The Economic Foundations of Regional Real Estate Markets: An Equity Markets Approach.

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Version: January 24, 2015

1.0 Introduction and literature review.

Possessing the ability to ascertain the direction and/or magnitude of future price changes in regional real estate markets would be of obvious utility. Additionally, understanding the relations between real estate prices in a region and the prices of other investment assets in the economy would be useful in the optimization of investment portfolios, and would provide market participants and policy makers with insights into the industries that most impact each region.

The starting point for forecasting any variable is the development of a model of how the variable tends to evolve over time. Ideally, one would like to be able to use conditions present at one point in time to predict the value of the variable at a future point in time.

Ghysels, Plazzi, Torous, and Valkanov (2012) provide an excellent synopsis of the academic literature related to forecasting real estate prices and they group past studies into three general categories.

The first group is comprised of those studies that have used autoregressive techniques, often within the context of testing the informational efficiency of the real estate market. These studies include Gau (1984) and Schindler (2011).

The second group regresses prices or returns on valuation ratios, such as price-to-income. Examples of these studies are Hamilton and Schwab (1985) and Gallin (2008).

The third group of papers use a set of regional and/or of national economic variables to forecast real estate prices. The logic behind using such variables is that they should be related to the supply and demand for real estate and thus, may provide a more comprehensive model of the price dynamics. Among these studies are Rosen (1984) and Plazzi, Torous, and Valkanov (2010).

One unique facet of forecasting real estate prices is the heterogeneity that exists in real estate markets across disparate geographic locations. For this reason those studies that have focused on variables related to supply and demand have incorporated both regional and national economic variables. There is no reason that a model that works well in one particular region will necessarily work well in another region.

Herein, we empirically determine the best model for each of a series of regional real estate price indices (commercial and residential), with such models being comprised of national macroeconomic variables, and a set of returns on equity indices representing 49 (or alternately, 10) different industries. It is hypothesized that industry returns will proxy for local economic influences. We then propose to investigate the ability of the models to forecast real estate prices out-of-sample.

The returns on equity indices for various industries may be related to regional real estate prices through a number of channels. There may be some wealth effects concomitant with higher equity returns, however, one would expect that ownership of the equity represented by the indices would be diffuse throughout the country, and therefore the wealth effects from stock *ownership* should not necessarily vary across regions. No, the more important channel through which industry equity returns are likely to influence regional real estate prices is through the implications that the stock prices have for the relative performance of the different industries. The stock prices are a reflection of the market's expectations regarding the future performance of the industries, and the industries, themselves, are more or less concentrated geographically. To the extent that higher stock prices for an industry are related to greater future prosperity for that industry, and to the extent that greater prosperity for that industry influences the decisions of businesses and residents in the area where the industry is located, the regional supply and demand for real estate will be impacted.

The use of equity indices to proxy for the economic underpinnings of regional economies has the further advantage that the data on equity returns is more readily available, at finer frequencies, than many local economic variables.

2.0 Methodology

The return on each of the regional real estate price indices is fit to the following model:

$$r_t = \alpha + \sum_{v=1}^{y}\sum_{k=1}^{n}\gamma_{v,k} r_{v,t-k} + \sum_{l=1}^{h}\lambda_l M_{t-l} + \sum_{i=1}^{m}\sum_{j=1}^{z}\beta_{i,j} I_{j,t-i} + \varepsilon_t \,, \qquad (1)$$

where r_t is the return on the real estate price index at time *t*, $I_{j,t}$ is the return on the j^{th} industry's stock price index at time *t*, M_t is a set of national macroeconomic variables, $\alpha, \gamma_k, \lambda_l$, and $\beta_{i,j}$ are coefficients to be estimated, and ε_t is an error term.

Using Hendry's general-to-specific (GTS) (Campos, Ericsson, and Hendry; 2005) selection criteria the best-fitting combination of the lagged industry returns is determined. The Hendry method begins with estimating the most general specification of potential, relevant, explanatory variables. If all of the explanatory variables are not significant at the required minimum threshold, the variable whose coefficient has the lowest t-statistic is removed from the model, and the model is re-estimated. This process is continued until all of the explanatory variables remaining in the model are significant.

Table 2 illustrates the GTS model selection process. Each column in Table 2 reports the t-statistics associated with the variables in the first column. All of the variables for which a t-statistic are reported are included in a regression where the change in the dependent variable is the percent change in the Case-Shiller House Price Index for New York City. In addition, the adjusted R-squared are reported for each of the regressions. The table illustrates the manner in which the variable with the lowest t-statistic is dropped from subsequent estimations, until after 27 iterations, one arrives at the best-fitting parsimonious model.

2.1 Model selection constraints and choices.

Hendry's GTS methodology allows one to systematically choose, among several potential variables, those variables that comprise the best-fitting model for a particular dependent variable. However, there are still many choices that a forecaster or model-builder must make, and these choices are made within a number of constraints.

2.1.1 A limited number of observations of the dependent variable.

It is a truism that any modeler would prefer to have more, rather than less, observations on which to construct his model. The more observations one is able to use, the more confidence one has about the convergence of the distributions of the variables, and the more accurate estimates become.

When one is constructing a model using ordinary least squares (OLS) and one can choose between a large number of potential explanatory variables (and their lags), then the number of observations of the dependent variable that are available becomes a limiting constraint. This is because an OLS regression cannot have more explanatory variables than observations of the dependent variable.

Considering the regional real estate price series, some are measured at quarterly frequencies and others at monthly frequencies. Further, the longest series begin in the early 1970's, while the shortest series begin in the 1990's. We fit models for all of these series; however, much of the analysis that is performed herein will focus on the Case-Shiller Housing price indices for 20 metropolitan regions. The primary reason for this focus arises out of the fact these are monthly series, many of which originate in the early 1970's; meaning that more observations of these series are available than for the other series.

Further, included in the models are lags of the other regional price indices (indeed these prove crucial in generating superior out-of-sample forecasts). There is nothing controversial, econometrically, about including lags of the other regional price series in the models. Indeed, to some extent this merely makes the models quasi vector-auto-regressions, such as those employed in Miao, Ramchander and Simpson (2011). However, it does further constrain the number of potential explanatory variables that can be included in the initial models. The reason is that if one is modeling the behavior of series X by regressing it on lags of series Y the number of observations that can be included in the model is the *lesser* of the number of observations of X and the number of observations of Y.

Thus, equation (1) as applied to the Case-Shiller price indices is constrained to having 169 observations when lags of all of the series are included. This is because the series for Dallas, Texas only has 169 observations. Most of the analysis is carried out using all 20 series, but one last estimation is performed excluding Dallas and this model produces the best results, overall for the remaining 19 series.

The commercial property index series are quarterly. This significantly reduces the number of observations available for analysis. Furthermore, the series begin in the early 1990's. For these commercial property indices there are, at most, 147 observations available. This is sufficient to estimate the models, but given the difference in number of observations, it would not be surprising if the forecasts produced from these models did not perform as well as those produced by the Case-Shiller indices, where more observations are available.

2.1.2 Value-weighted industry portfolios or equally-weighted industry portfolios.

Another choice that the modeler faces when using the returns on portfolios of equity securities is how to weight the individual securities within the portfolios. The "weight" on a security in a portfolio, is, of course, the percentage of the portfolio invested in that particular security. The two most prevalent, "passive" weightings of the securities within a given portfolio are to either use value-weights, or to equally weight the securities. When one uses value-weights the weight in the portfolio of a given security is the ratio of the market capitalization of the individual security to the total market capitalization of all of the securities in the portfolio. The weight on a security in an equally weighted portfolio is simply $1/n$, where n is the number of securities in the portfolio.

One of the main differences between the two weighting schemes is that value-weighted portfolios will be more heavily weighted toward large cap stocks and this mitigates the well-known "size-effect.," which is the propensity of smaller firms to produce higher returns than larger firms. For this reason, value-weighted returns are often preferred in academic studies, as a check that whatever phenomenon being studied is not an artifact of a weighting scheme that favors small stocks.

It is not entirely clear which weighting scheme should be used for our purposes here. It may be that an equally-weighted portfolio better captures the dynamics of the economic conditions where a particular firm is located, and thus we should use equally-weighted returns. This would be particular true, if there were geographic areas that were populated by a large number of small firms in the same industry.

We perform our analysis using both value-weighted and equally-weighted industry portfolios.

2.1.3 How fine to define the industries.

Conceptually an industry is defined as a group of firms that provide the same or similar products. Depending upon how one defines “similar” the number of firms in an industry will change. For example, defining an industry as all firms that install carpet will produce an industry of a given size. Alternately, if we define the industry as all firms that install any type of flooring, then the number of firms in this industry will necessarily be larger than the industry that was comprised of only carpet installers. Likewise, if we include manufacturers of flooring products in the industry definition, then, the number of firms grows again. Making the definition even broader, we could define the “industry” as all construction-related manufacturers and installers. It is true that in everyday parlance we might refer to such a broad definition as a sector rather than an industry, but this has not generally been the practice in the academic literature.

Regardless of whether we call them industries or sectors, the question remains: how broad a definition should we use? Intuitively, if our argument is that how well the firms are doing in a particular region impacts the real estate prices in that region, then it would seem that we would want as fine a definition of industries as possible, so as to more closely match the economic base of a given locale.

But this may also depend on the size of the economic base in question. It could be that real estate prices in regions with diverse economic bases might respond better to broader—more diverse—measures of industry returns.

An argument can be made that in going as fine as possible and allowing the model to determine which industries are most influential would be superior to using broader based industry measures. Specifically, 1) if fine measures of industry returns are needed then using fine measures of industry returns would be appropriate and 2) if broad measures are needed then the model selection methodology might be able to replicate the broad measures in that it may call for several of the more finely defined industries—those that, in aggregate, are equivalent to the more broadly defined measure—to be included in the model.

Thus, it would appear, theoretically, that using finer rather than broader measures would allow the modeler to have his cake and eat it to. Unfortunately, if broader industry measures are needed then this rationale relies on the model selection criteria to properly select the relevant finer industries that make up the broader industries. While the GTS selection criteria is currently the preferred model selection methodology, it is not perfect, and it is furthermore designed to ensure parsimony. Such parsimony may not allow enough finer industries into the model to adequately substitute for a broad industry measure.

While there are these, and other, theoretical considerations as to how fine we should define our industries, at the end of the day, this is an empirical question, and thus in one set of analyses we divide all firms into 49 industries and in an alternate set of analyses we divide all firms into 10 industries.

2.1.4 Should the model be selected over depth or over breadth?

The GTS model selection methodology requires one first to identify the relevant explanatory variables then to winnow them away until one has the best-fitting parsimonious model. The question that must first be addressed is: what are the relevant explanatory variables? To be sure, we seek here to model changes in real estate price indices as a function of past changes in real estate price indices, past changes in the unemployment rate, past changes in mortgage rates, and past returns on industry portfolios.

Yet a question remains: In our initial estimations, how many lags of the independent variables should we include? Here again we run up against the constraint imposed by the limited number of observations of the dependent variable. If we take the example of the Case-Shiller index for Dallas, Texas where we have 169 monthly observations. A model that includes one lag of all of the other Case-Shiller indices, one lag of the mortgage and unemployment rates, and one lag of each of the 49 industry returns, including the intercept term, would have 72 right-hand side variables, and an average of 2.34 observations of the dependent variable per explanatory variable. In general, the more observations of the dependent variable per explanatory variable the better, with some statisticians suggesting a general rule of thumb of about 30 observations per explanatory variable.

A model that is selecting over a breadth of different variables, necessarily cannot simultaneous selected over a depth (i.e., over many lags) of those same variables. Given the constraints, if one wished to choose the best lags to include in the model one could choose just a few explanatory variables at a time, but include a large number of lags of those variables.

We have chosen to select our models over a breadth of variables, rather than piece-wise selected over many lags. One reason we choose to use a number of explanatory variables and one-lag is because existing literature documents a high level of autocorrelation in monthly housing price series at a lag of one-month (e.g., Schindler, 2013).

2.1.5 What is the threshold for retention of a variable in a model?

The GTS model selection methodology requires estimation of the most general specification for a model, then one examines the minimum t-statistic of all the t-statistics for the independent variables. If the minimum t-statistic does not meet a threshold for significance, the variable associated with that t-statistics is removed and the model is re-estimated. This process continues until all of the variables remaining in the model have t-statistics that are significant at the threshold level or higher. In order to carry out this procedure one must first stipulate what the minimum threshold t-statistic is going to be. The higher the minimum threshold, the more parsimonious the resulting model. Ironically, parsimony is important but there are situations in which it may be costly. If one were overly parsimonious one may reject variables that could improve the fit of the model and one's forecasting ability.

T-statistics are generally significant at the 5% when they have a value of about 1.98. We have chosen a minimum threshold level of 2.00. We feel that this is the least controversial level for the minimum threshold. In essence, we require that all variables remaining in a model are significant at the 5% level. This may be arbitrary, but it is in line with general conventions in finance and other social sciences that require that the probability that a given coefficient is statistically equal to zero be 5% or less before one considers the variable to be "statistically significant."

It should be noted that there are *literally* an infinite number of possible threshold values from which to choose. Pragmatism would seem to dictate use of the least controversial number.

2.2 Data

Descriptive statistics of the percent changes in the various real estate price indices are reported in Table 1.

2.3 Measuring Performance

In order to assess the ability of the models to forecast out-of-sample, updating the models every 12 months, we use the following procedure:

1) All data from the beginning of the time series up to January 2009 are used in the GTS selection to determine the best fitting model.
2) One-month ahead forecasts for the follow 12 months are produced.
3) The model is re-estimated using all data up to January 2010, and the procedure is repeated.

This process is used for all 20 of the Case-Shiller Housing Price Indices, and results in 60 months (five years) of out-of-sample forecasts.

In another set of analyses we follow the same method, except the models are selected and updated every month rather than every 12 months.

The performance of the models in forecasting changes in housing price indices is measured relative to that of a simple autoregressive model of order one AR(1). Previous literature (e.g., Schindler, 2013) has documented the ability of a simple AR(1) model to outperform a random walk in predicting changes in housing price indices.

Over the same rolling windows that are used in the estimation of the industry-based models, the benchmark, AR(1), model is estimated as follows:

$$r_t = a + br_{t-1} + \xi_t, \tag{2}$$

Once the forecasts from the industry-related models and the AR(1) models are computed the root mean squared error (RMSE) of the forecasts are calculated as follows:

$$RMSE = \sqrt{\sum_{i=1}^{60} \frac{(H_i - F_i)^2}{60}}. \tag{3}$$

Where H_i is the actual i^{th} value of a housing price index and F_i is the forecast of the i^{th} value of a housing price index. The RMSE is a measure of the average error in forecasting a variable; and the lower the RMSE, the better the model performs in forecasting the variable.

To compare the industry-related models performance to that of the benchmark models we calculate the difference in the RMSE of the two models as a percentage:

$$\Delta RMSE_h = \frac{RMSE_{h,B} - RMSE_{h,I}}{RMSE_{h,B}} \times 100\,. \tag{4}$$

Where $\Delta RMSE_h$ is the difference in the *RMSE* for the h^{th} housing price index. $RMSE_{h,B}$ is the *RMSE* of the benchmark (AR(1)) model for the h^{th} housing price index and $RMSE_{h,I}$ is the *RMSE* of the industry equity return-based model for the h^{th} housing price index. If $\Delta RMSE_h$ is negative it indicates that the industry-based model reduces the RMSE over the AR(1) model when forecasting the index levels for that particular housing price index.

In addition, we compute statistics for a two-tailed t-test with the null hypothesis that there is no difference in the mean squared errors of the two models.

3.0 Results

Tables 3 and 4 report, for the Case-Shiller Indices the difference in RMSE for the industry-based models versus the benchmark models. Negative numbers indicate that the industry-based models produce lower RMSE than those of the benchmark model. Table 3 reports the results for the industry-based models that start the model selection process using 49 industry portfolios. Table 4 reports the results for the industry-based models that start the model selection process using 10 industry portfolios.

Each column in Tables 3 and 4 reports the performance results of models among which the selection processes slightly vary. It can be seen that regardless of selection method the industry-based models tend to produce lower RMSE than the benchmark models.

With the exceptions of Washington, DC and Cleveland, OH, the industry-based models seem to produce significantly lower RMSE than the benchmarks for markets in the Northeast and Midwest. For the Southeast, Southwest and Northwest markets the industry-based models do not appear to produce as consistent results.

That being said, at least one of the industry-based models produces significantly lower RMSE for 15 of the 20 series.

Tables 5 and 6 report the results for forecasting the mean and median house price (Table 5) and Commercial real estate prices (Table 6).

Tables 7 through 26 show the results of estimating models for the 20 Case-Shiller Indices using 49 equally-weighted industry portfolios. These models are estimated over the entire period and were not used for forecasting. Rather, the intent of providing these tables is to illustrate the interaction between the different industries and the housing price indices.

Appendices A and B report some of the models used to forecast the housing price series. Appendix A reports the models when the methodology uses 49 value-weighted industry portfolios and annual updating. Appendix B reports the models when the methodology uses 10 equally-weighted industry portfolios and annual updating. There are 20 Case-Shiller indices, and for each index the models are updated annually for 5 years, thus each appendix reports 100 models. Using the monthly updating method, which produces slightly better results, would require reporting 12 times as many models or 1,200 models.

4.0 Conclusion

For 15 of the 20 Case-Shiller metropolitan housing price indices, models that incorporate lags of the returns on industry-related equity portfolios are able to produce out-of-sample forecasts with root mean squared errors that are statistically significantly lower than the forecasts of a benchmark AR(1) model.

The composition of the models, which are updated either annually or monthly show some variation over time which is consistent with the findings in Gu (2002), who finds that the direction of autocorrelation in house price movements differ across areas and change over time.

Despite the changing nature of the models over time, we demonstrate methods of *model selection* that are able to produce superior forecasts over a five year period. The models employ frequent updating (annual or monthly), lags of the price indices, lagged changes in the unemployment rate, lagged changes in mortgage rates and lagged returns on equity portfolios comprised along industry lines.

The results of applying these methodologies to regional median and mean home prices or to quarterly commercial property indices are not as impressive.

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Table 1, Panel A: Descriptive statistics.

Market	Case-Shiller Housing Price Indices Mean Δ Price (%)	Standard Deviation (%)	Number of Observations
Northeast Markets			
Boston, MA	0.39	1.03	349
New York, NY	0.39	1.24	409
Washington DC	0.36	1.03	325
Southeast Markets			
Atlanta, GA	0.17	1.11	277
Charlotte, NC	0.24	0.62	373
Miami, FL	0.39	1.05	505
Tampa, FL	0.21	1.01	385
Midwest Markets			
Chicago, IL	0.29	1.15	337
Cleveland, OH	0.20	0.92	325
Detroit, MI	0.17	1.31	277
Minneapolis, MN	0.25	1.27	301
Southwest Markets			
Dallas, TX	0.17	0.87	169
Denver, CO	0.41	0.81	445
Phoenix, AZ	0.25	1.35	301
Las Vegas, NV	0.21	1.41	325
Northwest Markets			
Portland, OR	0.41	0.92	337
San Francisco, CA	0.43	1.33	409
Seattle, WA	0.35	1.02	289
Southern California Markets			
Los Angeles, CA	0.40	1.16	409
San Diego, CA	0.48	1.16	445

Table 1, Panel B: Descriptive statistics.

Median and Mean Home Price Census Regions (National Association of Realtors)			
Market	Mean Δ Price (%)	Standard Deviation (%)	Number of Observations
Median Existing Home Price			
Midwest	0.11	3.65	181
Northeast	0.28	4.15	181
West	0.23	3.40	181
South	0.21	3.26	181
Mean Existing Home Price			
Midwest	0.28	4.15	181
Northeast	0.21	3.14	181
West	0.27	3.24	181
South	0.20	2.75	181

Table 1, Panel C: Descriptive statistics.

NCREIF Commercial Property Indices*			
Market	Mean Δ Price (%)	Standard Deviation (%)	Number of Observations
East	2.51	2.69	145
West	2.35	2.49	145
South	2.00	1.98	145
Midwest	1.97	1.82	145

* Data is quarterly.

Table 2: Panel A. Illustration of the GTS model selection process.

Iteration	1	2	3	4	5	6	7	8	9	10	11	12
Constant	4.15	4.18	4.43	4.45	4.47	4.47	4.47	4.59	4.58	4.58	4.55	3.50
Manufacturing	1.98	2.01	2.02	2.23	2.22	2.65	2.64	2.66	2.79	2.76	2.75	2.30
Telecommunications	-1.02	-1.02	-1.01	-1.01	-1.04	-1.04	-1.09	-1.06	-1.14	-1.26	-1.24	-1.06
San Francisco, CA	2.58	2.60	2.61	2.64	2.63	2.65	2.63	2.60	2.59	2.62	2.67	2.69
Boston, MA	1.00	1.04	1.03	1.01	1.02	1.03	1.07	1.06	1.02	1.02	1.13	2.41
New York, NY	6.65	6.69	6.71	6.72	6.75	6.76	6.79	6.81	6.83	6.89	7.04	8.42
Utilities	-1.71	-1.74	-1.80	-1.82	-1.85	-1.84	-1.83	-2.14	-2.26	-2.20	-2.17	-1.89
Portland, OR	-0.70	-0.70	-0.71	-0.71	-0.73	-0.72	-0.75	-0.76	-0.74	-0.67	-0.66	-0.80
Tampa, FL	2.23	2.24	2.56	2.57	2.59	2.60	2.78	2.79	2.78	2.79	2.84	1.94
Cleveland, OH	2.36	2.40	2.40	2.41	2.42	2.44	2.42	2.40	2.39	2.39	2.47	2.02
Las Vegas, NV	-3.59	-3.60	-3.63	-3.67	-3.73	-3.78	-3.78	-3.80	-3.79	-3.78	-3.73	-3.60
San Diego, CA	3.19	3.20	3.21	3.23	3.23	3.29	3.32	3.33	3.31	3.31	3.32	2.03
Chicago, IL	1.79	1.80	1.80	1.80	1.80	1.80	1.93	1.97	1.97	1.95	1.98	1.24
Washington, DC	1.60	1.61	1.64	1.67	1.72	1.75	1.74	1.74	1.77	1.80	1.70	1.62
Denver, CO	-1.99	-2.00	-2.03	-2.04	-2.03	-2.10	-2.08	-2.09	-2.04	-2.07	-2.00	-1.92
Seattle, WA	1.13	1.13	1.12	1.13	1.13	1.12	1.10	1.10	1.20	1.10	0.97	-0.82
High Technology	-0.99	-0.99	-1.00	-0.99	-0.98	-0.98	-0.96	-0.95	-0.89	-0.67	-0.67	-0.99
Charlotte, NC	-0.88	-0.88	-0.94	-0.92	-0.91	-0.90	-0.89	-0.95	-0.92	-0.92	-0.98	-0.67
Phoenix, AZ	-0.75	-0.75	-0.76	-0.76	-0.81	-0.82	-0.84	-0.87	-0.88	-0.94	-0.83	-0.25
Los Angeles, CA	-0.73	-0.74	-0.73	-0.73	-0.70	-0.72	-0.74	-0.68	-0.67	-0.66	-0.68	0.18
Other	-1.05	-1.05	-1.06	-1.04	-1.02	-1.01	-1.00	-0.93	-1.07	-0.98	-0.94	0.11
Atlanta, GA	-0.78	-0.79	-0.78	-0.78	-0.82	-0.81	-0.76	-0.75	-0.77	-0.70	-0.54	
Detroit, MI	0.47	0.47	0.48	0.49	0.50	0.49	0.58	0.65	0.65	0.63		
Healthcare	0.63	0.63	0.62	0.62	0.64	0.67	0.65	0.61	0.60			
Mortgage Rates	0.42	0.42	0.42	0.44	0.43	0.45	0.48	0.51				
Energy	-0.37	-0.38	-0.38	-0.40	-0.39	-0.46	-0.48					
Minneapolis, MN	0.30	0.30	0.30	0.33	0.35	0.36						
Nondurable Goods	0.18	0.24	0.24	0.30	0.30							
Unemployment Rate	0.22	0.23	0.24	0.26								
Durable Goods	0.20	0.22	0.24									
Miami, FL	0.15	0.15										
Retail	0.05											
Adj. R2	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89

Table 2. Continued.

Iteration	13	14	15	16	17	18	1 9	20	21	22	23	24	25	26	27
Constant	3.60	3.61	3.82	3.87	3.77	1.59	1.59	1.59	1.55	1.67	1.85	1.23	1.10	0.91	0.71
Manufacturing	3.31	3.32	3.43	3.36	3.34	4.53	4.53	4.62	4.57	4.54	4.52	4.39	4.45	4.12	4.03
Telecommunications	-1.06	-1.09	-1.11	-1.17	-2.64	-3.54	-3.54	-3.66	-3.65	-3.61	-3.56	-3.24	-3.25	-2.81	-2.68
San Francisco, CA	2.74	2.76	2.83	2.79	2.83	2.36	2.36	2.45	2.36	3.30	3.16	3.28	3.77	3.53	3.50
Boston, MA	2.44	2.46	2.65	2.61	2.63	3.30	3.60	3.59	3.61	3.74	3.86	4.26	4.23	5.54	5.47
New York, NY	8.45	8.71	8.75	8.73	8.72	13.20	13.22	14.20	14.38	14.57	14.55	18.51	21.40	20.74	20.80
Utilities	-1.89	-1.88	-1.90	-1.84	-1.65	-2.53	-2.54	-2.53	-2.48	-2.54	-2.51	-1.71	-1.69	-1.07	
Portland, OR	-0.82	-0.83	-0.91	-1.24	-1.23	-1.43	-1.45	-1.45	-1.51	-1.63	-1.86	-0.94	-0.74		
Tampa, FL	1.97	2.00	2.10	2.29	2.28	2.48	2.48	2.59	2.52	2.52	2.35	0.61			
Cleveland, OH	2.04	2.08	2.12	2.16	2.14	1.55	1.57	1.63	1.49	1.52	1.44				
Las Vegas, NV	-3.62	-3.64	-3.72	-3.70	-3.74	-1.19	-1.22	-1.21	-1.26	-0.99					
San Diego, CA	2.09	2.66	2.76	2.74	2.71	0.56	0.55	0.76	0.82						
Chicago, IL	1.27	1.28	1.29	1.31	1.35	-0.73	-0.74	-0.71							
Washington, DC	1.62	1.62	1.64	1.64	1.66	0.24	0.33								
Denver, CO	-1.93	-2.14	-2.23	-2.38	-2.38	-0.21									
Seattle, WA	-0.85	-0.84	-0.84	-1.00	-0.90										
High Technology	-1.01	-0.99	-1.02	-0.92											
Charlotte, NC	-0.69	-0.68	-0.73												
Phoenix, AZ	-0.23	-0.21													
Los Angeles, CA	0.17														
Other															
Atlanta, GA															
Detroit, MI															
Healthcare															
Mortgage Rates															
Energy															
Minneapolis, MN															
Nondurable Goods															
Unemployment Rate															
Durable Goods															
Miami, FL															
Retail															
Adj. R2	0.89	0.89	0.89	0.89	0.89	0.86	0.86	0.86	0.86	0.86	0.86	0.87	0.87	0.87	0.87

Table 3: Models using 49 Industry portfolios. Case-Shiller House Price Indices

	Value-weighted Industry Portfolios				Equally-weighted Industry Portfolios			
	Annual Updating		Monthly Updating		Annual Updating		Monthly Updating	
Index	Δ RMSE (%)	(t-test)	Δ RMSE (%)	t-test	Δ RMSE (%)	t-test	Δ RMSE (%)	t-test
Northeast Markets								
Boston, MA	-16.76	(2.49**)	-17.92	(2.91***)	-11.37	(2.17**)	-11.19	(0.85)
New York, NY	-21.02	(2.56***)	-19.27	(2.32**)	-20.82	(2.43**)	-24.84	(3.01***)
Washington DC	-11.87	(1.07)	-6.73	(0.69)	-6.73	(0.55)	-10.04	(1.07)
Southeast Markets								
Atlanta, GA	-14.81	(1.81*)	-14.74	(1.64)	-6.23	(0.41)	-15.96	(2.16**)
Charlotte, NC	-6.27	(0.69)	-5.51	(0.56)	-0.49	(-0.12)	-3.42	(0.29)
Miami, FL	-3.59	(0.38)	-1.98	(0.11)	-6.36	(0.56)	-0.76	(-0.03)
Tampa, FL	26.81	(-2.24**)	26.66	(-1.74*)	7.46	(-0.69)	15.79	(-1.22)
Midwest Markets								
Chicago, IL	-24.35	(3.56***)	-25.61	(3.72***)	-27.47	(3.24***)	-30.92	(3.85***)
Cleveland, OH	-1.65	(1.13)	-0.40	(0.87)	5.46	(0.18)	-1.60	(1.12)
Detroit, MI	-27.87	(3.43***)	-23.50	(3.11***)	-23.99	(3.01***)	-23.01	(3.16***)
Minneapolis, MN	-20.52	(2.29**)	-26.97	(3.18***)	-19.68	(1.92*)	-21.92	(2.06**)
Southwest/ Mountain Markets								
Dallas, TX	16.49	(-1.06)	3.17	(0.06)	-3.87	(0.92)	-8.41	(1.59)
Denver, CO	-2.27	(0.36)	-7.07	(0.95)	-7.17	(1.16)	-2.14	(0.38)
Phoenix, AZ	14.42	(-1.85*)	6.19	(-0.93)	-2.70	(0.34)	-7.42	(0.79)
Las Vegas, NV	25.73	(-1.20)	29.01	(-1.32)	-9.44	(1.58)	-1.65	(0.04)
Northwest Markets								
Portland, OR	6.33	(-0.73)	-0.97	(0.06)	-6.43	(0.79)	-4.97	(0.67)
San Francisco, CA	-5.69	(0.68)	-2.53	(0.18)	-13.96	(1.74*)	1.82	(-0.44)
Seattle, WA	11.53	(-1.00)	6.61	(-0.61)	-2.00	(0.17)	-5.62	(0.75)
Southern California Markets								
Los Angeles, CA	-7.49	(1.19)	-15.71	(2.32**)	-7.11	(1.08)	-15.03	(2.53***)
San Diego, CA	4.50	(-0.19)	-1.58	(0.55)	1.16	(0.05)	-0.39	(0.53)

*, **, *** Indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Models using 10 Industry portfolios. Case-Shiller House Price Indices

	Equally-Weighted Industry Portfolios					
					Excluding Dallas, TX	
	Annual Updating		Monthly Updating		Monthly Updating	
Index	Δ RMSE (%)	(t-test)	Δ RMSE (%)	(t-test)	Δ RMSE (%)	(t-test)
Northeast Markets						
Boston, MA	-19.57	(2.86***)	-21.22	(3.16***)	-21.06	(3.14***)
New York, NY	-20.20	(2.66***)	-22.60	(2.72***)	-26.52	(3.19***)
Washington DC	-11.90	(1.10)	-17.16	(1.59)	-19.27	(2.27**)
Southeast Markets						
Atlanta, GA	-11.22	(1.35)	-16.06	(2.02**)	-13.90	(1.84*)
Charlotte, NC	-12.98	(1.58)	-10.86	(1.24)	-12.34	(1.94*)
Miami, FL	5.72	(-0.75)	0.33	(-0.16)	-5.12	(0.63)
Tampa, FL	18.55	(-1.10)	4.44	(-0.01)	6.14	(-0.25)
Midwest Markets						
Chicago, IL	-26.72	(3.74***)	-28.93	(4.06***)	-27.16	(3.99***)
Cleveland, OH	-1.41	(1.25)	-0.02	(0.97)	2.06	(0.82)
Detroit, MI	-23.78	(3.41***)	-23.10	(3.31***)	-23.16	(3.36***)
Minneapolis, MN	-21.81	(2.48**)	-30.28	(3.61***)	-30.75	(3.61***)
Southwest/ Mountain Markets						
Dallas, TX	-0.98	(0.71)	-6.93	(1.66*)	NA	NA
Denver, CO	-9.87	(1.67*)	-7.11	(1.20)	-7.28	(1.49)
Phoenix, AZ	-3.93	(0.54)	-6.25	(0.81)	-6.08	(0.91)
Las Vegas, NV	15.29	(-1.26)	6.04	(-0.61)	-3.16	(0.28)
Northwest Markets						
Portland, OR	-7.80	(1.20)	-13.72	(2.19**)	-11.84	(1.96**)
San Francisco, CA	-10.36	(1.52)	-7.41	(1.03)	-7.99	(1.17)
Seattle, WA	9.12	(-0.90)	-6.06	(1.32)	-2.49	(0.77)
Southern California Markets						
Los Angeles, CA	-15.22	(2.56***)	-14.09	(2.34**)	-12.81	(2.68***)
San Diego, CA	1.38	(0.28)	6.19	(-0.43)	-0.97	(0.49)

*, **, *** Indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Models using 10 Industry portfolios. Mean and Median Home prices.

Index	Value-Weighted Industry Portfolios Monthly Updating Δ RMSE (%) (t-test)	
Median Home Prices		
Midwest	6.76	(-1.31)
Northeast	1.46	(-0.39)
West	7.74	(-1.26)
South	2.39	(-0.29)
Mean Home Prices		
Midwest	3.01	(-0.88)
Northeast	8.25	(-2.52***)
West	6.93	(-1.34)
South	9.13	(-1.13)

Table 6: Models using 10 Industry portfolios. NCREIF Commercial Real Estate Indices

Index	Value-Weighted Industry Portfolios Monthly Updating Δ RMSE (%) (t-test)	
East	14.87	(-1.55)
West	10.07	(-0.57)
South	9.01	(-0.83)
Midwest	-18.51	(0.73)

*, **, *** Indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Northeast Markets:

Table 7: Boston, MA

Variable	Coefficient	(t-stat)
Textiles	0.01	(3.07***)
Computer Software	-0.01	(-2.79***)
Washington DC	0.13	(2.14**)
San Francisco, CA	0.17	(4.51***)
Denver, CO	0.29	(4.45***)
Chicago, IL	-0.19	(-4.64***)
Boston, MA	0.49	(8.74***)
Charlotte, NC	0.22	(3.38***)
Phoenix, AZ	-0.11	(-3.23***)
Constant	-0.000	(-1.06)
Adj R2	0.72	

Table 8: New York, NY

Variable	Coefficient	(t-stat)
Agricultural	0.01	(2.03**)
Steel	0.01	(3.16***)
Mines	-0.01	(-2.62***)
Utilities	-0.01	(-2.68***)
Computer Hardware	-0.01	(-2.83***)
Retail	-0.01	(-2.30**)
Food Services	0.02	(2.94***)
Washington DC	0.11	(2.67***)
Detroit, MI	-0.08	(-3.66***)
Cleveland, OH	0.08	(2.54***)
San Diego, CA	0.07	(2.25**)
Boston, MA	0.10	(2.43**)
Portland, OR	-0.08	(-2.10**)
Tampa, FL	0.17	(4.70***)
Atlanta, GA	0.08	(2.83***)
Las Vegas, NV	-0.06	(-2.72***)
New York, NY	0.42	(8.86***)
Seattle, WA	0.13	(3.43***)
Constant	0.000	(2.06**)
Adj R2	0.86	

*, **, *** Indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9: Washington DC

Variable	Coefficient	(t-stat)
Alcohol	0.03	(2.94***)
Toys	0.02	(2.20**)
Chemicals	0.03	(2.98***)
Electrical Equipment	-0.03	(-2.37**)
Business Services	-0.04	(-2.96***)
Computer Chips	0.02	(2.26**)
Washington DC	0.58	(8.45***)
Detroit, MI	-0.13	(-3.18***)
Minneapolis, MN	-0.18	(-3.65***)
San Diego, CA	0.29	(6.16***)
Dallas, TX	0.29	(4.82***)
Tampa, FL	0.20	(3.90***)
Constant	-0.000	(-0.87)
Adj R2	0.87	

Southeast Markets:

Table 10: Atlanta, GA

Variable	Coefficient	(t-stat)
Printing	-0.03	(-2.17**)
Rubber Products	-0.03	(-2.88***)
Cardboard and Boxes	0.03	(2.86***)
Transportation	0.04	(2.47***)
Food Services	-0.03	(-2.32**)
Real Estate	0.02	(2.27**)
Minneapolis, MN	-0.17	(-2.99***)
Cleveland, OH	0.18	(2.63***)
San Francisco, CA	0.19	(4.44***)
Chicago, IL	-0.39	(-5.07***)
Dallas, TX	0.24	(2.51***)
Atlanta, GA	0.73	(12.10***)
Seattle, WA	0.32	(4.18***)
Unemployment Rate	0.04	(2.28**)
Constant	-0.001	(-2.68***)
Adj R2	0.84	

*, **, *** Indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 11: Charlotte, NC

Variable	Coefficient	(t-stat)
Food	0.03	(2.36**)
Clothing	-0.02	(-2.13**)
Pharmaceuticals	-0.03	(-3.30***)
Rubber Products	-0.02	(-2.79***)
Fabricated Products	0.01	(2.18**)
Cardboard and Boxes	0.02	(2.22**)
Wholesale	0.03	(2.12**)
Washington DC	-0.19	(-3.03***)
Minneapolis, MN	-0.16	(-3.36***)
Chicago, IL	-0.11	(-2.04**)
Boston, MA	0.16	(2.54***)
Charlotte, NC	0.21	(2.78***)
Dallas, TX	0.37	(4.72***)
Miami, FL	0.14	(2.99***)
Seattle, WA	0.41	(6.08***)
Mortgage Rate	-0.04	(-3.18***)
Constant	-0.001	(-1.84*)
Adj R2	0.70	

Table 12: Miami, FL

Variable	Coefficient	(t-stat)
Toys	0.01	(2.17**)
Chemicals	0.03	(3.13***)
Mines	-0.02	(-2.74***)
Computer Hardware	-0.01	(-2.33**)
Washington DC	0.25	(5.53***)
Detroit, MI	-0.08	(-2.87***)
Phoenix, AZ	0.31	(7.30***)
Miami, FL	0.47	(9.29***)
Constant	-0.000	(-0.08)
Adj R2	0.85	

*, **, *** Indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 13: Tampa, FL

Variable	Coefficient	(t-stat)
Printing	-0.03	(-2.06**)
Chemicals	0.05	(3.68***)
Rubber Products	-0.02	(-2.22**)
Building Materials	0.03	(2.12**)
Fabricated Products	0.03	(3.48***)
Machinery	-0.03	(-2.68***)
Mines	-0.02	(-2.28**)
Retail	0.03	(2.42**)
Banking	-0.02	(-2.08**)
Minneapolis, MN	-0.16	(-3.06***)
Cleveland, OH	0.19	(3.21***)
Chicago, IL	-0.23	(-3.24***)
Phoenix, AZ	0.19	(3.36***)
Dallas, TX	0.32	(3.82***)
Miami, FL	0.27	(3.32***)
Tampa, FL	0.37	(4.45***)
New York, NY	0.31	(3.14***)
Constant	-0.001	(-2.04**)
Adj R2	0.87	

Midwest Markets:

Table 14: Chicago, IL

Variable	Coefficient	(t-stat)
Aerospace	-0.02	(-2.19**)
Coal	-0.01	(-2.26**)
Transportation	0.02	(2.02**)
Washington DC	0.28	(4.55***)
Cleveland, OH	0.26	(5.46***)
San Francisco, CA	0.12	(3.15***)
Boston, MA	-0.12	(-2.11**)
Charlotte, NC	0.31	(4.53***)
Phoenix, AZ	-0.19	(-4.52***)
Tampa, FL	0.24	(4.16***)
Atlanta, GA	0.25	(5.64***)
Las Vegas, NV	-0.08	(-2.60***)
Seattle, WA	0.25	(4.28***)
Constant	-0.001	(-2.05**)
Adj R2	0.83	

*, **, *** Indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 15: Cleveland, OH

Variable	Coefficient	(t-stat)
Toys	0.03	(2.08**)
Household Goods	0.07	(3.80***)
Pharmaceuticals	-0.03	(-2.12**)
Rubber Products	-0.03	(-2.28**)
Steel	0.03	(2.29**)
Aerospace	-0.03	(-2.08**)
Mines	-0.02	(-2.73***)
Computer Software	-0.03	(-2.41**)
Transportation	0.04	(2.43**)
Washington DC	0.20	(2.25**)
Minneapolis, MN	-0.27	(-5.03***)
San Diego, CA	0.27	(3.29***)
Portland, OR	-0.26	(-2.38**)
Dallas, TX	0.82	(8.30***)
Las Vegas, NV	-0.21	(-3.63***)
Seattle, WA	0.45	(4.03***)
Constant	-0.003	(-4.61***)
Adj R2	0.68	

Table 16: Detroit, MI

Variable	Coefficient	(t-stat)
Chemicals	0.03	(2.57***)
Oil	-0.04	(-3.62***)
Utilities	0.03	(2.29**)
Financial Services	-0.02	(-2.23**)
Detroit, MI	0.35	(7.46***)
San Francisco, CA	0.14	(2.91***)
Denver, CO	0.51	(6.39***)
Miami, FL	0.13	(2.43**)
Atlanta, GA	0.23	(3.99***)
New York, NY	-0.19	(-2.31**)
Constant	-0.001	(-2.88***)
Adj R2	0.75	

*, **, *** Indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 17: Minneapolis, MN

Variable	Coefficient	(t-stat)
Textiles	0.01	(3.08***)
Coal	0.01	(2.10**)
Oil	-0.02	(-2.06**)
Minneapolis, MN	0.28	(6.75***)
Cleveland, OH	0.31	(5.47***)
San Francisco, CA	0.18	(5.17***)
Denver, CO	0.50	(6.42***)
Constant	-0.001	(-3.03***)
Adj R2	0.78	

Southwest/Mountain Markets:

Table 18: Dallas, TX

Variable	Coefficient	(t-stat)
Agricultural	-0.02	(-3.65***)
Gold	-0.01	(-3.22***)
Mines	0.02	(4.16***)
Minneapolis, MN	-0.25	(-6.99***)
San Diego, CA	0.33	(5.18***)
Charlotte, NC	0.47	(6.63***)
Los Angeles, CA	-0.32	(-4.06***)
Dallas, TX	0.62	(9.15***)
Miami, FL	0.13	(2.59***)
Unemployment Rate	0.03	(2.33**)
Constant	0.000	(0.30)
Adj R2	0.73	

*, **, *** Indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 19: Denver, CO

Variable	Coefficient	(t-stat)
Tobacco	0.01	(2.22**)
Printing	-0.02	(-2.72***)
Fabricated Products	0.01	(2.09**)
Electrical Equipment	-0.02	(-2.39**)
Transportation	0.02	(2.43**)
Minneapolis, MN	-0.24	(-7.03***)
San Diego, CA	0.31	(6.51***)
Denver, CO	0.46	(5.78***)
Charlotte, NC	0.25	(3.59***)
Dallas, TX	0.31	(3.86***)
Las Vegas, NV	-0.11	(-3.28***)
Constant	-0.001	(-1.73*)
Adj R2	0.77	

Table 20: Phoenix, AZ

Variable	Coefficient	(t-stat)
Agricultural	-0.02	(-2.94***)
Food	0.03	(2.55***)
Chemicals	0.04	(3.58***)
Rubber Products	-0.02	(-2.51***)
Fire Arms	0.02	(2.50***)
Business Services	-0.03	(-2.58***)
Insurance	-0.05	(-4.64***)
Real Estate	0.02	(4.02***)
Financial Services	0.02	(2.79***)
Minneapolis, MN	-0.16	(-4.96***)
San Francisco, CA	0.07	(2.16**)
Phoenix, AZ	0.94	(22.94***)
Dallas, TX	0.39	(6.25***)
Miami, FL	0.12	(2.40**)
Atlanta, GA	-0.09	(-2.33**)
Seattle, WA	-0.16	(-2.83***)
Constant	-0.001	(-1.90*)
Adj R2	0.95	

*, **, *** Indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 21: Las Vegas, NV

Variable	Coefficient	(t-stat)
Real Estate	0.02	(3.24***)
San Diego, CA	0.27	(6.31***)
Las Vegas, NV	0.70	(19.10***)
Constant	-0.001	(-1.31)
Adj R2	0.78	

<u>Northwest Markets:</u>

Table 22: Portland, OR

Variable	Coefficient	(t-stat)
Printing	-0.04	(-4.03***)
Computer Chips	-0.02	(-2.70***)
Laboratory Equipment	0.02	(2.32**)
Retail	0.03	(2.74***)
Real Estate	0.02	(2.86***)
Minneapolis, MN	-0.25	(-5.63***)
Charlotte, NC	0.22	(2.64***)
Portland, OR	0.21	(2.47***)
Phoenix, AZ	0.18	(4.80***)
Dallas, TX	0.30	(3.91***)
New York, NY	0.20	(3.00***)
Seattle, WA	0.29	(3.30***)
Constant	-0.000	(-1.03)
Adj R2	0.81	

*, **, *** Indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 23: San Francisco, CA

Variable	Coefficient	(t-stat)
Toys	0.03	(2.56***)
Chemicals	0.05	(3.36***)
Building Materials	-0.05	(-2.71***)
Automobile	-0.03	(-2.85***)
Business Services	-0.07	(-3.18***)
Laboratory Equipment	0.02	(2.05**)
Real Estate	0.03	(2.96***)
Minneapolis, MN	-0.20	(-2.84***)
Cleveland, OH	0.19	(2.36**)
San Francisco, CA	0.83	(13.77***)
Chicago, IL	-0.23	(-2.79***)
Boston, MA	-0.28	(-2.94***)
Los Angeles, CA	0.32	(4.62***)
Dallas, TX	0.41	(3.76***)
Constant	-0.001	(-0.91)
Adj R2	0.86	

Table 24: Seattle, WA

Variable	Coefficient	(t-stat)
Printing	-0.03	(-3.24***)
Chemicals	0.02	(2.47***)
Mines	-0.02	(-2.75***)
Real Estate	0.02	(3.41***)
Minneapolis, MN	-0.20	(-5.64***)
San Diego, CA	0.12	(3.03***)
Charlotte, NC	0.30	(4.41***)
Phoenix, AZ	0.11	(2.99***)
Seattle, WA	0.64	(13.27***)
Constant	0.001	(1.60)
Adj R2	0.72	

*, **, *** Indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Southern California Markets:

Table 25: Los Angeles, CA

Variable	Coefficient	(t-stat)
Food	0.05	(4.50***)
Paper Products	0.02	(2.32**)
Insurance	-0.04	(-3.90***)
Minneapolis, MN	-0.23	(-7.22***)
San Diego, CA	0.23	(3.85***)
Phoenix, AZ	0.16	(4.44***)
Los Angeles, CA	0.68	(9.50***)
Dallas, TX	0.28	(5.63***)
Unemployment Rate	0.03	(2.12**)
Constant	-0.000	(-0.79)
Adj R2	0.92	

Table 26: San Diego, CA

Variable	Coefficient	(t-stat)
Food	0.07	(5.03***)
Toys	0.02	(2.33**)
Clothing	-0.03	(-2.90***)
Steel	-0.03	(-3.30***)
Fabricated Products	0.02	(2.81***)
Computer Software	-0.02	(-2.41**)
Banking	-0.03	(-3.21***)
Financial Services	0.04	(3.14***)
Minneapolis, MN	-0.21	(-5.65***)
San Diego, CA	0.72	(10.11***)
Los Angeles, CA	0.30	(4.13***)
Dallas, TX	0.23	(3.72***)
Constant	-0.001	(-1.80*)
Adj R2	0.88	

*, **, *** Indicate statistical significance at the 10%, 5%, and 1% levels, respectively.