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Do Industries Lead the Stock Market? Gradual Diffusion of Information and Cross-Asset Return Predictability

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Abstract: We test the hypothesis that the gradual diffusion of information across asset markets leads to cross-asset return predictability. Using thirty-four industry portfolios and the broad market index as our test assets, we establish several key results. First, a number of industries such as retail, services, commercial real estate, metal, and petroleum lead the stock market by up to two months. In contrast, the market, which is widely followed, only leads a few industries. Importantly, an industry's ability to lead the market is correlated with its propensity to forecast various indicators of economic activity such as industrial production growth. Consistent with our gradual-information-diffusion hypothesis, these findings indicate that the market reacts with a delay to information in industry returns about its fundamentals.

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Traditional theories of asset pricing assume that investors have unlimited information-processing capacity. However, this assumption does not hold for many traders, even the most sophisticated ones. Many economists recognize that investors are better characterized as being boundedly rational and subject to limited information processing capacity (see Shiller (2000), Sims (2001)). Even from casual observation, few traders can pay attention to all sources of public information much less understand their impact on the prices of the assets that they trade. Indeed, a large literature in social psychology documents the extent to which even attention is a precious cognitive resource.[1]

A number of papers have explored the implications of limited information processing capacity for asset prices.[2] For instance, Merton (1987) develops a static model of multiple stocks in which investors only have information about a limited number of stocks and only trade stocks that they have information about.[3] As a result, stocks that are less recognized by investors have a smaller investor base (neglected stocks) and trade at a greater discount because of limited risk sharing. More recently, Hong and Stein (1999) develop a dynamic model of a single asset in which information gradually diffuses across the investment public and investors are unable to perform the rational expectations trick of extracting information from prices. As a result, price under-reacts to the information and there is stock return predictability.

In this paper, we develop a hypothesis that is broadly related to these recent theories. Our hypothesis is that the gradual diffusion of information across asset markets leads to cross-asset return predictability. This hypothesis relies on two key assumptions. The first is that information that originates in one asset market that is valuable for other assets reaches investors in the other markets with a lag, i.e. news travels slowly across markets. The second assumption is that because of limited processing capacity, many (though not necessarily all) investors may not pay attention or be able to extract the information from the asset prices of markets that they do not participate in. These two assumptions taken together leads to cross-asset return predictability.

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[1] Nowadays, researchers in psychology take for granted that attention is limited and proceed to grapple with its other subtleties (see Kahneman (1973), Nisbett and Ross (1980), and Fiske and Taylor (1991)).
[2] We will review this literature in Section V.
[3] Related models of limited market participation include Brennan (1975) and Allen and Gale (1994).

Our hypothesis would appear to be a very plausible one for a few reasons. To begin with, few investors trade all assets. Put another way, limited participation is a pervasive feature of financial markets. Indeed, even among equity money managers, there is specialization along industries such as sector or market timing funds. Some reasons for this limited market participation include tax, regulatory or liquidity constraints. More plausibly, investors have to specialize because they have their hands full trying to understand the markets that they do participate in. As a result, they are unable to devote the attention needed to process potentially valuable information from other markets in a timely manner.[4]

We test our hypothesis by looking for cross-asset return predictability among industry portfolios and the broad market index. The basic idea behind our test is that investors who specialize in trading the broad market index, such as market timing funds, receive information arising from particular industries such as commercial real estate or metal only with a lag. As a result, the returns of industry portfolios that are informative about macroeconomic fundamentals will lead the aggregate market.

Out of thirty-four industry portfolios, we find that thirteen including commercial real estate, agriculture, non-metallic minerals, apparel, furniture, print, petroleum, leather, metal, transportation, utilities, retail and financial significantly lead the market by one month. Even after adding a variety of well-known proxies for risk, liquidity and investor sentiment in our regressions, the predictability of the market by these thirteen industry portfolios remains statistically significant.

More interestingly from our perspective are the patterns in the documented cross-predictability. For some industries such as retail and commercial real estate, its return this month is positively correlated with the return of the market the next month. For others such as metal and petroleum, this cross-serial correlation is negative. As we will argue below, these patterns are consistent with our hypothesis because high returns for some industries like retail mean good news for future economic activity and the market, while high returns for other industries such as petroleum mean just the opposite.

[4] Individual investors also participate in a limited number of markets as they hold very un-diversified portfolios (see, Blume, Crockett and Friend (1974), Blume and Friend (1978), King and Leape (1984)).

Importantly, the ability of these industries to lead the market is also economically significant. Among the strongest predictors of the market are the returns from financial, retail, print, and commercial real estate. For instance, a two standard deviation shock in the monthly returns of the retail industry portfolio leads to a change in next month's market return of around 2% or roughly 45% of the standard deviation of the market return. Other industries such as metal and petroleum generate somewhat smaller effects in the neighborhood of 28% of market volatility, which is still much larger than any of the well-known predictors such as inflation, term and default spreads or dividend yield. While most of these industries lead the market by one month, some such as petroleum and metal can forecast the market even two months out.

Moreover, the logic of our hypothesis suggests that the broad market index ought to also lead industry portfolios. In practice, the broad market index may be more widely followed than are industry indices. As a result, we do not expect to find as strong an evidence for the market leading other portfolios. Indeed, out of the thirty-four industries, the market only leads five.

We also attempt to verify a key auxiliary prediction of our model: the ability of an industry to lead the market ought to be strongly correlated with its propensity to forecast market fundamentals such as industrial production growth or other measures of economic activity. We do this by first using individual industry returns to separately forecast industrial production growth and the growth rate of the Stock and Watson (1989) coincident index of economic activity. Many of the same sectors that lead the market can also forecast these two proxies of market fundamentals. Indeed, industry returns that are positively (negatively) cross-serially correlated with the market are also positively (negatively) correlated with future economic activity. This finding strongly supports our hypothesis that the documented cross-predictability is due to the market reacting with a delay to information contained in industry returns about its fundamentals.

This prediction of our model implicitly assumes that the rate at which information from these industries diffuses to investors more broadly is roughly the same across industries. To see whether this is the case, we calculate the residual analyst coverage measure of Hong, Lim and Stein (2000) for each industry, which is simply the number of analysts following firms in a certain industry adjusted for the number of analysts that ought to cover that industry given its market capitalization. We assume that industries with large residual analyst coverage are the ones in which information is likely to diffuse relatively quickly to investors at large.[5] We find that even accounting for variation in this measure across industries, our earlier finding that the industries that strongly predict indicators of economic activity also lead the stock market still holds. Interestingly, consistent with our hypothesis, we also find some weak evidence that industries with abnormally high analyst coverage are less able to lead the market.

Our paper proceeds as follows. In Section I, we develop a simple model to make clear the assumptions behind our hypothesis and generate some testable predictions. We describe the data in Section II. We present our main empirical findings in Section III. We discuss additional robustness calculations in Section IV. We relate our paper to the literature in Section V and conclude in Section VI.

I. Model

A. Basic Setup

Our model considers the pricing of two assets (stocks) in a three-date economy, $t=0, 1, 2$. We assume for simplicity that the risk-free rate is zero. The two assets, X and Y, have terminal values at $t=2$ given by D_X and D_Y, which are jointly normal with means of zero and variances of $\sigma^2_{X,D}$ and $\sigma^2_{Y,D}$ and covariance $\sigma_{XY,D}$.

Investors either participate in market X or market Y. This limited market participation assumption may be motivated by exogenous reasons such as taxes or regulations. Alternatively, we can motivate it by introducing a fixed cost of participation in each market so that investors will only want to participate in one.[6]

Investors in asset X do not pay attention to any of the information pertaining to asset Y, and vice versa. This assumption is a simple way of capturing the idea that investors, due to limited cognitive capabilities, simply cannot devote attention to asset markets that they do not participate in. This may be because information from other

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[5] This is a reasonable assumption given that the presence of (sell-side) analysts typically reflects greater institutional interest in firms in that industry.

[6] As long as the fixed costs to participating in X and Y are not too different, there will be some investors participating in each market.

markets is less salient. Alternatively, investors may be too busy trying to figure out the market that they are in to process this information.

At $t=1$, investors in market X receive signal $S_X = D_X + \varepsilon_{X,S}$ about the terminal value of X and investors in market Y receive signal $S_Y = D_Y + \varepsilon_{Y,S}$ about the terminal value of Y. These signals are known to all participants at $t=2$. The noise in the signals $\varepsilon_{X,S}$ and $\varepsilon_{Y,S}$ are normally distributed with means of zero and variances of $\sigma^2_{X,S}$ and $\sigma^2_{Y,S}$ respectively. We assume that $\varepsilon_{X,S}$ and $\varepsilon_{Y,S}$ are independent of each other and all other shocks in the economy. The supply of assets are assumed to be Q_X and Q_Y shares outstanding for assets X and Y respectively.

We assume that investors have CARA preferences with a risk aversion coefficient of γ. Given the price function $P_{k,t}$, the investor in asset market k $(k=X,Y)$ solves the following optimization problem:

$$\begin{aligned} &\underset{\{\theta_k\}}{Max}\ E_{k,0}\left[-\exp\left(-\gamma W_{k,2}\right)\right] \qquad k=X,Y \\ &\qquad s.t.\ W_{k,t} = W_{k,t-1} + \theta_{k,t-1}\left(P_{k,t} - P_{k,t-1}\right), \end{aligned} \tag{1}$$

where $W_{k,t}$ and $\theta_{k,t}$, are the wealth and share holding of a representative investor in asset market k at time t (we do not index different investors in the same asset market for simplicity) and $P_{k,2} = D_k$. The solution to this problem and the equilibrium prices are obtained using standard techniques.

The equilibrium price in market k is given by:

$$P_{k,t} = E_{k,t}\left[D_k\right] - \lambda_{k,t} Q_k \qquad k=X,Y \tag{2}$$

where $E_{k,t}\left[D_k\right]$ is the conditional expectation of the terminal payoff of asset k at time t, $\lambda_{k,t} > 0$ is the standard risk discount at time t and Q_k is the supply of the asset.

B. Serial and Cross-Serial Correlations

Given the equilibrium prices described in equation (2), it is straightforward to calculate the serial and cross-serial correlations for assets *X* and *Y*. Let $R_{k,t} = P_{k,t} - P_{k,t-1}$ be the date *t* return for asset *k*. The two propositions that follow are self-explanatory and are given without proof.

Proposition 1: The own serial return correlations are zero, i.e. $Corr(R_{k,2}, R_{k,1}) = 0$ *for* $k=X,Y$. *The cross-serial return correlations,* $Corr(R_{Y,2}, R_{X,1})$ *and* $Corr(R_{X,2}, R_{Y,1})$*, are non-zero and may be positive or negative depending on the sign of the covariance of asset payoffs,* $\sigma_{XY,D}$.

Intuitively, investors in market *k* rationally condition on all information associated with market *k*. As a result, the price is efficient with respect to own asset information. Hence the own serial correlation is zero. However, investors in asset market *Y* ignore all information in *X*, including past returns. As a result, the time-1 return in market *X* predicts the time-2 return in market *Y*. If investors in market *Y* (*X*) condition on the time-1 return in market *X* (*Y*), then the cross-serial correlations would be zero.

Moreover, the results in Proposition 1 would remain even if we enriched the model to include the following sets of traders. First, even if some fraction of the investors in each market paid attention to information from the other market, there will still be cross-predictability, though it will be smaller in magnitude. Second, if there are limits of arbitrage (Shleifer and Vishny (1997)), then cross-predictability will remain in equilibrium even if there are arbitrageurs who try to profit from the cross-asset return predictability. We state this more formally in Proposition 2.

Proposition 2: Even if there are arbitrageurs who trade in both markets to exploit the cross-predictability, as long as they are risk averse, some cross-predictability will remain in equilibrium.

While our model is designed to generate positive cross-serial correlations even if own-serial correlations are zero, it is important to note that the model can be easily augmented to simultaneously generate own- and cross- serial correlations. If we additionally assume that some investors in asset k do not pay attention to S_k, then along with cross-serial correlation, there is positive serial correlation, i.e. $Corr(R_{k,2}\ ,\ R_{k,1}) > 0$ for $k=X,Y$. Intuitively, if investors in the same market pay attention to (or wake up to) public information at different points in time, then information gradually diffuses across investors in the same market (Hong and Stein (1999)), resulting in positive serial correlation as well as non-zero cross-serial correlation in asset returns.

C. Testable Predictions

In our empirical work, we test three specific predictions that are implied by our model. In the context of our model, think of the broad market index as asset Y and an industry portfolio that is informative of market fundamentals as asset X. Proposition 1 implies the following prediction.

Prediction 1: The broad market index is positively correlated with the lagged returns of industry portfolios that have information about market fundamentals, controlling for lagged market returns and well-known predictors such as inflation, term and default spreads, and dividend yield.

To the extent that aggregate market prices are informative about future payoffs to an industry, we would expect market returns to forecast industry returns if participants in a particular sector ignored market prices. In reality, the broad market index is likely to be widely followed by investors in all types of asset markets. As such, we would not expect the market to lead industries as strongly. So we expect Prediction 2 to hold:

Prediction 2: Since the broad market index is more widely followed than most industries, the market does not strongly lead industry portfolio returns, controlling for lagged industry returns and other predictors.

Finally, note from Prediction 1 that our model only implies that an industry will lead the market if it has information about market fundamentals. In other words, an industry with little information about economic activity will not forecast the market whether or not investors are paying attention to it. Indeed, it follows from this logic that an industry's ability to predict the market is correlated with the information that it has about market fundamentals. As a result, we have Prediction 3:

Prediction 3: The ability of an industry to forecast the market is related to its ability to forecast changes in market fundamentals such as industrial production growth or changes in other indicators of economic activity.

This prediction also distinguishes our gradual-information-hypothesis from other behavioral explanations of stock return predictability based on biased inferences on the part of a representative investor such as Daniel, Hirshleifer and Subrahmanyam (1998) and Barberis, Shleifer and Vishny (1998). For instance, Daniel, Hirshfleifer and Subrahmanyam would attribute our cross-asset return predictability finding to continuing overreaction to industry returns on the part of overconfident investors trading the aggregate market index. Their model, however, is silent on why the cross-asset return predictability that we document is strongly related to the informative-ness of an industry about market fundamentals.

By the same token, Barberis, Shleifer and Vishny would argue that our cross-asset return predictability findings are due to a conservatism bias of a representative investor who is slow to adjust to news in industry returns, i.e. they update to news a bit slower than a Bayesian would. The degree to which prices under-react to information depends on how slowly the investor updates to information. As such, their model would also not be able to rationalize this finding unless there is an additional assumption that investors are slower to adjust to news from certain industries than others.

More importantly, anecdotal evidence is also more consistent with our gradual-information-diffusion hypothesis. For instance, there is plentiful anecdotal evidence that limited market participation is pervasive and that such segmentation meant that equity investors paid little attention to many industries like the real estate market (see, e.g., Decker (1998)).

II. Data

Our data on industry portfolios come from two sources. From Ken French's website, we obtain monthly returns to thirty-eight value-weighted industry portfolios (see Fama and French (1997)). We have to drop five of these industries from our analysis because they have missing observations.[7] Since commercial real estate is not a separate portfolio and is likely to provide a good setting to test our hypothesis (see Section III), we augment this sample by constructing a real estate industry portfolio from an index of REIT returns obtained from the NAREIT website (www.nareit.com). We use the comprehensive, value-weighted REIT index of equity, mortgage, and hybrid REITs. Since the REIT data only goes back to January 1972, our baseline sample begins at 1972 so that we can compare across industries. So, counting real estate, we consider thirty-four industry portfolios in all over the sample period of January 1972 to December 2001. To demonstrate the robustness of our findings, we will also present results for industries going back to 1960 when data is available.

In addition to these indices, we also utilize the following variables. We use the returns of the CRSP value-weighted portfolio (denoted by RM) as the proxy for the broad market index. Inflation (INF), measured as the growth rate of the Consumer Price Index, is obtained from the DRI database. Also obtained from the DRI database is the term spread (TSPR), defined as the difference between the yield-to-maturity of the ten-year Note and the one-year Treasury Bill, and the default spread (DSPR), defined as the difference between the yield of BAA-rated and AAA-rated bonds. The market dividend yield (MDY) is the one-year dividend from the CRSP value-weighted market portfolio divided by the current price. The federal funds rate (FFR) is from the Federal Reserve Board. And from Ken French's website, we obtain HML (the portfolio of high book-to-market stocks minus low book-to-market stocks) and SMB (the portfolio of small stocks minus big stocks) (see Fama and French (1993)). We also calculate a time series of monthly market volatility from daily returns to the CRSP value-weighted portfolio as in French, Schwert and Stambaugh (1987), which is denoted by MVOL.

We will also use the following two macroeconomic variables. From the DRI database, we obtain a time series of the level of industrial production, which is available

[7] The five industries that we exclude from our analysis are GARBAGE (sanitary services), STEAM (steam supply), WATER (irrigation systems), GOVT (public administration) and OTHER (everything else).

at a monthly frequency. From Mark Watson's web page, we obtain a time series of the Stock and Watson (1989) coincident index of economic activity, which is also available at a monthly frequency. Their experimental coincident index is a weighted average of four broad monthly measures of U.S. economic activity. These measures are industrial production, real personal income, real manufacturing and trade sales and total employee hours in non-agricultural establishments. The detailed descriptions of this indicator are also available on Mark Watson's web page. The data for these time series range from 1972 to 2001 to match our sample for industry returns. We denote the monthly growth rates of industrial production and the Stock and Watson coincident index of economic activity by IPG and SWG, respectively. We will be interested in seeing how past industry returns forecast these two growth rates.

We will also be interested in seeing how past industry returns forecast the deviations of these two macroeconomic variables from a potentially stochastic trend. Band-pass filters are a popular method used by economists to de-trend these time series. Such filters de-trend a time series, say of industrial production, by subtracting industrial production in month t from a weighted average of the levels of industrial production surrounding month t (say from month $t+k$ to month $t-k$), where the weights are optimally chosen. Note that a simple first-difference is a special case of this filter, which highly weighs high-frequency fluctuations in industrial production. Band-pass filters allow us to put less weight on high-frequency fluctuations in industrial production and other macroeconomic time series and indeed retain the lower frequency fluctuations of our choice.

We use the popular band-pass filter developed by Baxter and King (1999), the codes for which are available on Marianne Baxter's website. In practice, different industries may forecast fluctuations in economic activity at different frequencies. Rather than filtering industrial production and the Stock and Watson index differently for different industries, for the sake of parsimony, we set the parameters of this filter to capture fluctuations in industrial production and the Stock and Watson index at frequencies between two and twelve months.[8] We call the deviations from trend for

[8] More specifically, the parameter k for the weighted average of industrial production around month t is 19 months.

industrial production and the Stock and Watson index calculated using the Baxter-King band-pass filter, IPD and SWD, respectively.

Table 1 provides summary statistics of these variables. All returns are in excess of the one-month T-Bill rate. The means and standard deviations are in monthly percentage points. Panel A of Table 1 lists the thirty-four industry portfolios (by their abbreviated names) along with their means and standard deviations. Panel B lists the statistics for the remaining variables. The names of the industry portfolios are taken from Fama and French (1997). We denote the real estate industry portfolio by RLEST. In most cases, the names are self-explanatory. More precise definitions of these indices are available on Ken French's website.

Notice that some of the industries are very related. For instance, OIL and PTRLM (petroleum) are treated as two different industries. The main difference between them is that OIL covers oil and gas extraction, while PTRLM covers petroleum refining and petroleum products. Two other industries that are also related are MINE and STONE, with the difference being that STONE covers non-metallic minerals except fuels. Finally, MTLPR or metal products is treated differently from METAL, which covers primary metal industries.

Importantly, MONEY includes financial, insurance and real estate. However, real estate comprises a miniscule part of MONEY. As such, we create a separate real estate portfolio (RLEST) by using the REIT index as a proxy. Moreover, we will also analyze a separate group of real estate stocks that comprise realty companies and real estate brokers. We get similar results as using RLEST or this alternative real estate portfolio.

III. Empirical Findings

A. Cross-Predictive Regressions Involving Industry and Market Returns

We begin by exploring the ability of industry returns to lead the market and vice versa. To see whether industries can forecast the market (Prediction 1), we estimate the following specification separately for each of the thirty-four portfolios:

$$RM_t = \alpha_i + \lambda_i R_{i,t-1} + \boldsymbol{A_i} \boldsymbol{Z_{i,t-1}} + e_{i,t} \qquad (3)$$

where RM_t is the excess return of the market in month t, $R_{i,t-1}$ is the excess return of industry portfolio i lagged one month and $\boldsymbol{Z_{i,t-1}}$ is a vector of additional market predictors. For each of these thirty-four time-series regressions, there are a total of 359 monthly observations.

We include a number of well-known market predictors in $\boldsymbol{Z_{i,t-1}}$ to address alternative explanations for why industry returns might forecast the market. Among them is lagged market (RM_{t-1}), inflation (Fama and Schwert (1977)), the term and default spreads (Fama and French (1988)), and the market dividend yield (Campbell and Shiller (1988)). These variables are typically thought to proxy for time varying risk. To the extent our results hold even with these predictors in the regressions, it suggests that our findings are not due to time varying risk. Additionally, we worry that industry returns may be forecasting market volatility, so we also include lagged market volatility in our set of control variables. Since some industries such as financials may proxy for changes in the liquidity of the aggregate market or be especially sensitive to monetary policy variables, we also include lagged changes in the Fed Funds rate, DFFR(-1) for good measure.

The coefficients of interest are the thirty-four λ_i's, which measure the ability of each of the industry portfolios to lead the market. Since many of these industries are likely to contain valuable information about market payoffs, we expect a significant number of these coefficients to be non-zero to the extent that our gradual-information-diffusion hypothesis holds.

Alternatively, rather than seeing whether different industries lead the market separately, we can augment specification (3) by simultaneously including all thirty-four industry returns. The cost of doing this is that the standard errors on our estimates will be very large since we only have a total of 359 observations and so we cannot estimate the effect of each industry on future market returns very precisely. The benefit of doing this is that since industry returns are contemporaneously correlated, we worry about issues related to omitted variables---in other words, some of our results may be biased by not simultaneously including all other industries.

It turns out that our results are not significantly affected by whether we run the forecasting regressions separately or by pooling all the lagged industry returns. So, for the sake of precision, we present the results using specification (3). In Section IV, we discuss the results when we pool all the industries in to one regression.

In addition, we will also attempt to forecast each of the thirty-four industry portfolios using market returns (Prediction 2). To do so, we use the following specification:

$$R_{i,t} = \mu_i + \delta_i RM_{t-1} + \boldsymbol{B_i S_{i,t-1}} + u_{i,t} \qquad (4)$$

where $R_{i,t}$ and RM_t are the same as in equation (3) and $\boldsymbol{S_{i,t-1}}$ includes the lagged return of industry i ($R_{i,t-1}$) and the same set of market predictors as $\boldsymbol{Z_{i,t-1}}$ (but excluding the lagged market return). The coefficients of interest are the thirty-four δ_i's. If only a handful of these parameters are significant, then it would suggest that the market is widely followed and information contained in the market for industries will have already been incorporated.

We first present the results for the case of metal. This allows us to thoroughly describe all the regression specifications used in our analysis without reporting the results of all specifications for every industry. Much of the discussion for this case also applies to the other industries.

In Panel A of Table 2, we report the results of various regressions that establish the predictive ability of the metal industry portfolio. In column (1), we run a forecasting regression of market return on a constant, lagged values of the metal portfolio and RM.[9] The coefficient on lagged metal is –0.106 and is statistically significant. Surprisingly, this coefficient is still statistically significant even after we control for other predictors such as TSPR, DSPR and MDY in column (2). Indeed, a two standard deviation shock in the monthly return of this index leads to a change in next month's market return of 1.39% (-0.107*2*6.5%) or roughly 32% of market volatility. This effect is quite economically significant. In column (3), we augment the specification in column (2) by adding in lagged changes in the Fed Funds rate, DFFR(-1) and lagged market volatility, but the coefficient of interest remains statistically significant.

[9] Indeed, we have also experimented with adding in multiple lags of the market: past month, two months previous and three months previous. Our results are unchanged.

Across columns (1) to (3), the usual market predictors such as INF, TSPR, DSPR and MDY are not very strong in this sample.[10] Only MDY is statistically significant across all specifications. This is not very surprising because with the exception of INF, the other predictors are generally found to only forecast the market at long horizons. When compared to INF, economically the strongest of the usual market predictors, metal does a much better job of forecasting the market. A two-standard deviation shock in inflation (INF) leads to a 0.52% (-0.979*2*0.268) movement in the market, which is only 12% of market volatility, compared to the 32% of market volatility figure implied by metal.

In Panel B of Table 2, we turn to Prediction 2, which involves looking at whether the broad market index leads metal. The structure of Panel B is similar to Panel A except that we are now attempting to forecast the metal industry portfolio instead of the market. Looking across columns (4)-(6), we conclude that the coefficient in front of lagged market is not statistically significant. In other words, it does not appear that the market leads the metal industry, consistent with Prediction 2. The coefficient in front of lagged metal is also statistically insignificant in columns (4) and (5) and is barely significant in column (6). Most of the industries that forecast the market do not exhibit much serial correlation in their returns. This is perfectly consistent with our hypothesis (Proposition 1) since industry returns can exhibit no serial correlation and still forecast the market.

We now see how many of these industries lead the market in Panel A of Table 3. Our regression specification includes a constant, lagged one-month industry return, lagged one-month market return, inflation, term and default spreads, and the market dividend yield.[11] Note that we are running this regression separately for each industry. Rather than report the coefficient of each of the independent variables for every one of the thirty-four regressions, we report just the coefficient of the particular lagged one-month industry return along with the R^2 of the regression.

The industries that have significant coefficients are denoted by asterisks. There are eight industries including commercial real estate (RLEST), furniture (CHAIR), print

[10] Results for regressors such lagged RM, INF, TSPR, DSPR and MDY are the same when we use other industry returns to forecast the market. Again, this is why we only present detailed results for only one of the industries.

(PRINT), leather (LETHR), metal (METAL), utilities (UTILS), retail (RTAIL) and money (MONEY) that have t-statistics of the corresponding lagged industry return that are greater than 1.96 in absolute value (or significant at the 5% level). Five additional industries, agriculture (AGRIC), stone (STONE), apparel (APPRL), petroleum (PTRLM) and transportation (TRANS), have t-statistics of about 1.8. So at the 10% level of significance (or t-statistics greater than 1.65 in absolute value), there are a total of thirteen industries that can significantly predict the market.[12]

Importantly, the signs on the predictability coefficients for these thirteen industries also make economic sense. For instance, the lagged return of the stone, petroleum and metal industry portfolios are negatively related to next period's market return as one might suspect since these are commodity (input) prices whose shocks have historically led the economy into a downturn. In contrast, retail, apparel and furniture sectors that when they are booming are generally thought to be signs of a thriving economy. The fact that the signs of these predictive relations are consistent with conventional wisdom on the relation of these industries to the macro-economy reassures us that these predictive regressions are indeed capturing the slow diffusion of sector information into the broad market index as opposed to being the result of chance (see also Section IV below).

Finally, note that our findings are not simply an artifact of industry returns being serially correlated. First, most of the industries represent a small fraction of the market. So it is not likely that they forecast the market simply because their returns are serially correlated and part of the market portfolio. Second, the time series of most of the industry portfolios that can lead the market such as commercial real estate, agriculture, stone, apparel, chair, petroleum, metal, and utilities are not serially correlated at a monthly frequency.[13]

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[11] Similar results hold when we augment the specification to include additional regressors such as the change in the Fed Funds rate, MVOL, SMB and HML are similar.

[12] Interestingly, we have replicated our findings using an alternative real estate industry portfolio from Ken French's website. This portfolio consists of small stocks such as realty companies and real estate brokers but excludes REITs, spanning 1970-2001. It is correlated with our real estate index but may not be as informative as RLEST since REITs are required to invest most of their resources in properties. However, it is comforting to know that our findings are robust to the real estate proxy.

[13] However, a number of other industry portfolios such as construction, smoke, textiles, retail and money exhibit positive serial correlation (see also Grinblatt and Moskowitz (1999)). We omit these results for brevity.

In Panel B of Table 3, we see how many industries the market is able to lead. Our regression specification again includes a constant, lagged one-month industry return, lagged one-month market return, inflation, term and default spreads, and the market dividend yield.[14] As in Panel A, rather than report the coefficient in front of each of the independent variables for every industry, we report in Panel B just the coefficient of the lagged one-month market return along with the R^2 of the regression. The market significantly leads about five industries. It leads agriculture (AGRIC), utilities (UTILS), retail (RTAIL), financial (MONEY) at the 5% level of significance and stone (STONE) at the 10% level of significance.

In Table 4, we take a more careful look at the ability of these industries to lead the market. We calculate the effect of a two-standard deviation shock to an industry's lagged monthly return on the next month's market return. In addition, we report the absolute value of this magnitude as a fraction of market volatility. The industries are listed in descending order, by the most economically significant industry first. As one might expect, the thirteen industries that have a statistically significant ability to predict the market are also among the leaders in terms of economic significance. MONEY is very significant, with a two standard deviation shock in its returns resulting in a movement of market returns that is seventy-four percent of market volatility. The next most economically significant is retail (RTAIL). Print (PRINT), services (SRVC) and commercial real estate (RLEST) round out the top six.

Interestingly, even some of the statistically insignificant industries produce quite sizeable economic effects. For instance, metal processing (MTLPR), chemicals (CHEMS), and construction (CNSTR), while statistically insignificant, produce sizeable moves in the market in excess of 20% of market volatility. To put these magnitudes in some perspective, recall that none of the well-known market predictors can generate such effects.

B. Additional Cross-Predictive Regressions at Various Horizons

[14] Similar results hold when we augment the specification to include additional regressors such as change in the Fed Funds rate or SMB and HML are similar.

An interesting empirical question that follows from the findings in Tables 2 and 3 is whether industries lead the stock market by more than one month? Our model only predicts that there is such cross-predictability but is silent on how many months industries ought to lead the stock market by. However, we know from the literature on stock market predictability that being able to predict next month's return is already quite an achievement as it is notoriously difficult to predict the market at long horizons. Indeed, Valkanov (2002) and Torous, Valkanov and Yan (2002) argue that previous findings on long horizon predictability are an artifact of not properly adjusting standard errors for the near random walk behavior of various predictors. As such, we would not expect our industry portfolios to predict the market at very long horizons.

In Table 5, we investigate whether these industry portfolios are able to lead the market by more than one month. Column (1) of Table 5 is identical to Panel A of Table 3 in which the dependent variable is next month's market return. We reproduce it here for comparison. Recall that the coefficient in front of the lagged industry return is statistically significant at the 10% level for thirteen industries and at the 5% level for eight industries. In column (2), the dependent variable is the market return over the next two months. Now the coefficient in front of the lagged industry return is statistically significant at the 10% level for eight industries and at the 5% level for three industries. RLEST, CHAIR, UTILS, RTAIL, and TRANS are no longer statistically significant. While the ability of these industries to predict the next two months of market return is weaker, it appears that they are still able to lead the market by more than one month.

In column (3), the dependent variable is the next three months of market return. All of the thirteen industries other than STONE and METAL are now statistically insignificant. Importantly, notice that at the 10% level of significance, only two industries have a statistically significant coefficient in front of lagged industry return and only one has such a coefficient at the 5% level. In other words, the evidence is consistent with it taking about two months for the information from industries to be completely incorporated into the broad market index.

We have also looked at cross-predictability at horizons of up to 6 months and find similar results. This is comforting since it tells us that our predictive regressions are informative and not subject to some bias that mechanically yields significant results.

C. Industry Returns and Market Fundamentals

In this section, we attempt to test Prediction 3: an industry's ability to predict the market ought to be correlated with its ability to forecast indicators of economic activity (i.e. market fundamentals). We begin by specifying the regression specification for forecasting market fundamentals:

$$X_t = \eta + \gamma_i R_{i,t-1} + \boldsymbol{C_i Z_i} + v_i \tag{5}$$

where X_t is the month t realization of the indicator of economic activity, $R_{i,t-1}$ is the previous month's return of industry i and the $\boldsymbol{Z_i}$'s are the same as in equation (3) except that we include two monthly lags of market. The coefficients of interest are the γ_i*'s,* which measure the ability of the various industry returns to predict the economic indicator of interest.

To the extent that Prediction 3 holds, we expect that the relationship between the λ_i*'s* and γ_i*'s* to be positive. In other words, the industries that can strongly forecast the market ought to also forecast market fundamentals. For instance, industries such as commercial real estate that have a positive λ_i ought to also have a positive γ_i. And industries such as metals or petroleum that have a negative λ_i ought to also have a negative γ_i.

To implement the regression specified in equation (5), we need to identify proxies for economic activity. We use two well-known measures that have been previously studied in the literature. The first is industrial production growth, IPG. We use this measure because it is one of the few measures of economic activity that is available at a monthly frequency. Moreover, industrial production growth is contemporaneously correlated with the aggregate market. Over the period of 1972-2001, IPG and RM have a contemporaneous correlation of 0.08.

The second measure of economic activity that we use is SWG, the monthly growth rate of the Stock and Watson (1989) coincident index of economic activity. Most importantly from our perspective is the fact that SWG is also contemporaneously correlated with the aggregate stock market. Over the period of 1972-2001, SWG and RM have a (monthly) contemporaneous correlation of 0.12.

In Panel A of Table 6, we determine which of the thirty-four industries can forecast industrial production growth. The regression specification is equation (5) but we only report the coefficient of lagged industry return. Eleven of the thirty-four industries are statistically significant at the 10% level and five are significant at the 5% level. Our finding that industries contain valuable information about future economic fundamentals is consistent with Lamont (2001), who finds that portfolios formed from industry returns can track various economic variables like industrial production growth, inflation and consumption growth.

More importantly, it appears that the industries that forecast the market (from Table 3) also forecast industrial production growth. Recall from Table 3 that STONE, PTRLM and METAL negatively forecast the market: higher returns in these industries in month t lead to lower returns in the market the next month. Interestingly, these three industries also forecast industrial production growth with a negative coefficient: higher returns in these industries in month t lead to lower industrial production growth the next month. This is exactly what we would expect with the slow incorporation of information into the broad market index. Moreover, RETAIL, MONEY, and RLEST, which are positively cross-serially correlated with the market, also forecast the market with a positive cross-predictive coefficient.

To formally see that an industry's ability to forecast the market is indeed correlated with its ability to forecast market fundamentals, we plot λ_i on the y-axis and γ_i on the x-axis in Figure 1(a). As a benchmark, recall that in an efficient market, we would expect to see all the λ_i's be around zero, i.e. the slope of the scatter plot ought to be zero. In contrast, we see a distinctly positive relationship between the λ_i's and γ_i's. In Figure 1 (a), we also plot the fitted values from a linear regression of λ_i's on γ_i's. The slope coefficient is 2.09 with a t-statistic of 2.49. In other words, there is a strong positive correlation between the ability of industries to forecast the market and their ability to forecast industrial production growth.

Importantly, we obtain similar results when we use SWG, the percentage change in the Stock and Watson coincident index of economic activity. The results are presented in Panel B of Table 6. Using this measure, we find that ten industries now are able to forecast market fundamentals at the 10% level of significance and three industries at the 5% level of significance. In Figure 1(b), we plot the fitted values from a linear regression of the λ_i's on γ_i's. The slope coefficient is 0.85 with a t-statistic of 2.02. In other words, there is a strong positive correlation between the ability of industries to forecast the market and their ability to forecast economic activity when we use an alternative measure of the change in market fundamentals.

In Panel C and D of Table 6, we report the analogous results using IPD (stochastically de-trended industrial production) and SWD (stochastically de-trended Stock and Watson coincident index of economic activity) as the measures of changes in market fundamentals. The results using these two variables are similar to those obtained using simple monthly growth rates. Moreover, there is again a strong relationship between the λ_i's and γ_i's using IPD and SWD. The results are reported in Figure 2(a) and (b). Indeed, there is a stronger positive relationship between the λ_i's and γ_i's using IPD and SWD than using IPG and SWG.

One potential worry is that the results in Figure 1 may be due to coincidence/measurement error. Suppose that, for whatever accidental reason, in our sample period, high returns for say the retail industry just happened to be followed by increases in industrial production. Since increases in industrial production will be naturally contemporaneously correlated with positive returns in the stock market, it is likely that retail will then also lead the market. In other words, in a given sample, the measurement error in our estimate of the coefficient of industry x returns on future industrial production is going to be correlated with the measurement error in our estimate of the coefficient of industry x returns on future market returns. This can generate a pattern like that in Figure 1 even if the underlying true coefficients are not related.[15]

One very conservative way to deal with this issue is to split the sample period in half, and for every industry, estimate one of the kinds of coefficients in the first half, and the other in the second half. (This is very conservative because there might be genuine time variation in the parameters.) We can then do similar exercises to Figure 1. We use the 1972-1985 sub-sample to estimate the γ_i's and the 1986-2001 sub-sample to estimate the λ_i's for IPG and SWG (and IPD and SWD)). (We get similar results if we use the 1972-1985 sub-sample to estimate λ_i's and the 1986-2001 sub-sample to estimate the γ_i's.) We then re-do the analyses in Figure 1. There is still a statistically significant relationship between the λ_i's and γ_i's using all four proxies of changes in fundamentals. Using this conservative estimation method, the t-statistics for IPG and SWG fall from around 2 to 1.7 and the results are largely unchanged for IPD and SWD. For brevity, we omit the figures. Hence, we can conclude that our findings in Figures 1 and 2 are not due coincidence/measurement error.

D. Residual Analyst Coverage and Cross-Asset Return Predictability

The analysis in Figure 1 assumed that the rate of diffusion of information from a particular industry to other markets is roughly the same across all industries. In reality, this assumption may not be true since some industries may be more highly monitored by investors than others. To this end, we attempt to measure the rate of information diffusion from a particular industry by using constructing a measure similar to the residual analyst coverage measure of Hong, Lim and Stein (2000). Hong, Lim and Stein use cross-sectional variation to regress the number of analysts covering a stock on the market cap of the stock to obtain a residual-analyst-coverage measure for each stock. This measure is the abnormal analyst coverage a stock obtains adjusted for its size as larger firms naturally have more analysts covering them. They argue that this residual analyst coverage measure is a proxy for the rate of information diffusion for the stock---the larger is the measure (or abnormally high analyst coverage), the more quickly information diffuses to investors who invest in the stock.

Using data from IBES from 1980-2000, we calculate an analogous residual-analyst-coverage measure for each of our industries. More specifically, for each year, we calculate log of one plus the total number of analysts covering the firms in each industry. Then for each year, we run a cross-sectional regression of this measure on the log of the market capitalization of that industry. The residuals from this cross-sectional regression give the residual analyst coverage for each industry. We then take the average of the time series of each of the thirty-four residual analyst coverage measures and call the

[15] We thank Owen Lamont for pointing this out to us.

industry i measure $RCOV_i$. This is our measure of the rate at which industry information diffuses to the broad investing public.

With this measure in hand, we look to see whether there is a correlation between the industries that can predict economic indicators and whether they attract analyst coverage. We find that there is virtually no correlation between these two characteristics. As such, we can be assured that our findings in Figure 1 are not due to the differential rate at which industry information diffuses to the public.

A related question is whether industries with low analyst coverage are also the ones that also lead the market. To the extent that the residual-analyst-coverage measure captures the rate at which information diffuses to the other market, we would expect that low coverage industries are the ones that would lead the market. To see whether this is the case, we regress the absolute value of λ_i on $RCOV_i$. The slope coefficient is of the predicted sign, -0.032, but only has a t-statistic of -0.7. As a result, we conclude that there is some very weak evidence that for industries whose information diffuses relatively quickly to the public, there is less cross-asset return predictability with the market.

IV. Robustness Checks

A. Sub-Periods

As a robustness check, we arbitrarily divided our sample into two equal sub-samples (1972-1985 and 1986-2001) to see whether the ability of these industries to lead the market differs across these sub-periods. We implement this sample split by augmenting specification in equation (3) by adding in a dummy variable that equals one if the observation is after 1985 and zero otherwise 1(Year > 1985) and this dummy interacted with the lagged industry return. The coefficient of interest is the interaction term involving lagged industry return and the indicator 1(Year > 1985). We expect that the coefficient in front of the interaction term to be zero for these industries. Among the thirty-four industries, not one industry has a coefficient in front of the interaction term that is statistically significant at the 10% level. This evidence strongly suggests that news travels slowly across industries even in today's financial markets. This finding is robust to different splits for the sample. We could have presented results for cut-off points ranging from 1985 to 1990 and it would not have made a big difference. We omit the results for brevity and these results are available upon request.

B. Extended Sample Going Back to the '60s

As we mentioned in Section II, the REIT data for our real estate industry portfolio only goes back to 1972. To allow us to compare results across different industries, we chose January 1972 as the beginning of our baseline sample. We have also re-done our analysis for industries going back to the sixties. Indeed, out of thirty-three industries, eight are significant at the 10% level and five are significant at the 5% level. Importantly, the eight industries that forecast the market in this extended sample also forecasted the market in our baseline sample. They are apparel, print, petroleum, leather, metal, utilities, retail and money. The industries that significantly lead the market in the baseline sample but do not in this extended sample are agriculture, stone, chair and transportation. But with the exception of agriculture, the other three industries still forecast the market with the same signs as they did in the baseline sample, though the magnitudes are a bit smaller, leading to t-stats in between 1 and 1.3. As such, we conclude that the same industries that forecasted the market in our baseline sample continue to do so in our extended sample. This indicates that our findings are remarkably robust. We also omit these results for brevity and they are also available upon request.

C. Forecasting The Market and Indicators of Economic Activity Using All Industries Simultaneously

Up to this point, we have looked at how industries separately forecast the market or various indicators of economic activity. The reason we treated industries separately was to improve the precision of our estimates since we have roughly about 360 monthly observations and 34 industries along with a host of other control variables. However, a cost of decreasing the standard errors of our estimates is the omitted variable bias due to industry returns being contemporaneously correlated. Certain industries may look like they forecast the market or economic activity but do not once we consider all industries jointly. So, a natural follow-up question is what happens when we include all industries in our forecasting specifications?

In Table 8, we answer this question by trying to forecast the market and economic indicators using all industries simultaneously along with the control variables specified in Table 3 and Table 6, respectively. The values of the F-tests (with thirty-four restrictions) under the various null hypotheses are reported. The first row reports the p-values for five separate null hypotheses. The first is whether the industry returns jointly do not forecast the market (RM). The p-value is 0.03, which means that we can strongly reject this null at the 5% level. The other four hypotheses are whether the industry returns can jointly forecast the various indicators of economic activity (IPG, SWG, IPD, and SWD). Again, in each case except for IPD, we can reject the null at the 5% level. In the case of IPD, we can reject it at the 10% level.

The second row reports the p-values for the null hypotheses that the control variables jointly do not forecast the market and the other indicators of economic activity. In each case, we cannot reject these null hypotheses at either the 5% or the 10% levels of significance. The third row reports the p-values for the null hypotheses that all industry returns and all control variables do not jointly forecast the market or indicators of economy activity. The results are similar to the first row in that we can reject that these variables do jointly have forecasting power.

We do not report the coefficients from the regressions in Table 8 for brevity. However, we wan to point out that the coefficients from forecasting regressions using all industries are similar to those coefficients obtained in Tables 3 and 6. For instance, eleven out of the thirteen significant industries in Table 3, including RLEST, AGRIC, STONE, PRINT, PTRLM, LETHR, METAL, TRANS, UTILS, RTAIL and MONEY, have similar coefficients when we forecast the market using all the industries simultaneously. The two significant industries in Table 3 that flip signs are APPRL and CHAIR. Moreover, we have also re-done the analysis in Figure 1 using the coefficients from these joint regressions and obtained similar results. So even though the coefficients are estimated much more imprecisely when we include all industries simultaneously, the economic messages that we obtained from Table 3, Table 6 and Figure 1 are confirmed.

V. Related Literature

To the best our knowledge, we are the first to document that the stock market is predictable by the lagged returns of a range of industry portfolios. We are also the first to link this cross-predictability to the delayed reaction of the market to information industry returns about indicators of economic activity (i.e. market fundamentals) such as industrial production growth. In independent work, Pollet (2002) finds that oil can predict stock returns and most interestingly that the Norwegian stock market (which is dominated by oil) leads the world stock market. His finding regarding the Norwegian market fits especially nicely with our gradual-information-diffusion hypothesis since the Norwegian market is likely to be off the radar screen of investors who trade the world market index.

Our paper is also related to the literature following Merton (1987) that attempts to see the effects of market segmentation and investor recognition on asset prices (see Amihud, Mendelson and Uno (1999), Kadlec and McConnell (1994), Foerster and Karolyi (1999)). Unlike these papers that focus on the effect of investor recognition and market segmentation on the mean level of asset prices, our paper focuses on the effects of limited information process capacity on cross-asset return predictability.

Our finding that the market does not strongly lead industry portfolios is also novel and surprising. For instance, conventional wisdom suggests that the more liquid security, the broad market index, ought to react to news in a more timely fashion than less liquid securities such as the real estate index. Hence, we would have expected the aggregate stock market to lead the real estate market or other industries. As such, our findings are distinct from the finding that the large stocks lead small stocks (Lo and Mackinlay (1990) and Jegadeesh and Titman (1995)).[16] Moreover, the lead-lag relationships we document occur at a much longer horizon of a couple of months as opposed to the one between large and small stocks which plays out over a couple of days.

Our paper is also related to a growing literature that looks at the effect of information-capacity constraints on behavior and asset pricing. Most recently, Sims (2001) develops a simple model that relaxes the assumption that agents can process information effortlessly by imposing an information capacity constraint. His model can generate stickiness in macroeconomic variables such consumption. Peng and Xiong

[16] A related paper to the literature on lead-lags is Lewellen (2002) who looks at cross-asset return predictability among portfolios. Our paper focuses instead on the whether industry portfolios can lead the stock market.

(2002) develop an asset-pricing model based on Sims (2001) to study asset price co-movements. Hirshleifer, Lim and Teoh (2002) develop a model of disclosure in which investors sometimes neglect either disclosed signals or the implications of non-disclosure. In contrast to our paper, these models do not have any implications for cross-asset return predictability or asset price predictability more generally.

VI. Conclusion

In this paper, we develop the hypothesis that the gradual diffusion of information across asset markets leads to cross-asset return predictability. We test our hypothesis by looking at cross-predictability among industry portfolios and the broad market index. Consistent with our gradual-information-diffusion hypothesis, we find that out of thirty-four industry portfolios, thirteen including commercial real estate, agriculture, non-metallic minerals, apparel, furniture, print, petroleum, leather, metal, transportation, utilities, retail and financial lead the market by up to two months. The market, which is widely followed, only leads a handful of industries. Importantly, the ability of an industry to lead the market is strongly correlated with its propensity to forecast indicators of economic activity such as industrial production growth. These findings indicate that the market incorporates information contained in industry returns about its fundamentals only with a lag.

The logic of our hypothesis suggests that the gradual diffusion of information across asset markets ought to be pervasive. As a result, we would expect to find cross-asset return predictability in many contexts beyond industry portfolios and the broad market index. The key to finding such cross-asset return predictability is to identify sets of assets who payoffs are likely correlated. As such, other contexts for interesting empirical work include looking at stocks within an industry or commodity prices and the broad market index. Much more work remains to be done on this topic.

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Table 1: Summary Statistics

The table presents summary statistics of the variables of interest. In Panel A, the variables are the returns of the thirty-four industry portfolios. In Panel B, RM is the CRSP value-weighted market portfolio return. INF is the CPI inflation rate. TSPR is the term spread between the 10-year Note and the one-year T-bill. DSPR is the default spread between BAA-rated and AAA-rated bonds. MDY is the dividend yield of the market portfolio. FFR is the federal funds rate. The portfolio returns HML and SMB are from Fama and French (1993). All returns are in excess of the one-month T-bill rate. MVOL is the market volatility. IPG is industrial production growth, SWG is the growth rate of the Stock and Watson (1989) coincident index of economic activity, IPD is detrended industrial production, and SWD is the detrended the Stock and Watson (1989) coincident index of economic activity. The data are at monthly frequency and in monthly percentage points, except for IPD and SWD. All variables are from January 1972 to December 2001.

Panel A: Industry Portfolio Returns

Industry	Mean	Std. Dev	Industry	Mean	Std. Dev.
RLEST	0.323	4.475	LETHR	0.555	7.467
AGRIC	0.647	7.238	GLASS	0.518	6.692
MINES	0.140	7.292	METAL	0.364	6.546
OIL	0.413	7.236	MTLPR	0.571	5.375
STONE	0.935	8.380	MACHN	0.389	6.426
CNSTR	0.325	7.252	ELCTR	0.701	6.718
FOOD	0.736	4.909	CARS	0.512	5.840
SMOKE	1.048	6.302	INSTR	0.390	5.651
TXTLS	0.398	6.249	MANUF	0.364	6.801
APPRL	0.304	7.084	TRANS	0.433	6.091
WOOD	0.405	7.804	PHONE	0.553	5.226
CHAIR	0.497	6.312	TV	0.943	6.598
PAPER	0.509	5.671	UTILS	0.457	4.123
PRINT	0.657	5.572	WHLSL	0.641	5.659
CHEMS	0.652	4.921	RTAIL	0.616	5.935
PTRLM	0.747	5.278	MONEY	0.637	5.173
RUBBR	0.402	6.199	SRVC	0.693	7.032

Panel B: Other Variables

Variable	Mean	Std.Dev
RM	0.521	4.405
INF	0.338	0.268
TSPR	0.152	0.120
DSPR	0.091	0.038
MDY	0.397	1.016
FFR	0.612	0.272
HML	0.118	3.372
SMB	0.471	3.218
MVOL	3.533	0.768
IPG	0.223	0.788
SWG	0.204	0.523
IPD	0.010	0.323
SWD	0.006	0.394

Table 2: Cross-Predictive Regressions Between Real Estate and Market Portfolios

Panel A presents the results from forecasting the market return in month t using variables at month t-1. Panel B presents analogous results from forecasting the real estate index in month t using information available at time t-1. RLEST is the REIT index return. RM is the CRSP excess value-weighted market portfolio return. INF is the CPI inflation rate. TSPR is the term spread between the 10-year Note and the one-year T-bill. DSPR is the default spread between BAA-rated and AAA-rated bonds. MDY is the dividend yield of the market portfolio. DFFR is the change in the federal funds rate. MVOL is the market volatility. The portfolio returns HML and SMB are from Fama and French (1993). In all columns, the least squares estimates, Newey-West t-statistics (in parentheses), adjusted R2, and number of observations are displayed. Newey-West serial correlation and heteroskedasticity robust t-statistics are calculated with 3 monthly lags. The sample period is January 1972 to December 2001. *Significant at 10% level. **Significant at 5% level.

Panel A: Dependent Variable--RM

	(1)	(2)	(3)	(4)	(5)
CONST	0.470	0.508	-0.443	-1.296	-0.891
	(2.178)**	(2.192)**	(-0.616)	(-0.838)	(-0.571)
RLEST(-1)	0.146	0.215	0.177	0.172	0.233
	(2.386)**	(2.556)**	(2.218)**	(2.121)**	(2.286)**
RM(-1)		-0.115	-0.133	-0.128	-0.200
		(-1.469)	(-1.746)*	(-1.716)*	(-2.055)**
INF(-1)			-0.979	-0.908	-0.965
			(-1.027)	(-0.977)	(-1.047)
TSPR(-1)			3.430	3.524	3.194
			(1.707)*	(1.416)	(1.274)
DSPR(-1)			9.872	8.298	8.527
			(1.471)	(1.206)	(1.229)
MDY(-1)			-0.287	-0.341	-0.152
			(-1.509)	(-1.711)*	(-0.426)
DFFR(-1)				-3.354	-3.985
				(-0.816)	(-1.011)
MVOL(-1)				0.277	0.181
				(0.724)	(0.470)
HML(-1)					-0.046
					(-0.461)
SMB(-1)					-0.153
					(-1.769)*
R2	0.022	0.03	0.058	0.061	0.067
T	359	359	359	359	359

Table 2 (Cont'd): Cross-Predictive Regressions Between Real Estate and Market Portfolios

Panel B: Dependent Variable--RLEST

	(1)	(2)	(3)	(4)	(5)
CONST	0.274	0.274	-1.965	-2.605	-2.851
	(1.123)	(1.144)	(-2.687)**	(-2.293)**	(-2.577)**
RM(-1)	0.092	0.067	0.078	0.080	0.126
	(1.346)	(0.808)	(0.972)	(0.970)	(1.643)
RLEST(-1)		0.039	0.015	-0.026	-0.069
		(0.367)	(0.142)	(-0.241)	(-0.659)
INF(-1)			0.366	0.402	0.434
			(0.370)	(0.427)	(0.466)
TSPR(-1)			7.039	6.808	7.042
			(3.694)**	(3.378)**	(3.467)**
DSPR(-1)			11.160	9.435	9.061
			(1.576)	(1.356)	(1.250)
MDY(-1)			0.106	0.051	-0.005
			(0.425)	(0.201)	(-0.011)
DFFR(-1)				-5.761	-5.406
				(-1.236)	(-1.159)
MVOL(-1)				0.239	0.295
				(0.884)	(1.129)
HML(-1)					0.051
					(0.428)
SMB(-1)					0.088
					(0.789)
R2	0.008	0.009	0.057	0.064	0.067
T	359	359	359	359	359

Table 3: Cross-Predictive Regressions Involving Various Industry and Market Portfolios

Panel A presents results of forecasting the market return in month t using various industry portfolio returns at month t-1 separately and other information available at month t-1. Panel B presents analogous results from forecasting various industry returns in month t using market returns at month t-1 and other information available at month t-1. The other forecasting variables are INF (the CPI inflation rate), TSPR (the term spread between the 10-year Note and the one-year T-bill), DSPR (the default spread between BAA-rated and AAA-rated bonds), and MDY (the dividend yield of the market portfolio). We only report the coefficients in front of the lagged industry (market) return in Panel A (Panel B). The least squares estimates, Newey-West t-statistics (in parentheses), and adjusted R2 are displayed. Newey-West serial correlation and heteroskedasticity robust t-statistics are calculated with 3 monthly lags. The sample period is January 1972 to December 2001. *Significant at 10% level. **Significant at 5% level.

Panel A: Forecast of RM using Industry Returns

	IND(-1)	R2		IND(-1)	R2
RLEST	0.177	0.058	LETHR	0.107	0.055
	(2.218)**			(2.586)**	
AGRIC	0.056	0.044	GLASS	0.016	0.039
	(1.884)*			(0.296)	
MINES	-0.057	0.044	METAL	-0.102	0.048
	(-1.514)			(-2.334)**	
OIL	-0.017	0.039	MTLPR	0.116	0.043
	(-0.367)			(1.263)	
STONE	-0.055	0.047	MACHN	-0.003	0.039
	(-1.791)*			(-0.052)	
CNSTR	0.07	0.043	ELCTR	-0.043	0.039
	(1.354)			(-0.488)	
FOOD	0.055	0.04	CARS	0.020	0.039
	(0.833)			(0.299)	
SMOKE	-0.006	0.039	INSTR	0.001	0.039
	(-0.168)			(0.005)	
TXTLS	0.055	0.042	MANUF	0.055	0.042
	(1.025)			(1.206)	
APPRL	0.088	0.047	TRANS	0.103	0.045
	(1.786)*			(1.757)*	
WOOD	-0.008	0.039	PHONE	-0.088	0.045
	(-0.252)			(-1.442)	
CHAIR	0.113	0.049	TV	0.040	0.04
	(2.113)**			(0.657)	
PAPER	-0.018	0.039	UTILS	0.163	0.051
	(-0.264)			(2.405)**	
PRINT	0.164	0.05	WHLSL	0.028	0.039
	(2.173)**			(0.358)	
CHEMS	-0.091	0.041	RTAIL	0.163	0.053
	(-1.102)			(2.287)**	
PTRLM	-0.114	0.049	MONEY	0.317	0.06
	(-1.884)*			(2.777)**	
RUBBR	0.027	0.039	SRVC	0.126	0.044
	(0.488)			(1.268)	

Table 3 (Cont'd): Cross-Predictive Regressions Involving Various Industry and Market Portfolios

Panel B: Forecast of Industry Returns using the Market

	IND(-1)	R2		IND(-1)	R2
RLEST	0.078	0.057	LETHR	-0.056	0.067
	(0.972)			(-0.444)	
AGRIC	0.195	0.019	GLASS	-0.006	0.052
	(2.230)**			(-0.041)	
MINES	0.07	0.017	METAL	0.079	0.012
	(0.599)			(0.678)	
OIL	-0.203	0.016	MTLPR	-0.066	0.044
	(-1.377)			(-0.436)	
STONE	0.193	0.018	MACHN	0.088	0.043
	(1.668)*			(0.579)	
CNSTR	-0.162	0.051	ELCTR	0.035	0.043
	(-1.129)			(0.210)	
FOOD	-0.142	0.039	CARS	-0.021	0.068
	(-1.524)			(-0.212)	
SMOKE	-0.109	0.039	INSTR	-0.07	0.033
	(-1.063)			(-0.521)	
TXTLS	-0.069	0.088	MANUF	0.099	0.051
	(-0.659)			(0.928)	
APPRL	-0.038	0.065	TRANS	-0.196	0.05
	(-0.272)			(-1.635)	
WOOD	0.04	0.023	PHONE	-0.04	0.03
	(0.304)			(-0.353)	
CHAIR	0.049	0.068	TV	-0.075	0.049
	(0.395)			(-0.648)	
PAPER	0.012	0.04	UTILS	-0.166	0.033
	(0.101)			(-2.074)**	
PRINT	-0.117	0.071	WHLSL	-0.047	0.048
	(-1.044)			(-0.358)	
CHEMS	0.085	0.023	RTAIL	-0.258	0.079
	(0.661)			(-2.379)**	
PTRLM	-0.026	0.01	MONEY	-0.433	0.06
	(-0.250)			(-2.354)**	
RUBBR	-0.101	0.05	SRVC	-0.282	0.04
	(-0.970)			(-1.167)	

Table 4: Industry Cross-Predictive Regressions: Economic Significance

The table reports estimates of the economic significance of the observed market forecastability of market returns using by industry returns. The column "Economic Significance" computes the response of the market return to a two-standard-deviation shock of the corresponding industry return. The column "Absolute Relative Significance" computes the absolute value from the "Economic Significance" column and divides it by the standard deviation of the market return. The portfolios are sorted in descending order of "Absolute Relative Significance."

	Economic Significance	Absolute Relative Significance		Economic Significance	Absolute Relative Significance
MONEY	3.283	0.745	MINES	-0.833	0.189
RTAIL	1.930	0.438	AGRIC	0.811	0.184
PRINT	1.825	0.414	MANUF	0.749	0.170
SRVC	1.766	0.401	TXTLS	0.692	0.157
LETHR	1.593	0.362	ELCTR	-0.573	0.130
RLEST	1.587	0.360	FOOD	0.544	0.123
CHAIR	1.433	0.325	TV	0.523	0.119
METAL	-1.338	0.304	RUBBR	0.333	0.076
UTILS	1.340	0.304	WHLSL	0.314	0.071
TRANS	1.260	0.286	OIL	-0.244	0.055
MTLPR	1.251	0.284	CARS	0.232	0.053
APPRL	1.247	0.283	GLASS	0.213	0.048
PTRLM	-1.200	0.272	PAPER	-0.207	0.047
CNSTR	1.010	0.229	WOOD	-0.131	0.030
STONE	-0.922	0.209	SMOKE	-0.078	0.018
PHONE	-0.920	0.209	MACHN	-0.044	0.010
CHEMS	-0.893	0.203	INSTR	-0.004	0.001

Table 5: Cross-Predictive Regressions Between Various Industry and Market Portfolios, At Various Horizons

This table presents forecasts of the market return using various industry portfolio returns (separately) at various horizons: next month, next two months, and next three months. The other forecasting variables are INF (the CPI inflation rate), TSPR (the term spread between the 10-year Note and the one-year T-bill), DSPR (the default spread between BAA-rated and AAA-rated bonds), and MDY (the dividend yield of the market portfolio). We only report the coefficient in front of the lagged industry return. The least squares estimates, Newey-West t-statistics (in parentheses), and adjusted R2 are displayed for each industry. Newey-West serial correlation and heteroskedasticity robust t-statistics are calculated with 3 monthly lags. The sample period is January 1972 to December 2001. *Significant at 10% level. **Significant at 5% level.

	Horizon (Months)					
	1		2		3	
	IND(-1)	R2	IND(-1)	R2	IND(-1)	R2
RLEST	0.177	0.058	0.005	0.054	0.029	0.071
	(2.218)**		(0.049)		(0.225)	
AGRIC	0.056	0.044	0.064	0.058	0.001	0.071
	(1.884)*		(1.632)		(0.013)	
MINES	-0.057	0.044	-0.093	0.062	-0.106	0.078
	(-1.514)		(-1.693)*		(-1.516)	
OIL	-0.017	0.039	-0.108	0.062	-0.084	0.074
	(-0.367)		(-1.611)		(-1.044)	
STONE	-0.055	0.047	-0.103	0.068	-0.102	0.08
	(-1.791)*		(-2.465)**		(-1.684)*	
CNSTR	0.07	0.043	0.034	0.054	-0.041	0.071
	(1.354)		(0.456)		(-0.462)	
FOOD	0.055	0.04	0.107	0.056	0.073	0.072
	(0.833)		(1.170)		(0.621)	
SMOKE	-0.006	0.039	-0.015	0.054	-0.072	0.073
	(-0.168)		(-0.214)		(-0.772)	
TXTLS	0.055	0.042	-0.004	0.054	-0.068	0.072
	(1.025)		(-0.041)		(-0.699)	
APPRL	0.088	0.047	0.126	0.062	0.011	0.071
	(1.786)*		(1.802)*		(0.119)	
WOOD	-0.008	0.039	-0.011	0.054	-0.034	0.071
	(-0.252)		(-0.196)		(-0.498)	
CHAIR	0.113	0.049	0.087	0.057	-0.042	0.071
	(2.113)**		(1.087)		(-0.449)	
PAPER	-0.018	0.039	-0.018	0.054	-0.148	0.075
	(-0.264)		(-0.152)		(-1.250)	
PRINT	0.164	0.05	0.235	0.065	0.094	0.072
	(2.173)**		(1.944)*		(0.653)	
CHEMS	-0.091	0.041	0.126	0.056	0.123	0.072
	(-1.102)		(0.985)		(0.890)	
PTRLM	-0.114	0.049	-0.212	0.071	-0.149	0.077
	(-1.884)*		(-2.414)**		(-1.464)	
RUBBR	0.027	0.039	0.057	0.055	-0.104	0.073
	(-0.488)		(0.677)		(-1.005)	

Table 5: (Cont'd) Cross-Predictive Regressions Between Various Industry and Market Portfolios, At Various Horizons

	Horizon (Months)					
	1		2		3	
	IND(-1)	R2	IND(-1)	R2	IND(-1)	R2
LETHR	0.107	0.055	0.113	0.063	0.056	0.072
	(2.586)**		(1.885)*		(0.720)	
GLASS	0.016	0.039	0.046	0.055	-0.077	0.072
	(0.296)		(0.584)		(-0.817)	
METAL	-0.102	0.048	-0.133	0.062	-0.224	0.087
	(-2.334)**		(-1.736)*		(-2.814)*	
MTLPR	0.116	0.043	0.153	0.057	0.040	0.071
	(1.263)		(1.192)		(0.288)	
MACHN	-0.003	0.039	0.054	0.055	0.146	0.075
	(-0.052)		(0.583)		(1.337)	
ELCTR	-0.043	0.039	0.067	0.055	0.009	0.071
	(-0.488)		(0.560)		(0.067)	
CARS	0.02	0.039	0.024	0.054	-0.122	0.074
	(0.299)		(0.260)		(-1.222)	
INSTR	-0.001	0.039	0.130	0.058	0.143	0.074
	(-0.005)		(1.075)		(1.085)	
MANUF	0.055	0.042	0.068	0.056	-0.065	0.072
	(1.206)		(1.039)		(-0.794)	
TRANS	0.103	0.045	0.071	0.055	-0.026	0.071
	(1.757)*		(0.780)		(-0.229)	
PHONE	-0.088	0.045	-0.011	0.054	0.112	0.074
	(-1.442)		(-0.119)		(1.186)	
TV	0.04	0.04	0.098	0.058	0.112	0.074
	(0.657)		(1.066)		(1.042)	
UTILS	0.163	0.051	0.106	0.057	0.201	0.077
	(2.405)**		(0.983)		(1.315)	
WHLSL	0.028	0.039	-0.037	0.054	-0.09	0.072
	(0.358)		(-0.322)		(-0.661)	
RTAIL	0.163	0.053	0.147	0.059	0.004	0.071
	(2.287)**		(1.441)		(0.038)	
MONEY	0.317	0.06	0.358	0.068	0.330	0.079
	(2.777)**		(2.205)**		(1.392)	
SRVC	0.126	0.044	0.215	0.062	0.247	0.079
	(1.268)		(1.608)		(1.687)*	

Table 6: Predictive Regressions of Measures of Economics Activity using Industry Portfolios

Panel A presents results of forecasting IPG, industrial production growth in month t, using various industry portfolio returns at month t-1 separately and other information available at month t-1. Panel B presents analogous results from forecasting SWG, the growth rate of the Stock and Watson (1989) index of economic activity in month t, using market returns at month t-1 and other information available at month t-1. Panels C and D present similar results of forecasting IPD and SWD, detrended industrial production and the detrended Stock and Watson (1989) index of economic activity in month t, respectively. The other forecasting variables are INF (the CPI inflation rate), TSPR (the term spread between the 10-year Note and the one-year T-bill), DSPR (the default spread between BAA-rated and AAA-rated bonds), and MDY (the dividend yield of the market portfolio). We only report the coefficient in front of the lagged industry return. The least squares estimates, Newey-West t-statistics (in parentheses), and adjusted R2 are displayed for each industry. Newey-West serial correlation and heteroskedasticity robust t-statistics are calculated with 3 monthly lags. The sample period is January 1972 to December 2001. *Significant at 10% level. **Significant at 5% level.

Panel A: Forecast of IPG using Industry Returns

	IND(-1)	R2		IND(-1)	R2
RLEST	0.011	0.080	LETHR	0.015	0.088
	(0.895)			(1.608)	
AGRIC	0.001	0.078	GLASS	0.019	0.085
	(0.159)			(1.739)*	
MINES	-0.001	0.078	METAL	-0.014	0.083
	(-0.199)			(-1.615)	
OIL	0.008	0.080	MTLPR	-0.009	0.078
	(1.112)			(-0.652)	
STONE	-0.014	0.093	MACHN	0.015	0.081
	(-2.529)**			(1.237)	
CNSTR	-0.003	0.078	ELCTR	0.017	0.081
	(-0.340)			(1.347)	
FOOD	-0.039	0.097	CARS	0.038	0.106
	(-3.115)**			(2.573)**	
SMOKE	-0.015	0.086	INSTR	-0.018	0.082
	(-1.917)*			(-1.163)	
TXTLS	0.022	0.092	MANUF	-0.008	0.08
	(1.889)*			(-0.730)	
APPRL	0.017	0.088	TRANS	-0.007	0.078
	(1.368)			(-0.689)	
WOOD	0.004	0.078	PHONE	-0.009	0.080
	(0.612)			(-0.909)	
CHAIR	0.001	0.078	TV	0.008	0.079
	(0.132)			(0.730)	
PAPER	0.010	0.079	UTILS	0.026	0.088
	(0.841)			(1.984)**	
PRINT	0.001	0.078	WHLSL	0.006	0.078
	(0.048)			(0.412)	
CHEMS	-0.037	0.090	RTAIL	-0.010	0.079
	(-2.075)**			(-0.700)	
PTRLM	-0.016	0.084	MONEY	0.030	0.084
	(-1.714)*			(1.344)	
RUBBR	0.022	0.088	SRVC	0.029	0.088
	(1.873)*			(1.792)*	

Table 6 (Cont'd): Predictive Regressions of Measures of Economics Activity using Various Industry Portfolios

Panel B: Forecast of SWG using Industry Returns					
	IND(-1)	R2		IND(-1)	R2
RLEST	0.076	0.091	LETHR	0.009	0.094
	(1.673)*			(0.365)	
AGRIC	-0.025	0.091	GLASS	-0.013	0.093
	(-1.332)			(-0.355)	
MINES	-0.016	0.091	METAL	-0.001	0.092
	(-1.002)			(1.933)*	
OIL	-0.017	0.091	MTLPR	-0.081	0.091
	(-1.682)*			(-2.535)**	
STONE	-0.022	0.105	MACHN	0.061	0.093
	(-2.181)**			(1.817)*	
CNSTR	0.010	0.090	ELCTR	0.042	0.092
	(0.335)			(0.881)	
FOOD	-0.018	0.105	CARS	-0.006	0.112
	(-0.394)			(-0.168)	
SMOKE	-0.014	0.098	INSTR	0.023	0.094
	(-0.527)			(0.373)	
TXTLS	-0.045	0.097	MANUF	0.018	0.094
	(-1.657)*			(0.456)	
APPRL	-0.004	0.097	TRANS	-0.034	0.091
	(-0.152)			(-0.972)	
WOOD	0.034	0.091	PHONE	-0.038	0.093
	(1.570)			(-1.307)	
CHAIR	-0.041	0.091	TV	-0.003	0.092
	(-1.260)			(-0.108)	
PAPER	0.045	0.091	UTILS	0.006	0.102
	(1.371)			(2.236)**	
PRINT	0.041	0.091	WHLSL	0.037	0.092
	(1.740)*			(0.562)	
CHEMS	-0.017	0.105	RTAIL	0.018	0.091
	(-0.33)			(0.584)	
PTRLM	-0.011	0.094	MONEY	0.106	0.093
	(-0.407)			(1.847)*	
RUBBR	-0.008	0.093	SRVC	0.002	0.100
	(-0.197)			(0.040)	

Table 6 (Cont'd): Predictive Regressions of Measures of Economics Activity using Industry Portfolios

Panel C: Forecast of IPD using Industry Returns

	IND(-1)	R2		IND(-1)	R2
RLEST	0.004	0.339	LETHR	0.003	0.332
	(0.840)			(1.117)	
AGRIC	0.002	0.333	GLASS	0.003	0.352
	(0.931)			(1.032)	
MINES	-0.001	0.333	METAL	-0.003	0.339
	(-0.039)			(-0.145)	
OIL	-0.001	0.342	MTLPR	0.006	0.334
	(-0.472)			(1.512)	
STONE	-0.005	0.347	MACHN	0.002	0.337
	(-1.659)*			(0.754)	
CNSTR	0.004	0.341	ELCTR	0.002	0.334
	(1.279)			(0.472)	
FOOD	0.011	0.339	CARS	0.002	0.339
	(2.788)**			(0.507)	
SMOKE	0.005	0.344	INSTR	0.007	0.347
	(1.589)			(1.844)*	
TXTLS	0.002	0.332	MANUF	0.005	0.361
	(0.679)			(1.788)*	
APPRL	0.002	0.337	TRANS	0.007	0.333
	(0.794)			(1.925)*	
WOOD	0.001	0.334	PHONE	0.006	0.334
	(0.247)			(1.672)*	
CHAIR	0.003	0.334	TV	0.000	0.336
	(1.025)			(0.031)	
PAPER	0.003	0.333	UTILS	0.006	0.334
	(0.848)			(1.206)	
PRINT	0.005	0.333	WHLSL	0.004	0.339
	(1.164)			(1.044)	
CHEMS	0.009	0.334	RTAIL	0.009	0.336
	(2.146)**			(2.556)**	
PTRLM	-0.006	0.336	MONEY	0.006	0.342
	(-1.372)			(1.513)	
RUBBR	0.002	0.333	SRVC	0.005	0.335
	(0.639)			(1.479)	

Table 6 (Cont'd): Predictive Regressions of Measures of Economics Activity using Various Industry Portfolios

	Panel D: Forecast of SWD using Industry Returns				
	IND(-1)	R2		IND(-1)	R2
RLEST	0.005	0.197	LETHR	0.003	0.197
	(0.905)			(0.757)	
AGRIC	0.002	0.195	GLASS	0.002	0.196
	(0.150)			(0.577)	
MINES	-0.001	0.195	METAL	-0.001	0.195
	(-0.186)			(-0.155)	
OIL	-0.002	0.196	MTLPR	0.004	0.197
	(-0.563)			(0.872)	
STONE	-0.009	0.216	MACHN	0.001	0.195
	(-2.744)**			(0.273)	
CNSTR	0.003	0.197	ELCTR	0.000	0.195
	(0.941)			(0.103)	
FOOD	0.009	0.203	CARS	-0.001	0.195
	(2.110)**			(-0.195)	
SMOKE	0.006	0.200	INSTR	0.005	0.198
	(1.585)			(1.229)	
TXTLS	0.000	0.195	MANUF	0.004	0.198
	(0.095)			(1.130)	
APPRL	0.000	0.195	TRANS	0.005	0.199
	(0.057)			(1.329)	
WOOD	-0.001	0.196	PHONE	0.010	0.204
	(-0.458)			(2.449)**	
CHAIR	0.002	0.196	TV	-0.002	0.196
	(0.730)			(-0.602)	
PAPER	0.002	0.196	UTILS	0.007	0.199
	(0.550)			(1.390)	
PRINT	0.002	0.196	WHLSL	0.003	0.196
	(0.390)			(0.617)	
CHEMS	0.008	0.201	RTAIL	0.007	0.200
	(1.645)			(1.684)*	
PTRLM	-0.008	0.202	MONEY	0.004	0.197
	(-1.847)*			(0.882)	
RUBBR	0.001	0.195	SRVC	0.004	0.197
	(0.273)			(0.874)	

Insert Table 7

Table 8: Forecasting the Market using all Industries Simultaneously

This table presents results of forecasting the market return in month t using all 34 industry portfolio returns at month t-1 and other information available at month t-1. The other forecasting variables are INF (the CPI inflation rate), TSPR (the term spread between the 10-year Note and the one-year T-bill), DSPR (the default spread between BAA-rated and AAA-rated bonds), and MDY (the dividend yield of the market portfolio). We only report the coefficients in front of the lagged industry returns. The least squares estimates, Newey-West t-statistics (in parentheses), and adjusted R2 are displayed. Newey-West serial correlation and heteroskedasticity robust t-statistics are calculated with 3 monthly lags. The sample period is January 1972 to December 2001. *Significant at 10% level. **Significant at 5% level.

	IND(-1)		IND(-1)	R2
RLEST	0.114	LETHR	0.058	
	(1.269)		(0.979)	
AGRIC	0.037	GLASS	0.037	
	(0.994)		(0.586)	
MINES	-0.020	METAL	-0.130	
	(-0.439)		(-1.697)*	
OIL	0.049	MTLPR	0.052	
	(0.729)		(0.480)	
STONE	-0.073	MACHN	0.098	
	(-1.584)		(1.015)	
CNSTR	0.062	ELCTR	-0.133	
	(1.055)		(-1.357)	
FOOD	-0.086	CARS	-0.077	
	(-0.831)		(-1.065)	
SMOKE	-0.033	INSTR	0.021	
	(-0.813)		(0.230)	
TXTLS	0.017	MANUF	-0.066	
	(0.254)		(-1.097)	
APPRL	-0.027	TRANS	0.066	
	(-0.414)		(1.025)	
WOOD	-0.096	PHONE	-0.114	
	(-1.793)*		(-2.015)**	
CHAIR	-0.003	TV	0.006	
	(-0.031)		(0.087)	
PAPER	0.121	UTILS	0.146	
	(1.232)		(1.830)*	
PRINT	0.071	WHLSL	-0.145	
	(0.695)		(-1.329)	
CHEMS	-0.156	RTAIL	0.106	
	(-1.546)		(1.062)	
PTRLM	-0.160	MONEY	0.093	
	(-2.007)**		(0.880)	
RUBBR	-0.027	SRVC	0.135	
	(-0.372)		(1.143)	

Figure 1(a): The Relationship between an Industry's Ability to Lead the Market and Its Ability to Predict Industrial Production Growth

The figure presents a scatter-plot of the coefficients λ_i obtained by forecasting RM using 34 industry returns and other conditioning information on the coefficients γ_i obtained by forecasting industrial production growth (IPG) using the same 34 industry returns. The linear relationship between the two sets of coefficients is plotted with a solid line. The slope of the line, Newey-West t-statistic and R2 are also presented.

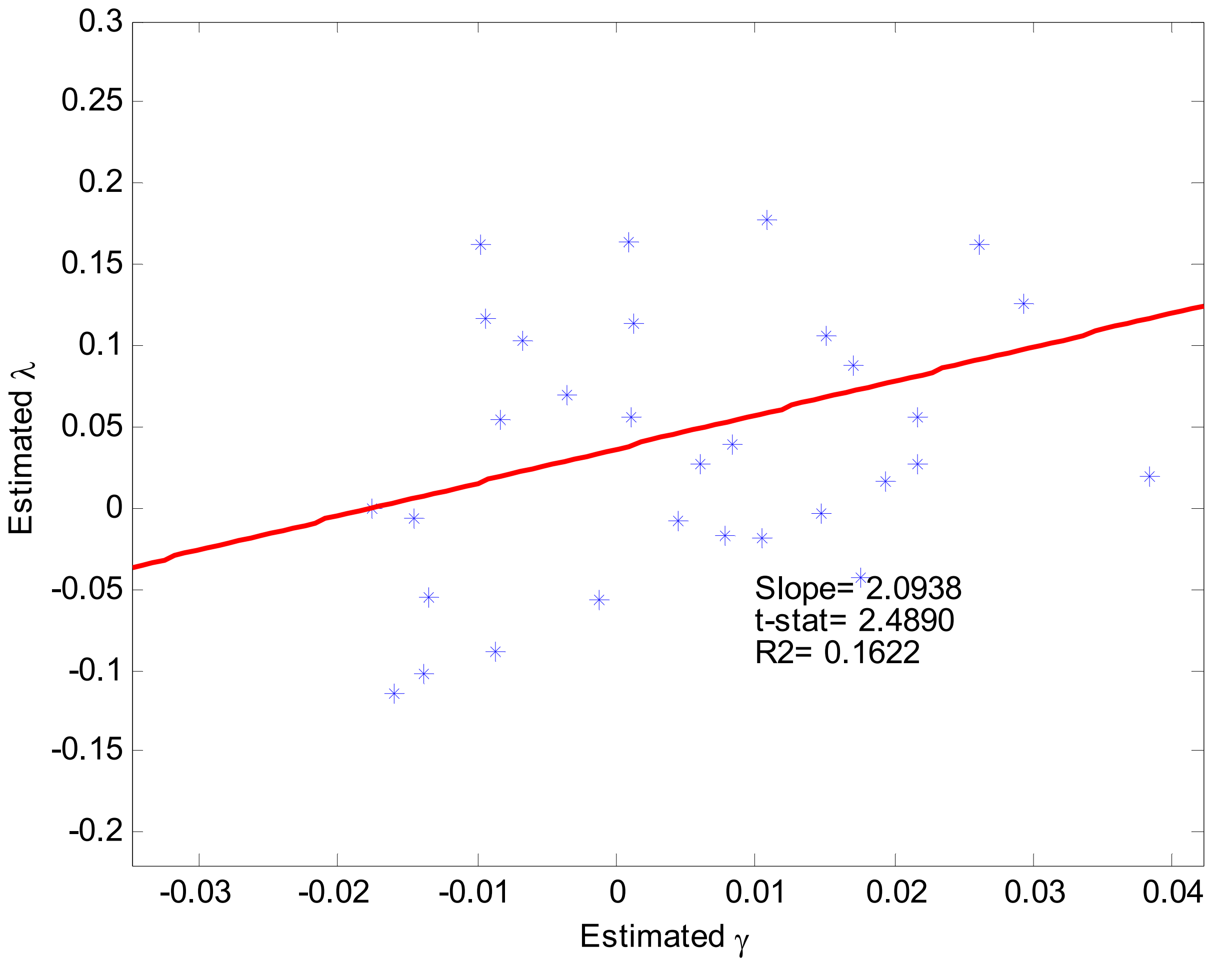

Figure 1(b): The Relationship between an Industry's Ability to Lead the Market and Its Ability to Predict the Growth Rate of Stock and Watson (1989) Index of Economic Activity

The figure presents a scatter-plot of the coefficients λ_i obtained by forecasting RM using 34 industry returns and other conditioning information on the coefficients γ_i obtained by forecasting the growth rate of the Stock and Watson (1989) coincident index of economic activity (SWG) using the same 34 industry returns. The linear relationship between the two sets of coefficients is plotted with a solid line. The slope of the line, Newey-West t-statistic and R2 are also presented.

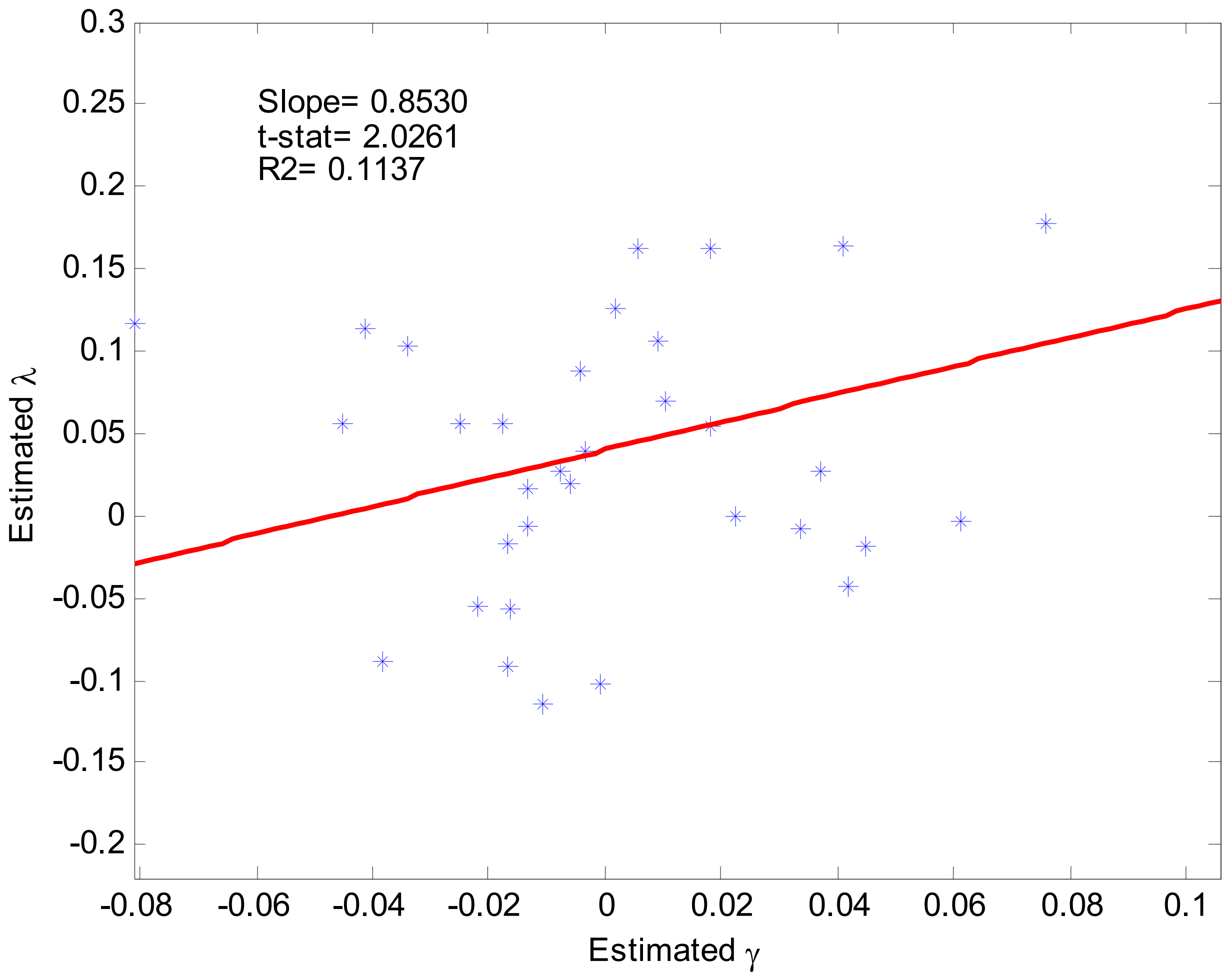

Figure 2(a): The Relationship between an Industry's Ability to Lead the Market and Its Ability to Predict Detrended Industrial Production

The figure presents a scatter-plot of the coefficients λ_i obtained by forecasting RM using 34 industry returns and other conditioning information on the coefficients γ_i obtained by forecasting detrended industrial production (IPD) using the same 34 industry returns. The linear relationship between the two sets of coefficients is plotted with a solid line. The slope of the line, Newey-West t-statistic and R2 are also presented.

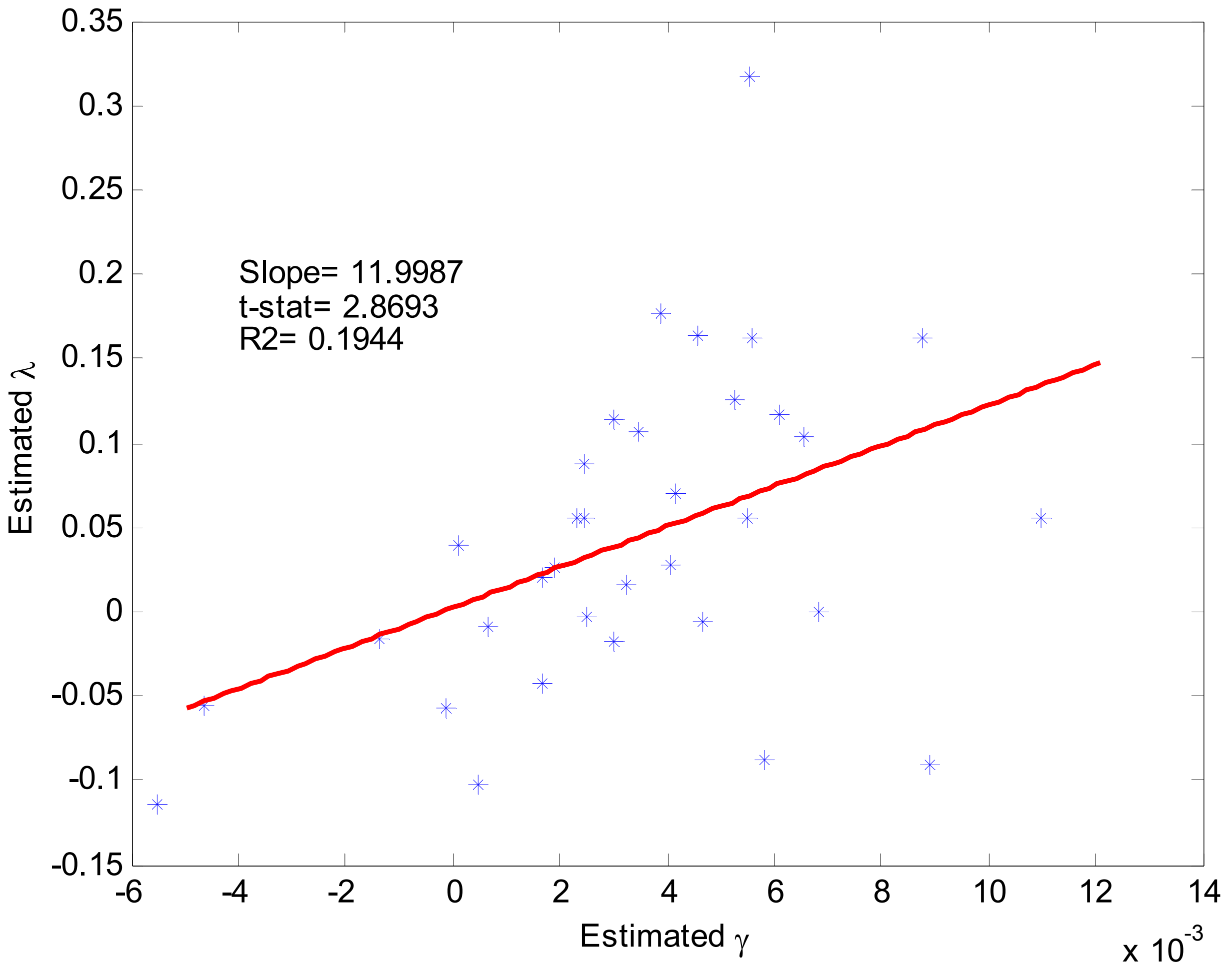

Figure 2(b): The Relationship between an Industry's Ability to Lead the Market and Its Ability to Predict the Detrended Stock and Watson (1989) Index of Economic Activity

The figure presents a scatter-plot of the coefficients λ_i obtained by forecasting RM using 34 industry returns and other conditioning information on the coefficients γ_i obtained by forecasting the detrended Stock and Watson (1989) coincident index of economic activity (SWD) using the same 34 industry returns. The linear relationship between the two sets of coefficients is plotted with a solid line. The slope of the line, Newey-West t-statistic and R2 are also presented.