

Commonalities in Private Commercial Real Estate Market Liquidity and Price Index Returns: International Evidence

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Abstract

We examine co-movements in private commercial real estate market liquidity in the US (apartment, office, retail) and for eighteen global cities using data from Real Capital Analytics over the period 2005–2018. Our measure of market liquidity is based on the difference between supply and demand price indexes (Fisher et al., 2003, 2007). We document for all analyzed markets much stronger commonalities in changes in market liquidity compared to commonalities in real price index returns, where we base the commonality measure on Roll (1988) and Karolyi et al. (2012). We further provide empirical evidence that space markets are less integrated than capital markets by analyzing co-movements in net-operating-income and cap rate spreads (over similar maturity bond yields). In a theoretical simulation model, we show that the strong integration of capital markets compared to space markets, is in fact the reason why market liquidity co-moves so strongly compared to returns. Our results are robust to changes in (i) the measure of commonality (principal component analysis), (ii) the measure of market liquidity (transaction volume and Amihud measure), and (iii) the sample period (excluding the Global Financial Crisis).

Keywords: Commercial real estate, Market Liquidity, Returns, Commonality

JEL: R30, C11, C41

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1. Motivation and research questions

Market liquidity – the ease of trading a property – and asset prices in real estate markets move together, which implies that changes in market liquidity tend to be pro-cyclical to changes in asset prices. This holds for commercial real estate markets (see for example Fisher et al., 2003; Clayton et al., 2008) as well as for residential real estate markets (see for example Goetzmann and Peng, 2006; De Wit et al., 2013). This paper compares for private commercial real estate asset markets commonalities in market liquidity changes to commonalities in price index returns. We analyze within-country as well as international co-movements.

Commonalities in market liquidity are in particular relevant for large investors in direct commercial real estate, such as pension funds and other institutional investors. Investors do not only face price risk, but also the risk of illiquidity, the uncertain time it takes to sell properties (Cheng et al., 2010, 2013). Depending on the degree of commonality in segments (for example apartments, offices, retail, and industrial) and regions within national and international markets it might be possible to diversify liquidity risk in their portfolio.

Several market liquidity metrics exist, relating to different dimensions of liquidity, such as transaction volume, turnover ratio, Amihud measure (Amihud, 2002), time-on-the-market, and trading frequency. For an extensive overview and discussion of liquidity measures we refer to Ametefe et al. (2016). In this paper we use as a measure for market liquidity the difference between supply and demand price indexes related to a standard price index, following Fisher et al. (2003, 2007) and Clayton et al. (2008). We use the method of Van Dijk et al. (2020), who derive supply and demand indexes in a repeat sales model framework. This approach has the advantage of effectively dealing with heterogeneity in commercial real estate assets without the need for many property characteristics or assessed values. Moreover, by using Bayesian techniques the supply and demand indexes can be robustly estimated in small samples.

Commonalities in private real estate *market returns* have been extensively researched. For example, Srivatsa and Lee (2012) examine the convergence of yields and rents of European offices markets, MacGregor and Schwann (2003) find common cycles in UK commercial real estate returns, and Van de Minne et al. (2018) find two common factors that summarize the variation in price index returns for 80 non-overlapping US commercial real estate markets. Clark and Coggin (2009) provide evidence of commonalities in US housing returns and Holly et al. (2011) look at the relationship between London, other UK, and New York housing returns.

The literature on commonalities in real estate *market liquidity* is much smaller. The commonality between returns and stock market liquidity risk for *listed* real estate has been examined by Hoesli et al. (2017). The authors find that commonalities in stock market liquidity result in risk factors for REIT returns, but that this only holds in bad times. Brounen et al. (2019) study the relation between liquidity and price returns in international listed real estate markets. They find wide variations across ten markets using four different liquidity measures (trading volume, stock turnover, Amihud measure and the number of zero return days). Moreover, they document evidence for international trend-chasing behavior. Most of the studies on private commercial real estate market liquidity analyze the dynamics of liquidity measures in just one market (for example Fisher et al., 2003, 2007; Clayton et al., 2008; Wiley, 2017). There are a few exceptions.

Ling et al. (2009) study the price dynamics and transaction activity for ten segments in private commercial real estate in the UK over the period 1987–2007. They find a statistically significant positive relationship between lagged turnover and contemporaneous capital returns. Devaney et al. (2017) study determinants of variations in transaction activity for a set of 49 US MSA office markets in the period 2002–2015. Van Dijk et al. (2020) note that for the US market liquidity movements tend to be stronger correlated across markets than price movements.

We add to the real estate literature by documenting commonalities in market liquidity, and price index returns for several private commercial real estate asset markets: 25 large US markets, the 6 largest US markets subdivided by sector (office, retail, and apartment), and 18 global gateway markets. We show empirically by using transaction data from Real Capital Analytics in the period from 2005Q1 to 2018Q4, that co-movements in market liquidity changes are much stronger than co-movements in price index real returns. We follow the method applied by Roll (1988) and Karolyi et al. (2012), a R^2 -based method, to measure the degree of commonality.

In order to justify the use of our empirical commonality measure and to understand the difference in commonality between liquidity changes and price index returns, we present simulation results from a theoretical “cap rate” model. We allow the different components, net-operating income, risk-free rate, risk premium and growth expectations, to co-move differently across markets. Moreover, we allow buyers and sellers to have different views on these components. We show which assumptions are required to generate stronger co-movements in market liquidity changes compared to price index returns. First, the cross-market co-movement in the risk premium component (determined by capital markets) needs to be stronger than the cross-market co-movement in rents (determined by space markets). We provide empirical evidence for this assumption by showing that space markets are less integrated than capital markets by analyzing co-movements in net-operating-income and cap rate spreads (over similar maturity bond yields). Second, sellers need to lag buyers “sufficiently” in their perception of risk premium compared to net-operating-income. The second assumption relates to “loss aversion” or anchoring (Bokhari and Geltner, 2011). The seller bought the property some time ago against the financing conditions that prevailed at that time. Hence, it is reasonable to assume that the current perception about financing conditions is a function of past financing conditions that applied to the property in question. Also, information asymmetries might play a role here, were sellers are not able to “digest” all possible market information instantaneously (Carrillo et al., 2015; Van Dijk and Francke, 2018).

In summary, we pose three questions related to private real estate asset markets:

- (i) “How strong is the co-movement in changes in market liquidity?”
- (ii) “How strong is the co-movement in real price index returns?”
- (iii) “Which factors drive the difference in commonality between market liquidity changes and real price index returns?”

The paper proceeds as follows. Section 2 provides details on the construction of market liquidity and commonality measures. Section 3 provides simulation results to justify the use of our empirical commonality measure and to understand the difference in commonality between liquidity and price. Section 4 gives the data description, documenting per market summary statistics on price index returns and changes in market liquidity.

Section 5 shows the degree of empirical commonality in both market liquidity changes and price index returns. In addition, this section shows degrees of integration for net-operating-income and risk premia. Section 6 provides results from three different robustness checks: (i) an alternative commonality measure by principal components, (ii) two alternative market liquidity measures: transaction volume and the Amihud measure, (iii) excluding the effect of the Global Financial Crisis. Finally, Section 7 concludes.

2. Methodology

2.1. Price index returns in real estate

Fundamentally, space market as well as capital market characteristics should be reflected in the price of real estate. We can express the prices in the celebrated “cap rate” model as follows¹:

$$P_{i,j,t} = \frac{NOI_{i,j,t}}{RF_{i,t} + RSP_{i,j,t} - G_{i,j,t}}, \quad (1)$$

where subscript i, j and t denote a market, property and time-period, respectively. NOI is the net operating income of the property, G the prospective growth rate, RF the risk-free rate, and RSP the risk premium. Rewriting Equation (1) in logs yields:

$$p_{i,j,t} = noi_{i,j,t} - \log(RF_{i,t} + RSP_{i,j,t} - G_{i,j,t}), \quad (2)$$

where the lowercase variables are the log-transformed uppercase variables. Property level price (capital) returns can be obtained by rewriting the log-model in first differences:

$$\Delta p_{i,j,t} = \Delta noi_{i,j,t} - \Delta \log(RF_{i,t} + RSP_{i,j,t} - G_{i,j,t}). \quad (3)$$

This equation implies that price returns in market i for period t are dependent on changes in both capital market variables (RF , RSP) and space market variables (noi , G).

Price indexes could be derived from a model that includes both local market conditions and property characteristics (time-invariant property characteristics cancel out in a repeat-sales setting):

$$p_{i,j,t} = \beta_{i,t} + x'_{i,j} \alpha + \varepsilon_{i,j,t}, \quad (4)$$

$$\Delta p_{i,j,t} = \Delta \beta_{i,t} + \Delta \varepsilon_{i,j,t}, \quad (5)$$

where $x_{i,j}$ is a K -dimensional vector of time-invariant property characteristics with corresponding coefficient vector α , and ε is an independent normally distributed error term with mean zero. $\beta_{i,t}$ ($\Delta \beta_{i,t}$) is the common log price index (return) for market i at time t . These common trends are the market-wide developments in prices. Relating this to the fundamental price Equation (3), these trends reflect market-wide trends in risk-free rates, risk premia, and NOI growth rates. The property characteristics usually capture property-specific variables, such as location, size, maintenance, parking facilities etc.

¹A “cap rate model” provides the value of a property based on income discounted into perpetuity, similar to a Gordon Growth Model in stock valuation.

Returning to our research question on commonalities, it is straightforward to see that commonalities in index returns across different markets (i.e. the co-movement in $\Delta\beta_{i,t}$ across different i) will be determined by the commonalities in changes of the separate components of Equation (3). The *NOI* and growth rate (G) are more likely to be determined by space markets, whereas the risk-free rate (RF) and the risk-premium (RSP) tend to be determined more by capital markets. Space markets are determined by local characteristics and capital markets tend to be nationally or even internationally integrated. Even though space markets may co-move across markets as well, it is reasonable to assume that this holds to a larger extent for capital markets. This is something we will assume in our theoretical simulation and will back-up empirically later on.

2.2. Market liquidity in real estate markets

In order to introduce our concept of market liquidity, we begin by disentangling the pricing Equation (5) into buyer and seller components.² Doing so, we get something commonly referred to in the literature as reservation prices of buyers and sellers (Fisher et al., 2003):

$$rp_{i,t}^b = noi_{i,t}^b - \log(RF_{i,t}^b + RSP_{i,t}^b - G_{i,t}^b), \quad (6)$$

$$rp_{i,t}^s = noi_{i,t}^s - \log(RF_{i,t}^s + RSP_{i,t}^s - G_{i,t}^s), \quad (7)$$

where rp denote (log) reservation prices. Superscripts b and s denote buyers and sellers, respectively. The other symbols are equivalent as discussed in the previous section. Note that buyers and sellers might have different perspectives on income, prospective growth rate, risk premium, and the risk-free rate.³ Again, we can reformulate Equations (6)–(7) in a linear model:

$$rp_{i,t}^b = \beta_{i,t}^b + x'_i \alpha^b + \varepsilon_{i,t}^b, \quad (8)$$

$$rp_{i,t}^s = \beta_{i,t}^s + x'_i \alpha^s + \varepsilon_{i,t}^s. \quad (9)$$

In this case, β_t^b and β_t^s are common trends across the reservation prices of all buyers and sellers, respectively. These common trends are the market-wide developments of the central tendencies of buyers' and sellers' reservation prices.

Reservation prices, however, are latent unobserved variables that are not readily available. Fisher et al. (2003, 2007) develop a method to disentangle buyers' and sellers' reservation prices from transactions data. Van Dijk et al. (2020) extend this method in a repeat sales and structural time-series framework such that the method can be applied on most transaction data-sets on a regional scale. Van Dijk et al. (2020) further propose a metric for market liquidity based on the difference of buyers' and sellers' reservation prices. To answer our question on commonalities, we use this method to construct demand and supply reservation price indexes as well as liquidity indexes on a regional scale. The model assumes that heterogeneous properties trade in a double-sided search market. Buyers and sellers base their valuation of a given property (reservation

²From now on we omit subscript j to simplify notation.

³Although the model does not assume this a priori, there should be a single risk-free rate for everyone as we will assume later in our theoretical simulation.

prices) on observable property characteristics. In this model, we observe a transaction if $rp_{i,t}^b > rp_{i,t}^s$.

Assuming equal bargaining power from either the buyer or seller side, the average asset price valuation β_t that we measure in general in price indexes per Equation (5) is halfway in-between buyers' and sellers' reservation price:

$$\beta_{i,t} = \frac{\beta_{i,t}^b + \beta_{i,t}^s}{2}. \quad (10)$$

Following Fisher et al. (2003), the indexes are transformed such that the mean of the buyers', sellers', and midpoint price indexes is equal. We start the log price index at an arbitrary value of 1.⁴ By looking at the difference between buyers' and sellers' reservation price indexes, we are able to construct a liquidity metric. The liquidity metric can be interpreted as the increase in buyers' reservation prices + the decrease in sellers' reservation prices as a percent of the current prevailing consummated transaction price that would bring the market to long-run average liquidity. In that case the liquidity metric would be equal to 0. The metric for a given market i at time t is defined as:

$$Liq_{i,t} = (\beta_{i,t}^b - \beta_{i,t}^s) - \beta_{i,t}. \quad (11)$$

The term $\beta_{i,t}^b - \beta_{i,t}^s$ denotes the time trend of the probability of sale per period, keeping constant the included property characteristics. The components of the liquidity metric can be estimated by a two-step approach (Heckman, 1979) using a probit model to estimate $\beta_{i,t}^b - \beta_{i,t}^s$ and an adjusted linear regression model to estimate $\beta_{i,t}$. For a more elaborate description of the variables, the model, and estimation procedure we refer to Van Dijk et al. (2020). The liquidity metric is theoretically and empirically closely related to other liquidity metrics based on for example the time-on-market in housing or the turnover rate (Van Dijk, 2018). The difference being mainly that this liquidity metric is quantified in the price dimension, relative to the currently prevailing price level.

Because the price and liquidity metrics are estimated for regional markets for which sometimes few transactions are available (the markets are said to have thin data), we estimate the price and liquidity indexes in a structural time-series framework to efficiently distinguish between signal and noise. The repeat-sales price index returns are assumed to follow a first-order autoregressive process. For more information on the smoothing procedures, see Van Dijk et al. (2020).⁵ We further recognize that the literature sometimes uses different market liquidity metrics. Therefore, we have devoted a robustness check that uses two alternative measures of market liquidity (transaction volume and the Amihud measure, see Section 6.2).

If we return to our fundamental pricing equations of buyers' and sellers' reservation prices (Equations 6–7), this has implications for what will be reflected in the price in-

⁴Note that, as with all indexes, β_t represents the relative longitudinal change over time.

⁵We do recognize that the metrics are smoothed in a different way and that this could potentially influence the integration metrics that we will discuss in the next section. However, by looking at the empirical results, it is clear that the price indexes are much smoother than the liquidity indexes. Because the liquidity indexes will contain more noise, this favors the integration of returns compared to changes in liquidity. This implies that our results on the integration of liquidity are probably on the conservative side.

dex ($\beta_{i,t}$) and in the liquidity metric ($Liq_{i,t}$). Price index returns essentially reflect the average of buyers' and sellers' changes in valuations. The market liquidity metric, however, is the *difference* between the valuations of buyers and sellers. As a consequence, common valuation of characteristics common to both buyers and sellers will cancel out. The remaining liquidity metric should thus reflect the characteristics that are different on differently valued to buyers and sellers. It is not straightforward to answer whether space or capital market characteristics cancel out in this case. We will show in a simulation framework in Section 3 that, with minimal assumptions, it will be mostly the space market components that will be cancelled out. Hence, changes in the liquidity metric will mostly reflect changes in the capital market components.

2.3. Measuring commonality

We employ two different measures for the commonality in market liquidity and returns. First, we use measures frequently applied in stock market research. More specifically, we model regional market returns on national (aggregate) market returns. See Roll (1988) and Morck et al. (2000) for stock return applications and Karolyi et al. (2012) for a stock market liquidity application. The regional real market index return $r_{i,t}$ for regional market i in period t can be expressed as:

$$r_{i,t} = \alpha_i^{Ret} + r_{m,t}^{-i} \beta_i^{Ret} + \varepsilon_{i,t}^{Ret}, \quad (12)$$

where $r_{m,t}^{-i}$ is the aggregate real market capital return for each country-asset class combination m (e.g. US commercial real estate, global gateway commercial real estate, US office etc.) in period t , excluding regional market i to prevent for simultaneity bias. We calculate the aggregate market capital return by taking the weighted (by the total number of transactions apart from regional market i over the whole sample) average return for each country-asset class combination. The commonality measure is the R^2 of Equation (12). The degree of integration for each country-asset class combination is calculated by the average R^2 of all regional markets within this combination. Note that we use real returns in order to prevent that common movements in inflation are captured by the R^2 -measure.

In order to determine the commonality in market liquidity we adapt the approach by Karolyi et al. (2012). We first filter per regional market i the liquidity by the following time series model:

$$Liq_{i,t} = a_i^{Liq} Liq_{i,t-1} + D_\tau + \omega_{i,t}^{Liq}. \quad (13)$$

Here, Liq is the estimated liquidity metric from Equation (11), D_τ are seasonal dummy variables. Following Karolyi et al. (2012) we include lagged liquidity in these filtering equations, such that we essentially take (cleaned) periodic innovations in liquidity.⁶ We use the residuals $\hat{\omega}_{i,t}^{Liq}$ to obtain measures of commonality in real estate market liquidity

⁶We acknowledge that this will result in a higher R^2 . The main results, however, still hold without including lags and leads in the liquidity regressions. Likewise, the results also hold when including leads and lags in the return equations. We opt to present our main analysis with leads and lags in the liquidity regression only to remain consistent with the literature.

for each regional market i by calculating the R^2 from the following model:

$$\hat{\omega}_{i,t}^{Liq} = \alpha_i^{Liq} + \sum_{j=-1}^1 \hat{\omega}_{m,t+j}^{Liq,-i} \beta_{i,j}^{Liq} + \varepsilon_{i,t}^{Liq}. \quad (14)$$

Here, $\hat{\omega}_{m,t}^{Liq,-i}$ denotes the weighted (again by the total number of transactions apart from regional market i over the whole sample) aggregate market residual from Equation (13) for country-asset class combination m , again excluding regional market i in calculating the aggregate market residual. Following Chordia et al. (2000) and Karolyi et al. (2012) we include one lead and lag of aggregate market liquidity in order to capture any lagged adjustment in commonality.

In order to provide explanation of our results, we will also run a similar integration analysis on NOI and cap rates. We will determine the degree of integration of NOI and risk premia (cap rate spreads) by the return Equation (12). Hence, in this case we have: $r_{i,t} \in \{\Delta noi, \Delta RSP\}$. We recognize that that risk premia and cap rate spreads are not the same because cap rate spreads will also include the growth component. However, for our purposes it is sufficient if the level of the risk premium is larger than the level of the growth rate. This is generally the case because we observe positive cap rate spreads. See also Section 3.

Because the above regressions from Equation (12) are essentially CAPM regressions, concerns may arise regarding the applicability of the CAPM to private real estate assets. For example, real estate is not solely an investment good and we already take regional market returns as “individual” returns. Additionally, the regional market indexes for prices and liquidity are already aggregated indexes from individual transactions. However, since we are interested in the R^2 from these regressions, and not in the market β , we expect that this should not pose a big problem. It is merely a statistical technique in order to determine the co-movement. Nevertheless, in order to provide extra robustness to our analysis, we apply a different statistical technique in order to determine the degree of market integration. More specifically, we perform a robustness check where we run several principal component analyses (PCA). Here, we determine the degree of integration by looking at how much information a common factor contains in explaining individual market variation (see Section 6.1).

3. Theoretical simulation framework

Before we examine the integration of market liquidity and returns empirically, we will present results based on simulated reservation price indexes. This sheds light on our empirical findings that we present in the remainder of this paper. Additionally, it provides extra comfort to the empirical measure for the degree of integration from Section 2.3. In this simulation exercise, we simulate buyers’ and sellers’ price indexes and calculate quarterly price indexes and the corresponding liquidity metric for 25 hypothetical markets for 56 periods. This will be similar to our empirical setup which runs from 2005Q1–2018Q4.

3.1. Simulation model

We start off by simulating the individual components from the buyers’ reservation price equation (Equation 6). We will simulate all components as correlated auto-

regressive processes with noise. The signal of the components are allowed to correlate across the markets according to correlation coefficient ϕ . To mimic our empirical setup for the US situation, we will simulate for 56 quarters from 2005Q1 to 2018Q4 for 25 markets. The auto-regressive process with noise is defined as:

$$x_{i,t} = \kappa_{i,t} + \eta_{i,t}, \quad (15)$$

$$\kappa_{i,t} = \mu(1 - \rho) + \rho\kappa_{i,t-1} + \varepsilon_{i,t}. \quad (16)$$

Here x is the simulated variable (e.g. NOI, risk-free rate, risk premium, or growth expectations) for regional market i at quarter t . Next, μ is the mean of the process and ρ is the auto-regressive term. For $|\rho| < 1$ the process is stationary, and for $\rho = 1$ the process is a non-stationary random walk. The innovations $\varepsilon_{i,t}$ over time are sampled from a multivariate normal distribution. We specify different variance-covariance matrices that contain the cross-market correlation structures of the signal for each variable x . That is, $\varepsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{\Sigma}_\varepsilon)$. Further, we assume normal i.i.d. noise for each series: $\eta \sim \mathcal{N}(\mathbf{0}, \mathbf{\Sigma}_\eta)$. To introduce information asymmetries between buyers and sellers, we assume that sellers observe changes in (some of the) individual components with a lag relatively to buyers. Buyers observe the true process: $x_{i,t}^b = x_{i,t}$.⁷ More specifically, we assume that sellers gradually adjust their perception about the component in their market according to the following equation:

$$x_{i,t}^s = \alpha_x x_{i,t-1}^s + (1 - \alpha_x) x_{i,t}^b. \quad (17)$$

Here, $\alpha_x \in [0, 1]$ denotes the “lag-factor”. Note that for $\alpha_x = 0$, the buyers’ and sellers’ perception about the component is equivalent. If this is the case for all components, there will be no difference between the buyers’ and sellers’ reservation prices and the liquidity metric would be 0 at all times. Empirically, this is an unlikely situation as liquidity tends to move over the cycle as well.

Next, we calculate the normal “midpoint” price indexes and our liquidity metric according to Equations (10) and (11), respectively. Similar to our empirical setup, we transform the indexes such that the mean of the buyers’, sellers’, and midpoint price indexes is equal.

3.2. Baseline calibration

We have calibrated some parameters in the baseline setup based on empirical facts as much as possible. The other parameters are calibrated such that the integration metrics are similar in size as the empirical results that we will document later in the paper. This additionally provides some insights in how the assumptions should be regarding the simulation parameters in order to replicate reality in a cap rate model.

Because there is only one risk-free rate for all market participants across all markets, we will assume a correlation of 1 between all markets and no seller lag.⁸ We assume

⁷In practice buyers also would not observe the true process, but here it is only relevant that sellers observe with a lag relatively to buyers.

⁸This will hold at least for a within-country analysis. For an international analysis, the correlation will be less than 1, but most likely still very high. In our empirical analysis, we use country-specific spread bases.

a rather high mean for the risk-free rate of 0.15 in order to prevent a negative log in Equations (6)–(7) in some simulations in highly persistent processes (i.e. $|\alpha|$ or $|\rho|$ is close to 1). This does not influence the results in terms of differences in correlations between prices and liquidity. Likewise, we fix the level of NOI across specifications, which also does not influence the results in terms of correlations in returns or market liquidity changes. Next, because the relative correlations and sizes of both log terms in the cap rate models from Equations (6) and (7) will matter, we will fix the growth expectations across the setups for tractability reasons.⁹ We will assume some correlation in growth expectations between the markets: 0.3. We assume no seller lag factor on the growth expectations. Additionally, we will assume similar starting values and variances (σ_ε^2 and σ_η^2) across the different simulations.¹⁰ We assume an AR-parameter ρ of 0.9 on both the risk premium and NOI as the levels of these variables. For the difference in correlation between liquidity changes and returns, the size of ρ does not matter. This leaves four free simulation parameters: (i) the correlation of the risk premium across markets, (ii) the correlation of NOI across markets, (iii) the seller lag factor of the risk premium, and (iv) the seller lag factor of NOI.

Table 1 shows the used variances, correlations, and starting values to autoregressive processes of the *baseline* setup. We have some empirical evidence of how high these correlations should be. The baseline assumes a 0.9 correlation of the risk premium across markets, which is similar to the empirical correlation over 2005–2018 in cap rate spreads (RCA, see also Section 5). We note that cap rate spreads are not the same as risk premia as cap rate spreads also include a growth component. However, because risk premia are the dominant component in cap rates spreads, it seems reasonable to assume a similar correlation for the baseline (see also footnote 9). Next, we assume a correlation of 0.3 in NOI changes across markets, which is about the same as the correlation that we empirically observe in the US market over 2005–2018. The other parameters are calibrated in order to obtain similar empirically found integration measures: a 0.8 seller smoothing factor on the risk premium and a 0.1 seller lag factor on NOI. This implies that sellers need to smooth about 8 times more in terms of the risk premium compared to NOI in order to generate empirically consistent results (see also Section 3.3).

The simulated liquidity and price indexes according to the baseline setup are shown in the Appendix in Figure A.14 and A.15, respectively. With these indexes, we can calculate our “empirical” commonality measures. Figure 2 shows the estimated average R^2 for the 25 simulated markets. The average R^2 for the changes in the liquidity metric is much higher than that of the returns, indicating that the integration of liquidity is higher. Figure 2 additionally shows the degree of integration according to the PCA-method, which we will also estimate as a robustness check for our empirical indexes in Section 6.1. The PCA-results also indicate that the integration of liquidity is stronger than that of returns among the simulated markets. This provides additional comfort that the integration measures that we propose are able to capture the variation of interest.

⁹ The correlation and seller lag assumptions on growth expectations are dominated if the level of the risk premium is sufficiently large compared to the level of growth expectations. This is generally the case because we observe positive cap rates.

¹⁰The effect of the variance depends on the signal/noise ratio, which we will assume to be fixed at 4 across markets. This does not influence the results if a large number of markets are included.

3.3. Other setups and two main assumptions

So far, we have calibrated our simulation setup to reflect the empirically observed situation as closely as possible. In order to determine how much these parameters may deviate from the baseline assumptions, we will provide additional simulation results based on different assumptions of the four free parameters. To do so, we let these parameters range between 0 and 1 with increments of 0.01 in four setups additional to our baseline. We keep the other parameters equivalent to the assumed values in the baseline, hence we can interpret our findings *ceteris paribus*. Figure 1 shows the average correlations between changes in (log) prices and changes in the liquidity metric across the 25 markets for different free parameter values. As we will show next, we are able to provide two main assumptions for market liquidity to be stronger correlated than returns across regions: The cross-market correlation in the risk premium component needs to be stronger than the cross-market correlation in NOI and the seller smooth lag factor in the risk premium needs to be sufficiently large compared to the seller smooth factor in NOI.

The first assumption is very much in line with the perception that capital markets tend to be stronger integrated across markets than space markets. Empirically, this assumption also holds as the correlation in cap rates tends to be much higher than the correlation in NOI. See also sections 3.2 and 5.1. Panels (a) and (b) of Figure 1 provide additional insights regarding this assumption in the simulation framework.

In panel (a) we allow for different values in the cross-market correlation in the risk premium and in panel (b) we allow for different values of cross-market correlation in NOI. The baseline values of the parameters are indicated by the dotted vertical lines. The plot in panel (a) shows that correlation in market liquidity increases more than the correlation in returns when the correlation in the risk premium increases. As such, when the cross-market correlation in risk premium is higher than the cross-market correlation in NOI, the correlation in changes in the liquidity metric will be higher than the correlation in returns. Panel (a) shows that, in our simulation setup, the correlation in the risk premium can be as low as 0.3 (the same as the correlation in NOI changes) in order for market liquidity to be stronger integrated than returns. Admittedly, it would be empirically difficult to observe differences in correlation for values lower than 0.6. Panel (b) shows a mirror image of that of panel (a): the correlation in returns increases stronger than the correlation in market liquidity when the correlation in the NOI increases. In other words, if the cross-correlation in NOI is smaller than the cross-correlation in risk premium, the correlation in the liquidity metric changes will be higher than the correlation in returns. In our setup, this implies that the correlation in NOI changes can be as high as 0.9.

The second assumption can be seen as a “loss aversion” or anchoring argument because of the relatively large degree of uncertainty in the risk premium compared to the NOI. The latter is a largely objective value. There is less scope for investors to use their judgment about what the NOI is. Hence, less scope for smoothing or lagging. The risk premium, in contrast, is not observable directly, because it is an *ex ante*, expected risk premium, dependent on perceptions of how much risk is there and what is the market’s current price of risk. Thus, the risk premium is much more subjective than is the NOI. This subjectivity allows for lagging and smoothing. Additionally, the seller bought the property some time ago against the financing conditions that prevailed at that time. Hence, it is reasonable to assume that the current perception about financing conditions is a function of past financing conditions that applied to the property in question. See

Bokhari and Geltner (2011) for evidence of anchoring in commercial real estate markets. We examine the implications of the second assumption in panels (c) and (d) of Figure 1.

Panel (c) of Figure 1 shows different average correlations for multiple values in the seller smoothing factor of the risk premium. Panel (d) shows the effect on average market correlations of different seller smoothing values for NOI. The results implicate that in case the seller smoothing factor in NOI is sufficiently small, changes in liquidity will be stronger correlated than returns. Sufficiently small in this case depends on the level of the cross-market correlations of NOI and risk premia as well as on the seller smoothing factor of the risk premium. In general, if the seller smooth factor of the risk premium is relatively large compared to the seller smooth factor, this will favor the correlation in liquidity changes. How much larger or smaller also depends on the levels of the correlations of NOI and risk premia. If the difference between these levels is smaller, the differential in the seller smooth factor in the risk premium and NOI also needs to be larger to generate stronger market liquidity integration. In our setup, with baseline assumption of correlations of the risk premium and NOI of 0.9 and 0.3, respectively, this implies that the seller smooth factor on the risk premium can be as low as 0.3. For higher values, liquidity will be stronger integrated (see panel c). Similarly, as shown in panel (d), for lower values of the seller smooth factor on NOI, liquidity changes will be stronger integrated. The seller smooth factor on NOI changes can be as high as 0.5 to observe higher correlation in liquidity changes in our simulation (see panel d).

[Place Table 1 about here]

[Place Figure 1 about here]

[Place Figure 2 about here]

4. Data

An overview of the markets for which the consummated quarterly price and liquidity indexes are estimated is included in Table 2. We use individual transactions data from Real Capital Analytics (RCA) in the period 2005Q1–2018Q4. We follow Van Dijk et al. (2020) and use MSAs as regional market segmentation as defined by RCA. In the US, we focus on the largest 25 MSAs, and additionally estimate indexes for other sub-asset classes within commercial real estate (i.e. apartment, office, retail). We additionally estimate indexes for 18 global markets. We use the same international markets that RCA identifies as “Global Commercial Real Estate Gateway” markets.

An important assumption of the methodology is that the whole population of properties should be included in the data. Because the data include transactions (and not individual properties that are not transacted), this assumption is met if all properties in the property universe are transacted at least once. In general, this is not the case in our data sources. However, the high capture rate of the datasets combined with length of the sample, provides comfort that we observe a sufficiently large part of the property universe. The coverage of the transactions for the US commercial real estate from RCA is larger than 90% for properties over \$2.5 million.¹¹ Also, for commercial real estate,

¹¹Note that, even though the price indexes take repeat sales as input, the determination of the liquidity metric also one only sales. Hence, the liquidity metric is representative for all sales and a “repeat sales bias” should not be a problem for the liquidity metric.

properties that are not in the data after 18 years might never become part of the investment universe that investors are interested in (i.e. properties that trade on a regular basis). For commercial real estate in other countries the capture rates are somewhat lower (these capture rates are not disclosed). Also, the price floors are higher internationally (€5 million for Europe and \$10 million for Asia-Pacific). This explains why there are relatively few transactions in some non-US markets (Table 2). Additionally, the capture rates are lower internationally before 2007Q1 compared to the period thereafter. Therefore, we will also focus part of the analysis on US markets only, where this should not be a problem. We also run a robustness check for a post-crisis sample in which the capture rates should be more constant. Table 2 reveals that the standard deviations in the changes in the liquidity metric are much higher than the standard deviations of the returns. This could have implications for our integration results as more noise will obscure commonalities. However, because changes in market liquidity are more noisy than returns, this will favor commonalities in returns. This implies that our results could be on the conservative side on this regard, See also footnote 5. We use CPI inflation for each country from the St. Louis Fed in order to calculate real returns.

We additionally use quarterly MSA-data on NOI per ft^2 and risk premia in the form of cap rate spreads.¹² For the US markets, we have access to NOI per ft^2 per MSA per quarter. For international markets, we do not have this data available. Therefore, in the analysis that concerns international markets, we opt to use the imputed rent instead. The imputed rent is defined as: $caprate \times price/ft^2$. Quarterly regional data on cap rates and risk premia (i.e. cap rate spreads), NOI of institutional properties per market, and price per ft^2 are also provided by RCA. The summary statistics of the percentage changes in NOI (log-changes) and changes in risk premia in basis-points are shown in Table A.3. Here, we can also see that the imputed rent changes do not always coincide with the changes in NOI for the US Global Gateway markets that are also included in the US-analysis. The high standard deviations of the imputed rent changes also indicate these are rather noisy.¹³ We distinguish between local asset markets and national/global capital markets. This implies that we should not see a strong within-market correlation between NOI growth and changes in cap rate spreads. A simple correlation analysis shows that this is indeed the case: there is only a small correlation of -0.1.

[Place Table 2 about here]

5. Co-movements in market liquidity, returns, net operating income and risk premium

To examine the extent of integration of market liquidity across markets, we first visually examine the degree to which both market liquidity metrics and price indexes co-move.

¹²Cap rates are NOI-based and the spread is over similar maturity bond yields. Note that it is mostly irrelevant over which base the spread is taken as the base is equivalent across markets within the same country. In the international analysis, it does matter, but the results are robust to using a different base such as the country-specific risk-free rate. Also, because our analysis concerns changes, it would only matter for the results if *changes* in the bases over time are different per market.

¹³We recognize that we should be careful in interpreting the results for these data. However, we only use them to produce one small result (i.e. the degree of integration in Global Gateway NOI), therefore we opt to continue to use these data such that we are able to provide all results for all markets.

As a second step, we run more formal tests on the commonality in changes in market liquidity and real price index returns. In order to put our findings in price and liquidity commonalities in perspective of our models from Sections 2.1–2.2 and our simulation framework from Section 3, we will also show degrees of integration for NOI and risk premia.

We will present the results for three different types of market type combinations: (i) US commercial real estate, (ii) US commercial real estate divided into separate asset classes (apartment, office, and retail), and (iii) international commercial real estate.

5.1. US commercial real estate

Market liquidity metrics for 25 different regional markets of US commercial real estate are plotted in Figure 3. Visually, it is clear that market liquidity shows a strong commonality across regions. The GFC of 2008–2009 is clearly visible in the decreasing liquidity metrics in all markets. Also the recovery in market liquidity to pre-crisis levels (2010–2014) is remarkably similar across different markets. Price indexes for the 25 US markets are shown in Figure 4. It is clear that there is substantial co-movement in prices across the different metropolitan areas, but also that the co-movement is much smaller than that of the liquidity indexes.

[Place Figure 3 about here]

[Place Figure 4 about here]

[Place Figure 5 about here]

[Place Figure 6 about here]

The more formal results of the degree of integration according to the R^2 for both liquidity and returns are shown in Figure 5. In general, market liquidity seems to be strongly integrated across markets and the integration of liquidity is much stronger than the integration of real returns. The R_{liq}^2 for US commercial real estate is about 0.54 on average, whereas the average R_{ret}^2 is around 0.30.¹⁴ To put these numbers in perspective, Karolyi et al. (2012) document R_{liq}^2 for US stock markets of about 0.23 on average. In other words, the integration in private real estate market liquidity seems to be much stronger.¹⁵

Note that the R^2 -bars of the in Figure 5 concern the average R^2 of all MSAs. Additionally, we can inspect the individual R^2 s for each market, i.e. the R^2 s from the regressions based on Equation (11). The R_{liq}^2 ranges from 0.25 to 0.78 and the R_{ret}^2 from 0.06 to 0.72. The correlation between the R_{liq}^2 and R_{ret}^2 of individual markets is about 0.27, which suggests that markets that co-move more with market liquidity also tend to co-move somewhat more with national aggregate returns. The market that shows the strongest co-movement with the national market, both in terms of market liquidity and real returns, is Los Angeles. The market that co-moves the least with national market in terms of liquidity is Detroit. In terms of returns, this is Washington D.C.

¹⁴Note that that the R_{liq}^2 is based on ω^{Liq} and effectively concerns changes in liquidity and returns reflect real price index changes.

¹⁵We recognize that the stock market analysis is based on a different frequency and different metric, which may drive the differences. Nevertheless, we feel it serves as a useful reference point.

In Section 3 we have theoretically shown that the relatively large regional co-movement in risk premia (cap rate spreads) compared to income might be the reason of the strong commonality in market liquidity. Figure 6 additionally provides empirical evidence for this claim for the 25 examined US MSAs. Here, we show the results of the R^2 analyses for changes in risk premia ($R^2_{\Delta r_{sp}}$) and NOI ($R^2_{\Delta noi}$) of the regional markets. The $R^2_{\Delta r_{sp}}$ is about 0.87 compared to only 0.24 for the $R^2_{\Delta noi}$.

5.2. US commercial real estate within asset class

To answer the question how strong the co-movement in real estate market liquidity within the same asset class within the same country, we estimate price and liquidity indexes for separate asset classes. We consider three different asset classes: (i) apartments, (ii) office, and (iii) retail. The liquidity indexes for these three asset classes for the six largest markets in the US, “The Big 6”, are shown in Figure 7.¹⁶ Visually, the co-movements in market liquidity seem to be very strong within each different asset class. Again, the co-movement in liquidity is much stronger than the co-movement in price indexes (compare Figure 7 to 8).

The R^2 metrics for both liquidity and returns for the three separate asset classes are shown in Figure 5. The figure also contains the integration analysis for all three asset classes of all six markets lumped together as a reference point “US CRE Big 6 Subtypes”. Overall, the co-movement in liquidity is strong in all asset classes, and the co-movement is stronger for market liquidity than for returns. The average R^2 s of the asset classes combined for market liquidity and real returns are 0.42 and 0.22, respectively. These results are slightly lower than those found for the 25 MSAs in Section 5.1, but similar in terms of difference between the degree of integration of liquidity and returns. The integration of market liquidity is the strongest within the retail market, where the average R^2 is 0.45. The difference between the R^2 of market liquidity and returns is also the largest for the retail markets. For returns, the co-movement in the office market prices is stronger than for the two other asset classes. The average R^2 over office market returns is 0.29. However, the co-movement in market liquidity is still stronger (0.38).

Figure 6 shows the degrees of integration for NOI and risk premia for the examined six markets for the different asset classes. Overall, the integration in risk premia is much stronger across the markets for the different asset classes than the integration in operating income. Interestingly, the integration of risk premia and the difference between the integration of risk premia and NOI is the largest for retail markets. The retail markets also showed the strongest integration in market liquidity compared to returns (Figure 5). Overall, these results strongly corroborate the claim that the relatively strong integration of cap rate spreads compared to NOI lies at the root of strong co-movements in market liquidity compared to returns.

[Place Figure 7 about here]
 [Place Figure 8 about here]

¹⁶These are Boston, Chicago, Los Angeles, New York, San Francisco, and Washington D.C. The number of observations in Washington D.C. apartments is too little and is omitted from the analysis.

5.3. Global commercial real estate

This section looks at the integration of liquidity and real returns of global commercial real estate markets. We consider 18 large international global gateway markets in the analysis. Figure 9 includes the market liquidity indexes for the global gateway markets. It is clear that co-movement in liquidity is less strong than for the US commercial real estate markets only. Nevertheless, the run-up to the GFC is visible in most markets, as is the GFC itself. The recovery after the GFC also occurs in all markets, mostly at the same pace. The co-movement of the price indexes of the 18 global markets is shown in Figure 10. It can clearly be observed that the co-movement in the price indexes is less than in the liquidity indexes.

More formally, the degree of integration for market liquidity and real returns per the R^2 measures are shown in Figure 5. Again, the degree of integration in market liquidity is much stronger than the integration of real returns. The average R^2 s for market liquidity innovations and real returns are 0.30 and 0.14, respectively. Note that the global integration measures are lower than those for US commercial real estate alone. Nevertheless, there is still evidence that market liquidity co-moves strongly internationally and the finding that liquidity co-moves stronger than returns also holds internationally.

Additionally, the co-movement in risk premia in the international case is also much stronger than that in income (Figure 6). The $R^2_{\Delta r_{sp}}$ is about 0.6 compared to an $R^2_{\Delta noi}$ of only about 0.03.¹⁷

[Place Figure 9 about here]

[Place Figure 10 about here]

To summarize, the R^2 analyses suggest that market liquidity co-moves much stronger than returns. This holds for US commercial real estate, for different real estate asset classes, as well as for international commercial real estate. Both theoretically and empirically, there is strong evidence that the relatively strong co-movement in cap rates compared to that in operating income lies at the root of the relatively strong co-movement in market liquidity compared to returns.

6. Robustness checks

In this section, we will present three different robustness checks: in (i) we use an alternative integration measure (PCA), in (ii) we use two alternative market liquidity measures, and in (iii) we look at the post-crisis sample to examine the effect of the GFC.

6.1. Alternative integration measure: PCA

In the first robustness check, we run a principal component analysis (PCA) to determine the degree of integration of returns and market liquidity. We look at the information in the first component with respect to individual market variations to determine this degree of integration. Intuitively, this measure is higher when the first component explains more of the variation in returns or market liquidity innovations. This implies that the

¹⁷Note again that we use highly noisy imputed rent movements here due to a lack of data availability of NOI for all international markets, so these results should be taken with a grain of salt.

markets are stronger integrated because their common factor is relatively more important for the variation in individual markets. Because the market liquidity metrics and price levels are non-stationary in all markets, we run the PCAs on real returns and changes in liquidity, which are stationary variables.¹⁸ The downside of the PCA compared to the R^2 -method is that regional market i is included in the calculation of the principal component, which introduces a simultaneity bias. This should be mitigated if many regional markets are compared in one setup, but could be a problem if the analysis does not include many markets.

In general, the PCA results confirm the main finding that liquidity is stronger integrated than returns. For the USA 25 MSAs, the first component seems to explain about 35% of the returns, compared to about 54% in changes in the liquidity metric (Figure 11). The PCA results show somewhat different results than the R^2 measure for the separate asset classes. The reason is that there are only 6 markets compared simultaneously (or 5 in the case of apartments due to the lack of observations in Washington D.C., see section 4). This will make the the PCA somewhat unreliable because a single market will for a large part be responsible for the variation in the common factor (i.e. the simultaneity bias is larger when the number of markets is small). Note that, contrary to the PCA-measure, the R^2 -measure excludes market i in calculating aggregate market returns or liquidity (see Equations (12)–(14)). Hence, in the R^2 -measure this should not be a problem. If we lump together the sub-asset categories in “US CRE Big 6 Subtypes” and perform the PCA on this set of markets, we do find stronger evidence that the comovement in liquidity changes is stronger than that of returns. In the international case, the percentages of variance explained by the first factor of market liquidity changes and returns are 0.34 and 0.26, respectively. Hence, there is a difference in terms of the degree of integration, but it is small. Also note that the simultaneity bias might be a bit larger than in the US case, because the international comparison includes 18 markets.

[Place Figure 11 about here]

6.2. Two alternative market liquidity measures

The second robustness check employs two different measures for market liquidity. The measure for market liquidity that we use for the main results allows specifically for the construction of market liquidity indexes for regional markets. Other proxies for different concepts of market liquidity used in the literature include the number of transactions, transaction volume, or the Amihud measure (Amihud, 2002; Ametefe et al., 2016). The downside of many other measures it that they can be too noisy for regional markets because of the (lack of) number of transactions. In this robustness check, we will consider two alternative measures that relate to at least several dimensions of market liquidity.¹⁹

¹⁸We run IPS and Maddala-Wu panel unit root tests Im et al. (2003); Maddala and Wu (1999) and find that all variables are stationary in first-differences. Results suppressed to conserve space, but available upon request.

¹⁹We refer to Ametefe et al. (2016) for an overview of these dimensions and the applications in private real estate. The literature generally considers five different dimensions: tightness, depth, resilience, breadth, and immediacy. Our main measure is a “transaction cost measure” and relates to tightness. Transaction volume is volume-based measure and relates to breadth. The Amihud measure is a price impact measure and relates to depth and resilience of the market.

Transaction volume is total transaction volume in a given quarter for a given market and is provided by RCA. The Amihud measure is defined as:

$$Amh_{i,t} = \frac{|Ret_{i,t}|}{Vol_{i,t}}. \quad (18)$$

Here, Amh is the Amihud measure for market i in quarter t , $|ret|$ is the absolute price index return, and Vol is total transaction volume.²⁰ Due to data availability, we are only able to run this robustness check for the USA 25 MSA markets.²¹

Figure 12 shows the R^2 integration measures for changes in log total volume (Δvol) and the Amihud measure (Amh). The figure additionally includes the degrees of integration for returns (ret) and the market liquidity measure (liq) as used in the main results as reference points. Of the three liquidity measures, the Amh and liq measures show the strongest degree of integration, remarkably similar at around 0.55. The Δvol measure is less integrated at around 0.45, but still much stronger than the degree of integration of real returns (0.30). Overall, the results that market liquidity is stronger integrated than returns are robust to the usage of different market liquidity measures.

[Place Figure 12 about here]

6.3. Effect of Global Financial Crisis

The third robustness check aims at examining the effect of the GFC. The GFC is an interesting period in terms of commonalities as most things went down, which implies that commonalities increase. It is also at this time when market liquidity might be important for investors that need to sell assets because they are in distress. Because the calculation of the integration measure requires a “large enough” time sample, we are not able to run the measures for the GFC only.²² Instead, we opt to estimate the degrees of integration for the post-GFC (2010–2018), and compare those to the estimates for the full sample (2005–2018). Differences between those degrees of integration are likely to be attributed to the GFC. Visually, it is already clear that the GFC might be a large driver in the large commonality of both market liquidity and returns. See, for example, Figures 3 and 4 for the 25 US MSAs.

Figure 13 shows the degrees of integration for the post-GFC sample period. These should be compared to Figure 5, which shows the degrees of integration for the whole sample. Overall, the degrees of integration are smaller than those over the whole sample. The finding that market liquidity is stronger integrated than returns remains robust. For market liquidity for the US 25 MSAs, the R^2_{Liq} for the shortened sample is about 0.32, compared to about 0.54 for the whole sample. Note, however, that the degree of integration of returns is also much smaller: 0.10 in the post-GFC sample versus 0.30 for the whole sample. In other words, integration of both market liquidity and returns is

²⁰Note that the original Amihud measure uses total return, in our case we only have data on price indexes, which relate to capital returns.

²¹Data is either not (reliably) available for the full sample or the resulting measures are too noisy.

²²Note that it is also not possible to leave the crisis out, because the regressions are time-series regressions that include lags.

less strong (stronger) after (during) the GFC. This makes intuitive sense as everything (such as market liquidity and returns) goes down in every market during a crisis and cross-market correlations move to 1. In fact, a back-of-the-envelope calculation suggests that the R_{Liq}^2 should be roughly 0.94 in the period 2005–2009, which largely includes the GFC.²³ The fact that market liquidity is stronger integrated in crisis times is also consistent with findings for the US stock market (Karolyi et al., 2012). Here it is shown that the R_{Liq}^2 during the GFC was about twice as large as during normal times (0.2 compared to 0.4). This finding is important to note for investors as it is likely that especially during these times investors might be in need for market liquidity (i.e. in case they need to sell off assets for cash needs).

The pattern of less integration in both returns and market liquidity, but stronger integration in market liquidity than in returns, can clearly be seen in most considered market combinations. The only notable exception is the US office market, where returns and market liquidity are similarly integrated (note that the difference was also smaller over the whole sample). We do not have a clear explanation for this, but we note that returns in the office market are relatively strongly integrated compared to other asset classes, both in the post-GFC and full sample. We leave a more thorough investigation for future research.

[Place Figure 13 about here]

7. Conclusion and possible extensions

In this paper, we have examined the commonality of private commercial real estate markets in terms of both returns and liquidity. To return to our three questions: (i) “How strong is the co-movement in changes in market liquidity?”, (ii) “How strong is the co-movement in real price index returns?”, and (iii) “Which factors drive the difference in commonality between market liquidity changes and real price index returns?”, we find the following.

Using data from Real Capital Analytics spanning the period 2005Q1–2018Q4, we document substantial co-movement in market liquidity dynamics. Based on the commonality measure of Roll (1988) and Karolyi et al. (2012), we find strong commonalities in market liquidity within the US for the 25 examined MSAs. We use the market liquidity metric based on differences in buyer and seller reservation prices from Fisher et al. (2003, 2007) and Van Dijk et al. (2020). For the largest 6 MSAs, we are also able to confirm strong commonalities for three different asset classes (apartment, office, and retail). Even for global commercial real estate (18 MSAs), we find substantial co-movement in market liquidity. For all these market combinations, we additionally find some co-movement in returns. However, the co-movement in returns is found to be much smaller than the co-movement in liquidity in all studied market combinations.

²³We obtain this rough approximation by solving $(1 - w) * R_{Liq,05-09}^2 + w * R_{Liq,10-18}^2 = R_{Liq,05-18}^2$ for $R_{Liq,05-09}^2$, where w is the number of time periods in the restricted sample divided by the number of time periods in the full sample (36/56).

In order to examine the underlying factors of this relatively strong co-movement in market liquidity, we present a theoretical simulation framework. Using this framework, we show that two main assumptions are required to simulate these results: (i) the cross-market co-movements in the risk premium need to be stronger than the co-movements in NOI and (ii) the seller lag in risk premium needs to be sufficiently large compared to the seller lag in NOI. Consistent with these assumptions, we hypothesize that the strong integration in market liquidity is driven by the fact that capital markets are stronger integrated than space markets. We confirm this argument empirically by showing that risk premia co-move much stronger than changes in NOI across markets.

We additionally find that our commonality findings are robust to the use of a different measure of integration (principal component analysis). Second, percentage changes in volume and the Amihud measure (two alternative market liquidity measures) also show stronger integration than price index returns. Third, by leaving out the GFC, we find that the degree of commonalities decreases. This suggests that the commonalities in market liquidity and returns increased strongly during the GFC. The finding that market liquidity is stronger integrated than returns, however, remains robust. The US office market is the only notable exception, where returns co-move relatively strong compared to other asset classes and compared to market liquidity. We leave a further investigation to future research, but note that the relatively strong co-movement in US office returns was also visible in the sample that includes the GFC.

We recognize at least two limitations to our research. First, we examine intertemporal changes in market liquidity across markets and not cross-sectional level differences between markets. It might still be the case that some markets are more liquid than others in levels. The same holds for individual properties, some properties might be more liquid than others. We only document findings related to market liquidity dynamics because we do not have a reliable measure for level differences between markets or for individual property liquidity. Also, diversification usually refers to dynamics of the variables that an investor would like to diversify on. Hence, we feel that price and liquidity dynamics capture a large part of this question. Second, because of data constraints, we are only able to include larger markets. Large markets may be inherently different than small markets, also in terms of co-movements with other markets. Most (international) capital will tend to flow to these large cities as opposed to the smaller cities. Hence, a large chunk of private real estate investment, happens in these large markets. This makes our sample – to some extent – maybe even more relevant for large investors.

The results are of interest for large private real estate investors such as pension funds and other institutional investors who are interested in spreading risk. Our results indicate that it is easier to spread risk in terms of returns and much more difficult to spread market liquidity risk. Market liquidity co-moves much stronger and is to a larger extent driven by capital market movements, which cannot be diversified easily in terms of geographical diversification or asset class diversification. Internationally, we do find less co-movement in both returns and market liquidity, which should make diversification easier. However, international diversification in market liquidity remains more difficult than diversification in returns because market liquidity also co-moves stronger than returns in the international case. The results are also important to understand for policymakers as policymakers are – at least partly – capable of directly influencing capital market movements by changing the lending rate or indirectly through risk premia through asset purchase programs. The results suggest that capital markets will strongly affect market

liquidity, effects that possibly need to be taken into account when implementing measures that affect capital markets.

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Tables

Table 1: Parameters used to simulate the different components in the simulation exercises.

Variable	Mean μ	Var σ_ε^2	Var σ_η^2	Corr ϕ	Sell lag α	AR-par ρ
<i>Baseline setup</i>						
<i>noi</i>	log(50000)	0.6	0.015	0.3	0.10	0.9
<i>R_f</i>	0.15	0.001	0.00025	1	0	0.9
<i>RSP</i>	0.10	0.02	0.005	0.9	0.8	0.9
<i>G</i>	0.01	0.001	0.00025	0.3	0	0.9
<i>Free setup (i)</i>						
<i>noi</i>	log(50000)	0.6	0.015	0.3	0.10	0.9
<i>R_f</i>	0.15	0.001	0.00025	1	0	0.9
<i>RSP</i>	0.10	0.02	0.005	\mathbf{x}_1	0.8	0.9
<i>G</i>	0.01	0.001	0.00025	0.3	0	0.9
<i>Free setup (ii)</i>						
<i>noi</i>	log(50000)	0.6	0.015	\mathbf{x}_2	0.10	0.9
<i>R_f</i>	0.15	0.001	0.00025	1	0	0.9
<i>RSP</i>	0.10	0.02	0.005	0.9	0.8	0.9
<i>G</i>	0.01	0.001	0.00025	0.3	0	0.9
<i>Free setup (iii)</i>						
<i>noi</i>	log(50000)	0.6	0.015	0.3	0.10	0.9
<i>R_f</i>	0.15	0.001	0.00025	1	0	0.9
<i>RSP</i>	0.10	0.02	0.005	0.9	\mathbf{x}_3	0.9
<i>G</i>	0.01	0.001	0.00025	0.3	0	0.9
<i>Free setup (iv)</i>						
<i>noi</i>	log(50000)	0.6	0.015	0.3	\mathbf{x}_4	0.9
<i>R_f</i>	0.15	0.001	0.00025	1	0	0.9
<i>RSP</i>	0.10	0.02	0.005	0.9	0.8	0.9
<i>G</i>	0.01	0.001	0.00025	0.3	0	0.9

Price indexes of 25 markets for 56 time periods are simulated. Var denotes the variance of the signal (σ_ε^2) and noise (σ_η^2) of the specified variable, Corr the correlation of the signals across the 25 markets, Mean the mean value of the random walk, the Sell lag the lag factor that sellers assume in determining their reservation prices, and the AR-par the autoregressive parameter of the process. x_1 - x_4 denote the variables that are assumed to be “free” in each setup.

Table 2: Overview of markets and summary statistics.

Market	<i>United States All Commercial</i>					
	Sales	Pairs	<i>ret</i> (%)	StdDev	Δ <i>liq</i> (%-pt)	StdDev
Atlanta	6717	2354	0.39	3.68	0.26	4.71
Austin	2190	713	0.61	1.96	0.43	6.56
Baltimore	2106	511	0.12	2.22	0.06	5.25
Boston	5070	1121	0.29	1.93	0.19	6.69
Charlotte	2422	736	0.15	2.08	0.56	5.62
Chicago	9781	2136	-0.01	2.49	0.03	3.98

Dallas	8458	2646	0.55	1.77	0.30	5.44
Washington DC	5819	1389	0.25	4.79	0.07	5.41
Denver	4011	1201	0.73	3.79	0.38	4.00
Detroit	2842	408	0.11	2.40	0.19	6.41
Houston	6228	1634	0.71	2.79	0.18	3.83
Los Angeles	26910	6408	0.70	2.09	0.02	2.90
Las Vegas	2626	588	0.01	4.00	-0.18	3.92
Miami	8029	2015	0.60	3.89	-0.14	4.57
Minneapolis	3370	736	0.19	2.35	0.25	5.81
New York City	25766	5709	1.26	4.70	0.08	3.20
Orlando	2555	795	0.24	3.00	0.17	5.50
Philadelphia	4595	832	0.41	4.38	0.04	4.64
Phoenix	5969	1955	0.33	3.60	-0.07	4.01
Portland	2726	558	0.48	1.72	0.35	3.82
Sacramento	2697	682	0.06	2.86	0.16	5.13
San Diego	4978	1293	0.34	2.14	-0.06	3.72
Seattle	5785	1428	0.87	4.22	0.15	5.13
San Francisco	12389	3046	1.18	3.20	0.08	3.50
Tampa	3152	943	0.45	4.51	-0.14	4.55
<i>Global Gateway All Commerical</i>						
Market	Sales	Pairs	ret (%)	StdDev	Δliq (%-pt)	StdDev
Amsterdam	5216	753	-0.12	2.92	1.29	5.36
Boston	5070	1121	0.29	1.93	0.19	6.69
Chicago	9781	2136	-0.01	2.49	0.03	3.98
Washington DC	5819	1389	0.25	4.79	0.07	5.41
German A cities	8945	1567	0.61	5.50	0.90	6.98
Hong Kong	8603	1073	2.06	3.75	0.86	6.20
Los Angeles	26910	6408	0.70	2.09	0.02	2.90
London	5473	1377	0.57	4.88	0.07	3.69
Melbourne	3243	537	0.86	3.83	1.15	6.53
Nordic A cities	3818	627	0.59	3.48	0.61	5.46
New York City	25766	5709	1.26	4.70	0.08	3.20
Paris	4738	638	0.42	2.02	1.08	4.84
Seoul	2776	488	0.21	2.45	1.15	3.96
San Francisco	12389	3046	1.18	3.20	0.08	3.50
Singapore	2309	344	1.73	5.77	0.78	9.21
Sydney	3895	713	0.75	3.38	0.58	4.25
Tokyo	6824	1400	0.58	3.18	0.02	3.23
Toronto	3352	586	0.99	4.31	1.11	5.57
<i>United States Subtypes</i>						
Market	Sales	Pairs	ret (%)	StdDev	Δliq (%-pt)	StdDev
Boston APT	500	90	0.72	2.15	-0.11	2.72
Chicago APT	590	130	0.14	1.13	0.24	5.20
Los Angeles APT	6467	1980	0.98	1.93	0.02	2.30
New York City APT	7370	2685	1.24	6.36	-0.01	3.09
San Francisco APT	2856	798	1.46	4.11	0.17	4.43

Boston OFF	1244	349	0.09	2.63	0.01	6.42
Chicago OFF	1362	375	0.15	1.95	-0.14	6.28
Washington DC OFF	1898	508	-0.26	1.39	-0.09	4.83
Los Angeles OFF	4001	1150	0.36	3.38	-0.07	4.09
New York City OFF	3824	712	0.55	2.53	-0.05	5.79
San Francisco OFF	2683	842	1.02	3.22	0.01	4.47
Boston RET	913	179	0.88	6.54	0.54	6.31
Chicago RET	1982	392	-0.21	2.74	-0.15	5.75
Washington DC RET	1096	258	0.72	8.12	0.15	6.91
Los Angeles RET	4914	1018	0.53	2.70	-0.23	4.15
New York City RET	5005	830	1.01	2.34	0.19	4.27
San Francisco RET	1838	296	0.45	2.05	-0.05	3.72

Sales is the total number of properties that are sold at least once and are therefore included in the sample, Pairs are the number of repeat sales pairs, *ret* are the average real quarterly returns in percentages, Δliq is the average quarterly change in the liquidity metric in percentage points, and StdDev denote the corresponding standard deviations.

Figures

Figure 1: Average correlations between 25 simulated markets of changes in (log) prices and changes in the liquidity metric for different parameter sets. Each subplot shows results for a different free parameter. Table 1 shows the parameters used in the simulation. The dotted vertical line shows the assumption of that specific parameter in the baseline simulation.

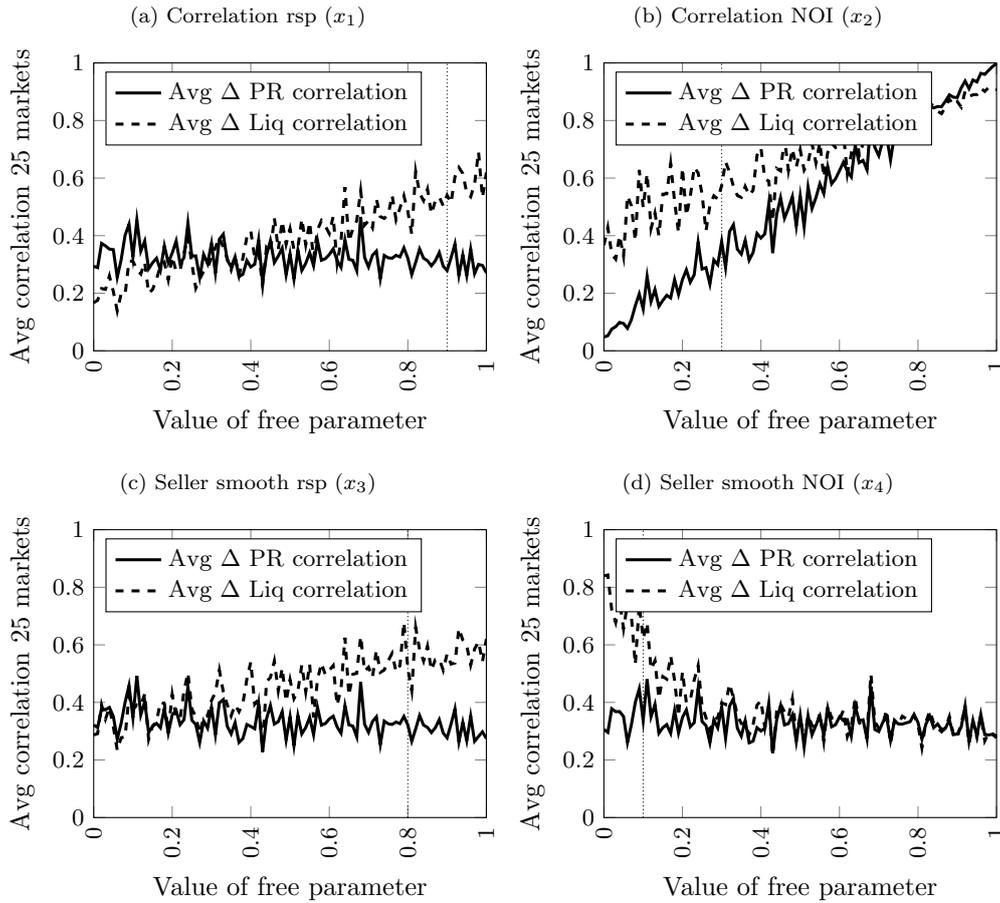


Figure 2: Simulated R^2 and PCA measures of integration of real returns and quarterly innovations in market liquidity the studied market combinations. The figure shows the R^2_{liq} metric from Karolyi et al. (2012) and R^2_{ret} metric from Roll (1988) and explained variance by the first factor of a PCA.

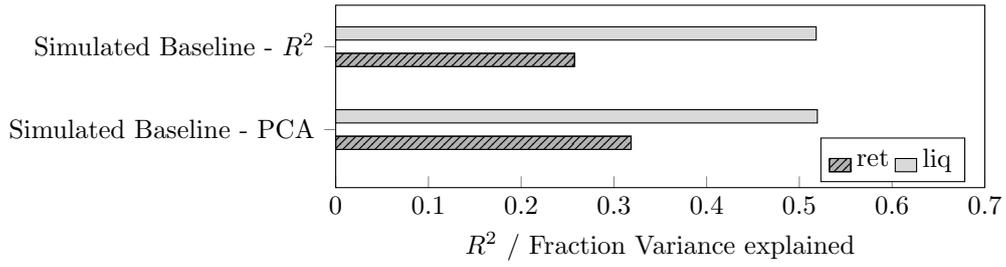


Figure 3: Commercial real estate market liquidity for 25 US MSAs.

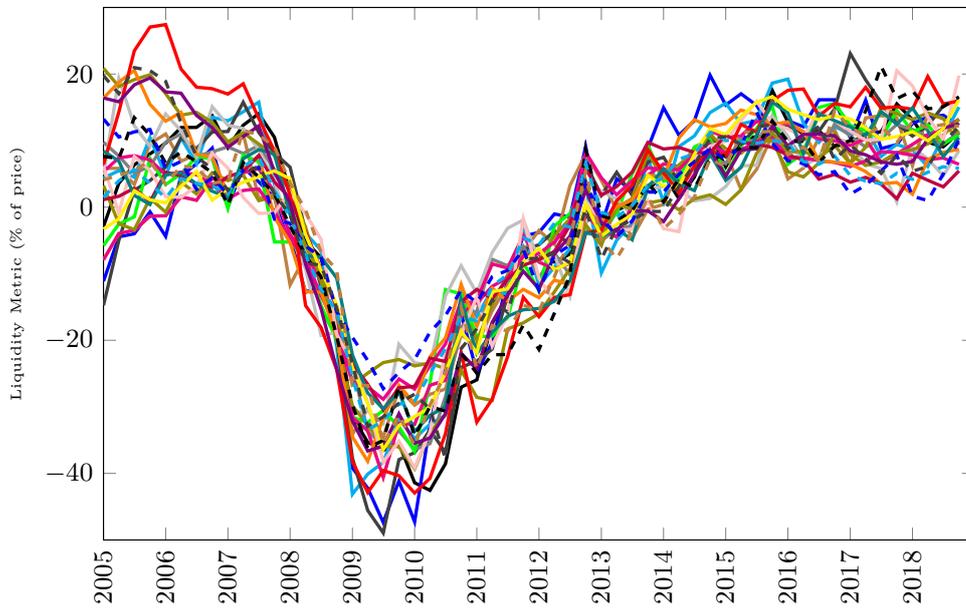


Figure 4: Commercial real estate log price indexes for 25 US MSAs.

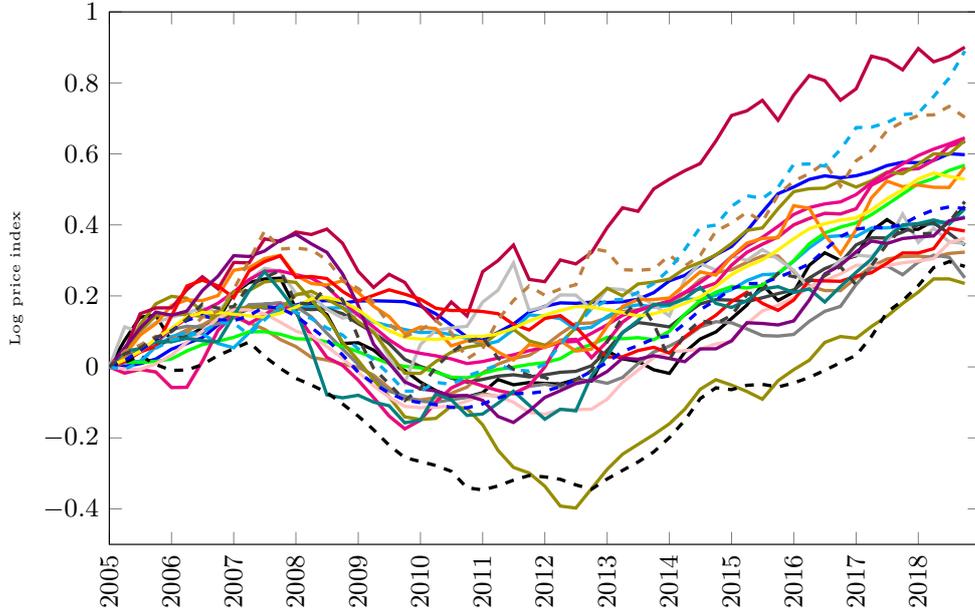


Figure 5: Empirical R^2 measures of integration of real returns and quarterly innovations in market liquidity the studied market combinations. The figure shows the R_{liq}^2 and R_{ret}^2 metrics from Karolyi et al. (2012) and Roll (1988).

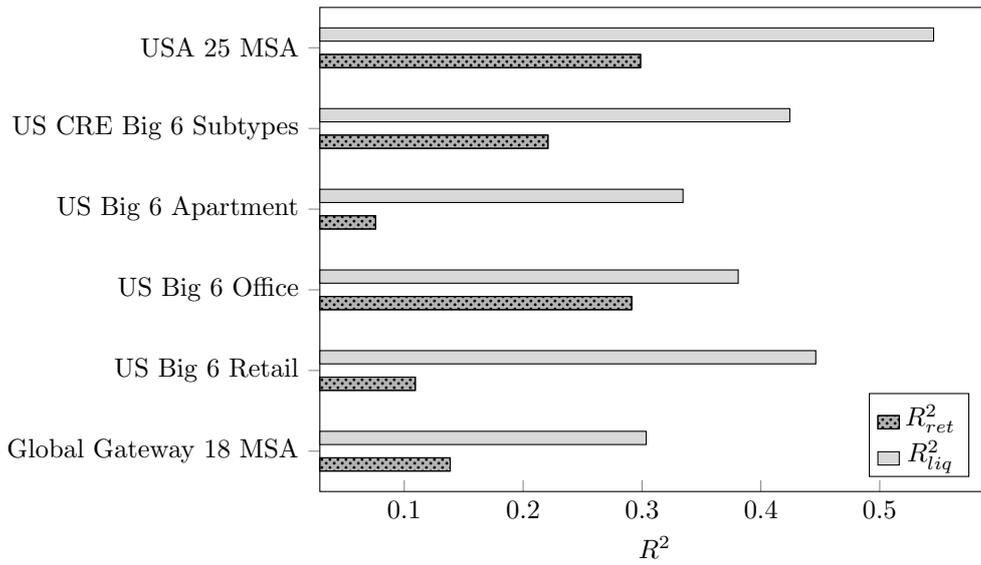


Figure 6: Empirical R^2 measures of integration of changes in risk premia (Δr_{sp}) and changes in NOI (Δnoi) in the studied US market combinations. The figure shows the $R^2_{\Delta r_{sp}}$ and $R^2_{\Delta noi}$ metrics based on Karolyi et al. (2012) and Roll (1988).

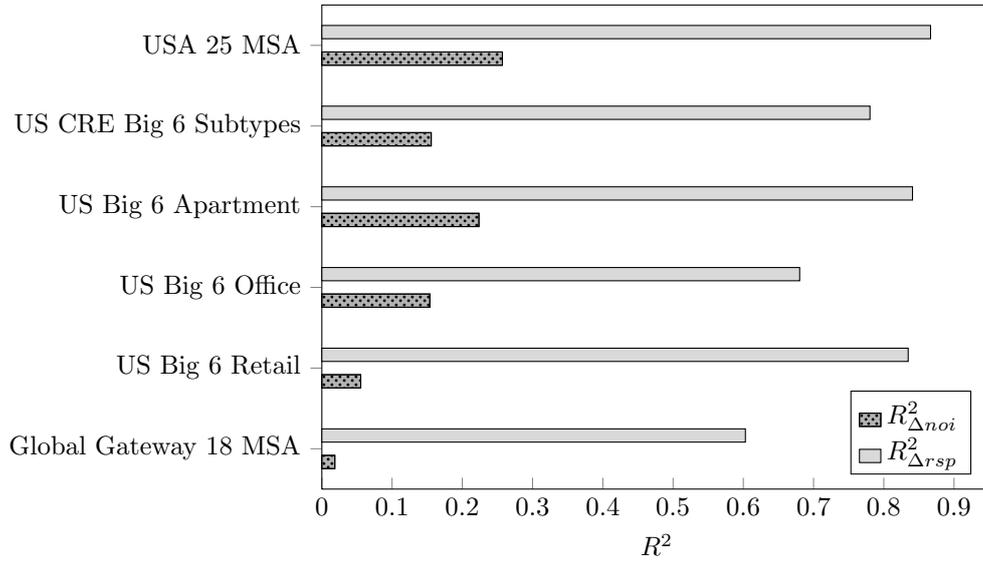
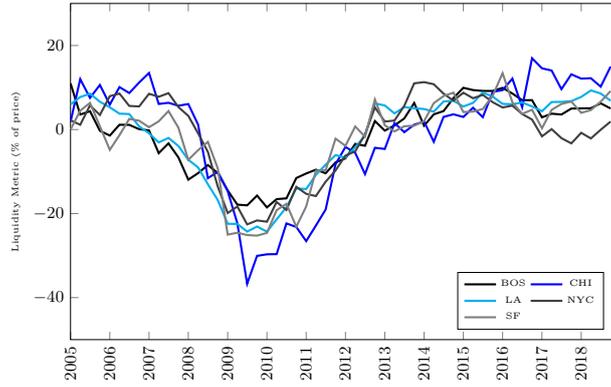
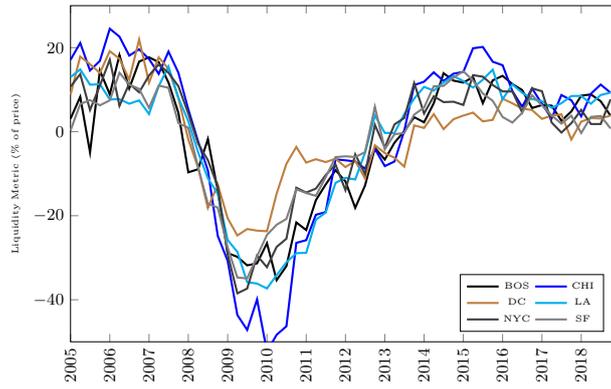


Figure 7: Commercial real estate market liquidity for 6 big US MSAs for different asset classes.

(a) US Apartments



(b) US Office



(c) US Retail

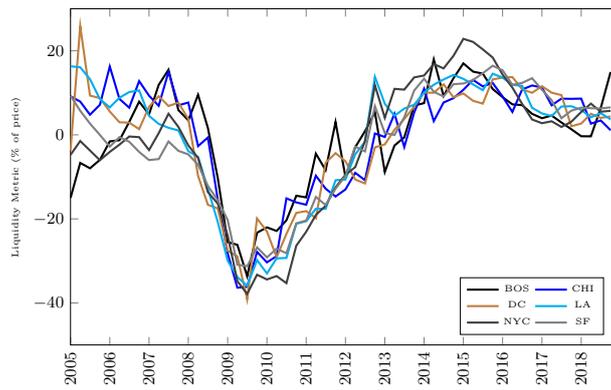
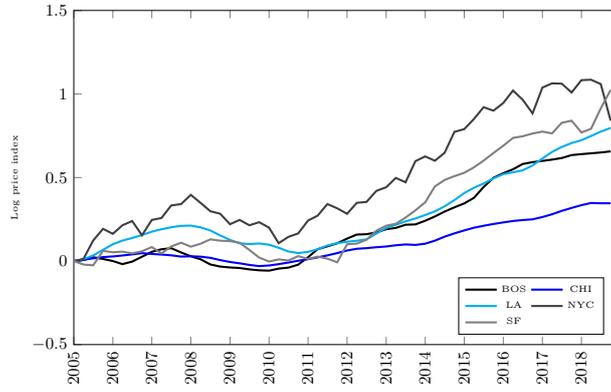
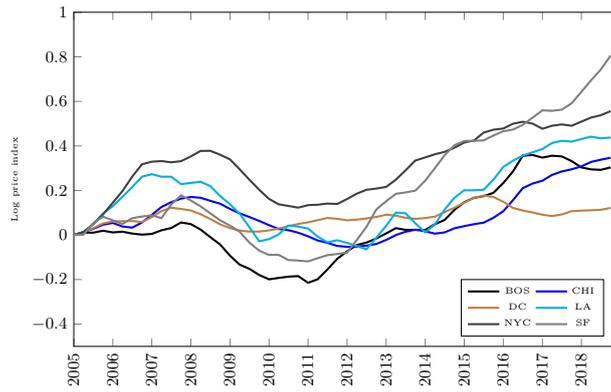


Figure 8: Commercial real estate log price indexes for 6 big US MSAs for different asset classes.

(a) US Apartments



(b) US Office



(c) US Retail

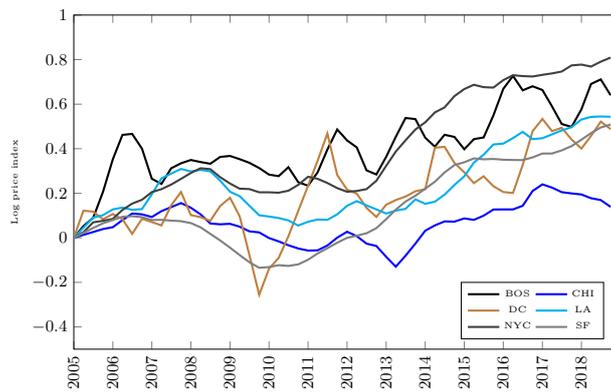


Figure 9: Commercial real estate market liquidity for 18 Global Gateway markets.

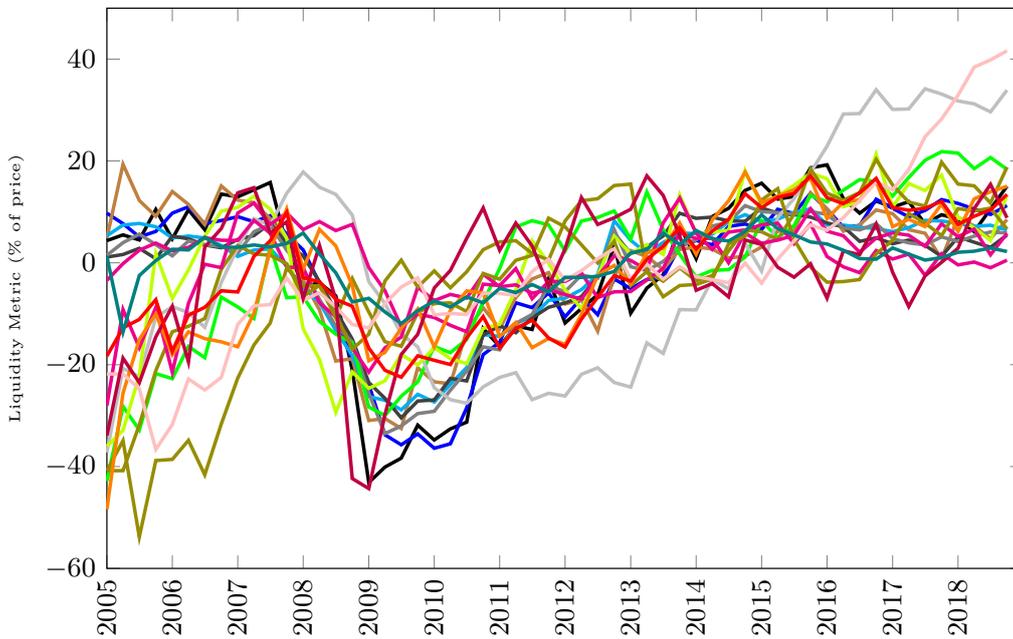


Figure 10: Commercial real estate log price indexes for 18 Global Gateway markets.

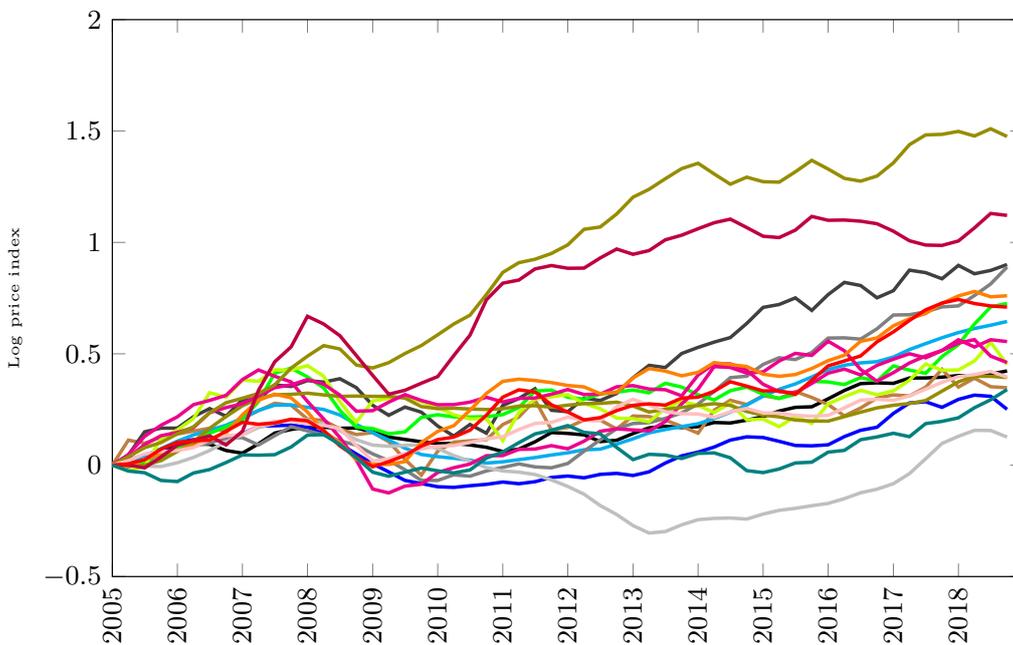


Figure 11: Robustness check (i): PCA measures of integration of real returns and quarterly innovations in market liquidity the studied market combinations. This figure shows the explained variance by the first factor of a PCA for all studied market combinations.

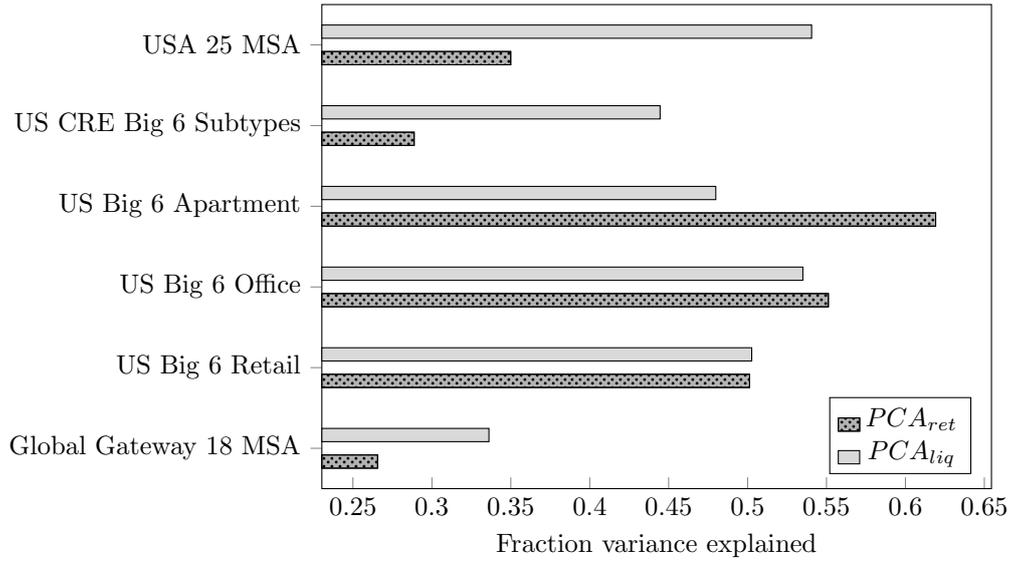


Figure 12: Robustness check (ii): R^2 measures of integration for two alternative market liquidity measures: transaction volume ($R^2_{\Delta vol}$) and Amihud measure (R^2_{Amh}). This Figure also includes integration measures of returns (R^2_{ret}) and the main market liquidity measure (R^2_{liq}) based on as reference points.

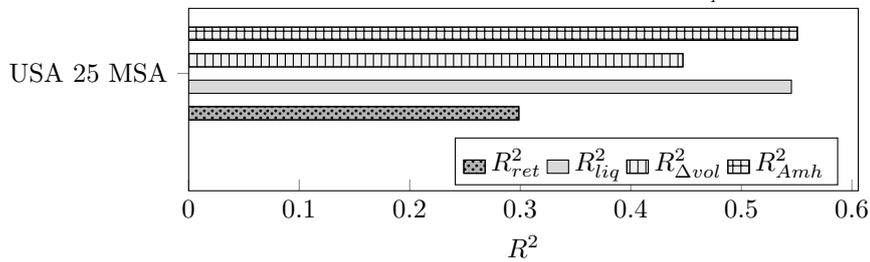
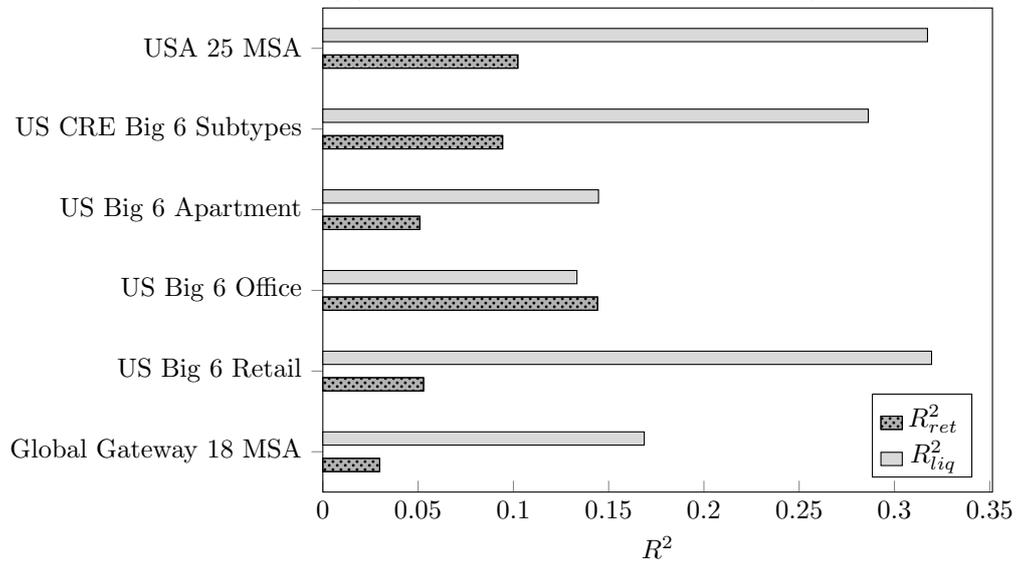


Figure 13: Robustness check (iii): R^2 measures for post-GFC sample period (2010Q1–2018Q4).



Appendix A. Additional Figures and Tables

Figure A.14: Market liquidity for 25 simulated markets.

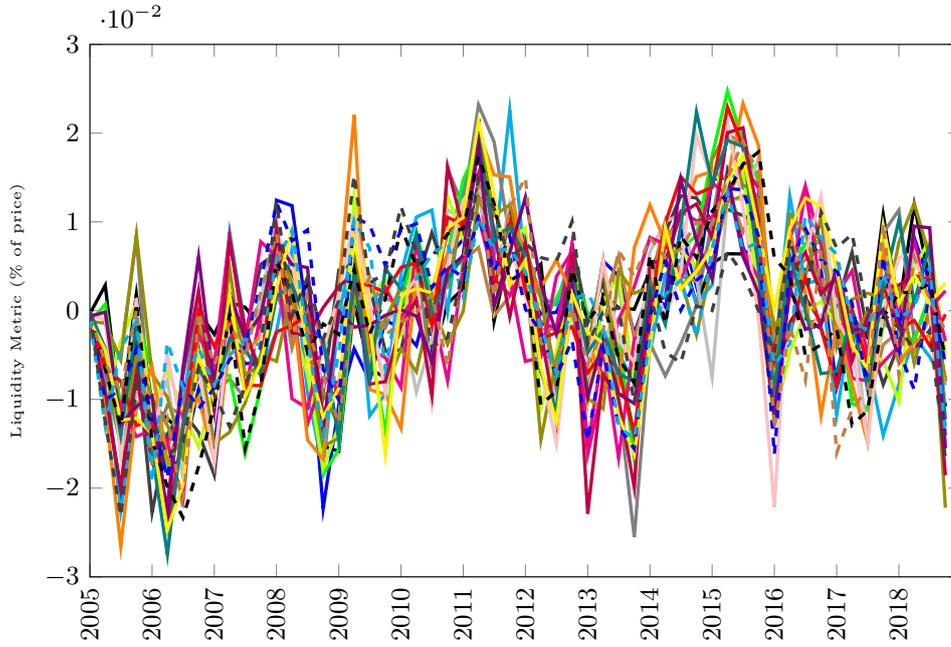


Figure A.15: Log price indices for 25 simulated markets.

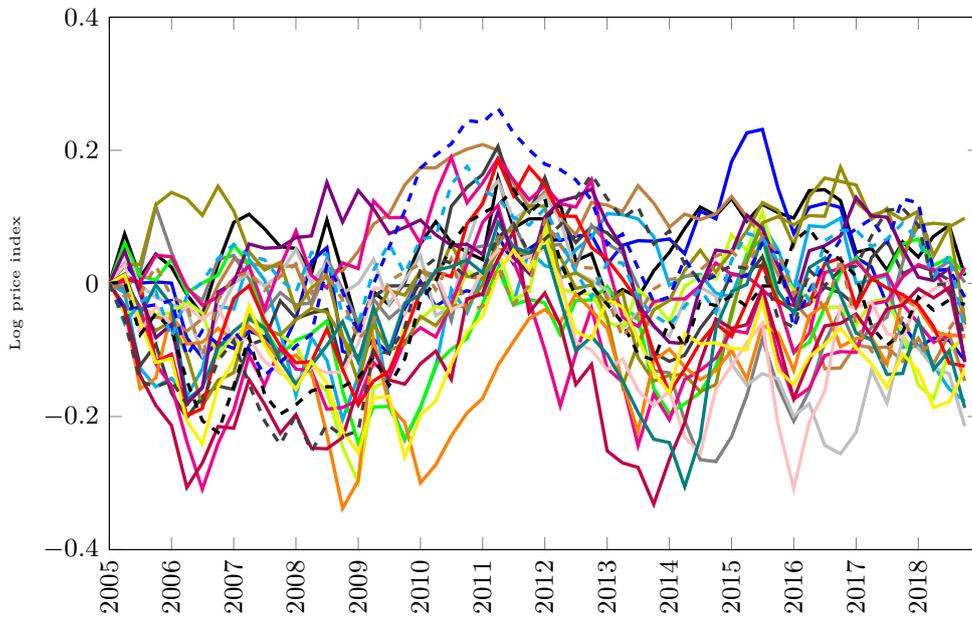


Table A.3: Summary statistics of MSA-specific changes in log net operating income (noi) and changes in risk premia (RSP).

<i>United States All Commercial</i>				
Market	Δ_{noi} (%)	StdDev	ΔRSP (BPS)	StdDev
Atlanta	0.36	1.05	0.15	34.15
Austin	1.34	1.45	-0.79	33.82
Baltimore	0.35	1.16	-0.22	35.45
Boston	1.24	1.55	-0.72	33.81
Charlotte	1.20	1.98	1.53	41.22
Chicago	0.21	1.05	0.02	34.15
Dallas	0.39	1.12	-0.89	35.44
Washington DC	0.34	0.80	-0.64	33.29
Denver	0.92	1.34	-0.94	33.98
Detroit	NA	NA	0.89	44.47
Houston	0.60	1.53	-0.29	35.79
Los Angeles	0.52	0.99	-1.27	32.67
Las Vegas	0.30	2.90	-0.27	38.45
Miami	0.51	1.22	-0.66	34.61
Minneapolis	0.83	1.18	-0.54	32.39
New York City	0.46	1.19	-1.24	34.43
Orlando	0.90	1.95	0.00	31.62
Philadelphia	0.41	1.66	-0.35	34.30
Phoenix	0.26	1.44	-0.40	34.64
Portland	0.62	1.14	-1.09	33.51
Sacramento	0.45	1.94	0.71	34.22
San Diego	0.70	1.34	-0.12	32.13
Seattle	0.73	0.93	-0.94	33.35
San Francisco	1.12	1.07	-1.02	32.57
Tampa	0.58	1.60	0.19	34.82
<i>Global Gateway All Commercial</i>				
Market	Δ_{noi} (%)	StdDev	ΔRSP (BPS)	StdDev
Amsterdam	-0.02	9.04	9.08	40.39
Boston	0.30	20.04	-0.72	33.81
Chicago	-0.26	44.98	0.02	34.15
Washington DC	-1.09	59.20	-0.64	33.29
German A cities	0.49	16.52	5.57	33.97
Hong Kong	2.33	11.20	-3.49	42.66
Los Angeles	1.09	29.61	-1.27	32.67
London	-0.19	7.29	2.12	37.12
Melbourne	0.42	35.45	4.55	43.85
Nordic A cities	-0.28	22.70	6.61	42.58
New York City	0.30	15.02	-1.24	34.43
Paris	0.46	11.64	6.03	29.34
Seoul	-0.13	31.90	2.16	43.85
San Francisco	0.70	9.46	-1.02	32.57
Singapore	-1.33	15.01	-6.43	53.00

Sydney	0.99	26.11	4.06	45.54
Tokyo	-1.23	13.17	2.28	15.38
Toronto	-0.39	21.53	-0.66	36.89
<i>United States Subtypes</i>				
Market	Δ_{noi} (%)	StdDev	ΔRSP (BPS)	StdDev
Boston APT	0.91	1.37	-0.06	42.58
Chicago APT	1.57	1.30	0.66	34.52
Los Angeles APT	0.76	1.00	0.05	32.14
New York City APT	0.70	2.40	-0.37	36.41
San Francisco APT	1.42	1.29	0.25	34.08
Boston OFF	1.00	1.38	-0.65	42.53
Chicago OFF	0.38	1.82	0.41	47.66
Washington DC OFF	0.35	0.84	0.39	37.86
Los Angeles OFF	0.37	1.35	-1.11	36.77
New York City OFF	0.57	1.51	-0.08	37.43
San Francisco OFF	0.93	1.61	-2.18	36.01
Boston RET	0.33	1.92	0.28	36.32
Chicago RET	0.50	1.58	0.48	35.16
Washington DC RET	0.54	1.29	0.43	38.55
Los Angeles RET	0.67	1.31	-0.31	34.30
New York City RET	1.09	2.29	-0.93	34.00
San Francisco RET	0.67	2.23	-0.18	35.11

Δ_{noi} are the average quarterly differences in NOI/ft^2 in percentages, ΔRSP is the average quarterly change in risk premia (cap rate spreads) in basis-points, and Std-Dev denote the corresponding standard deviations. The Global Gateway percentage changes in NOI are based on imputed rents.