Forecasting Real Estate Prices\textsuperscript{*}

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Abstract

This chapter reviews the evidence of predictability in US residential and commercial real estate markets. First, we highlight the main methodologies used in the construction of real estate indices, their underlying assumptions and their impact on the stochastic properties of the resultant series. We then survey the key empirical findings in the academic literature, including short-run persistence and long-run reversals in the log changes of real estate prices. Next, we summarize the ability of local as well as aggregate variables to forecast real estate returns. We illustrate a number of these results by relying on six aggregate indexes of the prices of unsecuritized (residential and commercial) real estate and REITs. The effect of leverage and monetary policy is also discussed.

Keywords: real estate, predictability, market efficiency, REIT.

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1 Introduction

The importance of real estate as an asset class cannot be overstated. Its total value in the US as of 2005 was about $35 trillion, of which $25 trillion was in residential properties (Case (2007)). By comparison, at the end of the same year, the capitalization of the US stock market was in the neighborhood of $17 trillion. Moreover, recent history suggests that fluctuations in real estate prices, whether in bubble or burst mode, have the potential to buoy up or wreak havoc on the financial sector and the rest of the economy. Some of that impact is due to leverage and the fact that real estate is the easiest asset to borrow against, especially from a household’s perspective. Indeed, in 2005, about $12 trillion of outstanding mortgage debt had been issued against the value of properties.1

But the connection between real estate and the macroeconomy is not a bubbles-only phenomenon. Case, Quigley, and Shiller (2005) show that variations in real estate prices have had a significant effect on aggregate consumption in the US, in fact more significant than the stock market, even before the recent volatility in the residential market. Reinhart and Rogoff (2009) document this to be the case more universally across a number of countries and over longer time periods. From an economic perspective, understanding what drives real estate values is no less important than is understanding the pricing dynamics of other asset classes, such as stocks, bonds, commodities, and currencies.

The real estate market is different from other financial markets in several important aspects. It is characterized by extreme heterogeneity due to the location and physical attributes of a property. Participants in that market face large transaction costs, carrying costs, illiquidity, and tax considerations. They also face large search costs stemming from real estate’s heterogeneity. Investors cannot exploit forecast decreases in property values, because of the impossibility to short sale the asset and the absence of liquid real estate futures contracts. These large frictions suggest that the real estate market might generally not be efficient in the sense that other financial markets are (e.g., Fama (1970)). But before we can talk about market efficiency, which implies that some investors are able to take advantage of profit opportunities, we first must investigate whether price changes are in fact statistically predictable.

The presence of frictions does not imply that predicting real estate returns is an easy task. In

1Federal Reserve Board’s Statistics and Historical Data (1.54). http://www.federalreserve.gov/econresdata/releases/mortoutstand/mortoutstand20090331.htm
practice, the opposite is true. An illustration of this fact can be gleaned from the transcripts of the Federal Open Market Committee’s (FOMC) 2006 discussions, which were held at the peak of the recent housing bubble. This was a time when a growing consensus amongst economists that residential prices were inflated coincided with a growing uncertainty about their future direction. The transcripts reveal that most FOMC participants shared the opinion that we were in for a “a soft landing or a period of stabilization after several years of strong price appreciation.” Now, with the benefit of hindsight and the Great Recession behind us, we know that this prediction was considerably off the mark. Long-horizon forecasts can be equally challenging to make. One such forecast was formulated by Mankiw and Weil (1989) who argued that the rise of housing prices in the 1970s and 1980s was mostly due to the Baby Boom generation entering the residential market. Based on these findings and reasoning that future demand for housing will decrease over the next twenty years, the authors predicted that “real housing prices will fall substantially - indeed, real housing prices may well reach levels lower than those experienced at any time in the past forty years.” Now, twenty or more years after Mankiw and Weil (1989) formulated this forecast, we have observed that the trends and volatility in the housing market were driven by factors other than demographic fundamentals.

In this chapter, we review the literature on return predictability in real estate markets. Many of the papers on this topic involve the use of indices at the city, regional, or national level rather than individual property prices. This is due to one obvious reason: real estate transactions are very infrequent. Hence, as a starting point, we discuss the construction and underlying assumptions behind some of the most widely used residential and commercial real estate indices. The distinction between residential and commercial properties is important as they tend to have different dynamics and return properties (Geltner and Miller (2006)). The difference is not surprising as a household’s decision to purchase a home—presumably driven not only by investment considerations but also by the need to consume a housing unit—is quite different from that of an investor looking to purchase a retail property (Flavin and Yamashita (2002)). Perhaps the most transparent residential index is the median sales price, versions of which are provided by the Census Bureau and the National Association of Realtors (NAR). While it is easy to construct and interpret, it does not adjust for the quality of properties that are on the market and thus confounds fluctuations in prices with fluc-

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tuations in real estate attributes. The fact that it is not a “constant quality” index makes it less desirable than some of the alternatives which specifically adjust for property attributes. Examples of constant-quality indices include, for residential properties, the Case-Shiller and the Federal Housing Finance Agency (FHFA) repeat-sales prices and, for commercial properties, the National Council of Real Estate Investment Fiduciaries’s Transaction-Based (TBI) hedonic prices. We discuss these and other indices in some detail in Section 2, because their statistical properties are determined as much by assumptions behind their construction as by market forces. Understandably, much creative energy and papers have been devoted to this topic. Without reliable indices, empirical research in real estate is virtually impossible.

To get a glimpse into the aggregate real estate data, in Figures 1 and 2 we plot three residential and three commercial indices that have been widely used in the literature and whose properties we will analyze in this Chapter. It is immediately clear that the three time-series in Figure 1 do not exhibit the same dynamics despite the fact that they are all intended to measure the same price appreciation of houses in the US. For instance, the growth rate (not the level) of the Case-Shiller index has a serial correlation of 0.939. Some of that serial correlation is due to the way the index is constructed and some of it is undoubtedly due to economic frictions. The same statistic for the growth rate of the Census median price is -0.517. Similarly dramatic differences are evident in Figure 2, where the price of a real estate investment trusts (REIT) portfolio exhibits volatility that dwarfs that of the other two indices. Before we can use these time-series, we have to understand how they are constructed, what they measure, and whether they are suitable for forecasting. In Section 2.1, we discuss the various types of real estate indices, provide details behind their constructions and, in Section 2.2, we present their summary statistics.

Predictive regressions in the real estate literature in many respects mirror those in other asset classes. The forecasted quantity, often future price changes or returns, is regressed on a set of predetermined variables, which are chosen to test a set of economic hypotheses. It is useful to divide predictive regressions into three categories based on the predictors and maintained hypotheses. First, if the predictor is lagged returns as in Gau (1984), Gau (1985), Linneman (1986), Guntermann and Smith (1987), Rayburn, Devaney, and Evans (1987), Case and Shiller (1989), McIntosh and Henderson (1989), Gyourko and Voith (1992), Kuo (1996), Hill, Sirmans, and Knight (1997),

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3 The indices are defined in detail below.
Hill, Sirmans, and Knight (1999), Gu (2002), and Schindler (2011), this is a test of weak-form market efficiency (Fama (1970)). However, simple serial dependence tests in real estate are complicated by the fact that the price changes of some indices are serially correlated by construction, making it difficult to disentangle spurious correlations from actual market inefficiencies. The evidence of weak-form market efficiency is presented in Section 3.1.

Second, valuation ratios – such as the rent-price ratio or price-income ratio – are often used as predictors (e.g., Hamilton and Schwab (1985), Meese and Wallace (1994), Geltner and Mei (1995), Capozza and Seguin (1996), Lamont and Stein (1999), Malpezzi, Himmelberg, Mayer, and Sinai (2005), Campbell, Davis, Gallin, and Martin (2009), Gallin (2008)). We review predictive regression with valuation ratios in Section 3.2. Such regressions are motivated either by the valuation ratios’ ability to detect deviations and slow adjustments toward an equilibrium or because they proxy for time variation in expected returns. However, predictive regressions are inherently reduced-form expressions and cannot identify the economic reasons underlying the time-variation without further modeling structure (Fama and French (1988a)). Also, the evidence points out that valuation ratios are not able to capture all the variation in the conditioning set.

Third, a richer set of hypotheses can be tested by including property- and/or region-specific economic variables, whose aim is to proxy for demand and supply shocks in the real estate market. Such predictors, used, amongst others, by Rosen (1984), Linneman (1986), Skantz and Strickland (1987), Case and Shiller (1990), Abraham and Hendershott (1996), Pace, Barry, Gilley, and Sirmans (2000), MacKinnon and Al Zaman (2009), and Plazzi, Torous, and Valkanov (2010), include demographic variables, income variables, construction costs, and zoning restrictions. One can argue that these regressions account more fully for the heterogeneity in real estate investments. The evidence from these regressions is reviewed in Section 3.3.

Real estate data present some unique challenges in forecasting settings. First, the predictive results have to take into account high transaction costs, which in real estate can be 6 percent, or even higher, of the property value. In addition to the statistical significance, the coefficient estimate must be large enough to cover those costs. Second, the available real estate data is relatively short in its duration and is observed at a monthly or quarterly frequency.\footnote{A notable exception is Eichholtz (1997) whose bi-annual residential index of Amsterdam properties spans the period 1628 to 1973.} Sparse datasets are available from the 1970s, but most empirical work is done with series starting from the 1980s.
or later. The lack of longer and higher-frequency data renders estimation and hypothesis testing difficult. Third, the in-sample fit of predictive regressions is often traced to dichotomous variables for geographical location, coastal proximity, or whether a commercial property is of a certain type (apartments, retail space, offices, or industrial buildings). While these fixed-effects are important in accounting for the heterogeneity of the asset, they are not predictors in the usual sense of the word. They do not change over time and cannot be the source of time-series predictability. Fourth, the predictability evidence is mainly based on in-sample statistics. It is rarely evaluated with mean squared prediction errors (MSPE) or other out-of-sample analysis (West (2006)), mainly because of the severe data limitations. Finally, and related to the previous point, parameter stability and the robustness of the forecasting model are rarely investigated (e.g., Rossi (forthcoming)).

A real-estate-related market that does not suffer from the high transaction costs and infrequent observations issues is that of publicly-traded real estate investment trusts. REITs are exchange-traded funds that derive most of their income from real estate investments and whose returns provide a remarkably clean venue for testing whether or not real estate returns are forecastable. They are traded frequently on a centralized exchange, have relatively low transaction costs, and their total returns, price appreciations, and dividend-price ratio are readily observable. Moreover, REITs are required to distribute at least 90 percent of their taxable income as dividends in order to benefit from a tax-exempt status\(^5\) which makes them particularly appropriate for testing predictive relations. For these reasons, the REIT market has been given particular attention in the real estate literature and we are also devoting special attention to it in Section 4. All this does not imply that empirical work with REITs does not have its limitations. For instance, investing in a REIT is not the same as investing in the underlying commercial property market. The risk-return characteristics of the investments might be different. Ross and Zisler (1991) document that REITs have the risk-return characteristics of small-cap stocks and co-move more with the stock market rather than the underlying real estate market. Hence, the evidence from the REIT predictability literature must be taken with a few caveats.

We supplement the summary of existing findings with our own set of predictive regressions estimated with three residential and three commercial real estate indices at the national (US) level with monthly and quarterly data from the late 1970s or early 1980s (depending on the series) to

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\(^5\)For an investment trust to be qualified as a REIT and to benefit from reduced corporate tax liabilities, it must satisfy a few requirements. See Internal Revenue Code Sect. 856(a).
the end of 2010. We choose to work mainly with aggregate indices as they are available over a long time span and allow us to keep a common set of predictors. Some cross-sectional results are provided using metropolitan level data for residential properties. Following the literature, we run various specifications of the predictive regressions. For all non-REIT indices, the data restricts us to stay with in-sample comparisons. However, with REITs, we are able to estimate a more complete (and interesting) predictive system, to adjust the estimates for known small-sample biases, to impose relevant economic restrictions, to look for predictability at various horizons, and out-of-sample. These results are discussed in Sections 3 and 4.

While the data and empirical methods in the real estate literature are remarkably diverse, they tend to produce a common set of findings, most of which we are able to observe in our aggregate predictive regressions. These stylized facts can be summarized as follows:

- Price changes of repeat-sales and hedonic indices are very positively serially correlated at monthly and quarterly frequency, whereas median price indices exhibit negative serial correlation. The serial correlation of REIT returns is similar to that of small-cap stocks.

- Transaction costs and other frictions are too large for the serial correlation to translate into economic gains for the non-REIT and REIT data.

- Valuation ratios, such as the rent-price ratio or the income-price ratio, have some predictive power, in-sample. It is mostly attributable to time varying expected returns rather than to exploitable market inefficiencies.

- Variables, such as construction costs, demographic changes, and regulatory restrictions, have a sizeable impact on future real estate returns. However, the out-of-sample properties of these forecasts are largely unexplored.

- For REITs, there is weak in-sample evidence of return predictability and stronger evidence for rent-growth predictability. The evidence for out-of-sample predictability is not strong.

- Leverage is positively related to future returns.

We should point out that several of these results obtain in pooled regressions with more cross-sectional than time-series observations. Hence, their “predictive” nature should be taken with some
caution. This is a general theme in real estate research, as the lack of good time-series data prevents us from applying the standard forecasting toolbox. For instance, it precludes the use of what some might consider to be the ultimate forecast evaluation tool: out-of-sample predictive measures, such as the MSPE comparison. The MSPE analysis is mostly asymptotic in nature and, as West (2006) points out, is not useful for studies with only a handful of observations for out of sample evaluation. However, the lack of a long time-series data also raises a host of new interesting questions, such as how to use the richness of the cross-section in formulating and evaluating forecasts.

The portfolio implications of investing in housing have been studied by Ross and Zisler (1991), Goetzmann (1993), Flavin and Yamashita (2002), and Cauley, Pavlov, and Schwartz (2007). Recent papers by Lustig and Van Nieuwerburgh (2005), Campbell and Cocco (2007), and Piazzesi, Schneider, and Tuzel (2007) investigate the connection between housing, consumption, and asset pricing. Becker and Shabani (2010) examine the implications of large household debt (a mortgage) on investment decisions. As a next step, it would be interesting to incorporate predictable real estate returns in the optimal investment decision of households. The portfolio setting would provide a natural measure of the economic importance of real estate return predictability in absolute terms and relative to the predictability of stock and bond returns. A first step in that direction is the work of MacKinnon and Al Zaman (2009) and Plazzi, Torous, and Valkanov (2010).

Following the recent real estate crisis, two research areas have generated considerable interest. First, there has been renewed attention on the role of leverage on house price dynamics. Theoretical work by Stein (1995), McDonald (1999), Spiegel (2001), and Ortalo-Magné and Rady (2006) and the empirical findings of Linneman and Wachter (1989), Genesove and Mayer (1997), and Lamont and Stein (1999), Brown (2000), and Aoki, Proudman, and Vlieghe (2004) suggest that leveraged properties are more sensitive to economic shocks. The main amplifying channel in those papers is due to the fact that a household’s ability to borrow is directly tied to asset values. While not all of the papers we discuss in that section contain direct evidence of real estate predictability, they all suggest that leverage is an important determinant of house price dynamics. In related work, Mian and Sufi (2009), (2010a) analyze the effect of the recent credit expansion on real estate prices. We review this literature in Section 5.1. Second, the recent real estate crisis has focused attention on the effect of monetary policy on real estate prices which we investigate in Section 5.2. Section 6 concludes and offers some direction of the current research.
2 The Real Estate Data

In this section, we summarize the availability of US real estate data.\textsuperscript{6} The focus is on price indices which can naturally be categorized, based on the construction methodology, into four groups: median-price indices, repeat-sales indices, hedonic indices, and stock-market-based indices. In each category, the indices can track either residential or commercial properties.\textsuperscript{7} In subsection 2.1, when introducing the various indices, we pay particular attention to the way they are constructed and the effect of the construction on subsequent forecasting regressions. Subsection 2.2 presents summary statistics for several well-known indices that will be used in the rest of this chapter.

2.1 Real Estate Index Definitions

2.1.1 Median Price Indices

Median price indices track the price at which the median priced home within a particular area trades in a given period. At present, residential median-price indices are provided for U.S. single-family homes by the Federal Housing Finance Agency, the Census Bureau (new homes)\textsuperscript{8}, and by the National Association of Realtors (existing homes)\textsuperscript{9}. They are all available at monthly frequency, but the sample spans vary (see Table 1).

The appeal of median price indices stems from the ease with which they can be computed and their unambiguous interpretation. However, they ignore potentially important changes in the characteristics of the dwellings being sold. In particular, if high-quality and low-quality homes are put on the market at different times, the corresponding median prices may exhibit spurious time series fluctuations due mainly to differences in the quality of the properties. Moreover, it is reasonable to expect the mix of homes sold to be correlated with local economic conditions as more expensive homes will tend to be put on the market in expansionary times. These considerations suggest that a median price index provides not only a noisy but also a systematically biased estimate of the behavior of home prices in a particular market. Because of this, attempts have been made to keep the

\textsuperscript{6}While we try to cover as much ground as possible, the increasing interest in real estate and the lower cost of information acquisition have resulted in an increase of available data sources.

\textsuperscript{7}A third useful categorization is to decompose a property value into land and improvements. Unfortunately, we do not have access to good data on land values.

\textsuperscript{8}See http://www.census.gov/const/www/newressalesindex.html.

\textsuperscript{9}See http://www.realtor.org/.
quality of the median house constant through time when constructing these indices. Corrections also include stratification methods which adjust for compositional changes in the transactions, as in Prasad and Richards (2008).

By far, the two most popular methods to explicitly control for quality and infrequent trading of real estate properties are repeat-sales regressions and hedonic models which we review next.

2.1.2 Repeat-Sales Indices

Repeat-sales indices use information about homes that transact at least twice during the sample period to infer market-wide price movements. Let \( P_{i,t} \) be the price of home \( i \) at the end of period \( t \), and \( p_{i,t} \), its logarithmic transformation. The standard repeat-sales approach models \( p_{i,t} \) as the sum of two components:

\[
p_{i,t} = p_{i,t}^m + e_{i,t}
\]

where \( p_{i,t}^m \) denotes the aggregate real estate index – an equally-weighted portfolio of properties – and \( e_{i,t} \) is a property-specific mean-zero stochastic drift. Shocks to \( e_{i,t} \), denoted by \( \varepsilon_{i,t} = e_{i,t} - e_{i,t-1} \), are assumed to be i.i.d. both cross-sectionally as well as over time, with finite variance \( \sigma^2_\varepsilon \).

We are interested in obtaining estimates of \( p_{i,t}^m \) using a sample of \( I \) individual property transaction prices, but we don’t have observations for the same property in each period. Instead, we have information for home \( i, i = \{1, ..., I\} \), on the date of its initial purchase \( t_i \), the date of its first sale \( t_i + h_i \), with \( h_i \geq 1 \), and the corresponding prices. The subscript \( i \) captures the fact that the transaction dates \( t_i \) and \( t_i + h_i \) are dwelling-specific. Then, following (1), the log return during the \([t_i; t_i + h_i]\) period can be expressed as:

\[
p_{i,t_i+h_i} - p_{i,t_i} = p_{i,t_i+h_i}^m - p_{i,t_i}^m + \sum_{\tau=t_i+1}^{t_i+h_i} \varepsilon_{i,\tau}.
\]

Motivated by this expression, the standard repeat-sales regression (RSR) approach of Bailey, Muth, and Nourse (1963) consists of estimating via ordinary least squares the following cross-sectional regression

\[
y_i = \beta X_i + u_i.
\]
where the dependent variable $y_i$ is the holding period return for home $i$, or $y_i = p_{i,t_i+h_i} - p_{i,t_i}$. The regressor $X_i$ is a dummy variable that contains values for each time period, except for the first. It equals 1 on the first sale date $t_i + h_i$, $-1$ on the purchase date $t_i$, and 0 otherwise. If the purchase period $t_i$ coincides with the first period of the sample, then the purchase date dummy is omitted. If there are a total of $T + 1$ periods, then the $T \times 1$ vector $\hat{\beta}$ provides an estimate of the log price of the aggregate index, or $\hat{p}_m = \hat{\beta}_t$. The value of the log price in the initial period is normalized to zero.

The OLS estimator of (3) is, however, not efficient. In particular, the variance of the error term $u_i = \sum_{\tau=t_i+1}^{t_i+h_i} \varepsilon_{i,\tau}$ increases linearly with the interval of time between the two transaction dates, or $\sigma_{u_i}^2 = h_i \sigma_\varepsilon^2$. As a result, the OLS estimator overweighs the information on transactions that occur after longer time intervals, ignoring the larger noise embedded in their price changes. In this context, the best linear unbiased estimator (BLUE) is a GLS estimator of (3) where each observation is weighted by the inverse of the square root of its holding period. The resultant error terms are now i.i.d. and the system satisfies the Gauss-Markov conditions. This GLS estimator coincides with the maximum likelihood estimator when we assume normality of the underlying $\varepsilon_{i,s}$ (Goetzmann (1992) and references therein).

Case and Shiller (1987) extend model (1) to allow for the presence of noise in individual home prices. Formally, the log price of property $i$ is expressed as

$$p_{i,t} = p_{m,i,t} + e_{i,t} + n_{i,t}$$  \hspace{1cm} (4)

where $n_{i,t}$ is a normal i.i.d. noise factor with finite variance $\sigma_n^2$ which captures imperfections in the housing market. The variance $\sigma_n^2$ is constant across properties because it is determined by market-wide conditions. The three components are assumed to be uncorrelated amongst each other at all leads and lags. Iterating equation (4) over the transaction period $[t_i; t_i + h_i]$, we obtain that $\sigma_{u_i}^2$ now equals the sum of a fixed component, $2\sigma_n^2$, plus a component which is linearly increasing in the length of the holding period, $h_i \sigma_\varepsilon^2$.

The weighted repeat sales (WRS) method of Case and Shiller (1987) adapts the GLS estimator to account for the presence of a constant term in the variance of the error. Its construction is based on a three-step procedure. In the first step, regression (3) is estimated by OLS and the correspond-
ing residuals $\hat{u}_t$ are stored. The second step consists of a weighted least square regression of these residuals squared on a constant and on the time interval between transactions. The constant term of this regression represents an estimate of $2\sigma^2_n$ whereas the slope is an estimate of $\sigma^2_{\epsilon}$. In the third step, a GLS regression of (3) is run where each observation is weighted by the inverse of the square root of the corresponding fitted value from the second step.

Using this methodology, Case and Shiller (1987) construct real estate price indices for Atlanta, Chicago, Dallas, and San Francisco/Oakland relying on nearly 40,000 pairs of transactions over the 1970-1986 period. Compared to median-based indices, the resultant series do not exhibit marked seasonal patterns and display considerable cross-sectional and time-series fluctuations. Further, the weighting implied by the WRS has a substantial effect on the quarter-to-quarter changes in the index as compared to the RSR approach. The improvement is largely attributable to the common component in the error variance, $\sigma^2_n$, being quite substantial, on the order of 6% to 7%. By looking at the ratio between the standard deviation of the estimated index and the average standard error of the estimates, they also show that their WRS index captures quite precisely the level of aggregate prices and its annual differences. Quarterly differences, on the other hand, are quite noisy and poorly estimated.

A variant of the Case and Shiller (1987) methodology has been proposed by Goetzmann and Spiegel (1995). They document that including an intercept term in the matrix $X$ of dummy variables helps reduce biases in the estimation. This fixed “non-temporal” component in housing returns most likely relates to property-specific improvements occurring at the time of a sale, which can be as high as 2% to 3% of the investment. Alternative repeat-sales methodologies include shrinkage-type estimators and Bayesian approaches (e.g., Kuo (1996) and Goetzmann (1992)). Goetzmann (1992) compares the performance of various RSR estimators using simulation on a cross-section of common stocks during a given year. He finds that there seems to be little, if any, advantage to using anything more sophisticated than the GLS estimator when focusing on monthly data and the number of repeat sales observations is large enough relative to the number of intervals estimated.

An appealing feature of the repeat-sales estimator is the fairly limited amount of variables that are required to construct the index, consisting at the very least of prices changes and dates of individual property transactions. Measures of homes characteristics and quality are not directly
used in the estimation but may be needed to identify and exclude properties which have undergone
major quality changes—such as renovations, expansions, or re-zoning—between transactions. The
estimation procedure is computationally tractable, and standard econometric procedures can be
used to construct the relevant statistics.

On the other hand, repeat-sales estimators make use of just a limited number of transactions as
the information on homes that transacted once is neglected. Also, homes that are sold repeatedly
may not be representative of the population as a whole, thus giving rise to a selection bias problem
(Clapp, Giaccotto, and Tirtiroglu (1991), Gatzlaff and Haurin (1998), Quigley (1995)). From a sta-
tistical perspective, the estimation may be inaccurate because of the singularity or near-singularity
of the matrix $X$. This will occur when no or very few transactions are available in a given period.
The practical solution in such a case is to omit the redundant columns, and to calculate the index
over longer time intervals. Single-period returns are then assigned the average return during those
periods. The accuracy of the index increases at lower frequencies, but autocorrelation is induced
in the higher frequency returns. This issue has no clear solution and tends to be more relevant as
we attempt to construct indices in thin markets where the number of properties is large relative to
the turnover.

An additional concern is represented by spurious autocorrelation in returns arising from over-
lapping information. Due to the presence of the house-specific noise component, the estimates of
$p^m$ may exhibit serial correlation in first differences even if house prices truly follow a random
walk. The sign of this serial correlation is not clear and depends on the timing of the sales of the
homes relied upon, but it tends to be negative over short time intervals.\textsuperscript{10} Longer (one-year) returns
are instead more precisely estimated and generally display positive autocorrelation. The autocor-
relation properties of the index returns are clearly of importance when analyzing predictability, an
issue we will return to in Section 3.1.\textsuperscript{11} Lastly, the $\beta$ estimates and thus the whole time series
of the index may change as new information becomes available and the coefficients in (3) are re-
estimated. These revisions may be substantial, on the order of one to two percentage points on an
annual basis (Abraham and Schauman (1991)). Moreover, they tend to be insensitive to sample

\textsuperscript{10}Webb ((1981a),(1981b), and (1981b) show that under some conditions the autocorrelation in return errors approaches -0.5 as the number of
observations goes to infinity.

\textsuperscript{11}Another concern is that, as noted by Goetzmann (1992), RSR methods estimate the average cross-sectional log return (geometric average),
which is lower than the log of the arithmetic average return by Jensen’s inequality. This issue is not alleviated by augmenting the number of
observations.
size, with systematic and persistent dynamics (Clapp and Giaccotto (1999), Clapham, Englund, Quigley, and Redfearn (2006)).

For the residential real estate market, the most well-known repeat-sales indices are the S&P/Case-Shiller Home Price Indices and the HPI Index constructed by the Federal Housing Finance Agency. The S&P/Case-Shiller Home Price Indices are based on the repeat-sales methodology as modified by Case and Shiller (1987) (see Standard and Poor’s (2008)). The index tracks monthly changes in the value of single-family homes both nationally as well as in individual metropolitan areas. The indices are calculated monthly using a three-month moving average and published with a two-month lag. The national index is a quarterly indicator for the nine U.S. Census divisions, and captures approximately 75% of the U.S. residential housing stock by value. For the national index, for most of the MSAs indices, and for the Composite 10 index the data begins in 1986, while all remaining metropolitan indices and the Composite 20 begin in 2000. To account for sample selection, sales that occur within six months of one another are excluded owing to the likelihood that the homes have been renovated.

The methodology behind the repeat-sales indices provided by the Federal Housing Finance Agency (FHFA) is a variant of Case and Shiller (1987). The difference is that the second step also involves a quadratic term in the regression of squared residuals on the time interval between transactions. Further details about its construction are provided by Calhoun (1996). Monthly indices for the U.S. and Census divisions based on sales price data are available since January 1991. Quarterly data estimated using both sales prices and appraisal data for the U.S., Census divisions, and metropolitan areas start in the first quarter of 1975.

Recently, repeat-sale indices have been introduced into commercial real estate markets. Prominent among these are the Moody’s/REAL commercial property price index (CPPI) and the CoStar commercial repeat sales index (CCRSI).

It is important to emphasize that these indices only track price appreciation. That is, they only account for changes in prices and ignore any intermediate cash flow over the period the home is being held. These cash flows include explicit or implicit rent, tax effects, and maintenance costs.

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12 Another popular series is the Conventional Mortgage Home Price Index (CMPHI) jointly created by Freddie Mac and Fannie Mae based on mortgages purchased or securitized. See http://www.alliemae.org/cmphp.html.

13 Time-series data and further information on the index construction can be found at the website http://www.standardandpoors.com and http://www.macromarkets.com/index.shtml.
Clearly, true measures of (excess) returns to real estate must reflect all inflows and outflows arising from the trading and management of a dwelling. An average implied rent and a rent-to-price ratio series for the Case-Shiller and FHFA indices has been constructed by the Lincoln Institute based on the methodology of Davis, Lehnert, and Martin (2008).\textsuperscript{14}

### 2.1.3 Hedonic Indices

In hedonic models, the price of a property is expressed as a function of a set of characteristics which determine its quality (such as square footage, number of bedrooms, etc.) and other factors (such as proximity to a school).\textsuperscript{15} This relation may arise as the equilibrium outcome of a competitive market with heterogenous goods whose characteristics enter the agent’s utility function (Rosen (1974)).

An important classification of hedonic models pertains to the functional form relating the property price and its characteristics. The standard semi-log formulation assumes a linear specification of the type

\[ p_{i,t} = \beta Z_i + \delta D + \epsilon_{i,t} \tag{5} \]

where \( p_{i,t} \) is the log transaction price of property \( i \) in period \( t \), \( Z_i \) is a \( C \times 1 \) vector of property attributes (also known as hedonic variables) including a constant term, and \( D \) is a \( T - 1 \times 1 \) vector of time dummies, one for each period except the first. The OLS estimates of \( (\beta, \delta) \) in (5) are obtained by pooling the information of all transactions and have an immediate interpretation. The estimates of \( \beta \) measure the marginal utility an investor derives from having one additional unit of a characteristic, also known as a shadow price. The parameter estimates of \( \delta \) capture, by contrast, the period-specific change in log price once the effect of property characteristics has been accounted for. Similar to repeat-sales models, the vector \( \hat{\delta} \) is then regarded as an estimate of the log price of the quality-adjusted aggregate index, or \( \hat{p}_{tn} = \hat{\delta}_t \). The value of the log price in the initial period is again normalized to zero.

Semi-log hedonic models are often preferred for their ease of estimation. Standard errors and statistical tests are easily computed. Linear models are, however, clearly prone to model mis-

\textsuperscript{14}The data are downloadable at http://www.lincolninst.edu/resources/.
\textsuperscript{15}For an extensive discussion of hedonic models, see Hill (2011).
specification. Several researchers have explored alternative specifications which allow for greater flexibility through nonparametric functional forms or second-order expansions (see Halvorsen and Pollakowski (1981), Wallace (1996), and Clapp (2004)). These models have been found to provide superior out-of-sample predictive performance compared to linear ones (Pace (1993)), but their estimation requires the availability of large datasets and shadow prices are not easily obtainable.

Another key element in the implementation of hedonic models is the choice of the appropriate set of characteristics. The most commonly used characteristics are lot size, square footage, number of bedrooms, number of bathrooms, and age (Wallace (1996), Sirmans, MacDonald, Macpherson, and Zietz (2006)). Others include garage space and the presence of air conditioning, a swimming pool, and a fireplace. In general, this list is dictated by data availability. Moreover, several variables that may affect pricing such as the amount of traffic noise and sunlight exposure are not directly measurable or observable. This renders hedonic models prone to both omitted variable and selection bias, as missing observations for some characteristics may lead to data censoring toward, for example, high quality buildings. As in any regression-type approach, the maintained assumption for consistency of the estimates is that the included variables are not correlated with omitted determinants.¹⁶ A perhaps comforting result is the evidence that shadow prices for the same characteristics resulting from the estimation of the semi-log model on different databases appear to be rather stable (Sirmans, MacDonald, Macpherson, and Zietz (2006)). In addition, location identifiers (such as zip codes, location dummies for proximity to the ocean or nearby lakes) are usually included in the regression in order to account for unobserved heterogeneity, as in Campbell, Giglio, and Pathak (2011).

Several studies compare the relative performance of hedonic and repeat-sales models. Meese and Wallace (1997) exploit the fact that repeat-sales estimators can be viewed as constrained versions of a dynamic hedonic model in which it is assumed that (i) homes that sold twice are representative of the whole market and (ii) the shadow prices of the attributes are constant over time and therefore cancel out in the construction of the index. They reject both of these assumptions using data on transactions prices and characteristics for 50,000 homes located in the cities of Oakland and Fremont, California. In addition, they find that repeat-sales indices tend to be very volatile. They attribute this behavior to sample selection bias, non-constancy of the characteristics’ shadow

¹⁶Shiller (2008) argues that hedonic models are subject to the risk that researchers “cherry pick” the functional form and characteristics to obtain the desired results. This argument, however, applies broadly to all empirical studies.
prices, and sensitivity to small-sample problems which all make these approaches less suitable to study efficiency in local markets. Surprisingly, they find that the time series properties of the readily-available median sales price index were very close to those of a hedonic Fisher Ideal index. Similar conclusions are reached by Clapp and Giaccotto (2002) looking at the empirical distribution of prediction errors using data for Dade Country, Florida.

As in the case for repeat-sales models, hedonic models provide estimates of the average log return, and not of the log return of the average property. They rely on the assumption that the set of houses that transact is representative of the market as a whole. If instead the sample of house sold varies with economic conditions, the resultant indices may be systematically biased. The magnitude of this bias can be analyzed by comparing hedonic models with price indices based on censored regression procedures, as in Gatzlaff and Haurin ((1997), (1998)).

An alternative way of constructing hedonic-based indices which does not require data on properties characteristics is to take advantage of appraisal valuations. Appraisals are estimates of the current value of a property provided either by the owner (so called “internal appraisals”) or by a professional agent (“external appraisals”). The key insight here is that while an appraisal value may represent a noisy estimate of a property’s true market value, it serves as a valuable hedonic variable, summarizing a building’s characteristics which are either observable, such as its size, or are unobservable, such as its quality. For the U.S. commercial real estate market, a popular index which is based primarily on appraisal values is the National Property Index (NPI) constructed by the National Council of Real Estate Investment Fiduciaries, NCREIF.\footnote{See http://www.ncreif.org/data.aspx.} NCREIF assets are institutional-grade commercial properties managed by investment fiduciaries on behalf of tax-exempt investors, mostly pension funds. The commercial properties are acquired in the private market for investment purposes only.\footnote{When a property is sold or is subject to a change of use, it exits the database. Due to changes in its composition and the type of assets included, the NPI index may therefore not be representative of the commercial real estate market as a whole.} Based on the information provided by its members, NCREIF constructs quarterly indices for the aggregate commercial real estate as well as indices disaggregated by property type and region. The indices are value-weighted by each property market value, and include cash flows from net operating income and capital expenditures. The series for the U.S., industrial properties, retail properties, and offices start in the first quarter of 1978, while the index for apartments is available from 1984.
However, a well-known drawback of using appraisal valuations is that the resultant returns respond with a lag to changes in actual market values and are much smoother (Fisher (2005)). The Transaction-Based Index (TBI) constructed by the MIT Center for Real Estate uses the information on transaction prices of properties sold from the NCREIF database to provide a more timely measure of market movements.\textsuperscript{19} The index is based on the two-stage methodology of Fisher, Geltner, and Pollakowski (2007) which combines the information of infrequent transaction prices with that of frequent appraisal valuations. In the first stage, quarterly transaction data are used to estimate a hedonic price model in which corresponding transaction prices are regressed against properties’ lagged appraisal values as well as several dummy variables controlling for time, property type, and location. The estimated coefficients from this regression are then used in a second stage to construct predicted prices based on the appraisal values and other characteristics of those properties that did not transact in a given quarter.\textsuperscript{20} In order to construct the aggregate TBI Index, the first-stage estimates are then applied to a representative property mirroring the average characteristics of the data. The methodology can also be used to construct pseudo–market prices for individual properties, as in Plazzi, Torous, and Valkanov (2011). The nation-wide index is available quarterly from 1984:Q1, while property-specific indices for apartments, industrial properties, retail properties, and offices start in 1994:Q1.\textsuperscript{21}

2.1.4 Hybrids

A combination of two or more types of indices might attenuate the deficiencies in the individual approaches. Along those lines, Case, Pollakowski, and Wachter (1991), Case and Quigley (1991), Quigley (1995), and Meese and Wallace (1997) combine repeat-sales and nonparametric hedonic methodologies in the construction of hybrid indices. The specification of Case and Quigley’s (1991) hybrid model is appealingly simple. It involves estimating the repeal-sales model (3) and the hedonic model (5) jointly in a GMM system of equations.

\textsuperscript{19}See http://web.mit.edu/cre/research/credl/tbi.html.

\textsuperscript{20}The methodology also accounts for transaction sample selection bias in the first stage using a Heckman (1979) two-step approach and applies Bayesian noise filtering technique to reduce the effect of noise in the quarterly series due to the limited number of transactions. See Fisher, Geltner, and Pollakowski (2007) for further details on this estimation procedure.

\textsuperscript{21}The starting date for the property-specific indices is motivated by the need of a sufficient number of transactions to estimate the model parameters separately within each property.
Hill, Sirmans, and Knight (1997) improve upon the estimation of Case and Quigley (1991) hybrid model. More specifically, they use hedonic regressions to estimate the effect of depreciation (the shadow price of a building’s age) and impose a first-order autoregressive process for the error term to capture sluggish adjustments to economic shocks. They then jointly estimate a repeat-sales regression consistent with this error structure via maximum-likelihood and document substantial efficiency gains in terms of lower standard errors and narrower interval estimates for the resultant index. Hybrid indices seem to offer improvements over either the repeat-sales or the purely hedonic models (Case, Pollakowski, and Wachter (1991) and Meese and Wallace (1997)), which illustrates well the fact that the adoption of one particular model to the exclusion of all others is likely to result in the suboptimal use of information. The intuition for this results is analogous to that in the forecast combinations literature (Timmermann (2006)).

2.1.5 Stock Market-Based Indices

Institutions and individuals can take positions in the commercial real estate market by investing in REITs. REITs are stock-market traded equity claims on commercial real estate investments, but unlike other common stock, they are subject to a strict payout policy, which binds them to pay at least 90 percent of the taxable income in dividends and as a result affords them preferred tax status.²²

Market-based indices can be obtained from the trading of individual REIT stocks. These indices are usually constructed as value-weighted averages of firm-specific REIT returns. The two standard data sources here are the CRSP/Ziman Real Estate Data Series and the FTSE NAREIT US Real Estate Index Series. Both indices track the performance of the US market and provide disaggregated information across REIT types (equity, mortgage, and hybrids). The CRSP Index is available from 1979, while the NAREIT data starts in 1972. The CRSP Index also provides separate indices for Apartments, Industrial and Offices, and Retail. Due to the strict payout rule, REITs offer an ideal testing venue for studying real estate dynamics as their returns mimic those

²²In order to qualify as a REIT, a company must comply with certain provisions within the U.S. Internal Revenue Code. As required by the tax code, a REIT must: Be an entity that is taxable as a corporation; Be managed by a board of directors or trustees; Have shares that are fully transferable; Have no more than 50 percent of its shares held by 5 or fewer individuals during the last half of the taxable year; Invest at least 75 percent of its total assets in qualifying real estate assets, which include interests in real property, interests in mortgages on real property, or shares in other REITs; Derive at least 75 percent of its gross income from real estate related services, such as rents from real property or interest on mortgages financing real property; Have no more than 25 percent of its assets consist of stock in taxable REIT subsidiaries; Pay annually at least 90 percent of its taxable income in the form of shareholder dividends.
of the underlying asset, which is commercial real estate.

A few caveats are, however, in order when using REIT data. First, the overall value of the 163 REITs traded at the end of 2010 was about $366 billion, and thus represent quite a small fraction of the approximately $10 trillion estimated value of non-residential real estate market. Hence, REITs may not constitute a representative sample of the U.S. commercial real estate market as a whole. Second, the number of traded REITs varies considerably over time, from about 100 trusts in the early 1980s to slightly less than 200 during the mid 2000s. Third, the market is characterized by a few large companies and many smaller REITs. This description is consistent with the fact that in 2009 the average market cap of REITs was $1.37 billion, while the median market cap was only $0.618 billion. An investment in REITs exposes investors to the risks inherent in small-cap stocks. Finally, many REIT companies have a significant amount of debt and their observed returns are thus those of the levered company, not of the underlying asset. Hence, we expect REIT returns to exhibit higher average returns and volatility than those of the underlying commercial real estate market.

2.1.6 Other Methods

The non-observability of the true underlying price process has also prompted some researchers to apply filtering techniques to extract the information of true prices embedded in noisy transaction prices. Engle, Lilien, and Watson (1985) use an EM algorithm (based upon Kalman filtering and smoothing) to estimate unobservable rent-price ratios, by relying on hedonic prices and a present value model between prices and future rents. For forecasting real house prices in the U.K., a Kalman filter model with time-varying coefficients has been used by Brown, Song, and McGillivray (1997). Giaccotto and Clapp (1992) use Monte Carlo simulation to show that Bayesian-type techniques based on a Kalman filter should be preferred by appraisers to estimate current true prices.

Finally, the increasing availability of large databases has lead researchers to explore the use of spatial econometric techniques that control for geographical and temporal dependence in real estate prices.23 Spatial dependence refers to the fact that properties which are in geographical proximity

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to each other will tend to be subject to similar shocks. Moreover, the location of a dwelling may play an important role in its pricing due to the presence of factors such as proximity to schools, parks, and malls. We would then expect the error components in hedonic regressions to be more correlated the closer the two properties are to each other. In contrast, temporal dependence refers to the fact that the parameters of hedonic models (the attribute prices) may change over time. This is similar to modeling time-varying coefficients in standard regression analysis. Error terms which refer to transactions occurring in distant periods are then likely to be less correlated. Explicitly accounting for these two sources of correlation helps reduce the bias and improves the efficiency of the estimators. Application of spatial models to housing can be found in Can (1992), Pace, Barry, Clapp, and Rodriguez (1998), Pace, Barry, Gilley, and Sirmans (2000), and Nappi-Choulet Pr. and Maury (2009).

2.2 Summary Statistics

**Residential:** For residential properties, we have three data sources—one median price index and two repeat-sales indices. First, the Census Bureau provides median and average prices of US residential properties at monthly frequency. Second, Standard and Poor’s/Case-Shiller (Case-Shiller) construct repeat-sales prices that are available at various frequencies and aggregation levels. A national index is constructed quarterly and a monthly version for the 10 largest metropolitan areas (C10) is also available. In addition, we compute a monthly equally-weighted average across all available areas at a point in time and label it as “EW”. Third, the Federal Housing Finance Agency’s (FHFA) repeat-sales House Price Index is available monthly (Purchase Only, since February 1991) and quarterly (All Transactions, since 1975) at the national level. We compute log price changes of all indices, which cannot be interpreted as returns in the usual sense of the term since the levels do not account for rents. Rent-to-price data for the Case-Shiller and FHFA data are from the Lincoln Institute at quarterly frequency. This data is also used to obtain growth in rents. Unfortunately, we do not have access to residential hedonic price data.

In Panel A of Table 1, we report summary statistics – annualized means, annualized standard deviations, skewness, and AR(1) coefficient– for log price changes of all indices as well as the rent growth rate and the rent-to-price ratios. The average growth rate of the Census median sales
index is 5.5%. It is higher than the 3.1% to 3.8% growth rates observed in either of the repeat-sales series. Moreover, the standard deviation of the median sales index, at 12.9%, is significantly higher than the 2% to 4.8% observed for the Case-Shiller and FHFA indices. All indices are negatively skewed, but the skewness in repeat-sales indices is larger in absolute value.

From a time-series perspective, the most significant difference between the median and the repeat-sales indices is the level of time-dependence. Changes in log levels of the Census series are significantly negatively correlated, with an AR(1) coefficient of -0.517. The Case-Shiller C10 and EW monthly log changes exhibit an AR(1) coefficient of 0.939 and 0.927, respectively. To a significant extent, this dependence reflects the fact that, as explained above, the Case-Shiller indices are constructed as a three-month moving average of an underlying series. Indeed, if we take the quarterly index, the AR(1) coefficient is significantly lower (0.602). The FHFA monthly and quarterly log changes also have large positive AR(1) coefficients of 0.708 and 0.688, respectively.

The average rent growth rate for the repeat-sale indices is 3%. The series exhibit very little volatility and high serial correlation (0.900). The rent-to-price ratio is 4.5% for both indices. Its standard deviation is very small compared to that of the log price changes, but it is extremely persistent, with AR(1) coefficients of 0.988 (Case-Shiller) and 0.994 (FHFA). Given that these estimates are downward-based (Andrews (1993)), there is little doubt that these series are close to non-stationary. The high level of persistence in the rent-to-price ratio is similar to that observed in valuation ratios (dividend-price, earnings-price) of the US stock market (Welch and Goyal (2008)). The average return from residential real estate can be computed by adding the average price appreciation and the average rent-to-price ratio. Over our sample, it is 7.6% for both repeat-sales indices.

**Commercial:** Commercial properties naturally fall into one of four categories: apartments (Apt), industrial properties (Ind), offices (Off), and retail properties (Rtl). Indices are available for each of these categories as well as for the overall commercial real estate market. The first source of commercial real estate values is the NPI from the National Council of Real Estate Investment Fiduciaries (NCREIF). An alternative hedonic index, based on the work by Fisher, Geltner, and Pollakowski (2007), is the transactions-based index (TBI).

Repeat-sales commercial real estate indices are relatively new. One such index, the Moodys/REAL
commercial property price index (CPPI) provides monthly data at the aggregate level and quarterly series by property type from 2001 to the present. While this time span is too short for forecasting exercises, we include the CPPI for completeness and provide summary statistics. We have no doubt that repeat-sales indices will play a growing role in commercial real estate.

REIT is a value-weighted index of all publicly-traded REITs in the CRSP-Ziman database. Using monthly returns with and without dividends, we construct its dividend-price ratio and dividend growth rate (see Appendix A.2 for details). Since REIT is a stock-market based index, it presents a unique opportunity to investigate the performance and predictability of commercial real estate returns without the complications inherent in hedonic and repeat-sales indices. It is therefore not surprising that many academic papers have been written on REIT return predictability and so we will also devote special attention to this market. However, recalling that the market capitalization of all REITs represents but a small fraction of the total value of all US commercial properties, the economic importance of this market is somewhat limited.

Panel B of Table 1 contains summary statistics for the NPI, TBI, CPPI, and REIT indices. Whenever available, we also report summary statistics for rent growth rates (or dividend growth, in the case of REITs) and rent-to-price ratios (dividend-price ratios, for REITs). With the exception of CPPI, all return series include cash flows distributions (net rents or dividends).

The NPI and TBI indices have comparable means of 8.5% (NPI) and 7.6% (TBI). However, their volatilities and AR(1) coefficients are very different. Indeed, the AR(1) coefficient for the overall NCREIF index is 0.779. By contrast, the AR(1) coefficient of the TBI is only 0.038. The low serial correlation in the log price changes makes the TBI particularly appealing from an economic perspective. The rent growth rate of the TBI exhibits moderate serial dependence (AR(1) coefficient of 0.368) whereas its rent-to-price ratio is extremely persistent (AR(1) coefficient of 0.965). The changes in the log CPPI have a very low average mean of 1.1%. This is mostly due to the sample over which these statistics were calculated. The CPPI series are also quite volatile and exhibit moderate dependence (AR(1) of 0.452).

The average REIT returns, at the bottom of Panel B, Table 1, have a mean of about 10.4% and

24 The CPPI tracks same-property realized round-trip price changes based on transactions data provided by Real Estate Analytics, LLC (REAL). The RCA database aims at collecting price information for every commercial property transaction in the U.S. over $2,500,000 in value. Thus, it reflects a more extensive set of properties than those in the NCREIF portfolio. See Geltner and Polliakowski (2007) and http://mit.edu/cre/research/credl/rca.html.

25 Unfortunately, a longer time span is not available.
a standard deviation of 17.9%. These numbers are higher than for the other commercial real estate indices. Since REIT is a stock index, it is useful to compare its return and volatility with that of the market-wide portfolio return. The CRSP value-weighted portfolio return has an average of 10.9% and a standard deviation of 16.3% over a similar period, which implies a higher Sharpe ratio than that of REITs. REIT returns have a relatively higher serial correlation of 0.146, which is in line with that of small-cap stocks in the US stock market.

**Conditioning Variables:** The conditioning variables we select proxy for time variation in the state of the economy and thus in the prevailing investment opportunity set. These variables have also been shown to successfully capture time variation in expected returns of the aggregate U.S. stock market and bond returns. These include the lagged aggregate stock market (Campbell and Vuolteenaho (2004)), its dividend-price ratio (Fama and French (1988b), Lettau and Van Nieuwerburgh (2008)), the relative 3-month Treasury bill calculated as the current rate minus its twelve-month moving average (Hodrick (1992)), the inflation rate (Fama and Schwert (1977)), the term spread as difference between the 5-year and 3-month log yields (Fama and French (1989)), the Cochrane and Piazzesi (2005) tent-shaped combination of forward rates, and industrial production growth (Fama (1990)). Summary statistics, reported in the bottom panel of Table 1, show a wide range of persistence with AR(1) coefficients ranging from 0.29 for Industrial Production growth to as high as 0.93 for the Term Spread. Details on the data source and construction are provided in Appendix A.2.

3 Forecasting Real Estate Returns

The extensive predictability literature in finance and real estate considers variations of the following linear predictive regression:

\[ r_{t+1} = \alpha + \beta'X_t + \epsilon_{t+1} \]  

(6)

where \( r_{t+1} \) is a return (or price change) and \( X_t \) is a vector of variables, observable at time \( t \). Predictability in \( r_{t+1} \) may arise because of two distinct economic reasons. First, it might be due to market inefficiency if some available information is not incorporated in prices in a timely manner by market participants (e.g., Fama (1970)). Second, predictability might be due to time-variation in
expected returns (e.g., Campbell and Shiller (1988)). Unfortunately, the existence of predictability in a reduced-form regression (6) does not allow us to trace its economic provenance. Also, the existence of predictability does not necessarily imply that the market is inefficient in the usual sense of the term (Fama (1970)). For a market to be inefficient, investors should be able to exploit some of the serial dependence. This point is discussed in detail by Case and Shiller (1989) in the context of residential real estate.

Linear models are deceptively simple. An extensive literature has investigated their statistical properties (estimation and inference) and out-of-sample predictive performance (Rapach and Zhou (2012) in this Handbook). Statistical complications arise because the predictor $X_t$ is often persistent and its innovations are correlated with $\epsilon_{t+1}$, which induces bias in the estimation of $\beta$ (Stambaugh (1999)). Moreover, excessive noise in the returns series renders hypothesis testing unreliable. We will revisit some of these issues below.

In this section, we review the literature on real estate predictability. We also report estimates from our own predictive regressions using the indices introduced above. The discussion is organized around the kind of predictive information that is included in $X_t$ and the implied hypotheses.

### 3.1 Serial Dependence in Real Estate Returns and Weak-Form Market Efficiency

We start off with the simplest information set $X_t$, that of past returns, $r_t$. In this case, regression (6) tests for serial correlation in returns and weak-form market efficiency. Several studies in the real estate literature find that returns (or price changes) exhibit positive serial correlation, including Gau (1984), Gau (1985), Linneman (1986), Guntermann and Smith (1987), Rayburn, Devaney, and Evans (1987), Case and Shiller (1989), McIntosh and Henderson (1989), Gyourko and Voith (1992), Kuo (1996), Hill, Sirmans, and Knight (1997), Hill, Sirmans, and Knight (1999), Gu (2002), and Schindler (2011). However, the evidence on whether this predictability can be exploited for financial gains is less clear.

In one of the earliest papers of weak-form efficiency for the US real estate market, Gau (1985) investigates the persistence in monthly returns to commercial real estate in Vancouver during the 1971-1980 period. Rather than using simple returns, he works with abnormal returns, defined as
returns adjusted for various sources of systematic risk. The cross-sectional risk-adjustments alter
the unconditional mean of the returns series, but have little effect on their dynamics. Gau (1985)
finds that the forecasting errors from predicting abnormal returns using past price information
are too small to be exploitable by a trading strategy. Linneman (1986) uses hedonic prices, also
adjusted for risk, to test for market efficiency in the Philadelphia residential market. He finds
evidence of serial dependence in the data, but concludes that the predictability is insufficient “to
cover the high transaction costs associated with transacting real estate.” Guntermann and Smith
(1987) apply a portfolio approach to uncover the autocorrelation of aggregate unanticipated total
returns to residential real estate in 57 MSAs using the Federal Housing Administration data over
the 1968-1982 sample. Their study is one of the first to explicitly take into account rental income in
computing returns. They document positive predictability over horizons of one to three years, and
negative autocorrelation at the four- to ten-year horizon. This pattern is consistent with short-run
momentum and long-run reversal. Consistent with Linneman (1986), the persistence is not large
enough for various trading rules to appear profitable once transaction costs are considered.

Rayburn, Devaney, and Evans (1987) and McIntosh and Henderson (1989) reach similar con-
clusions using different datasets and methodologies. Rayburn, Devaney, and Evans (1987) com-
pute ten indices for the Memphis single-unit residential market during the 1970-1984 period. While
some of the indices exhibit significant serial correlation, the authors conclude that the transaction
costs faced in that market are simply too high for a market-timing strategy to be profitable. McIn-
tosh and Henderson (1989) use ARMA models to test for weak-form market efficiency. They
estimate the ARMA models with transactions data for the Dallas-Fort Worth office properties mar-
ket over the 1979-1985 period. They find that, although the estimated parameters of the processes
are significant, their out-of-sample mean square forecasting errors and mean absolute forecasting
errors are higher than those of the unconditional mean. Hence, they conclude that commercial real
estate returns in that market are unpredictable.

In an influential study, Case and Shiller (1989) test for weak-form efficiency in four U.S. singe-
family markets: Atlanta, Chicago, Dallas, and San Francisco/Oakland. They do so using their
weighted repeat sales (WRS) index (Case and Shiller (1987)). To reduce errors-in-variables issues,
they randomly partition their sample of transactions into two groups and obtain two corresponding
WRS indices for each of the four cities. They then regress quarterly observations on the annual
return in one index on the one-year lagged annual return of the other index. This approach, which can be seen as instrumental variables (IV), produces consistent, albeit biased, estimates of the autoregressive coefficient. Case and Shiller (1989) document substantial predictability in real and excess returns to housing, with predictive $R^2$ ranging from 0.11 to as high as 0.48 corresponding to average trading profits between 1% and 3%. They also find it much harder to forecast individual properties returns using the city-wide index, due to the large amount of noise-to-signal ratio in such data. Out-of-sample performance deteriorates considerably due to measurement error in estimating the aggregate index using only a subset of the sample. Moreover, the random partitioning approach implies that the estimates and forecasts will change if we alter the partitioning of the data.

Kuo (1996) argues that tests of market efficiency by partitioning the sample, as done in Case and Shiller (1989), help to alleviate the errors-in-variables problem but still produce biased estimates, as is the case with noisy instruments. He proposes an alternative Bayesian approach to estimate an AR(2) model based on repeat-sales. His setup explicitly models the unknown true indices as random variables and hence does not necessitate partitioning the repeat-sales sample. The posterior means of the AR(2) coefficients in Kuo (1996) and the corresponding autocorrelation functions suggest that the repeat-sales indices are more dependent than found in previous studies. Hill, Sirmans, and Knight (1999) use the methodology in Hill, Sirmans, and Knight (1997) to test for the presence of random walk in the Case and Shiller (1989) data. Their test is based on the idea that a random walk process for prices would induce heteroskedasticity in repeat-sales indices. They show that the GLS procedure of Case and Shiller (1989) can be improved upon by accounting for a stationary, autoregressive component in house prices. They revisit the original Case and Shiller data and reject the hypothesis that house prices follow a random walk. Schindler (2011) provides recent evidence of predictability in the Case-Shiller real and nominal log nominal price changes, computed for the national and 20 metropolitan areas indices. He uses parametric variance-ratio tests of serial correlation and as well as non-parametric runs tests of independence in the series. Not surprisingly, he finds strong evidence for dependence in the price changes, with some indices exhibiting strong positive autocorrelation even at 24 monthly lags. Perhaps more surprising is his finding that, after comparing different buy-and-hold and dynamic trading strategies, the author concludes that in some markets, the persistence in the data is large enough to be exploitable. It is worth mentioning that the markets with the largest gains from the trading strategies – Los Angeles,
Las Vegas, San Diego, and San Francisco are also the markets that have exhibited the largest bubbles. Hence, it is not clear whether these strategies would fare equally well out-of-sample.

Gu (2002) studies the autocorrelation properties of quarterly returns to the Conventional Mortgage Home Price Index (CMHPI) for all U.S. states, the District of Columbia, nine Census Divisions, and an aggregate index for the US during the 1975–1999 period. He finds that the degree of persistence and the sign of correlation varies geographically as well as over time. The instability of the results across locations and different time periods suggest that the significant noise in real estate data renders inference unreliable. This is particularly true since most datasets have relatively few time-series observations. The findings in Gu (2002) also point to the difficulty of comparing the results of weak-form efficiency studies in real estate using information from different markets, datasets (some aggregated, others not), sample periods, and methodologies. Given the heterogeneity in the asset and the imperfection of the data, it is not surprising to find heterogeneity in the results.

A growing literature uses regime switching models to capture real estate price dynamics. In a regime switching model, the time-series properties of a series depend on the realization of an underlying state variable. The prolonged booms and busts that characterize real estate prices therefore represent a natural framework of application. Moreover, it is reasonable to expect substantial variation in regimes across different areas and property types owing to the reliance of real estate to local economic and geographic conditions. Shifts in house price dynamics may arise, for example, because of a changing relationship between housing, income, and interest rates (see e.g. Muehlbauer and Murphy (1997)) or from the interaction between credit-constrained households, lenders, and developers (Spiegel (2001)).

Theoretically, the entire conditional density of a process may depend on the current state realization. In practice, for tractability, the empirical applications have mainly adopted first-order

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26 Following the influential work of Hamilton (1989), regime switching models have been extensively used in the macroeconomic and finance literature to capture nonlinearities in exchange rates (Engel and Hamilton (1990)), interest rates (Gray (1996), Garcia and Perron (1996), Bansa and Zhou (2002)), stock returns (Perez-Quiros and Timmermann (2001), Granger and Hyung (2004), Guidolin and Timmermann (2008)), GDP growth (Diebold and Rudebusch (1999)), and GNP growth (Hamilton (1989)).

27 Using Monte Carlo simulations, Van Norden and Vigfusson (1998) provide evidence that regime-switching tests for bubbles suffer from a downward bias distortion even with relatively large samples – i.e., they reject the null of no bubble too often – but display considerable power in detecting nonstationarities. This makes them suitable to capture the persistent real estate cycles.

28 Similarly, Guirguis, Giannikos, and Anderson (2005) find evidence of parameters instability in the relationship between real estate prices and the fraction of the population aged between 25 and 35, real disposable income, stock of owner occupied dwellings, the expected nominal capital gains, the nominal post-tax mortgage interest rate. They interpret this fact as evidence of structural changes and suggest the use of time-varying coefficient methods coupled with Kalman filter.
autoregressive regime switching models:

\[ r_t = c_{s_t} + \phi_{s_t} r_{t-1} + \epsilon_t \tag{7} \]

where \( \epsilon_t \sim N(0, \sigma_{s_t}^2) \). In this context, returns follow an AR(1) process whose intercept, slope, and error variance depend on the realization of the regime variable \( s_t \). Thus, the data-generating process is subject to jumps in the unconditional mean, persistence, and level of volatility. The choice of the number of regimes \( n \) that better describes the data is usually chosen by likelihood ratio tests or information criteria. However, due to the availability of relatively short time-series, most of the existing studies rely on low-order models with two or three regimes (Crawford and Fratantoni (2003)). The fact that prices of direct investments in real estate are available at low frequency – monthly, at the very best – also complicates the detection of short-lived regimes. The estimates are obtained using maximum likelihood (Hamilton (1994)).

Among the empirical studies, Crawford and Fratantoni (2003) compare the in-sample and out-of-sample forecasting performance of regime switching models to that of ARIMA processes and GARCH models on the annualized growth rates in the state-level OFHEO quarterly return series from 1979 until 2001. Their approach parallels that of Perez-Quiros and Timmermann (2001) for the stock market. The authors document considerable heterogeneity in the time-series properties of residential returns across states. For example, past returns explain only 6% of the variance of returns to Ohio but about 75% in the case of California. Their data exhibits a strong degree of persistence and nonlinearity in the volatility process which is modeled as an EGARCH. They also observe that the time-series patterns seem to be better captured by a two-states regime model, which deliver much lower in-sample RMSEs and \( R^2 \). Out-of-sample, however, ARMA models display better forecasting properties (lower MSFE), probably due to the tendency of regime switching models to overfit in-sample.\(^{29}\) Interestingly, this last finding is consistent with Gu (2002)’s analysis on CMHPI data.

Another stream of papers makes a connection between a high degree of positive serial correlation in returns and bubbles in real estate markets. For example, Gyourko and Voith (1992) analyze autocorrelation in median house prices for 56 MSAs during 1971-1989. They find significant dif-

\(^{29}\)Perez-Quiros and Timmermann (2001) document that even when the data are generated by a regime switching process, simple autoregressive models may provide better short-term forecasts.
ferences in autocorrelations across areas, which they interpret as evidence of market inefficiency. At the same time, they argue that a global component drives residential prices and that “the national economy strongly influences local housing markets.” Glaeser, Gyourko, and Saiz (2008) use the FHFA/OFHEO data to show that large price increases in residential properties were almost entirely experienced in cities where housing supply is more inelastic. Hence, they argue that boom-bust housing cycles are largely driven by housing supply rather than demand shocks.

The stylized facts that emerge from this literature can therefore be summarized as follows: (i) Most residential indices exhibit serial correlation in the changes in the log prices; (ii) the serial correlation is positive at horizons up to a few years; (iii) at longer horizons, we observe a reversal, or a negative serial correlation in returns; (iv) the economic significance of this serial correlation and whether it can be exploited by market participants is still an open question. To illustrate these findings, we run simple autoregressive tests, which are mostly descriptive in nature. The goal is to replicate some of the key dynamics outlined above for returns in the aggregate residential and commercial real estate markets. As we don’t have access to the disaggregated data used in the construction of the indices, we cannot replicate the more involved estimation specifications.

We consider the following long-horizon regression:

\[ r_{t+1:t+H} = \alpha(H) + \beta(H) r_{t-H+1:t} + \varepsilon_{t+1:t+H} \] (8)

where \( r_{t+1:t+H} \) is the log change of a price index over \( H \) periods. For \( H = 1 \), equation (8) collapses to an AR(1) model. Long-horizon return regressions (8) are used frequently in empirical finance to investigate the behavior or equity returns at various horizons (e.g., Fama and French (1988a)). Versions have also been used in the residential real estate literature by Guntermann and Smith (1987) and in the commercial real estate literature by Plazzi, Torous, and Valkanov (2010). Under the null hypothesis that the price process has no predictable component, \( \beta(H) \) should be zero at all horizons. Deviations from the null hypothesis imply that there are predictable dynamics at different horizons.

In Figure 3, we provide the results from this regression estimated for four indices, two residential and two commercial. We choose indices that exhibit various degrees of serial correlation. For
residential, we use the median and FHFA/OFHEO indices\textsuperscript{30} whereas for commercial, the comprehensive TBI and REIT indices. For all regressions, we plot the least squares estimates of $\beta(H)$, $H = 1, \ldots, 48$ months with a solid line along with 2 times the Newey-West standard errors (dotted line), based on $H$ lags. The Census median index exhibits negative serial correlation at short horizons. As the horizon increases, the correlation turns positive between 12 and 24 months and then reverts to zero. With the exception of the short-horizon negative correlation, we cannot reject the null that the Census median forecast changes are uncorrelated. The picture is quite different for the repeat-sales FHFA/OFHEO data. We observe a strong degree of serial correlation at short and medium horizons. The $\beta(H)$ estimates are positive and significant for horizons up to 30 months. Then, the serial correlation turns negative but insignificant.

The TBI index is not serially correlated at the very short horizon. The estimates of $\beta(H)$ turn significantly positive for horizons between 6 and 18 months. Then, similarly to the FHFA/OFHEO index, we observe a reversal and a negative, albeit not significant, correlation in long-horizon returns. Finally, the REIT index exhibits a positive but insignificant correlation at the one-month horizon, which is typical for small-cap stocks (Campbell, Lo, and MacKinlay (1997)). As the horizon increases, we notice a negative drift in the estimates which turns significant after about 30 months. This is consistent with the model in Fama and French (1988a) who show that in the presence of a small mean reverting component in returns, the estimate of $\beta(H)$ will be negative at long horizons. This evidence supports the presence of a small predictable component in REIT prices.

The results in Figure 3 show the main salient findings in the real estate literature, namely positive serial correlation in the price changes at short horizons of up to 2-3 years and reversals at horizons beyond 3 years. In the case of the FHFA/OFHEO and TBI indices, the positive serial correlation is due partly to the construction of the index, as discussed in section 2.1, and partly to market inefficiencies in real estate markets. The construction of an index that captures a quality-adjusted price without introducing artificial dynamics remains an important topic of research. The current indices, especially those that are filtered, are appropriate for capturing the state of the real estate market. However, their excessive serial correlation does not make them suitable for forecasting exercises. Moreover, the majority of the studies cited above reach the conclusion that

\footnote{The Case-Shiller is even more serially correlated than the FHFA/OFHEO index. This is due to its construction, which takes a three-month average of an underlying repeat-sales index.}
high transaction costs render the observed predictability hard to exploit by market participants.

3.2 Predictability Based on Valuation Ratios

Valuation ratios, such as the dividend-price, the book-to-market, and the earnings-price, have a long-standing tradition as predictors of equity returns (see Rapach and Zhou (2012) in this Handbook and references therein). Analogous ratios have been used in the real estate literature, some of which are the rent-to-price (Hamilton and Schwab (1985), Meese and Wallace (1994), Geltner and Mei (1995), Capozza and Seguin (1996), Campbell, Davis, Gallin, and Martin (2009), Himmelberg, Mayer, and Sinai (2005), Gallin (2008), Plazzi, Torous, and Valkanov (2010)), the loan-to-value (Lamont and Stein (1999)), and the price-to-income ratio (see, e.g., Malpezzi (1990), (1999)). The economic reason for the use of ratios as predictors of future returns is straightforward and hinges on the plausible assumption that the variables used to form the ratios are co-integrated in logs (Engle and Granger (1987)). To see that, consider the log rent-price ratio. If log rents and log prices are co-integrated, then the log rent-price ratio must be a mean-reverting process. If at time $t$, the ratio is higher than its unconditional mean, the mean reversion implies that either expected returns would be high or that expected growth in rents would be low, or a combination of the two (Campbell, Davis, Gallin, and Martin (2009), Plazzi, Torous, and Valkanov (2010)). Similar logic applies to most valuation ratios.

To understand the appeal of the rent-price ratio to forecast either future rent growth or future returns, it is useful to introduce some notation. Let $H_t$ denote rents net of all operating expenses of a property and $P_t$ denotes its current price. Then the rent-price ratio is $H_t/P_t$ and we denote its log transformation by $hp_t \equiv \ln(H_t) - \ln(P_t)$. It is also known as the capitalization, or cap, rate of the property. We will use the terms rent-price ratio and cap rate interchangeably from now on. Following Campbell and Shiller (1988), Campbell, Davis, Gallin, and Martin (2009) and Plazzi, Torous, and Valkanov (2010) show that $hp_t$ can be expressed as

$$hp_t = k + E_t \left[ \sum_{j=0}^{\infty} \rho^j r_{t+1+j} \right] - E_t \left[ \sum_{j=0}^{\infty} \rho^j \Delta h_{t+1+j} \right]$$

where $r_{t+1+j}$ is the future return of the property, $\Delta h_{t+1+j}$ is the future growth in its rents, and $k$
and $\rho$ are linearization constants. In other words, fluctuations in the log cap rate must be able to predict either future returns, or future growth in rents, or both.

Expression (9) is the basis for the following long-horizon regressions:

\[
\begin{align*}
r_{t+1:t+H} &= \beta_r(H)h_{pt} + \tau_{t+1:t+H}^r \\
\Delta h_{t+1:t+H} &= \beta_d(H)h_{pt} + \tau_{t+1:t+H}^d
\end{align*}
\]

where $r_{t+1:t+H} \equiv \sum_{j=1}^{H} r_{t+j}$ and $\Delta d_{t+1:t+H} \equiv \sum_{j=1}^{H} \Delta d_{t+j}$ approximate, respectively, the first and second term in (9) for a large $H$.\[^{31}\] These approximations are appealing because $r_{t+1:t+H}$ and $\Delta d_{t+1:t+H}$ represent the log $H$-period return and rent growth, respectively. The forecasting regression are estimated at various horizons, ranging from one period ($H = 1$) to several years ahead. The framework above has been used to investigate predictability of residential, commercial, and REIT returns. Given the extensive literature about REITs, we devote more attention to that literature in a separate section.

One might wonder why should the cap rate alone predict future real estate returns. Shouldn’t other variables, such as construction costs, local economic conditions, zoning laws, and demographic trends be part of the set of explanatory variables? The assumption that the cap rate is the only conditioning variable is equivalent to assuming that all other economic factors are successfully summarized by that one quantity. In other words, this ratio captures all relevant economic fluctuations and it is the sole state variable. To the extent that some of the current economic information is not embedded in that ratio, the model will be misspecified.

Most of the literature focuses on return (or price appreciation) predictability in expression (10). A notable exception is the work of Hamilton and Schwab (1985). The authors use a semi-logarithmic hedonic model to estimate the rent and value of constant quality properties in 49 urban housing markets surveyed by the Annual Housing Survey in the mid-1970s. They then explore the ability of the rent-price ratio to forecast future growth in rents. They find a significant negative relation between the rent-price ratio (not in logs) and future growth in rents. Using aggregate REIT data, our regressions support their findings (section (4)).

Meese and Wallace (1994), Capozza and Seguin (1996), Gallin (2008), and Campbell, Davis,\[\text{\footnotesize\[^{32}\]The constant $\rho$ is usually close to unity.}\]
Gallin, and Martin (2009) are some of the studies testing for return predictability within the above framework while Himmelberg, Mayer, and Sinai (2005) offer a slightly broader approach. Gallin (2008) estimates equations (10) and (11) using quarterly repeat-sales index data from 1970:Q1 to 2005:Q4. The two equations are estimated separately at four-years-ahead horizons ($H = 16$). He finds that the rent-price ratio has a positive relation with future returns and a negative relation with future rent growth rates, as predicted by expression (9). In his work, the coefficient $\beta_d(H)$ in the rent growth regression is statistically significant, whereas $\beta_r(H)$ in the return regression is not. Hence, from an statistical perspective, the evidence of rent-price predicting future returns is tenuous. Meese and Wallace (1994) formulate a different test which they carry out with transaction level data for Alameda and San Francisco counties in Northern California. They find evidence of short-run violations but long-run consistency with the present value relation and argue that high transaction costs might be the reason behind the differences across horizons. Capozza and Seguin (1996) point out that the predictive power of the cap rate is best observed once they account for other cross-sectional differences in rental versus owner-occupied housing. They use a pooled sample of 64 metropolitan areas across the US from 1960 to 1990 and most of the data is from the decennial Census of Housing and Population.

In a recent work, Campbell, Davis, Gallin, and Martin (2009) also use expression (9) as a starting point of their analysis. Rather than assuming that future returns are an adequate proxy for expected returns, the authors follows Campbell (1991) and use vector autoregression (VAR) to forecast the future quantities in (9). One of the forecasting variables is the log rent-price ratio. Based on the VAR estimates, they document predictable variations in expected returns and expected rent growth for 23 metropolitan markets, four regional markets, and the national housing market over the 1975-2007 period with quarterly data. Consistent with the results of Gallin (2008), the rent-price ratio explains a larger fraction of the variability of expected returns than of expected rent growth. This is true for the entire sample and even during the boom subsample of 1997-2007. However, the statistical significance of the return predictability is not compelling. Interestingly, the Campbell, Davis, Gallin, and Martin (2009) real estate results are very similar to those of Campbell (1991) for the US stock market, which suggests that there is a higher degree of commonality between the two markets.

To illustrate the degree of real estate predictability by the log rent-price ratio, we run short-
horizon equivalents of regression (10). The data is sampled at quarterly frequency and \( H = 1 \), which implies that we forecast returns one quarter ahead. We include the lagged return in addition to the lagged log rent-price ratio in the regressions because of the high degree of serial correlation documented in the previous section. The regressions are estimated for residential properties with the Census, Case-Shiller, and FHFA/OFHEO databases, and for commercial properties with the NCREIF, TBI, and REIT indices.

The residential results are presented in Table 3, Panel B.\(^ {32} \) The results from the Census data are the most discouraging, from a predictability perspective. The point estimate in front of lagged log rent-price ratio is 0.008 with a Newey-West \( t \)-statistic of 0.255. This lack of predictability might be due to the fact that the Census median returns series do not adjust for the quality of properties. Some evidence pointing in that direction is presented in the next subsection. The Case-Shiller and FHFA/OFHEO estimates are positive, as suggested by expression (12), but still statistically insignificant. The large \( R^2 \)s of 0.559 and 0.409 are mostly due to the serial correlation in returns, which is captured by the lagged return term, \( r \). We also tried a specification without lagged returns, but the results were very similar.

In Table 4, we display the predictive regressions results for commercial real estate returns. The specifications are directly comparable with those for residential properties in Table 3. And the results are very much in agreement. More precisely, we observe a positive relation between the log rent-price ratio and future commercial real estate returns. While the point estimates are slightly larger for all three indices, and especially for the TBI, the Newey-West \( t \)-statistics are in the range of 1.044 to 1.218. The inability to reject the null of no predictability might be due to a lack of power of our test, especially given the presence of noise in the returns series. We will be able to explore the lack of power direction a bit further in the case of REITs, as we have market-based monthly observations over a longer time span. In sum, these results suggest that while there is a positive relation between the log rent-price ratio and future returns, as suggested by expression (6), it is not statistically significant in our samples. Admittedly, short-horizon predictability, even if it were present, is hard to detect in real estate indices that are so serially correlated.

The price-income ratio is suggested by Malpezzi (1999) as another predictor of real estate price changes. The underlying assumption behind this ratio is that there is an equilibrium relationship

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\(^{32}\)We cannot run the residential regressions at monthly horizons, because the rent-price ratio data is only available quarterly.
between house prices and household income. In other words, 
k_t \equiv P_t/Y_t = Z_t \delta + \eta_t,
where 
P_t
is the price of a property, 
Y_t
is the income of an investor, and 
Z_t
is a vector of variables that capture time variation in economic conditions. The average price-income ratio 
k_t
mean reverts to the unconditional mean 
k. A temporary deviation of 
P_t/Y_t
above 
k
implies that the ratio will mean revert either because future prices will have to come down or the income level has to increase, or both. Malpezzi suggests the following predictive regression to capture these dynamics:

\[ dP_t = \beta_0 + \beta_1 \left( \frac{P_{t-1}}{Y_{t-1}} - k \right) + \ldots + \beta_n \left( \frac{P_{t-n}}{Y_{t-n}} - k \right) + X_\alpha + \epsilon_t. \] (12)

In addition to the error-correction terms \( \left( \frac{P_{t-j}}{Y_{t-j}} - k \right) \), the variables in \( X \) proxy for market conditions, regulatory environment, demographic changes, and other factors. Negative \( \beta_j \)'s reflect the tendency of prices to mean-revert when the price-to-income ratio exceeds the equilibrium values. Malpezzi (1999) also offers asymmetric versions of expression (12) by including non-linear error-correction terms, but they were shown to be statistically insignificant.

Malpezzi (1999) estimates equation (12) using a pooled regression approach across MSA regions from two datasets: a repeat-sales index and a hedonic price index. In most specifications, the \( \beta_j \) estimates are statistically different from zero, which suggests that house price changes are predictable by the lagged price-income ratio. This evidence is consistent with the studies that use the cap rate as a predictor and generally confirms the fact that there is a forecastable component in house price indices. Malpezzi (1999) also finds that other variables, such as mortgage rates, population growth and housing regulations, have an effect on future prices beyond the lags of the price-income. For instance, the stringency of the regulatory environment raises prices consistently, suggesting that supply shocks are important in determining house price dynamics (Glaeser, Gyourko, and Saiz (2008)). An inelastic housing supply is also suggested by the evidence that higher growth rates of population and income are associated with future price changes. Finally, higher mortgage rates predict lower price changes.

The vast majority of studies on real estate predictability estimate regressions (10) and/or (11) by OLS, equation by equation. However, if future returns and future rent growth are correlated (and there is no reason to believe that they are not), then equation-by-equation OLS regressions suffer from an omitted-variables bias. This argument has been made by Lettau and Ludvigson
(2001) and Koijen and Van Binsbergen (2010) in the context of stock returns. The reason is that, in the presence of a correlation, the rent-to-price ratio is not sufficient to capture the time variation in the predicted variables and may understate their degree of time-variation. The same point has been made by Plazzi, Torous, and Valkanov (2010) in the case of commercial real estate predictability. To circumvent this issue, Plazzi, Torous, and Valkanov (2010) assume a first-order autoregressive process for the unobserved expected returns and expected rent growth and link it to the reduced form OLS regression coefficient in the rent-to-price ratio regression. They estimate the parameters of the underlying processes on a panel of quarterly returns to apartments, industrial properties, offices, and retail properties for 53 MSAs over the 1994-2003 period. Because of the added structure in the predictive regressions, they are able to identify and estimate substantial variations in both expected returns and expected rent growth in the time-series and across property types (in the 2%-20% range).

While the use of valuation ratios in predictive regressions has its appeal, an obvious drawback is that the predictive ratio might not be capturing all the time variation in the conditioning information set. This is yet another reason to suspect that the results for such regressions may suffer from omitted-variables bias. But even if a ratio were a sufficient proxy for the time variation in economic conditions, the reduced form version of regressions (10) and (11) do not allow us to understand the economic forces that are behind the predictive relation. Is the forecastability due to demographic changes or other demand shocks? Or is it driven by supply shocks, such as tighter real estate regulations and zoning laws? What role, if any, do slowly-adjusting construction costs play? Those questions can only be answered if additional conditioning variables are introduced in the predictive regressions.

3.3 Predictability Based on Economic Variables

There is considerable evidence that economic variables, other than past returns or valuation ratios, are associated with future appreciations in property values, as shown by Rosen (1984), Linneman (1986), Skantz and Strickland (1987), Case and Shiller (1990), Abraham and Hendershott (1996), Pace, Barry, Gilley, and Sirmans (2000), MacKinnon and Al Zaman (2009), and Plazzi, Torous, and Valkanov (2010), among others. The empirical framework in most of these papers is the predictive
regression (6) with conditioning information $X_t$ that includes demographic variables (population growth, percentage of population within a certain age), income and employment variables, construction costs, housing starts, tax rates, zoning restrictions, and other regulatory variables. The selection of the conditioning information is dictated by the data, the level of aggregation, and the methodology.

Linneman (1986) uses data from the Annual Housing Survey for the Philadelphia residential market in 1975 and 1978 to test whether a wide set of property characteristics are associated with future changes in property values. He first regresses 1975 residential values on a broad set of structural and neighborhood characteristics. This first step is the estimation of a hedonic model on a set of property-specific variables. The author interprets the residuals, i.e. the difference between the market and the estimated values, as market mispricings. Positive residuals are an indication that a property is “overvalued” relative to the model. Linneman (1986) finds that the 1975 residuals are significantly correlated with 1978 property prices. He interprets this as a test of semi-strong form of market efficiency, but argues that the correlation is not large enough to cover the transaction costs associated with residential real estate, which he sets equal to a proportional round-trip 12% annual fee. Thus, he concludes that the market was semi-strong efficient.

Linneman’s (1986) work is one of the first to document persistence in changes in residential values. However, it is not a predictive model in the strict sense of the term. In regression (6), we are looking to relate systematic changes in $X_t$ with future returns. Most of the property characteristics in his hedonic model are fixed-effects and do not change with time. Rather, this is a good test of the validity of a hedonic model. The documented correlation between the model mispricings and subsequent values might be an indication that either the model is misspecified or that the Philadelphia real estate market was slow to incorporate the shadow prices of the property attributes into the market valuation. The lack of additional years of observations does not unfortunately allow the author to look into the time-series properties of the mispricings.

In an interesting study, Skantz and Strickland (1987) investigate house price dynamics following an unexpected disaster, Houston’s widespread flood on July 26, 1979, which affected several subdivisions of the city. The authors compare values in an affected subdivision to another one that did not directly suffer from the flood. Akin to an event-study exercise, their goal is to compare home values in affected and unaffected subdivisions pre- and post-flood. To estimate quality-
adjusted prices, they use a hedonic regression of values on square footage, lot size, time, age, and a dummy for type of financing. They find that prices in the flooded subdivision did not decrease immediately after the flood, which suggests that residential values already reflected the higher flood risk. They also document that house prices started to adjust downwards a year after the event, mainly because of an increase in flood insurance premia. The fact that, net of insurance premia costs, home prices are not affected by a natural disaster is a compelling evidence in favor of market efficiency.

Case and Shiller (1990) test for predictability in the excess total returns (returns minus the Tbill rate) of four metropolitan areas (Atlanta, Chicago, Dallas, San Francisco) with a number of conditioning variables including lagged returns. The return data is computed from repeat-sales indices, rental data from the 1970 Census, and residential rent from the Bureau of Labor Statistics. The larger information set allows the authors to test a stronger version of the market efficiency hypothesis than in Case and Shiller (1989). The dataset is at quarterly frequency, from 1970 to 1986. The conditioning variables, the majority of which are available at metropolitan level, are: the rent-price ratio, the mortgage payment-income ratio, construction costs-price ratio, employment growth rate, real per capital income growth, growth rate in construction costs, percentage change in adult population (between ages 25 and 44), the percentage change in marginal tax rate, and housing starts divided by the population. The forecasting variable of interest is the excess return over the next four-quarters. Case and Shiller (1990) show that the economic predictors are able to capture a significant fraction of the fluctuations in future real estate returns; their fully-specified predictive regressions have an $R^2$ of 0.336 to as much as 0.615 (their Tables 7, 8, and 9). From the included variables, real per capita income growth and the increase in the adult population are strongly positively related with future annual excess returns. The sign is consistent with economic intuition, namely, improved economic conditions and demographic booms both put demand pressure on house prices. Two measures of fundamental value, the price-rent ratio and construction costs divided by price, also forecast future returns with a positive sign. To put things in perspective, the rent-price ratio alone has an in-sample $R^2$ of 0.109 (Tables 8 and 9). Variables such as the growth rate of employment, marginal individual income tax rate, and houses starts are also found to be important predictors. Overall, the addition of control variables increases the in-sample $R^2$ from about 10% to as much as 60%, thus rejecting the hypothesis of a semi-strongly efficient mar-
ket. Their analysis is, however, in-sample and the pooled regression (across cities) use overlapping observations and do not explicitly account for cross-sectional correlation in the residuals.

Abraham and Hendershott (1996) explore the systematic predictability patterns of residential properties and link them to supply shocks. They express the growth in real estate prices as a linear function of lagged state variables such as the growth in real construction costs, the growth in real income per working age adult, the growth in employment, and the change in real after-tax rate. The error term of this regression is interpreted as a deviation from a market equilibrium and, therefore, a proxy for a bubble as it reflects adjustment dynamics and data noise. Working on the repeat-sales house price indices from Freddie Mac-Fannie Mae for 30 MSAs, they find that coastal and inland cities respond quite differently to the conditioning variables. Deviations from equilibrium values, or bubbles, are more pronounced in those markets. Their results imply that predictability in the residential market is to some degree related to measures of local supply elasticity such as the availability of desirable land.

Predictability tests, in the form of vector autoregressions (VARs), are used by Zhong-Guo (1997) to analyze the fluctuations in values of single-family homes in the US. The author investigates the joint relationship between sales volume and median sales prices from the National Association of Realtors using a VAR error correction model. Their Granger-causality tests indicate that sales affect price significantly, but home prices affect sales only weakly. Zhong-Guo (1997) goes a step further and provides out-of-sample evidence based on the VAR, which is quite unusual in the real estate literature. To do that, the VAR is estimated using 1970-1990 data and the subsequent 1991-1994 sample is used as an out-of-sample test of where both sales and price for housing are forecasted using a recursive method. Zhong-Guo (1997) documents substantial predictive power for both median prices ($R^2 = 0.86$) and sales ($R^2 = 0.77$).

Pace, Barry, Gilley, and Sirmans (2000) argue for the importance to model spacial as well temporal dependence of errors that go beyond simple predictive regressions. They introduce semi-parametric models which account for spatial and temporal dependence in the errors and show that they provides better one-step-ahead forecasts of log sales prices compared to hedonic models, controlling for housing characteristics, time, and space with continuous and indicator variables. In their empirical analysis, they use data from the city of Baton Rouge.
The papers thus far have focused on predictability in the residential market. Similar studies have been conducted with commercial real estate data. For instance, MacKinnon and Al Zaman (2009) analyze the predictability of returns to direct real estate investment, proxied by the TBI index, and REITs in the context of a long-horizon asset allocation problem. Their in-sample analysis reveals that TBI returns are predictable by variables such as lagged REIT returns, bond returns, and the T-bill interest rate, while cap rates and employment growth show only limited predictive power. This result is noteworthy especially because, as we saw in Table (1), price changes in the TBI index are close to uncorrelated. The mean-reversion in direct real estate investment makes it a less risky asset for long-horizon investors. As a result, for reasonable target values of the total portfolio expected return, the fraction of wealth invested in commercial properties is found to be no lower than 17%. Interestingly, in their application, the correlation between REITs and TBI returns is high enough to make REITs a redundant asset class when investors have access to direct investment in commercial properties.

The interaction between prices, vacancy rates, transactions volume, housing stock, and rents is the focus of Wheaton and Torto (1988). The authors consider deviations from equilibrium and adjustment dynamics between vacancy and rents in the office market. They do so by regressing office rents on vacancy rates, accounting for the possibility in trends in the structural vacancy rates. They document a statistically significant and qualitatively strong relationship between current excess vacancy and future real rent changes. Then, the estimated equation is used to forecast six-year ahead vacancy rates and a decline in office rents.

The rental market, and its response to a legislative reform—the Tax Reform Act of 1986—are the focus of DiPasquale and Wheaton (1994). The authors argue that this Act had economically significant supply and demand effects on the rental properties markets. One goal of their paper is to disentangle and quantify those effects. A second one is to trace out the response (if any) of the rental prices to the new tax reform. They find that an increase in the capital cost of home ownership has had a significant impact on the demand for rental housing. DiPasquale and Wheaton (1994) also forecast that, over the next ten years, real rents will increase by 8 percent as a direct result of the legislation. These numbers are economically meaningful, especially given the low variability of rents over the decades preceding the 1986 legislation.

For a recent investigation on the European market, see Fugazza, Guidolin, and Nicodano (2007).
Evidence for predictability in commercial real estate returns and rent growth is also provided by Plazzi, Torous, and Valkanov (2010) using three principal components extracted from the level and change in population, employment, per-capita income, and construction costs. In particular, either the first or first and second principal components – which load on the level and growth in population and income as well as on construction costs – are found to be significant at the 1% level or better across all four property types. When the cap rate and a coastal dummy are also included, the adjusted $R^2$ in the returns predictive regressions range from 17% (for offices) to 37% for retail properties. In the rental growth predictive regressions, the adjusted $R^2$ are from 8% for offices to 14% for apartments. Interestingly, the cap rate remains significant even after the inclusion of these principal components, which suggests that the valuation ratio it is truly capturing time-varying dynamics rather than mere cross-sectional differences. Consistent with the findings in Abraham and Hendershott (1996), Plazzi, Torous, and Valkanov (2010) document cross-sectional differences in predictability depending on density and land-use restrictions. Evidence of return predictability is drawn primarily from locations characterized by lower population density and less stringent land-use restrictions. By contrast, rent growth predictability is more likely observed in locations characterized by higher population density and more severe land-use restrictions.

We revisit the predictability of aggregate real estate indices by conditioning variables other than lagged returns or log rent-price ratio. Panels A and B of Table 3 present various specifications of regression (6), estimated with monthly and quarterly residential data. In Panel A, we observe that the inclusion of the stock market’s dividend-price ratio ($dp_m$), which is a proxy for the state of the equity market, has a negative effect on future residential returns. The effect is statistically significant for the Case-Shiller and FHFA/OHFEO indices. The relative T-Bill rate and the Cochrane and Piazzesi (2005) bond factor are significant for the repeat-sales indices. In the fourth, most comprehensive specification, the inclusion of lagged returns and all other economic variables reveals that, at monthly horizons, the data is simply too serially correlated for any of the additional predictors to be statistically significant.

In the quarterly predictability regressions, Panel B of Table 3, we observe that several economic variables are statistically significant in explaining future fluctuations in real estate price changes. More specifically, for the Case-Shiller index, the stock-market’s dividend-price ratio, the relative T-Bill rate, inflation, and the Cochrane and Piazzesi (2005) bond factor are significant at conventional
levels. The results for the FHFA/OFHEO are similar, albeit less significant. In all specifications, the log rent-price ratio is insignificant. Also, the Census median price index remains the least forecastable of the three indices.

In Table 4, we present the equivalent results for commercial properties with quarterly data. As in the previous table, the stock market’s log dividend price ratio is negative and significantly related to future returns of the NCREIF and TBI indices. In the third specification of the regressions, higher industrial production growth leads to higher future changes in the same two indices. In the case of NCREIF, the term spread is also statistically significant but its point estimate is negative. The NCREIF is the most forecastable index, with as much as 70.9 percent of its changes being predicted, in-sample, by the economic variables. For the TBI, the explanatory power drops to 25.5 percent. REIT returns are the least predictable, as the joint explanatory power of all predictor yields an adjusted $R^2$ of 15.4 percent.

A recurring theme in the extant real estate literature is that the predictability of returns varies across geographic regions (e.g., Case and Shiller (1989), Gyourko and Voith (1992), Abraham and Hendershott (1996), Gu (2002), Crawford and Fratantoni (2003), Fratantoni and Schuh (2003), Capozza, Hendershott, and Mack (2004), and Hill (2004)). In a particularly exhaustive study of 62 metropolitan areas from 1979 to 1995, Capozza, Hendershott, and Mack (2004) note that “the dynamic properties of housing markets are specific to the given time and location being considered.” The economic sources of heterogeneity in predictive regressions are the same ones that determine house price dynamics, namely, demographic changes, regulations and zoning restrictions, local economic conditions, as well as heterogeneous responses to global macro-economic shocks. While differences in datasets, variable definitions, and methodologies make it hard to compare results across studies, quantifying the predictive ability of economic variables across metropolitan areas is of clear interest.

To illustrate the cross-sectional differences, we run predictive regressions similar to the ones discussed in Tables 3 and 4, but with MSA-level (rather than national) indices. To do so, we compute quarterly log price changes of 25 MSA regions from FHFA/OHFEO over the 1991-2010 period. For each region, we regress the one-period-ahead price changes on the same set of conditioning variables that were used in Table 3. In other words, we run 25 MSA-level regressions, whose coefficient estimates, $t$-statistics, and $R^2$s are comparable to those for the aggregate FHFA/OFHEO
index, reported in the very last column of Table 3. Rather than tabulating a large number of statistics, in Figure 4, we summarize the average predictive coefficients on each variable across regions (top-left panel), the average $t$-statistics (top right), the number of significant coefficients across regions (bottom left), and the average $R^2$ (bottom right).

The average coefficient on lagged returns is about 0.2, with an average $t$-statistic of nearly 2, and is statistically significant in 13 out of the 25 metropolitan areas. Interestingly, the most strongly significant predictors in the top-right panel – the lagged return, the market dividend-price ratio, and the RTB – are the same ones that were significant in the aggregate regressions (Table 3). Here, an additional predictor, the CP factor, displays a comparable importance. The same four variables appear as the most frequently significant across metropolitan areas, with the addition of inflation, suggesting that their average $t$-statistics are not driven by a few outliers. The fact that inflation and industrial production do not reach (on average) statistical significance might indicate the need for MSA-specific measures of economic activity. Our regressions, which are designed to capture common movements across MSAs price changes (because the predictors are the same across MSAs), show that at least some of the time-variation in residential returns is attributable to systematic, market-wide fluctuations. Abraham and Hendershott (1996), Capozza, Hendershott, and Mack (2004), and Del Negro and Otrok (2007) report similar findings. The average $R^2$ is 49%, in line with the 48% value documented for the national series. There is, however, considerable dispersion in the individual regressions $R^2$ (bottom-right plot), ranging from 25% for St. Louis, MO-IL to as high as 79% for Los Angeles-Long Beach-Glendale, CA.

As a more direct test of the presence of common factors in the cross-section of 25 MSAs, we extract the first 10 principal components of their covariance matrix. In the top panel of Figure 5, we plot the fraction of the total variance explained by each of these components. Strikingly, the first principal component explains slightly less than 70% of the covariance, while the other components are much less important. This evidence supports the findings in Figure 4 and the assertion that macro-economic fluctuations are behind some of the time-variation, at least over our sample period. Of course, a significant part of the unexplained variance is due to local factors. The bottom panel in the figure displays the fraction explained by the first component over the 2001 to 2010 period, estimated with a 40-quarter rolling window basis. Interestingly, the common component increased significantly during the 2008-2010 period, undoubtedly as a result of the bust
of the residential real estate bubble and the subsequent financial crisis.

4 REITs

The publicly-traded REIT market holds a special place in the real estate predictability literature. This is because REITs’ cash flows are closely linked to commercial real estate\(^{34}\), yet the funds are traded on the US stock exchange, are relatively liquid, have small transaction costs relative to other real estate investments, and their returns are observable at high frequency. Moreover, for a corporation to be considered a REIT for tax-purposes, it must distribute at least 90 percent of its taxable income as dividends. This unambiguous link between cash flows and dividends makes REITs particularly suitable for predictability tests.

We devote particular attention to REITs for two additional reasons. First, the data is available at higher frequency and over a longer time span than other datasets. This allows us to correct the parameter estimates for well-known, small-sample biases and to cast the predictive system in a GMM framework. Cross-equations restrictions, imposed by the model, may provide further efficiency gains in the estimation. These improvements will ultimately allow us to verify whether more precise parameter estimates and better in-sample fit obtain by using longer and less noisy series. Second, the longer sample allows us to investigate the (pseudo) out-of-sample performance of the forecasts. Thus far, most of the discussion had focused on estimation and in-sample performance. However, as is well-known in the stock market forecasting literature, in-sample fit does not necessarily translate into successful out-of-sample performance (Welch and Goyal (2008)). The disconnect between in-sample and out-of-sample results is likely due to parameter estimation error, structural breaks (Rossi (forthcoming) in this Handbook) or more general model misspecifications. We investigate the out-of-sample predictability of REITs by also incorporating some new insights.


\(^{34}\)Internal Revenue Code Section 856(a)(5).
most of these studies can be framed into the following predictive system:

\[
\begin{align*}
    r_{t+1} &= \mu_r + \beta_r x_t + \tau_{r,t+1}^r \\
    \Delta d_{t+1} &= \mu_d + \beta_d x_t + \tau_{d,t+1}^d \\
    x_{t+1} &= \mu_x + \phi x_t + \tau_{dp,t+1}^{dp}
\end{align*}
\]  

(13)  
(14)  
(15)

The one-period regressions are sometimes augmented by investigating the predictability of long-horizon returns \( r_{t+1:t+H} \equiv H^{-1} \sum_{j=1}^{H} r_{t+j} \) and dividend growth \( \Delta d_{t+1:t+H} \equiv H^{-1} \sum_{j=1}^{H} \Delta d_{t+j} \), as in equations (10) and (11) above. The conditioning variable \( x_t \) is usually the log dividend-price ratio. Multiple predictors are also considered, in which case \( \beta_r, \beta_d \), and \( x_t \) are vectors.

Liu and Mei (1992) is one of the earlier studies to investigate the predictability of REIT returns. Using monthly data from 1972 to 1989, they consider one-period forecasts of returns as in (13) with the T-Bill rate, the spread between yields of AAA-rated bonds and the T-Bill, the dividend-price ratio of the US stock market, and the dividend-price ratio (or cap rate) of the REIT portfolio. They find that the log dividend-price ratio and the T-Bill forecast future REIT returns. Moreover, they argue that REIT returns are more predictable than are the returns of the stock market portfolio. As a measure of predictability, they use the adjusted \( R^2 \) in the regression, which in the case of REITs is 0.175 and only 0.087 for the overall market. They also note that REITs are about as predictable as is a portfolio return of small-cap stocks, whose \( R^2 \) is 0.165. This makes economic sense as REITs fall, on average, in the small-caps category of stocks.

Building upon these results, Mei and Liu (1994) compare the out-of-sample performance of a market-timing trading strategy to that of a buy-and-hold portfolio of REIT firms. They use the conditioning variables in Liu and Mei (1992) to forecast four real-estate-based portfolios: equity REITs (eREIT), real estate building companies (builders), real estate holding companies (owners), and mortgage REITs (mREIT). They also consider the return of the well-diversified US stock market and of portfolios sorted by size. The out-of-sample performance is measured by the \( R^2 \) of the model relative to the unconditional mean. For their builders portfolio, the \( R^2 \) is 0.136, while in the case of the mREIT and eREIT portfolios, it is lower at 0.109 and 0.083, respectively. The authors also consider three trading strategies: buy-and-hold, long-only, and a long-short portfolio. Their results suggest that the market timing strategies outperform the simple buy-and-hold for real...
estate assets, but the same is not necessarily true for common stocks. Hence, they conclude that
the predictability in real estate returns might be exploitable.

Two other studies also report evidence of predictability in REITs, but are more ambivalent
about the economic significance. Nelling and Gyourko (1998) compare equity REITs to small-
and mid-cap firms over the extended 1975-1995 period. They find significant predictability at
monthly horizons, but argue that it might not be large enough to cover transaction costs in these
small-cap stocks. They also document that the extant predictability has not been constant through
time: it is weakest at the beginning of their sample and strongest after 1992. More recently,
Serrano and Hoesli (2010) extend the work of Nelling and Gyourko (1998) by looking at REITs in
ten countries with data up to 2007. Their results suggest that, in more mature and well-established
REIT markets, REIT returns are more predictable than are the stock market returns of the country.
REITs in the US, the Netherlands, and Australia exhibit the most predictability. Trading strategies
based on the forecasting regressions are able to outperform a buy-and-hold benchmark portfolio
in all ten countries, and the gains are significant enough to cover transaction costs in about half of
them.

Several papers have gone beyond the simple univariate, linear forecasting models of equations
(13-15). Brooks and Tsolacos (2001) employ a number of time-series models – univariate and
multivariate – to assess the predictability of securitized real estate returns in the U.K. They find
that a VAR model which incorporates financial spreads exhibits a better short-term out-of-sample
forecasting performance than univariate time series models. However, trading rules based on these
forecasts do not deliver excess returns over a buy-and-hold strategy once transaction costs are
taken into account. In a follow-up paper, Brooks and Tsolacos (2003) compare the predictability of
REITs using ARMA, VAR, and neural networks models in five European countries. They conclude
that whilst no single technique is universally superior, the neural networks model generally makes
the most accurate predictions for one-month horizons. For the U.S., Serrano and Hoesli (2007)
examine the usefulness of using financial assets, direct (non-REIT) real estate, and the Fama and
French (1993) factors to forecast equity REIT returns and compare the predictive potential of time
varying coefficient (TVC) regressions, VAR systems, and neural networks models. Their results
indicate that the best predictions obtain with neural networks models, especially when the model
includes stock, bond, real estate, size, and book-to-market factors. Although there is no consensus
in the literature as to what forecasting technique works best, there is a general trade-off between the complexity of the model and its forecasting accuracy.

Performance continuation and reversals are also related to the time series properties of asset returns and have been the subject of many studies in the financial economics literature. For securitized real estate, Mei and Gao (1995) examine serial persistence of weekly returns and argue that a contrarian-based strategy is profitable only if transaction costs are ignored. Using a filter-based rule, Cooper, Downs, and Patterson (1999) show that a contrarian strategy is in many cases more profitable than its associated execution costs. Graff and Young (1997) use different frequencies and find positive momentum effects with yearly data, evidence of performance reversals with monthly data, and no evidence of momentum or reversals with quarterly data. Finally, Stevenson (2002) provides international evidence of momentum effects over short and medium term horizons, as well as little support for price reversals.

To highlight and update the results we just discussed, we test for predictability using the monthly equity REIT series from the CRSP/Ziman database during the full 1980-2010 period. We construct monthly dividends using total and without-dividends returns as in Fama and French (1988b). The dividend series is then calculated as sum of the current and past 11 months dividends. The log dividend-price ratio is defined as the log dividend minus the log of the level in the current month. The left-hand side variables are the real log return and dividend growth, deflated by the CPI Index.\footnote{Working with nominal or excess returns yield very similar results.} We also look at the results for the REIT portfolios of companies that hold mainly apartment buildings (Apt), industrial buildings and offices (Ind & Off), and retail properties (Rtl), as they may exhibit different predictability properties.

Table 5 presents OLS estimates of equations (13) and (14) for all REITs, Apt, Ind & Off, and Rtl. The predictive regressions are estimated over horizons of $H = \{1, 3, 6, 12\}$ months. Some studies compute long-horizon returns by overlapping one-period returns whereas others consider non-overlapping windows. We provide both sets of results. Panel A displays the estimates for the return regressions (13) and Panel B displays those for the dividend-growth regression (14). It is well-known that the persistence of the dividend-price ratio ($\phi$ in (15) close to one) and a negative correlation of the predictor innovations with those of returns (correlation of $\tau_{t+1}^r$ and $\tau_{t+1}^{dp}$) induce significant small-sample bias in the OLS estimates in regression (13) (Stambaugh
Therefore, the displayed coefficient estimates are adjusted for the small-sample bias using Stambaugh’s (1999) correction. In the non-overlapping results, the $t$-statistics are calculating with Newey and West (1987) standard errors with four lags. In the overlapping data, the lag in the Newey and West (1987) errors equals the number of overlapping observations $H$.

In Panel A of Table 5, the positive OLS estimates of $\beta_r$ at various horizons show that the log dividend-yield is positively related to future REIT returns. This is true for the entire REIT portfolio and especially for retail properties. Interestingly, industrial and office properties exhibit little predictability at any horizon. Plazzi, Torous, and Valkanov (2010) document a similar finding, namely, that industrial and office property returns are the least predictable, using a different dataset. As the horizon increases, we observe an increase in the $t$-statistics. For overlapping returns, they reach customary significance levels at the yearly horizon. This result supports the claim in previous studies that returns are predictable at long horizons. However, we observe that the non-overlapping long-horizon results are not significant which raises the possibility that the high $t$-statistics might be the product of distorted inference, due to the severe serial correlation, induced by the overlap (Valkanov (2003)).

The OLS estimates of $\beta_d$ in Panel B are negative, as implied by the log-linearized expression (9). The point estimates are larger in magnitude than those in Panel A and, more importantly, they are statistically significant, with $t$-statistics for overlapping REITs in the $-3.5$ range. For industrial and office properties, the predictability is even more significant as the $t$-statistics are about $-5$. This finding mirrors the Plazzi, Torous, and Valkanov’s (2010) results that those properties exhibit the most predictable rent growth rates. It is comforting to observe that estimates and $t$-statistics using overlapping and non-overlapping dividend growth data yield very similar results. The $R^2$ in the overlapping and non-overlapping regressions is 0.2 for all REITs and as high as 0.4 to 0.5 for industrial and office properties. The strong ability of the dividend-price ratio to predict REITs dividend growth rates is in sharp contrast with the findings for the aggregate stock market (Lettau and Van Nieuwerburgh (2008)). This difference may be partly attributable to the strict payout policy that makes REITs dividends less prone to artificial smoothing, or to the nature of REIT cash flows.

The mixed predictability results of returns might be due to the lack of statistical power of our tests. Recent work by Lettau and Van Nieuwerburgh (2008) suggests that estimation and inference
in long-horizon regressions can be improved by noting that the predictive system (13)–(15) implies the following time-series restriction relating one-period and $H$-period slope coefficients:

$$\beta_r(H) = \beta_r \left( \frac{1 - \phi^H}{1 - \phi} \right) \quad \text{and} \quad \beta_d(H) = \beta_d \left( \frac{1 - \phi^H}{1 - \phi} \right). \quad (16)$$

In addition, the Campbell and Shiller (1988) present-value identity imposes a restriction between the predictive regression coefficients:

$$\beta_r - \beta_d = 1 - \rho \phi \quad (17)$$

where $\rho$ is the log-linearization coefficient. This expression is nothing but a restatement of the fact that, owing to the variability of $dp$, we must observe either return predictability, dividend growth predictability, or both. These observations suggest that more efficient estimates of $\beta_r$ and $\beta_d$ can be obtained through a GMM estimator which imposes the above restrictions across different horizons $H$, as in Lettau and Van Nieuwerburgh (2008) and Plazzi, Torous, and Valkanov (2010).

In Table 5 we report the one-month coefficients $\beta_r$ and $\beta_d$, estimated with GMM using horizons of \{1, 3, 6, 12\} months. The estimates of $\beta_r$ in Panel A remain positive and statistically insignificant for all REITs and for the various property types. The estimates of $\beta_d$ (Panel B) are negative and smaller in magnitude than those in the unrestricted OLS regressions. However, their $t$-statistics have increased both with overlapping and non-overlapping data. The OLS and GMM results point to the same three conclusions. First, there is a positive but largely insignificant in-sample relation between the log dividend-price ratio and future returns. Second, the log dividend-price ratio forecasts dividend growth rates with a negative sign and the estimates are statistically significant. Finally, industrial and office properties seem to exhibit the least returns predictability and the most dividend growth predictability. This last finding merits further attention as it might provide further insights about the underlying economic sources behind the trade-off in predictability between returns and dividend growth rates.

The empirical discussions were thus far framed around in-sample fit in predictive regressions. However, the ultimate test of such regressions resides in whether they can produce accurate out-of-sample forecasts. Recently, the stock market predictability literature has found that significant predictors do not necessarily produce accurate out-of-sample forecasts. For instance, Welch and
Goyal (2008) have documented that stock return predictors do not outperform the simple unconditional mean in a (pseudo) out-of-sample comparison. As a measure of relative forecasting accuracy, Welch and Goyal (2008) use the out-of-sample (as opposed to in-sample) $R^2$ defined as:

$$R^2_{OOS} = 1 - \frac{\sum_{t=1}^{T} (r_t - \hat{r}_{t|t-1})^2}{\sum_{t=1}^{T} (r_t - \bar{r}_{t|t-1})^2}$$  \hspace{1cm} (18)$$

where $\hat{r}_{t|t-1}$ and $\bar{r}_{t|t-1}$ are the predicted value and the historical average return, respectively, estimated using information up to and including time $t - 1$.

We take this opportunity to look at the out-of-sample predictive power of conditioning variables in REIT regressions. In addition to the log dividend-price ratio, we consider the same commonly-used predictors that were discussed in Tables 3 and 4.

We conduct the out-of-sample comparison by splitting the sample in two periods. A first 180-month period, corresponding to the 1980-1995 sample, is used to estimate first the forecasting model. Then, the estimates from that sample are taken to form the first forecasts of returns and dividend growth for January, 1996. Subsequently, we include the January 1996 observations to re-estimate the models and formulate forecasts for February, 1996 and so on until December, 2010. We do this at horizons of $H = \{1, 3, 6\}$ months. Given the limited time-series, longer horizons are not possible.

In Panel A of Table 6, we present the monthly in-sample (column “IS”) and out-of-sample (column “OOS unc”) $R^2$s. The “unc” stands for “unconstrained” to differentiate those results from some constrained ones, discussed below. From the definition of $R^2_{OOS}$ in equation (18), positive values imply that the model delivers a lower mean square forecasting error (MSFE) than the unconditional mean. Looking down the IS column for real returns, we notice that several predictors have in-sample predictive power. However, the OOS unc column reveals that, with the exception of the lagged stock market return, the OOS $R^2$ are all negative. In other words, the MSFEs of all but one forecasting variables are higher than that of the unconditional mean. A combined forecast, obtained by equally-weighting all 8 predictions, does well in-sample but its out-of-sample performance barely beats the unconditional mean (last row in Panel A).

Campbell and Thompson (2008) show that imposing economic constraints on the OOS forecasts of stock market returns results in significant improvements in their OOS $R^2$. Following their

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36For the Cochrane and Piazzesi (2005) factor, we construct out-of-sample estimates by re-estimating the coefficients using only information available up to time $t - 1$. 

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work, we consider several non-linear constraints. The first one (column “sign($\beta_r$)”) restricts the estimated coefficient in a given period to have the expected sign. The second constraint (column “OOS $\hat{\tau} > 0$”) imposes non-negativity of the forecasted real return. In column “OOS both”, the forecast must satisfy both constraints. In periods when a constraint is violated, the historical average is used instead as a forecast. The OOS results from the three constraints are displayed in Table 6. Imposing the sign($\beta_r$) constraint brings several of the negative OOS $R^2$s into positive territory and increases the OOS $R^2$s of the combined forecast. The $\hat{\tau} > 0$ and joint constraints lead to modest improvements in the predictions. In Panels B and C, we present the results at quarterly and semi-annual horizons and observe several differences with respect to the monthly results. The log dividend-price ratio, which was insignificant at monthly frequency, is more significant in-sample. In Panel C, its in-sample $R^2$s is as high as 3.862 percent. Similar increases in IS $R^2$s occur for $dp_m$, and $TSP$. However, this in-sample fit does not translate into OOS performance. Indeed, the MSFE of $dp$ is 15.211 percent higher than that of the unconditional mean. Some predictors, such as the $CP$ factor exhibit improvement in OOS forecasting power. Imposing the constraints does not help the log dividend-yield but does lead to a better performance of $IP$.

The results in Tables 5 and 6 all point toward weak evidence of in-sample predictability at long horizons. Econometric refinements, designed to reduce bias and increase efficiency of the estimates, do not alter significantly this conclusion. The OOS forecasting exercise suggests that most of the predictors yield MSFEs similar to or higher than the unconditional mean. This is true whether or not we impose economic constraints. The in-sample significance of our predictive results appears somewhat smaller than documented in previous studies. This difference may be partly due to the fact that our sample includes the particularly volatile 2007 to 2010 period and to the downward bias adjustment. Perhaps the most novel result in the tables is that the dividend growth of REITs is forecastable in-sample, although the OOS results are, once again, much weaker.

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37 For the dividend-price ratio, the Campbell and Shiller (1988) decomposition implies a positive coefficient. For the other variables, we impose the same positivity constraint, although the guidance from economic theory is less clear. The sign constraints are broadly consistent with the prior of counter-cyclical risk premia.

38 Other types of constraints could be imposed to enhance forecastability. See, for example, Pettenuzzo, Timmermann, and Valkanov (2011).
5 Real Estate, Leverage, and Monetary Policy

5.1 The Effect of Leverage

The relation between real estate prices and leverage is a natural one, especially in the residential market. While in principle any asset could be used as collateral, housing is by far the easiest asset to borrow against. As reported above, at the peak of the recent US residential bubble, about $12 trillion of outstanding mortgage debt had been issued against the value of properties, which at the time were worth in the neighborhood of $25 trillion (Case (2007)). In the UK, Aoki, Proudman, and Vlieghe (2004) report that about 80 percent of all household borrowing is secured on housing. High levels of home borrowing are bound to have an effect on house price dynamics and some of the studies that analyze this relationship are Linneman and Wachter (1989), Stein (1995), Lamont and Stein (1999), Spiegel (2001), Aoki, Proudman, and Vlieghe (2004), Ortalo-Magné and Rady (2006).

Stein (1995) proposes a static fully-rational model that explains the joint relationship between house prices, trading volume, and leverage. In his framework, households must repay any existing loan and make a down-payment prior of moving to a new home. If real estate prices experience a negative exogenous shock to their income, the home-equity portion for families with a high level of leverage may not be enough to meet the down-payment of a larger house. These households may therefore decide not to move, thus creating a decrease in demand which further depresses prices. On the contrary, following a positive income shock, these financially constrained families prefer to move to their desired location promptly, thus increasing prices and volume. Stein’s (1995) model implies that the mix of leverage and liquidity constraints amplifies the effect of changes in asset values on the demand for housing. In cities where a large fraction of families are highly leveraged, the impact of fundamental shocks on house prices will be significantly higher, thus giving rise to self-reinforcing effects. As a result, home prices would display pronounced boom-to-bust cycles which may appear incompatible with an efficient capital market dynamics.40

39 Alternatively, they may also try to list their home for a relatively high price as this represents a low-cost alternative. This would explain why even in falling markets there is some inertia in the decrease of prices.

40 The model’s main predictions hold as long as the market for renting does not represent a costless alternative than buying a new home. Tax and moral hazard reasons suggest that renting is not a perfect substitute for direct ownership, so that the most efficient way to consume new housing is owner-occupied. The magnitude of these effects can be big as a large fraction of all home sales are to repeat buyers.
McDonald (1999), Spiegel (2001), and Ortalo-Magné and Rady (2006) are three additional papers that investigate the theoretical links between leverage and real estate prices. Spiegel (2001) shows that the presence of credit constraints can lead to construction cycles. As an implication of his model, he shows that leverage and developer construction decisions forecast time variation in expected housing returns. Ortalo-Magné and Rady (2006) propose a life-cycle model in which households differ in their income and thus ability to afford down-payment on a home. Young agents are constrained in their ability to borrow to purchase their first “starter” home. Moreover, changes in the price of starter homes shifts the agents’ demand for trade-up homes, thus establishing a link between the price of a starter homes and the price of trade-up homes. While the modeling assumptions are different from Stein’s (1995), the two papers rely on the same amplifying effects of leverage and emphasize the role of down-payments and liquidity constraints.

The empirical predictions of Stein (1995) are investigated by Lamont and Stein (1999) whose main focus is on the effect of leverage on future house price fluctuations. Working on a sample of 44 metropolitan areas available at annual frequency between 1984 and 1994, they look at the fraction of all owner-occupants with an outstanding mortgage balance to house value ratio greater than 80 percent. This measure is meant to capture the relative presence of “constrained mover” families which play a destabilizing effect in Stein’s (1995) model. Lamont and Stein (1999) find that leverage plays an important role in predicting future real estate prices in two distinct ways. First, lenders and borrowers may be willing to take on high leveraged positions just if they foresee house prices to rise. Consistent with this expectation hypothesis, high leverage today is found to positively correlate with future price appreciation. In their sample, real estate prices are predictable by lagged price changes, with a positive sign, and negatively by the lagged price-income ratio. These effects suggest that housing prices are driven by local economic conditions, short-run momentum, and long-run reversal to fundamentals.

An second important finding of Lamont and Stein (1999) is the economically and statistically large effect of leverage when it is interacted with changes in income. While shocks to income seem to be fully absorbed by real estate prices within four years, there are considerable cross-sectional differences in the response of house prices depending on the initial distribution of debt levels. In high-leverage cities, housing prices react quickly to an income shock and overshoot in the short-run. This effect peaks in the fourth year, when prices start to mean-revert to their
new long-run level. By contrast, low-leverage cities display a more gradual response to the same economic shock and a smooth transition to the new equilibrium level. These effects are consistent with the main prediction of Stein (1995). Even if the level of leverage in an area is ultimately an endogenous variable, their analysis suggests a causal relationship which runs from changes in leverage to house price fluctuations. An empirical limitation of the their findings, however, is that they use homeowners’ estimates of their home value rather than true market prices.

Several other methods have been used to quantify the effect of leverage on the demand for residential and commercial properties. Linneman and Wachter (1989) document that wealth and income constraints lead to a lower probability of home ownership. Using data from the Federal Reserve Board’s 1977 Survey of Consumer Credit and the 1983 Survey of Consumer Finances, they show that mortgage market innovations tend to relax financial constrains. However, the authors do not investigate price effects as a function of the constraints. Genesove and Mayer (1997) use data from the Boston condominium market in the early 1990’s to show that an owner’s level of leverage determines his behavior as a seller and might have an impact on transaction prices. They find that leveraged owners tend to set a higher asking price, their properties stay longer on the market, and conditional on selling, the transaction price is higher than that of less leveraged owners. These findings are broadly consistent with the predictions of Stein (1995) and Ortalo-Magné and Rady (2006). Brown (2000) compares the performance of highly-leveraged mortgage REITs (typically 80 percent leverage or more) to those of less leveraged properties held by property management companies. They consider the period of the late 1980s and early 1990s, which was characterized by large declines in commercial real estate values. The authors find that the leveraged mortgage REITs were net sellers of highly leveraged assets, whereas equity REITs were net buyers. Moreover, the returns of mortgage REITs were significantly more negative that those of equity REITs. The overall evidence of the 1989 and 1990 period suggests that high levels of debt forced mortgage REITs to sell assets at fire sale prices, thus resulting in large losses.

The importance of collateral to lower borrowing costs is also considered by Aoki, Proudman, and Vlieghe (2004) who note that house prices may have a direct effect on consumption via the credit market. Their theoretical model is supported by the empirical evidence in Case, Quigley, and Shiller (2005), (2011) that price changes in real estate have a large impact on aggregate consumption. In the Aoki, Proudman, and Vlieghe (2004) model, a house represents collateral for home-
owners, and borrowing on a secured basis against ample housing collateral is generally cheaper than borrowing against little collateral or on an unsecured basis, such as a personal loan or credit card. Therefore, an increase in housing prices makes more collateral available to homeowners, which in turn encourages them to borrow more to finance their desired level of consumption and housing investment. Looking at structural changes in the UK’s retail financial market, they also show that cheaper access to home equity means that, for a given house price increase, more borrowing will be devoted to consumption relative to housing investment. The response of consumption to an unanticipated change in interest rates will therefore be larger, and the response of house prices and housing investment will be smaller.

The links between credit supply, leverage, and housing prices played a crucial role in the 2007 subprime crisis and have received particular scrutiny in the recent academic literature. Those papers differentiate themselves from the previous leverage literature in one important aspect: they look at the supply and quality of loans and not only at the loan-to-value ratio. For instance, Mian and Sufi (2009) use zip-code data to analyze causes and effects of the mortgage credit expansion and the subsequent crisis. They find that mortgage origination during the 2002-2005 period was stronger in zip codes with a larger fraction of subprime applicants. The same areas, however, exhibit a sharp decrease in income and employment growth in both absolute and relative terms with respect to other zip codes in the same county. Thus, more credit was given in zip codes with worsening relative prospects. This evidence is clearly inconsistent with an income-based explanation, for which mortgages were sold because of improved productivity or income of borrowers.

Importantly, Mian and Sufi (2009) also test whether the increase in credit has been driven by expectations of future house price appreciation. Their identification strategy exploits the index of housing supply elasticity based on land-topology metrics developed by Saiz (2010). House price growth in elastic MSAs is expected not to exceed the inflation rate for house construction costs, as supply can quickly accommodate any increased demand (Glaeser, Gyourko, and Saiz (2008)). Historically, the bulk of house price appreciations have been concentrated in MSAs with inelastic supply. Based on this evidence, one would expect not to observe any increase in lending in elastic MSAs areas, as these do not have good prospects for house price appreciations. Contrary to this prediction, even zip codes in elastic MSAs with a greater fraction of subprime lenders experienced an increase in the relative fraction of originated mortgages sold for securitization and a positive

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relative mortgage origination growth. These results are supportive of a supply-based hypothesis, one in which the increased in credit supply through more relaxed lending practices, a decrease in the price of debt (the subprime-prime spread), and an increase in securitization in high subprime zip codes all lead to a reduction in denial rates and to an increase in house prices. Moreover, 2002-2005 was the only period in the last eighteen years when house prices where negatively correlated to income growth, and thus to fundamentals. Also, it was a period of great expansion of the subprime lending industry.

In a companion paper, Mian and Sufi (2010a) show that borrowing against the increase in home equity by US homeowners resulted in increased levels of leverage and increased defaults from 2006 to 2008. This is an interesting “feedback effect” from home prices to leverage. The Mian and Sufi (2010a) estimation strategy is based on an instrumental variable estimator which makes use of the Saiz (2010) house price elasticity measure to identify the pure effect of house appreciation which is unrelated to an increase in permanent income. The authors document that, during 2002 to 2006, the average homeowner extracted about 25 to 30 cents of every dollar increase in his home equity. This home-equity-based borrowing channel is much stronger for more financially constrained households, such as younger, low quality borrowers, and high credit card users. Since the proceeds from the extra borrowing are not used to purchase new houses or pay down high credit card balances, the authors conclude that they must be used either for consumption or for maintenance. They estimate that, on aggregate, about 53% of the increase in homeowners’ debt from 2002 to 2006, or about $1.25 trillion, was due to home-equity borrowing. Defaults of these existing homeowners represented 39% of total new defaults in the U.S. during the same period. The Mian and Sufi (2010a) paper shows the importance of a feedback effect, resulting from an increase in collateral values and impacting the availability of new credit. Their results are consistent with the aggregate evidence of a wealth effect in Case, Quigley, and Shiller (2011).

This recent work suggests that the extraordinary credit expansion to subprime borrowers put a demand pressure on residential housing during the mid 2000s. The increase in individual leverage was fueled by existing homeowners borrowing against the increase in the value of their homes. Most of the new mortgages were adjustable, i.e. with a low starter rate switching to a floating rate in the following years. Starting in 2006, as interest rates started to rise, households and especially
subprime borrowers found themselves unable to meet the payments, and began to default. In sum, there is mounting evidence that supply of credit and cross-sectional variation in leverage are key-variables in explaining housing dynamics during that period.

Overall, these studies corroborate the claim that exogenous economic shocks lead to larger price fluctuations in leveraged properties. The work of Lamont and Stein (1999) and Brown (2000) suggests that the amplification mechanism derives from the fact that, in real estate, the ability to borrow is directly linked to asset values. An exogenous decrease in those values can lead to a reduction in asset demand, as the borrowing capacity has decreased. However, more research is needed to document whether positive and negative economic shocks lead to an asymmetric response in prices. Also, the Mian and Sufi papers might suggest that the supply of subprime credit in the mid 2000s fueled to a large extent the subsequent house price increases.

5.2 Monetary Policy and Real Estate

Under the premise that monetary policy can stimulate economic activity by reducing borrowing costs, and given that the real estate market is heavily reliant on credit, it is reasonable to ask what is the effect of monetary policy shocks on real estate prices and sales volume. An emerging literature is looking at this question, with recent contributions by Fratantoni and Schuh (2003), Del Negro and Otrok (2007), and Hamilton (2008).

Due to the geographical heterogeneity of real estate, it is unlikely that a monetary policy shock will have the same effect on all regional markets. In fact, it has been documented that the impact of monetary actions varies across regions (Carlino and DeFina (1998), (1999)) and is a function of local economic conditions. It is therefore possible that the response of real estate prices to monetary policy shocks may differ across regions in magnitude and duration. Based on this premise, Fratantoni and Schuh (2003) quantify the importance of regional heterogeneity in housing markets with respect to monetary policy shocks. They start off with a model in which the monetary authority sets the global monetary policy and the mortgage rate serves as the central channel for monetary transmission. At the regional level, income, housing investment, and housing prices are determined by households and firms. Fratantoni and Schuh (2003) contrast the standard method of

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41 See Mian and Sufi (2010b) for a review.
estimating the effect of monetary policy with one in which regional heterogeneity matters. Following the standard approach first, the authors estimate a structural VAR model of log non-housing deflator, log housing deflator, log per-capita non-housing GDP, log real per-capita housing investment, FED funds rate, and a nominal rate on a 30-year mortgage during the 1966-1998 period. Their VAR estimates suggest that a monetary shock has a significantly larger and more rapid effect on the housing than non-housing sector and that monetary policy accounts for a large fraction of fluctuations in the housing sector. However, since housing supply and demand are determined locally, this motivates their regional heterogeneous-agent VAR (HAVAR) analysis.

A HAVAR model involves the estimation of regional VARs which are then aggregated on a national level. The authors show that aggregating these VARs induces non-linearities in the form of time variation (aggregation across heterogeneous regions) and state dependence, due to prevailing economic conditions at the time of the monetary policy intervention. They estimate their model on MSA-level data of housing starts (from the Bureau of Labor Statistics), housing prices (from the FHFA repeat sales transactions), and state-level income (from the Census Bureau). Using a balanced panel of 27 MSAs over 1986:Q3 to 1996:Q2, they estimate unrestricted VARs via OLS and look at the effect of monetary policy tightening, defined as a transitory 100-basis points shock to the FED funds rate, on regional income, housing investment, and house appreciation. The resulting impulse-response functions show that the magnitude and duration of the regional responses vary widely across areas. For instance, monetary tightening is moderately less effective when the economy is experiencing a coastal housing boom. Their key finding is that there are economically and statistically significant differences between the dynamic responses of the HAVAR model they develop and the conventional VAR approach. Peak responses to monetary shocks can vary by more than 1%, and mean lags, by more than one year, depending on local conditions.

In a complementary work, Del Negro and Otrok (2007) use a dynamic factor model to decompose house price movements into regional shocks and a common national component. The motivation for the decomposition is the considerable empirical heterogeneity in the growth rate of house prices across states. They use the FHFA/OFHEO data during the 1986-2005 period. The dynamic factor model is estimated via Bayesian methods and the common component is identified from the idiosyncratic movements. Del Negro and Otrok (2007) find that, historically, fluctuations in housing prices have been mainly driven by local factors. Interestingly, growth rates of
housing are far less correlated across states than are growth rates in real per capita income. This heterogeneity is due to the fact that states have different exposures to the common business cycle. However, in the more recent period, many states display an increase in house prices due to the national factor. The authors investigate whether this increased correlation may be due to monetary policy intervention. Interestingly, the impact of monetary policy shocks on house prices is found to be fairly small. Thus, the authors conclude that the Fed expansionary policy was not behind the recent boom in house prices.

Hamilton (2008) uses a new, high-frequency measure of monetary policy shocks—daily innovations in the 1- and 2-month-ahead futures contracts—and traces out its effect on the housing market. More specifically, he estimates the response of new homes sold (reported by the Census Bureau) following monetary policy shocks. The main finding in the empirical analysis, which is carried out at the aggregate level, is that sales respond with a considerable lag to monetary shocks. He attributes the delay of several months to heterogeneity in search time across households. It would be interesting to extend Hamilton’s (2008) approach and investigate the impact of Fed policy shocks on real estate prices. However, it is fair to say that this, and the other papers in this literature, suggest that monetary policy actions have an important role to play in understanding real estate price fluctuations.

6 Concluding Remarks

How difficult is it to predict changes in real estate prices? In this chapter, we revisit this question from the perspective of the academic real estate literature. However, before we can even tackle the question of predictability, we must step back and address an even more basic issue: constructing reliable real estate price indices in light of the fact that the underlying asset is extremely heterogeneous, faces high transaction costs, and is inherently illiquid. Various indices have been proposed and all have limitations. Recently much interest has focused on repeat-sales indices, both for commercial and residential properties. However, while these indices may be suitable for capturing the current state of the market, they might not necessarily be ideal for forecasting future market prices.

Researchers have explored a variety of predictors of real estate price changes beyond simple autoregressive models. A partial list of the most successful forecasting variables include: valu-
ation ratios such as the rent-to-price and income-to-price ratios; local economic variables, such as the employment rate, income growth, construction costs; demographic trends such as population growth; local space market variables such as housing starts, vacancy rates, and transactions volume; proxies for zoning restrictions; measures of leverage and monetary policy action. The interpretation and success of the predictive models varies considerably as do the datasets on which they have been tested. From a statistical perspective, evaluating the accuracy of real estate forecasts is a challenge: the lack of a sufficiently long time-series of price data has prevented researchers from conducting meaningful out-of-sample MSFE comparisons. Most of the reported evidence is in-sample and exploits cross-sectional differences. However, from an economic perspective, whether the profits from exploiting predictable patterns in real estate prices are enough to cover transaction and search costs is still an unresolved issue.

A notable exception is the REITs market, for which exchange-traded returns are available for a relatively long timespan. In-sample results highlight some predictability of REIT returns, especially at yearly horizons. Significantly more predictability is observed in the growth rates of their cashflows. Out-of-sample predictions of REIT returns mimic those of the aggregate stock market, where unconstrained forecasts perform relatively poorly, although economic constraints may provide some improvements. Linking REITs returns to those of the underlying properties may be an interesting application to trace the origin of the extant predictability.
Appendix

A   Data sources

A.1   Real Estate Data

Residential: The Census Median and Average Sales Prices of New Homes Sold are obtained from the Census. The S&P/Case-Shiller indexes are the NSA series from Macromarkets. FHFA/OFHEO NSA Purchase only monthly and All-Transactions quarterly indexes are from the Federal Housing Finance Agency website.

The 25 metropolitan areas in the FHFA/OFHEO Purchase Only Indexes tape are: Atlanta-Sandy Springs-Marietta, GA; Baltimore-Towson, MD; Chicago-Joliet-Naperville, IL (MSAD); Cleveland-Elyria-Mentor, OH; Dallas-Plano-Irving, TX (MSAD); Denver-Aurora-Broomfield, CO; Edison-New Brunswick, NJ (MSAD); Houston-Sugar Land-Baytown, TX; Los Angeles-Long Beach-Glendale, CA (MSAD); Miami-Miami Beach-Kendall, FL (MSAD); Minneapolis-St.Paul-Bloomington, MN-WI; Nassau-Suffolk, NY (MSAD); New York-White Plains-Wayne, NY-NJ (MSAD); Oakland-Fremont-Hayward, CA (MSAD); Philadelphia, PA (MSAD); Phoenix-Mesa-Glendale, AZ; Pittsburgh, PA; Riverside-San Bernardino-Ontario, CA; St. Louis, MO-IL; San Diego-Carlsbad-San Marcos, CA; Santa Ana-Anaheim-Irvine, CA (MSAD); Seattle-Bellevue-Everett, WA (MSAD); Tampa-St. Petersburg-Clearwater, FL; Warren-Troy-Farmington Hills, MI (MSAD); Washington-Arlington-Alexandria, DC-VA-MD-WV (MSAD).

Commercial: NCREIF indexes are from the NCREIF website. The Transaction-Based Index (TBI) and the Moody’s/REAL Commercial Property Price Index (CPPI) are from the MIT center for real estate. REIT indexes are from the CRSP/Ziman All-Equity tape.

42http://www.census.gov/const/uspricemon.pdf
43http://www.macromarkets.com/csi_housing/sp_caseshiller.asp
45http://www.ncreif.org/tbi-returns.aspx
46http://web.mit.edu/cre/
A.2 Financial and Macro Variables

The aggregate stock market is the value-weighted NYSE/AMEX/NASDAQ index. The dividend-price ratio is constructed following Fama and French (1988b) as sum of current and previous 11-month (or 3 quarters, for quarterly data) dividends over the current price index. The 3-month rate is the Fama Risk-free rate, average of bid and ask. The inflation rate is the return to the CPI index. The Cochrane and Piazzesi (2005) factor is constructed using Fama-Bliss Discount Bond Yields. The source for all these series is the Center for Research in Security Prices (CRSP). Industrial Production is obtained from the Federal Reserve Bank of St. Louis.
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———, 1981c, Trading Activity and the Variance of an Index Number, Working Paper, Department of Mathematics, Chicago State University.


Table 1: Summary Statistics

Annualized mean, annualized standard deviation, skewness, and first-order autoregressive coefficient for returns/price changes, rent/dividend growth, and rent/dividend-price ratio of aggregate real estate indices and conditioning variables. For residential real estate (Panel A), the indices are: the Census Median and Average; the Case-Shiller aggregate US, Composite 10 (C10), and equally-weighted average of available MSA indices (EW); the FHFA/OFHEO quarterly All-Transactions and monthly Purchase Only indices. Rent growth and the rent-price ratio for the Case-Shiller and OFHEO indices are from the Lincoln Institute. For commercial real estate (Panel B), the indices are from NCREIF, TBI, CPPI, and CRSP/Ziman REIT for the aggregate market (All) and separately for apartments (Apt), industrial properties (Ind), offices (Off), and retail properties (Rtl). In Panel C, the Financial and Macro Variables are the CRSP Value-Weighted NYSE/AMEX/NASDAQ index, the 3-month Treasury bill minus its twelve-month moving average (RTB), the return on the CPI index (CPI), the term spread as difference between the 5-year and 3-month yields (TSP), the Cochrane-Piazzesi (2005) interest rate factor (CP), and industrial production growth (IPG). Begin date reports the first return observation. The monthly (M) or quarterly (Q) frequency of each index is also denoted.

<table>
<thead>
<tr>
<th>Begin date</th>
<th>Returns/Price changes</th>
<th>Dividend/Rent Growth</th>
<th>Dividend/Rent-to-price Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std</td>
<td>Skew</td>
</tr>
<tr>
<td><strong>Panel A: Residential Real Estate</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Census Median (M)</td>
<td>Feb 1963</td>
<td>0.055</td>
<td>0.129</td>
</tr>
<tr>
<td>Census Average (M)</td>
<td>Feb 1975</td>
<td>0.056</td>
<td>0.131</td>
</tr>
<tr>
<td>Case-Shiller US (Q)</td>
<td>1987:Q2</td>
<td>0.031</td>
<td>0.048</td>
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<tr>
<td>Case-Shiller C10 (M)</td>
<td>Feb 1987</td>
<td>0.038</td>
<td>0.031</td>
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<tr>
<td>Case-Shiller EW (M)</td>
<td>Feb 1987</td>
<td>0.033</td>
<td>0.027</td>
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<tr>
<td>FHFA/OFHEO US (Q)</td>
<td>1975:Q2</td>
<td>0.046</td>
<td>0.025</td>
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<tr>
<td>FHFA/OFHEO US (M)</td>
<td>Feb 1991</td>
<td>0.031</td>
<td>0.020</td>
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<tr>
<td><strong>Panel B: Commercial Real Estate</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCREIF All (Q)</td>
<td>1978:Q1</td>
<td>0.085</td>
<td>0.045</td>
</tr>
<tr>
<td>NCREIF Apt (Q)</td>
<td>1984:Q1</td>
<td>0.083</td>
<td>0.045</td>
</tr>
<tr>
<td>NCREIF Ind (Q)</td>
<td>1978:Q1</td>
<td>0.087</td>
<td>0.045</td>
</tr>
<tr>
<td>NCREIF Off (Q)</td>
<td>1978:Q1</td>
<td>0.078</td>
<td>0.059</td>
</tr>
<tr>
<td>NCREIF Rtl (Q)</td>
<td>1978:Q1</td>
<td>0.089</td>
<td>0.040</td>
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<tr>
<td>TBI All (Q)</td>
<td>1984:Q2</td>
<td>0.076</td>
<td>0.092</td>
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<tr>
<td>TBI Apt (Q)</td>
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<tr>
<td>TBI Off (Q)</td>
<td>1994:Q2</td>
<td>0.095</td>
<td>0.090</td>
</tr>
<tr>
<td>TBI Rtl (Q)</td>
<td>1994:Q2</td>
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<td>0.089</td>
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<tr>
<td>CPPI All (Q)</td>
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<tr>
<td>CPPI Off (Q)</td>
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<td>CPPI Rtl (Q)</td>
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<td>REIT Apt (M)</td>
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<tr>
<td>REIT Ind &amp; Off (M)</td>
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<td>0.225</td>
</tr>
<tr>
<td>REIT Rtl (M)</td>
<td>Jan 1980</td>
<td>0.121</td>
<td>0.200</td>
</tr>
<tr>
<td><strong>Panel C: Financial and Macro Variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CRSP VW (M)</td>
<td>Jan 1978</td>
<td>0.109</td>
<td>0.163</td>
</tr>
<tr>
<td>RTB (M)</td>
<td>Jan 1978</td>
<td>-0.011</td>
<td>0.039</td>
</tr>
<tr>
<td>CPI (M)</td>
<td>Jan 1978</td>
<td>0.038</td>
<td>0.013</td>
</tr>
<tr>
<td>TSP (M)</td>
<td>Jan 1978</td>
<td>0.014</td>
<td>0.011</td>
</tr>
<tr>
<td>CP (M)</td>
<td>Jan 1978</td>
<td>0.011</td>
<td>0.020</td>
</tr>
<tr>
<td>IPG (M)</td>
<td>Jan 1978</td>
<td>0.020</td>
<td>0.025</td>
</tr>
</tbody>
</table>
Table 2: Correlation Matrix
Correlation matrix of quarterly returns to the Census Median, Case-Shiller Composite 10, FHFA/OFHEO US Monthly, NCREIF All, TBI All, and REIT All indices during the common 1991:Q2-2010:Q4 sample period.

<table>
<thead>
<tr>
<th></th>
<th>Census Median</th>
<th>CS10</th>
<th>FHFA/OFHEO</th>
<th>NCREIF</th>
<th>TBI</th>
<th>REIT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Census Median</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CS10</td>
<td>0.148</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FHFA/OFHEO</td>
<td>0.029</td>
<td>0.803</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCREIF</td>
<td>0.080</td>
<td>0.425</td>
<td>0.335</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TBI</td>
<td>0.029</td>
<td>0.340</td>
<td>0.329</td>
<td>0.604</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>REIT</td>
<td>0.334</td>
<td>0.374</td>
<td>0.181</td>
<td>0.280</td>
<td>0.220</td>
<td>1</td>
</tr>
</tbody>
</table>
Table 3: Forecasting Residential Real Estate

OLS slope estimates of the regression of returns on the Census Median, Case-Shiller Composite 10, and FHFA/OFHEO US Monthly indices on a constant (not reported) and the following lagged conditioning variables: the return and rent-price ratio of the index \(r\) and \(dp\) respectively, the return and dividend-price ratio of the aggregate stock market \(r_m\) and \(dp_m\) respectively, and the financial and macro variables as defined in Table 1. The rent-price ratio for the Census Median in Panel B is the average between the Case-Shiller and FHFA/OFHEO rent-price ratios. In Panel A, the horizon is monthly from February 1991 until December 2010. In panel B, the horizon is quarterly from 1991:Q2 until 2010:Q4. In parenthesis below the estimates, Newey and West (1987) HAC t-statistics based on four lags are reported.

<table>
<thead>
<tr>
<th></th>
<th>Census</th>
<th>Case-Shiller</th>
<th>FHFA/OFHEO</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Monthly</strong></td>
<td></td>
<td>--------------</td>
<td>------------</td>
</tr>
<tr>
<td>(r)</td>
<td>-0.569</td>
<td>0.938</td>
<td>0.725</td>
</tr>
<tr>
<td>((r_m))</td>
<td>0.058</td>
<td>0.017</td>
<td>0.017</td>
</tr>
<tr>
<td>(dp_m)</td>
<td>-0.005</td>
<td>-0.016</td>
<td>-0.007</td>
</tr>
<tr>
<td>RTB</td>
<td>-0.055</td>
<td>0.491</td>
<td>0.234</td>
</tr>
<tr>
<td>CPI</td>
<td>0.013</td>
<td>0.259</td>
<td>0.237</td>
</tr>
<tr>
<td>TSP</td>
<td>0.224</td>
<td>-0.118</td>
<td>-0.163</td>
</tr>
<tr>
<td>CP</td>
<td>-0.153</td>
<td>0.251</td>
<td>0.186</td>
</tr>
<tr>
<td>IPG</td>
<td>0.370</td>
<td>0.076</td>
<td>-0.081</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.317</td>
<td>0.881</td>
<td>0.501</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Census</th>
<th>Case-Shiller</th>
<th>FHFA/OFHEO</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel B: Quarterly</strong></td>
<td></td>
<td>--------------</td>
<td>------------</td>
</tr>
<tr>
<td>(r)</td>
<td>-0.523</td>
<td>0.765</td>
<td>0.661</td>
</tr>
<tr>
<td>(dp)</td>
<td>0.008</td>
<td>0.017</td>
<td>0.009</td>
</tr>
<tr>
<td>(r_m)</td>
<td>-0.005</td>
<td>0.052</td>
<td>0.006</td>
</tr>
<tr>
<td>(dp_m)</td>
<td>-0.008</td>
<td>-0.046</td>
<td>-0.020</td>
</tr>
<tr>
<td>RTB</td>
<td>-0.050</td>
<td>1.460</td>
<td>0.747</td>
</tr>
<tr>
<td>CPI</td>
<td>0.125</td>
<td>0.579</td>
<td>0.567</td>
</tr>
<tr>
<td>TSP</td>
<td>0.001</td>
<td>-0.417</td>
<td>-0.624</td>
</tr>
<tr>
<td>CP</td>
<td>0.011</td>
<td>0.709</td>
<td>0.567</td>
</tr>
<tr>
<td>IPG</td>
<td>0.065</td>
<td>-0.035</td>
<td>-0.067</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.273</td>
<td>0.559</td>
<td>0.409</td>
</tr>
</tbody>
</table>
Table 4: Forecasting Commercial Real Estate

OLS slope estimates of the regression of returns on the NCREIF All, TBI All, and REIT All indices on a constant (not reported) and lagged conditioning variables. Variables definition follows from Table 3. The horizon is quarterly from 1985:Q1 until 2010:Q4. In parenthesis below the estimates, Newey and West (1987) HAC t-statistics based on four lags are reported.

<table>
<thead>
<tr>
<th></th>
<th>NCREIF</th>
<th>TBI</th>
<th>REIT</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>r</td>
<td>0.812</td>
<td>0.045</td>
</tr>
<tr>
<td></td>
<td>(13.869)</td>
<td>(0.440)</td>
<td>(-1.748)</td>
</tr>
<tr>
<td></td>
<td>dp</td>
<td>0.011</td>
<td>0.036</td>
</tr>
<tr>
<td></td>
<td>(-0.611)</td>
<td>(-1.156)</td>
<td>(0.165)</td>
</tr>
<tr>
<td></td>
<td>r_m</td>
<td>0.053</td>
<td>0.049</td>
</tr>
<tr>
<td></td>
<td>(1.226)</td>
<td>(0.706)</td>
<td>(0.206)</td>
</tr>
<tr>
<td></td>
<td>dp_m</td>
<td>-0.025</td>
<td>-0.028</td>
</tr>
<tr>
<td></td>
<td>(-2.951)</td>
<td>(-2.763)</td>
<td>(-2.245)</td>
</tr>
<tr>
<td></td>
<td>RTB</td>
<td>0.591</td>
<td>0.486</td>
</tr>
<tr>
<td></td>
<td>(1.901)</td>
<td>(0.738)</td>
<td>(1.211)</td>
</tr>
<tr>
<td></td>
<td>CPI</td>
<td>0.390</td>
<td>0.148</td>
</tr>
<tr>
<td></td>
<td>(1.368)</td>
<td>(0.367)</td>
<td>(0.709)</td>
</tr>
<tr>
<td></td>
<td>TSP</td>
<td>-1.283</td>
<td>-0.702</td>
</tr>
<tr>
<td></td>
<td>(-2.926)</td>
<td>(-1.042)</td>
<td>(-1.293)</td>
</tr>
<tr>
<td></td>
<td>CP</td>
<td>0.329</td>
<td>0.213</td>
</tr>
<tr>
<td></td>
<td>(1.121)</td>
<td>(0.456)</td>
<td>(1.142)</td>
</tr>
<tr>
<td></td>
<td>IPG</td>
<td>0.696</td>
<td>1.202</td>
</tr>
<tr>
<td></td>
<td>(2.824)</td>
<td>(3.304)</td>
<td>(3.178)</td>
</tr>
<tr>
<td></td>
<td>R^2</td>
<td>0.636</td>
<td>0.030</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.184</td>
<td>0.058</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.484</td>
<td>0.191</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.709</td>
<td>0.255</td>
</tr>
</tbody>
</table>

80
Table 5: Forecasting REITs

Slope coefficients of the regressions of $H$-month real returns (Panel A) and real dividend growth (Panel B) on the aggregate CRSP/Ziman All-Equity REIT index (All) and separately for apartments (Apt), industrial properties and offices (Ind & Off), and retail properties (Rtl) on a constant (not reported) and lagged log dividend-price ratio. OLS results are shown for separate monthly horizons. The table also reports the one-month two-stage GMM estimates which impose the present value constraint (equation 17) across equations and the short-long horizon relationship (equation 16) across horizons $H = \{1, 3, 6, 12\}$. The coefficients are bias-adjusted following Stambaugh (1999). The $t$-statistics are Newey and West (1987) based on four lags for non-overlapping and $H$ lags for overlapping returns. The sample is monthly from December 1980 until December 2010.

### Panel A: Real Returns

<table>
<thead>
<tr>
<th>Estimation, Horizon</th>
<th>All</th>
<th>Apt</th>
<th>Ind &amp; Off</th>
<th>Rtl</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\beta_r$</td>
<td>$t(\beta_r)$</td>
<td>$R^2$</td>
<td>$\beta_r$</td>
</tr>
<tr>
<td>OLS, $H=1$</td>
<td>0.001</td>
<td>0.013</td>
<td>0.002</td>
<td>-0.002</td>
</tr>
<tr>
<td>OLS, $H=3$</td>
<td>0.031</td>
<td>0.820</td>
<td>0.009</td>
<td>0.022</td>
</tr>
<tr>
<td>OLS, $H=6$</td>
<td>0.117</td>
<td>1.490</td>
<td>0.039</td>
<td>0.080</td>
</tr>
<tr>
<td>OLS, $H=12$</td>
<td>0.280</td>
<td>1.684</td>
<td>0.092</td>
<td>0.200</td>
</tr>
<tr>
<td>GMM, $H = {1, 3, 6, 12}$</td>
<td>0.013</td>
<td>1.126</td>
<td>-</td>
<td>0.010</td>
</tr>
</tbody>
</table>

### Panel B: Real Dividend Growth

<table>
<thead>
<tr>
<th>Estimation, Horizon</th>
<th>All</th>
<th>Apt</th>
<th>Ind &amp; Off</th>
<th>Rtl</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\beta_d$</td>
<td>$t(\beta_d)$</td>
<td>$R^2$</td>
<td>$\beta_d$</td>
</tr>
<tr>
<td>OLS, $H=1$</td>
<td>-0.015</td>
<td>-3.232</td>
<td>0.029</td>
<td>-0.026</td>
</tr>
<tr>
<td>OLS, $H=3$</td>
<td>-0.051</td>
<td>-3.465</td>
<td>0.094</td>
<td>-0.081</td>
</tr>
<tr>
<td>OLS, $H=6$</td>
<td>-0.119</td>
<td>-3.361</td>
<td>0.162</td>
<td>-0.182</td>
</tr>
<tr>
<td>OLS, $H=12$</td>
<td>-0.261</td>
<td>-3.551</td>
<td>0.230</td>
<td>-0.384</td>
</tr>
<tr>
<td>GMM, $H = {1, 3, 6, 12}$</td>
<td>-0.018</td>
<td>-9.716</td>
<td>-</td>
<td>-0.031</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Estimation, Horizon</th>
<th>All</th>
<th>Apt</th>
<th>Ind &amp; Off</th>
<th>Rtl</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\beta_d$</td>
<td>$t(\beta_d)$</td>
<td>$R^2$</td>
<td>$\beta_d$</td>
</tr>
<tr>
<td>OLS, $H=1$</td>
<td>-0.015</td>
<td>-2.753</td>
<td>0.029</td>
<td>-0.026</td>
</tr>
<tr>
<td>OLS, $H=3$</td>
<td>-0.049</td>
<td>-3.063</td>
<td>0.095</td>
<td>-0.082</td>
</tr>
<tr>
<td>OLS, $H=6$</td>
<td>-0.120</td>
<td>-3.586</td>
<td>0.170</td>
<td>-0.205</td>
</tr>
<tr>
<td>OLS, $H=12$</td>
<td>-0.230</td>
<td>-4.629</td>
<td>0.213</td>
<td>-0.396</td>
</tr>
<tr>
<td>GMM, $H = {1, 3, 6, 12}$</td>
<td>-0.019</td>
<td>-6.696</td>
<td>-</td>
<td>-0.035</td>
</tr>
</tbody>
</table>
Table 6: Forecasting REITs In-Sample and Out-Of-Sample

In-sample (IS) and Out-Of-Sample (OOS) $R^2$, as defined in equation (18), for the predictive regression of real returns and real dividend growth to the aggregate CRSP/Ziman All-Equity REIT index at the monthly (Panel A), quarterly (Panel B), and semi-annual (Panel C) frequency. The forecasters are defined as in Table 4. “Combined” refers to the average forecast across all forecasters. Specification ‘unc” is the unconstrained regression; specification “sign($\beta_r$)” and “$r > 0$” replace the forecast with the unconditional mean when the slope coefficient or the forecast, respectively, are negative; specification “both” imposes both constraints. The OOS results are based on a 180-month burn-in period. The full sample is monthly observations from December 1980 until December 2010.

<table>
<thead>
<tr>
<th>Forecaster</th>
<th>Real returns</th>
<th>Real Dividend-Growth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>IS OOS</td>
<td>OOS OOS OOS</td>
</tr>
<tr>
<td></td>
<td>unc sign($\beta_r$) $\hat{r}$ both</td>
<td></td>
</tr>
<tr>
<td>----------</td>
<td>--------------</td>
<td>----------------------</td>
</tr>
<tr>
<td><strong>Panel A: Monthly</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$dp$</td>
<td>0.181 -0.686 -0.571 -0.321 -0.205</td>
<td>2.866 -1.873</td>
</tr>
<tr>
<td>$r_m$</td>
<td>4.760 4.022 4.022 1.885 1.885</td>
<td>0.572 0.985</td>
</tr>
<tr>
<td>$dp_m$</td>
<td>0.005 -0.637 -0.572 -0.324 -0.260</td>
<td>0.008 -1.160</td>
</tr>
<tr>
<td>RTB</td>
<td>0.071 -2.005 0.000 -1.565 0.000</td>
<td>0.058 -2.015</td>
</tr>
<tr>
<td>CPI</td>
<td>0.641 -3.105 0.000 -3.075 0.000</td>
<td>0.047 -1.846</td>
</tr>
<tr>
<td>TSP</td>
<td>0.313 -0.488 -0.488 -0.406 -0.406</td>
<td>0.559 -10.616</td>
</tr>
<tr>
<td>CP</td>
<td>0.250 -0.385 -0.318 0.211 0.278</td>
<td>1.739 -4.108</td>
</tr>
<tr>
<td>IP</td>
<td>2.805 -0.227 0.327 -0.985 -0.411</td>
<td>2.320 -1.920</td>
</tr>
<tr>
<td>Combined</td>
<td>2.093 0.187 0.620 -0.226 0.241</td>
<td>6.862 0.291</td>
</tr>
<tr>
<td><strong>Panel B: Quarterly</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$r_m$</td>
<td>0.470 1.463 2.218 0.770 1.526</td>
<td>0.230 -0.319</td>
</tr>
<tr>
<td>$dp_m$</td>
<td>0.121 -2.406 -2.406 -1.284 -1.284</td>
<td>0.002 -1.442</td>
</tr>
<tr>
<td>RTB</td>
<td>0.031 -3.792 0.000 -3.704 0.000</td>
<td>0.258 -0.290</td>
</tr>
<tr>
<td>CPI</td>
<td>0.690 -6.142 -0.445 -3.737 -0.445</td>
<td>0.268 0.297</td>
</tr>
<tr>
<td>TSP</td>
<td>2.156 -1.007 -1.007 0.749 0.749</td>
<td>0.602 -15.706</td>
</tr>
<tr>
<td>CP</td>
<td>0.798 0.638 0.649 0.638 0.649</td>
<td>2.536 -3.415</td>
</tr>
<tr>
<td>IP</td>
<td>2.240 1.059 2.156 -0.162 1.150</td>
<td>3.116 -3.049</td>
</tr>
<tr>
<td>Combined</td>
<td>2.093 -1.319 -0.166 -1.270 -0.045</td>
<td>6.862 -0.266</td>
</tr>
<tr>
<td><strong>Panel C: Semi-Annual</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$r_m$</td>
<td>0.480 0.377 0.611 0.377 0.611</td>
<td>0.016 -1.645</td>
</tr>
<tr>
<td>$dp_m$</td>
<td>0.450 -3.825 -3.825 -2.314 -2.314</td>
<td>0.002 -2.137</td>
</tr>
<tr>
<td>RTB</td>
<td>0.001 -4.650 0.000 -4.650 0.000</td>
<td>0.526 -0.418</td>
</tr>
<tr>
<td>CPI</td>
<td>0.001 -3.694 -0.017 -3.694 -0.017</td>
<td>0.658 0.912</td>
</tr>
<tr>
<td>TSP</td>
<td>2.955 -0.984 -0.984 -0.522 -0.522</td>
<td>1.076 -19.220</td>
</tr>
<tr>
<td>CP</td>
<td>0.193 1.216 1.095 1.216 1.095</td>
<td>5.412 -5.349</td>
</tr>
<tr>
<td>IP</td>
<td>1.240 -1.267 2.143 -1.888 1.469</td>
<td>5.580 -5.200</td>
</tr>
<tr>
<td>Combined</td>
<td>2.093 -2.625 -1.340 -2.164 -0.890</td>
<td>6.862 -2.492</td>
</tr>
</tbody>
</table>
Figure 1: Residential Real Estate Indices

Time series plot of the Census Median, Case-Shiller Composite 10, and OFHEO. All series are sampled quarterly and normalized at one in 1991:Q1.
Figure 2: Commercial Real Estate Indices

Time series plot of the NCREIF All, TBI All, and CRSP/Ziman REIT All indices. All series are sampled quarterly and normalized at one in 1984:Q4.
Figure 3: Long-Horizon Return Autocorrelations

The thick solid line reports the OLS slope coefficients $\beta_H$ in the regression of $H$-month overlapping returns on a constant and their $H$-period lagged value, $r_{t+1:t+H} = \alpha + \beta(H) r_{t-H:t} + \epsilon_{t+1:t+H}$. The dashed lines denote the point estimate plus or minus two Newey and West (1987) HAC standard errors based on $H$ lags. The plots are (from top to bottom) for the Census Median index quarterly sampled, FHFA/OFHEO Quarterly series, TBI All, and REIT All quarterly sampled. The X-axis reports the horizon $H$ in months. The sample period is as in Table 1.

85
Figure 4: Predicting Residential Real Estate MSA Returns

Summary of the predictive regression of each of the 25 MSAs OFHEO Purchase Only quarterly return series on a constant, its own lagged return, the aggregate OFHEO rent-to-price ratio, and macro and financial variables as defined in Table 3. The regressors are all jointly included as in the largest specification of Tables 3 and 4. For each regressor (except the constant) across MSA, the Figure shows in the top left panel the average slope coefficient, in the top right panel the average t-statistic, and in the bottom left panel the number of t-statistics greater than two in absolute value. The bottom right panel displays the R² for each regression. The list of MSAs is reported in Appendix A.1. The sample is quarterly observations from 1991:Q2 until 2010:Q4.
**Figure 5: Principal Component Analysis by MSA**

The top plot reports the percentage explained by the first 10 principal components extracted from the covariance matrix of returns to the 25 MSAs OFHEO Purchase Only quarterly series. The bottom plot shows the percentage explained by the first component based on 40-quarter rolling windows. The full sample is quarterly observations from 1991:Q2 until 2010:Q4.