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The Predictability of Real Estate Excess Returns: An Out-of-Sample Economic Value Analysis

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The Predictability of Real Estate Excess Returns: An Out-of-Sample Economic Value Analysis[♣]

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Abstract

We study the recursive, out-of-sample realized predictive performance of a rich set of predictor choices and models, spanning linear and Markov switching frameworks when the forecast target is represented by excess NCREIF and equity NAREIT returns. We find considerable pockets of predictive power, especially at the short- and intermediate horizons and for private real estate returns, both in absolute term and in comparison to a simple, but powerful, historical sample mean benchmark. We then test whether such forecasting accuracy may translate to positive, risk-adjusted out-of-sample performance in a recursive mean-variance portfolio allocation exercise, selecting weights of stocks, bonds, cash, and real estate (private or public). Consistently, we find that especially in the case of private real estate, significant improvements in realized Sharpe ratios and mean-variance utility scores are achieved from a range of strategies, exploiting predictability at intermediate horizons, especially when supported by Markov switching models. These results are robust the inclusion of transaction costs and extend to public real estate.

Key words: Public real estate, REITs, private real estate, predictability, mean-variance portfolios.

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1. INTRODUCTION

Asset return predictability and more importantly the ability to use such predictability to allow investors to better exploit investment opportunities, thus generating positive risk-adjusted profits (henceforth, *economic value*) is a topic as old as finance itself (see, e.g., for review Malkiel, 2003 and Pesaran, 2010). The interest in these questions is justified by the enormous practical (in asset and risk management) and intellectual (for asset pricing and as a reflection of the impact of preferences and technology on market efficiency) implications of the very existence of predictability.[1] Similarly, because of its unique features, i.e., asset heterogeneity, lower liquidity, higher transaction costs, and generally strong connections with business and policy cycles (Ling and Naranjo, 1999; Wong et al., 2012), real estate, as an asset class, has also been the focus to an extensive literature that has investigated the extent and exploitability of forecastable time variation in real estate investment opportunities (see, e.g., Chun et al., 2004; Fugazza et al., 2007, 2009; Karolyi and Sanders, 1998; Liu and Mei, 1992, 1994; MacKinnon and Al Zaman, 2009; Nelling and Gyourko, 1998; Rerhing, 2012; and Serrano and Hoesli, 2010).

While the research on predictability in real estate is certainly extensive (see for survey Ghysels et al., 2013), less is known about the economic value of predictability when assessed within the context of a realistic asset menu including stocks and bonds, besides real estate investments, under plausible estimates of transaction costs, and in comparison to the standard benchmarks used in the empirical finance literature.

The objectives of our research are threefold. First, we investigate the strength and exploitability of predictability in privately held and public (i.e., traded through real estate investment trust (REIT) vehicles) real estate, using a framework for both, which is as homogeneous as possible in terms of length of the back-testing exercise, methodologies, and data. Second, predictability is assessed using univariate and multivariate, both single-state linear and multi-state, regime switching regression models that exploit the information in a relatively wide range of forecast instruments. Resorting to both linear and non-linear predictive frameworks, especially of the

[1] Two explanations exist for the existence of predictability in asset returns. First, predictability may result from business cycle movements and changes in investors' perceptions of risk that are reflected in time-varying risk premia. Second, predictability may reflect an inefficient market populated with overreacting and irrational investors. Ling et al. (2000) contain references to this debate. In our paper, we take the existence of both linear and nonlinear predictability patterns as an empirical fact and investigate whether such patterns may produce economic value in back-testing exercises.

Markov regime switching type, appears to be important in the light of the recent literature on the presence and portfolio implications of non-linear dynamics in real estate returns (see, e.g., Case et al., 2014; Guirguis et al., 2005; Ling and Naranjio, 1997; Okunev et al., 2000). Furthermore, in the spirit of Ling et al. (2000) and Ling and Naranjo (2015), we resort to prediction variables that have either a potentially relevant, sectoral information content (such as the earnings-price ratio, the growth rate of capital expenditures, the growth rate of the income from the properties covered by the NCREIF index, the dividend yield of the FTSE NAREIT Index, the price-to-book value ratio, and the price-to-funds-from-operations ratio) or a well-established asset pricing or business cycle forecast power (e.g., interest rates, the growth rate of the private consumption expenditures for nondurable goods, Michigan's index of Consumer Sentiment, the equity market portfolio return, and the returns of momentum portfolios in real estate). Third, we conduct a recursive, back-testing analysis of the portfolio performance of alternative predictors and statistical models (linear vs. non-linear) with reference to the standard benchmark in the empirical finance literature, i.e., a naïve, rolling historical sample mean predictor for excess returns, which has been found to be hard to out-perform by simple predictive regression frameworks (see, e.g., Campbell and Thompson, 2008; Goyal and Welch, 2008).[2]

We report three important empirical findings that are largely novel within a unified framework of recursive estimation, forecast back-testing, and portfolio value assessment. First, we find evidence of statistically significant predictive accuracy of a variety of Markov switching (MS) predictive regressions at intermediate horizons (6 months) for both private (as proxied by the NCREIF index) and public real estate (as proxied by the equity FTSE NAIRET index) excess returns. The predictive power of the MS models extends across different predictors and their combination and holds in comparison to both linear models as well as the historical sample mean. Therefore, it is measured and tested both in terms of the observed reduction in the root mean squared forecast error (henceforth, *RMSFE*) and in term of out-of-sample (henceforth, OOS) R-square (henceforth, R^2_{OOS}). Moreover, and this is the only key difference between private and public real estate, the results extend to the short-term, one-quarter ahead horizon in the case

[2] This represents a key step to prevent us from concluding that predictability or economic value exist in Markov switching models only in comparison to simple predictive regressions that are however well-known to carry limited forecasting power and risk-adjusted value in standard portfolio exercises.

of NCREIF excess returns and to long-term, 60-month ahead horizon in the case of equity REIT data. Interestingly, while richly specified predictive regressions, including all predictors, have been reported to yield poor forecasting performance (see, e.g., Goyal and Welch, 2008), under regime switching this does not appear to be the case. In fact, there is no clear sub-set or a single predictor that emerges as conducive to particularly accurate forecasts from the analysis, as often the MS predictive model including all instruments leads to the lowest RMSFE or the highest R^2_{OOS}. Second, the resulting forecasts and optimal portfolio weights appear sensible. The allocations are average do not take extreme values and while in the models, characterized by an MS predictive structure, the volatility of the resulting optimal weights is increased, as expected, the increase is only moderate compared to a historical sample mean benchmark. Interestingly, we find that while in the case of private real estate, the MS models outperform in the 3 and 6-month horizons the sample mean and linear benchmarks as they tend to load *less* heavily on real estate, in the case of public real estate at H = 6 months, MS models lead to a strong realized performance because they load *more* on equity REITs. This implies that real estate in general carries a favorable differential in timing exploitability that investors may profit from through tactical changes in their optimal allocations. Such timing emerges fully from our analysis of the H-step ahead predicted coefficients, loading on the different forecast variables, that displays rich time variation, especially in correspondence to and surrounding the 2007-2010 Great Financial Crisis (henceforth GFC).

Third, statistical predictability leads to a large improvement in risk-adjusted portfolio performance in OOS back-testing exercises. This result emerges in three ways: higher realized mean portfolio returns, higher ex-post Sharpe ratios, and positive differentials in realized, OOS mean-variance utility, which may be also interpreted as the maximum up-front (hence, riskless) fee an investor would be ready to pay to access a strategy that exploits predictability in solving mean-variance problems. The finding of positive and large economic value is particularly strong in the case of private real estate, for intermediate investment horizons (H = 6, when also the statistical accuracy of most of our models is the highest), and for intermediate levels of risk aversion ($\gamma = 5$). Although weaker and limited to the case of H = 6 months, we also report risk-adjusted profits from exploiting predictability in the case of public real estate. The result is not limited to MS predictive regressions, although it tends to be stronger (especially in terms of utility gain) in such models, largely due to the MS regressions' flexibility to pick up regime shifts and unstable econometric relations. Furthermore, our results are not affected by imposing in our recursive back-testing exercises that a sequence of H-period investors pay realistically-sized transaction costs. Although such costs reduce the realized mean returns and Sharpe ratios, these decreases are not large enough to affect our baseline findings. On the other hand, because recursive implementation of a portfolio strategy, supported by sample mean forecasts for excess asset returns, implies non-negligible transaction costs, taking the latter into account often leads to increasing the reported utility gains. However, it must be emphasized that—probably because the predictive performances are weaker and in the case of quarterly NCREIF data supported by shorter time series—in the case of long-term investors with a H = 60 months horizon, we find no evidence of economic value or at best of modest value but in linear, single-state models.

Our forecasters selection draws from the work of Ling et al. (2000) who use a large set of both fundamentals-based and time-series variables to reach a specification of a linear predictive model that best forecasts the difference between REIT returns and the returns of either stock or small capitalization stocks and of T-bills, as in our paper. Even though they just entertain linear models, Ling et al. (2000) resort to stepwise regression methods, which represents an early form of machine learning regression forest algorithm, to select the best fitting combination of K explanatory variables (that is, out of a total of 2^K regressions) using a 60-month rolling window scheme. With reference to a variety of alternative asset menus, they report that, under typical transaction costs, active trading strategies that only allow switching among asset classes that include REITs are dominated by a REIT buy-and-hold strategy during a 1980-1996 sample on a risk-adjusted basis. Although the spirit of our efforts takes steps from Ling et al.'s (2000) research, in this paper we perform a comparison of public vs. private real estate predictability, using an expanding window back-testing strategy (that is consistent with MS models endogenously picking up regime shifts in the data). We further employ multiple investment horizons (see Pagliari, 2017) including a 60-month one, and resort to mean-variance portfolio strategies that consistently penalize risk both ex-ante when the allocation shares are selected, and ex post. Moreover, while Ling et al. entertain the existence of structural instability through recursive model re-selection and by picking the best set of predictors using stepwise algorithms, we explicitly resort to MS techniques in which the regime-dependent coefficients are time-varying and the lack of inclusion of a predictor (in Ling et al.) is simply captured by its estimated coefficient turning out to be very small. Partly because of these differences in methodologies, but also due to the significantly expanded times series, we report results on the economic value of predictability that are more encouraging than Ling et al.'s, even though such favorable evidence emerges mostly for private real estate.

Our research is also inspired by studies that have examined, often using non-linear modelling devices, whether there is evidence of time-variation within predictability relationships (see, e.g., Case et al., 2014; Crawford and Fratantoni 2003; Hung et al. 2008; Liow et al., 2011; and Sa-Aadu et al. 2010). There is indeed an increasing awareness in finance at large (see e.g., Henkel et al. 2011) that that most (if not all) asset classes may be best characterized as going through persistent bull vs. bear phases, in which their basic risk-return features would differ, as reflected by considerable instability of standard predictive relationships. In particular, Sa-Aadu et al. (2010) have examined the gains in portfolio performance when mean-variance investors diversify into different asset classes—including REITs—with particular focus on differential gains across good and bad market regimes. They find that real estate, commodities and precious metals are the asset classes that deliver the biggest gains when consumption growth is low and/or volatile, that is, when investors care the most for such benefits, such as during economic downturns. However, Sa-Aadu et al. (2010) compute the shifts in the Hansen-Jagannathan volatility bounds and measure the reduction in the standard deviation of minimum variance portfolios when an asset class is added to a base portfolio in a given regime. Moreover, their asset allocation exercise is performed on an in-sample basis. In contrast, we adopt an explicit OOS stance and focus on the realized, recursive performance gains, deriving from a variety of predictability models and predictors. Bianchi and Guidolin (2013) use multivariate, vector MS models with regimes to capture the presence of multiple statistical states in excess REIT returns, jointly with the common states in stocks and long-term government bonds. They compare such simple MS models with vector autoregressions that include predictors representing or forecasting business cycle conditions. With reference to a January 1972 - December 2009 sample, they report that linear models are not able to capture or approximate non-linear, bull-and-bear type Markov switching dynamics in asset returns, either in a statistical, or in an economic asset allocation perspective. However, because they attempt to identify common regimes across multiple asset classes, by construction their analysis cannot be geared towards estimating the economic value of predictability in real estate only. The analysis under regimes is never extended to the predictive relationships, as it would be extremely complex to estimate such large-scale, non-linear frameworks. Moreover, their analysis is confined to REITs, which although a key segment of the real estate class, fail to represent the bulk of commercial real estate market in the US and therefore cannot exhaust the role of this asset class in practical portfolio decisions.

The rest of this paper is structured as follows. Section 2 describes the distinctive methodology of our paper and provides details on the statistical models that we use, on the asset allocation strategy that we test to estimate economic value, and on the structure of the recursive, back-testing exercise that we perform. Section 3 describes the data. Section 4 reports the key empirical results concerning statistical predictability at various horizons. Section 5 investigates whether and under what conditions the evidence of statistical predictability may be translated into effective, positive risk-adjusted performance. Section 6 concludes.

2. METHODOLOGY

2.1. *Predictive Regression Models*

To forecast excess returns on private and public real estate, we adopt two alternative approaches. First, similarly to Goyal and Welch (2008), we use a set of standard linear predictive regressions of the type:

$$r_{t-H+1}^{H} = \alpha^{H} + \boldsymbol{\beta}^{H\prime}\boldsymbol{x}_{t-H} + \sigma^{H}\varepsilon_{t-H+1}^{H}, \tag{1}$$

where r_{t-H+1}^{H} is the cumulative H-period excess return between $t-H+1$ and t, $\boldsymbol{x}_{t-H}$ is a K x 1 vector that collects all the predictors at time t - H, $\varepsilon_{t-H+1}^{H} \sim D(0,1)$ is an IID standardized residual, σ^{H} is the error volatility, and H is the forecasting horizon. We set H to equal 3, 6, and 60 months in the case of private real estate (i.e., 1, 2 and 20 quarters), and 1, 6, and 60 months in the case of public real estate.[3] α^{H} and $\boldsymbol{\beta}^{H}$ are the regression coefficients estimated by OLS. As for $\boldsymbol{x}_t$, we use the available predictive variables (see Section 3), both, one at a time and altogether in a so-called "kitchen-sink" model (see, e.g., Goyal and Welch (2008) and Rapach et al. (2010) for a discussion of the poor performance of this framework, justifying its the derogatory description). Since we are interested in the out-of-sample predictive accuracy of the alternative models, we estimate the coefficients recursively, in an expanding-window fashion, to produce OOS forecasts of the

[3] The difference in the shortest periods considered for private vs. public real estate is due to private real estate data only being available on quarterly basis.

excess returns over a period spanning from January 2005 through December 2018.[4] More specifically, our forecast at time t for the excess return between time t and $t + H$ is given by:

$$\hat{r}^{H}_{t-H+1|t-H} = \hat{\alpha}^{H} + \hat{\boldsymbol{\beta}}^{H\prime}\boldsymbol{x}_{t-H}, \tag{2}$$

where $\hat{\alpha}^{H}$ and $\hat{\boldsymbol{\beta}}^{H\prime}$ are estimated using all the information available at time t.

Second, we consider the possibility that the predictive relationships may be non-linear and regime-dependent. Therefore, following Dal Pra et al. (2018), we estimate a set of Markov-switching (MS) regressions of the form:

$$r^{H}_{t-H+1} = \alpha^{H}_{S_t} + \boldsymbol{\beta}^{H\prime}\boldsymbol{x}_{t-H} + \sigma^{H}_{S_t}\varepsilon^{H}_{t-H+1}, \tag{3}$$

where S_t is an unobservable state variable that captures instabilities in the predictive relationship and the remaining terms are defined as in equation (1). S_t is governed by a discrete, first order, ergodic, irreducible, homogenous Markov process with a transition probability matrix $\mathbf{P}^{H}$, with elements

$$\Pr(S_t = i|S_t = j) = p_{i,j}, \tag{4}$$

where $p_{i,j}$ is the probability of switching from regime j to regime i. In our application we consider a number of regimes, K, equal to two.[5] As it is well known (see, e.g. Guidolin and Pedio, 2018), even relatively simple MS regressions may capture substantial non-normalities, which tend to be typical for real estate time series (see, e.g., Byrne and Lee, 1997; Neil Myer and Webb, 1993). In addition to the MS Intercept Heteroskedasticity (MSIH) model in (3), in which also $\sigma^{H}_{S_t}$ depends on the Markov regime, we also estimate a Markov-switching Intercept (MSI) model, where the

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[4] More specifically, for example, in the case of public real estate and H = 1, we exploit all the information available in December 2004 to forecast the excess return as of (the end of) January 2005; in the case of H = 6, we exploit the information available at the end of July 2004 to predict the cumulative, 6-month excess return over the period August 2004 – January 2005; in the case of H = 60, we use the information available in January 2000 to forecast the 60-month excess return over the period February 2000 – January 2005. A similar logic is applied to private real estate, but with quarterly frequency.

[5] At least in-sample, the fit of the model would benefit from setting K > 2. In this sense, our results may be interpreted as providing a lower bound to the actual empirical results, one could obtain. However, it is unclear whether increasing the number of regimes may improve the OOS predictive accuracy. To balance between empirical fit and estimation burden, especially in the case of private real estate, for which we have shorter available time series, we focus on the case of K = 2.

volatility of the shocks does not depend on the regimes (while the intercept and the regression coefficients do). Because the state variable is unobservable, we can only obtain an inference concerning S_t, based on the past realizations of the excess returns, r_t^H. The vector of model parameters $\boldsymbol{\theta}$ (i.e., $\alpha, \boldsymbol{\beta}, \boldsymbol{\sigma}, \mathbf{P}$ where the dependence on H has been dropped to save space) can be estimated in two steps through the expectation-maximization (EM) algorithm proposed by Dempster et al. (1977) and Hamilton (1989), a filter that allows the iterative calculation of the one-step-ahead forecasts of the state probabilities, $\hat{\boldsymbol{\xi}}_{t+1|t}$, given the information set Ω_t, which are in turn used to construct the log-likelihood function to be maximized.[6] In particular, in the first step of the algorithm, we assume the parameters in $\boldsymbol{\theta}$ to be known with certainty and we iteratively derive the time series sequences of filtered probabilities, $\{\hat{\xi}_{t|t}\}_{t=1}^{T}$, where

$$\hat{\boldsymbol{\xi}}_{t|t} = \Pr(\boldsymbol{\xi}_t|\Omega_t, \boldsymbol{\theta}) = \frac{\Pr\left(r_t^H|\boldsymbol{\xi}_t, \Omega_{t-1}\right)\Pr(\xi_t|\Omega_{t-1})}{\Pr\left(r_t|\ \Omega_{t-1}\right)} \tag{5}$$

is the real-time inference on the state probabilities conditional on the information set at time t, Ω_t, which can obtained through the application of the Bayes' law, exploiting the fact that the time t - 1 posterior $\Pr(\boldsymbol{\xi}_{t-1}|\Omega_{t-1}, \boldsymbol{\theta})$ can be used as the new prior $\Pr(\boldsymbol{\xi}_t|\Omega_{t-1}, \boldsymbol{\theta})$ at time t. From the vector of filtered probabilities, it is possible to derive the one-step-ahead predicted probabilities as:

$$\hat{\boldsymbol{\xi}}_{t+1|t} = \Pr(\boldsymbol{\xi}_{t+1}|\Omega_t, \boldsymbol{\theta}) = \mathbf{P}'\hat{\boldsymbol{\xi}}_{t|t}. \tag{6}$$

Since we are interested in the OOS predictive accuracy of our MS models, we recursively estimate the model parameters with all available information and at each iteration we obtain the H-step-ahead forecast.

2.2. *Asset Allocation Strategy*

In order to assess whether any economic value may be derived from the forecasts produced by our predictive models, we implement an asset allocation exercise similar to Campbell and Thompson (2008), Goyal and Welch (2008), and Rapach et al. (2010) where an investor maximizes a standard mean-variance (MV) utility function over terminal wealth,

[6] A detailed discussion of the estimation of MS regressions through the EM algorithm can be found in Guidolin and Pedio (2018).

$$\mathrm{U}(W_{\mathrm{t}+H}) = E_t[\mathrm{W}_{t+H}] - \frac{\gamma}{2} Var_t[W_{\mathrm{t}+H}] \tag{7}$$

with an investment horizon H and a risk aversion coefficient γ equal to either 2, 5 or 10. Her asset menu consists of a risk-free asset, proxied by the 3-month (1-month in the case of monthly data) Treasury bill, the 10-year Treasury bond, the S&P 500, and private (or public) real estate. Terminal wealth depends on realized asset returns and on the selected portfolio weights in standard, linear ways. This allows us to optimize an objective function that reflects total H-period portfolio returns. An investor determines the optimal weights to be assigned to the risky assets at time t according to the formula

$$\boldsymbol{\omega}^* = \frac{1}{\gamma}\frac{\hat{\boldsymbol{r}}^H_{t-H+1|t-H}}{\widehat{\boldsymbol{\Sigma}}_{t-H+1|t-H}}, \tag{8}$$

where $\hat{\boldsymbol{r}}^H_{t-H+1|t-H}$ is a 3 x 1 vector containing the forecasts of the cumulative excess returns of the risky assets over the period from $t+1$ to $t+H$ and $\widehat{\boldsymbol{\Sigma}}_{t-H+1!t-H}$ is an expanding-window historical estimate of the covariance matrix. The allocation to the risk-free asset is simply equal to $1-\boldsymbol{\omega}^*$.[7] While the forecasts of the real estate excess returns are obtained from the predictive regressions described in Section 2.1, the historical mean is used as a forecast of the returns of each of the other assets in the investor's menu. This choice is motivated by the fact that we want to isolate the utility gain produced by exploiting predictability in real estate excess returns only. As a result, we compare the realized utility of an asset allocation based on a simple IID model where the best forecast for the excess return of an asset is its historical average with the realized utility of a recursive portfolio exercise, in which the forecasts of real estate excess returns are based on our predictive models. Therefore, we compute the average, realized utility level as

$$\tilde{\mathrm{v}}(H) = \tilde{\mu}_p(H) - \frac{1}{2}\gamma\tilde{\sigma}^2_p(H), \tag{9}$$

where $\tilde{\mu}_p(H)$ and $\tilde{\sigma}^2_p(H)$ are the sample mean and variance of the ex-post, realized returns over the OOS period from the optimal H-horizon portfolio, both under the assumption that the investor may exploit predictability of real estate excess returns and under the assumption of IID excess returns for all the assets. The difference between the two utility levels is the utility gain

[7] Following Campbell and Thompson (2008) and Rapach et al. (2010), we constrain the weights of the risky assets to lie between 0% and 150%, so that $w_i = 0$ if $w_i < 0$, and $w_i = 150\%$ if $w_i > 0$.

arising from using a predictive model for real estate returns and can be interpreted as the per-period risk-free compensation, an investor is willing to pay, to switch from a strategy based on the historical sample mean to a strategy based on either linear or MS predictability. A predictive model generates economic value with respect to its historical mean counterpart, if the utility gain is positive.

In our back-testing strategy, we consider a set of "overlapping" investors: the first investor determines the allocation to be held between time t and (the end of) $t + H$- 1 based on her forecast at time t for cumulative excess returns of the assets over the period [t+1, $t + H$]; the second investor determines the allocation to be held between time $t + 1$ and $t + H$ based on her forecast at time $t + 1$ for cumulative excess returns of the assets over the period [$t + 2$, $t + H + 1$], and so on. For simplicity, the initial wealth of each investor is normalized to be equal to one. In addition, we perform our asset allocation exercise both in the absence and in presence of transaction costs. When transaction costs are assumed, the investor pays a round-trip fee (proportional to the weights assigned to the asset) equal to 10 basis points for T-bonds and 25 basis points in the case of real estate and equities. These levels are in line with those assumed, for example, by Ling et al. (2000).[8] It is important to note that also an investor who does not exploit predictability incurs transaction costs (proportionate to the optimal weights that she derives using the historical mean as the best forecast for real estate returns); therefore, the presence of transaction costs does not necessarily favor the benchmark allocation vs. the allocation that exploits predictability.

3. DATA

To proxy for returns on publicly traded real estate, we obtain monthly returns of the FTSE NAREIT US Equity REIT Index, provided by the National Agency of Real Estate Investment Trusts (NAREIT). The index is based on the recorded trading prices of all REITs listed on the New York Stock Exchange, the NYSE ARCA, and the NASDAQ. The use of this index is inspired by a long literature (see, e.g., Ciocchetti et al. 2002; Ghysels et al., 2012; Lee and Chiang, 2010; and Zhou

[8] While Ling et al. (2000) also experiment with higher transaction costs, their sample refers the 1980s and 1990s when transaction costs were arguably higher than during our 2005-2018 sample period. It seems therefore that adopting their alleged "low cost" configuration may be sensible for our purposes.

and Lai, 2008) as a good proxy for US public real estate returns, due to the underlying stocks being relatively liquid and the transaction price-driven reliability of the data. To compute excess returns, we subtract the 1-month Treasury Bill rate retrieved from the Federal Research Economic Data (FRED) repository of the Federal Reserve Bank of Saint Louis.

We also collect data on eight predictors, which we use alternatively and in combination. The first set of predictors includes four fundamental variables: the dividend yield (DY), the price-to-book ratio (PBOOK), the price-to-funds-from-operations ratio (PFFO) and the growth rate of the income reported by the equity REITs (INCG). We retrieve historical data for these variables from SNL Financial. Although FTSE NAREIT index return data is available from 1972 (through NAREIT), PBOOK, PFFO and INCG are only available from January 1993, therefore we are forced to limit our public real estate analysis to the sample period January 1993 – December 2018.

Following Ling et al. (2000), we also include one macroeconomic variable, namely the percentage change in private consumption expenditures for nondurable goods (CONS), the lag of the S&P 500 Index (LMKT), which is a proxy for the current market conditions, and a momentum variable, namely the monthly compounded return of the NAREIT Index over the previous six months (REITMOM). Finally, following previous studies that have shown some predictive power of sentiment variables for real estate returns (see, for instance, Akinsomi, 2014; Clayton et al., 2009), we include the change in the Index of Consumer Sentiment (ICS), computed on the basis of the Survey of Consumers, conducted by the University of Michigan in collaboration with Thomson Reuters.[9] Although the FTSE NAREIT index data are available from 1972, the PBOOK and the PFFO are only available from January 1993, therefore we are forced to limit our public real estate analysis to the sample period January 1993 – December 2018.

Turning to private real estate, we obtain total returns of the National Council of Real Estate Investment Fiduciaries (NCREIF) Property Index (also known as NPI), available at quarterly frequency from NCREIF. NPI is an appraisal-based index that tracks the historical performance of a large number of commercial real estate properties located in the US, acquired (at least in part) on behalf of tax-exempt institutions and held in a fiduciary environment. Although the properties included in the index may use leverage, NPI returns are reported on unlevered basis. In the case of private real estate, excess returns are obtained by subtracting the 3-month

[9] The Index of Consumer Sentiment is available at hiip://www.sca.isr.umich.edu/charts.html.

Treasury bill rate (to be consistent with the quarterly nature of the data) from the FRED repository.

In principle, it would be ideal to use the same set of predictors also for private real estate returns. However, this is not entirely possible due to data availability constraints. In particular, private properties do not pay dividends, and therefore we replace the dividend yield with the earning-price (EP) ratio, computed as net operating income (NOI) divided by the market value of the properties covered by the index. In addition, while the PFFO and PBOOK ratios are not available for private real estate, we are able to compute the growth rate of the capital expenditure (CAPEX). Similarly, we compute the growth rate of the income generated by the properties included in the index (INCG). We obtain NOI, CAPEX and market value data for the properties underlying the NPI index from NCREIF. We also include ICS, CONS and LMKT as previously defined, with the only difference that they are now sampled at a quarterly frequency, while the real estate momentum variable (NCREIFMOM) is the quarterly compounded return of the NPI over the previous six quarters. The sample period for the analysis of private real estate returns predictability spans from the fourth quarter of 1978 through the end of 2018, as this is the longest period for which both the NCREIF returns and the predictors are available.[10]

In Table 1, we report the summary statistics of private (Panel A) and public (Panel B) real estate excess returns and of the respective predictive variables. All data concerning public real estate are reported at monthly frequency, while those concerning private real estate are at quarterly frequency. We note that public real estate displays a higher mean excess return than private real estate; indeed, a monthly excess return of 0.65% scales up to an annualized excess return of 7.8%, while the annualized return of private real estate is approximately 4.5%. However, NCREIF returns are considerably less volatile than REITs returns, as their annualized volatility is only 4%, in contrast with an annualized volatility of approximately 13% for NAREIT index returns. Both excess return series are non-normal and display negative skewness and fat tails (their kurtosis is in excess of 3), in line with recent results by Cotter and Roll (2015). Similarly, the predictive variables are also non-normal; while all growth rates are generally leptokurtic, the accounting ratios tend to be platykurtic.

[10] However, to avoid losing an excessive number of observations, in the case of NCREIFMOM, we fill the initially missing values with momentum estimates based on REITs data, available since 1972.

4. EMPIRICAL RESULTS ON PREDICTIVE PERFORMANCE

4.1. Estimation Results and Resulting Forecasts

As discussed in Section 2.1, we recursively estimate both linear and MS predictive regressions (eight models for private real estate and nine for public real estate) of H-horizon excess returns over an expanding 2005-2018 pseudo OOS. Moreover, also the historical sample mean of H-horizon returns is recursively updated by including one additional observation with each available period. We do not report all outputs of these estimation problems for brevity.[11] However, in Figures 1 and 2 we present graphically some of the outputs implied by our recursive estimates. In particular, Figure 1 displays the *predicted* beta coefficients from the forecast regressions. The betas are the standard OLS estimates in the case of the linear model, but are H-step ahead predicted in the case of the MS models because they are the weighted averages of the regime-specific betas, with weights corresponding to the H-step ahead predicted probabilities from Hamilton's filtering algorithm (see the discussion in Section 2.1).[12] Figure 2 shows instead the forecasts that are recursively computed in real time from the predictive models. Because these graphs cannot be produced for all the alternative models that we entertain in this paper, for brevity we focus on the "All predictors" (or kitchen sink) regression predictive models. The graphs derived from the remaining models carry similar qualitative features and are available from the Authors upon request.

Panels A and B of Figure 1 display the predicted betas at 3- and 6-month horizons, respectively, from the models forecasting H-period NCREIF returns. We have omitted a panel with a 60-month predicted betas, as these are rather smooth over time, but qualitatively similar to panel B. Based on Panel A two observations are notable. First, with rare exceptions (but this is not a necessary condition, as the fact that ML estimates of the MS slope coefficients ought to straddle OLS estimates is neither an implication of the problem nor it

[11] The outputs are available from the Authors upon request. Such tables and plots consist of in-sample outputs and are only indirectly related to the forecasting performance of the different models and their power to generate economic value. For instance, MS models (differently from linear predictive regressions) tend to imply increasing R-squares that exploit their non-linear flexible features, but this is known to not always imply a satisfactory forecasting performance.

[12] In particular, Figures 1 and 2 refer to the MSIH model.

has been imposed), the MS predicted betas oscillate—often rather strongly—around the OLS estimates. For instance, the OLS coefficient associated with the EP ratio smoothly oscillates between 1 and 4 and tends to decline (with a brief respite between 2009 and 2010) over our back-testing OOS period; the ML estimates of the coefficient associated with the EP predictor tend to take two rather different, extreme values: a zero or even negative (but never significant) value in one regime and a large and highly statistically significant coefficient in the other regime. A predicted probability-weighted average of such two extreme betas tends to give a strongly time-varying predicted beta, that oscillates between zero (or a small negative value) and values as large as 10. Yet, also the MS predicted EP beta tends to display a decaying pattern over time, i.e., the EP ratio predicts NCREIF excess returns with a weakening strength. Second, because MS models are flexible enough to suddenly transition between regimes, the predicted 3-month betas tend to be highly reactive to the data. For instance, the NCREIF momentum variable sees the associated MS coefficient decline from almost 0.5 in late 2009 to zero by the end of 2011, i.e., the predictive power of momentum completely evaporated in a matter of 7-8 quarters as a result of the GFC of 2008-2009. The observations from Panel A also extend to Panel B, where 6-month ahead predicted betas are reported, even though in this case the fluctuations of the MS coefficients are less pronounced, as one would expect of longer-term forecasts.

Panels C (for the 1-month horizon) and D (6-month horizon) of Figure 1 display the predicted betas from the models estimated on REIT excess returns. Although, the predictors used in this case are not identically the same as those applied to NCREIF index return forecasting, it is clear, especially in panel C, that the gyrations of the MS coefficients are exacerbated by using monthly data. For instance, in Panel A, the MS beta for the personal consumption growth predictor oscillates between -0.7 and 0.3, while the linear beta is a rather flat, never statistically significant, -0.1; in Panel C, when public real estate data are used, the regime switching slope oscillates between -1.5 and 2.5, with a few rather visible spikes, while the linear beta is again smooth, close to zero but slightly positive over the second half of the sample. A similar comment may be fairly applied to panels B vs. D. However, a comparison between the results for NCREIF vs. REIT excess returns does reveal one structural difference: even at a multi-step horizon, the recursively predicted MS betas in the case of private real estate tend to oscillate but to express non-zero values throughout the entire OOS back-testing sample; in the case of public real estate data, the majority of the predicted MS slopes tame off and converge towards zero after 2011 (PFFO and, to some extent, DY and INCG are exceptions to this pattern). Because a non-trivial (i.e., when it implies non-constant filtered probabilities) MS predictive regression may forecast zero betas all the time only if both betas are close to zero, this means that the post-GFC sample is characterized by remarkable loss of predictability in the case of the public real estate. This observation squares well with the literature, which has observed that most predictability of equity returns tends to be generated during recessions and bear markets (see, e.g., Henkel and Martin, 2011): if equity REITs can be considered as a way to trade real estate through stock-like vehicles (see, e.g., Boudry et al. 2012; Clayton and MacKinnon, 2001; Lee and Chiang, 2010), then this empirical regularity appears to be easy to rationalize. Finally, similarly to the patterns observed in Panels A and B for private real estate, in Panels C and D concerning public real estate data, there is considerable variation during the sub-period 2008-2011, when our estimations fully incorporate the impact of the considerable losses on the real estate asset class incurred during the GFC.

In Figure 2 we show how the predicted betas contribute in originating forecasts of H-period real estate excess returns and offer intuition for the results that follow, concerning comparative forecasting performance and optimal asset allocation. For brevity, similarly to Figure 1, we only display the forecasts referring to the “All Predictors” model. Panel displays the plots of NCREIF excess return forecasts for H = 3, 6, and 60 months, while Panel B shows the forecasts for equity REITs and H = 1, 6, and 60 months. In panel A, for H = 3 and 6, it is clear that none of the models really anticipates the dynamics of the realized returns. However, the MS model suffers from the shortest lag in correspondence of the GFC, i.e., the regime switching flexibility is exploited to react before and more strongly vs. the linear model. Moreover, while a linear model would end up under-estimating the overall, cumulative effects of the GFC on NCREIF excess returns (the trough occurs 7-8 quarters too late and misses the negative return by almost 5%), this does not occur in the case of H = 60 months, when both models seem in fact to over-react to the GFC, although the extent of such bias turns out to be stronger for simpler, linear predictive regressions.[13] In panel B, with reference to H-period REIT excess returns forecasts, at the 1-month horizon it is visible that while a linear model leads to excessively smooth and essentially helpless forecasts, the MS model at least captures the high volatility of the 2007-2010 sub-sample, often moving the forecasts in the appropriate direction. Interestingly, while for H = 6 months, none of the models seem to offer accurate predictions, for H = 60, MS would have correctly predicted the positive and rising excess REIT returns between 2012 and 2014, following the bear regime, triggered by the GFC. This could have given considerable timing opportunities to an investor basing her asset allocation decisions on the MSIH model.

4.2. Recursive OOS Performance

Tables 2 and 3 and 3 report three realized OOS performance measures for three models, a predictive single-state regression (1), MSI (2) and MSIH (3) predictive regime switching regressions for NCREIF and REIT excess returns forecasts, respectively. The measures are the standard root mean squared forecast error (RMSFE), defined as the square roof of the sample mean of the OOS squared prediction errors, the difference between the RMSFE of a MS model and of a corresponding linear model, and Campbell and Thompson's (2008) OOS R-squared defined as:

$$\begin{aligned} R^2_{OOS}(\mathcal{M},H) &\equiv 1-\frac{\sum_{t=H}^{T}\left(r_t^H-\hat{r}_{t|t-H}(\mathcal{M},H)\right)^2}{\sum_{t=H}^{T}\left(r_t^H-\bar{r}_{t-H}(H)\right)^2} \\ &= 1-\frac{MSFE(\mathcal{M},H)}{MSFE(sample\ mean,H)}, \end{aligned} \tag{10}$$

where r_t^H is the cumulative H-period return, $\hat{r}_{t|t-H}(\mathcal{M},H)$ is the H-horizon forecast based on information up to time t – H under model $\mathcal{M}$, while $\bar{r}_t(H)$ is the recursively estimated sample mean up to time t – H. Clearly, $R^2_{OOS}(\mathcal{M},H)$ > 0 if and only if $MSFE(\mathcal{M},H) < MSFE(sample\ mean,H)$, i.e., when the given model $\mathcal{M}$ yields an OOS predictive performance that is stronger than that of the sample mean. MSI/MSIH and the linear model

[13] Moreover, all models seem to systematically under-predict the actual values of the series. Note that this is possible, although grossly sub-optimal in OOS tests, even though by construction the in-sample residuals are forced to have zero mean.

are said to "correspond" when they involved the same predictors, the former with regime switching coefficients, the latter with coefficients that are constant over time. We analyze three alternative forecast horizons, H = 3, 6, and 60 months in Table 2 and H = 1, 6, and 60 months in Table 3.

In Table 2, both MSI and MSIH outperform the linear predictive regressions at short and intermediate horizons. For instance, at H = 3 months, the best linear model (including all predictors with a RMSFE of 0.0235) is severely outperformed by MSI with a RMSFE of 0.0166 (the improvement is then 0.7% per quarter) and also by MSIH with a RMSFE of 0.0208. In a RMSFE metric, the best predictive model is an MSI that includes all the predictors. Even though (in fact, at all horizons) there are occasional selections of predictors for which also linear models yield a positive R^2_{OOS} (these are large for models based on the consumer sentiment index), at H = 3 and 6 months, all MSI and MSIH models lead to positive and rather large estimates of R^2_{OOS} with a peak of 0.629 at H = 3, for the MSI model that includes all predictors. Interestingly, at the longest predictive horizons, while most of the MSI predictive regression (with exception of those based on the EP ratio and on all the predictors) display positive R^2_{OOS} and deliver more accurate forecast than their linear counterparts, there is less pronounced evidence of the ability of MSIH models to beat a simple historical mean. Yet, at short and intermediate horizons, obviously the evidence of forecasting power for MSI and largely also MSIH is strong and widespread, with the largest improvements over both the single-state model and the sample historical mean achieved by models that predict using individual personal income growth or including all predictors on the right-hand side.

Table 3 reports instead comparative predictive accuracy measures with reference to publicly traded real estate vehicles. The results are qualitatively similar to those in Figure 2, but slightly weaker in the following ways. MS models starkly outperform linear models as well as the historical sample mean only at intermediate forecast horizons; they are generally better than the benchmarks at H = 60 months, but the distance is typically smaller, and they fail to predict more accurately at H = 1 month.

In summary, while in the case of private real estate returns, short-term forecasting is successful, while there is less evidence in favor of long-term forecasting, the opposite obtains in the case of public real estate excess returns. This result could be partially driven by the lower total number of observations for private real estate, due to the lower frequency of data. On one hand, at H = 6, while all MSI and MSIH predictive regressions imply positive and large R^2_{OOS}, all linear models lead to negative R^2_{OOS}. The positive R^2_{OOS} become massive in the case of MSI predictive regressions with specific forecast instruments, such as PFFO (0.219) and lagged market returns (0.217), and one case of MSIH model when the predictor is consumption growth (0.248). Correspondingly, for these models, the reduction in RMSFE vs. the linear benchmark tends to be substantial, for instance from 0.1835 (linear) to 0.1598 (MSI) when PFFO is the only predictor. Interestingly, the MS models including all predictors imply small or negative R^2_{OOS}, probably as a result of collinearity that leads to unstable coefficient estimates and hence de-grades the realized forecasting performance. On the other hand, at H = 1 month, with rare exceptions, all models—linear and non-linear—lead to negative R^2_{OOS}s and in fact the RMSFE of MSI and MSIH are worse than those from simple regressions.[14]

In an Appendix available from the Authors upon request, we have also investigated the stability of these comparative OOS predictability performances over time through a simple split of our back-testing period between 2005-2011 vs. 2012-2018, with the former containing a potential forecasting breakdown caused by the GFC and the effects of the emergency policy measures undertaken by the authorities, see Tables A1 and A2. Such a split is sensible in the light of the differential ability of linear vs. MS models to track the dynamics of excess returns during the GFC. The Appendix shows that the relative performance of our models is remarkably stable over time in the case of NCREIF excess returns (Table 2). There is some weak evidence of unstable predictive performances in the case of equity REIT excess returns, in the sense that the distance between linear and MS predictive models grows larger (in favor of the latter models) during the 2012-2018 sub-sample, after the GFC.

5. ECONOMIC VALUE ANALYSIS

[14] The case of H = 60 months sits in between, in the sense that while the MS models struggle to guarantee positive R^2_{OOS} (even though a few of them lead to R^2_{OOS} in excess of 0.5), RMSFE tends to favor both MSI and MSIH over linear models.

In this Section we investigate whether and how, the excess return forecasts examined in Section 4 may have supported the generation of economic value—either in terms of ex-post realized MV utility or realized Sharpe ratios—when recursively implemented in real time, between January 2005 and December 2018. As discussed in Section 2, we perform the asset allocation exercises under two alternative assumptions concerning the level/presence of transaction costs: without transaction costs, and by imposing a proportional transactions costs of 0.25% for the S&P 500 and the NCREIF or NAREIT Index, and of 0.10% for Treasury bonds. As discussed in detail in Section 2.2, the utility gain measures the risk-free compensation, an investor is willing to pay to switch from a strategy based on the historical sample mean to a strategy based on predictability and/or MS. The remaining performance measures in Tables 4-6 (as well as the supplementary tables in an Appendix) are self-explanatory. While Tables 4-6 concern the case in which the coefficient of risk aversion γ is set to 5, we have also performed robustness checks for the cases $\gamma = 2$ and 10. In what follows, we omit to report fully tabulated results for these two cases, although these are available in an Appendix.

5.1. Private Real Estate

Table 4 shows the recursive portfolio performance results when the asset allocation problem is based on quarterly data and solved at a quarterly frequency, and the asset menu is composed of private real estate, the S&P 500 equity portfolio, 10-year government bonds, and cash, represented by 3-month T-bills. The realized OOS MV performances reflect the relative OOS predictive accuracy measures in Table 2 across forecast horizons: while simple linear models struggle to generate positive utility gains also at H = 6 and 60 months, MSI and MSIH models instead do and with relatively large amounts. For instance, in the presence of transaction costs and at H = 6, an MSI model implies that an investor should be ready to pay between 3.65 and 5.49 percent to access the strategies that exploit predictability and regimes instead of a sample mean-based forecast, while the single-state framework leads to an economic value estimate between -0.23 and 5.13 percent that however strongly depends on the specific selection of the model. As one would expect, the Sharpe ratios follow similar patterns, with MSI yielding performance scores ranging between 0.812 and 0.883, to be contrasted with a range 0.506 and 0.856 for the linear benchmark. If one considers the "all predictors" model however, the differences across single- and multi-state the differences are modest, and in fact the linear model turns out to be competitive vs. the MSIH model, with implied Sharpe ratios that are comparable with the MSI results.[15] Such differences are however stronger at a 3-month, short prediction horizon. For instance, the model based on NCREIF momentum in the presence of transaction costs, leads to a Sharpe ratio of 0.733 and a certainty equivalent annualized utility gain of 0.25% in the linear case, but to a Sharpe ratio of 0.888 and a realized utility gain of 2.57% under MSI.[16]

On the other hand, we need to emphasize that a strong forecasting performance as the one reported in Table 2 for NCREIF excess returns (and H = 3 and 6 months), is *not* sufficient to imply that economic value may be generated in Table 4: the literature is replete of case studies, in which a solid statistical performance at predicting returns fails to be followed by the generation of positive differential management fees (see, e.g., Timmermann, 2008). Equivalently, the strong performance of a predictive model may imply heterogeneous estimates of forecast accuracy under alternative loss functions. Our evidence that there is a good association between statistical and economic value performance in Tables 2 and 4 represents a genuine, non-trivial result.

Interestingly, the inclusion of transaction costs tends to increase most utility gain estimates. This occurs because the utility gain is computed with reference to a sample mean benchmark and transaction costs appear to hit more heavily the benchmark vs. the predictability frameworks. For the case of $\gamma = 5$, Table 5 reports evidence providing insights why this is the case. The effect derives from the simple fact that even though, as intuition suggests, sample mean-based portfolio strategies imply less volatile weights, these also tilt on average the optimal portfolios towards asset classes that absorb higher transaction costs on average. Therefore, while the Sharpe ratios are obviously decreasing in the levels of transaction costs, the percentage fees required to switch away from strategies that exploit predictability—being always estimated with reference to a sample mean benchmark—may vary non-monotonically. More generally, even though the statistics on the optimal recursive weights are similar, the sample mean leads to portfolios that

[15] In fact, on average for H = 3 and 6 months, MSI tends to generally outperform MSIH, even though occasional exceptions can be isolated. Because MSIH implies more delicate estimation issues vs. MSI, in the text we tend to focus on MSI.

[16] In Tables 4 and 5, the results for the realized recursive mean returns generally mimic (in fact, they support because these are obvious ingredients to the calculation of both Sharpe ratio and MV certainty equivalence scores) those commented for the realized Sharpe ratios and the utility gains. In line with the general comments reported in the main text, because there is no evidence of predictive power at H = 60, both the linear and the MS models (in particular, MSI) fail to generate economic value when compared to the sample mean benchmark. Of course, one needs to remember that using a H = 60 horizon implies a loss of data to perform the back-testing with reference to the last portion of the sample and this implicitly limits the assessment of the economic value to 2005-2013 only giving a considerable weight to the realized returns during the GFC.

load heavily on the maximum allowed weight of 150%, while other strategies also tilt the portfolios towards private real estate but to a lower extent (in the case of H = 6 months, on average, 128% under simple regression predictability and 124% under MS models).[17] Yet, these average and median statistics hide considerable variation over time that is the highest under the MS models that retain the power to advise the MV framework to switch in and out of NCREIF holdings (the standard deviation is 57% under H = 6 months) and also long-term bonds (the standard deviation is 30%). Such variability over time represents to some extent genuine, valuable market timing that especially in the case of MS models generates positive economic value.

Tables A3 and A4 in the Appendix extend Table 4 to the cases of $\gamma = 2$ and 10. The results are qualitatively homogeneous when compared to Table 4 with a few interesting remarks on the effects of increasing risk aversion. First, as γ increases, the evidence of economic value becomes stronger, especially for short investment horizons and in the case of the MSI model. For instance, for H = 3 and under transaction costs, when $\gamma = 2$, the best MSI model includes all predictors and leads to an increase in realized utility vs. the sample mean of 2.0% per year, when $\gamma = 5$ the best MSI model just includes EP as a predictor and yields a compensatory fee of 2.6% , and when $\gamma =$ 10 the best MSI model is based on momentum and would have seen an investor ready to pay up to 6.8% per year to switch away from the benchmark. Second, as γ increases, the distance between MSI and MSIH (in favor of the former) tends to fade, especially at intermediate and long horizons. Therefore, while in Table 4 under $\gamma = 5$, the outperformance of MSI over MSIH is moderate and admits occasional reversals, under $\gamma = 2$ the distance is stark: when an investor is aggressive, relying on a predictability models explicitly targeted towards forecasting mean excess returns (as opposed to also the variance of the shocks to excess returns) offers a positive pay-off. For instance, under $\gamma = 10$ the best MSI model leads to a utility gain of 9.86% vs. 10.38%

[17] Because the NCREIF index is appraisal-based, it tends to suffer from excessive smoothing that artificially reduced its reported volatility. This translates in upward-biased Sharpe ratios and in optimal mean-variance portfolio heavily tilted towards this asset class. However, the point of our paper is not really to provide stringent, normative portfolio advice to investors, but to perform a comparison—for given properties of the data—across models with and without predictability, linear and non-linear, given that all models will be estimated and implemented on the basis of identical excess return series. Moreover, one can rationalize our decision to investigate both NCREIF and equity NAREIT series as a way to take the smoothing bias into account, instead of proceeding to an unsmoothing of the series that is by necessity perilous because it needs to be based on a model (see, e.g., Bond et al., 2012).

(although the predictors are different in the two cases). Third, and across all models, we note that the realized, ex-post mean portfolio returns decline as γ increases, as one would expect given the structure of the objective function maximized. Interestingly, this effect does not involve the Sharpe ratio, an indication that objectives that are optimized ex-ante do not always need to be optimized ex-post. For instance, under H = 6 months and accounting for transaction costs, under $\gamma = 2$ the "all predictors" model leads to a mean of 7.05% under the linear model, with a Sharpe ratio of 0.65; under $\gamma = 5$, the "all predictors" linear model leads to a mean of 5.59% under the linear model, with a Sharpe ratio of 0.86; under $\gamma = 10$, the corresponding statistics are 4.95% and 0.92 but are originated by MSI. Partially in line with a "low variance puzzle" (see Ang et al. 2006, and Ooi et al. 2009 in the case of REITs), it seems that an investor caring more for the variance may achieve a higher risk-adjusted performance despite the lower targeted mean.

Given the patterns that emerged from some panels in Figure 2, suggesting that the statistical accuracy of different models may have suffered from instability, in Panel A of Table 6 we perform a stability analysis with reference to private real estate. As in Section 4, we have computed the standard performance measures with reference to a 2005-2011 vs. a 2012-2018 sub-sample. For brevity, we only report statistics for the case of $\gamma = 5$, a short investment horizon, and the MSIH model, but results are similar across other horizons and for the MSI framework. Even though the portfolio results for the two sub-samples are rather different—realized mean portfolio returns and Sharpe ratios are considerably lower in the first sub-sample that includes the GFC—the insights are robust over time: for all predictor selections (including the "all predictors" case), MS models lead to higher realized mean returns, Sharpe ratios, and an increase in OOS realized utility vs. the corresponding linear model, with identical predictor(s). Interestingly, however, predictability generates a higher required performance fee requested by an investor in the first sub-sample than in the second, even though the sign of both sets of estimates is positive.

Panel B of Table 6 performs a stability analysis with reference to public real estate based on computing standard performance measures with reference to 2005-2011 vs. 2012-2018 sub-samples, with reference to the case of H =1 month. As in Panel A, the results for the two sub-samples are rather different—realized mean portfolio returns and Sharpe ratios are considerably lower in the first sub-sample that includes the GFC—the insights are robust over time: for all predictor selections (including the "all predictors" case), linear models lead to lower realized mean returns, Sharpe ratios, and an increase in OOS realized utility vs. the corresponding MS model, with identical predictor(s). Therefore, results appear to be reasonably robust as to the absence of economic value for H = 1. A similar, unreported analysis confirms instead that economic value can be generated for H = 6 months.

5.2. Public Real Estate

Table 7 shows OOS portfolio results when the asset menu is composed of equity REITs, the S&P 500 equity portfolio, 10-year government bonds, and cash, represented by 1-month T-bills and $\gamma = 5$. Tables A5 and A6 in the Appendix show related performance results for the cases of $\gamma = 2$ and 10. Although some evidence of economic value from predictability persists, the gains in realized utility acquire an interesting inverted "U shape", in the sense that the gains only obtain (irrespective of the fact that transaction costs are taken into account) at the intermediate horizon, H = 6 months, while they stop showing up at the shortest horizon of 1 month (the result concerning the long, 60-month horizon are similar to those in Table 4). Moreover, at a one-month horizon, not only MSI and MSIH generate lower realized utility vs. a sample mean benchmark, but also vs. a linear predictive regression. For instance, while under transaction costs, the best linear model yields a Sharpe ratio of 0.103 but implies a negative fee of -3.16%, the best MS model (MSI) implies a Sharpe ratio of 0.099 and a negative performance fee of -7.31%. However, the case of H = 60 months is also interesting: as we have seen in Table 3, excess equity REIT returns may be predicted on an OOS basis, but an investor with $\gamma = 5$ would not be able to extract positive economic value from a trading strategy based on such forecasts. This is of course unsurprising as the underlying loss functions are sufficiently heterogeneous, that to obtain different results has been known to frequently occur (see the survey in Rapach and Zhou, 2013).

Additionally, even when economic value can be generated, as in the case of H = 6 months, the improvement in MV utility is weaker vs. the one reported in Table 4. On the one hand, because we are dealing with forecasts of different excess returns series and with different samples and frequencies, this is to be expected. On the other hand, the differences are rather large. For instance, the best MSIH model (that includes consumer confidence as a predictor) implies a Sharpe ratio of 0.216 that exceeds the corresponding linear model with 0.064; the former model also implies a fee of 1.58% to switch to it from using the sample mean, vs. -7.90% in the latter case. The corresponding Sharpe ratios are 0.790 and 0.637 for identical models applied to a dynamically solved portfolio problem applied to the NCREIF index, stocks, and bonds; the associated compensatory fees are instead 3.84% and 0.95%.

Tables A5 and A6 in the Appendix show the results for the cases of $\gamma = 2$ and 10, generalizing the analysis in Table 7. Even though the general qualitative conclusions drawn under $\gamma = 5$ are confirmed, a few additional insights emerge. First, in the case of public real estate, as γ increases, the evidence of economic value becomes *weaker*. For instance, for H = 6 and with transaction costs, when $\gamma = 2$, the best MSI model includes lagged market value and leads to an increase in realized utility vs. the sample mean of 5.8% per year, when $\gamma = 5$ the best MSI model just includes ICS as a predictor and yields an annualized compensatory fee of 2.7%, and when $\gamma = 10$ the best MSI model is based on personal consumption growth and would have seen an investor ready to pay only up to 0.9% per year to switch away from the sample mean benchmark. As in Section 5.1, and across all models, the realized, ex-post mean portfolio returns decline as γ increases, while the Sharpe ratio varies non-monotonically or even increases, an indication that objectives that are optimized ex-ante do not always need to be optimized ex-post. For instance, under H = 6 months and accounting for transaction costs, under $\gamma = 2$ the "all predictors" MSI model leads to a mean of 1.23% under the linear model, with a Sharpe ratio of 0.16; under $\gamma = 5$, the "all predictors" MSIH model leads to a mean of 0.95%, with a Sharpe ratio of 0.15; under $\gamma = 10$, the corresponding statistics are 0.66% and 0.16 and are originated by the MSIH once more.

Table 8 is interesting because, compared to Table 5, it shows mean and median portfolio allocations that are less extreme, even under a recursive historical sample mean benchmark, even though now a clear tilt appears towards 10-year Treasury bonds, while the allocation to real estate turns out to be on average very close to that for equities. This is partially justified by the lower mean historical performance and by the higher risk, as seen in Table 1. Interestingly, the predictability-driven strategies remain more volatile over time vs. the historical sample mean, even though the table shows that simpler linear models are as volatile as MS models are. Moreover, it is evident that the historical mean is superior to all predictability models in terms of realized OOS performance due to a higher mean and median allocation to real estate. At H = 60 months, a historical sample mean-based portfolio strategy allocates on average 81% (median is 67%) to REITs, a linear predictive regression 32% (median is 0%), and an MSI model allocates on average 52% (median is again 0%). Moreover, the higher allocations of the first model to public real estate do not come from a sacrifice of the equity or government bond positions, as the stronger commitment to real estate appears to be financed by larger leverage.

6. CONCLUSION

While research on predictability in real estate is certainly extensive, less is known about the economic value of predictability when assessed within the context of realistic asset menu of real estate, stocks and bonds, and under plausible estimates of transaction costs. We examine the predictability of excess real estate returns from recursive out-of-sample and economic value perspectives. For a range of investment horizons and risk-aversion parameters we compute the realized forecasting and mean-variance asset allocation performance of a variety of predictors and models (linear and non-linear) and document the existence of considerable pockets of predictive power, especially in the short- and intermediate horizons and for private real estate, both in absolute terms and in comparison to a simple, but powerful historical sample mean benchmark. We then test whether such forecasting accuracy may translate into a positive, risk-adjusted out-of-sample performance in a recursive mean-variance portfolio allocation exercise that involves the selection of weights to be attributed to stocks, government bonds, cash, and either private or public real estate. We find that especially in the case of private real estate, there are large improvements in realized Sharpe ratios and mean-variance utility scores, which are achieved with a range of strategies that exploit predictability at intermediate horizons, especially when supported by Markov switching models. These results are consistent with the differential degree of tradability of the two types of real estate and robust to taking transaction costs into account.

Our analysis is unique in the distinct methodology it uses, the significantly expanded time series of real estate returns, as well as in considering not just public, but also private real estate. We document results on the economic value of predictability that are more encouraging than those reported previously in the literature (see, e.g., Ling et al. 2000).

This study helps further our understanding of the economic value of predictability in real estate and of the interaction among alternative loss functions, in particular, statistical vs. trading/portfolio-based ones. There are at least three main ways, in which our research can be extended. First, a range of additional, alternative predictors may be investigated. Ling et al. (2000) and Bianchi and Guidolin (2013) for example use slightly richer set of predictors of macro- and business-cycle types but stop short from assessing their OOS forecast power in recursive exercises. Therefore, our results may also be interpreted as an example that places at best a lower bound to the economic value that investors could obtain from exploiting predictability in real estate markets. Second, and in the same spirit, in this paper we have identified the class of "non-linear" prediction models with MS models, also in line with the existing tradition in real estate finance. However, there are other types of models that have been estimated on excess real estate returns—for instance, threshold models in Füss et al. (2012)—and it would be interesting to systematically test the power of such alternative models to generate economic value in OOS experiments. Of course, following Bianchi and Guidolin (2013), the MS models entertained in this paper may be generalized, although at the price of considerable computation and estimation complexity, to fully-fledged MS VAR models in which excess real estate returns and the predictors are all endogenous and therefore placed on equal footing. However, there is no clear prior as to whether such a strategy, albeit more elegant and internally consistent, may have the power to affect the results in any special direction. Third, we have computed measures of economic value under mean-variance preferences even for long-horizon problems, which may be problematic because mean-variance is inherently static. A variety of papers, e.g., Bianchi and Guidolin (2013), Fugazza et al. (2009), MacKinnon and Al Zaman (2009), have used instead more complex preferences such as power, constant-relative risk aversion utility that however would force an analyst to perform numerical optimization. Yet, especially in the presence of MS dynamics, such preferences would take into full account the complex dynamics of higher-order predicted moments (such as skewness and kurtosis) implied by MS. Moreover, the portfolio problem could be set up as a fully dynamic one, in which an investor refrains from simple buy-and-hold over the entire investment horizon H. Finally, in the asset allocation stage our back-testing exercise has rather rigidly separated, private from public real estate. This is justified by their different sample sizes and frequencies, but of course—at the cost of losing much information concerning the predictability of REIT excess returns—one may endeavor to change this rigid choice, as in Seiler et al. (2001) among many others. We leave sthese exciting extensions for future research.

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Table 1: Summary Statistics

The table reports the summary statistics for quarterly excess returns on the NCREIF National Property Index over the three-month Treasury Bill (NCREIFTBL), the monthly excess returns of the FTSE NAREIT Index over the one-month Treasury Bill (REITTBL), and for the associated forecasting variables. The sample period for NCREIF returns is October 1978 – December 2018 (162 quarters); the sample period for the FTSE NAREIT Index returns is February 1993 – December 2018 (311 months). EP is the lagged earning price computed as net operating income divided by the market value of the properties covered by the index. CAPEX is the growth rate of capital expenditures. CONS is the growth rate of the private consumption expenditures for nondurable goods. ICS is the growth rate of the Michigan's Index of Consumer Sentiment. INCG is the growth rate of the income from the properties covered by the indices. LMKT is the lagged return of the S&P 500 (the lag is one month for the predictive regressions involving monthly data and three months for those involving quarterly data). NCREIFMOM is the quarterly compounded return of the NCREIF Index over the previous six quarters. DY is the lagged dividend yield of the NAREIT Index. PBOOK is the price-to-book value ratio and PFFO is the price-to-funds-from-operations ratio, both for REITs. REITMOM is the monthly compounded return of the NAREIT Index over the previous six months.

Panel A - Private Real Estate (Quarterly Frequency)

	Mean	St. Dev.	Median	Skewness	Kurtosis	Minimum	Maximum	Jarque Bera
NCREIFTBL	1.12%	2.00%	1.44%	-1.89	9.06	-8.73%	4.49%	346.23
EP	1.73%	0.32%	1.78%	-0.39	2.02	1.11%	2.23%	10.76
CAPEX	0.57%	0.19%	0.53%	1.33	5.77	0.19%	1.39%	99.99
CONS	7.55%	4.75%	7.12%	0.54	4.21	-4.16%	22.90%	17.87
ICS	1.40%	14.27%	1.51%	0.20	3.89	-35.57%	49.18%	6.49
INCG	3.87%	5.92%	3.08%	2.50	15.71	-5.71%	44.41%	1267.18
LMKT	2.10%	7.05%	2.59%	-1.60	10.27	-37.24%	23.02%	428.35
NCREIFMOM	8.79%	7.28%	10.11%	-1.95	8.30	-24.97%	20.26%	293.53

Panel B - Public Real Estate (Monthly Frequency)

	Mean	St. Dev.	Median	Skewness	Kurtosis	Minimum	Maximum	Jarque Bera
REITTBL	0.65%	5.55%	0.92%	-1.51	13.82	-37.77%	27.02%	1640.02
DY	5.35%	1.67%	5.00%	0.46	1.87	3.19%	9.13%	27.68
PBOOK	2.33	0.52	2.37	0.03	1.94	1.39	3.57	14.71
PFFO	0.15	0.04	0.15	-0.10	1.58	0.08	0.22	26.90
ICS	0.86%	9.18%	0.30%	0.26	4.01	-28.00%	34.95%	16.79
CONS	1.98%	2.19%	2.14%	-2.21	13.19	-10.91%	7.06%	1604.92
LMKT	0.59%	3.53%	1.02%	-1.45	9.82	-22.80%	11.35%	714.66
REITMOM	0.87%	2.58%	1.09%	-2.07	14.46	-16.72%	10.05%	1930.00
INCG	0.46%	0.22%	0.43%	0.92	4.38	0.12%	1.51%	68.63

Table 2: Private Real Estate - Realized Out-of-Sample Performances

The table shows realized (pseudo) out-of-sample (OOS) performance of a set of linear and MS predictive regressions for the NCREIF Property Index excess returns over three different forecasting horizons (three, six, and 60 months, respectively), when the predictive variables are used one at a time or altogether. The OOS period starts in January 2005 and ends in December 2018. The table reports the root mean square forecast error (RMSFE) and the OOS R^2 (R_OSS) (a positive OOS R^2 implies that the model has a better predictive performance than a simple historical mean). In the case of the MS models, the table also reports ΔRMSFE, the difference between the RMSFE of the linear model and that of the MSI and MSIH models, respectively: a positive value of ΔRMSFE means that the MS model has a better forecasting performance than its linear counterpart. MS models that display a better forecasting accuracy than both the historical mean and their linear counterparts are denoted with *.

Panel A - 3 months

	LINEAR		MSI			MSIH		
	RMSFE	R_OOS	RMSFE	ΔRMSFE	R_OOS	RMSFE	ΔRMSFE	R_OOS
EP	0.0293	-0.1594	0.0210	**0.0082***	**0.4013**	0.0260	**0.0032***	**0.0823**
CAPEX	0.0269	**0.0237**	0.0216	**0.0052***	**0.3654**	0.0229	**0.0040***	**0.2900**
CONS	0.0274	-0.0163	0.0225	**0.0049***	**0.3168**	0.0231	**0.0043***	**0.2771**
ICS	0.0244	**0.1959**	0.0191	**0.0053***	**0.5080**	0.0197	**0.0047***	**0.4762**
INCG	0.0272	-0.0034	0.0214	**0.0058***	**0.3788**	0.0219	**0.0054***	**0.3525**
LMKT	0.0271	**0.0089**	0.0224	**0.0047***	**0.3234**	0.0230	**0.0040***	**0.2810**
NCREIFMOM	0.0263	**0.0602**	0.0233	**0.0030***	**0.2645**	0.0262	**0.0002***	**0.0727**
All Predictors	0.0235	**0.2537**	0.0166	**0.0069***	**0.6286**	0.0208	**0.0027***	**0.4158**

Panel B - 6 months

	LINEAR		MSI			MSIH		
	RMSFE	R_OOS	RMSFE	ΔRMSFE	R_OOS	RMSFE	ΔRMSFE	R_OOS
EP	0.0595	-0.2585	0.0432	**0.0162***	**0.3350**	0.0509	**0.0086***	**0.0795**
CAPEX	0.0524	**0.0224**	0.0400	**0.0124***	**0.4307**	0.0420	**0.0104***	**0.3732**
CONS	0.0536	-0.0222	0.0434	**0.0102***	**0.3288**	0.0513	**0.0023***	**0.0634**
ICS	0.0483	**0.1709**	0.0403	**0.0080***	**0.4225**	0.0425	**0.0058***	**0.3571**
INCG	0.0533	-0.0099	0.0407	**0.0126***	**0.4105**	0.0432	**0.0100***	**0.3348**
LMKT	0.0533	-0.0102	0.0453	**0.0080***	**0.2701**	0.0441	**0.0092***	**0.3093**
NCREIFMOM	0.0547	-0.0628	0.0498	**0.0048***	**0.1163**	0.0595	-0.0049	-0.2612
All Predictors	0.0520	**0.0374**	0.0413	**0.0107***	**0.3939**	0.0393	**0.0127***	**0.4494**

Panel C - 60 months

	LINEAR		MSI			MSIH		
	RMSFE	R_OOS	RMSFE	ΔRMSFE	R_OOS	RMSFE	ΔRMSFE	R_OOS
EP	0.0595	-0.2585	0.3774	-0.3179	-0.4922	0.4501	-0.3906	-1.1224
CAPEX	0.0524	**0.0224**	0.2426	-0.1902	**0.3832**	0.2674	-0.2149	**0.2512**
CONS	0.0536	-0.0222	0.2652	-0.2116	**0.2633**	0.2773	-0.2237	**0.1943**
ICS	0.0483	**0.1709**	0.2839	-0.2356	**0.1559**	0.3130	-0.2647	-0.0264
INCG	0.0533	-0.0099	0.2657	-0.2124	**0.2605**	0.2836	-0.2303	**0.1575**
LMKT	0.0533	-0.0102	0.2613	-0.2080	**0.2848**	0.2976	-0.2443	**0.0721**
NCREIFMOM	0.0547	-0.0628	0.2811	-0.2264	**0.1725**	0.2930	-0.2383	**0.1008**
All Predictors	0.0520	**0.0374**	0.3526	-0.3005	-0.3021	0.3735	-0.3215	-0.4615

Table 3: Public Real Estate - Realized Out-of-Sample Performance

The table shows the realized (pseudo) out-of-sample (OOS) performance of a set of linear and MS predictive regressions for the REIT Index excess returns over three different forecasting horizons (one, six, and 60 months, respectively), when the predictive variables are used one at a time or altogether. The OOS period starts in January 2005 and ends in December 2018. The table reports the root mean square forecast error (RMSFE) and the OOS R^2 (R_OSS) (a positive OOS R^2 implies that the model has a better predictive performance than a simple historical mean). In the case of the MS models, the table also reports ΔRMSFE, the difference between the RMSFE of the linear model and that of the MSI and MSIH models, respectively: a positive value of ΔRMSFE means that the MS model has a better forecasting performance than its linear counterpart. MS models that display a better forecasting accuracy than both the historical mean and their linear counterparts are denoted with *.

Panel A - 1 month

	LINEAR		MSI			MSIH		
	RMSFE	R_OOS	RMSFE	ΔRMSFE	R_OOS	RMSFE	ΔRMSFE	R_OOS
DY	0.0672	-0.0077	0.0690	-0.0019	-0.0644	0.0731	-0.0059	-0.1929
PBOOK	0.0672	-0.0090	0.0692	-0.0020	-0.0696	0.0698	-0.0025	-0.0868
PFFO	0.0671	-0.0067	0.0718	-0.0046	-0.1508	0.0704	-0.0032	-0.1052
ICS	0.0671	-0.0045	0.0706	-0.0036	-0.1137	0.0701	-0.0030	-0.0976
CONS	0.0685	-0.0483	0.0698	-0.0012	-0.0868	0.0719	-0.0034	-0.1534
LMKT	0.0671	-0.0043	0.0747	-0.0076	-0.2453	0.0656	**0.0015***	**0.0392**
REITMOM	0.0683	-0.0417	0.0720	-0.0036	-0.1560	0.0687	-0.0004	-0.0549
INCG	0.0669	**0.0005**	0.0763	-0.0094	-0.3007	0.0687	-0.0018	-0.0535
All Predictors	0.0711	-0.1296	0.0690	**0.0021**	-0.0625	0.1145	-0.0434	-1.9283

Panel B - 6 months

	LINEAR		MSI			MSIH		
	RMSFE	R_OOS	RMSFE	ΔRMSFE	R_OOS	RMSFE	ΔRMSFE	R_OOS
DY	0.1855	-0.0519	0.1613	**0.0242***	**0.2049**	0.1734	**0.0121***	**0.0809**
PBOOK	0.1830	-0.0239	0.1615	**0.0215***	**0.2025**	0.1730	**0.0100***	**0.0852**
PFFO	0.1835	-0.0292	0.1598	**0.0236***	**0.2189**	0.1741	**0.0094***	**0.0733**
ICS	0.1870	-0.0696	0.1633	**0.0237***	**0.1846**	0.1778	**0.0093***	**0.0338**
CONS	0.1853	-0.0498	0.1661	**0.0192***	**0.1569**	0.1569	**0.0284***	**0.2476**
LMKT	0.1810	-0.0021	0.1600	**0.0211***	**0.2174**	0.1805	**0.0005***	**0.0036**
REITMOM	0.1857	-0.0538	0.1632	**0.0224***	**0.1853**	0.1772	**0.0084***	**0.0399**
INCG	0.1819	-0.0114	0.1600	**0.0218***	**0.2169**	0.1730	**0.0088***	**0.0845**
All Predictors	0.2103	-0.3526	0.1798	**0.0305***	**0.0116**	0.1953	**0.0151**	-0.1659

Panel C - 60 months

	LINEAR		MSI			MSIH		
	RMSFE	R_OOS	RMSFE	ΔRMSFE	R_OOS	RMSFE	ΔRMSFE	R_OOS
DY	0.5785	-0.8594	0.4467	**0.1318**	-0.1087	0.4860	**0.0925**	-0.3122
PBOOK	0.5517	-0.6908	0.3950	**0.1566***	**0.1330**	0.4360	**0.1156**	-0.0563
PFFO	0.5739	-0.8298	0.4362	**0.1377**	-0.0572	0.4462	**0.1277**	-0.1060
ICS	0.4555	-0.1525	0.3192	**0.1362***	**0.4338**	0.3570	**0.0984***	**0.2918**
CONS	0.4472	-0.1110	0.2878	**0.1594***	**0.5400**	0.3380	**0.1092***	**0.3653**
LMKT	0.4242	**0.0001**	0.2864	**0.1379***	**0.5444**	0.3169	**0.1073***	**0.4420**
REITMOM	0.4142	**0.0466**	0.2812	**0.1330***	**0.5605**	0.3170	**0.0972***	**0.4416**
INCG	0.4396	-0.0738	0.2683	**0.1713***	**0.5999**	0.3245	**0.1151***	**0.4150**
All Predictors	0.6646	-1.4539	0.5956	**0.0690**	-0.9710	0.6283	**0.0363**	-1.1933

Table 4: Private Real Estate – Mean-Variance Realized OOS Performance ($\gamma = 5$)

The table shows the realized (pseudo) out-of-sample performance for a sequence of recursive mean-variance asset allocations in 3-month T-bills, the S&P 500, 10-year Treasury bonds, and the NCREIF Index that exploit the forecasts from linear, MSI and MSIH models when transaction cost are considered (TC) and when they are not included (No TC). Transactions costs are set to 0.25% for the S&P 500 and the NCREIF Index and to 0.10% for Treasury bonds. The utility gain measures the risk-free compensation an investor is ready to pay to switch from a strategy on the historical sample mean to a strategy based on predictability and/or MS.

Panel A - 3 months

	LINEAR						MSI						MSIH					
	Mean Exc. Return		Sharpe Ratio		Utility Gain		Mean Exc. Return		Sharpe Ratio		Utility Gain		Mean Exc. Return		Sharpe Ratio		Utility Gain	
	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC
EP	4.27%	4.91%	0.6380	0.7331	0.0015	0.0008	5.92%	6.58%	0.9284	1.0323	0.0259	0.0257	4.65%	5.29%	0.7321	0.8301	0.0138	0.0129
CAPEX	4.70%	5.40%	0.6744	0.7739	-0.0011	-0.0012	5.73%	6.40%	0.8440	0.9434	0.0137	0.0137	5.32%	5.97%	0.8134	0.9129	0.0159	0.0154
CONS	4.81%	5.48%	0.7101	0.8101	0.0049	0.0049	5.17%	5.85%	0.8310	0.9364	0.0223	0.0216	5.25%	5.90%	0.8238	0.9270	0.0194	0.0191
ICS	4.98%	5.65%	0.7269	0.8270	0.0048	0.0049	5.73%	6.39%	0.8497	0.9462	0.0148	0.0144	5.49%	6.12%	0.8526	0.9481	0.0201	0.0190
INCG	4.74%	5.44%	0.6836	0.7842	0.0002	0.0002	5.72%	6.38%	0.8308	0.9293	0.0113	0.0113	5.55%	6.21%	0.8122	0.9100	0.0108	0.0107
LMKT	4.47%	5.17%	0.6290	0.7262	-0.0068	-0.0069	5.26%	5.93%	0.8161	0.9185	0.0176	0.0172	4.91%	5.57%	0.7468	0.8465	0.0109	0.0104
NCREIFMOM	5.13%	5.79%	0.7327	0.8294	0.0025	0.0026	5.54%	6.19%	0.8882	0.9935	0.0257	0.0253	5.52%	6.16%	0.8621	0.9623	0.0213	0.0209
AllPredictors	5.58%	6.23%	0.9121	1.0185	0.0290	0.0286	5.80%	6.44%	0.7911	0.8782	0.0009	0.0003	5.41%	6.04%	0.8485	0.9469	0.0209	0.0201

Panel B - 6 months

	LINEAR						MSI						MSIH					
	Mean Exc. Return		Sharpe Ratio		Utility Gain		Mean Exc. Return		Sharpe Ratio		Utility Gain		Mean Exc. Return		Sharpe Ratio		Utility Gain	
	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC
EP	3.75%	4.03%	0.5061	0.5440	0.0109	0.0105	5.74%	6.05%	0.8749	0.9224	0.0522	0.0518	4.49%	4.78%	0.7423	0.7877	0.0525	0.0515
CAPEX	4.93%	5.27%	0.5877	0.6279	-0.0017	-0.0018	5.99%	6.31%	0.8432	0.8884	0.0411	0.0409	5.76%	6.08%	0.8599	0.9063	0.0488	0.0485
CONS	4.84%	5.17%	0.6042	0.6451	0.0067	0.0066	5.67%	5.99%	0.8830	0.9309	0.0549	0.0543	4.79%	5.10%	0.6379	0.6795	0.0187	0.0186
ICS	5.10%	5.43%	0.6369	0.6780	0.0095	0.0095	5.90%	6.21%	0.8139	0.8573	0.0365	0.0363	5.55%	5.86%	0.7895	0.8319	0.0384	0.0379
INCG	5.00%	5.34%	0.5994	0.6401	0.0003	0.0003	5.97%	6.29%	0.8416	0.8867	0.0411	0.0409	5.71%	6.03%	0.8245	0.8705	0.0427	0.0425
LMKT	4.80%	5.13%	0.5739	0.6140	-0.0022	-0.0023	5.45%	5.77%	0.8490	0.8961	0.0527	0.0520	5.05%	5.38%	0.6831	0.7246	0.0243	0.0236
NCREIFMOM	5.13%	5.45%	0.6392	0.6797	0.0093	0.0093	5.48%	5.79%	0.8120	0.8571	0.0449	0.0444	4.94%	5.24%	0.6968	0.7404	0.0310	0.0307
AllPredictors	5.59%	5.90%	0.8555	0.9028	0.0513	0.0509	5.66%	5.97%	0.8705	0.9163	0.0527	0.0522	5.75%	6.05%	0.8519	0.8957	0.0475	0.0469

Panel C - 60 months

	LINEAR						MSI						MSIH					
	Mean Exc. Return		Sharpe Ratio		Utility Gain		Mean Exc. Return		Sharpe Ratio		Utility Gain		Mean Exc. Return		Sharpe Ratio		Utility Gain	
	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC
EP	3.39%	3.41%	0.4928	0.4944	-0.0048	-0.0054	4.34%	4.37%	0.5711	0.5733	-0.0134	-0.0139	3.86%	3.88%	0.5276	0.5296	-0.0111	-0.0115
CAPEX	4.50%	4.53%	0.6289	0.6331	-0.0005	-0.0005	4.55%	4.58%	0.6151	0.6190	-0.0062	-0.0062	4.52%	4.55%	0.6400	0.6442	0.0017	0.0017
CONS	4.49%	4.52%	0.6247	0.6288	-0.0016	-0.0017	4.61%	4.64%	0.5797	0.5831	-0.0194	-0.0195	4.53%	4.56%	0.6384	0.6426	0.0011	0.0011
ICS	4.46%	4.49%	0.6338	0.6381	0.0020	0.0020	4.55%	4.58%	0.6323	0.6364	-0.0011	-0.0011	4.43%	4.46%	0.6300	0.6339	0.0017	0.0017
INCG	4.47%	4.50%	0.6297	0.6339	0.0004	0.0004	4.53%	4.56%	0.6149	0.6188	-0.0058	-0.0058	4.49%	4.52%	0.6441	0.6482	0.0037	0.0037
LMKT	4.49%	4.52%	0.6247	0.6288	-0.0015	-0.0015	4.57%	4.60%	0.6084	0.6123	-0.0089	-0.0090	4.53%	4.56%	0.6403	0.6445	0.0017	0.0017
NCREIFMOM	4.48%	4.51%	0.6315	0.6358	0.0008	0.0008	4.59%	4.62%	0.6024	0.6060	-0.0113	-0.0114	4.50%	4.53%	0.6389	0.6431	0.0022	0.0022
AllPredictors	3.56%	3.58%	0.5767	0.5790	0.0147	0.0143	4.31%	4.34%	0.5614	0.5638	-0.0156	-0.0160	4.25%	4.27%	0.5565	0.5587	-0.0151	-0.0155

Table 5: Private Real Estate – Mean-Variance Weights ($\gamma = 5$)

The table reports the mean, median, and standard deviation of the optimal MV weights of the risky assets over the OOS period January 2005 – December 2018 when the historical mean, a linear, and a MS model based on the entire set of predictive variables are used to forecast NCREIF returns over the three different investment horizons. The weight of the risk-free asset is not reported because it is equal to one minus the sum of the weights in the three risky assets.

Horizon	**3 months**			**6 months**			**60 months**		
				Panel A - Historical Mean Forecasts					
	S&P 500	10y Treasury	NCREIF	S&P 500	10y Treasury	NCREIF	S&P 500	10y Treasury	NCREIF
Mean	70.88%	150.00%	150.00%	62.69%	150.00%	150.00%	71.64%	150.00%	107.97%
Median	72.91%	150.00%	150.00%	65.02%	150.00%	150.00%	53.05%	150.00%	150.00%
St. Dev.	9.19%	0.00%	0.00%	9.46%	0.00%	0.00%	51.92%	0.00%	62.85%
				Panel B - Linear Model Forecasts					
	S&P 500	10y Treasury	NCREIF	S&P 500	10y Treasury	NCREIF	S&P 500	10y Treasury	NCREIF
Mean	73.57%	145.13%	128.95%	65.86%	145.23%	127.63%	71.64%	150.00%	36.32%
Median	72.44%	150.00%	150.00%	65.61%	150.00%	150.00%	50.77%	150.00%	32.80%
St. Dev.	19.33%	16.85%	52.57%	17.05%	17.22%	52.97%	51.61%	0.00%	37.27%
				Panel C - Markov Switching Model					
	S&P 500	10y Treasury	NCREIF	S&P 500	10y Treasury	NCREIF	S&P 500	10y Treasury	NCREIF
Mean	87.64%	150.00%	150.00%	61.76%	141.37%	123.96%	71.94%	150.00%	75.89%
Median	90.93%	150.00%	150.00%	61.46%	150.00%	150.00%	52.65%	150.00%	69.33%
St. Dev.	10.18%	0.00%	0.00%	23.63%	30.48%	56.96%	51.39%	0.00%	63.06%

Table 6: Mean-Variance Realized OOS Performance over Subsamples ($\gamma = 5$)

Panel A of the table shows the realized (pseudo) out-of-sample performance for a sequence of recursive mean-variance asset allocations in 3-month T-bills, the S&P 500, 10-year Treasury bonds, and the NCREIF Index for an investment horizon of three months over two subsamples assuming the presence of transaction costs. Panel B of the table shows the realized (pseudo) out-of-sample performances for a sequence of recursive mean-variance asset allocations in 1-month T-bills, the S&P 500, 10-year Treasury bonds, and the FTSE NAREIT Index for an investment horizon of one month over two subsamples assuming the presence of transaction costs. Transactions costs are set to 0.25% for the S&P 500, the FTSE NAREIT and the NCREIF Index and to 0.10% for Treasury bonds. The utility gain measures the risk-free compensation an investor is ready to pay to switch from a strategy on the historical sample mean to a strategy based on predictability and/or MS.

Panel A - Private Real Estate

	First Subsample: January 2005 - December 2011						Second Subsample: January 2012 - December 2018					
	LINEAR			MSIH			LINEAR			MSIH		
	Mean Exc. Return	Sharpe Ratio	Utility Gain	Mean Exc. Return	Sharpe Ratio	Utility Gain	Mean Exc. Return	Sharpe Ratio	Utility Gain	Mean Exc. Return	Sharpe Ratio	Utility Gain
EP	3.06%	0.3678	0.0025	4.02%	0.5065	0.0215	5.44%	1.2137	0.0020	5.26%	1.1998	0.0026
CAPEX	3.91%	0.4427	-0.0022	5.32%	0.6426	0.0259	5.46%	1.2029	0.0007	5.32%	1.2071	0.0027
CONS	4.08%	0.4800	0.0080	5.16%	0.6450	0.0313	5.52%	1.2013	0.0000	5.33%	1.2109	0.0029
ICS	4.65%	0.5338	0.0083	5.81%	0.7136	0.0341	5.29%	1.1752	0.0000	5.17%	1.1986	0.0035
INCG	3.97%	0.4526	0.0002	5.82%	0.6642	0.0188	5.49%	1.1992	0.0001	5.29%	1.2066	0.0029
LMKT	3.51%	0.3905	-0.0102	4.49%	0.5414	0.0172	5.39%	1.1737	-0.0013	5.31%	1.1968	0.0018
NCREIFMOM	4.82%	0.5390	0.0044	5.69%	0.7113	0.0365	5.42%	1.1932	0.0002	5.35%	1.1913	0.0008
AllPredictors	5.95%	0.7945	0.0518	5.71%	0.7123	0.0364	5.22%	1.1543	-0.0012	5.11%	1.1711	0.0016

Panel B - Public Real Estate

	First Subsample: January 2005 - December 2011						Second Subsample: January 2012 - December 2018					
	LINEAR			MSIH			LINEAR			MSIH		
	Mean Exc. Return	Sharpe Ratio	Utility Gain	Mean Exc. Return	Sharpe Ratio	Utility Gain	Mean Exc. Return	Sharpe Ratio	Utility Gain	Mean Exc. Return	Sharpe Ratio	Utility Gain
DY	0.00%	0.0008	-0.0005	-0.02%	-0.0033	-0.0146	0.25%	0.0864	0.0025	0.23%	0.0672	-0.0100
PBOOK	-0.03%	-0.0046	-0.0397	0.34%	0.0388	-0.0759	0.28%	0.0955	0.0038	0.23%	0.0672	-0.0099
PFFO	-0.17%	-0.0275	-0.0165	0.33%	0.0410	-0.0559	0.25%	0.0863	0.0024	0.27%	0.0854	-0.0030
ICS	0.16%	0.0299	0.0118	0.04%	0.0048	-0.0479	0.30%	0.0888	-0.0075	0.28%	0.0793	-0.0128
CONS	-0.12%	-0.0155	-0.0606	-0.06%	-0.0066	-0.0950	0.29%	0.0966	0.0020	0.27%	0.0838	-0.0037
LMKT	0.22%	0.0398	0.0046	-0.18%	-0.0269	-0.0281	0.28%	0.0772	-0.0132	0.24%	0.0697	-0.0119
REITMOM	0.39%	0.0512	-0.0458	0.51%	0.0722	-0.0294	0.22%	0.0663	-0.0079	0.23%	0.0682	-0.0095
INCG	0.02%	0.0030	-0.0383	0.20%	0.0267	-0.0461	0.42%	0.1262	-0.0061	0.36%	0.1140	-0.0026
AllPredictors	0.73%	0.0775	-0.0865	0.51%	0.0468	-0.1275	0.57%	0.1469	-0.0177	0.62%	0.1636	-0.0146

Table 7: Public Real Estate – Mean-Variance Realized OOS Performance ($\gamma = 5$)

The table shows the realized (pseudo) out-of-sample performance for a sequence of recursive mean-variance allocations in 1-month T-bills, the S&P 500, 10-year Treasury bonds, and the FTSE NAREIT Index that exploit the forecasts from linear, MSI and MSIH models when transaction cost are considered (TC) and when they are not included (No TC). Transactions costs are set to 0.25% for the S&P 500 and the FTSE NAREIT Index and to 0.10% for Treasury bonds. The utility gain measures the risk-free compensation an investor is ready to pay to switch from a strategy on the historical sample mean to a strategy based on predictability and/or MS.

Panel A - 1 month

	LINEAR						MSI						MSIH					
	Mean Exc. Return		Sharpe Ratio		Utility Gain		Mean Exc. Return		Sharpe Ratio		Utility Gain		Mean Exc. Return		Sharpe Ratio		Utility Gain	
	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC
DY	0.15%	0.47%	0.0338	0.1057	0.0011	0.0010	0.07%	0.41%	0.0139	0.0776	-0.0196	-0.0194	0.07%	0.41%	0.0148	0.0842	-0.0117	-0.0116
PBOOK	0.13%	0.45%	0.0261	0.0905	-0.0135	-0.0135	0.15%	0.48%	0.0250	0.0822	-0.0345	-0.0343	0.18%	0.53%	0.0295	0.0883	-0.0381	-0.0379
PFFO	0.06%	0.38%	0.0132	0.0818	-0.0063	-0.0062	0.06%	0.40%	0.0099	0.0700	-0.0311	-0.0309	0.27%	0.62%	0.0470	0.1092	-0.0278	-0.0277
ICS	0.24%	0.56%	0.0547	0.1291	0.0042	0.0041	0.14%	0.49%	0.0257	0.0866	-0.0286	-0.0285	0.19%	0.54%	0.0349	0.0998	-0.0228	-0.0225
CONS	0.06%	0.39%	0.0111	0.0686	-0.0326	-0.0324	0.15%	0.51%	0.0236	0.0804	-0.0451	-0.0447	0.14%	0.49%	0.0219	0.0767	-0.0490	-0.0488
LMKT	0.24%	0.60%	0.0530	0.1298	-0.0017	-0.0015	0.13%	0.47%	0.0271	0.0980	-0.0074	-0.0071	0.04%	0.39%	0.0085	0.0786	-0.0119	-0.0115
REITMOM	0.28%	0.62%	0.0508	0.1129	-0.0250	-0.0248	0.28%	0.62%	0.0446	0.0992	-0.0430	-0.0431	0.35%	0.71%	0.0690	0.1378	-0.0141	-0.0138
INCG	0.26%	0.60%	0.0482	0.1113	-0.0214	-0.0211	0.25%	0.60%	0.0434	0.1022	-0.0332	-0.0329	0.25%	0.59%	0.0458	0.1101	-0.0219	-0.0218
AllPredictors	0.61%	1.00%	0.1026	0.1682	-0.0316	-0.0314	0.76%	1.16%	0.0994	0.1519	-0.0731	-0.0727	0.53%	0.92%	0.0793	0.1378	-0.0507	-0.0504

Panel B - 6 months

	LINEAR						MSI						MSIH					
	Mean Exc. Return		Sharpe Ratio		Utility Gain		Mean Exc. Return		Sharpe Ratio		Utility Gain		Mean Exc. Return		Sharpe Ratio		Utility Gain	
	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC
DY	0.53%	0.58%	0.1032	0.1147	0.0486	0.0146	0.69%	0.75%	0.1231	0.1338	0.0033	0.0033	1.01%	1.08%	0.1789	0.1909	0.0060	0.0059
PBOOK	0.57%	0.63%	0.0960	0.1063	-0.0203	-0.0056	0.76%	0.81%	0.1407	0.1517	0.0102	0.0101	0.96%	1.03%	0.1750	0.1869	0.0090	0.0088
PFFO	0.46%	0.52%	0.0904	0.1020	0.0190	0.0135	0.92%	0.98%	0.1703	0.1817	0.0109	0.0107	0.91%	0.97%	0.1672	0.1790	0.0104	0.0102
ICS	0.53%	0.59%	0.0637	0.0713	-0.0790	-0.0655	0.99%	1.05%	0.2058	0.2178	0.0267	0.0263	1.14%	1.21%	0.2158	0.2271	0.0158	0.0152
CONS	0.37%	0.43%	0.0473	0.0550	0.0117	-0.0538	0.85%	0.91%	0.1780	0.1904	0.0254	0.0252	1.17%	1.23%	0.1958	0.2061	-0.0009	-0.0013
LMKT	0.45%	0.50%	0.0790	0.0892	0.0539	0.0000	0.84%	0.90%	0.1690	0.1808	0.0212	0.0210	0.94%	1.00%	0.1787	0.1906	0.0152	0.0149
REITMOM	0.55%	0.61%	0.0975	0.1078	0.0011	0.0010	0.84%	0.90%	0.1635	0.1748	0.0164	0.0161	1.08%	1.15%	0.1849	0.1962	0.0017	0.0014
INCG	0.45%	0.51%	0.0876	0.0986	0.0118	0.0129	0.83%	0.89%	0.1667	0.1785	0.0211	0.0209	1.04%	1.11%	0.2007	0.2132	0.0173	0.0170
AllPredictors	0.74%	0.81%	0.1042	0.1136	-0.0339	-0.0340	0.82%	0.89%	0.1464	0.1573	0.0044	0.0042	0.95%	1.02%	0.1507	0.1609	-0.0117	-0.0118

Panel C - 60 months

	LINEAR						MSI						MSIH					
	Mean Exc. Return		Sharpe Ratio		Utility Gain		Mean Exc. Return		Sharpe Ratio		Utility Gain		Mean Exc. Return		Sharpe Ratio		Utility Gain	
	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC	TC	No TC
DY	1.41%	1.42%	0.1781	0.1789	-0.0090	-0.0092	1.50%	1.51%	0.1800	0.1807	-0.0186	-0.0188	1.44%	1.45%	0.1717	0.1724	-0.0212	-0.0214
PBOOK	1.45%	1.46%	0.1922	0.1930	0.0007	0.0005	1.61%	1.62%	0.1915	0.1923	-0.0196	-0.0198	1.54%	1.55%	0.1866	0.1875	-0.0163	-0.0165
PFFO	1.37%	1.38%	0.1791	0.1800	-0.0023	-0.0025	1.55%	1.56%	0.1798	0.1806	-0.0252	-0.0254	1.52%	1.53%	0.1771	0.1779	-0.0245	-0.0246
ICS	1.55%	1.56%	0.1995	0.2006	-0.0044	-0.0044	1.69%	1.70%	0.1947	0.1956	-0.0258	-0.0259	1.65%	1.66%	0.1871	0.1880	-0.0290	-0.0291
CONS	1.55%	1.56%	0.2032	0.2045	-0.0005	-0.0004	1.71%	1.72%	0.1823	0.1831	-0.0432	-0.0433	1.68%	1.70%	0.1796	0.1804	-0.0430	-0.0431
LMKT	1.55%	1.56%	0.1951	0.1962	-0.0078	-0.0078	1.69%	1.70%	0.1959	0.1968	-0.0244	-0.0244	1.66%	1.67%	0.1863	0.1872	-0.0314	-0.0315
REITMOM	1.58%	1.59%	0.1885	0.1894	-0.0191	-0.0191	1.70%	1.71%	0.1935	0.1943	-0.0280	-0.0282	1.70%	1.71%	0.1894	0.1903	-0.0330	-0.0331
INCG	1.48%	1.49%	0.1970	0.1980	0.0014	0.0014	1.68%	1.69%	0.1950	0.1959	-0.0244	-0.0245	1.71%	1.72%	0.1914	0.1923	-0.0309	-0.0310
AllPredictors	1.31%	1.32%	0.1811	0.1818	0.0073	0.0070	1.39%	1.40%	0.1892	0.1900	0.0045	0.0043	1.45%	1.46%	0.1815	0.1822	-0.0109	-0.0112

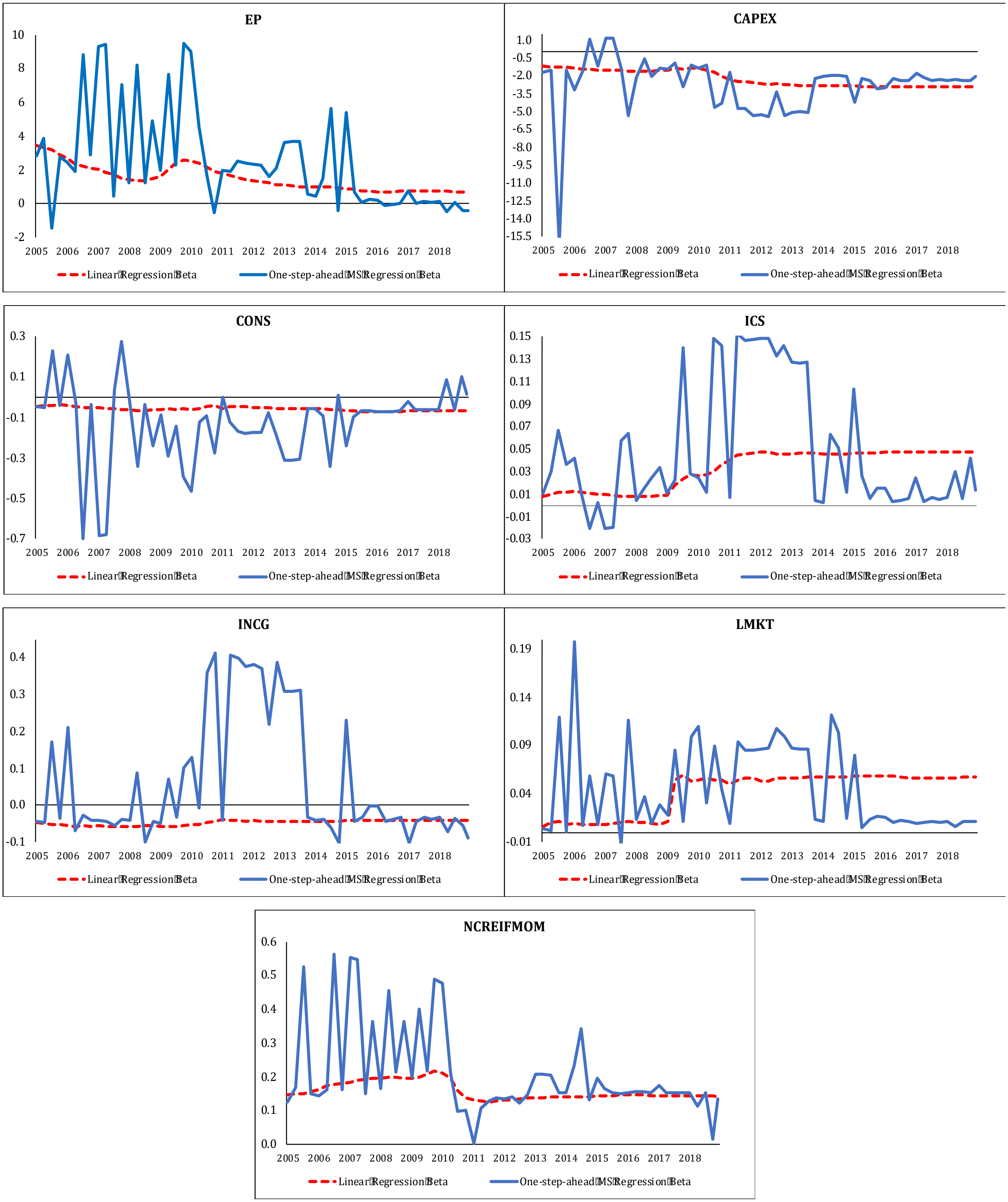
Table 8: Public Real Estate – Mean-Variance Weights ($\gamma = 5$)

The table reports the mean, median, and standard deviation of the optimal MV weights of the risky assets over the OOS period January 2005 – December 2018 when the historical mean, a linear, and a MS model based on the entire set of predictive variables are used to forecast FTSE NAREIT index returns over the three different investment horizons. The weight of the risk-free asset is not reported because it is equal to one minus the sum of the weights in the three risky assets.

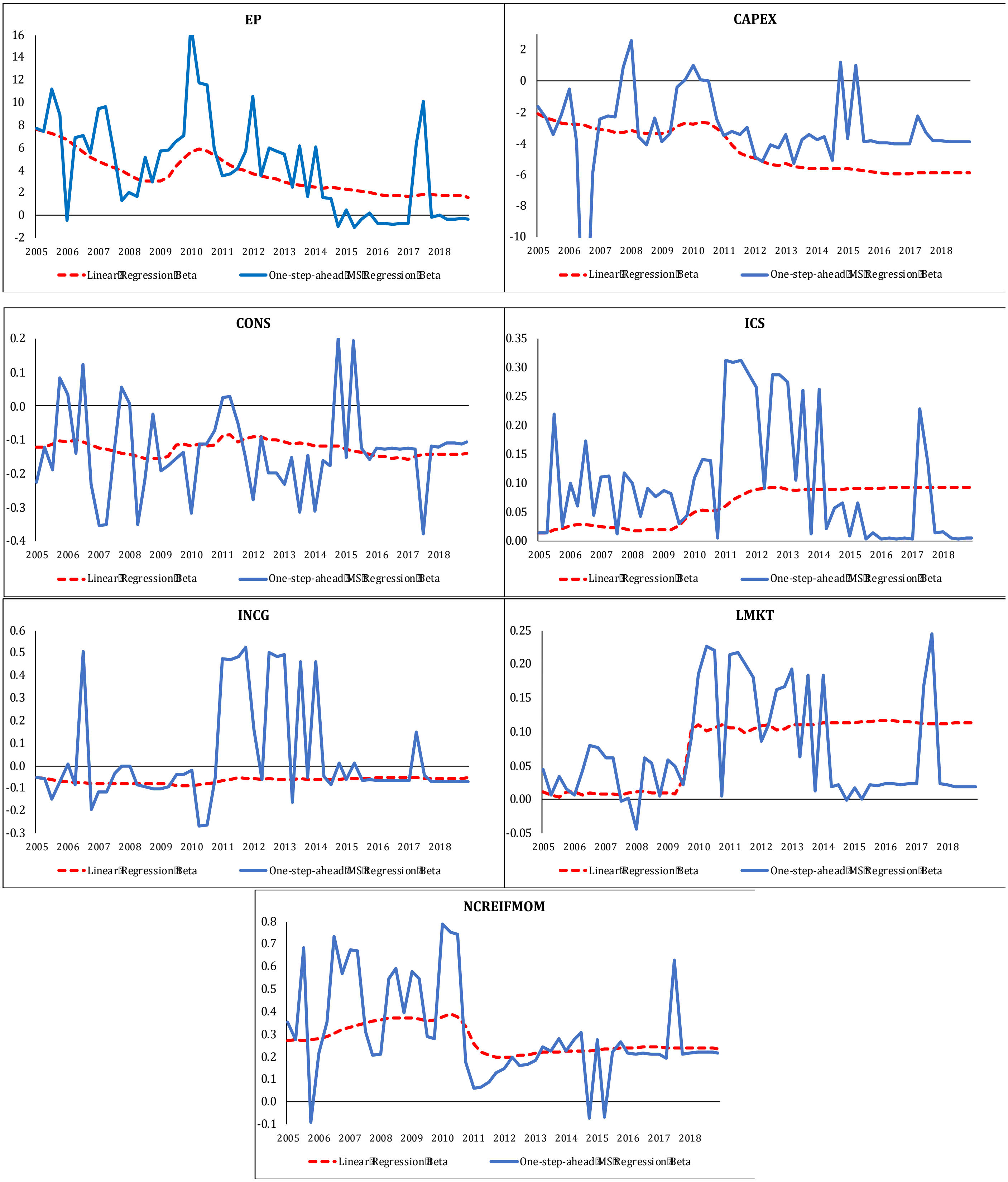
Horizon	**3 months**			**6 months**			**60 months**		
Panel A - Historical Mean Forecasts									
	S&P 500	10y Treasury	REITS	S&P 500	10y Treasury	REITS	S&P 500	10y Treasury	REITS
Mean	35.04%	132.79%	38.49%	40.11%	138.13%	38.96%	104.26%	142.47%	80.66%
Median	33.84%	147.81%	22.67%	44.18%	150.00%	20.35%	107.26%	150.00%	67.04%
St. Dev.	12.98%	20.33%	29.96%	12.90%	16.91%	31.72%	29.45%	32.34%	52.58%
Panel B - Linear Model Forecasts									
	S&P 500	10y Treasury	REITS	S&P 500	10y Treasury	REITS	S&P 500	10y Treasury	REITS
Mean	58.86%	126.59%	47.01%	55.23%	129.55%	54.76%	106.27%	144.95%	31.76%
Median	51.73%	148.84%	7.06%	46.80%	150.00%	19.98%	110.26%	150.00%	0.00%
St. Dev.	52.18%	37.20%	60.81%	51.04%	30.00%	63.16%	31.94%	25.39%	55.81%
Panel C - Markov Switching Model									
	S&P 500	10y Treasury	REITS	S&P 500	10y Treasury	REITS	S&P 500	10y Treasury	REITS
Mean	56.78%	121.90%	51.06%	41.76%	131.37%	61.61%	102.20%	143.10%	51.52%
Median	51.33%	147.86%	12.66%	29.04%	150.00%	46.42%	107.40%	150.00%	0.00%
St. Dev.	53.22%	43.87%	62.48%	46.60%	29.56%	60.51%	32.90%	31.08%	64.64%

Figure 1: OOS Beta Coefficients (All Predictors Model)

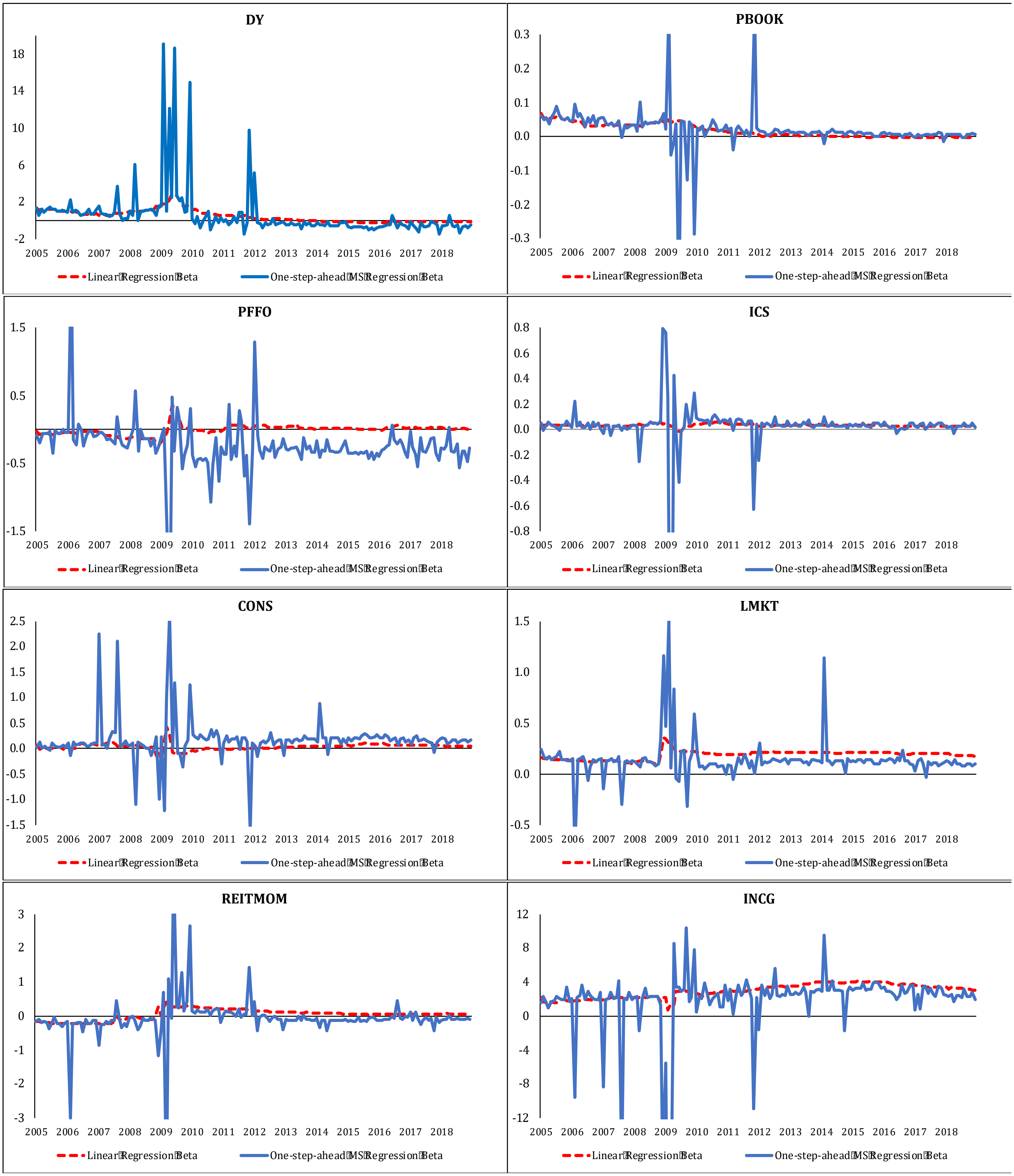
Panel A – Private Real Estate (3-month Horizon)



Panel B – Private Real Estate (6-month Horizon)



Panel C – Public Real Estate (1-month Horizon)



Panel D – Public Real Estate (6-month Horizon)

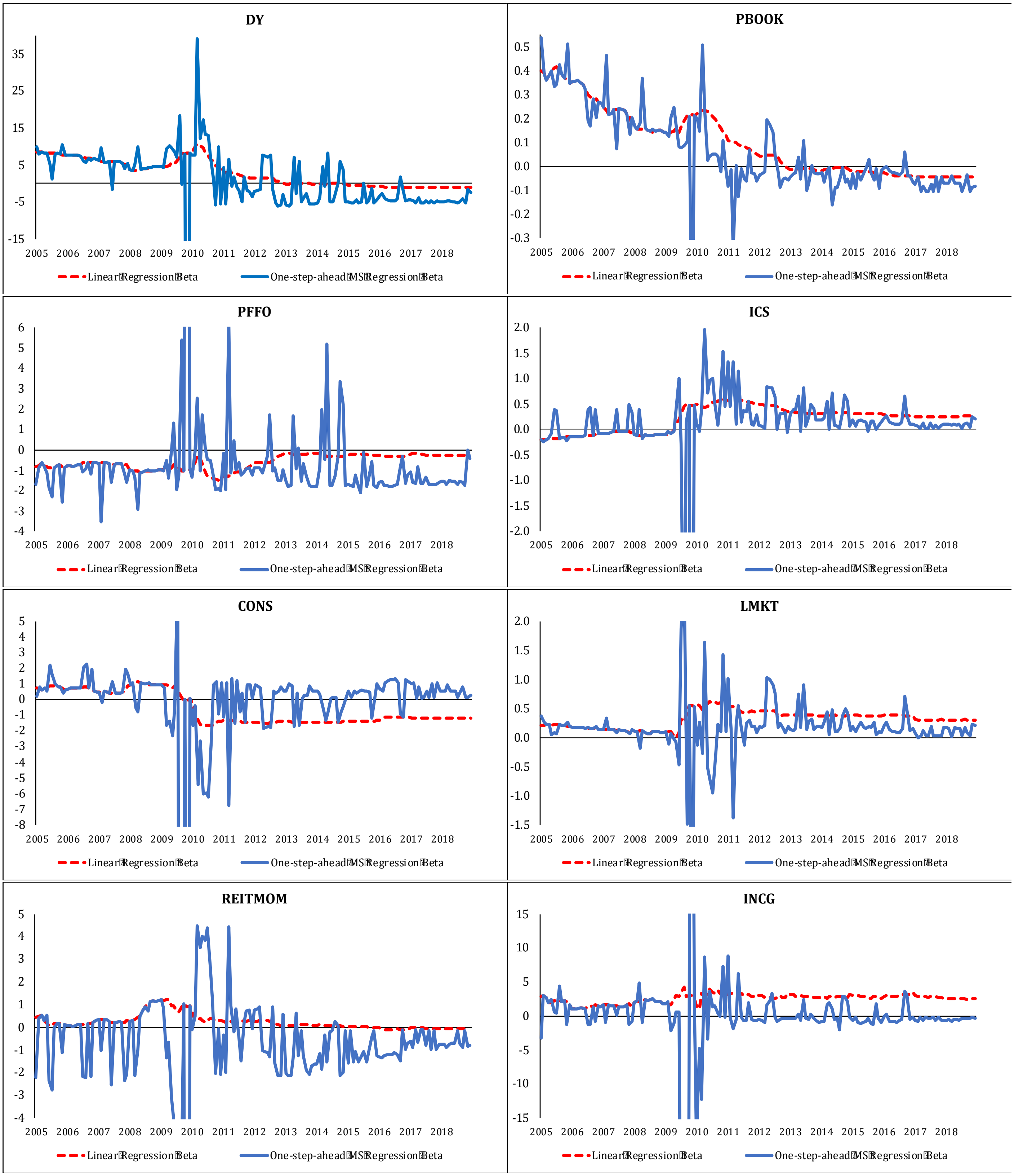
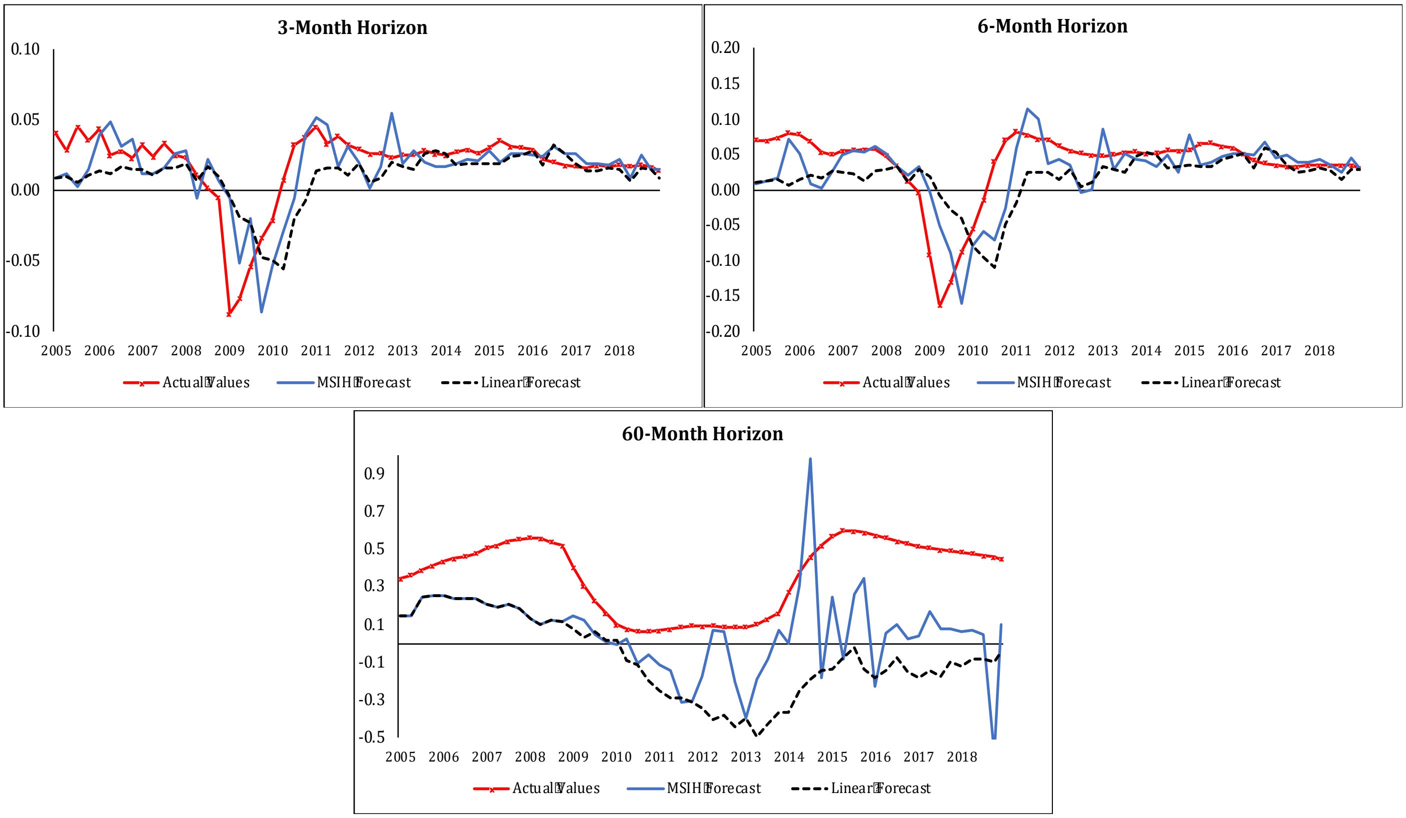


Figure 2: Forecasts (All Predictors Models)

Panel A – Private Real Estate



Panel B – Public Real Estate