and as forecast by us at the MSA level for all properties in June 2021 for June 2022 (in Table 14). More data and analysis is needed to confirm the current forecast SCXs across all property types at the MSA level. That is left to future research. At the same time, the default and valuation results of Section 5 (for more than 25000 properties) utilizing actual SCXs and the statistical significance of the estimates depicted in Figure 10 used for linear estimates of SCXs with Eq. (19), do provide support for these observations.

6.6 Discussion

This treatment using linear estimates of SCXs out of sample finds that CRE property values in MSAs characterized by greater workforce contribution to the nation were more negatively impacted during the Covid pandemic than those MSAs with sparser workforce contribution. Consistent with findings pertaining to residential and multifamily value projections found in Gupta, Mittal, Peeters and Van Nieuwerburgh (2021) and in broader CRE projections as found in Barkham, Levy and Luo (2020), the projections for the 1-year forward SCXs indicated a recovery underway through June 2022 in CRE values and the broader economy overall with a return to cities effect. Many of the denser workforce MSAs while projected to recover, are still not projected to retrace to (or improve upon) pre-Covid economic valuations out to June 2022. This contrasts with those MSAs with less dense workforce contributions. Necessarily, as policy changes manifest and are reported, so too will our forecasts change linking current information to 1 year ahead projections. To our knowledge, only our research has produced CRE forecasts at the MSA level independent of market prices utilizing economic proximity and our distancing methodology. Moreover, our ability to project these forecasts with a stable and accurate methodology represents a disclosure of the meaning of macroeconomic variables to benchmark CRE valuation at the MSA level.

In conjunction, this section corresponds to our *third main result*: SCXs provide a reliable 1-year forecast benchmark of CRE values directly reflective of current macroeconomic data and independent of market prices.

7 Summary

The CRE market in the US faces an inherent information content deficit. This deficit is marked by infrequent transactions which can be ascribed in part to idiosyncratic property characteristics and large asset size. We claim one root aspect of this deficit is found in the disconnect between the accurate use macroeconomic indicators to assess CRE risk. Our quantitative methodology discloses important links between the macroeconomy and CRE valuation in SCXs projected from public information. This is new to the literature. SCXs appear to provide insights into CRE property valuation and lifetime default estimations that improve upon those made with actual cap rates in the present, and the future. Given the comparative accuracy that SCXs provide, legitimate questions are raised as to the validity of a geographic centric lending paradigm in CRE and the sensitivity of that market to macroeconomic influences. We provide some answers in this study.

Specifically, benchmark cap rate indices at the MSA level do not exist in nature. In contrast, by our method, all-property type benchmark SCXs are projected from macroeconomic indicators independent of asset characteristics, market valuations, and (ex-ante) property locations. We do not claim that specific property valuations within an MSA are equivalent nor that actual cap rates for all properties in an MSA are equivalent. However, we do claim that SCXs projected for MSAs provide better insights into CRE risk than actual cap rates for more than 25101 properties totaling \$700 billion in valuation over 15 years of origination from 2000-2015.

Additionally, as shown in the valuation section, SCX estimates may provide considerably different valuations of CRE properties than actual market consensus cap rates (higher and lower). This is as expected given the improved accuracy in lifetime default estimation provided by SCXs, particularly outside of CBDs. These facts may be of interest to regulatory policymakers in stress test evaluation and bank capital adequacy requirements as well as, more tactically, in the context of risk management, origination and investment. The results suggest a possible misspecified reliance upon location of a property by the CRE market which may have been too coarse a benchmark measure which did not accurately discern the macroeconomic public information content influence on property values. This, in turn, may have erroneously influenced actual valuation estimates and lending practices at the time of loan origination.

Ongoing relationships between CRE and the macroeconomy can be monitored with SCXs to provide insights independent of market consensus of price (and risk) which are traditionally embedded in market cap rates. The benefit of such monitoring can be seen in our preliminary test case during the Covid pandemic when a fundamental tenet of the use of space in private and public interaction was challenged with mandated (and now often preferred) social distancing. The results of our treatment during Covid further support our methodology. Were the data from NCREIF made available to the authors, we could do many comparisons between linear estimates of SCXs (Section 6) and actual SCXs (Section 3). Without such data, those comparisons are not possible and this is left to future research.

Finally, our treatment of SCXs during Covid sets the stage for further research on use cases of SCXs with consideration of population density, county level influences of infection rates, and political party on projected CRE values; and this is underway. Expansions of this new methodology can be made to property-type levels and more granular county level SCX projection. These extensions might provide further insights. This study leaves opens the question as to the origins of the apparent misplaced reliance upon geographic proximity and coarser notions of location, rather than economic proximity, which is left to future work.

Our findings of better lifetime default estimation, model stability, and market price independent insights into CRE valuation, suggest that SCXs represent a new set of hard information content, suitable for more objective risk monitoring of CRE values at MSA, State and National levels than can be obtained through market pricing by our study. SCXs may assist in better benchmark valuation estimates of illiquid CRE assets facing informational constraints. By distilling the signals of the macroeconomy into CRE valuation benchmarks independent of geographic location, asset specific characteristics and market pricing, SCXs provide an innovative source of hard information content for the CRE market.

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Tables

Table 1: Summary statistics of CRE loans

	Totals		Averages			Totals by proptype					
Location	# loans	($mm)	occ (%)	age (yrs)	loan ($mm)	MF	LO	IN	OF	RT	OT
non-CBDs	19906	$256,758	89.2	9.2	$13	2463	1993	2952	3393	8419	686
Atlanta	173	$4,283	84.4	8.7	$25	17	30	17	57	45	7
Baltimore	81	$1,457	90	10.7	$18	10	7	13	24	18	9
Boston	54	$4,257	87.5	9.8	$79	0	5	6	35	5	3
Charlotte	157	$2,127	89.3	7.6	$14	16	22	25	42	45	7
Chicago	255	$8,688	88.8	11	$34	27	28	23	73	84	20
Cincinnati	80	$1,002	91.6	11.8	$13	16	2	6	25	29	2
Cleveland	80	$1,460	88.6	9.3	$18	11	7	5	20	36	1
Dallas	251	$4,343	89	11.2	$17	55	12	24	78	80	2
Dayton	42	$483	87.9	9.8	$12	6	3	8	7	18	0
Denver	136	$2,684	89.7	9.8	$20	5	7	18	49	50	7
Detroit	26	$376	84.9	14.4	$14	7	3	3	9	4	0
Fort Worth	89	$929	90.3	12	$10	16	8	18	13	34	0
Houston	489	$7,293	89.5	10.7	$15	111	38	54	135	145	6
Indianapolis	120	$1,796	86.2	9.6	$15	13	15	16	31	39	6
Jacksonville	109	$2,195	91.5	12.4	$20	17	6	27	19	23	17
Kansas City	67	$1,197	86.6	8.7	$18	7	9	7	18	25	1
Los Angeles	446	$8,732	91.9	12.9	$20	54	19	64	136	143	30
Miami	126	$2,622	87.6	10.8	$21	9	12	22	32	43	8
Milwaukee	58	$778	90.7	9.9	$13	5	9	6	23	14	1
Minneapolis	93	$2,325	88.5	10.6	$25	5	10	16	30	27	5
New Orleans	30	$707	81.9	7.2	$24	1	12	4	9	4	0
New York	776	$35,252	93.1	17.4	$45	251	54	38	243	101	89
Norfolk	35	$516	92.5	10.2	$15	2	5	2	15	10	1
Oakland	31	$227	83.7	7.9	$7	1	1	13	5	7	4
Oklahoma City	79	$1,078	87.6	7.8	$14	11	5	22	19	20	2
Philadelphia	121	$2,649	90.4	11.1	$22	18	8	9	33	42	11
Phoenix	191	$2,712	88.4	10.7	$14	18	10	40	41	78	4
Pittsburgh	70	$903	91.5	7.6	$13	10	8	7	18	19	8
Richmond	63	$949	86.5	7.2	$15	9	8	7	14	17	8
Saint Paul	64	$762	92.6	8.9	$12	1	4	9	25	23	2
San Diego	223	$4,672	89	11.5	$21	6	41	28	74	60	14
San Francisco	110	$3,106	93.7	12.8	$28	19	10	13	37	19	12
San Jose	47	$1,006	92	15.3	$21	4	5	9	14	12	3
Seattle	96	$3,647	89.3	10.5	$38	7	22	13	25	12	17
St. Louis	10	$242	87.6	19.5	$24	0	2	4	3	0	1
Tampa	105	$1,308	87.2	10.6	$12	15	14	9	31	34	2
Washington, DC	212	$11,892	90.6	9.7	$56	13	32	12	118	24	13
Totals (Avg *)	25101	$387,416	89.3*	9.7*	$15*	3256	2486	3569	4973	9808	1009

This table provides summary statistics for the 25,101 commercial mortgages in our sample grouped by CBD and non-CBD location classification. The header provides the total number of loans and aggregate loan amount at origination. Next, we provide averages for occupancy rate, property age, and loan size (all at the time of origination). The final columns provide counts for the number of loans in the sample corresponding to property types of multifamily/apartments (MF), lodging/hotel (LO), industrial (IN), office (OF), retail (RT), and mixed-use/other (OT). The rows at the bottom of the table provide sums for the totals and property types and arithmetic means for occupancy rate, property age, and loan size. Total loan balances by property type are provided in the final row. Source: Intex.

Table 2: Summary characteristics of Defaulted CRE Loans

Proptype	MF	OF	RT	LO	IN	OT	All
# of defaults	65	271	429	111	92	45	1013
ln(avg prop size)	16.1260	16.4524	16.0708	16.3669	16.1300	16.0358	16.2127
ln(avg uwnoi)	13.4080	13.7548	13.3799	13.8237	13.4480	13.3527	13.5356
avg (actual cap rate)	0.0729	0.0726	0.0716	0.0845	0.0733	0.0727	0.0736
avg (SCX)	0.0750	0.0757	0.0772	0.0757	0.0772	0.0777	0.0765
avg LTV (%)	78.46	76.35	75.91	72.96	77.95	76.57	76.09
occupancy (%)	86.45	87.92	88.03	65.14	86.61	85.00	85.13
loan spread (bps)	124.83	128.28	127.30	151.64	130.82	140.06	130.96

This table provides mean statistics for the 1,013 loans that defaulted within our total sample of 25,019 commercial mortgages. The header provides the property types of multifamily/apartments (MF), office (OF), retail (RT), lodging/hotel (LO), industrial (IN), and other (OT). Source: Intex.

Table 3: NCREIF cap rate OLS regressions at National level with different lead horizons

	_cons	hpi	ue	creditslope	mortgagerate	crechargeoff	AdjRsq
ncrcap	0.1229351***	-0.0001663***	0.0013552**	-0.0000121	-0.0020652***	-0.0051508***	0.7787
	(0.0096087)	(0.0000169)	(0.0006557)	(0.0000164)	(0.0007501)	(0.0009556)	
ncrcap1qlead	0.1159048***	-0.0001641***	0.0019079***	-0.000000447	-0.0016585**	-0.0048744***	0.7850
	(0.0095583)	(0.0000167)	(0.0006505)	(0.0000163)	(0.0007471)	(0.0009456)	
ncrcap2qlead	0.1175822***	-0.0001702***	0.0012491*	0.00000914	-0.0015143**	-0.0037029***	0.7807
	(0.0097087)	(0.0000169)	(0.0006604)	(0.0000166)	(0.0007591)	(0.0009578)	
ncrcap3qlead	0.1074003***	-0.0001621***	0.0017346***	0.0000222	-0.0007768	-0.0036347***	0.7906
	(0.0095442)	(0.0000167)	(0.0006487)	(0.0000165)	(0.0007466)	(0.0009402)	
ncrcap4qlead	0.1041068***	-0.000161***	0.0014758**	0.0000314*	-0.0003436	-0.002943***	0.8001
	(0.0093689)	(0.0000164)	(0.0006387)	(0.0000163)	(0.0007325)	(0.0009248)	

This table summarizes the results of five OLS regression. The data is at the US-level for dependent and independent variables. The results summarize the estimates,and Adjusted R-squared values of the OLS appear in the row adjacent to the dependent variable label. Standard errors of the estimates appear in parentheses immediately below the estimates. The dependent variable is the US level NCREIF cap rate observed with varying lead time ranging from no quarter leads (time t, 'ncrcap0qlead') to four quarter leads (time t+4, 'ncrcap4qlead'). The independent variables are the FHFA house price index ('hpi'), the unemployment rate ('ue'), the corporate credit slope (Baa-Aaa), the conforming FNMA 30-year mortgage rate ('mortgagerate'), and the commercial real estate charge off rate ('crechargeoff'). ***/**/* indicate 1%, 5% and 10% significance levels.

Table 4: OLS for 60 supralocations

Numeric Code, j	Supralocations	_cons	crechargeoff	creditslope	hpi	mortgagerate	ue	Adj R-sq
1	Alaska	0.0569***	-0.0375***	-0.0006***	0.405**	0.0798***	-0.0298**	0.626
2	Alabama	0.3047***	-0.0391**	-0.0007	-0.5896**	-0.0186***	-0.0026**	0.441
3	Arkansas	0.1775***	0.0546***	-0.0005***	0.4682*	-0.0126***	0.0006*	0.245
4	Arizona	0.2881***	-0.0752***	-0.0008*	0.5189	-0.0140***	0.0008***	0.759
5	California	0.5511***	-0.0523***	-0.0011***	-0.1535*	-0.0332***	-0.0143*	0.742
6	Colorado	0.3303***	-0.0580***	-0.0010***	-0.5307*	-0.0189***	0.0015	0.649
7	Connecticut	0.2765***	-0.0722***	-0.0006***	-0.2203**	-0.0077***	-0.007	0.629
8	DC	0.52***	-0.0219***	-0.0009***	0.2565	-0.0267***	-0.0218	0.548
9	Delaware	0.0339***	1.4308***	-0.0046***	-2.9421***	0.247***	-0.1141	0.983
10	Florida	0.3856***	-0.0152***	-0.0008***	0.8226***	-0.0240***	-0.0115	0.761
11	Georgia	0.1364***	-0.0769***	-0.0010***	-0.5202	0.0005***	0.0136***	0.821
12	Hawaii	0.3829***	-0.0274***	-0.0009	-0.1171	-0.013***	-0.0215	0.623
13	Iowa	0.0202***	-0.0515***	0***	0.4004	0.026	0.0026	0.568
14	Idaho	0.3315***	-0.0625***	-0.0009***	-0.2528***	-0.0184***	-0.0012***	0.737
15	Illinois	0.4298***	-0.0383***	-0.0008***	-0.0401***	-0.0288***	-0.0113	0.767
16	Indiana	0.2773***	-0.0400***	-0.0007***	-0.1236	-0.0134***	-0.005***	0.741
17	Kansas	0.2395***	-0.0307***	-0.0009	-0.0785	-0.0053***	-0.0054***	0.774
18	Kentucky	0.2954***	-0.0413***	-0.0006**	-0.3258	-0.0139***	-0.0065	0.515
19	Louisiana	0.4238**	-0.0379**	-0.0015	0.5519	-0.0330	0.0052	0.784
20	Massachusetts	0.5507***	-0.0404***	-0.0012***	-0.3993	-0.0278***	-0.0269***	0.8
21	Maryland	0.4053***	-0.0307***	-0.0007***	0.7276***	-0.0229***	-0.0179***	0.712
22	Maine	0.3362***	-0.0576***	-0.0009***	0.0456	-0.0191***	-0.0022**	0.733
23	Michigan	0.2652***	-0.0386***	-0.0008***	0.2468	-0.0158***	0.0002	0.724
24	Minnesota	0.2325***	-0.0552***	-0.0007***	-0.4272	-0.0110***	0.0026***	0.725
25	Missouri	0.1342***	-0.0563***	-0.0004**	-0.2168	-0.0002***	0.0027	0.805
26	Mississippi	0.4247***	-0.0208***	-0.0008***	0.3057	-0.0251***	-0.0154	0.849
27	Montana	0.3288***	-0.0614***	-0.0009***	-0.3168***	-0.0179***	-0.001***	0.736
28	North Carolina	0.2397***	-0.0623***	-0.0007*	-0.3741	-0.0104***	0.0024	0.682
29	North Dakota	0.3320***	-0.0604***	-0.0009***	-0.1334	-0.0184***	-0.0034	0.734
30	Nebraska	0.1743***	-0.0690***	-0.0008**	-1.2551	-0.017***	0.0348	0.711
31	New Hampshire	0.3002***	-0.0452***	-0.0006***	-0.0097	-0.0115***	-0.0088	0.557
32	New Jersey	0.3882***	-0.0401***	-0.0009***	0.4753	-0.0249***	-0.0074	0.717
33	New Mexico	0.1924***	-0.0502***	0***	0.7064***	-0.0146***	-0.0017	0.398
34	Nevada	0.3192***	-0.0148***	-0.0007	0.8142***	-0.0164***	-0.0102***	0.746
35	New York	0.6344***	-0.0643***	-0.0013***	0.1806	-0.0374***	-0.0239	0.719
36	Ohio	0.2349***	-0.0433***	-0.0008***	-0.2859***	-0.0166***	0.0045*	0.811
37	Oklahoma	0.2700***	-0.0651***	-0.0010**	-0.2651	-0.0179***	0.0103	0.841
38	Oregon	0.4040***	-0.0393***	-0.0005***	0.2554***	-0.0224***	-0.0154	0.733
39	Pennsylvania	0.4250***	-0.0318***	-0.0007***	0.4223***	-0.0263***	-0.0173***	0.726
40	Rhode Island	0.4475***	-0.0450***	-0.0010***	-0.2847***	-0.0191***	-0.0083***	0.752
41	South Carolina	0.2412***	-0.0519***	-0.0015	-0.1773**	0.011***	-0.0001**	0.781
42	South Dakota	0.2268***	-0.0439***	-0.0011***	-0.5193	-0.0054***	0.0054	0.622
43	Tennessee	0.2815***	-0.0675***	-0.0009**	-0.5484	-0.0159***	0.0107	0.742
44	Texas	0.2415***	-0.0546***	-0.0008***	0.0745*	-0.0147***	0.0053	0.716
45	Utah	0.4293***	-0.0315***	-0.0008	-0.2909	-0.0246***	-0.0153***	0.737
46	Virginia	0.2527***	-0.0339***	-0.0003***	0.9157***	-0.0142***	-0.009	0.545
47	Vermont	0.4106***	-0.0215***	-0.0008***	0.6612***	-0.0213***	-0.0220	0.634
48	Washington	0.3407**	-0.0552***	-0.0009***	0.0811	-0.0188***	-0.0052	0.735
49	Wisconsin	0.4150***	-0.0355***	-0.0010***	-0.0209*	-0.0180***	-0.0134**	0.658
50	West Virginia	0.3853***	-0.0371***	-0.0009***	0.199	-0.0288***	-0.007	0.629
51	Wyoming	0.0894***	-0.0108***	-0.0003***	0.0125*	-0.0051***	-0.0004***	0.582
52	US - Nation	0.3521***	-0.055***	-0.0009***	0.1391***	-0.0192***	-0.0068***	0.82
53	East NorthCentral	0.3031***	-0.0499***	-0.0009***	-0.0025***	-0.0158***	-0.0025	0.817
54	Mideast	0.3405***	-0.0351***	-0.0008***	0.1205***	-0.0184***	-0.008***	0.731
55	Northeast	0.4692***	-0.0535***	-0.0009***	-0.1186	-0.0251***	-0.0175	0.76
56	Southeast	0.2953***	-0.0452***	-0.0008	-0.0062***	-0.0164***	-0.0011**	0.763
57	Southwest	0.4227***	-0.0456***	-0.0011***	-0.4465*	-0.0240***	-0.009	0.786
58	Midwest	0.2082***	-0.0579***	-0.0006	0.1292**	-0.0106***	0.0042	0.729
59	West NorthCentral	0.2447***	-0.0637***	-0.0008***	-0.5812	-0.0046***	-0.0016	0.853
60	Western Pacific	0.4676***	-0.0610***	-0.0010	-1.0840	-0.0150***	-0.0160***	0.821

This table summarizes the estimates and R-squared values for the 60 supralocation OLS. ***/**/* indicate 1%, 5% and 10% significance levels.

Table 5: Distance examples for period 1 and period 80 for MSA=k=1

Period,t=1,k=MSA=1						Period,t=80,k=MSA=1					
UE_k	HPI_k	j∈[1,60]	UE_j	HPI_j	d_{kt}	UE_k	HPI_k	j∈[1,60]	UE_j	HPI_j	d_{kt}
5.4	-0.01601	1	10.6000	0.0179	2.3284	6.6	-0.0124	1	6.8000	-0.0247	0.9924
		2	8.1000	0.0027	1.2700			2	10.4000	-0.0172	0.6947
		3	8.6000	0.0109	1.7834			3	8.7000	0.0104	1.8692
		4	7.9000	-0.0065	0.7541			4	10.4000	0.0071	1.6747
		5	9.2000	-0.0104	0.7875			5	12.2000	-0.0074	0.9394
		6	6.5000	0.0328	3.0536			6	8.1000	-0.0239	0.9549
		7	8.1000	-0.0218	0.6178			7	9.1000	-0.0175	0.5580
		8	8.9000	0.0045	1.4351			8	10.7000	0.0369	4.0232
		9	6.3000	-0.0076	0.5523			9	7.6000	0.0358	3.8876
		10	8.7000	-0.0028	1.0283			10	10.7000	-0.0035	0.9474
		11	5.5000	-0.0042	0.7360			11	10.7000	-0.0039	0.9269
		12	3.4000	-0.0528	2.3301			12	6.9000	-0.0380	2.0642
		13	5.8000	0.0278	2.7393			13	5.2000	-0.0123	0.2123
		14	7.8000	0.0293	2.8629			14	7.8000	-0.0250	1.0323
		15	9.3000	0.0155	2.0941			15	10.4000	-0.0370	2.0619
		16	6.9000	0.0227	2.4362			16	9.4000	-0.0030	0.8673
		17	4.8000	0.0038	1.2448			17	6.8000	-0.0101	0.1911
		18	7.9000	0.0012	1.1681						
		19	8.2000	0.0199	2.2991						
		20	9.4000	-0.0201	0.7834						
		21	7.4000	-0.0142	0.3876						

This table shows distance calculations $d_{k,t}$ for periods $t = 1$ and $t = 80$ for $k = 1$.

Table 6: Shannon Entropy score statistics for 402 MSAs

MSA#	MSA Name	Shannon Entropy Score
msa110	El Centro, CA	2.6763
msa402	Yuma, AZ	3.0657
msa38	Bismarck, ND	3.2579
msa216	Lincoln, NE	3.3058
msa11	Ames, IA	3.3515
msa121	Fargo, ND-MN	3.3561
msa341	Sioux Falls, SD	3.4296
msa300	Rapid City, SD	3.5861
msa274	Omaha-Council Bluffs, NE-IA	3.7183
msa53	Burlington-South Burlington, VT	3.7334
msa174	Iowa City, IA	3.7869
msa144	Grand Island, NE	3.7987
msa124	Fayetteville-Springdale-Rogers, AR-MO	3.8246
msa100	Des Moines-West Des Moines, IA	3.8252
msa143	Grand Forks, ND-MN	3.8259
msa218	Logan, UT-ID	3.8758
msa230	Mankato-North Mankato, MN	3.9029
msa227	Madison, WI	3.9038
msa81	Columbia, MO	3.9099
msa71	Cheyenne, WY	3.9345
msa63	Cedar Rapids, IA	3.9738
msa295	Provo-Orem, UT	3.9912
msa272	Oklahoma City, OK	4.0216
msa307	Rochester, MN	4.0270
msa229	Manhattan, KS	4.0317
msa159	Harrisonburg, VA	4.0372
msa10	Amarillo, TX	4.0387
msa383	Waterloo-Cedar Falls, IA	4.0437
msa79	College Station-Bryan, TX	4.0592
msa241	Minneapolis-St. Paul-Bloomington, MN-WI	4.0865
msa17	Asheville, NC	4.0881
msa228	Manchester-Nashua, NH	4.1014
msa209	Lawrence, KS	4.1106
msa310	Rockingham County-Strafford County, NH (MSAD)	4.1137
msa175	Ithaca, NY	4.1463
msa318	Salt Lake City, UT	4.1580
msa14	Ann Arbor, MI	4.1624
msa23	Austin-Round Rock, TX	4.1712
msa158	Harrisburg-Carlisle, PA	4.1776
msa104	Dubuque, IA	4.1878
msa291	Portland-South Portland, ME	4.2042
msa40	Bloomington, IL	4.2077
msa69	Charlottesville, VA	4.2265
msa197	La Crosse-Onalaska, WI-MN	4.2376
msa353	State College, PA	4.2396
msa35	Billings, MT	4.2436
msa340	Sioux City, IA-NE-SD	4.2514
msa166	Honolulu ('Urban Honolulu'), HI	4.2530
msa223	Lubbock, TX	4.2587
msa271	Ogden-Clearfield, UT	4.2663
msa347	Springfield, MO	4.2795
msa382	Washington-Arlington-Alexandria, DC-VA-MD-WV (MSAD)	4.2849
msa335	Sheboygan, WI	4.2875
msa306	Roanoke, VA	4.2982
msa299	Raleigh, NC	4.2997
msa204	Lancaster, PA	4.3138
msa99	Denver-Aurora-Lakewood, CO	4.3157
msa214	Lexington-Fayette, KY	4.3240

MSA#	MSA Name	Shannon Entropy Score
msa239	Midland, TX	4.3423
msa138	Gainesville, GA	4.3508
msa74	Cincinnati, OH-KY-IN	4.3513
msa16	Appleton, WI	4.3533
msa257	Nashville-Davidson--Murfreesboro--Franklin, TN	4.3534
msa50	Brunswick, GA	4.3610
msa45	Boulder, CO	4.3640
msa137	Gainesville, FL	4.3651
msa211	Lebanon, PA	4.3701
msa327	Santa Fe, NM	4.3798
msa359	Tallahassee, FL	4.3821
msa285	Phoenix-Mesa-Scottsdale, AZ	4.3835
msa172	Idaho Falls, ID	4.3844
msa106	Durham-Chapel Hill, NC	4.3924
msa65	Champaign-Urbana, IL	4.3924
msa349	St. Cloud, MN	4.3935
msa242	Missoula, MT	4.4009
msa395	Winchester, VA-WV	4.4072
msa18	Athens-Clarke County, GA	4.4073
msa130	Fort Collins, CO	4.4109
msa5	Albany-Schenectady-Troy, NY	4.4200
msa43	Boise City, ID	4.4227
msa354	Staunton-Waynesboro, VA	4.4242
msa236	Miami-Miami Beach-Kendall, FL (MSAD)	4.4248
msa84	Columbus, IN	4.4263
msa304	Richmond, VA	4.4378
msa153	Greenville-Anderson-Mauldin, SC	4.4526
msa21	Auburn-Opelika, AL	4.4723
msa332	Seattle-Bellevue-Everett, WA (MSAD)	4.4735
msa372	Valdosta, GA	4.4762
msa368	Tulsa, OK	4.4784
msa195	Knoxville, TN	4.4814
msa350	St. George, UT	4.4923
msa58	Cape Coral-Fort Myers, FL	4.4956
msa367	Tucson, AZ	4.4987
msa276	Oshkosh-Neenah, WI	4.4999
msa173	Indianapolis-Carmel-Anderson, IN	4.5081
msa385	Wausau, WI	4.5110
msa62	Casper, WY	4.5122
msa82	Columbia, SC	4.5134
msa199	Lafayette-West Lafayette, IN	4.5138
msa320	San Antonio-New Braunfels, TX	4.5180
msa399	York-Hanover, PA	4.5204
msa190	Kansas City, MO-KS	4.5233
msa85	Columbus, OH	4.5306
msa70	Chattanooga, TN-GA	4.5318
msa182	Jefferson City, MO	4.5340
msa212	Lewiston, ID-WA	4.5341
msa94	Davenport-Moline-Rock Island, IA-IL	4.5346
msa363	The Villages, FL	4.5445
msa319	San Angelo, TX	4.5546
msa249	Morgantown, WV	4.5564
msa116	Enid, OK	4.5564
msa222	Louisville/Jefferson County, KY-IN	4.5587
msa39	Blacksburg-Christiansburg-Radford, VA	4.5633
msa171	Huntsville, AL	4.5634
msa292	Portland-Vancouver-Hillsboro, OR-WA	4.5651
msa345	Springfield, IL	4.5704
msa54	California-Lexington Park, MD	4.5751
msa303	Reno, NV	4.5753
msa168	Houma-Thibodaux, LA	4.5764
msa378	Waco, TX	4.5820

MSA#	MSA Name	Shannon Entropy Score
msa256	Naples-Immokalee-Marco Island, FL	4.5836
msa146	Grand Rapids-Wyoming, MI	4.5841
msa177	Jackson, MS	4.5882
msa44	Boston, MA (MSAD)	4.5898
msa114	Elkhart-Goshen, IN	4.5914
msa28	Baton Rouge, LA	4.5936
msa224	Lynchburg, VA	4.5956
msa90	Dallas-Plano-Irving, TX (MSAD)	4.5986
msa265	North Port-Sarasota-Bradenton, FL	4.6014
msa210	Lawton, OK	4.6125
msa68	Charlotte-Concord-Gastonia, NC-SC	4.6177
msa205	Lansing-East Lansing, MI	4.6218
msa163	Hilton Head Island-Bluffton-Beaufort, SC	4.6288
msa365	Topeka, KS	4.6390
msa103	Dover, DE	4.6442
msa169	Houston-The Woodlands-Sugar Land, TX	4.6449
msa75	Clarksville, TN-KY	4.6459
msa217	Little Rock-North Little Rock-Conway, AR	4.6527
msa330	Savannah, GA	4.6528
msa376	Virginia Beach-Norfolk-Newport News, VA-NC	4.6540
msa80	Colorado Springs, CO	4.6597
msa179	Jacksonville, FL	4.6649
msa240	Milwaukee-Waukesha-West Allis, WI	4.6665
msa46	Bowling Green, KY	4.6698
msa140	Gettysburg, PA	4.6756
msa255	Napa, CA	4.6803
msa77	Cleveland-Elyria, OH	4.6836
msa391	Wichita, KS	4.6901
msa129	Fond du Lac, WI	4.6903
msa55	Cambridge-Newton-Framingham, MA (MSAD)	4.6920
msa374	Victoria, TX	4.6972
msa109	Eau Claire, WI	4.6976
msa283	Peoria, IL	4.6985
msa41	Bloomington, IN	4.6989
msa13	Anchorage, AK	4.7023
msa396	Winston-Salem, NC	4.7035
msa149	Greeley, CO	4.7035
msa198	Lafayette, LA	4.7053
msa293	Prescott, AZ	4.7062
msa87	Corvallis, OR	4.7065
msa67	Charleston-North Charleston, SC	4.7083
msa148	Great Falls, MT	4.7096
msa287	Pittsburgh, PA	4.7167
msa19	Atlanta-Sandy Springs-Roswell, GA	4.7171
msa352	St. Louis, MO-IL	4.7291
msa6	Albuquerque, NM	4.7367
msa270	Odessa, TX	4.7377
msa91	Dalton, GA	4.7377
msa235	Merced, CA	4.7385
msa88	Crestview-Fort Walton Beach-Destin, FL	4.7405
msa193	Kingsport-Bristol-Bristol, TN-VA	4.7429
msa380	Warner Robins, GA	4.7445
msa384	Watertown-Fort Drum, NY	4.7492
msa390	Wichita Falls, TX	4.7496
msa233	Medford, OR	4.7515
msa339	Silver Spring-Frederick-Rockville, MD (MSAD)	4.7540
msa47	Bremerton-Silverdale, WA	4.7562
msa275	Orlando-Kissimmee-Sanford, FL	4.7591
msa48	Bridgeport-Stamford-Norwalk, CT	4.7655
msa180	Jacksonville, NC	4.7657
msa7	Alexandria, LA	4.7674
msa187	Kahului-Wailuku-Lahaina, HI	4.7685

MSA#	MSA Name	Shannon Entropy Score
msa93	Daphne-Fairhope-Foley, AL	4.7685
msa131	Fort Lauderdale-Pompano Beach-Deerfield Beach, FL (MSAD)	4.7685
msa37	Birmingham-Hoover, AL	4.7774
msa150	Green Bay, WI	4.7785
msa52	Burlington, NC	4.7786
msa360	Tampa-St. Petersburg-Clearwater, FL	4.7786
msa194	Kingston, NY	4.7801
msa298	Racine, WI	4.7811
msa244	Modesto, CA	4.7816
msa397	Worcester, MA-CT	4.7818
msa78	Coeur d'Alene, ID	4.7864
msa388	West Palm Beach-Boca Raton-Delray Beach, FL (MSAD)	4.7908
msa59	Cape Girardeau, MO-IL	4.7914
msa151	Greensboro-High Point, NC	4.7917
msa4	Albany, OR	4.7919
msa64	Chambersburg-Waynesboro, PA	4.7951
msa181	Janesville-Beloit, WI	4.7978
msa26	Bangor, ME	4.7997
msa373	Vallejo-Fairfield, CA	4.8004
msa282	Pensacola-Ferry Pass-Brent, FL	4.8024
msa324	San Luis Obispo-Paso Robles-Arroyo Grande, CA	4.8030
msa142	Goldsboro, NC	4.8080
msa370	Tyler, TX	4.8095
msa273	Olympia-Tumwater, WA	4.8106
msa208	Las Vegas-Henderson-Paradise, NV	4.8122
msa105	Duluth, MN-WI	4.8127
msa34	Bend-Redmond, OR	4.8151
msa329	Santa Rosa, CA	4.8161
msa1	Abilene, TX	4.8170
msa133	Fort Wayne, IN	4.8199
msa132	Fort Smith, AR-OK	4.8210
msa186	Joplin, MO	4.8222
msa101	Detroit-Dearborn-Livonia, MI (MSAD)	4.8243
msa301	Reading, PA	4.8248
msa119	Evansville, IN-KY	4.8275
msa145	Grand Junction, CO	4.8295
msa51	Buffalo-Cheektowaga-Niagara Falls, NY	4.8306
msa226	Madera, CA	4.8378
msa358	Tacoma-Lakewood, WA (MSAD)	4.8428
msa266	Norwich-New London, CT	4.8443
msa348	Springfield, OH	4.8451
msa139	Gary, IN (MSAD)	4.8463
msa342	South Bend-Mishawaka, IN-MI	4.8467
msa260	New Haven-Milford, CT	4.8478
msa161	Hattiesburg, MS	4.8504
msa369	Tuscaloosa, AL	4.8519
msa401	Yuba City, CA	4.8544
msa336	Sherman-Denison, TX	4.8555
msa178	Jackson, TN	4.8559
msa247	Montgomery County-Bucks County-Chester County, PA (MSAD)	4.8561
msa394	Wilmington, NC	4.8582
msa89	Cumberland, MD-WV	4.8587
msa277	Owensboro, KY	4.8587
msa118	Eugene, OR	4.8589
msa248	Montgomery, AL	4.8622
msa188	Kalamazoo-Portage, MI	4.8636
msa152	Greenville, NC	4.8653
msa323	San Jose-Sunnyvale-Santa Clara, CA	4.8655
msa381	Warren-Troy-Farmington Hills, MI (MSAD)	4.8671
msa33	Bellingham, WA	4.8674
msa225	Macon, GA	4.8682
msa313	Sacramento--Roseville--Arden-Arcade, CA	4.8694

MSA#	MSA Name	Shannon Entropy Score
msa24	Bakersfield, CA	4.8705
msa83	Columbus, GA-AL	4.8707
msa102	Dothan, AL	4.8723
msa25	Baltimore-Columbia-Towson, MD	4.8737
msa2	Akron, OH	4.8746
msa176	Jackson, MI	4.8751
msa267	Oakland-Hayward-Berkeley, CA (MSAD)	4.8765
msa281	Parkersburg-Vienna, WV	4.8796
msa96	Decatur, AL	4.8845
msa279	Palm Bay-Melbourne-Titusville, FL	4.8858
msa201	Lake County-Kenosha County, IL-WI (MSAD)	4.8861
msa112	Elgin, IL (MSAD)	4.8868
msa362	Texarkana, TX-AR	4.8876
msa165	Homosassa Springs, FL	4.8881
msa157	Hanford-Corcoran, CA	4.8978
msa57	Canton-Massillon, OH	4.8987
msa263	Newark, NJ-PA (MSAD)	4.9031
msa312	Rome, GA	4.9058
msa185	Jonesboro, AR	4.9064
msa366	Trenton, NJ	4.9076
msa315	Salem, OR	4.9083
msa36	Binghamton, NY	4.9107
msa254	Myrtle Beach-Conway-North Myrtle Beach, SC-NC	4.9107
msa314	Saginaw, MI	4.9130
msa122	Farmington, NM	4.9146
msa311	Rocky Mount, NC	4.9169
msa290	Port St. Lucie, FL	4.9192
msa219	Longview, TX	4.9246
msa246	Monroe, MI	4.9254
msa183	Johnson City, TN	4.9261
msa322	San Francisco-Redwood City-South San Francisco, CA (MSAD)	4.9266
msa269	Ocean City, NJ	4.9294
msa98	Deltona-Daytona Beach-Ormond Beach, FL	4.9320
msa156	Hammond, LA	4.9348
msa328	Santa Maria-Santa Barbara, CA	4.9357
msa141	Glens Falls, NY	4.9369
msa192	Killeen-Temple, TX	4.9372
msa243	Mobile, AL	4.9377
msa86	Corpus Christi, TX	4.9379
msa261	New Orleans-Metairie, LA	4.9379
msa207	Las Cruces, NM	4.9399
msa308	Rochester, NY	4.9478
msa162	Hickory-Lenoir-Morganton, NC	4.9523
msa155	Hagerstown-Martinsburg, MD-WV	4.9524
msa393	Wilmington, DE-MD-NJ (MSAD)	4.9524
msa251	Mount Vernon-Anacortes, WA	4.9534
msa284	Philadelphia, PA (MSAD)	4.9581
msa126	Flint, MI	4.9604
msa29	Battle Creek, MI	4.9631
msa134	Fort Worth-Arlington, TX (MSAD)	4.9653
msa245	Monroe, LA	4.9659
msa108	East Stroudsburg, PA	4.9672
msa379	Walla Walla, WA	4.9682
msa9	Altoona, PA	4.9683
msa127	Florence, SC	4.9689
msa321	San Diego-Carlsbad, CA	4.9693
msa333	Sebastian-Vero Beach, FL	4.9708
msa258	Nassau County-Suffolk County, NY (MSAD)	4.9734
msa364	Toledo, OH	4.9744
msa392	Williamsport, PA	4.9749
msa346	Springfield, MA	4.9762
msa147	Grants Pass, OR	4.9766

MSA#	MSA Name	Shannon Entropy Score
msa351	St. Joseph, MO-KS	4.9779
msa316	Salinas, CA	4.9785
msa289	Pocatello, ID	4.9800
msa252	Muncie, IN	4.9813
msa123	Fayetteville, NC	4.9848
msa170	Huntington-Ashland, WV-KY-OH	4.9854
msa135	Fresno, CA	4.9912
msa264	Niles-Benton Harbor, MI	4.9915
msa189	Kankakee, IL	4.9929
msa203	Lakeland-Winter Haven, FL	4.9934
msa286	Pine Bluff, AR	4.9934
msa107	Dutchess County-Putnam County, NY (MSAD)	4.9955
msa334	Sebring, FL	4.9967
msa27	Barnstable Town, MA	4.9970
msa49	Brownsville-Harlingen, TX	4.9970
msa200	Lake Charles, LA	4.9977
msa296	Pueblo, CO	4.9981
msa259	New Bern, NC	5.0000
msa128	Florence-Muscle Shoals, AL	5.0018
msa115	Elmira, NY	5.0032
msa113	Elizabethtown-Fort Knox, KY	5.0034
msa220	Longview, WA	5.0039
msa111	El Paso, TX	5.0061
msa389	Wheeling, WV-OH	5.0071
msa125	Flagstaff, AZ	5.0075
msa120	Fairbanks, AK	5.0125
msa356	Sumter, SC	5.0204
msa72	Chicago-Naperville-Arlington Heights, IL (MSAD)	5.0220
msa344	Spokane-Spokane Valley, WA	5.0234
msa213	Lewiston-Auburn, ME	5.0269
msa66	Charleston, WV	5.0331
msa294	Providence-Warwick, RI-MA	5.0346
msa325	San Rafael, CA (MSAD)	5.0361
msa95	Dayton, OH	5.0370
msa215	Lima, OH	5.0394
msa160	Hartford-West Hartford-East Hartford, CT	5.0398
msa250	Morristown, TN	5.0398
msa73	Chico, CA	5.0424
msa167	Hot Springs, AR	5.0428
msa305	Riverside-San Bernardino-Ontario, CA	5.0432
msa12	Anaheim-Santa Ana-Irvine, CA (MSAD)	5.0441
msa76	Cleveland, TN	5.0460
msa42	Bloomsburg-Berwick, PA	5.0473
msa191	Kennewick-Richland, WA	5.0494
msa196	Kokomo, IN	5.0507
msa206	Laredo, TX	5.0520
msa357	Syracuse, NY	5.0529
msa400	Youngstown-Warren-Boardman, OH-PA	5.0563
msa262	New York-Jersey City-White Plains, NY-NJ (MSAD)	5.0573
msa377	Visalia-Porterville, CA	5.0625
msa337	Shreveport-Bossier City, LA	5.0681
msa20	Atlantic City-Hammonton, NJ	5.0683
msa117	Erie, PA	5.0698
msa231	Mansfield, OH	5.0707
msa238	Midland, MI	5.0711
msa343	Spartanburg, SC	5.0711
msa234	Memphis, TN-MS-AR	5.0729
msa268	Ocala, FL	5.0745
msa202	Lake Havasu City-Kingman, AZ	5.0747
msa136	Gadsden, AL	5.0763
msa317	Salisbury, MD-DE	5.0765
msa184	Johnstown, PA	5.0812

MSA#	MSA Name	Shannon Entropy Score
msa309	Rockford, IL	5.0820
msa221	Los Angeles-Long Beach-Glendale, CA (MSAD)	5.0825
msa8	Allentown-Bethlehem-Easton, PA-NJ	5.0838
msa237	Michigan City-La Porte, IN	5.0838
msa326	Santa Cruz-Watsonville, CA	5.0876
msa280	Panama City, FL	5.1008
msa61	Carson City, NV	5.1025
msa32	Beckley, WV	5.1042
msa371	Utica-Rome, NY	5.1184
msa361	Terre Haute, IN	5.1194
msa154	Gulfport-Biloxi-Pascagoula, MS	5.1222
msa386	Weirton-Steubenville, WV-OH	5.1261
msa56	Camden, NJ (MSAD)	5.1312
msa355	Stockton-Lodi, CA	5.1318
msa297	Punta Gorda, FL	5.1319
msa164	Hinesville, GA	5.1392
msa97	Decatur, IL	5.1528
msa92	Danville, IL	5.1543
msa288	Pittsfield, MA	5.1549
msa387	Wenatchee, WA	5.1577
msa302	Redding, CA	5.1774
msa331	Scranton--Wilkes-Barre--Hazleton, PA	5.1775
msa15	Anniston-Oxford-Jacksonville, AL	5.1792
msa22	Augusta-Richmond County, GA-SC	5.1826
msa232	McAllen-Edinburg-Mission, TX	5.1871
msa3	Albany, GA	5.1919
msa338	Sierra Vista-Douglas, AZ	5.1972
msa253	Muskegon, MI	5.2002
msa60	Carbondale-Marion, IL	5.2075
msa31	Beaumont-Port Arthur, TX	5.2103
msa278	Oxnard-Thousand Oaks-Ventura, CA	5.2176
msa398	Yakima, WA	5.2378
msa30	Bay City, MI	5.2455
msa375	Vineland-Bridgeton, NJ	5.2524
mean		4.7004
standard deviation		0.3844

This table shows the rank ordered summary statistics (from lowest to highest) for 402 Shannon Entropy scores calculated from the synthetic MSA cap rates and actual supralocational cap rates over the period Q4 1991 to Q2 2015.

Table 7: Mean square errors from LOOCV test

Numeric Code, $j \in [1, 60]$	Supralocations	Mean Square Error
40	Rhode Island	0.35%
60	NCREIF_Western Pacific	0.39%
57	NCREIF_Southwest	0.45%
30	Nebraska	0.47%
53	NCREIF_East North Central	0.47%
59	NCREIF_West North Central	0.49%
6	Colorado	0.51%
13	Iowa	0.52%
17	Kansas	0.55%
18	Kentucky	0.55%
56	NCREIF_Southeast	0.56%
27	Montana	0.57%
43	Tennessee	0.61%
16	Indiana	0.63%
31	New Hampshire	0.64%
29	North Dakota	0.65%
14	Idaho	0.66%
55	NCREIF_Northeast	0.68%
24	Minnesota	0.68%
2	Alabama	0.69%
35	New York	0.73%
1	Alaska	0.76%
58	NCREIF_Midwest	0.81%
9	Delaware	0.84%
46	Virginia	0.88%
48	Washington	0.89%
37	Oklahoma	0.91%
28	North Carolina	0.95%
47	Vermont	0.99%
50	West Virginia	1.14%
51	Wyoming	1.27%
23	Michigan	1.46%
19	Louisiana	1.54%
45	Utah	1.76%
8	Washington, DC	2.25%
12	Hawaii	2.45%
41	South Carolina	2.51%
39	Pennsylvania	3.30%
22	Maine	3.40%
20	Massachusetts	3.62%
52	US - nation	4.65%
15	Illinois	4.73%
10	Florida	5.13%
25	Missouri	6.09%
38	Oregon	7.24%
5	California	7.34%
7	Connecticut	7.72%
11	Georgia	8.25%
21	Maryland	8.67%
26	Mississippi	8.88%
3	Arkansas	11.67%
42	South Dakota	12.95%
4	Arizona	14.13%
34	Nevada	14.43%
33	New Mexico	19.06%
44	Texas	23.19%
54	NCREIF_Mideast	24.25%
49	Wisconsin	27.04%
36	Ohio	27.18%
32	New Jersey	31.65%
	MSE - All	5.30%

This table summarizes the mean square errors (MSE) computed using the Leave One Amount Cross-Validation (LOOCV) technique. The columns provide the numerical code, the name of the j-th supralocation and the MSE from the LOOCV test, respectively. The average MSE was 5.30% as reported in the final row of the table.

Table 8: Paired t-test and summary statistics

	Total Loans		Non-Defaulted Loans		Defaulted Loans	
	actualcap	SCX	actualcap	SCX	actualcap	SCX
Mean	0.07007	0.07378	0.06994	0.07367	0.07307	0.07654
Variance	0.00045	0.00006	0.00044	0.00006	0.00088	0.00004
Observations	25,083	25,083	24,071	24,071	1,012	1,012
Pearson Correlation	-0.05965		-0.06334		-0.04198	
Hypothesized Mean Difference	0.00000		0.00000		0.00000	
df	25,082		24,070		1,011	
t Stat	-25.35452		-25.30470		-3.60033	
P(T<=t) one-tail	0.00000		0.00000		0.00017	
t Critical one-tail	1.64491		1.64492		1.64636	
P(T<=t) two-tail	0.00000		0.00000		0.00033	
t Critical two-tail	1.96006		1.96006		1.96231	

This table provides the summary results for the paired t-test applied to the actual and synthetic cap rates corresponding to the origination date on 25,101 CRE transactions. The reported statistics are for the non-defaulted and defaulted subsets. Cap rates greater than 50% were excluded.

Table 9: Cumulative lending probabilities at or below cap rate upper boundaries

	Total Loans		Non Defaulted Loans		Defaulted Loans	
Cap Rate	actualcap	SCX	actualcap	SCX	actualcap	SCX
7.00%	0.4987	0.3167	0.5011	0.3229	0.4588	0.1439
6.00%	0.3183	0.0411	0.3170	0.0433	0.3300	0.0036
5.00%	0.1732	0.0014	0.1698	0.0015	0.2188	0.0000
4.00%	0.0792	0.0000	0.0758	0.0000	0.1329	0.0000
3.00%	0.0301	0.0000	0.0279	0.0000	0.0736	0.0000

This table provides the results for the paired t-test applied to the actual and synthetic cap rates corresponding to the origination date on 25101 CRE transactions. The statistics are for non-defaulted and defaulted subsets. We exclude actual cap rates greater than 50%.

Table 10: Valuation statistics

	properties		
	all	non defaulted	defaulted
number of properties	25083	24071	1012
synthetic value	$628,295,272,395	$610,603,768,427	$17,691,503,967
actual UW value	$706,124,906,978	$685,863,114,677	$20,261,792,301
difference	$(77,829,634,583)	$(75,259,346,250)	$(2,570,288,334)
ratio (wtd mean) synthetic/actual	0.88978	0.89027	0.87315
nominal mean synth/actual	0.96266	0.96269	0.96198
nominal min synth/actual	0.20617	0.20617	0.20617
nominal max synth/actual	5.69317	5.69317	4.23399
nominal median synth/actual	0.92843	0.93052	0.89363
nominal kurtosis synth/actual	24.96369	25.99173	12.13431
nominal stdev synth/actual	0.31301	0.30835	0.40873

This table provides valuation statistics for the private loan data using actual cap rates and corresponding SCXs at the point of origination. Source: Intex.

Table 11: Logistic regression - Treatment 1

	Panel A: All		Panel B: CBD only		Panel C: Non CBD only	
	(i)	(ii)	(i)	(ii)	(i)	(ii)
cons	-3.228507***	-6.571107***	-3.9056897***	-7.15312***	-3.128669***	-6.455659***
	(0.0441904)	(0.3387108)	(.1558658)	(0.874274)	(0.0491975)	(0.3685678)
caprate (actual)	.8331781**		4.894396***		0.5957658	
	(.4177213)		(1.807289)		(0.4770939)	
caprate (SCX)		46.32364***		48.85778***		45.88012***
		(4.526286)		(11.65481)		(4.927489)
Adj-Pseudo R-sq	0.0002	0.0041	0.0015	0.0031	0.0001	0.0043
Prob chi2	0.0461	0.0000	0.0068	0.0000	0.2118	0.0000
Obs	25101	25101	5195	5195	19906	19906

This table shows the results of logistic regressions with 0,1 indicator of loan default for the sample. The independent variables are:actual cap rate in columns (i) msa synthetic cap rate (SCX) in columns (ii). Panel A captures the entire sample; Panel B the CBD properties; and Panel C the non-CBD properties. Estimates are provided along with standard errors in parentheses. ***/**/*/' indicate 0.1%, 1%, 5% and 10% significance for Wald z-values

Table 12: Logistic regression - Treatment 2

	Panel A: All		Panel B: CBD only		Panel C: Non CBD only	
	(i)	(ii)	(i)	(ii)	(i)	(ii)
_cons	-2.135964***	-5.445156***	-2.51904***	-5.755882***	-1.642249***	-4.926696***
	(0.2221568)	(0.4036153)	(0.5220886)	(1.002803)	(0.2321479)	(0.4326184)
caprate (actual)	0.6873697		4.242379***		0.5254299	
	(0.4414735)		(1.846048)		(0.5005424)	
caprate (SCX)		46.00407***		48.65101***		45.53765***
		(4.573642)		(11.72515)		(4.968723)
occpct	-0.0129654***	-0.0133184***	-0.0128622***	-0.0134254***	-0.0129051***	-0.0133027***
	(0.0015615)	(0.0015635)	(0.0040888)	(0.0040364)	(0.0016923)	(0.001696)
propage	-0.0137843***	-0.0116875***	-0.0125176*	-0.0124223*	-0.0139661***	-0.0114937***
	(0.0033768)	(0.003344)	(0.007349)	(0.0072263)	(0.0037987)	(0.0037801)
cbd	0.4487141***	0.4505224***				
	(0.0920274)	(0.092203)				
prp_fxd	-0.2044051	-0.2146195	-0.0843447	-0.0759683	-0.2427588	-0.2522155
	(0.1567765)	(0.1571089)	(0.3503293)	(0.350645)	(0.1753219)	(0.1757145)
Adj-Pseudo R-sq	0.0047	0.0085	0.0034	0.0061	0.0038	0.0080
Prob chi2	0.0000	0.0000	0.0003	0.0000	0.0000	0.0000
Obs	25101	25101	5195	5195	19906	19906

This table shows the results of logistic regressions with 0,1 indicator of loan default for the sample. The independent variables are:actual cap rate in columns (i) msa synthetic cap rate (SCX) in columns (ii). Panel A captures the entire sample; Panel B the CBD properties; and Panel C the non-CBD properties. Estimates are provided along with standard errors in parentheses. ***/**/*/' indicate 0.1%, 1%, 5% and 10% significance for Wald z-values

Table 13: Logistic regression - Treatment 3

	Panel A: All				Panel B: CBD only				Panel C: non-CBD only			
	(i)	(ii)	(iii)	(iv)	(i)	(ii)	(iii)	(iv)	(i)	(ii)	(iii)	(iv)
_cons	-1.795667***	-4.039471***	-1.097695***	-3.498225***	-2.164676***	-4.154393***	-1.460711**	-3.67379***	-1.326086***	-3.561278***	-0.6271674**	-3.011455***
	(0.2235718)	(0.4660155)	(0.2716481)	(0.4817134)	(0.5249973)	(1.179183)	(0.6564918)	(1.229433)	(0.2332104)	(0.4994363)	(0.2873467)	(0.5161302)
caprate (actual)	0.9138623***		0.9155617***		5.006876***		5.081549***		0.7532925*		0.7503497*	
	(0.4140675)		(0.417609)		(1.934122)		(1.912539)		(0.4397526)		(0.4408342)	
caprate (SCX)		30.05074***		33.4522***		30.45716**		34.55862**		29.94889***		33.26209***
		(5.325379)		(5.439026)		(13.75627)		(14.31072)		(5.777469)		(5.883821)
occpct	-0.0131264***	-0.0133039***	-0.0131963***	-0.0134009***	-0.0126872***	-0.0133576***	-0.0126349***	-0.0132959***	-0.013111***	-0.0132988***	-0.0132014***	-0.0134228***
	(0.001555)	(0.0015575)	(0.0015576)	(0.0015605)	(0.0040816)	(0.0040248)	(0.00408)	(0.0040245)	(0.0016855)	(0.0016894)	(0.001689)	(0.0016935)
propage	-0.011782***	-0.0110729***	-0.0117838***	-0.0110209***	-0.0121205	-0.0124782*	-0.0120805	-0.0124056*	-0.0115546***	-0.010705***	-0.0115501***	-0.0106502***
	(0.0033626)	(0.0033447)	(0.003364)	(0.0033448)	(0.0074021)	(0.0073026)	(0.0074042)	(0.0072983)	(0.0037859)	(0.0037778)	(0.003787)	(0.0037777)
cbd	0.4340318***	0.4428436***	0.4347555***	0.444102***								
	(0.0922478)	(0.0922991)	(0.0922891)	(0.0923434)								
prp_fxd	-0.1468917	-0.1669184	-0.1539132	-0.1778631	-0.0392335	-0.0317022	-0.0507974	-0.0425155	-0.1816708	-0.2032251	-0.1873637	-0.2141602
	(0.1573038)	(0.1574485)	(0.1574304)	(0.1575736)	(0.3512744)	(0.3512873)	(0.3515278)	(0.3515253)	(0.1759596)	(0.1761186)	(0.1761099)	(0.176264)
lend_fxd	-0.7003789***	-0.4872252***	-0.8027001***	-0.5955145***	-0.8012297***	-0.534565***	-0.894481***	-0.6266869***	-0.687417***	-0.4796798***	-0.7917612***	-0.5903175***
	(0.0647368)	(0.0734939)	(0.068053)	(0.075003)	(0.1717053)	(0.197639)	(0.1784187)	(0.199032)	(0.0699762)	(0.0791817)	(0.0737219)	(0.0810013)
vix			-0.0434109***	-0.0493803***			-0.0449567*	-0.0503346*			-0.0433049***	-0.0491935***
			(0.0097565)	(0.0098353)			(0.0257139)	(0.0259446)			(0.0105545)	(0.0106327)
Pseudo R-sq	0.0096	0.0107	0.0105	0.0113	0.0079	0.0068	0.0084	0.0072	0.0089	0.0099	0.0098	0.0108
Prob chi2	0..000	0..000	0..000	0..000	0..000	0..000	0..000	0..000	0..000	0..000	0..000	0..000
Obs	25101	25101	25101	25101	5195	5195	5195	5195	19906	19906	19906	19906

This table shows the results of logistic regressions with 0,1 indicator of loan default for the sample. The independent variables are:actual cap rate in columns (i) msa synthetic cap rate (SCX) in columns (ii). Panel A captures the entire sample; Panel B the CBD properties; and Panel C the non-CBD properties. Estimates are provided along with standard errors in parentheses. ***/**/*/' indicate 0.1%, 1%, 5% and 10% significance for Wald z-values

Table 14: Forecast SCXs for top 25 MSAs (by workforce) 12/2019:6/2022

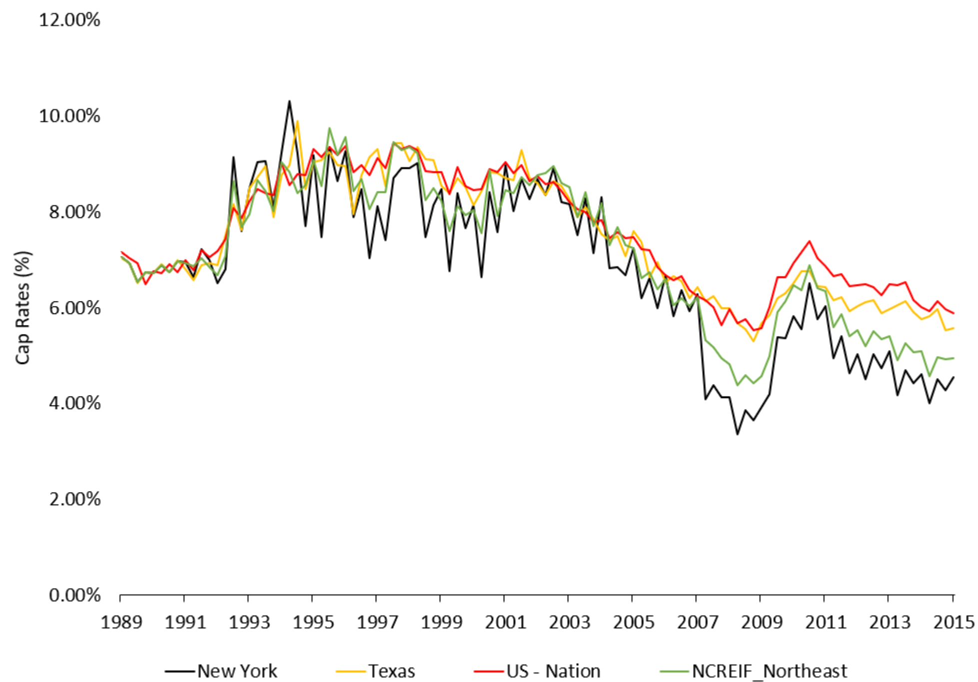
MSA	% US workforce	Dec-19	Mar-20	Jun-20	Sep-20	Dec-20	Mar-21	Jun-21	Sep-21	Dec-21	Mar-22	Jun-22	6/21	6/22
Detroit-Warren-Dearborn, MI	1.47%	6.73%	6.46%	6.24%	6.26%	6.37%	5.96%	8.56%	8.39%	7.55%	5.99%	5.76%	183.24	-280.26
Orlando-Kissimmee-Sanford, FL	0.92%	6.18%	5.74%	5.53%	5.44%	5.57%	5.45%	8.02%	8.73%	7.47%	5.64%	5.38%	183.71	-263.84
LosAngeles-LongBeach-Anaheim,CA	4.81%	6.46%	6.09%	5.86%	5.75%	5.82%	6.22%	8.35%	8.24%	7.67%	6.48%	6.15%	189.30	-220.02
Philadelphia-Camden-Wilmington,PA-NJ-DE-MD	2.23%	6.55%	6.13%	5.89%	5.80%	5.93%	6.26%	7.91%	7.39%	7.30%	6.14%	5.81%	136.35	-209.67
Dallas-FortWorth-Arlington, TX	2.93%	6.72%	6.24%	5.91%	5.93%	6.09%	6.21%	6.92%	6.52%	5.72%	5.87%	4.86%	20.41	-206.66
Chicago-Naperville-Elgin, IL-IN-WI	3.38%	6.53%	6.08%	5.81%	5.76%	5.89%	5.92%	7.34%	6.86%	6.60%	5.96%	5.51%	81.02	-183.68
St. Louis, MO-IL	1.05%	6.74%	6.32%	5.94%	6.04%	6.09%	5.96%	6.18%	5.77%	5.58%	5.71%	4.49%	-56.32	-168.49
Miami-FortLauderdale-PompanoBeach, FL	2.23%	6.43%	6.04%	5.81%	5.69%	5.85%	5.89%	7.20%	6.97%	6.40%	5.93%	5.53%	76.98	-166.99
Baltimore-Columbia-Towson, MD	1.06%	6.44%	5.94%	5.66%	5.57%	5.72%	5.71%	6.75%	6.38%	5.74%	5.60%	5.15%	30.90	-160.29
NewYork-Newark-JerseyCity, NY-NJ-PA	7.09%	6.63%	6.16%	5.91%	5.84%	5.98%	5.83%	7.67%	7.41%	7.49%	6.35%	6.11%	103.97	-156.40
Seattle-Tacoma-Bellevue, WA	1.58%	6.59%	6.15%	5.90%	5.83%	5.91%	6.14%	6.76%	6.42%	5.69%	5.62%	5.22%	17.84	-153.97
Riverside-San Bernardino-Ontario, CA	1.52%	6.48%	6.10%	5.87%	5.78%	5.87%	5.94%	7.27%	7.17%	6.68%	6.03%	5.73%	79.38	-153.62
Phoenix-Mesa-Scottsdale, AZ	1.84%	6.53%	6.22%	5.98%	5.93%	6.00%	6.01%	6.71%	5.98%	5.92%	5.81%	5.43%	18.15	-128.63
Portland-Vancouver-Hillsboro, OR-WA	0.96%	7.07%	6.52%	6.26%	6.20%	6.33%	6.49%	6.29%	5.99%	5.60%	5.67%	5.01%	-78.01	-127.22
Houston-The Woodlands-Sugar Land, TX	2.46%	6.84%	6.36%	6.12%	6.08%	6.26%	6.13%	6.51%	6.43%	5.82%	6.09%	5.49%	-32.54	-102.08
Tampa-St. Petersburg-Clearwater, FL	1.15%	6.29%	5.97%	5.74%	5.72%	5.78%	5.57%	6.37%	6.13%	5.65%	5.56%	5.50%	8.54	-87.71
Charlotte-Concord-Gastonia, NC-SC	0.99%	6.93%	6.53%	6.33%	6.33%	6.43%	6.37%	6.03%	5.73%	5.49%	5.82%	5.16%	-89.64	-87.26
Atlanta-Sandy Springs-Roswell, GA	2.26%	6.77%	6.28%	6.00%	6.07%	6.18%	6.02%	5.83%	5.52%	5.36%	5.57%	5.07%	-94.85	-75.91
Washington-Arlington-Alexandria, DC-VA-MD-WV	2.42%	6.79%	6.47%	6.29%	6.25%	6.33%	6.31%	6.69%	6.44%	6.20%	6.21%	5.97%	-10.62	-72.29
Boston-Cambridge-Newton, MA-NH	2.00%	6.46%	6.15%	5.94%	5.84%	5.90%	5.89%	6.26%	6.15%	6.02%	5.74%	5.72%	-20.16	-53.95
Denver-Aurora-Lakewood, CO	1.23%	6.95%	6.59%	6.41%	6.41%	6.48%	6.32%	6.05%	5.88%	5.74%	5.98%	5.58%	-90.67	-46.56
San Diego-Carlsbad, CA	1.12%	6.59%	6.29%	6.10%	6.01%	6.08%	6.13%	6.24%	6.09%	5.84%	5.88%	5.78%	-35.07	-45.81
Minneapolis-St. Paul-Bloomington, MN-WI	1.43%	6.85%	6.52%	6.31%	6.31%	6.42%	6.21%	6.10%	5.93%	5.82%	6.05%	5.78%	-74.77	-32.48
Austin-Round Rock, TX	0.92%	7.06%	6.59%	6.45%	6.47%	6.59%	6.33%	5.22%	5.17%	5.35%	5.68%	5.08%	-184.15	-13.88
San Francisco-Oakland-Berkeley, CA	1.79%	6.95%	6.58%	6.33%	6.27%	6.35%	6.26%	5.75%	5.63%	5.42%	5.91%	5.72%	-119.77	-3.96

A.3

This table shows SCXs for the top 25 MSA by eligible workforce in the US. The first column provides the MSA name, the second column the percent of the US workforce located in the MSA. The third through thirteenth columns provide the 12 month forecasted SCXs based on data from the prior 12 month period, from December 2019 through June 2022. The fifteenth and sixteenth columns show changes in bps for the projected SCXs from December 2019 to June 2021 and June 2021 to June 2022, respectively. The table data is reported with sort from smallest to largest changes captured in the last (change from June 2021 to June 2022).

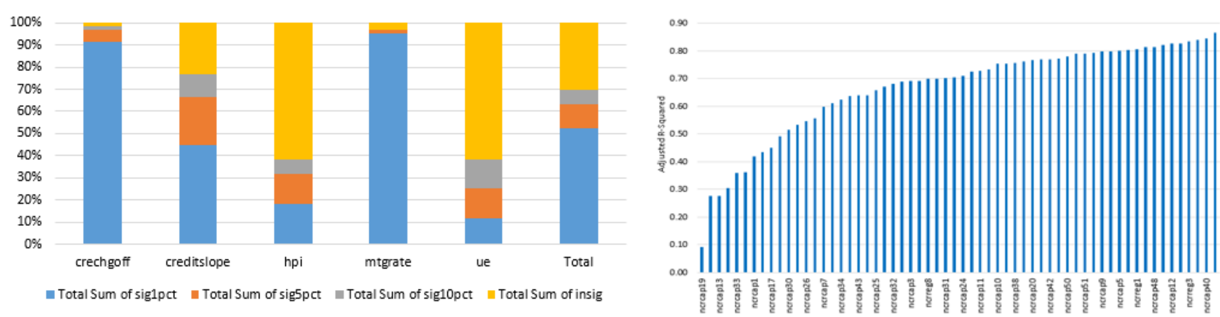
Figures

Figure 1: NCREIF cap rates



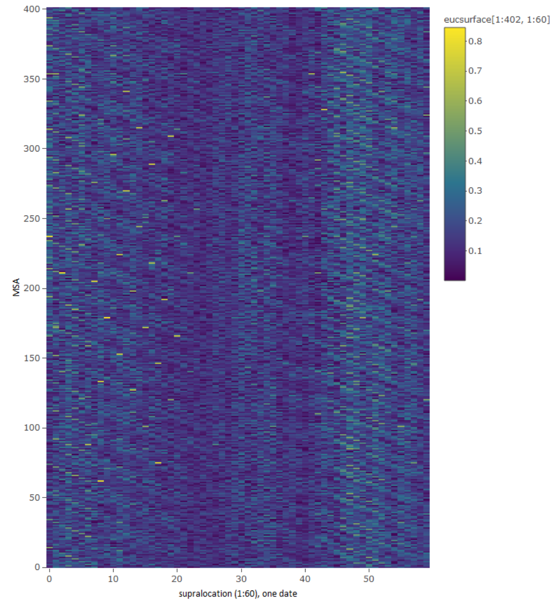
This figures shows 4 of 60 cap rate indices constructed from NCREIF data as described from aggregated NOI and property values aggregated across property types within geographic locations. Depicted are the time series for US - Nation, US States of New York and Texas, and NCREIF region of the Northeast. The cap rates are computed quarterly. Source: NCREIF.

Figure 2: Statistical summaries for 60 NCREIF cap rate OLS



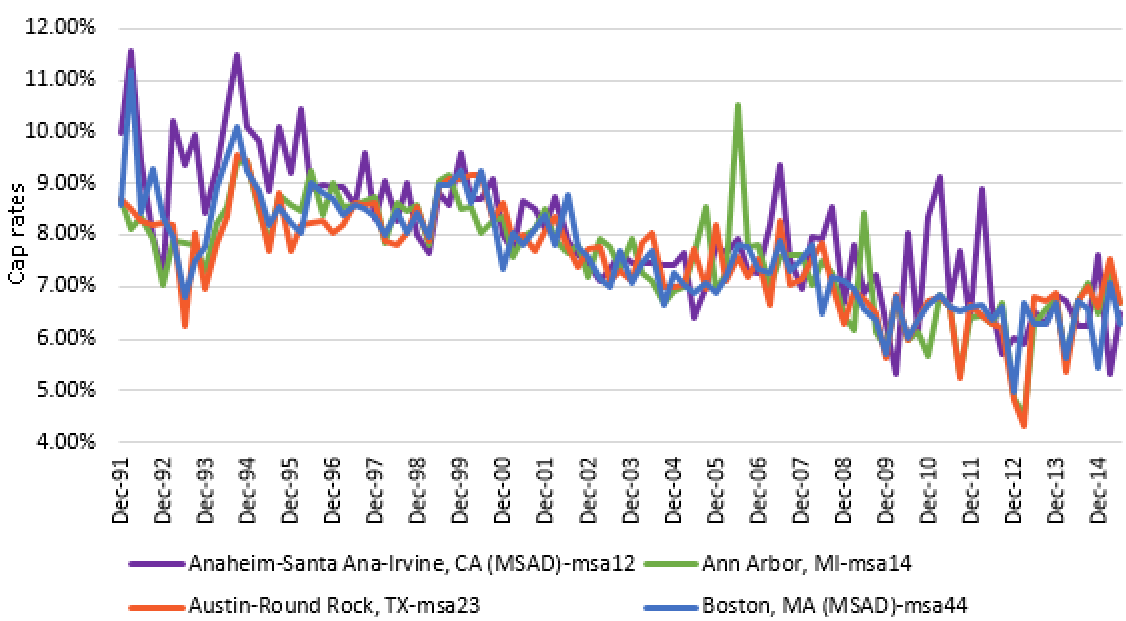
This figure summarizes the results for the 60 OLS regressions corresponding of the form $C_{j,\,t} = \alpha + \beta_1 \mathrm{HPI}_{j,\,t-4} + \beta_2 \mathrm{UE}_{j,\,t-4} + \beta_3 \mathrm{CreditSlope}_{j=1,t-4} + \beta_4 \mathrm{MtgRate}_{j=1,t-4} + \beta_5 \mathrm{CREchgoff}_{j=1,t-4} + \epsilon_t$ with j =1:60 supralocations (1:51 states, 1 US nation, 8 NCREIF regions. The dependent variable $C_{j,\,t}$ is the cap rate index for the j-th location. The first two independent variables, are j-th locational values for the house price index returns and the unemployment rate. The last three independent variables are the corporate bond credit slope, the FHLMC 30 year conforming mortgage rate, and the CRE charge off rate which are all captured at the National level (j = 1). The plot on the left shows the composition of the significance of each of the independent variables. The plot on the right shows the R-squared values. All regressions were significant as measured by the F-test.

Figure 3: Economic proximity Euclidean distances for MSAs x supralocations



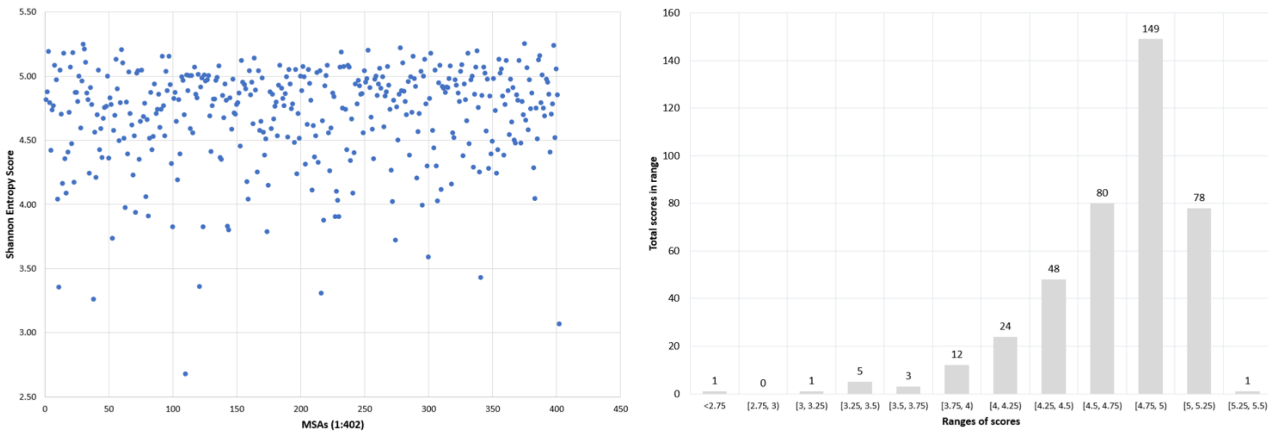
This figure summarizes the distribution of Euclidean distanced economic proximities calculated on one date (quarter 93) between 402 MSAs and 60 supralocations. The x-axis corresponds to the 60 supralocations and the y-axis to the 402 MSAs.

Figure 4: Four synthetic cap rate indices



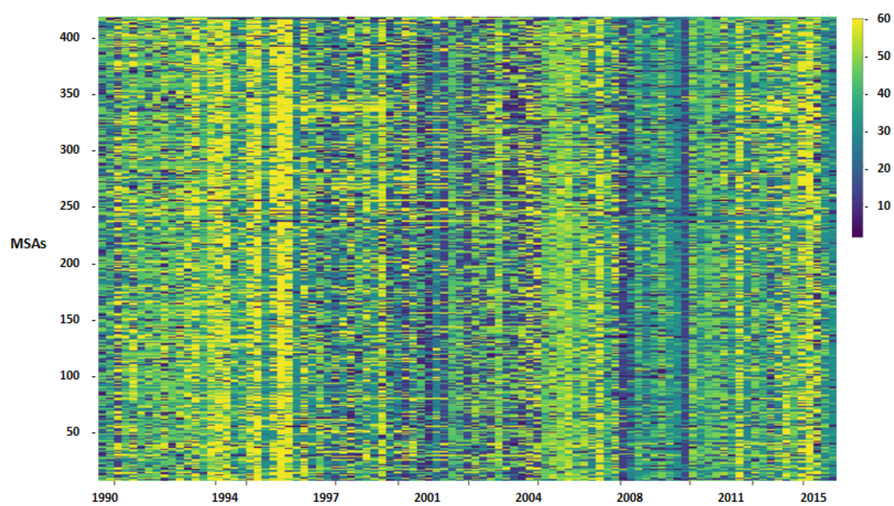
This figure shows four synthetic cap rate indices ($\tilde{C}$) for 4 of 402 total MSAs. Depicted are Anaheim-Santa Ana-Irvine, CA; Ann Arbor, MI; Austin-Round Rock, TX; and Boston, MA.

Figure 5: Shannon's Entropy scores for 402 MSAs



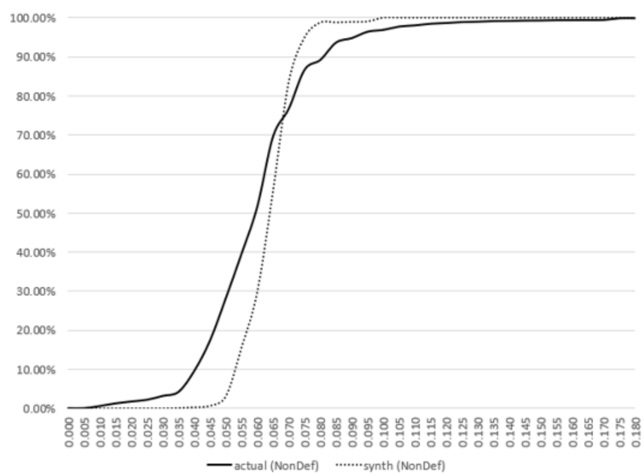
This figure provides the Shannon Entropy score for 402 MSAs. The score is defined as the negative logarithm of base 2 of the probability mass function for categorical variables. In this context, the categorical variables are the MSAs and supralocations and the probability represents the percentage of quarters of the j-th MSA in the k-th supralocation observed over 95 quarters. The plot on the left shows the scores x MSA locations. The plot on the right aggregates the frequency of scores in bins of 0.25 from 2.75 to 5.

Figure 6: Supralocations corresponding to minimum economic proximity



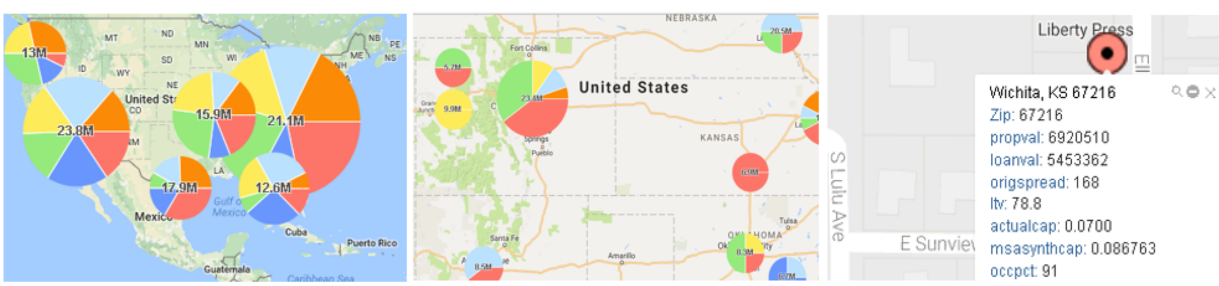
This figure summarizes the distribution of supralocations selected from the distancing procedure (1:60 as indicated in the legend) and mapped to each of the 402 MSAs in each quarter in the sample period (95 quarters). The x-axis corresponds to the quarters and the y-axis to the MSAs.

Figure 7: Cumulative cap rate distributions at origination



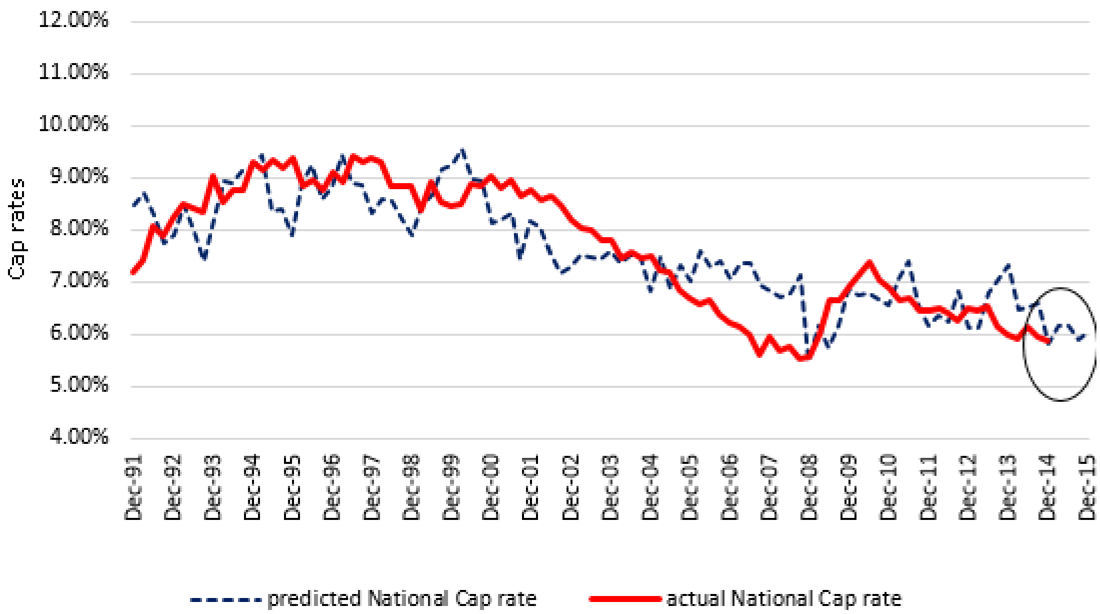
This figure depicts the cumulative distributions of actual cap rates at origination and corresponding synthetic MSA level cap rates at origination partitioned by the default indicator. The solid lines reflects the cumulative distribution for the actual cap rates at origination, while the dotted lines reflect the synthetic cap rates at origination that corresponded the MSA level in which the property is located. The plot on the left shows the comparison between actual and synthetic for the 24,089 loans that did not default. The plot on the right shows the comparison for the 1,013 loans in our sample that defaulted over the CMBS loan sample period Q1 2000 to Q2 2015. The x-axis shows cap rates in increments of 0.005; the y-axis shows the proportion of loan counts; and the lines reflect the cumulative sum of the proportional count of loans as a percent of total loans in the category with corresponding cap rates at origination in the interval.

Figure 8: Locational mapping of CRE loan defaults



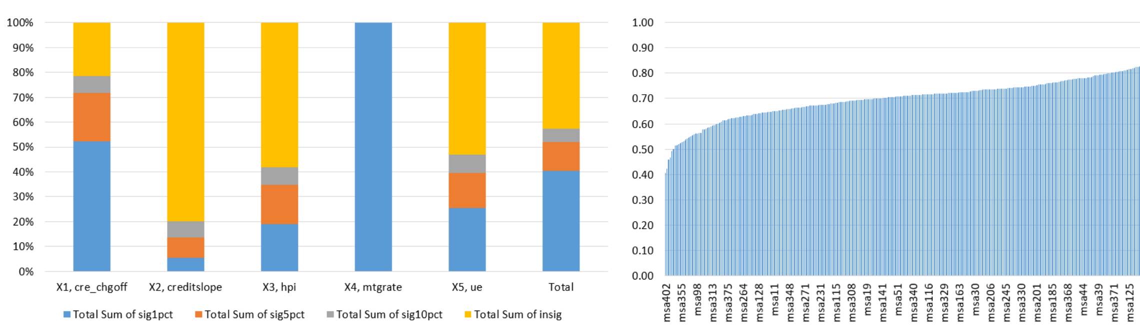
This figure depicts the increasing granularity geographically contained in our data set which permits us to identify at the zip-code, CBD, MSA, State, Regional and National levels. Source: Intex.

Figure 9: Actual and predicted synthetic cap rates (National)



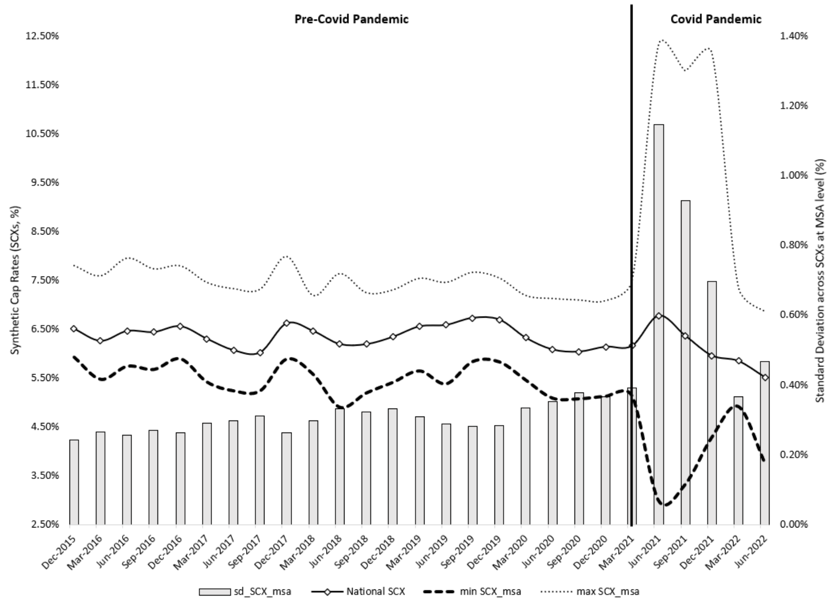
This figure provides plots reflecting actual and synthetic cap rates at the National level.

Figure 10: Statistical significance 402 synthetic cap rate OLS

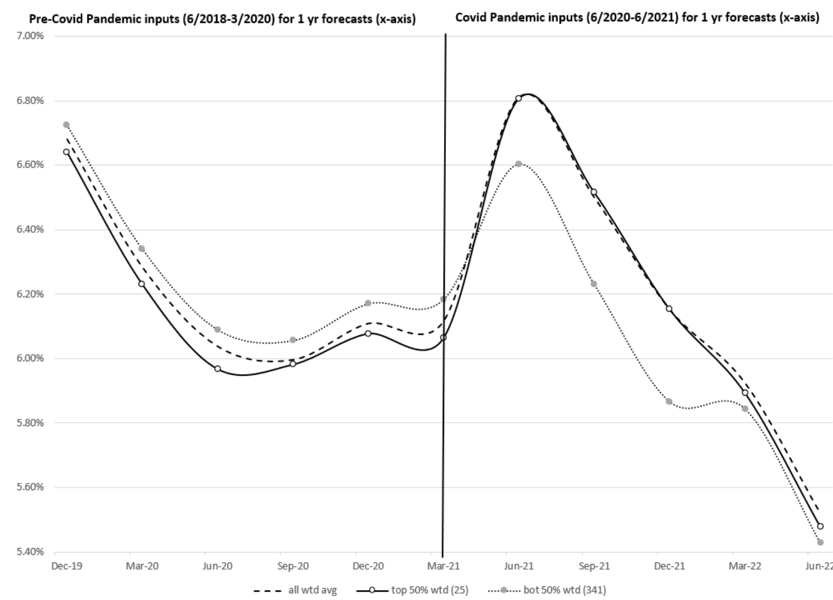


This figure summarizes the results for the 402 OLS regressions corresponding of the form $\tilde{\mathrm{C}}_k = \alpha + \beta_1 \mathrm{HPI}_{k,\,t-4} + \beta_2 \mathrm{UE}_{k,\,t-4} + \beta_3 \mathrm{CreditSlope}_{j=1,\,t-4} + \beta_4 \mathrm{MtgRate}_{j=1,\,t-4} + \beta_5 \mathrm{CREchgoff}_{j=1,\,t-4} + \epsilon_t$ with $j \in [1, 60]$ supralocations and $k \in [1, 402]$ MSAs. The plot on the left shows the composition of the significance of each of the independent variables normalized across all 402 OLS regressions. The plot on the right shows the R-squared values for each of the 402 OLS regressions. All regressions were significant as measured by the F-test.

Figure 11: National SCXs (quarterly)



(a) Simple average SCX (December 2015-June 2022)



(b) Weighted Average SCX (weighted by MSA workforce, December 2019-June 2022)

This figure shows the National 1 year forecast SCXs, quarterly. Figure (a.) depicts the National SCX from December 2015 through June 2022 as a simple average, along with its standard deviation. Also depicted are the actual minimum and maximum MSA SCXs, for those periods, quarterly. The vertical line in March 2021, separates the pre-Covid period from the current-intra-Covid period. Figure (b.) depicts weighted average SCXs, where the weights are the percent of the US workforce associated with that MSA. Three series are depicted: all MSAs (National), the top 50% of MSAs by eligible workforce percent of the total US workforce, and the bottom 50% of MSAs by eligible workforce percent of the total US workforce. The lines are smoothed for presentation style.