

Industrial Space Demand

January 2011

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**Prepared for and Funded by
the NAIOP Research Foundation**

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Executive Summary

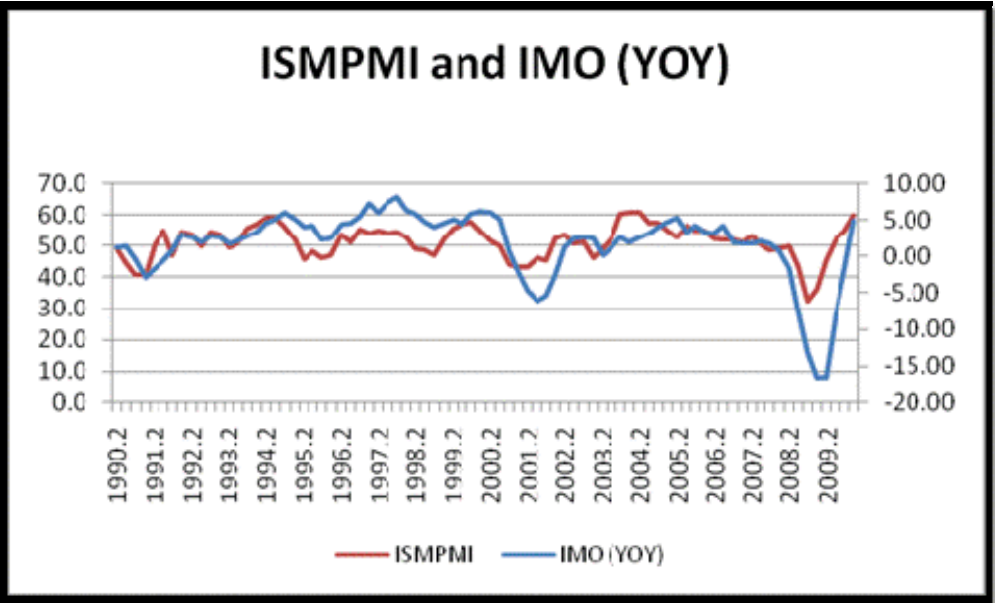
Goals and Process:

- The goal of the research project was to create a model that can forecast changes in demand for industrial real estate.
- This is important to enhance decisions making for the following applications:
 - Acquisitions/Dispositions
 - Development Timing
 - Financing Terms
 - Property Management and Leasing
- The process involved performing tests on more than 40 economic and real estate variables as follows:
 - Looked for strong correlations (relationships)
 - Looked for leading relationships (variables that change prior to industrial real estate demand changes)
 - Refined the variables down to a manageable level
 - Built a simple, yet powerful model

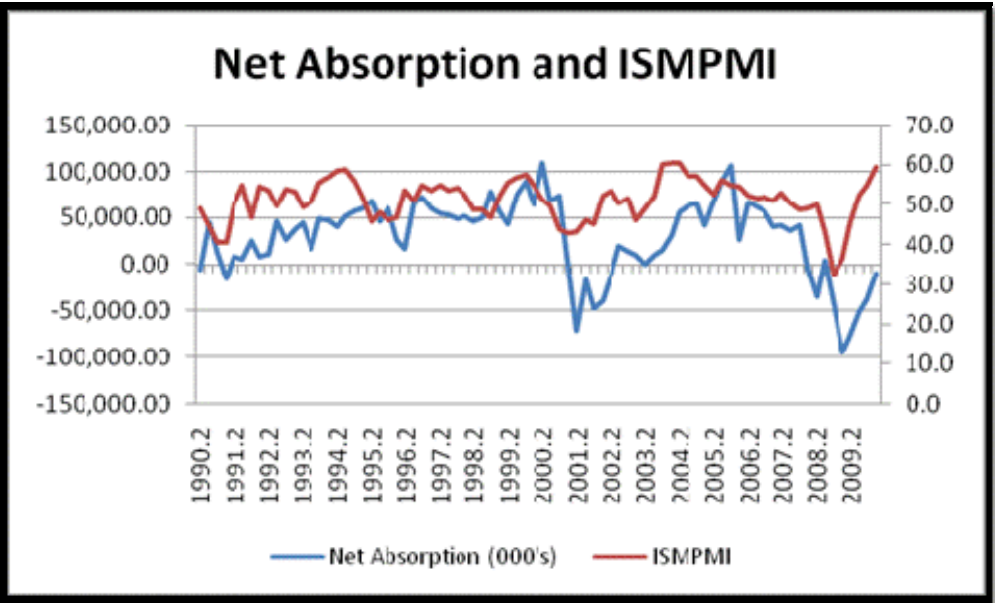
The Model:

- The final model encompasses the entire supply chain with the use of two main variables that lead change in demand for real estate:
 - Institute for Supply Chain Management¹ PMI (ISMPMI)
 - This variable leads demand by 4 quarters with the prior quarter also impacting demand.
 - The variable survey's "boots on the ground" people about their expectations regarding:
 - New Orders
 - Production
 - Employment
 - Deliveries
 - Inventories
 - Federal Reserve Board's Index of Manufacturing Output (IMO)
 - This variable measures manufacturing production in the U.S.
 - It is a measure of actual output produced and leads change in demand by 2 to 3 quarters.
- These relationships are easy to see graphically.
 - First, the survey of the supply managers shows an expectation of increased manufacturing activity and then the activity follows. What this implies is that the ISMPMI leads the IMO which is clear below:

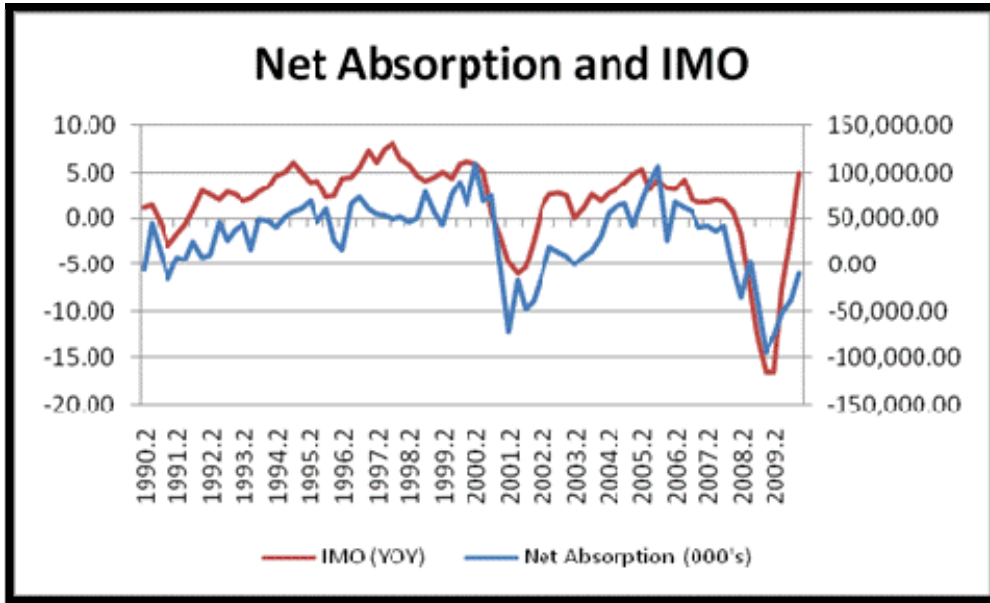
¹ The Institute of Supply Management (ISM) is not involved in the forecasting model or determination of industrial real estate demand. ISM is solely acting as a supplier of raw data (ISMPMI) in this research project and all resulting products.



- As such, it is easy to see that the ISMPMI leads changes in demand as shown below:

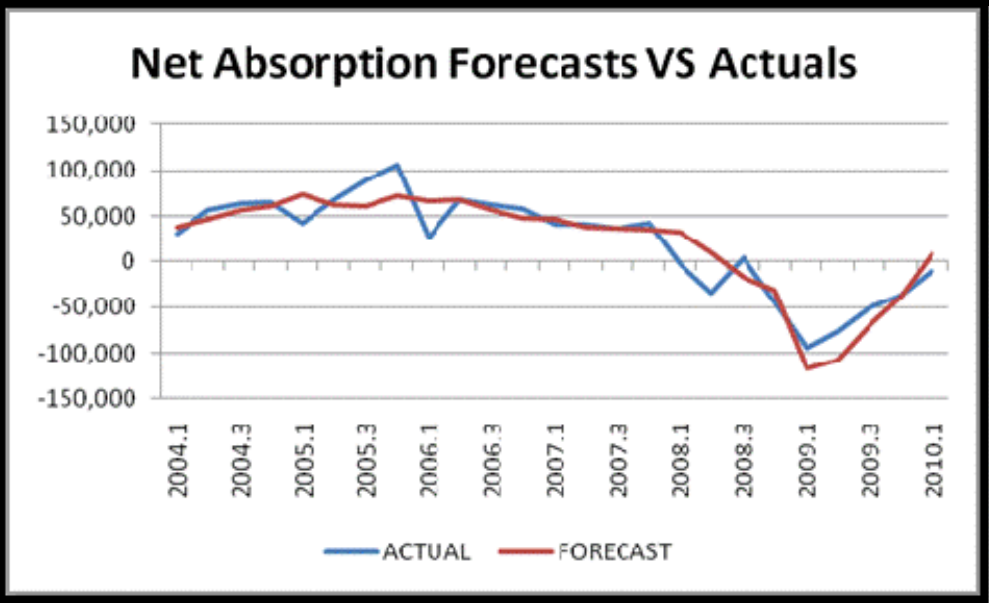


- And, it is easy to see that the changes in the IMO also lead demand, albeit by a shorter time frame. Once these two variables have moved, real estate demand follows.



The Results and Product:

- The model provides a quality, unbiased forecast of demand for industrial real estate. This simply means that it accurately forecasts future demand AND it does not systematically over or under estimate demand as illustrated below:



- The model accurately forecasted the market's latest downturn
 - Accurately predicted the market flattening (the slowing of the negative net absorption in 2010Q1).
 - When the model was off, the average error was very small and did not systematically under or overstate demand.
 - The model does not seem to be “fooled” by a quarter of increase or decrease that defies the overall trend of the market (See Mid 2005 and Early 2008).
 - The index is a usable measure that will be updated quarterly for use by NAIOP members and the industrial real estate community to make better decisions.
 - The quarterly index will appear on the NAIOP Web site.
 - The new forecast will contain a short summary discussion for media release that explains what happened in the prior quarter and what the forecast is for the subsequent quarter.
 - As such, the index will be used as an investment “dashboard” on the NAIOP Web site.
 - Developers can see changes in demand and decide whether to ramp up or slow down development.
 - Owners can use the measure to make smarter leasing decision and hold better negotiating power.
 - Lenders can use the measure to make more confident decision regarding development and acquisition loans.

Industrial Space Demand

Introduction

Predicting demand for industrial space has been and continues to be more challenging to forecast relative to the other main property types. There are several commonly stated reasons for this (Twist 2002). First, an extremely large share of the industrial space is held by owner-users. Second, there are many sub-property types with heterogeneous users within each of these groupings. Finally, the available data is relatively short and contains periods where the market is rarely found to be in a state of equilibrium.

In contrast, demand for apartments and retail can be gleaned by looking at demographic factors including population growth, household growth, household income and housing affordability conditions. Office employment and office space usage trends tend to be able to capture the majority of the variation in the demand for office space (McIntosh, Liang, and Kim, 1997). In this whitepaper, we build off of prior studies in the industrial sector to provide a robust statistical model that has high out-of-sample forecasting properties for determining national industrial demand.

The Process

We examined nearly 40 real estate, economic and stock market variables that should theoretically be related to demand for industrial space². These variables included varying measures of employment, GDP, exports and imports, as well as air, rail and shipping data. Early works, such as Wheaton and Torto (1990), and in fact most current works use industrial or manufacturing employment to forecast demand for industrial space. We found, as with Twist (2002) that total employment tends to have the better forecasting properties than other sub-employment categories. The rationale is simple, as total employment increases, regardless of the industry in which it is derived; more goods are produced and consumed, thus increasing the usage of industrial space. Others, such as Mueller and Laposa (1994), suggest using population metrics as the key explanatory variables for industrial net absorption. However, as Hughes (1994) points out, much of the industrial property usage is not population serving. In fact, Twist (2002) finds that population growth and industrial demand have a correlation of only 6 percent. We also tested freight flows and other air, rail and shipping metrics, including stock price returns from companies operating in these sectors. We did not find these variables to have strong forecasting properties.

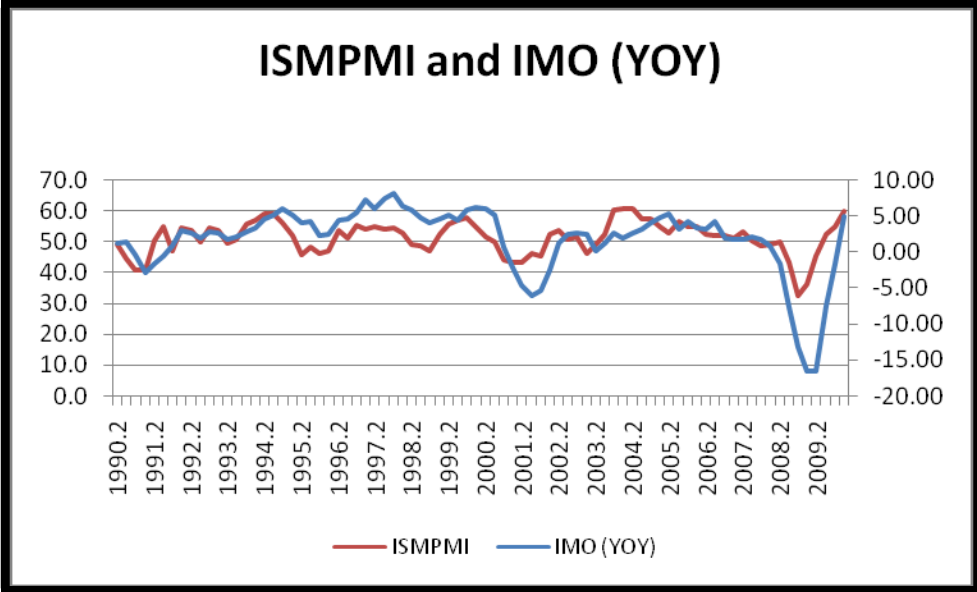
² The full set of variables considered is available upon request.

In the end, we found two important variables that capture the majority of the variation in demand: the Federal Reserve Board's Index of Manufacturing Output (IMO) and the PMI Index from the Institute of Supply Management (ISMPMI). Perhaps most importantly, both variables are **LEADING** indicators of demand which is important as we then do not have to forecast the inputs to our forecasting model³.

The IMO is released monthly by the Federal Reserve Board of Governors. The index measures the quantity of goods produced, excluding mining and utilities. The ISMPMI is constructed using a survey of purchasing managers expectations. The Institute's monthly survey has five components which are new orders, production, employment, deliveries and inventories. It is interesting to note that the ISMPMI leads the IMO. In essence, the ISMPMI is a leading indicator of production in the industrial sector. Next, the actual goods are produced, as portrayed and captured in the IMO data, which still leads firms in their decision making on how much industrial real estate they will demand. In essence, these two variables together encompass the full supply chain and thus prove to be effective and unbiased in forecasting demand. Exhibit 1 shows the leading relationship between the ISMPMI and the IMO. Exhibits 2 and 3 show the strong leading relationships between the ISMPMI and industrial demand and the IMO and industrial demand, respectively.

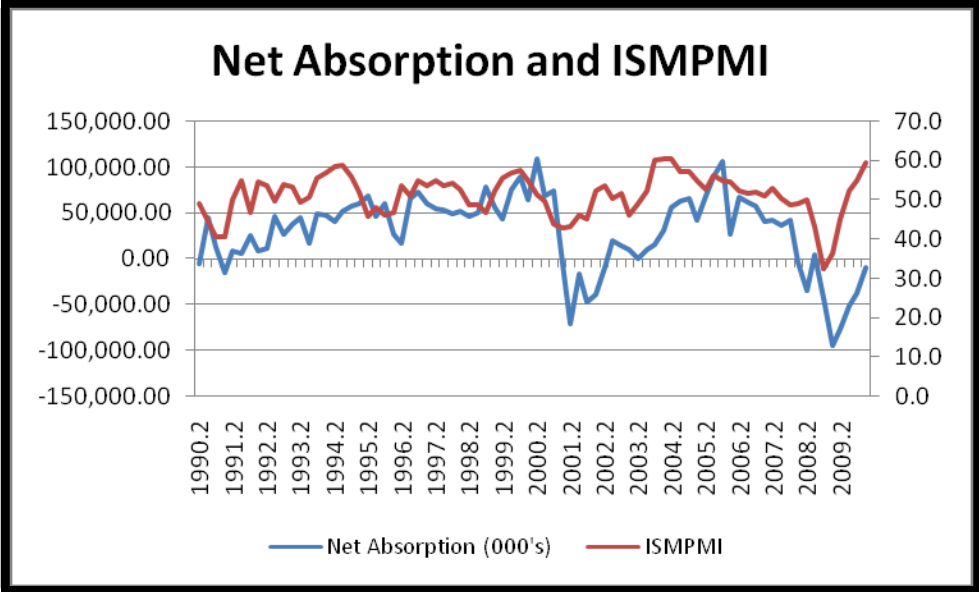
³ Many times, forecasting models include explanatory variables which are contemporaneous to the variable being forecasted. This suggests that the forecaster must forecast the explanatory variables. Each of those variables has their own forecasting errors and these errors compound with the errors in the primary model. As such, our model, which forecasts industrial demand ahead one quarter, utilizes only historical/actual data, which relieves us of the types of errors mentioned.

Exhibit 1: ISMPMI and IMO



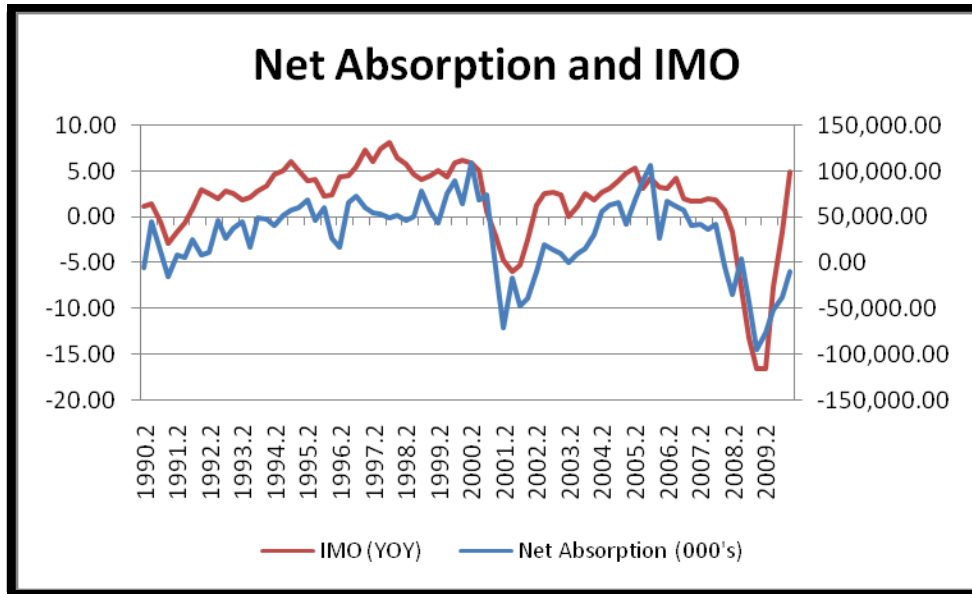
Source: Federal Reserve Board of Governors, ISM, and Anderson, Guirguis.

Exhibit 2: Net Absorption and ISMPMI



Source: CBRE, ISM, and Anderson, Guirguis.

Exhibit 3: Net Absorption and IMO



Source: CBRE, Federal Reserve Board of Governors, and Anderson, Guirguis.

Data and Methodology

As mentioned above, the main explanatory variables utilized in our empirical model are the ISMPMI and the IMO. Our historical data series for net absorption was obtained from CBRE. The initial model can be stated as follows:

$$\text{Net Absorption} = \beta_0 + \beta_1 \text{Net Absorption}_{t-1} + \beta_2 \text{Net Absorption}_{t-3} + \beta_3 \text{IMO}_{t-2} + \beta_4 \text{IMO}_{t-3} + \beta_5 \text{ISMPMI}_{t-1} + \beta_6 \text{ISMPMI}_{t-4} + e_t \quad (1)$$

Due to the high instability in the industrial real estate market generated by current crises in the real estate and the financial markets, we utilize the Kalman Filter approach where the regression parameters are allowed to vary with time. As illustrated by numerous studies (e.g., Hatemi and Roca, 2006; Guirguis et al., 2005; Harvey, 1997; and Brown et al., 1997), a Kalman filter model generates more accurate out-of-sample forecasts than those generated by static models where the regression coefficients are constant over time. The time varying Kalman Filter model employed in our paper can be specified as follows:

The Measurement Equation:

$$y_t = X_t \beta_t + u_t, \text{ with } \text{Var}(u_t) = \eta_t \quad (2)$$

where $y_t = \text{Net Absorption}$, and $X_t = (\text{Net Absorption}_{t-1}, \text{Net Absorption}_{t-3}, \text{IMO}_{t-2}, \text{IMO}_{t-3}, \text{ISMPMI}_{t-1}, \text{ISMPMI}_{t-4})$

The State Equation:

$$\beta_t = A_t \beta_t + v_t \text{ with } \text{Var}(v_t) = M_t \quad (3)$$

where A_t controls the process through which β_t shrinks back towards the mean. Following Doan, Litterman, and Sims (1984), we specify the shrinkage process as follows:

$$\beta_t = \lambda \beta_{t-1} + (1 - \lambda) (\text{mean vector}) + v_t \quad (4)$$

where $0 \leq \lambda \leq 1$, and mean vector = $[0 \ 1 \ 0 \ 0 \ 0 \ 0 \ 0]$

To initialize the state vector and the covariance matrices, we use the mean and the covariance matrix of β_s , and calculate the hyper-parameters (relative tightness) from the maximized log conditional likelihood function over the sample period 1990:02 to 2003:03. However, our choice of the shrinkage factors (.88) has been dictated by the average value of λ that minimizes the Mean Absolute Forecasting Error (MAFE) and maximizes both the Root Mean Squared Forecasting Errors (RMSRF) and Theil U (U) statistics for the out-of-sample forecasting during 2008 and 2009.

We initially estimate the model for the time period from 1990:02 to 2003:03 and calculate the estimated β based on the available information up to 2003:03 ($\beta_{t-1|t-1}$) and its variance-covariance matrix ($\Sigma_{t-1|t-1}$). Next, we update our estimates of β for the 2003:04 by employing Kalman Filter as follows:

$$S_t = A_t \Sigma_{t-1} A_t' + M_t \quad (5)$$

$$\Sigma_t = S_t - S_t X_t' (X_t S_t X_t' + \eta_t)^{-1} X_t S_t \quad (6)$$

$$\beta_{t|t} = A_t \beta_{t-1|t-1} + S_t X_t' (X_t S_t X_t' + \eta_t)^{-1} X_t (y_t - X_t A_t \beta_{t-1|t-1}) \quad (7)$$

Then, we utilize $\beta_{t|t}$ to predict the net absorption rate at 2004:1. Next, we expand the starting and ending date of our sample by one quarter and estimate our equation for the sample period that runs from 1990:03 to 2003:04, and we utilize the estimates to execute Kalman Filter and calculate the one-quarter forecast for 2004:02. We repeat this process until our forecasts cover the sample periods run from 2004:01 to 2010:01.

Next, we construct the Occupied Stock Index (or total demand for space index) as follows:

$$\text{Occupied Stock Index}_t = \text{Occupied Stock}_{t-1} + \text{One Quarter Forecasting}_{t|t-1} \quad (8)$$

To evaluate the out-of-sample performance of our model, we examine the properties of the out-of-sample forecasting according to the following criteria. The desirable properties require the forecasting errors to be normally distributed around zero. The tendency of the model to over-predict (under-predict) can be detected by a left (right) skewed distribution with a statistically significant negative (positive) mean. Additionally, highly inaccurate forecasts can result in excess negative kurtosis. We begin by testing separately for excess kurtosis and skewness. We also test jointly for excess kurtosis and skewness (normality) using the parametric Jarque-Bera test. Table 1 indicates that the models produce forecasting errors with means not statistically different from zero at the 1 percent level. Additionally, the model generates normally distributed forecasting errors with statistically insignificant skewness and excess kurtosis.

Table 1: Desirable Properties of the Forecasting Errors

This table presents means, skewness, excess kurtosis, and Jarque-Bera normality test of the 25 one-step forecasting errors calculated from the recursive Kalman Filter. The p-values of the estimated statistics are reported in parentheses.

| | |
|-----------------|--------|
| Statistics | |
| Mean | 658 |
| (Significance) | (.152) |
| Skewness | -.599 |
| (Significance) | (.250) |
| Excess Kurtosis | -.134 |
| (Significance) | (.905) |
| Jarque-Bera | 1.515 |
| (Significance) | (.468) |

Next, we examine the forecasting performance of our model by calculating the Theil's U^2 ; mean forecasting error (MFE); mean absolute forecasting error (MAFE); and root mean squared forecasting error (RMSFE) for the 25 forecast points from 2004:01 to 2010:01 (see table 2).

Table 2 shows some interesting empirical findings. First, R^2 for the out-of-sample forecasts (Theil's U^2) reveals that our model can predict 83 percent of the sum of the squared deviations of the dependent variable about its mean. Similarly, the MAFE shows a high tendency for generating a symmetric distribution with positive and negative forecast errors canceling out. More precisely, when the model was off, the average error was only 3 percent of average demand.

Table 2: Out of Sample Forecasting Statistics

This table presents the Theil's U^2 , mean forecasting error (MFE), mean absolute forecasting error (MAFE), and root mean squared forecasting error (RMSFE) for the 25 one-step forecasts from the recursive Kalman Filter.

Out of Sample Forecasting (One Quarter)

$$MFE = \sum_{i=1}^{25} \frac{1}{25} (y_i^f - y_i) = 658$$

$$MAFE = \sum_{i=1}^{25} \frac{1}{25} (|y_i^f - y_i|) = 16361$$

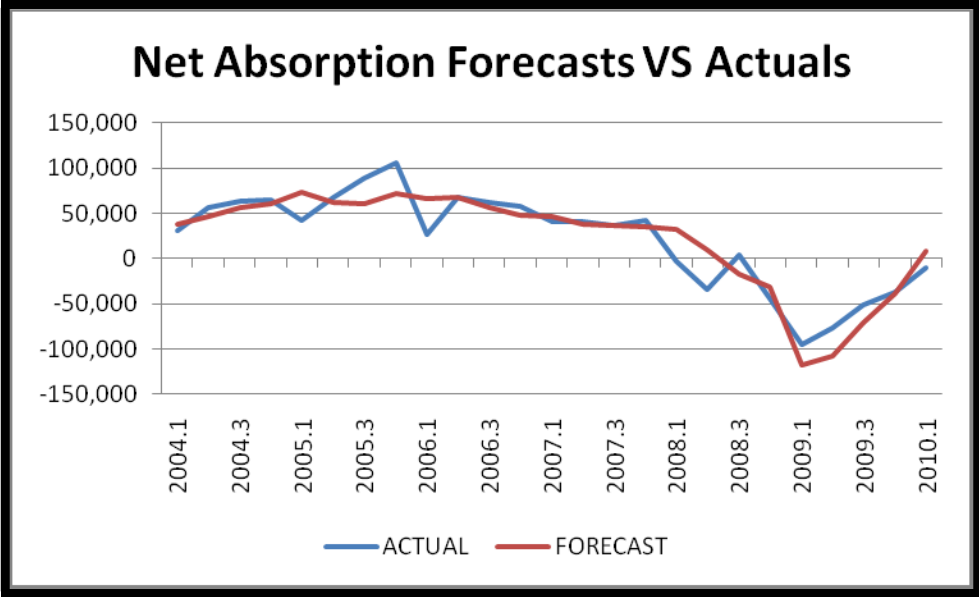
$$RMSFE = \sqrt{\sum_{i=1}^{25} \frac{1}{25} (y_i^f - y_i)^2} = 21165$$

$$U = 1 - \frac{RMSFE}{\sqrt{\sum_{i=1}^{25} \frac{1}{25} [y_i^f]^2 + \sum_{i=1}^{25} \frac{1}{25} [y_i]^2}} = 0.83258$$

y^i = one-quarter out-of-sample forecast of the Net Absorption

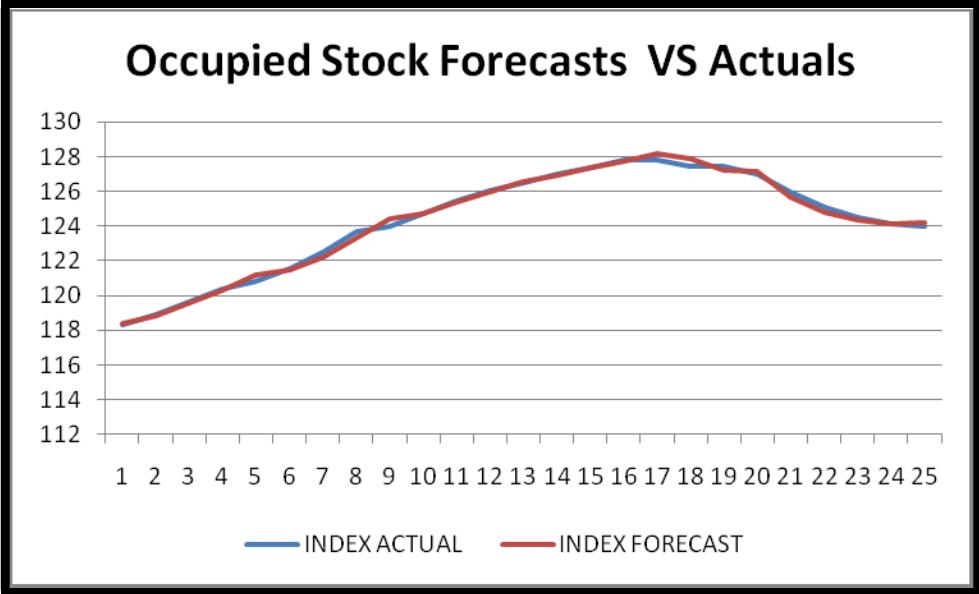
The actual results are plotted versus the forecasts for both the quarterly net absorption numbers and for the total industrial demand index in Exhibits 4 and 5 below:

Exhibit 4: Out of Sample Forecasts – Kalman Filter Model: Net Absorption



Source: CBRE, Federal Reserve Board of Governors, ISM, Anderson, Guirguis.

Exhibit 5: Out of Sample Forecasts – Kalman Filter Model: Demand Index



Source: CBRE, Federal Reserve Board of Governors, ISM, Anderson, Guirguis

Conclusions:

In this white paper, we developed a forecasting model for the demand for industrial space at the national level. Utilizing variables that comprise the entire supply chain and **lead** the demand for space, the model is able to capture the majority of changes in demand, as shown by out-of-sample forecasting tests.

While the Leading Economic Indicators have been able to forecast recessions and expansions, our indices are constructed to forecast industrial real estate demand expansions, peaks, declines and troughs. As such, the indices will provide valuable information to the market and aid in better decision making for transactions, property management, leasing, financing, and capital structure. The index is a usable measure that will be updated quarterly for use by NAIOP members and the industrial real estate community to make better decisions.

The quarterly index will appear on the NAIOP Web site. Each quarter, the new forecast will contain a short summary discussion for media release that will explain what happened in the prior quarter and what the forecast is for the subsequent quarter. As such, the index will be used as an investment “dashboard” on the NAIOP Web site.

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