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The Effect of Lock-Ups on the Suggested Real Estate Portfolio Weight

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We test relative illiquidity, exemplified through a temporary lock-up, as a partial explanation for the gap between theoretical and empirical weights for real estate in a multi-asset portfolio. Since asset correlations are known to increase in bear markets, which reduce their diversification benefits, the ex-ante knowledge of a lock-up in an asset class that offers diversification benefits in bull markets (Hung et al., 2008) may reduce the optimal weight that an investor wishes to put in it ex-ante. By using dynamic multiperiod portfolio policies by Brandt and Santa-Clara (2006), and introducing a lock-up in line as per de Roon et al. (2009), we study the effects of a partial lock-up on the weight for REITs in a U.S. stock and bond portfolio. We find support for our prediction, in the form of lower weights for the illiquid asset once a lock-up is introduced.

Keywords

Asset Allocation; Illiquidity; Lock-Up; Multi-period Portfolio Optimization; REITs

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1. Introduction

Many assets are relatively illiquid, at least in the short run. The recent financial crisis has demonstrated how, for e.g., hedge and real estate funds can be forced to introduce lock-ups, or extend them, during severe market conditions. Venture capital is another example of a relatively illiquid asset. Institutional portfolios typically hold many types of such illiquid or temporarily locked-up assets. Whereas there are some theoretical studies on the effect of illiquidity on portfolio choice, see for e.g., Longstaff (2001), Schwartz and Tebaldi (2006), and Vath et al. (2007), there is a rather limited amount of studies on how the ex-ante knowledge of a potential illiquidity problem or a lock-up affects the weights of an illiquid asset and the other assets in portfolio optimization. Typically, studies on the effects of illiquidity on portfolio choice rely on adjusting the moments (return and/or variance) of the return distribution for the illiquid asset[1], such as in the analysis by Bond et al. (2006) on U.K. commercial real estate in a multi-asset portfolio.[2]

Our purpose is to contribute to the literature on optimal weights for real estate in multi-asset portfolios. Prior studies have often been unable to solve the contradiction (pointed out, for e.g., by Chun and Shilling (1998) and Geltner et al. (2007)) between high theoretical weights[3] for real estate in portfolio optimization studies, and low empirical weights observed in institutional asset portfolios. Bond et al. (2006), for e.g., despite their efforts to adjust for illiquidity, their report suggests weights of 20% for real estate, while the average empirical weight in U.K. pension fund portfolios in 2003 was 6%. Partially successful efforts to explain the discrepancy also include Chun et al. (2000), Craft (2001) and Brounen et al. (2010), who argue that the weight which should be allocated to real estate is much more in line with the actual institutional weight when an asset-liability framework is used rather than an asset only framework, and Kallberg et al. (1996), who consider the effects of real estate market imperfections, such as indivisible assets and no short sales. Recently, Cheng et al. (2011) argue that given real estate returns are not independent and identically distributed, the conventional way of applying the modern portfolio theory (MPT) to mixed-asset portfolio selection is questionable.

[1] See for e.g., Cao and Teiletche (2007) for ways to deal with estimation problems for illiquid assets.

[2] Exceptions are studies such as Ghysels and Pereira (2008), who directly model the relationship between illiquidity and the conditional distribution of returns for a sample of NYSE stocks, and González and Rubio (2011), who build in a reference for liquidity in the utility function, as well as impose constraints on illiquidity in a mean-variance portfolio optimization problem by using Spanish stocks. In the market microstructure literature, illiquidity is also analyzed through its effects on bid-ask spreads, as well as returns, as in Amihud and Mendelson (1986), who show that expected stock returns are an increasing function of illiquidity costs.

[3] Typically, optimization studies have reported weights between 15% to 30% for real estate in a multi-asset portfolio, see for e.g., Ennis and Burik (1991), Ziobrowski and Ziobrowski (1997), Hoesli et al. (2004) and Fisher et al. (2007).

We argue that if portfolio rebalancing for the real estate part of a portfolio is not possible in the short run due to its relative illiquidity, its relative weight (and the weight difference between the actual and its desired weight) in a multi-asset portfolio is likely to increase during a bear market (given that real estate falls less than the stocks in the portfolio). Furthermore, if, as reported by Hung et al. (2008), real estate assets such as real estate investment trusts (REITs) in a time-varying setting add value to a portfolio only in up markets (due to their lower correlation with other assets in such circumstances), to be partially locked-up in real estate during periods when it is less useful may hurt portfolio performance. Rational investors who are aware of a potential lock-up might anticipate its arrival, and invest less beforehand on such an asset, which may explain the empirically observed lower weight for real estate as compared to theoretical weights estimated under a perfect rebalancing assumption. Our tests utilize REITs as a test asset upon which we impose a simulated lock-up, thus allowing us to investigate effects on marginal portfolio demand. Since real estate assets in general are likely to have more restrictive rebalancing opportunities than REITs, our tests provide an estimate of the upper bound of the portfolio demand for real estate that is facing lock-up or illiquidity restrictions. We report evidence in line with this prediction: introducing a lock-up for REITs lowers the optimal weight for that asset class. These weight decreases can be expected to have a similar or higher magnitude for the broader class of real estate, which can account for the observed weight differences between actual observed institutional portfolios and portfolio optimization studies.

We use the multi-period optimization method by Brandt and Santa-Clara (2006), complemented with a simulated, imposed lock-up for the REIT test asset in line with de Roon et al. (2009) for hedge funds. Based on the results of, for e.g., Glascock et al. (2000) and Oikarinen et al. (2011), who present evidence for linkages between securitized and direct real estate[4], we use a U.S. monthly series for REITs as a liquid proxy for the relatively illiquid broader asset class of real estate.[5] Since REIT data are available from the early 1970s,

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[4] Also, Bond and Hwang (2003) show that direct and securitized real estate have a similar volatility process, while Pagliari et al. (2005) report that the return and volatility of REITs and direct real estate are undistinguishable from a statistical perspective once leverage and property mix are taken into account.

[5] The relative liquidity of REITs is much lower than that of stocks, which motivates our use of them as a proxy for a relatively illiquid asset compared to stocks and bonds. Brounen et al. (2009), for instance, calculate a liquidity ratio defined as the inverse of the illiquidity measure by Amihud (2002), and report dramatically lower values for REITs as compared to stocks. By using securitized real estate data, we also avoid many of the measurement problems associated with direct real estate. The reliability of the estimated correlation and volatility patterns for direct real estate have been questioned due to problems with data quality (appraisal smoothing and time aggregation which create artificial autocorrelation). Therefore, direct real estate data typically require rather ad hoc de-smoothing to ensure comparability with stock and bond return dynamics. Direct real estate data are also only available in quarterly

we produce empirical results by using one of the longest possible high-frequency time series available for real estate assets. We investigate the effect of a complete rebalancing lock-up (for 3 and 6 months) for a simulated illiquid asset in a portfolio that also includes stocks, bonds, and money market investments. We do this both in an unconditional as well as conditional setting, and with or without short sales constraints for the simulated illiquid asset. Finally, we contribute by testing multi-asset strategies for a data set that includes at least part of the recent financial crisis.

In our in-sample tests for the time period from 1972 to 2011, we find that the weight for the simulated illiquid asset (REITs) is in general lower than that in prior studies on real estate weights, and reduced to values around 13% (9%) once a 3-month (6-month) lock-up for REITs is introduced. These values come close to empirically observed values for real estate, particularly considering that a weight level of 9-13% may be regarded as an upper bound on real estate assets which are in fact, more illiquid than our simulated REITs with lock-ups. The results are rather similar in our unconditional and conditional tests. An analysis of the certainty equivalents for the unlocked versus locked strategies indicate an annualized lock-up cost of around 1% to 3% for the illiquid asset.

The structure of this paper is as follows. First, in Section 2, the methodologies used in our analyses are presented. In Section 3, we present the data. The results from different portfolio strategies are reported in Section 4, and final conclusions are given in Section 5.

2. Multi-Period Asset Allocation with Lock-Up

In this paper, we will use the methodology of Brandt and Santa-Clara (2006) complemented with a lock-up in line with that of de Roon et al. (2009) (in their case, applied to hedge funds) [6]. We will describe the approach in the following sub-sections.

2.1 The Unconditional Case

A dynamic trading strategy is called for if the first and second moments of asset returns exhibit predictability. If, due to illiquidity, one asset class is temporarily “locked-up” (i.e. the amount invested in it cannot be changed, at least not downwards), a dynamic trading strategy may also be called for, since

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frequency, thus posing practical problems for accurate portfolio parameter estimation due to the lack of data for adequately lengthy time periods.

[6] de Roon et al. (2009) study the effect of a lock-up for hedge funds in a portfolio. By using U.S. data from December 1989 to December 2007 for stocks, bonds, and hedge funds in both unconditional and conditional frameworks with the market dividend-price ratio as the state variable, they find that a three-month lock-up for hedge funds costs the investor 4.2% per annum. Investors compensate for the lock-up by making adjustments to their equity and bond holdings.

the lock-up can generate a systematic hedging demand, which affects the demand for other asset classes during subsequent time periods. However, computing optimal dynamic trading strategies has proven to be problematic, since closed-form solutions are seldom available. Different numerical solution methods such as the solving of partial differential equations, Monte-Carlo simulations, and discretizing state-space have been used in the literature, while practitioners still mainly rely on the static Markowitz approach.

Brandt and Santa-Clara (2006) have developed a novel approach for dynamic portfolio selection which is easy to implement, and allows the use of most of the refinements developed for the Markowitz model, such as portfolio constraints, shrinkage estimation, and the combination of prior beliefs with the information contained in historical return data (i.e. the estimation of dynamic trading strategies). Their method solves the portfolio problem in one step as the optimal choice (which maximizes the investor's utility) is determined among simple multi-period trading strategies. In a single-period setting with i.i.d. returns, their solution leads to the well-known Markowitz solution. With some return predictability, their approach is related to that of Ferson and Siegel (2001), who model conditional means and covariances as known functions of the state variables, and then derive optimal portfolio weights by maximizing a mean-variance utility function. The resulting portfolio weights can then be shown to be functions of the state variables. Brandt and Santa-Clara (2006) directly model the portfolio weights as functions of state variables instead, and find the coefficients that maximize the investor's utility.

The key idea in the methodology by Brandt and Santa-Clara (2006) is to consider all the paths through which, in a multi-period setting, an initial unit of money can "travel" through the investment period. Assume that there are two risky asset classes, A and B, and two time periods. By following the notation of Brandt and Santa-Clara (2006), the invested amount (one) plus the risk-free rate at time points t (at the beginning of the first period, ranging from t to t+1) and t+1 (at the beginning of the second period, ranging from t+1 to t+2) are denoted by R_t^f and R_{t+1}^f. Let r_{t+1}^A and r_{t+1}^B stand for the end-of-period excess returns when investing in asset classes A and B over the first time period (from t to t+1). Then, a two-period excess return $r^p_{t\to t+2}$ for a portfolio that invests in a risk-free rate, and asset class A (with some beginning-of-period weights w^A_t and w^A_{t+1} for investments in the risky Asset A) is

$$\begin{aligned} r^p_{t\to t+2} &= \left(R_t^f + w_t^A r_{t+1}^A\right)\left(R_{t+1}^f + w_{t+1}^A r_{t+2}^A\right) - R_t^f R_{t+1}^f \\ &= w_t^A\left(r_{t+1}^A R_{t+1}^f\right) + w_{t+1}^A\left(r_{t+2}^A R_t^f\right) + (w_t^A r_{t+1}^A)(w_{t+1}^A r_{t+2}^A) \\ &\approx w_t^A\left(r_{t+1}^A R_{t+1}^f\right) + w_{t+1}^A\left(r_{t+2}^A R_t^f\right) \end{aligned} \tag{1}$$

i.e. in the last step above, the cross-product of the two excess returns and the two weights is assumed to be approximately equal to zero as the excess returns are expected to be small over short time horizons. Brandt and Santa-

Clara (2006) argue that the magnitude of the cross-product (the compounding term) is typically of the order of 1/100th of a percent per year. They also study the impact of ignoring the compounding terms in a model for monthly excess stock and bond returns, with rebalancing frequencies from monthly to annual, and investment horizons that range from 1 to 20 years. They conclude that, consistent with their intuition, the compounding terms are relatively unimportant for short horizons.[7]

A generalization of Equation (1) for multiple risky assets is straightforward. For two risky assets, the two-period portfolio return will be

$$\begin{aligned} r^{p}_{t\to t+2} &\approx w^{A}_{t}\left(r^{A}_{t+1}R^{f}_{t+1}\right) + w^{B}_{t}\left(r^{B}_{t+1}R^{f}_{t+1}\right) + w^{A}_{t+1}\left(r^{A}_{t+2}R^{f}_{t}\right) + w^{B}_{t+1}\left(r^{B}_{t+2}R^{f}_{t}\right) \\ &\approx w^{\prime}_{t}\left(r^{\prime}_{t+1}R^{f}_{t+1}\right) + w^{\prime}_{t+1}\left(r^{\prime}_{t+2}R^{f}_{t}\right) \end{aligned} \qquad (2)$$

where w'_{t+1} and w'_{t+1} are weight vectors and r_{t+1}' and r_{t+2}' are return vectors. The portfolio problem boils down to solving for the risky asset weights which maximize the investor's utility function, i.e. to e.g. solve a two-period quadratic utility optimization problem of the following form for an investor:

$$\max E_t\left[r^{p}_{t\to t+2} - \frac{\gamma}{2}\left(r^{p}_{t\to t+2}\right)^{2}\right] \qquad (3)$$

where γ is a coefficient of relative risk aversion. Given a time series from t to T, the optimal weight matrix w'' for a two-period dynamic strategy is given by:

$$w'' = \frac{1}{\gamma}\left[\sum_{t=1}^{T-2} \mathrm{r}^{\mathrm{p}}_{\mathrm{t\to t+2}}{}' \, \mathrm{r}^{\mathrm{p}}_{\mathrm{t\to t+2}}\right]^{-1}\left[\sum_{t=1}^{T-2} \mathrm{r}^{\mathrm{p}}_{\mathrm{t\to t+2}}{}'\right] \qquad (4)$$

where the first set of elements of w'' represents the fraction of wealth invested in risky assets in the first period, and the second set of elements represents the fraction of wealth invested in risky assets in the second period.

Next, by following de Roon et al. (2009), assume that a portfolio includes one liquid and one illiquid asset, i.e. assume that Asset A is liquid whereas whatever amount is invested in Asset B in the first period remains fixed for the next period (a two-period lock-up). In that case, the two-period portfolio excess return takes the following form:

$$\begin{aligned} r^{p}_{t\to t+2} &= \left(R^{f}_{t} + w^{A}_{t}r^{A}_{t+1}\right)\left(R^{f}_{t+1} + w^{A}_{t+1}r^{A}_{t+2}\right) - R^{f}_{t}R^{f}_{t+1} + w^{B}_{t}r^{B}_{\mathrm{t\to t+2}} \\ &\approx w^{A}_{t}\left(R^{f}_{t+1}r^{A}_{t+1}\right) + w^{A}_{t+1}\left(R^{f}_{t}r^{A}_{t+2}\right) + w^{B}_{t}r^{B}_{\mathrm{t\to t+2}} \end{aligned} \qquad (5)$$

where $r^{B}_{t\to t+2}$ is the two-period return for the illiquid (locked-up) Asset B.

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[7] However, for horizons beyond five years, the quality of their approximation substantially deteriorates.

2.2 The Conditional Case

Conditional portfolio policies can be implemented in a straight-forward fashion by allowing portfolio weights to be determined (typically linearly) by observable state variables z_t. For liquid Asset A and illiquid Asset B, this implies that:

$$w_t^A = \beta_{A1} z_t \quad w_{t+1}^A = \beta_{A2} z_{t+1} \quad \text{and} \quad w_t^B = \beta_B z_t \tag{6}$$

Although z_t could be an S-dimensional vector of the state variables at time t, in this paper, we are using one state variable at a time due to data limitations. The two-period return for the conditional strategy with one liquid and one illiquid asset will then be:

$$r_{t\to t+2}^p \approx \beta_{A1} z_t\left(R_{t+1}^f r_{t+1}^A\right) + \beta_{A2} z_{t+1}\left(R_t^f r_{t+2}^A\right) + \beta_B z_t r_{\mathrm{t\to t+2}}^B \tag{7}$$

where the βs can be viewed as the unconditional weights in a portfolio problem with scaled returns (returns scaled by the state variable). The investment problem is then to find the set of parameters β that maximize a multi-period quadratic utility as in Equation (3). The unconditional weights that maximize the conditional expected utility at all dates should also maximize the unconditional expected utility.

The unconditional and conditional methods above can be generalized from the two-period asset allocation problem to an L-period problem with lock-up constraints for some risky assets. While a straightforward optimization can give negative unconditional weights, non-negativity constraints can easily be implemented in the unconditional case. Also, in the conditional case, negative weights can be ruled out by empirically restricting the size of parameter β to values which, together with in-sample values of the state variable, do not result in the investment of negative amounts in the underlying assets. Also, shrinkage estimation e.g. can be implemented. For more details that concern the methods, see Brandt and Santa-Clara (2006), and de Roon et al. (2009).

2.3 Application Details

In the first part of this paper, we estimate optimal portfolio weights in the unconditional case, by using real estate as the asset with a lock-up, and stocks and bonds as the two other asset classes (in excess of the risk-free rate). As robustness tests, we later discuss results from conditional analyses where we, in line with de Roon et al. (2009), only use one state variable at a time out of the following set: the dividend yield, default spread, and term premium.[8] Our basic return interval is the monthly one, and the multi-period asset allocation problem is that of 3 or 6 periods, i.e. 3 or 6 months.[9] In line with de Roon et

[8] de Roon et al. (2009) also test the short-term interest rate as a state variable.

[9] The three-month interval seems to be the most reasonable proxy for the actual lock-up often present in real estate funds. The choice of the length of the horizon for the

al. (2009), we minimize the effect of the starting point by estimating three different sets of strategies, each starting one month later than the prior one. We report average statistics for these strategies. In strategies with a lock-up, real estate is assumed to have a 3-period (6-period) (simulated) lock-up, while investments in stocks and bonds can freely be rebalanced in the beginning of each month.[10] Both unconstrained as well as short sales constrained strategies will be estimated for an investor who has quadratic utility as in Brandt and Santa-Clara (2006). More specifically, we estimate (in unconditional and conditional frameworks, with or without short sales constraints), the Brandt and Santa-Clara (2006) model with $\gamma = 5$, with initial weights scaled to sum up to 1 (i.e. the tangency portfolio). We use excess returns in estimations, so during sub-periods other than the initial one in a multi-period strategy, the unscaled weights do not need to sum up to one, meaning that the remaining portion is borrowed/lent in the risk-free rate. In the table, we report relative weights for the three risky assets.

The set of resulting monthly returns from different portfolio strategies will be analyzed by using Sharpe ratios, the certainty equivalent, and, naturally, we will focus on the resulting weights for the real estate assets as compared to a setting without a lock-up for them. The significance between the Sharpe ratios for a strategy without a lock-up and its locked-up pair will be compared, and significance tested in line with a serial correlation that preserves the bootstrap method by Ledoit and Wolf (2008).

3. Data

Our data set consists of stocks, bonds, and REIT data for the U.S. from January 1972 to December 2011. For stocks, we use the value-weighted CRSP index. For bonds, we use the Fama Bond Portfolio (Treasuries), with maturities greater than 10 years, also obtainable from the CRSP. The returns for real estate are computed from the FTSE NAREIT U.S. Real Estate Index (All REITs). The 1-month Treasury bill is used as a proxy for the risk-free rate. As instruments in the conditional analyses, we use the term spread (10 year federal government bond yield, downloaded from www.federalreserve.gov, in excess of the 3 month T-Bill rate), the dividend yield (measured as the 1-month return difference between the returns on the CRSP value-weighted index in its total return and price index forms), and the

asset allocation problem is also related to data availability. Our sample of 40 years of data (1972-2011) at a monthly frequency allows us to perform an analysis for 3- and 6-month investment/lockup horizons with good accuracy.

[10] The imposing of a lock-up on real estate means its weight cannot be changed by the investor during the lock-up. However, changing market prices cause some month-to-month variation in real estate portfolio weights. This return impact is fully taken into account in optimizations (it might decrease or increase the need for weight updates for the upcoming month in case a lock-up has ceased), although in the tables we report average real estate weights before the monthly return impact.

default spread (the difference between Moody's yield on seasoned corporate all-industries AAA- and BAA-rated bonds, also from www.federalreserve.gov).

Descriptive statistics for our data are reported in Table 1, and a correlation matrix of the state variables and asset returns is reported in Table 2. Table 1 shows that during our time period, REITs have offered higher returns and risks only during the sub-period 1972 to 1981. During 1992 to 2001, in turn, the assets have offered returns more in line with what is typically expected, with stock returns being highest both in terms of risk and return (a return of roughly 1% per month, and a monthly volatility of 4.2%), REITs that offer a return of 0.9% and a volatility of 3.4%, and bonds a return of 0.7% and a volatility of 2.2%. Table 2 shows that the correlations between stocks, bonds, and REITs have been rather low, with the Stock-REIT correlation being the highest (0.6332), but also that the alternative instruments used in our conditional analyses have rather low simultaneous correlations with the assets.

4. Results from Different Portfolio Strategies

The strategies are executed by using the asset classes of stocks, bonds, and REITs (and the money-market as the residual asset). Figures 1a and 1b illustrate the three asset class weights over 3-month horizons with REIT investments treated both as free and locked. Figure 1a displays interesting time-varying relative hedging characteristics of the assets. REITs are shorted in month two with simultaneous large long positions in stocks and bonds. This pattern is reversed for month three. Given the large monthly turnover, Figure 1b shows asset weights with short sales constraints. Monthly varying borrowing and lending at a risk-free rate is still allowed as optimal for a relative risk aversion equal to 5.

Table 3 reports the results for the unconditional strategies with and without a simulated lock-up, and with and without short-sales constraints for real estate, both for 3 and 6 month periods. In the 3-month case, which allows for short sales, the REIT weight is on average 9.64%. The high weight turnover for REITs evident in Figure 1a reflects the high degree of correlation with those assets substituting for each other over time. Imposing a short sales constraint on REITs, in the rightmost two columns of Table 3, attenuates such hedging ability. Asset weight turnovers are also much lower. The disallowing of short selling of real estate yields an average weight well in line with the previous literature of 0.288 (28.8%). However, when a 3-month lockup is imposed on the real estate asset, the average allocation drops to 0.1297 (12.97%). The resulting weight of 13% is smaller than typically obtained in portfolio optimization models for real estate in a multi-asset portfolio, and closer to the empirical weight for real estate in institutional portfolios.

Table 1 Descriptive Statistics

This table reports the descriptive statistics for our raw data. Panel A reports, for the whole time period of January 1972 to December 2011, the means, medians, standard deviations, and skewness and kurtosis values for monthly arithmetic returns for STOCKS (the CRSP value-weighted index), BONDS (the CRSP Fama Bond Portfolio with maturities greater than 10 years), and REITs (the FTSE NAREIT US All-REIT index), together with T-BILL, the 3-month T-Bill rate. We also report corresponding values for our instruments: the default spread DEFSPR (the difference between Moody's yield on seasoned corporate all-industries AAA- and BAA-rated bonds), the dividend yield DIVYIELD (the 1-month return difference between the logarithmic returns on the CRSP value-weighted index in its total return and price index forms), the term spread TERMSPR (the difference between the 10 year federal government bond yield and the 3-month T-Bill rate), and 3M_T_BILL, (the 3 month T-Bill yield). Skewness and kurtosis values significant at the 5% level (2-sided tests) are denoted by boldface. In Panels B to E, we report the means and standard deviations for four sub-periods: 1972 to 1981 (120 obs), 1982 to 1991 (120 obs.), 1992 to 2001 (120 obs.), and 2002 to 2011 (118 obs.).

Panel A. 1972-2011								
	STOCKS	BONDS	REITs	T-BILL	DIVYIELD	TERMSPR	DEFSPR	3M_T-BILL
Mean	0.0089	0.0075	0.0089	0.0044	0.0279	1.7146	1.1108	5.4100
Median	0.0126	0.0073	0.0111	0.0043	0.0265	1.9100	0.9600	5.1450
Stdev	0.0467	0.0290	0.0522	0.0026	0.0110	1.3305	0.4740	3.2258
Skewness	-0.5452	0.4503	-0.3973	0.5929	0.3194	-0.5777	1.6978	0.5970
Kurtosis	2.0476	2.3069	7.3191	0.7152	-0.9531	-0.2338	3.4668	0.7059
Panel B. 1972-1981								
Mean	0.0070	0.0030	0.0077	0.0063	0.0386	0.9103	1.2043	7.7099
Median	0.0052	0.0007	0.0093	0.0054	0.0400	1.3450	1.0200	6.8700
Stdev	0.0486	0.0298	0.0608	0.0027	0.0074	1.5128	0.4517	3.2525

(Continued…)

(Table 1 Continued)

Panel C. 1982-1991								
	STOCKS	BONDS	REITs	T-BILL	DIVYIELD	TERMSPR	DEFSPR	3M_T-BILL
Mean	0.0137	0.0127	0.0086	0.0062	0.0356	2.1348	1.3451	7.6193
Median	0.0156	0.0116	0.0061	0.0061	0.0350	2.3050	1.2150	7.6350
Stdev	0.0479	0.0317	0.0332	0.0016	0.0063	0.9739	0.4298	1.8312
Panel D. 1992-2001								
Mean	0.0104	0.0069	0.0093	0.0037	0.0184	1.6398	0.7201	4.5051
Median	0.0149	0.0068	0.0108	0.0039	0.0180	1.4100	0.6900	4.9050
Stdev	0.0421	0.0216	0.0342	0.0009	0.0055	1.1397	0.1131	0.9861
Panel E. 2002-2011								
Mean	0.0104	0.0069	0.0093	0.0037	0.0184	1.6398	0.7201	4.5051
Median	0.0149	0.0068	0.0108	0.0039	0.0180	1.4100	0.6900	4.9050
Stdev	0.0421	0.0216	0.0342	0.0009	0.0055	1.1397	0.1131	0.9861

Table 2 Correlation Matrix of Asset Returns and Instruments

This table reports the correlation coefficients between our assets (total returns) and instruments by using data for the whole time period from January 1972 to December 2011. The assets are: returns for STOCKS (the CRSP value-weighted index), BONDS (the CRSP Fama Bond Portfolio with maturities greater than 10 years), and REITs (the FTSE NAREIT US All-REIT index), together with T-BILL, the 3-month T-Bill rate. The instruments are: the default spread DEFSPR (the difference between Moody's yield on seasoned corporate all-industries AAA- and BAA-rated bonds), the dividend yield DIVYIELD (the 1-month return difference between the logarithmic returns on the CRSP value-weighted index in its total return and price index forms), the term spread TERMSPR (the difference between the 10 year Federal government bond yield and the 3-month T-Bill rate), and 3M_T_BILL (the 3 month T-Bill yield).

	STOCKS	BONDS	REITs	T-BILL	DIVYIELD	TERMSPR	DEFSPR	3M_T-BILL
STOCKS	1.0000							
BONDS	0.1107	1.0000						
REITs	0.6332	0.1198	1.0000					
T-BILL	-0.0066	0.0430	-0.0360	1.0000				
DEFSPR	0.0963	0.0565	0.0532	0.6623	1.0000			
DIVYIELD	0.0460	0.1113	0.1004	-0.5474	-0.0746	1.0000		
TERMSPR	0.0728	0.0338	0.0797	0.2067	0.5074	0.1695	1.0000	
3M T-BILL	0.0139	0.0390	-0.0217	0.9864	0.6883	-0.5359	0.2360	1.0000

Table 3 Performance of Unconditional In-Sample Portfolio Strategies

This table reports the statistics that concern the performance and characteristics of estimated multi-period (3-and 6 months) unconditional and in-sample portfolio strategies for data for the time period of January 1970 to December 2011. Our assets are stocks (the CRSP value-weighted index), bonds (the CRSP Fama Bond Portfolio with maturities greater than 10 years, and the FTSE NAREIT US All-REIT index together with the 3-month T-Bill rate. The statistics reported are the mean excess return and the standard deviation, the Sharpe ratio, and the certainty equivalent (CEV), followed by average relative weights and weight turnover measures for the risky assets (stocks, bonds, and real estate). The weight turnover statistics are calculated as the mean absolute value of weight changes implied by the strategy between specific sub-quarter periods. Significance testing of Sharpe ratios (*, **, *** denote 10, 5 or 1% significance levels) between strategies without a lock-up, and their locked-up versions, uses serial correlation that preserve the bootstrap method by Ledoit and Wolf (2008) with B=1,000 bootstrap re-samples, and expected block size b=5.

Panel A. Period of 3 months	No constraint for short sales		RE short-sales constrained	
	No lock-up	Lock-up for REITs	No lock-up	Lock-up for REITs
Mean excess return	0.007	0.004	0.0053	0.004
St. deviation	0.0387	0.0353	0.0377	0.0353
Sharpe ratio	0.6272**	0.3885	0.4826	0.3885
Certainty equivalent	0.0924	0.0636	0.0739	0.0636
Average bond weight	0.6214	0.6685	0.6006	0.6685
(weigh turnover)	0.4855	0.5678	0.4461	0.5678
Average stock weight	0.2822	0.2018	0.1114	0.2018
(weigh turnover)	0.5176	0.4131	0.4996	0.4131
Average REIT weight	0.0964	0.1297	0.2881	0.1297
(weigh turnover)	0.9475	0.0187	0.3708	0.0187

Panel B. Period of 6 months	No constraint for short sales		RE short-sales constrained	
	No lock-up	Lock-up for REITs	No lock-up	Lock-up for REITs
Mean excess return	0.0102	0.0072	0.0095	0.0072
Standard deviation	0.034	0.0348	0.0342	0.0348
Sharpe ratio	1.0360***	0.7177	0.9616***	0.7177
Certainty equivalent	0.14	0.1033	0.1316	0.1033
Average bond weight	0.5073	0.5467	0.5031	0.5467
(weigh turnover)	0.6252	0.9226	0.8252	0.9226
Average stock weight	0.2441	0.2097	0.1536	0.2097
(weigh turnover)	0.8685	0.5233	1.2304	0.5233
Average REIT weight	0.2487	0.2436	0.3433	0.2436
(weigh turnover)	1.0831	0.3388	0.9399	0.3388

Figure 1a Monthly Asset Weights for Unlocked and Locked REITs Estimated over January 1972-December 2011

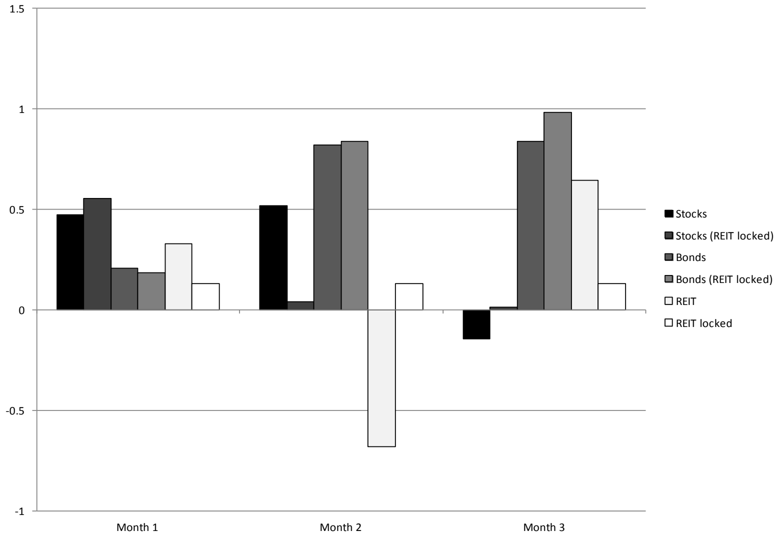
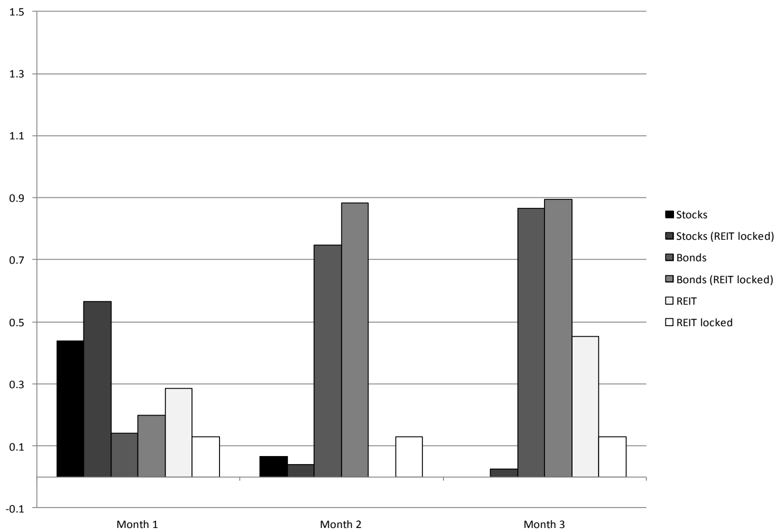


Figure 1b Monthly Asset Weights for Unlocked and Locked REITs, All Asset Weights Short Sales Constrained Estimated over January 1972-December 2011



Illiquidity in the form of a 3-month lockup for real-estate hurts performance. The drop in the Sharpe ratio (from 0.6272 to 0.3885) between unlocked and locked real estate is statistically significant in the case without short sales. In terms of the certainty equivalents, the economic cost is about 1% (0.0739-0.0636) in the (real estate asset) short sales constrained case and 2.9% (0.0924-0.0636) in the unrestricted case.

By using 6-month returns, the pattern is similar as that for 3-month returns, but the scale is different. When optimizing over periods of 6 months, even when allowing short sales, the weight for REITs is now always above 20%. When constrained, the weight for REITs falls from close to 34% in the no lock-up case, to 24.4% with a 6-month lock-up for REITs.

We also perform conditional in-sample strategies by using three alternative instruments; the dividend yield, term spread, and default spread. In these time-varying estimations, weights were estimated, but it turned out that our instruments had generally weak forecasting power during the sample period. The portfolio strategy results are therefore qualitatively very similar to the unconditional results and thus not reported here but are available upon request from the authors.

In order to rule out the possibility that the locked real estate weight is not merely caused by unrealistically large negative positions in stocks and bonds with high turnover, Table 4 reports the results for optimal strategies when all assets face a short sales constraint. Not surprisingly, the asset turnovers are now much lower, especially for the 6-month case reported in Table 4b. Interestingly, performance is not much affected compared to Table 3, where short sales of stocks and bonds were allowed. In the 3-month case, there is a very slight (statistically insignificant) increase in performance going from unlocked to locked real estate, which is due to monthly variation in the allocation to the residual risk free asset being also affected by the imposing of the lock up on the real estate asset. The average real estate weight drops from 24.59% to 13.04%, again displaying levels more closely observed in typical actual real estate holdings of large institutional investors. Now, a corresponding drop (0.2385 to 0.0882) is also observed in the 6-month case (Panel B of Table 4).

We conjecture that time-varying (bull vs. bear market) correlations especially between the returns on stocks and real estate may be picked up by our multi-period optimization procedure. Table 5 shows that correlations between stocks and real estate appear to rise when the market is going into a cyclical trough (as defined by the National Bureau of Economic Affairs). In three periods of downturns, the correlation increases are statistically significant.[11] The harm from being forced to stay in real estate (due to a lock-up) when the relative diversification benefits from real estate assets are lower (due to higher correlations with stocks) may be reflected in the lower weight for real estate in the lock-up case.

[11] On the other hand, bonds do not display a correlation pattern with real estate that would be significantly different in good and bad times.

Table 4 Performance of Unconditional In-Sample Portfolio Strategies without Short Sales

This table reports the statistics that concern the performance and characteristics of estimated multi-period (3 and 6 months) unconditional and in-sample portfolio strategies for data for the time period of January 1970 to December 2011 constraining short sales to be non-negative for all assets in all months. Our assets are stocks (the CRSP value-weighted index), bonds (the CRSP Fama Bond Portfolio with maturities greater than 10 years, and the FTSE NAREIT US All-REIT index together with the 3-month T-Bill rate. The statistics reported are the mean excess return and the standard deviation, Sharpe ratio, and certainty equivalent (CEV), followed by average relative weights and weight turnover measures for the risky assets (stocks, bonds, and real estate). The weight turnover statistics are calculated as the mean absolute value of weight changes implied by the strategy between specific sub-quarter periods. Significance testing of Sharpe ratios (*, **, *** denote 10, 5 or 1% significance levels) between strategies without a lock-up, and their locked-up versions, uses serial correlation that preserve the bootstrap method by Ledoit and Wolf (2008) with B=1,000 bootstrap re-samples, and expected block size b=5.

Panel A. Period of 3 months	All assets short-sales constrained	
	No lock-up	Lock-up for REITs
Mean excess return	0.0048	0.0041
St. deviation	0.0375	0.0344
Sharpe ratio	0.4433	0.4151
Certainty equivalent	0.069	0.0674
Average bond weight	0.5854	0.659
(weigh turnover)	0.4233	0.5172
Average stock weight	0.1687	0.2105
(weigh turnover)	0.3386	0.4013
Average REIT weight	0.2459	0.1304
(weigh turnover)	0.5854	0.659
Panel B. Period of 6 months	All assets short-sales constrained	
	No lock-up	Lock-up for REITs
Mean excess return	0.0081	0.0063
St. deviation	0.0359	0.0314
Sharpe ratio	0.7779**	0.6914**
Certainty equivalent	0.1111	0.0987
Average bond weight	0.4212	0.4988
(weigh turnover)	0.4539	0.4051
Average stock weight	0.3404	0.413
(weigh turnover)	0.2502	0.2572
Average REIT weight	0.2385	0.0882
(weigh turnover)	0.4212	0.4988

Table 5 Asset Correlations and the Economic Cycles, 1972-2011

Correlation coefficients between the returns of stocks (bonds) and REITS are compared between periods which lead into a cyclical trough according to the NBER and the subsequent period of trough. The joint significance of Fisher transformed pairwise correlation tests (z-score), which test the null hypothesis in that at least some of the cyclical downturns have increased the correlation between stocks (bonds) and REITs, is tested with the Bonferroni method with a significance level of 0.05/6 (comparisons) = 0.0083.

	Correlation of Stocks and REITs				**Correlation of Bonds and REITs**			
	Before trough	During trough	z-score	Prob.	Before trough	During trough	z-score	Prob.
1972-1975	0.814	0.676	0.886	0.812	-0.018	0.321	-0.983	0.163
1976-1981	0.718	0.989	-2.892	0.002	0.486	0.359	0.261	0.603
1982-1983	0.017	0.909	-3.471	0.000	-0.312	0.830	-3.483	0.000
1984-1992	0.668	0.871	-1.150	0.125	0.247	0.374	-0.307	0.380
1992-2001	0.321	0.414	-0.236	0.407	0.204	-0.617	2.031	0.979
2002-2009	0.492	0.845	-2.528	0.006	0.012	-0.017	0.105	0.542
Joint significance				Yes				No

5. Summary and Conclusions

Assets with low liquidity may harm portfolios by preventing optimal weight changes. They may also cause a substitution, or hedging, demand in the other assets. Portfolio optimization models which take such effects into consideration by other means than imposing liquidity costs on the moments of the return distribution have only recently been proposed. We contribute to the empirical study of such models by investigating the in-sample performance of a multi-period optimization method by Brandt and Santa-Clara (2006), utilizing a simulated lock-up on a relatively liquid real estate asset, REITs, in line with de Roon et al. (2009), in order to isolate marginal portfolio demand effects of lock-ups and other portfolio rebalancing related frictions, such as short sales constraints.

Our real estate test asset is based on the NAREIT all REIT series which is available from the early 1970s, giving us one of the longest high-frequency time series available for the real estate asset class. Through this, we also contribute to the literature on the optimal weight for real estate in a multi-asset portfolio. Prior studies have been typically unable to solve the contradiction between high theoretical weight for real estate in portfolio optimization studies, and low empirical weight observed in institutional asset portfolios.

In our in-sample tests for a full time period from 1972 to 2011, we find that the weight for the simulated illiquid real estate asset (REITs) is, in the short-sales constrained, locked-up case, much lower than the weight without a lock-up. For 3-month returns, a reasonable proxy for a typical lock-up period for a real estate fund, the weight is about 13% once a lock-up for REITs is introduced. This value comes close to the observed values for real estate in institutional portfolios. Given that real estate assets in general are likely to face more stringent illiquidity and lock-up constraints that hinder portfolio rebalancing, we regard a portfolio weight of 13% as the upper bound. In line with this interpretation, somewhat lower weights also result if more severe short sales restrictions constrain investors.

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