Market Segmentation and Cross-Predictability of Returns*

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Abstract

We present evidence supporting the hypothesis that due to investor specialization and market segmentation, value-relevant information diffuses gradually in financial markets. Using the stock market as our setting, we find that (i) stocks that are in economically related supplier and customer industries cross-predict each other's returns, (ii) the magnitude of return cross-predictability declines with the number of informed investors in the market as proxied by the level of analyst coverage and institutional ownership, and (iii) changes in the stock holdings of institutional investors mirror the model trading behavior of informed investors.

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A growing body of empirical and theoretical research relaxes some of the stringent assumptions of the efficient markets hypothesis, and posits that gradual diffusion of information among investors explains the observed predictability of returns (Hong and Stein, 1999). To test the gradual diffusion of information hypothesis, the literature has focused mainly on studying the lagged price response of assets to their own past returns and their interaction with variables thought to affect the speed of information diffusion. This approach has been used out of necessity because information flow is a complex and unobservable process that is difficult to measure directly as separate from an asset's own past return.

In this paper, we explore a new channel of information flow that is separate from an asset's own past return, namely delayed price response to shocks that originate in related firms in supplier and customer industries. By examining the factors affecting the delay, we provide some of the first direct evidence on the gradual diffusion of information hypothesis, and on market segmentation as an underlying reason. The central contribution of our paper is, thus, to show that investor specialization and the resulting informational segmentation of markets have significant effects on the formation of prices, and that gradual diffusion of information from economically related industries is pervasive. Our measures of information flow, stock returns in supplier and customer industries, also allow us to explore untested implications of return cross-predictability that arise in limited-information models among assets with correlated fundamentals.[1]

A long line of previous work studies return predictability based on publicly available information, and builds on modeling ingredients that are also necessary for there to be return cross-predictability. The main ingredients in this literature are: (i) information about fundamentals is dispersed (Hayek, 1945), (ii) at least some investors can process only a subset of publicly available information (Hong and Stein, 1999) because either they have limited information-processing capabilities (Simon, 1955, Jensen and Meckling, 1992) or searching over all possible forecasting models using publicly available information itself is costly (Hong, Stein and Yu, 2007), and (iii) there are limits to arbitrage (De Long, Shleifer, Summers and Waldmann, 1990, Shleifer and Summers, 1990, Shleifer and Vishny, 1997). With these assumptions, new informative signals get incorporated into prices partially because at least some investors do not adjust their demand by performing the Grossman-Stiglitz (1980) rational expectations inference of recovering informative signals from observed prices. As a result of this failure on the part of some investors, returns exhibit predictability.

To obtain cross-predictability in a limited information model, two additional assumptions are needed: firms in different industries or segments of the market have correlated fundamentals (A1), and as in Hong, Torous and Valkanov (2007), investors specialize along these boundaries to some degree (A2) which renders markets informationally segmented. Our analysis of cross-predictability along the supply chain proceeds by providing evidence on these two important assumptions. We find that industry profits along the supply chain are indeed correlated, and that analysts, who are among the most important producers of information, cover a few stocks and even fewer industries, suggesting that the production of new information is specialized. While most, if not all, analysts undoubtedly have some knowledge of related stocks or industries, all that a gradual diffusion of information model needs is that some producers of information be specialists and that they not be the source of some new information produced in related markets.

We then present four sets of cross-predictability findings that are consistent with the predictions of a gradual diffusion of information model. First, stock- and industry-level returns exhibit strong cross-predictability effects based on lagged returns in supplier and customer industries. By excluding small and illiquid stocks, we further verify that the cross-predictability results are not driven by delayed price response among small stocks (lead-lag effect) or stale prices.

Second, the extent of cross-predictability is negatively related to the level of information in the market. Ranking stocks by the level of analyst coverage or by the level of institutional ownership, stocks in the top quintile exhibit no cross-predictability whereas stocks in the bottom quintile exhibit two to three times more cross-predictability than the average stock.

Third, we find that the way in which institutional investors trade is consistent with the model trading behavior of informed investors exploiting the cross-market content of informative signals. Specifically, institutions increase their ownership in a stock at the same time that they increase their ownership in supplier and customer industries, and decrease their ownership in a stock at the same time that they decrease their ownership in supplier and customer industries. We also find similar results using returns in supplier and customer industries, consistent with the joint behavior of returns and informed trade in limited-information models.

Fourth, we show that self-financing trading strategies based on cross-predictability effects yield economically and statistically significant premiums. Specifically, a trading strategy that consists of buying industries with high returns in supplier industries over the previous month and simultaneously selling industries with low returns in supplier industries over the previous month yields an annual premium of 7.3%. A similar trading strategy based on previous-month customer industry returns yields an annual premium of 7.0%. Both trading strategies are consistently profitable over the sample period, and returns from them exhibit little exposure to well-known return factors such as the Fama-French SMB, HML and MOM factors. Moreover, we find that the return series of long/short equity hedge funds, which are thought to exploit predictability effects, are significantly correlated, both economically and statistically, with the return series from the trading strategies described above.

The rest of the paper proceeds as follows. Section I provides a discussion of the setting including our empirical design, and relates the paper to previous research. Section II explains our data sources, and presents our main findings about cross-predictability. We explore various trading strategies in Section III, and provide concluding remarks in Section IV.

I. The Setting

A. Cross-Predictability in Limited-Information Models

A limited-information model in the spirit of Hong, Torous and Valkanov (2007) underlies our tests about the various aspects of cross-predictability. This subsection provides a summary overview of model basics and assumptions required to demonstrate how the specialization of investors in their information gathering efforts can lead to informationally segmented markets and consequently to cross-predictability in asset returns.

To fix ideas, suppose that there are two markets, three dates, and two types of investors, informed and uninformed, with both types of investors able to invest in both markets. Informed investors specialize in one of the markets for which, at some intermediate stage, they receive an informative signal about the eventual cash flow. Uninformed investors do not receive an informative signal, and at least some of them, do not process information because either they have limited-information processing capabilities, or processing information is costly for them.

In this setting, it is fairly straightforward to show that returns exhibit predictability based on publicly available information. When the informative signal arrives at the intermediate stage, it is incorporated into the price through the demand of informed investors – but only partially because at least some uninformed investors, due to their limited information-processing capabilities, do not perform the Grossman-Stiglitz (1980) rational expectations inference of recovering the informative signal from the observed price to adjust their demand. As a result of this failure on the part of some uninformed investors, returns exhibit positive auto-correlation.

With two asset markets, returns exhibit cross-predictability as a consequence of two additional assumptions: (i) the two markets have correlated fundamentals, and therefore an informative signal in one market has information content about the eventual payoff in the other market, and (ii) the two markets are informationally segmented. Due to the specialization of informed investors, an informative signal originating in one of the markets is received only by those investors who happen to specialize in that market, and not by investors who specialize in the other market. As a result, informative signals with cross-market content are incorporated into prices only partially, and returns exhibit cross-predictability – note that this spillover effect is different from a lead-lag effect because either market can cross-predict the other when there is a new signal, rather than one market always leading or always lagging another.

The limited-information setting outlined above has the following testable predictions. First, cross-predictability is to be expected across assets with correlated fundamentals, and to be of the same sign as the correlation of fundamentals. Second, allowing the number of informed investors to vary, the magnitude of cross-predictability should be lower where there are more informed investors. Intuitively, when the amount of information-impounding demand is high in a given market, and informative signals are by and large incorporated fully, there is little left to be predicted. Third, allowing informed investors to exploit the cross-market content of their signals, their trades in fundamentally related markets should be correlated because while information acquisition activities may involve specialization, trading need not.[2]

B. Empirical Design

It is important that we also motivate our empirical design. Why do we test for cross-predictability effects along the supply chain? And, why do we focus on economic boundaries defined by industries?

Firms close to each other along the supply chain are likely to face correlated cash flow shocks, a necessary ingredient for there to be cross-predictability in limited-information models. Supplier and customer firms may have correlated cash flows because they interact with each other either directly through their trading relationships or indirectly through market prices for their inputs and outputs. Firms along the supply chain may also face relatively similar demand or technological shocks. The Benchmark Input-Output Surveys of the Bureau of Economic Analysis (BEA Surveys, hereafter) provide data on the amount of goods and services traded among industries that allow us to identify supplier and customer industries.

Economic boundaries defined by industries are likely to also represent informational boundaries induced by investor specialization. This is because the skills necessary to investigate and evaluate a given firm are likely to be useful in understanding other same-industry firms. Indeed, important economic agents such as equity analysts and money managers tend to specialize along industry lines.

The empirical design can alternatively focus on economic boundaries defined by companies. Indeed, Menzly and Ozbas (2004), and Cohen and Frazzini (2008) use COMPUSTAT's customer information database to identify economically related stocks. However, for the purposes of the present paper, we have ultimately decided for two reasons that the BEA Surveys represent the best empirical approach to identify the set of economically related stocks for a given stock or industry. First, only the smallest stocks exhibit cross-predictability effects based on lagged COMPUSTAT customer returns. This raises natural questions as to whether return cross-predictability is an economically important phenomenon worthy of study if it is limited to small stocks. Second, using the customer information database to identify supplier firms (in effect, by using reported relationships in the reverse direction) and then testing for cross-predictability effects from supplier firms yield no significant results. This is because the customer firms reported in COMPUSTAT are typically much larger than the reporting firm. In comparison, the BEA Surveys enable us to identify for each firm broad portfolios of supplier and customer firms whose returns contain economically important information regardless of the size of the firm in question. As a result, cross-predictability effects based on the BEA Surveys are robust even to the exclusion of small stocks.

C. Related Literature

Our findings relate to a large literature on return predictability, one strand of which explores lead-lag relations among stocks. In an influential paper, Lo and MacKinlay (1990) document that large stocks lead small stocks. Our paper, by showing that cross-predictability effects are robust to the exclusion of small stocks and monthly return observations without a closing price in the previous month, addresses an important concern of this literature that observed lead-lag relations could be an artifact of thin markets and non-synchronous prices.

In a recent paper, Hong, Torous and Valkanov (2007) document that in the US several important industries such as commercial real estate, petroleum, metal, retail, financial, and services lead the overall stock market as well as various economic indicators. Moreover, they show that the eight largest non-US markets exhibit similar patterns. A natural interpretation of their findings is that information of macroeconomic importance in certain industries diffuses gradually to the rest of the market. In addition to the contributions we discuss below, our findings differ from those of Hong, Torous and Valkanov (2007) in that we establish pervasive cross-predictability effects throughout the supply chain by focusing on returns in immediate supplier and customer industries.

Another strand of the literature following Lo and MacKinlay (1990) investigates the role of informed traders with proxies such as analyst coverage and institutional ownership like we do. Brennan, Jegadeesh and Swaminathan (1993) show that many-analyst firms lead few-analyst firms, suggesting that many-analyst firms adjust to common information faster than few-analyst firms do. Badrinath, Kale and Noe (1995) show that high-institutional ownership stocks lead low-institutional ownership stocks. Because we use return innovations in a relatively contained set of supplier and customer industries as opposed to return innovations in market-wide portfolios of stocks which these previous papers use, we are able to establish an important role for informed traders in impounding relatively less common information into stock prices.

In another related paper, Hong, Lim and Stein (2000) document that stocks with more analyst coverage exhibit less price momentum. This is consistent with the idea that stocks with more analyst coverage adjust faster to value-relevant information, though the source as well as the nature of the information to which stocks adjust in their study remain unclear. In this respect, our findings complement theirs by showing that stocks with more analyst coverage adjust faster to value-relevant information originating in supplier and customer industries.

Finally, by relating the trading behavior of institutional investors to returns in supplier and customer industries, we contribute to the literature investigating the joint behavior of stock returns and informed trade in "disagreement models" as articulated by Hong and Stein (2007). Earlier work by Cohen, Gompers and Vuolteenaho (2002) shows that institutional investors profit from the momentum effect in prices. We further show that the holdings of institutional investors change in a manner consistent with trading strategies that profit from the cross-predictability effect in prices.

II. Empirical Results

A. Data

A.1. CRSP and COMPUSTAT

Our return data come from the Center for Research in Security Prices (CRSP) monthly returns database. The sample period is from July 1963 to June 2005. Consistent with standard practice, we use NYSE, AMEX, and Nasdaq stocks, and exclude closed-end funds, real estate investment trusts, American Depositary Receipts, foreign companies, primes and scores. We obtain financial statement and other company information through the Merged COMPUSTAT-CRSP database.

A.2. Benchmark Input-Output Surveys

We use a series of Benchmark Input-Output Surveys of the Bureau of Economic Analysis to identify supplier and customer industries for a given stock or industry (see Fan and Lang, 2000, Matsusaka 1993). BEA Surveys provide a detailed picture of the interdependent structure of the U.S. economy by assigning gross output to industry accounts and by reporting the amount of inter-industry flow of goods and services in the Use Table.

BEA Surveys are published roughly once every five years to coincide with the Economic Census conducted by the U.S. Census Bureau, and we draw on 11 different surveys (2002, 1997, 1992, 1987, 1982, 1977, 1972, 1967, 1963, 1958 and 1947) on a rolling basis to measure supplier and customer relations. We adopt this approach primarily to improve measurement accuracy because each survey provides a historical snapshot, and thus, may be inadequate for describing the structure of the U.S. economy for our entire sample period. For the first part of our analysis testing the underlying economics of cross-predictability, we use data from a given survey until a new snapshot is provided by the following survey. Specifically, we use data from the 1963 Survey between 1963 and 1966, the 1967 Survey between 1967 and 1971, and so on. For the second part of our analysis investigating various trading strategies based on cross-predictability effects, we delay using any data from a given survey until the end of the year in which the survey is publicly released. The different BEA Surveys mentioned above were released during 2007, 2002, 1997, 1994, 1991, 1984, 1979, 1974, 1969, 1964, and 1952, respectively.

For the purposes of our analysis, we merge three separate industry accounts, namely, 2301 (new nonresidential construction), 2302 (new residential construction) and 2303 (maintenance and repair construction) in the 1997 and 2002 BEA Surveys into a single account because the three industry accounts stake overlapping claims on the same North American Industry Classification System (NAICS) codes and firms. In pre-1997 BEA Surveys based on Standard Industrial Classification (SIC) codes, we merge industry account pairs 1-2 (livestock and agricultural products), 5-6 (metallic ores mining), 9-10 (nonmetallic minerals mining), 11-12 (construction), 20-21 (lumber and wood products), and 33-34 (footwear, leather, and leather products) because the industry accounts within each pair stake overlapping claims on the same SIC codes. In addition, we drop miscellaneous industry accounts related to government, import and inventory adjustments because they do not appear to correspond to any clear economic activity or industry.

We use BEA SIC and NAICS code dictionaries to assign each stock to an industry based on the stock's reported SIC or NAICS code in COMPUSTAT.[3] In case this information is missing in COMPUSTAT, we use the reported code in CRSP. Based on industry assignments, we then calculate value-weighted monthly industry returns. We require that there be a market capitalization at the end of June of a given year for a stock to be included in the analysis for the subsequent 12 months. We impose this requirement primarily to stabilize the composition of industry portfolios.

After calculating industry portfolio returns, we further form two separate portfolios for each industry, one composed of supplier industries and another composed of customer industries. In calculating monthly returns for these portfolios, we use data on the flow of goods and services to and from the industries in question as portfolio weights. These portfolio weights are shares of an industry's total purchases from other industries in calculating supplier industry returns, and its total sales to other industries in calculating customer industry returns. For testing limited-information models of gradual information diffusion, this portfolio weighting scheme has the desired properties of (i) identifying the set of economically related supplier and customer industries for a given industry, and (ii) reflecting the relative economic importance of related industries as proxied by the amount of inter-industry trade.

A.3. I/B/E/S and 13F Holdings

We use the I/B/E/S database, both its detail and summary history files, to construct measures of analyst coverage and earnings expectations for each stock on CRSP. Because the I/B/E/S files are historical snapshots, we use historical cusip codes to link the two databases. Finally, we use Thomson Financial's 13F Holdings database to construct measures of institutional ownership for each stock on CRSP where we again use historical cusip codes to link the two databases.

B. Preliminary Evidence

We begin by presenting preliminary evidence on two important assumptions in limited-information models for there to be cross-predictability from supplier and customer industries. These two assumptions are that (i) firms in a given industry have correlated fundamentals with firms in their respective supplier and customer industries, and (ii) informed investors specialize in their information gathering activities.

To see whether firms along the supply chain have correlated fundamentals, we construct firm- and industry-level measures of profitability, and estimate panel regressions of the form:

$$ROA_{it} = \alpha_i + \theta^{\text{market}} ROA_t^{\text{market}} + \theta^{\text{supplier}} ROA_{it}^{\text{supplier}} + \theta^{\text{customer}} ROA_{it}^{\text{customer}} + e_{it} \tag{1}$$

where ROA_{it} is the return on assets of firm or industry i in year t. We measure firm-level return on assets as the ratio of cash flow to total assets (COMPUSTAT data item 6), and cash flow as the sum of earnings before extraordinary items (item 18) and depreciation and amortization (item 14). We calculate industry- and market-level ROA by aggregating firm-level ROA with a portfolio approach using firm assets as portfolio weights. We then calculate $ROA_{it}^{\text{supplier}}$ and $ROA_{it}^{\text{customer}}$ for each industry by weighting the industry-level ROA of supplier and customer industries with the flow of goods and services to and from the industries in question, similar to our approach for calculating returns in supplier and customer industries. Depending on the specification, α_i represents firm- or industry-level fixed effects which control for unmodeled heterogeneity across firms and industries. Finally, we use robust standard errors that are adjusted for double clustering (Thompson, 2009, Petersen, 2009) by firm and year for the firm-level specification, and by industry and year for the industry-level specification. So, the remaining source of independence is between different firms or industries in different years.

[Table I about here]

The results in Table I confirm the validity of our empirical design for testing cross-predictability, and show that firms along the supply chain indeed have correlated fundamentals. In column 1, where we present firm-level evidence, firm-level ROA is positively correlated with contemporaneous ROA in supplier and customer industries over and above the market-wide ROA_t as evidenced by statistically significant coefficients on $ROA_{it}^{\text{supplier}}$ (0.471) and $ROA_{it}^{\text{customer}}$ (0.465).

We report a similar specification in column 2 where the unit of analysis is an industry instead of a firm. The results here too confirm the validity of our supply chain approach at the industry level. Specifically, industries along the supply chain have correlated fundamentals over and above the market-wide ROA_t as evidenced by statistically significant coefficients on $ROA_{it}^{\text{supplier}}$ (0.398) and $ROA_{it}^{\text{customer}}$ (0.164).

We next attempt to address the assumption of specialization among informed investors by presenting evidence about the specialization of equity analysts, who probably constitute one of the most informed group of market players. Recall that for there to be cross-predictability of returns in limited-information models, informative signals need to be dispersed among informed investors. To shed some light on this issue, we provide histograms below of the average number of different stocks and industries covered by an analyst in any given month by using the analyst's entire record in the I/B/E/S detail history file. We restrict our analysis to the period from January 1982 to June 2005 due to data quality concerns about the pre-1982 I/B/E/S data – the number of analyst estimates display a large jump from 1981 to 1982. For the purposes of the graph, we consider only earnings per share forecasts and assume that an analyst remains actively engaged in a stock for a twelve-month period after making an EPS forecast on that stock. We also truncate the average number of stocks and industries covered by an analyst at their 95th percentiles for presentation.

As both graphs in Figure 1 illustrate, equity analysts appear to be highly specialized in their information gathering efforts. The median (across all analysts) of the average number of stocks covered by an analyst in any given month is 6.60 whereas in comparison, the average number of stocks that satisfy our sample requirements and thus could hypothetically be covered by an analyst

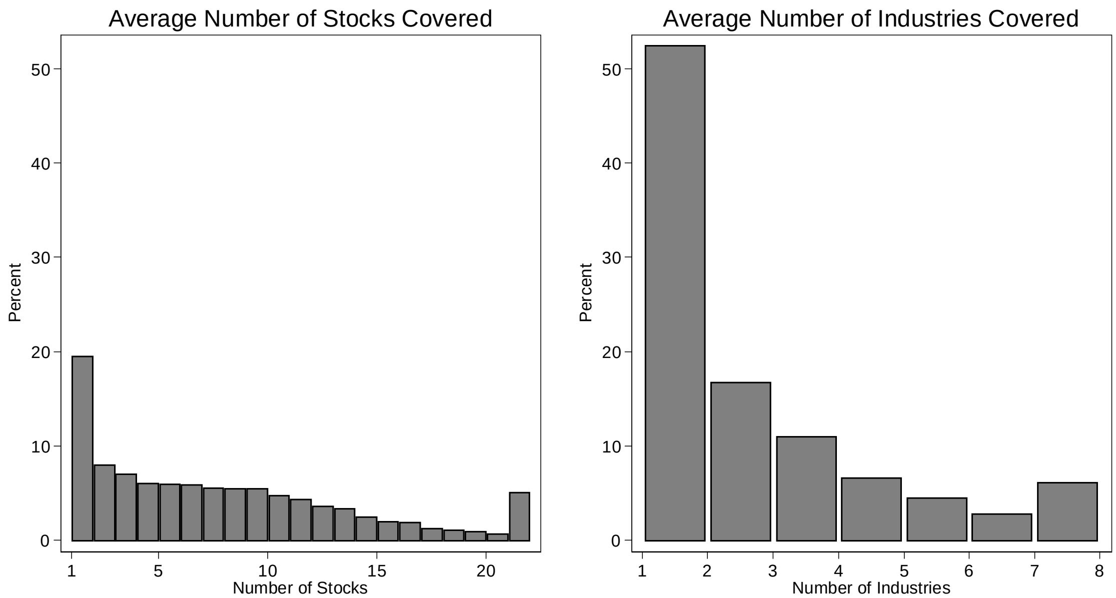

Figure 1: Average Number of Stocks and Industries Covered by Equity Analysts

during the same sample period is about 6,036. Moreover, the corresponding statistic for the number of industries covered is 1.91 which indicates that the specialization of equity analysts can partly be explained by their specialization along industry lines. Furthermore, we find similar results regarding analyst specialization along the supply chain, our empirical setting. Consistent with the assumption of specialization in information gathering activities, the median analyst produces information in supplier industries that in total provide only 8.64% of the covered firm's inputs, as indicated by active coverage of a stock in the firm's supplier industries. The corresponding statistic is 8.73% for customer industries that buy the covered firm's output. This evidence is not to suggest that analysts know nothing about any firm in related supplier and customer industries, but rather the evidence supports the assumption of limited-information models that information production is specialized to some degree.

C. *Stock- and Industry-Level Cross-Predictability Effects*

We now test whether stock-level returns are cross-predictable based on lagged returns in supplier and customer industries. For this, we conduct Fama-MacBeth (1973) regressions of the form:

$$r_{i,t} = \alpha_t + \lambda_t^{\text{supplier}} r_{i,t-1}^{\text{supplier}} + \lambda_t^{\text{customer}} r_{i,t-1}^{\text{customer}} + \Lambda_t Z_{i,t-1} + e_{i,t} \tag{2}$$

where $r_{i,t}$ is the return of stock i in month t, $r_{i,t-1}^{\text{supplier}}$ is the return on the portfolio of supplier industries of stock i in month $t-1$, $r_{i,t-1}^{\text{customer}}$ is the return on the portfolio of customer industries of stock i in month $t-1$, and $Z_{i,t}$ is a vector of lagged control variables known to predict $r_{i,t}$ such as short-term reversal and medium-term continuation at the stock (Jegadeesh and Titman, 1993) and industry level (Moskowitz and Grinblatt, 1999). For short-term reversal, we use $r_{i,t-1}$, the return of stock i in the previous month $t-1$. We use $r_{i,t-2:t-12}$, the return of stock i over a period of eleven months covering months $t-12$ through $t-2$, to control for medium-term continuation at the stock level. We divide this variable by 11 in our regressions to maintain comparability with other variables. For medium-term continuation at the industry level, we use $r_{i,t-1}^{\text{industry}}$, the value-weighted industry return in month $t-1$ of which stock i is a member. Further including estimated return betas such as market, HML and SMB to control for risk as well as firm characteristics such as book-to-market and size do not affect the results, and so we omit them for brevity.

[Table II about here]

We report the time-series average of each regression coefficient (obtained from monthly cross-sectional regressions) along with the time-series t-statistics in Table II. The time-series averages can be interpreted as premiums that can be replicated with self-financing trading strategies whose weighted loading on the specific regressor variable equals one and zero on others (Fama, 1976).

The results in column 1 confirm that lagged returns in supplier and customer industries cross-predict stock-level returns as evidenced by statistically significant coefficients on $r_{i,t-1}^{\text{supplier}}$ (0.114) and $r_{i,t-1}^{\text{customer}}$ (0.071). Importantly, the coefficient estimates are also economically significant – the combined premium on the two portfolios are comparable to known medium-term continuation effects as represented by the coefficients on $r_{i,t-2:t-12}$ (0.072) and $r_{i,t-1}^{\text{industry}}$ (0.134). Consistent with short-term reversal, the coefficient on $r_{i,t-1}$ (-0.062) is negative.

In column 2, we exclude stocks with market capitalizations below the 20th NYSE percentile to address the possibility that thin markets might be driving our cross-predictability results. The estimated coefficients on $r_{i,t-1}^{\text{supplier}}$ (0.105) and $r_{i,t-1}^{\text{customer}}$ (0.058) are smaller, but they remain statistically significant and the combined premium is still comparable to medium-term continuation effects as represented by the coefficients on $r_{i,t-2:t-12}$ (0.099) and $r_{i,t-1}^{\text{industry}}$ (0.117). The coefficient on $r_{i,t-1}$ (-0.047) is smaller in magnitude as one might expect following the exclusion of small stocks with potential thin trading problems. In column 3, we exclude monthly return observations without a closing price (with a bid/ask average instead) in the previous month to address the possibility that non-synchronous prices might be behind our results, and find that the estimated coefficients on $r_{i,t-1}^{\text{supplier}}$ (0.117) and $r_{i,t-1}^{\text{customer}}$ (0.059) are still significant.

Next, we test whether the stock-level cross-predictability effects also hold at the industry level. There are good reasons for exploring this next step. One can reasonably argue that industry-level returns are economically more important than stock-level returns in some sense because they are value-weighted. Moreover, Moskowitz and Grinblatt (1999) show that there is momentum in industry-level returns. They conjecture that momentum may be susceptible to aggregate shocks and that the associated premium may represent compensation for taking on undiversifiable risk. If cross-predictability effects also survive the industry aggregation, then it is quite possible that its premium represents compensation for taking on undiversifiable risk, and thus, could be a permanent feature of stock returns. Furthermore, limited-information models predict economically related assets to exhibit cross-predictability, regardless of whether the unit of analysis is a stock or an industry as long as the process of aggregation does not result in the complete elimination of market segmentation. For these reasons, we see the tests using industry-level returns as being more than a robustness exercise.

Using industry-level returns, we conduct Fama-MacBeth regressions of the same form as (2) where now $r_{i,t}$ is the return of industry i in month t, $r_{i,t-1}^{\text{supplier}}$ is the return on the portfolio of supplier industries of industry i in month $t-1$, $r_{i,t-1}^{\text{customer}}$ is the return on the portfolio of customer industries of industry i in month $t-1$. The only lagged control variable is $r_{i,t-1}$, which is the return of industry i in month $t-1$. As before, including estimated betas on the market, HML and SMB do not affect the results, and so we omit them for brevity.

The results in column 4 confirm the main prediction of limited-information models at the industry level. Lagged returns in economically related supplier and customer industries cross-predict industry-level returns as evidenced by statistically significant coefficients on $r_{i,t-1}^{\text{supplier}}$ (0.113) and $r_{i,t-1}^{\text{customer}}$ (0.075). Interestingly, the coefficient on $r_{i,t-1}$ (0.032) is smaller for industry-level returns than it is for stock-level returns. The decline in the predictive power of $r_{i,t-1}$ for value-weighted industry-level returns suggests that there is an important size effect and that large firms in an industry lead same-industry small firms consistent with the recent work of Hou (2007).

D. The Effect of Informed Investors

A clear prediction of limited-information models is that the magnitude of cross-predictability should be lower where there are more informed investors – whose information-impounding demand leaves little to be predicted. We now turn to testing this prediction.

In testing the effect of informed investors on cross-predictability, we work with stock-level returns rather than industry-level returns to preserve the degree of cross-sectional heterogeneity of information conditions and investor types at the stock level. We employ two different stock-level proxies to test for the effect of informed investors: the amount of analyst coverage and the presence of institutional investors as owners in the stock. Both proxies have been used in prior research to establish an important role for informed investors in incorporating common information into prices (Brennan, Jegadeesh and Swaminathan, 1993, and Badrinath, Kale and Noe, 1995).

To construct our stock-level analyst coverage measure, we make use of analyst forecast data in the I/B/E/S detail history file and consider only forecasts of earnings per share, which is the most commonly available type of analyst forecast. We obtain similar results using other types of analyst forecasts such as sales or dividends per share with the limitation of a thin sample until the late 1990s. We restrict our analysis to post-1982 data in I/B/E/S due to data quality concerns.

To proxy for the amount of analyst coverage for a stock, we calculate two different measures counting the number of analysts who are actively following the stock on a monthly basis. The first measure assumes that an analyst is active if the analyst has made a forecast for the stock within the last twelve months. By allowing for such a long grace period, we hope to account for some analysts who appear to release their forecasts once a year. The obvious drawback of this approach is that we might erroneously consider the stale forecast of an inactive analyst. To rectify this concern, we construct a second measure where we require an analyst to have made a forecast for the stock during a given month to be considered active for that month.

To see whether the cross-predictability effects based on lagged returns in supplier and customer industries are weaker for stocks with higher analyst coverage, we augment our Fama-MacBeth regressions in the following form:

$$r_{i,t} = \alpha_t + \sum_{j=1}^{5} \lambda_t^j A_{t-1}^j r_{i,t-1}^{\text{related}} + e_{i,t} \tag{3}$$

where $r_{i,t}$ is the return of stock i in month t, A_{t-1}^j is an indicator variable equal to one if the level of analyst coverage for stock i in month $t-1$ places the stock in the j^{th} quintile and zero otherwise, and $r_{i,t-1}^{\text{related}}$ is the return on the portfolio of related supplier and customer industries of stock i in month $t-1$. In the Internet Appendix, we further allow for cross-sectional differences in expected returns across the different quintiles by including the indicator variables A_{t-1}^j directly in the specification. We also exclude stocks with market capitalizations below the 20th NYSE percentile. None of these variations affect our conclusions. For brevity, we report specification where we use a composite variable $r_{i,t-1}^{\text{composite}}$ for $r_{i,t-1}^{\text{related}}$, which we calculate by taking the average of $r_{i,t-1}^{\text{supplier}}$ and $r_{i,t-1}^{\text{customer}}$. This composite variable has the benefit of reducing the number of parameters to be estimated while being model-justified. Indeed, limited-information models require that assets be economically related for there to be cross-predictability, and beyond that make no distinction between supplier and customer industries.

[Table III about here]

We report our results on analyst coverage in the first two columns of Table III. The results in column 1 are based on our first measure of analyst coverage whereas the results in column 2 are based on the second. Regardless of the measure used, we find that stocks with low analyst coverage exhibit more cross-predictability than stocks with high analyst coverage. Importantly, the magnitude of the cross-predictability effects declines monotonically across the analyst coverage quintiles. Furthermore, we find large spreads across the analyst coverage quintiles – stocks in the lowest quintile of analyst coverage exhibit significant cross-predictability whereas stocks in the highest quintile of analyst coverage exhibit no cross-predictability at conventional levels. Overall, the results are supportive of limited-information models if the number of analysts can be considered as a good proxy for the supply of information to the market and hence indirectly for the number of informed investors.

In our next set of results in Table III, we test whether the cross-predictability effects based on lagged returns in supplier and customer industries are weaker for stocks with more institutional owners. For this exercise, we use Thomson Financial's 13F Holdings database which contains the stock-level holdings of institutional money managers collected from mandatory quarterly 13f filings made with the Securities Exchange Commission under the Securities Exchange Act Section 3(a)(9) and Section 13(f)(5)(A). To proxy for the effect of institutional investors using these data, we sum up the holdings of institutional investors in the stock at a given quarter-end report date and then divide the total by the number of outstanding shares at the time to compute the percentage ownership by institutional investors (we obtain qualitatively similar results using an alternative proxy, namely, the number of different institutional investors in the stock at a given quarter-end report date). We restrict our analysis to holdings data with a report date 1980 or later because the database contains very few observations with a report date prior to 1980.

In column 3, A^j_{t-1} is now an indicator variable equal to one if the institutional ownership in stock i at the end of month $t-1$ based on the then most recent quarterly holdings data places the stock in the j^{th} quintile and zero otherwise. We find that stocks with low institutional ownership exhibit more cross-predictability than stocks with high institutional ownership. Moreover, the magnitude of the cross-predictability effects declines monotonically across the institutional ownership quintiles, and the resulting spread across the institutional ownership quintiles is even larger than those across the analyst coverage quintiles in columns 1 and 2. All in all, we take these results to be also supportive of limited-information models if institutional investors can generally be considered to be more informed than other investors. In the Internet Appendix, we investigate whether the repeated use of the same quarterly holdings data in multiple monthly cross-sectional regressions pose statistical problems, and find that robust standard errors that allow for clustering at the year-quarter level do not change our conclusions.

E. *Evidence on Institutional Trading*

Another untested implication of limited-information models is that when informed investors are allowed to trade in markets other than the one in which they specialize to acquire informative signals, they trade simultaneously in fundamentally related markets to exploit the cross-market content of their signals.

Assuming that institutional investors are more informed than the rest of the investor population, we test this implication by estimating panel regressions of the form:

$$\Delta IO_{i,q} = \alpha_i + \gamma_q + \beta^{\text{related}} \Delta IO_{i,q}^{\text{related}} + e_{i,q} \tag{4}$$

where $\Delta IO_{i,q}$ is the change in the percentage ownership of institutional investors in stock i from quarter $q-1$ to quarter q, $\Delta IO_{i,q}^{\text{related}}$ is the change in the percentage ownership of institutional investors in the related industries ($\Delta IO_{i,q}^{\text{supplier}}$, $\Delta IO_{i,q}^{\text{customer}}$) of stock i from quarter $q-1$ to quarter q. We use the flow of goods and services as portfolio weights in constructing $\Delta IO_{i,q}^{\text{supplier}}$ and $\Delta IO_{i,q}^{\text{customer}}$ as we have done in constructing $r_{i,t-1}^{\text{supplier}}$ and $r_{i,t-1}^{\text{customer}}$. We include stock-level fixed effects α_i to control for potential biases that could arise due to unobserved heterogeneity across stocks even though we consider changes and not levels. We further include year-quarter fixed effects γ_q to control for systematic fund inflows and outflows that ultimately should affect institutional holdings. Finally, we compute robust standard errors that allow for the clustering of error terms at the industry-year level to allay concerns about the possible persistence of fund flows across different quarters within a year at the industry level – note that any systematic persistence of fund flows across different quarters within a year is already modeled by the inclusion of year-quarter fixed effects γ_q.

[Table IV about here]

We report the results of this analysis in the first two columns of Table IV. Given our earlier findings of positive return cross-predictability, we expect institutional investors to relatively increase their ownership in a stock at the same time that they increase their ownership in supplier and customer industries, and relatively decrease their ownership in a stock at the same time that they decrease their ownership in supplier and customer industries. Therefore, we expect β^{related} to be positive also. Consistent with this, we find that changes in institutional ownership at the stock level are positively related to changes in institutional ownership in related industries as evidenced by statistically significant coefficients on $\Delta IO_{i,q}^{\text{supplier}}$ (0.073) in column 1 and $\Delta IO_{i,q}^{\text{customer}}$ (0.055) in column 2.

We explore the joint behavior of returns and contemporaneous informed trade next by replacing $\Delta IO_{i,q}^{\text{related}}$ with $r_{i,q}^{\text{related}}$ in (4) and estimating panel regressions of the form:

$$\Delta IO_{i,q} = \alpha_i + \gamma_q + \beta^{\text{related}} r_{i,q}^{\text{related}} + e_{i,q} \tag{5}$$

where $r_{i,q}^{\text{related}}$ is the return on the portfolio of related industries ($r_{i,q}^{\text{supplier}}$, $r_{i,q}^{\text{customer}}$) of stock i in quarter q. Using returns in related supplier and customer industries as information proxies also addresses the possibility that the results above are spurious and driven by reasons other than information.

Once again, given our earlier findings of positive return cross-predictability, we expect institutional investors to be increasing their ownership in a stock when returns in related industries are high, and to be decreasing their ownership in a stock when returns in related industries are low. The results support this prediction as evidenced by statistically significant coefficients on $r_{i,q}^{\text{supplier}}$ (0.009) in column 3, and on $r_{i,q}^{\text{customer}}$ (0.007) in column 4.

Overall, we take the results in Table IV to be uniformly supportive of limited-information models. The trading behavior of institutional investors appears to be consistent with the trading behavior of informed investors. The one unanswered question, however, is the extent to which institutional investors profit from the trading behavior that we document because we lack holdings data at a higher frequency than quarterly. Although there is little that we can do about what is obviously a data issue, we partly address this question in the next section by studying the profitability of various trading strategies that institutional investors could potentially use to exploit cross-predictability.

III. Self-Financing Trading Strategies

In this section, we analyze the profitability of self-financing trading strategies that are based on the cross-predictability effects documented in the previous section. Because an important objective of the analysis from our perspective is to assess the economic significance of cross-predictability, we exclusively report on trading strategies that involve the buying and selling of industries as opposed to trading strategies that involve the buying and selling of individual stocks. The use of industries (which are value-weighted portfolios of stocks) should address potential concerns that thin markets could be driving the results or that transactions costs could render the trading strategies unattractive. In trading strategies reported in the Internet Appendix, we exclude stocks with market capitalizations below the 20th NYSE percentile in the formation of value-weighted industry portfolios and obtain similar results.

The way we construct our self-financing trading strategies using industries is fairly standard. At the beginning of each month, we sort industries into five bins based on returns in supplier and customer industries in the previous month. We allocate industries with previous month related industry returns in the bottom quintile to the first bin, industries with previous month related industry returns in the second quintile to the second bin, and so on. After sorting industries in this fashion, we form value-weighted portfolios for each of the five bins, and calculate returns on these portfolios for the ensuing one-month period. Self-financing trading strategies consist of buying the high portfolio (industries with previous month related industry returns in the top quintile) and selling the low portfolio (industries with previous month related industry returns in the bottom quintile).

[Table V about here]

Table V reports the mean and standard deviation of monthly excess returns for the five portfolios described above (reported figures are annualized). Looking at Panel A in which industries are sorted according to returns in supplier industries in the previous month ($r_{i,t-1}^{\text{supplier}}$), the mean excess return over the next month is 10.0% for the high portfolio and 2.8% for the low portfolio. A self-financing trading strategy that exploits the return difference between the two portfolios yields 7.3% annually with a Sharpe ratio of about 0.7. In Panel B, we sort industries according to returns in customer industries over the previous month ($r_{i,t-1}^{\text{customer}}$). There is again a visible positive trend in mean excess returns across the five portfolios. A self-financing trading strategy that exploits the return difference between the high portfolio and low portfolios yields 7.0%. Finally, we sort industries on the basis of composite returns in supplier and customer industries in the previous month ($r_{i,t-1}^{\text{composite}}$ as defined earlier) in Panel C. A self-financing trading strategy of buying the high portfolio and selling the low portfolio yields 8.7%.

The results in Table V show that the profitability of self-financing trading strategies based on cross-predictability effects can be significant. In what follows next, we check whether the returns from these trading strategies are exposed to well-known return factors, and whether the return series of long/short equity hedge funds, which are thought to exploit predictability effects, contain any traces of these trading strategies. We also report on a wide range of trading strategies with alternative formation and holding periods.

A. *Return Factor Exposure*

A potential concern that one might have is that the returns from the self-financing trading strategies laid out in Table V are not abnormal because they contain a significant amount of systematic risk. Alternatively, it could be that they are highly exposed to already well-known return factors, and so we might not be documenting anything new.

To address these concerns, we take the monthly returns from the trading strategies reported in Table V, and regress them on the excess market return as well as the Fama-French HML, SMB and MOM return factors. We report the estimated betas in Table VI.

[Table VI about here]

Except for statistically significant exposure to the momentum factor MOM (0.102 for the supplier strategy in column 1 and 0.144 for the composite strategy in column 3), the monthly trading returns appear to be fairly orthogonal to the market (which is not surprising because of the long-short nature of the trading strategies) as well as the Fama-French HML and SMB return factors. The significance of MOM in columns 1 and 3 suggests that the momentum factor may be proxying, at least in part, for sustained information diffusion from related industries – indeed, we report below that cross-predictability effects continue for up to a year. The annualized monthly intercept,

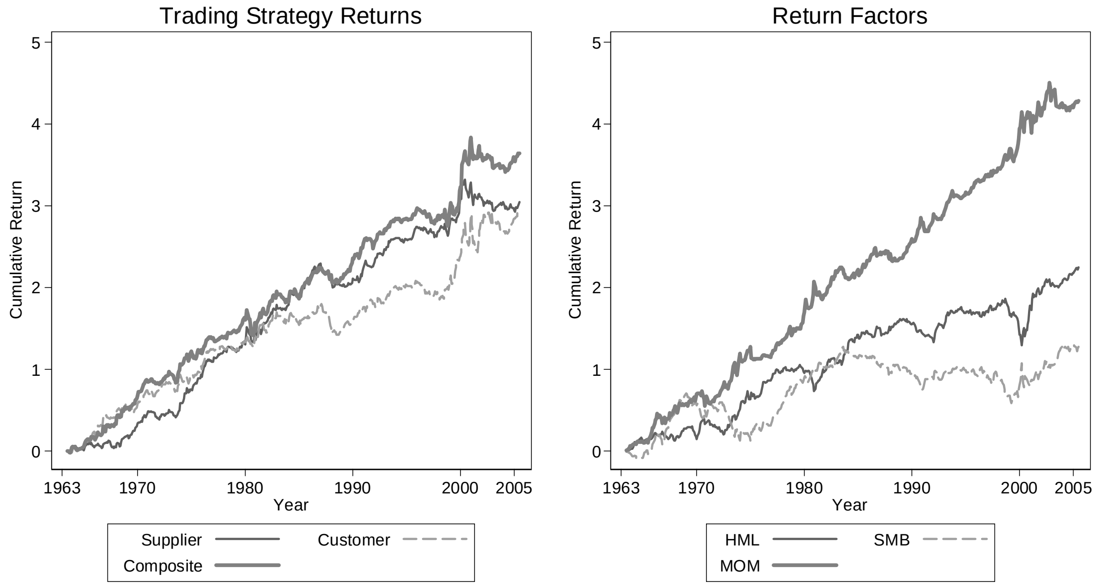

Figure 2: Cumulative Returns (July 1963 - June 2005)

our main coefficient of interest, is 6.2% for the supplier strategy, 5.7% for the customer strategy, and 6.9% for the composite strategy, which are similar to the annualized returns reported earlier. We also check whether the return exposures vary along the business cycle by including interaction terms with a business-cycle indicator variable based on NBER recession dates, and find similar monthly alphas.

Another concern that one might have is that a small number of industries enter the trading strategies in some excessive way, and as a result drive the profitability of the trading strategies reported in Table V. We find that while there is some heterogeneity in inclusion probabilities, the amount is not excessive so as to drive our results. We find that the maximum inclusion probability of an industry rarely exceeds three percent in any of the strategy-leg combinations (short or long in the supplier, customer and composite strategies) and that, when it does, the industry in question also appears in the opposite leg of the strategy with a similarly high probability. This shows that the profitability of the trading strategies is not driven by simply going long and short in industries with historically high and low returns, respectively.

Finally, we plot cumulative returns from the three trading strategies against HML, SMB and MOM in Figure 2. All three strategies appear to be consistently profitable over the sample period.

B. Evidence from Long/Short Equity Hedge Funds

We next test whether the return series of long/short equity hedge funds, which constitute a group of sophisticated market participants most likely to exploit predictability effects, are correlated with the return series from the three (supplier, customer and composite) trading strategies analyzed above. If return cross-predictability were an economically important phenomenon, one would expect these hedge funds to exploit it and their returns series to show traces of our trading strategies.

We use the Credit Suisse/Tremont Long/Short Equity Hedge Fund Index to measure the returns of long/short equity hedge funds. This is an asset-weighted, net-of-fees index used by many in the industry for benchmarking purposes. Unfortunately, its main drawback is that it starts in January 1994, and so our findings are limited to a short sample period from January 1994 to June 2005. With this caveat in mind, we regress the long/short equity hedge fund return series on the return series from our trading strategies. In the regressions, we further include the excess CRSP value-weighted market return, and Fama-French SMB, HML and MOM factors as control variables.

[Table VII about here]

We report our results in four columns in Table VII. Column 1 reports a specification without any of the trading strategies to provide a baseline. The coefficient on the excess market return is quite high at about 0.5, despite the implicit market neutrality claim of long/short equity hedge funds. In addition, their returns appear to have a SMB component of about 0.2 and a MOM component of about 0.2. The net-of-fees alpha is indistinguishable from zero, which is consistent with a competitive market outcome and also similar to what we know about mutual funds (Carhart, 1997). Importantly, we find that the coefficients on all three trading strategies (0.071 on the supplier strategy in column 2, 0.060 on the customer strategy in column 3, and 0.080 on the composite strategy in column 4) are positive and statistically significant. These results indicate that long/short equity hedge funds indeed engage in trading strategies that profit from the cross-predictability effect in prices. The magnitude of the coefficients on the three trading strategies also seems economically significant, considering the many different trading strategies that these hedge funds could be implementing.

In the Internet Appendix, we consider the profitability of standard J/K self-financing strategies to shed some light on the speed of information diffusion. These strategies select industries based on related industry returns over the past J months and hold them over the next K months, and involve the buying and selling of value-weighted portfolios as before. Among the strategies that we consider, short-term strategies such as 1/1 seem to be the most profitable. While this indicates that cross-predictability effects are strong in the short term, we find that other trading strategies with longer formation and holding periods also offer statistically significant profits. For example, the yield on the 1/12 composite strategy is 2.1%. Comparing this with the yield on the corresponding 1/1 strategy (8.7%), it is clear that cross-predictability effects are not limited to the first month after portfolio formation. To see this, note that the yield on the 1/12 strategy is the average of the first month return, the second month return, and so on through to the twelfth month return. If there were no cross-predictability effects after the first month, the yield on the 1/12 strategy would have been about 0.7% (8.7% divided by twelve), and not 2.1% as observed. Further exploring cross-predictability in event-time, we find that there is more to cross-predictability than just the short term, and that cross-predictability effects continue for up to a year beyond the first month after portfolio formation.

IV. Conclusion

In this paper, we find evidence that firm- and industry-level returns are cross-predictable based on lagged returns in supplier and customer industries. The effects appear to be economically significant – trading strategies designed to exploit them generate annual premiums as high as 8.7%. In addition, we find evidence that cross-predictability effects are weaker for stocks with high levels of analyst coverage and institutional ownership. Moreover, we document that the trading behavior of institutional investors mimic that of an informed investor profiting from cross-predictable returns. All of these findings are consistent with limited-information models in which value-relevant information diffuses gradually across informationally segmented markets due to the specialization of information producers and/or informed investors.

Our work can be fruitfully extended in several directions. First, limited-information models take investor specialization and market segmentation as given, and explore their implications for information diffusion and price formation. Alternatively, one can exploit the empirical design of this paper based on supply chain relationships to explore the fundamental drivers of investor specialization, how it arises and why. For example, at an aggregate level, why do some industries enjoy higher levels of analyst coverage and institutional ownership than others? At the level of an analyst, which pieces of news are worth collecting and analyzing, and which ones are not? In preliminary work, we compare the impact of shocks from a single large source with the impact of comparable shocks generated by combining shocks from multiple smaller sources. Interestingly, we find that single-source shocks, which are relatively easier to collect and analyze, are incorporated into prices faster than comparable multiple-source shocks. We also find that stock-level analyst expectations exhibit continuation and cross-predictability like returns do. The evidence on continuation is consistent with the underreaction feature of Hong and Stein's (1999) model due to differential information. Perhaps even the analysts following a given stock are differentially informed due to differences in their workload profiles, as there is significant variation in the number of stocks covered by analysts (Figure 1).

Our focus in this paper has been on supplier and customer industries to test the various aspects of positive cross-predictability across assets with positively correlated fundamentals. The supply chain framework based on the BEA Survey has worked well in large part because supplier and customer industries almost always have positively correlated fundamentals with each other. A worthwhile future extension would be to test negative cross-predictability by identifying instances in which certain shocks benefit some industries and hurt others, thereby temporarily causing a negative correlation of fundamentals. More generally, our empirical framework provides a novel measure of information flow that can be used to expand existing work on other forms of return predictability such as post-earnings announcement drift and on the role played by various market players such as analysts.

Another extension of our work would be to investigate the extent of cross-predictability between the equity market and the corporate bond market. Since these two markets have their own specialist investors who trade financial claims based on the same underlying real assets, the potential for cross-predictability seems high.

More work lies ahead before we know whether cross-predictability is widespread in other stock markets. Fortunately, the BEA Survey is a common type of census analysis carried out in most OECD countries. In addition to exploring cross-predictability internationally, a cross-country study can shed some light on the relation between financial development and the speed with which related industry information is priced. We believe these are interesting questions for future research.

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Notes

[1] We note that cross-predictability effects are different from lead-lag effects where one market either always leads or always lags another market, e.g. large stocks always lead small stocks. With cross-predictability, a market can sometimes lead and sometimes lag another related market depending on where information originates.

[2] In a previous version of the paper, we derived these predictions by extending Hong, Torous and Valkanov (2007). This analysis and several other complementary analyses are provided in the Internet Appendix available at http://www.afajof.org/supplements.asp.

[3] Firms that operate in multiple industries pose a conceptual problem. In the Internet Appendix, we show that our cross-predictability results are fairly similar for single-segment and multi-segment firms. Classifying a multi-segment firm according to its reported code in COMPUSTAT representing the firm's main business appears to constitute a good enough method to identify the firm's main economic exposure for our purposes.

Table I

Supply Chain Fundamentals

This table presents stock- and industry-level panel regressions of annual return on assets (ROA) on contemporaneous market-wide ROA and ROA in related supplier and customer industries. The industries are based on the Benchmark Input-Output Surveys of the Bureau of Economic Analysis. Assets are measured with COMPUSTAT item 6. Cash flow is measured as the sum of earnings before extraordinary items (item 18) and depreciation and amortization (item 14). Market-wide and industry ROA are weighted by firm assets. Supplier (customer) ROA is calculated by weighting the industry ROAs of supplier (customer) industries by the inter-industry flow of goods and services reported in the Survey. Stock- and industry-level specifications include stock and industry fixed effects in columns 1 and 2, respectively. t-statistics are reported in parentheses. Standard errors are heteroskedasticity consistent and adjusted for double clustering by stock and year in column 1, and by industry and year in column 2. ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, or 10% level, respectively.

Dependent Variable: ROA	(1)	(2)
ROA_{market}	0.725***	0.172***
	(5.16)	(2.60)
$ROA_{supplier}$	0.471***	0.398***
	(2.68)	(4.53)
$ROA_{customer}$	0.465***	0.164*
	(2.98)	(1.90)
Fixed Effects	Yes	Yes
Clustered Standard Errors	Yes	Yes
R^2	0.592	0.394
N obs	275,291	3,002

Table II

Cross-Predictability Effects in Stock and Industry Returns

This table presents time-series averages of coefficient estimates from monthly cross-sectional regressions of stock returns in columns 1 through 3 and industry returns in column 4. Supplier (customer) returns consist of supplier (customer) industry returns weighted by the inter-industry flow of goods and services reported in the Benchmark Input-Output Surveys of the Bureau of Economic Analysis. All return variables are in excess of the risk-free rate. t-statistics are reported in parentheses. Standard errors assume independence across monthly regressions. ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, or 10% level, respectively.

	(1)	(2)	(3)	(4)
Constant	0.005**	0.006**	0.006**	0.006**
	(2.01)	(2.33)	(2.45)	(2.35)
$r_{supplier,t-1}$	0.114***	0.105***	0.117***	0.113***
	(5.03)	(4.37)	(5.04)	(4.88)
$r_{customer,t-1}$	0.071***	0.058***	0.059***	0.075***
	(4.11)	(3.26)	(3.46)	(4.27)
$r_{stock,t-1}$	-0.062***	-0.047***	-0.067***	
	(14.44)	(10.41)	(13.84)	
$r_{stock,t-2:t-12} \times \frac{1}{11}$	0.072***	0.099***	0.099***	
	(4.07)	(5.01)	(5.37)	
$r_{industry,t-1}$	0.134***	0.117***	0.137***	0.032***
	(15.52)	(12.33)	(15.29)	(2.83)
R^2	0.028	0.051	0.034	0.091
T	492	492	492	503
Sample excludes	-	< 20th NYSE percentile	No closing price at end of month t-1	

Table III

Analyst Coverage, Institutional Ownership and Cross-Predictability Effects

This table presents time-series averages of coefficient estimates from monthly cross-sectional regressions of stock returns on lagged related industry returns interacted with lagged analyst coverage and institutional ownership. $r_{composite}$ represents returns in related industries, and is calculated as the average of $r_{supplier}$ and $r_{customer}$. Analyst coverage for a stock in a given month is measured as the number of analysts who have made an EPS forecast for the stock within the last twelve months (column 1) or the number of analysts who have made an EPS forecast for the stock in that month (column 2). Institutional ownership is measured as the percentage of outstanding shares owned by institutions (column 3). Stocks are ranked into five quintiles based on analyst coverage and institutional ownership. All return variables are in excess of the risk-free rate. t-statistics are reported in parentheses. Standard errors assume independence across monthly regressions. ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, or 10% level, respectively.

	(1)	(2)	(3)
Constant	0.008*	0.008*	0.008**
	(1.95)	(1.89)	(1.97)
$r_{composite,t-1}$ x $Rank_{t-1}$ (1st Quintile - Low)	0.293***	0.300***	0.380***
	(4.98)	(4.95)	(5.89)
$r_{composite,t-1}$ x $Rank_{t-1}$ (2nd Quintile)	0.299***	0.259***	0.317***
	(5.12)	(4.65)	(5.55)
$r_{composite,t-1}$ x $Rank_{t-1}$ (3rd Quintile)	0.185***	0.201***	0.244***
	(3.27)	(3.71)	(4.50)
$r_{composite,t-1}$ x $Rank_{t-1}$ (4th Quintile)	0.143**	0.157**	0.177***
	(2.37)	(2.61)	(3.16)
$r_{composite,t-1}$ x $Rank_{t-1}$ (5th Quintile - High)	0.027	0.034	0.067
	(0.43)	(0.55)	(1.12)
R^2	0.014	0.012	0.012
T	281	281	303

Table IV

Change in Institutional Ownership

This table presents panel regressions in which quarterly changes in institutional ownership at the stock level are regressed on contemporaneous changes in institutional ownership in related industries in columns 1 and 2, and on contemporaneous quarter returns in related industries in columns 3 and 4. Related supplier and customer industries are based on the inter-industry trade data reported in the Benchmark Input-Output Survey of the Bureau of Economic Analysis. All return variables are in excess of the risk-free rate. All specifications include stock and year-quarter fixed effects. t-statistics are reported in parentheses. Standard errors are heteroskedasticity consistent and adjusted for clustering at the industry-year level. ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, or 10% level, respectively.

	(1)	(2)	(3)	(4)
$\Delta IO_{supplier,q}$	0.073***			
	(2.78)			
$\Delta IO_{customer,q}$		0.055***		
		(2.77)		
$r_{supplier,q}$			0.009***	
			(2.80)	
$r_{customer,q}$				0.007**
				(2.28)
R^2	0.052	0.052	0.052	0.052
N obs	500,250	500,250	500,250	500,250

Table V

Self-Financing Trading Strategies

This table reports the mean and standard deviation of monthly excess returns on value-weighted portfolios of industries formed on the basis of related industry returns in the previous month (reported figures are annualized). Industries are sorted into five bins at the beginning of each month according to returns in related industries in the previous month. Self-financing trading strategies reported in the last column consist of buying the high (5) portfolio (top quintile) and selling the low (1) portfolio (bottom quintile).

Panel A: Industries Sorted on $r_{supplier,t-1}$

	Low (1)	(2)	(3)	(4)	High (5)	H - L
Mean return	0.028	0.054	0.056	0.072	0.100	0.073
Standard deviation	0.159	0.175	0.178	0.178	0.162	0.110
Sharpe ratio	0.173	0.306	0.313	0.406	0.617	0.660

Panel B: Industries Sorted on $r_{customer,t-1}$

	Low (1)	(2)	(3)	(4)	High (5)	H - L
Mean return	0.016	0.060	0.052	0.065	0.085	0.070
Standard deviation	0.176	0.166	0.157	0.165	0.184	0.134
Sharpe ratio	0.090	0.361	0.333	0.395	0.463	0.520

Panel C: Industries Sorted on $r_{composite,t-1}$

	Low (1)	(2)	(3)	(4)	High (5)	H - L
Mean return	0.013	0.036	0.074	0.071	0.100	0.087
Standard deviation	0.169	0.165	0.172	0.174	0.172	0.132
Sharpe ratio	0.077	0.220	0.430	0.409	0.582	0.658

Table VI
Return Factor Exposure

This table presents the return factor exposure of monthly returns from self-financing trading strategies formulated on the basis of returns in related industries in the previous month. Monthly trading returns are regressed on monthly CRSP value-weighted market return, and Fama-French SMB, HML and MOM factors. t-statistics are reported in parentheses. ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, or 10% level, respectively.

Trading strategy based on:	$r_{supplier,t-1}$	$r_{customer,t-1}$	$r_{composite,t-1}$
Alpha	0.005***	0.005***	0.006***
	(3.42)	(2.61)	(3.22)
$R_{market} - R_f$	0.017	0.051	0.038
	(0.48)	(1.08)	(0.89)
SMB	0.016	-0.065	0.004
	(0.35)	(1.15)	(0.07)
HML	-0.013	0.054	0.015
	(0.24)	(0.82)	(0.23)
MOM	0.102***	0.068	0.144***
	(2.89)	(1.59)	(3.41)
R^2	0.019	0.012	0.024
N obs	503	503	503

Table VII

Credit Suisse/Tremont Long/Short Equity Hedge Fund Index

This table presents the return factor exposure of the benchmark hedge fund index compiled by Credit Suisse/Tremont for long/short equity hedge funds. Excess monthly return on the long/short equity hedge fund index is regressed on excess CRSP value-weighted market return, Fama-French SMB, HML and MOM factors, and returns from self-financing supplier, customer and composite cross-predictability trading strategies. The sample period is from January 1994 to June 2005. t-statistics are reported in parentheses.

	(1)	(2)	(3)	(4)
Alpha	0.001	0.001	0.001	0.001
	(1.17)	(1.01)	(0.78)	(0.92)
$R_{market} - R_f$	0.488***	0.489***	0.497***	0.487***
	(15.26)	(15.59)	(15.96)	(15.99)
SMB	0.216***	0.216***	0.220***	0.215***
	(6.62)	(6.74)	(6.95)	(6.89)
HML	-0.027	-0.014	-0.021	-0.019
	(0.64)	(0.33)	(0.52)	(0.48)
MOM	0.219***	0.212***	0.222***	0.205***
	(9.71)	(9.52)	(10.14)	(9.40)
Supplier Strategy		0.071**		
		(2.52)		
Customer Strategy			0.060***	
			(3.08)	
Composite Strategy				0.080***
				(3.78)
R^2	0.806	0.815	0.819	0.825
N obs	138	138	138	138

Internet Appendix to "Market Segmentation and Cross-Predictability of Returns"*

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This document contains supplementary material to the paper titled "Market Segmentation and Cross-Predictability of Returns." The document contains two sections. Section 1 studies a limited-information model whose predictions about cross-predictability are tested in the paper. Section 2 reports tables that were prepared in response to questions raised during the review process and may be of general interest to the reader, but are not reported in the paper.

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1 A Model of Cross-Predictability

In this section, we study a limited-information model in which dispersed information diffuses slowly across markets with correlated fundamentals and leads to cross-predictability in returns. The model is inspired by Hong and Stein (1999) with respect to dispersed information, and by Hong, Torous and Valkanov (2007) with respect to the study of markets with correlated fundamentals, and formally extends the latter in two directions: (i) we introduce uninformed investors, who do not have informative signals, to study their effect on cross-predictability, and (ii) we relax the assumption that informed investors invest only in the market about which they acquire informative signals to study the joint behavior of stock returns and informed trade across related markets.

The analysis proceeds in two steps. We first consider a single asset market in isolation to study return predictability. We then consider two asset markets with correlated fundamentals to study return cross-predictability.

1.1 Return Predictability in a Single Market

Suppose that there are three dates $\{t-1, t, t+1\}$, a single risky asset in zero supply that pays a liquidating dividend d at date $t+1$, and a riskless asset whose gross payoff is normalized to 1 and hence is the numeraire. (The zero-supply assumption is for simplicity and without loss of generality. A positive supply of the risky asset would merely lead to unconditional risk premia at dates $t-1$ and t, and hence would not affect the analysis.) There are n investors in the economy with constant absolute risk aversion parameter a. Investors trade the risky asset at dates $t-1$ and t with market clearing prices denoted p_{t-1} and p_t, respectively, and then consume the liquidating dividend at date $t+1$. Their common prior belief at date $t-1$ is that $d \sim N\left(\bar{d}, \sigma_d^2\right)$. At date t, an informative but noisy signal s about d arrives where $s = d + \varepsilon$ and ε is an independent normally distributed noise term with mean 0 and variance σ_ε^2. The informative signal allows investors who receive it to update their beliefs about d and adjust their demands for the risky asset at date t.

Proposition 1 *When every investor receives the informative signal s about d, equilibrium prices do not exhibit predictability.*

Proof: After receiving the informative signal s at date t, investors solve the following optimization problem:

$$\max_{x_t} E\left[-e^{-aW_{t+1}} \mid s\right] \tag{1}$$

Substituting in $W_{t+1} = W_t - p_t x_t + d x_t$ and then evaluating the expectation, the optimization problem is:

$$\max_{x_t} \; - e^{-a\left(W_t - p_t x_t + E_{d|s} x_t - \frac{1}{2} a \sigma^2_{d|s} x_t^2\right)}. \tag{2}$$

Investor demand for the risky asset at date t is therefore given by

$$x_t = \frac{E_{d|s} - p_t}{a\sigma^2_{d|s}} \tag{3}$$

where

$$E_{d|s} = \bar{d} + \underbrace{\frac{\sigma_d^2}{\sigma_d^2 + \sigma_\varepsilon^2}}_{\beta_s} \left(s - \bar{d}\right) \tag{4}$$

$$\sigma^2_{d|s} = \sigma_d^2 \left(1 - \frac{\sigma_d^2}{\sigma_d^2 + \sigma_\varepsilon^2}\right). \tag{5}$$

Posterior beliefs about the liquidating dividend come from a normal projection of s on d

$$d = \bar{d} + \beta_s \left(s - \bar{d}\right) + \eta_s \tag{6}$$

where the residual uncertainty about the liquidating dividend η_s is distributed $N\left(0, \sigma^2_{d|s}\right)$. By the optimality of the projection

$$\eta_s \perp \left(s - \bar{d}\right). \tag{7}$$

Given that market clearing at date t requires $nx_t = 0$, substituting in investor demand yields

$$p_t = \bar{d} + \beta_s \left(s - \bar{d}\right). \tag{8}$$

Note that p_t fully incorporates the informative signal s as given by the optimal projection.

Back at date $t-1$, investors solve the following optimization problem:

$$\max_{x_{t-1}} E\left[-e^{-aW_{t+1}}\right] \tag{9}$$

Substituting in $W_{t+1} = W_t - p_t(s)\, x_t(s) + dx_t(s)$ and $W_t = W_{t-1} - p_{t-1}x_{t-1} + p_t(s)\, x_{t-1}$, the optimization problem is:

$$\max_{x_{t-1}} E\left[-e^{-a(W_{t-1}-p_{t-1}x_{t-1}+p_t(s)x_{t-1}-p_t(s)x_t(s)+dx_t(s))}\right]. \tag{10}$$

Given that $p_t(s) = \bar{d} + \beta_s \left(s - \bar{d}\right)$ and $x_t(s) = 0$, the optimization problem is:

$$\max_{x_{t-1}} \; - e^{-a\left(W_{t-1}-\left(p_{t-1}-\bar{d}\right)x_{t-1}-\frac{1}{2}a\beta_s^2\sigma_s^2x_{t-1}^2\right)}. \tag{11}$$

Investor demand for the risk asset at date $t-1$ is therefore given by

$$x_{t-1} = \frac{\bar{d} - p_{t-1}}{a\beta_s^2\sigma_s^2}. \tag{12}$$

Given that market clearing at date $t-1$ requires $nx_{t-1} = 0$, substituting in investor demand yields

$$p_{t-1} = \bar{d}. \tag{13}$$

Without loss of generality, define returns

$$r_t = p_t - p_{t-1} \tag{14}$$

$$r_{t+1} = p_{t+1} - p_t. \tag{15}$$

Evaluating the lagged beta of r_t on r_{t+1},

$$\frac{Cov\left(r_{t+1}, r_t\right)}{Var\left(r_t\right)} = \frac{Cov\left(d - \bar{d} - \beta_s\left(s-\bar{d}\right), \beta_s\left(s-\bar{d}\right)\right)}{Var\left(\beta_s\left(s-\bar{d}\right)\right)} \tag{16}$$

$$= \frac{Cov\left(\eta_s, \beta_s\left(s-\bar{d}\right)\right)}{Var\left(\beta_s\left(s-\bar{d}\right)\right)} \tag{17}$$

$$= 0 \qquad \left[\eta_s \perp \left(s-\bar{d}\right)\right] \tag{18}$$

it is clear that equilibrium prices do not exhibit continuation because the informative signal is fully incorporated at $t = 1$.■

This neoclassical result follows from the fact that every investor adjusts his or her demand for the risky asset at date t after receiving s. When every individual demand incorporates the information in s, aggregate demand and p_t do so as well and equilibrium prices do not exhibit predictability – in the sense that the residual uncertainty $(d - p_t)$ left at date t is orthogonal to p_t. As the next proposition shows, however, when only a fraction $\alpha \in (0, 1)$ of the investor population receives the informative signal, and as a result investors differ in their information sets, equilibrium prices can exhibit predictability, in particular continuation defined as $Cov\left(d - p_t, p_t - p_{t-1}\right) > 0$.

Proposition 2 *When only a fraction $\alpha \in (0, 1)$ of the investor population receives the informative signal s about d, equilibrium prices exhibit continuation.*

Proof: For α fraction of the population (n_i/n), demand for the risky asset after receiving the informative signal s at date t is

$$x_t^i = \frac{E_{d|s} - p_t}{a\sigma_{d|s}^2} \tag{19}$$

whereas for $(1 - \alpha)$ fraction of the population (n_u/n), demand for the risky asset at date t is

$$x_t^u = \frac{\bar{d} - p_t}{a\sigma_d^2}. \tag{20}$$

Given that market clearing at date t requires $\alpha n x_t^i + (1 - \alpha)\, n x_t^u = 0$, substituting in investor demands x_t^i and x_t^u yields

$$p_t = \bar{d} + \underbrace{\frac{\alpha\sigma_d^2}{\alpha\sigma_d^2 + (1 - \alpha)\,\sigma_{d|s}^2}}_{\gamma} \beta_s \left(s - \bar{d}\right). \tag{21}$$

Note that $0 < \gamma < 1$ and hence p_t does not incorporate the informative signal s fully as given by the optimal projection.

Back at date $t-1$, investors solve the following optimization problem:

$$\max_{x_{t-1}} E\left[-e^{-aW_{t+1}}\right] \tag{22}$$

Substituting in $W_{t+1} = W_t - p_t(s)\, x_t(s) + dx_t(s)$, $W_t = W_{t-1} - p_{t-1}x_{t-1} + p_t(s)\, x_{t-1}$ and $p_t(s)$, the optimization problem is:

$$\max_{x_{t-1}} E\left[-e^{-a\left(W_{t-1}-p_{t-1}x_{t-1}+\left(\bar{d}+\gamma\beta_s\left(s-\bar{d}\right)\right)x_{t-1}-\left(\bar{d}+\gamma\beta_s\left(s-\bar{d}\right)\right)x_t(s)+dx_t(s)\right)}\right]. \tag{23}$$

Further substituting in $x_t^i(s) = \frac{E_{d|s}-p_t(s)}{a\sigma_{d|s}^2}$ for informed investors who will receive s at date t and taking the expectation yield

$$\max_{x_{t-1}^i} \; -C_{t-1}^i e^{-a\left(W_{t-1}-\left(p_{t-1}-\bar{d}\right)x_{t-1}-\frac{1}{2}a\sigma_d^2\left(\frac{\alpha^2\sigma_d^2}{\alpha^2\sigma_d^2+\sigma_\varepsilon^2}\right)x_{t-1}^2\right)} \tag{24}$$

where

$$C_{t-1}^i = \sqrt{\frac{\left(\alpha\sigma_d^2+\sigma_\varepsilon^2\right)^2}{\left(\sigma_d^2+\sigma_\varepsilon^2\right)\left(\alpha^2\sigma_d^2+\sigma_\varepsilon^2\right)}}. \tag{25}$$

In computing the expectation, we use the result

$$E\left[-e^{-a\left(\xi+\psi\left(d-\bar{d}\right)+\phi\left(d-\bar{d}\right)^2\right)}\right] = -\frac{1}{\sqrt{1+2a\phi\sigma_d^2}}e^{-a\left(\frac{\xi\left(1+2a\phi\sigma_d^2\right)-\frac{1}{2}a\psi^2\sigma_d^2}{1+2a\phi\sigma_d^2}\right)} \tag{26}$$

and the fact that $s = d+\varepsilon$ and ε is orthogonal to d. Solving for x_{t-1}^i yields

$$x_{t-1}^i = \frac{\left(\bar{d}-p_{t-1}\right)}{a\sigma_d^2}\frac{\alpha^2\sigma_d^2+\sigma_\varepsilon^2}{\alpha^2\sigma_d^2}. \tag{27}$$

For uninformed investors who will not become informed at date t, substituting in $x_t^u = \frac{\bar{d}-p_t(s)}{a\sigma_d^2}$ yields

$$\max_{x_{t-1}^u} \; -C_{t-1}^u e^{-a\left(W_{t-1}-\left(p_{t-1}-\bar{d}\right)x_{t-1}-\frac{1}{2}a\sigma_d^2\left(\frac{\alpha^2\sigma_d^4+\alpha^2\sigma_d^2\sigma_\varepsilon^2}{\alpha^2\sigma_d^4+\alpha^2\sigma_d^2\sigma_\varepsilon^2+\sigma_\varepsilon^4}\right)x_{t-1}^2\right)} \tag{28}$$

where

$$C_{t-1}^u = \sqrt{\frac{\left(\alpha\sigma_d^2+\sigma_\varepsilon^2\right)^2\left(\alpha^2\sigma_d^4+\sigma_\varepsilon^4\right)}{\left(\alpha^2\sigma_d^4+2\sigma_d^2\sigma_\varepsilon^2+\sigma_\varepsilon^4\right)\left(\alpha^2\sigma_d^4+\alpha^2\sigma_d^2\sigma_\varepsilon^2+\sigma_\varepsilon^4\right)}}. \tag{29}$$

Solving for x_{t-1}^u yields

$$x_{t-1}^u = \frac{\left(\bar{d} - p_{t-1}\right)}{a\sigma_d^2} \frac{\alpha^2\sigma_d^4 + \alpha^2\sigma_d^2\sigma_\varepsilon^2 + \sigma_\varepsilon^4}{\alpha^2\sigma_d^4 + \alpha^2\sigma_d^2\sigma_\varepsilon^2}. \tag{30}$$

Given that market clearing at date $t-1$ requires $\alpha n x_{t-1}^i + (1-\alpha) n x_{t-1}^u = 0$, substituting in investor demands x_{t-1}^i and x_{t-1}^u yields

$$p_{t-1} = \bar{d}. \tag{31}$$

Evaluating the the lagged beta of r_t on r_{t+1},

$$\begin{aligned}
\frac{Cov\left(r_{t+1}, r_t\right)}{Var\left(r_t\right)} &= \frac{Cov\left(p_{t+1} - p_t, p_t - p_{t-1}\right)}{Var\left(p_t - p_{t-1}\right)} && (32)\\
&= \frac{Cov\left(\left(1-\gamma\right)\beta_s\left(s - \bar{d}\right) + \eta_s, \gamma\beta_s\left(s - \bar{d}\right)\right)}{Var\left(\gamma\beta_s\left(s - \bar{d}\right)\right)} && (33)\\
&= \frac{\left(1-\gamma\right)\gamma\beta_s^2\left(\sigma_d^2 + \sigma_\varepsilon^2\right)}{\gamma^2\beta_s^2\left(\sigma_d^2 + \sigma_\varepsilon^2\right)} && (34)\\
&= \frac{1-\alpha}{\alpha}\frac{\sigma_\varepsilon^2}{\sigma_d^2 + \sigma_\varepsilon^2} && (35)
\end{aligned}$$

equilibrium prices exhibit continuation because the informative signal is not fully incorporated at date t.■

Equilibrium prices exhibit continuation because some investors do not receive s and those investors also fail to infer s from publicly available information p_t to adjust their demand for the risky asset at date t. While informed investors adjust their demand, due to limited risk bearing capacity, they do not completely make up for the lack of adjustment in uninformed demand. As a result, aggregate demand and p_t incorporate the information in s only partly and equilibrium prices exhibit continuation – in the sense that the residual uncertainty $(d - p_t)$ left at date t is positively correlated with p_t. This feature of the model is common to a broad class of "disagreement models" as articulated by Hong and Stein (2007). Skill-based differences in information acquisition and processing costs among investors could plausibly result in heterogeneous beliefs and lead to such equilibria in which investors with information acquisition and processing costs below a certain threshold choose to become informed and others choose to remain uninformed. Moreover, the magnitude of continuation decreases in α. This is because the more there are informed investors in the market, the more information is impounded into p_t, and the less predictable residual uncertainty is left at date t.

1.2 Cross-Predictability Among Two Markets

We now turn to return cross-predictability. Suppose that there are two risky assets $k \in \{1, 2\}$ both in zero supply paying correlated liquidating dividends d_1 and d_2 at date $t + 1$. The common prior belief at date $t - 1$ is that $(d_1, d_2) \sim N\left(\bar{d}1, \Sigma\right)$ where

$$\Sigma = \begin{bmatrix} \sigma_d^2 & \rho\sigma_d^2 \\ \rho\sigma_d^2 & \sigma_d^2 \end{bmatrix}. \tag{36}$$

At date t, two informative but noisy signals, s_1 about d_1 and s_2 about d_2, arrive where $s_1 = d_1 + \varepsilon_1$, $s_2 = d_2 + \varepsilon_2$, and ε_1 and ε_2 are independent normally distributed noise terms with mean 0 and variance σ_ε^2. Reflecting the specialization of market participants in gathering information about only a subset of assets, one group of investors (α_1 fraction of the investor population) receives s_1 and another group of investors (α_2 fraction of the investor population) receives s_2. For simplicity, we assume that the two groups, which respectively receive informative signals s_1 and s_2, are disjoint.

Proposition 3 *When α_1 fraction of the investor population receives the signal s_1 and another α_2 fraction of the investor population receives the signal s_2, equilibrium prices exhibit cross-predictability.*

Proof: For α_k fraction of the population, demand for the risky assets after receiving the informative signal s_k at date t for $k \in \{1, 2\}$ and $j \neq k$ is,

$$X_t^{i[s_k]} = \frac{1}{a}\Sigma_{s_k}^{-1}\left(\begin{bmatrix} E_{d_1|s_k} \\ E_{d_2|s_k} \end{bmatrix} - P_t\right) \tag{37}$$

where

$$E_{d_k|s_k} = \bar{d} + \frac{\sigma_d^2}{\sigma_d^2 + \sigma_\varepsilon^2}\left(s_k - \bar{d}\right) \tag{38}$$

$$E_{d_j|s_k} = \bar{d} + \frac{\rho\sigma_d^2}{\sigma_d^2 + \sigma_\varepsilon^2}\left(s_k - \bar{d}\right) \tag{39}$$

$$\sigma^2_{d_k|s_k} = \sigma_d^2\left(1 - \frac{\sigma_d^2}{\sigma_d^2 + \sigma_\varepsilon^2}\right) \tag{40}$$

$$\sigma^2_{d_j|s_k} = \sigma_d^2\left(1 - \rho^2\frac{\sigma_d^2}{\sigma_d^2 + \sigma_\varepsilon^2}\right) \tag{41}$$

$$\Sigma_{s_k} = \begin{bmatrix} \sigma^2_{d_1|s_k} & \rho\sigma_d^2\left(1 - \frac{\sigma_d^2}{\sigma_d^2+\sigma_\varepsilon^2}\right) \\ \rho\sigma_d^2\left(1 - \frac{\sigma_d^2}{\sigma_d^2+\sigma_\varepsilon^2}\right) & \sigma^2_{d_2|s_k} \end{bmatrix} \tag{42}$$

For $(1 - \alpha_1 - \alpha_2)$ fraction of the population, demand for the risky asset at date t is

$$X_t^u = \frac{1}{a}\Sigma^{-1}\left(\bar{d}1 - P_t\right). \tag{43}$$

Given that market clearing at date t requires $\alpha_1 n X_t^{i[s_1]} + \alpha_2 n X_t^{i[s_2]} + (1 - \alpha_1 - \alpha_2)\, n X_t^u = 0$, substituting in investor demands $X_t^{i[s_1]}$, $X_t^{i[s_2]}$ and X_t^u for $k \in \{1, 2\}$ and $j \neq k$ yields

$$p_{k:t} = \bar{d} + \underbrace{\frac{\alpha_k\alpha_j\left(1-\rho^2\right)\sigma_d^4 + \alpha_k\sigma_d^2\sigma_\varepsilon^2}{\alpha_1\alpha_2\left(1-\rho^2\right)\sigma_d^4 + \left(\alpha_1+\alpha_2\right)\sigma_d^2\sigma_\varepsilon^2 + \sigma_\varepsilon^4}}_{\gamma_{d_k,s_k}}\left(s_k - \bar{d}\right) \tag{44}$$

$$+ \underbrace{\frac{\alpha_j\rho\sigma_d^2\sigma_\varepsilon^2}{\alpha_1\alpha_2\left(1-\rho^2\right)\sigma_d^4 + \left(\alpha_1+\alpha_2\right)\sigma_d^2\sigma_\varepsilon^2 + \sigma_\varepsilon^4}}_{\gamma_{d_k,s_j}}\left(s_j - \bar{d}\right) \tag{45}$$

As for equilibrium prices at date $t-1$, lengthy calculations that are similar to those in the proof of Proposition 2 yield

$$p_{1:t-1} = p_{2:t-1} = \bar{d}. \tag{46}$$

For brevity, we omit these lengthy calculations and note that in any case $p_{1:t-1}$ and $p_{2:t-1}$ enter only as constants in the cross-predictability expressions below and therefore that they are not key to establishing the claim of the proposition.

In addition, note that for $k \in \{1,2\}$ and $j \neq k$, the normal projection of s_k and s_j on d_k is given by

$$d_k = \bar{d} + \underbrace{\frac{\left(1-\rho^2\right)\sigma_d^4 + \sigma_d^2\sigma_\varepsilon^2}{\left(1-\rho^2\right)\sigma_d^4 + 2\sigma_d^2\sigma_\varepsilon^2 + \sigma_\varepsilon^4}}_{\beta_{d_k,s_k}}\left(s_k - \bar{d}\right) \tag{47}$$

$$+\underbrace{\frac{\rho\sigma_d^2\sigma_\varepsilon^2}{\left(1-\rho^2\right)\sigma_d^4 + 2\sigma_d^2\sigma_\varepsilon^2 + \sigma_\varepsilon^4}}_{\beta_{d_k,s_j}}\left(s_j - \bar{d}\right) + \eta_{d_k}. \tag{48}$$

By the optimality of the projections

$$\eta_{d_1}, \eta_{d_2} \perp \left(s_1 - \bar{d}\right),\ \left(s_2 - \bar{d}\right). \tag{49}$$

Without loss of generality, we define returns $r_{k:t} = p_{k:t} - p_{k:t-1}$ and $r_{k:t+1} = p_{k:t+1} - p_{k:t}$ for $k \in \{1,2\}$ as before and evaluate the lagged cross-beta of $r_{j:t}$ on $r_{k:t+1}$ for $j \neq k$ where

$$\begin{aligned} Cov\left(r_{k:t+1}, r_{j:t}\right) &= Cov(\left(\beta_{d_k,s_k} - \gamma_{d_k,s_k}\right)\left(s_k - \bar{d}\right) + \left(\beta_{d_k,s_j} - \gamma_{d_k,s_j}\right)\left(s_j - \bar{d}\right) + \eta_{d_k}, \\ &\quad \gamma_{d_j,s_k}\left(s_k - \bar{d}\right) + \gamma_{d_j,s_j}\left(s_j - \bar{d}\right)) \end{aligned} \tag{50}$$

$$\begin{aligned} &= \left(\left(\beta_{d_k,s_k} - \gamma_{d_k,s_k}\right)\gamma_{d_j,s_k} + \left(\beta_{d_k,s_j} - \gamma_{d_k,s_j}\right)\gamma_{d_j,s_j}\right)\left(\sigma_d^2 + \sigma_\varepsilon^2\right) \\ &\quad + \left(\left(\beta_{d_k,s_k} - \gamma_{d_k,s_k}\right)\gamma_{d_j,s_j} + \left(\beta_{d_k,s_j} - \gamma_{d_k,s_j}\right)\gamma_{d_j,s_k}\right)\rho\sigma_d^2 \end{aligned} \tag{51}$$

and

$$Var\left(r_{j:t}\right) = Var\left(\gamma_{d_j,s_k}\left(s_k - \bar{d}\right) + \gamma_{d_j,s_j}\left(s_j - \bar{d}\right)\right) \tag{52}$$

$$= \left(\gamma_{d_j,s_k}^2 + \gamma_{d_j,s_j}^2\right)\left(\sigma_d^2 + \sigma_\varepsilon^2\right) + 2\gamma_{d_j,s_k}\gamma_{d_j,s_j}\rho\sigma_d^2. \tag{53}$$

Further substituting in β_{d_k,s_k}, β_{d_k,s_j}, γ_{d_k,s_k}, γ_{d_k,s_j}, γ_{d_j,s_k} and γ_{d_j,s_j}, the lagged cross-beta is

$$\rho\sigma_\varepsilon^4 \frac{\left(1-\rho^2\right)\alpha_k\alpha_j\left(2-\alpha_k-\alpha_j\right)\sigma_d^2 + \left(\alpha_k\left(1-\alpha_k\right) + \alpha_j\left(1-\alpha_j\right)\right)\sigma_\varepsilon^2}{\rho^2\alpha_k^2\sigma_\varepsilon^4\left(\sigma_d^2+\sigma_\varepsilon^2\right) + 2\rho^2\alpha_k\alpha_j\left(\left(1-\rho^2\right)\alpha_k\sigma_d^2 + \sigma_\varepsilon^2\right) + \alpha_j^2\left(\sigma_d^2+\sigma_\varepsilon^2\right)\left(\left(1-\rho^2\right)\alpha_k\sigma_d^2 + \sigma_\varepsilon^2\right)^2} \tag{54}$$

which shows that equilibrium prices exhibit cross-predictability in the sign of ρ when fundamental payoffs are correlated ($\rho \neq 0$).■

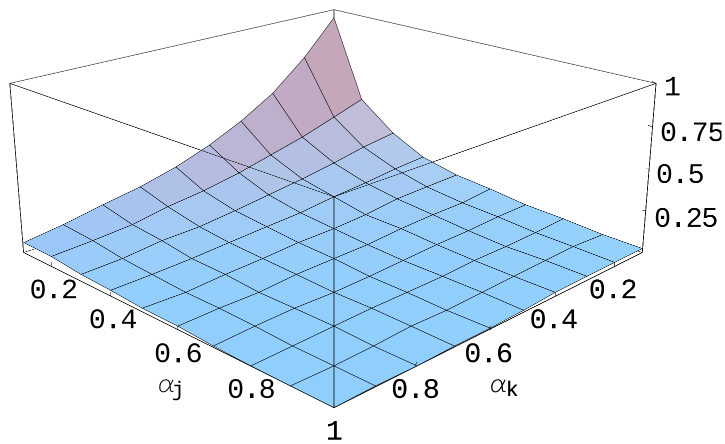

Figure 1: Lagged cross-beta of $r_{j:t}$ on $r_{k:t+1}$ ($\rho = 0.5$, $\sigma_d = 0.8$, $\sigma_\epsilon = 0.4$)

Equilibrium prices exhibit cross-predictability for the same reasons that they exhibit continuation. Some investors do not receive s_1 and hence do not adjust their demand for the first risky asset at date t. Likewise, some investors do not receive s_2 and hence do not adjust their demand for the second risky asset at date t. Consequently, both $p_{1:t}$ and $p_{2:t}$ incorporate the information in s_1 and s_2 partly and equilibrium prices exhibit cross-predictability – in the sense that the residual uncertainty left in $(d_k - p_{k:t})$ at date t is correlated with $p_{j:t}$ for $k \in \{1, 2\}$ and $j \neq k$.

1.3 Testable Predictions

In the model, the cross-predictability effect in returns declines with the number of informed investors in the market. This is because informative signals received by informed investors in the intermediate stage are incorporated into prices more fully when there are more informed investors. Figure 1 plots the relation between the presence of informed investors and cross-predictability.

The model also sheds light on how informed investors trade to exploit their informational advantage over uninformed investors. Specifically, when informed investors trade in one of the markets due to new information, they also trade in the other market. Previous work has found evidence in support of this in the context of a single market – institutional investors trade to take advantage of the continuation effect in prices (Cohen, Gompers and Vuolteenaho, 2002). Hence, an untested prediction of the model is whether institutional investors also trade to take advantage of the cross-predictability effect in prices.

2 Supplementary Results

2.1 Single-segment vs. multi-segment firms

In the paper, each stock is assigned to a BEA industry based on the stock's reported SIC or NAICS code in COMPUSTAT, which represents the firm's main business. While this is likely to be a good approximation for single-segment firms whose operations are concentrated in one industry, it is not clear whether this is also a good approximation for multi-segment firms, which operate in multiple industries. To investigate this issue, we estimate the first specification in Table II for single-segment and multi-segment firms separately. To form these two samples that are mutually exclusive, we use information from COMPUSTAT's segment files. If a firm is reported as having only one segment for the time period in question, we classify the firm as a single-segment firm. If a firm is reported as having more than one segment, we classify the firm as a multi-segment firm. In assigning multi-segment firms to BEA industries, we follow the same procedure as in the paper and use the reported SIC or NAICS code in COMPUSTAT, which has the desired property of representing the firm's main business, and thus, its main economic exposure.

The results of this exercise are reported in Table IA.I. The coefficient estimates for single-segment and multi-segment firms are presented in columns 1 and 2, respectively. The coefficient estimates in both columns are similar to those for the whole sample reported in column 1 in Table II, and also, similar to each other. The t-statistics are lower than before due to smaller sample sizes, and a shorter sample period (COMPUSTAT's segment files only start in 1979). Compositional issues and the potential industry misclassification of multi-segment firms therefore do not appear to have a significant impact on our analyses.

2.2 Differences in expected returns across analyst coverage and institutional ownership quintiles

In addition to the specifications reported in Table III, we estimate additional specifications that allow for cross-sectional differences in expected returns across the different analyst coverage and institutional ownership quintiles. Specifically, Table IA.II reports panel regressions with monthly fixed effects and appropriate monthly clustering of standard errors, instead of Fama-MacBeth regressions – mainly to improve the efficiency of the estimates since the specification is significantly longer with direct quintile effects.

To provide a benchmark, Panel A reports estimates from specifications without the direct quintile effects. These estimates are similar to those reported in Table III. Panel B reports estimates from specifications with the direct quintile effects. Again, the primary coefficients of interest, namely quintile interactions with lagged returns in related industries, are similar to those in Panel A and Table III.

2.3 Small stocks

By excluding stocks with market capitalizations below the 20th NYSE percentile, column 2 in Table II addresses the possibility that thin markets might be driving the stock-level cross-predictability results. Table IA.III repeats the same analysis for Table III. While the spreads between the low and high quintile interactions are smaller than those in Table III, the declining pattern of cross-predictability across the quintile interactions is still evident.

2.4 Difference in data frequency: *quarterly* institutional ownership and *monthly* stock returns

The Fama-MacBeth regressions in column 3 in Table III rely on quarterly institutional ownership data. For each monthly cross-sectional regression, we sort stocks into quintiles based on their level of institutional ownership in the previous quarter. This procedure implies that we use institutional ownership as of December, Year X-1 to sort stocks in January, February, and March of Year X, institutional ownership as of March, Year X to sort stocks in April, May, and June of Year X, institutional ownership as of June, Year X to sort stocks in July, August and September, and institutional ownership as of September, Year X to sort stocks in October, November, and December of Year X.

A potential statistical issue with this procedure is that the use of the same quarterly institutional ownership data in three separate monthly cross-sectional regressions may induce correlation among the estimated coefficients, and unless this correlation is accounted for, the standard errors may be understated. Although this is unlikely to be a problem because the estimated coefficients are interactions of institutional ownership quintiles and lagged returns in related industries (which differ across monthly regressions), we investigate this concern by computing robust standard errors that account for the correlation of coefficient estimates within a given quarter. The results of this exercise are reported in Table IA.IV (corresponding to column 3 in Table III). The t-statistics with robust standard errors are only slightly smaller, and none of the conclusions are affected.

2.5 Trading strategies excluding small stocks, and alternative trading strategies

To address the general concern that trading profits may be driven by small stocks, the paper considers trading strategies that buy and sell value-weighted industry portfolios in Table V. To further address the concern that value-weighting may not be enough (because low capitalization

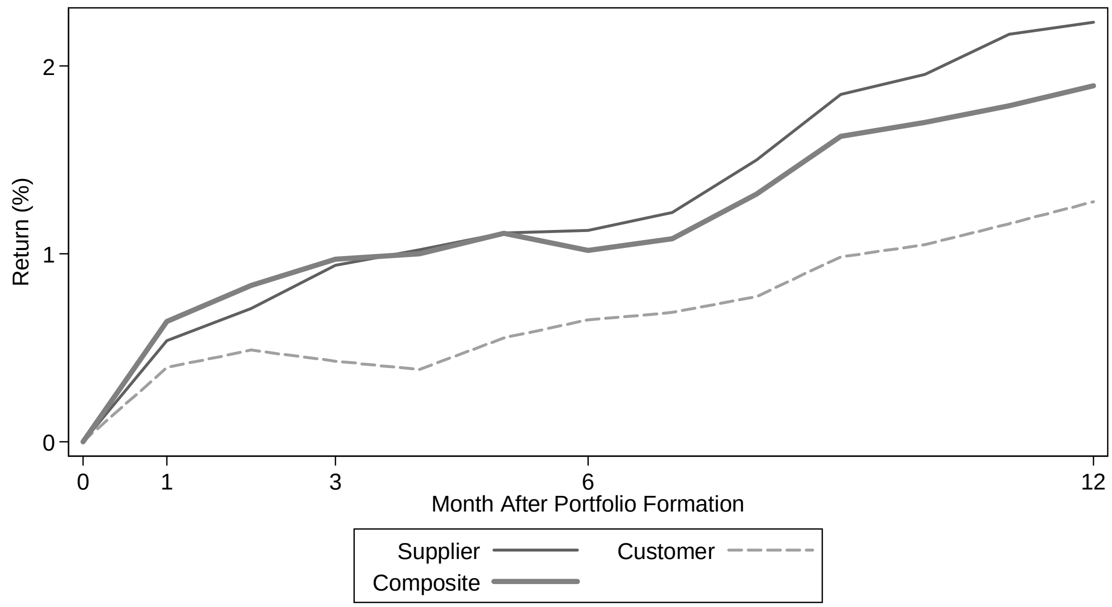

Figure 2: Performance of Trading Strategies in Event Time

stocks still need to be bought and sold), we repeat the analysis in Table V by excluding stocks with market capitalizations below the 20th NYSE percentile. Table IA.V presents the results of this analysis, and shows that the trading profits reported in the paper are not driven by small stocks.

A related analysis in Table IA.VI explores different formation and holding periods. We find low-volume trading strategies with holding periods as long as 12 months that yield more than 2%. Finally, Figure 2 shows the performance of trading strategies in event time.

2.6 BEA Surveys

The Use Table data on the amount of inter-industry flow of goods and services that we use to identify supplier and customer industries (see Section 3.1.2, Benchmark Input-Output Surveys) are freely available from the Bureau of Economic Analysis and can be downloaded from their web site (http://www.bea.gov/industry/index.htm#benchmark_io, accessed on June 5, 2009). Table

IA.VII lists the industries in the 1987 survey, and Table IA.VIII provides the dictionary linking SIC codes to industries.

References

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Hong, Harrison, and Jeremy Stein, 2007, Disagreement and the stock market, *Journal of Economic Perspectives* 21, 109-128.

Hong, Harrison, Walter Torous, and Rossen Valkanov, 2007, Do industries lead stock markets? *Journal of Financial Economics* 83, 367-396.

Table IA.I

Cross-Predictability Effects for Single-Segment and Multi-Segment Firms

This table presents time-series averages of coefficient estimates from monthly cross-sectional regressions of stock returns. The sample includes single-segment firms in column 1, and multi-segment firms in column 2. Supplier (customer) returns consist of supplier (customer) industry returns weighted by the inter-industry flow of goods and services reported in the Benchmark Input-Output Surveys of the Bureau of Economic Analysis. All return variables are in excess of the risk-free rate. t-statistics are reported in parentheses. Standard errors assume independence across monthly regressions. ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, or 10% level, respectively.

	(1)	(2)
Constant	0.006	0.008**
	(1.56)	(2.58)
$r_{supplier,t-1}$	0.102***	0.111***
	(2.96)	(3.84)
$r_{customer,t-1}$	0.078***	0.074***
	(2.84)	(3.52)
$r_{stock,t-1}$	-0.061***	-0.062***
	(12.23)	(11.07)
$r_{stock,t-2:t-12}$	0.004***	0.003**
	(2.83)	(2.07)
$r_{industry,t-1}$	0.133***	0.122***
	(9.75)	(11.82)
R^2	0.025	0.028
T	318	318
Sample:	Single-segment	Multi-segment

Table IA.II

Analyst Coverage, Institutional Ownership and Cross-Predictability Effects

This table presents panel regressions in which monthly stock returns are regressed on lagged related industry returns interacted with lagged analyst coverage and institutional ownership. $r_{composite}$ represents returns in related industries, and is calculated as the average of $r_{supplier}$ and $r_{customer}$. Analyst coverage for a stock in a given month is measured as the number of analysts who have made an EPS forecast for the stock within the last twelve months (column 1) or the number of analysts who have made an EPS forecast for the stock in that month (column 2). Institutional ownership is measured as the percentage of outstanding shares owned by institutions (column 3). Stocks are ranked into five quintiles based on analyst coverage and institutional ownership. All return variables are in excess of the risk-free rate. All specifications include year-month fixed effects. Robust standard errors (heteroskedasticity consistent and adjusted for clustering at the year-month level) are reported in brackets. ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, or 10% level, respectively.

Panel A: Without Own Effects			
	(1)	(2)	(3)
Constant	0.007***	0.007***	0.007***
	[0.001]	[0.001]	[0.001]
$r_{composite,t-1}$ x $Rank_{t-1}$ (1st Quintile - Low)	0.287**	0.277**	0.329***
	[0.120]	[0.119]	[0.106]
$r_{composite,t-1}$ x $Rank_{t-1}$ (2nd Quintile)	0.246**	0.217*	0.283***
	[0.119]	[0.122]	[0.109]
$r_{composite,t-1}$ x $Rank_{t-1}$ (3rd Quintile)	0.167	0.171	0.206*
	[0.122]	[0.120]	[0.107]
$r_{composite,t-1}$ x $Rank_{t-1}$ (4th Quintile)	0.083	0.107	0.128
	[0.126]	[0.125]	[0.111]
$r_{composite,t-1}$ x $Rank_{t-1}$ (5th Quintile - High)	-0.003	-0.002	0.048
	[0.135]	[0.131]	[0.115]
R^2	0.119	0.119	0.091
N obs	967,217	967,217	1,544,198

Panel B: With Own Effects

	(1)	(2)	(3)
Constant	0.007***	0.004***	0.006***
	[0.001]	[0.001]	[0.002]
$Rank_{t-1}$ (2^{nd} Quintile)	-0.002*	0.002***	0.002
	[0.001]	[0.001]	[0.001]
$Rank_{t-1}$ (3^{rd} Quintile)	-0.001	0.003***	0.001
	[0.001]	[0.001]	[0.002]
$Rank_{t-1}$ (4^{th} Quintile)	0.000	0.004***	0.002
	[0.002]	[0.001]	[0.002]
$Rank_{t-1}$ (5^{th} Quintile - High)	0.001	0.004**	0.002
	[0.002]	[0.002]	[0.003]
$r_{composite,t-1}$ x $Rank_{t-1}$ (1^{st} Quintile - Low)	0.287**	0.283**	0.332***
	[0.121]	[0.119]	[0.107]
$r_{composite,t-1}$ x $Rank_{t-1}$ (2^{nd} Quintile)	0.250**	0.218*	0.282**
	[0.119]	[0.123]	[0.109]
$r_{composite,t-1}$ x $Rank_{t-1}$ (3^{rd} Quintile)	0.169	0.170	0.207*
	[0.122]	[0.120]	[0.107]
$r_{composite,t-1}$ x $Rank_{t-1}$ (4^{th} Quintile)	0.082	0.104	0.127
	[0.125]	[0.125]	[0.111]
$r_{composite,t-1}$ x $Rank_{t-1}$ (5^{th} Quintile - High)	-0.006	-0.008	0.046
	[0.135]	[0.131]	[0.115]
R^2	0.119	0.119	0.091
N obs	967,217	967,217	1,544,198

Table IA.III

Analyst Coverage, Institutional Ownership and Cross-Predictability Effects

This table presents time-series averages of coefficient estimates from monthly cross-sectional regressions of stock returns on lagged related industry returns interacted with lagged analyst coverage and institutional ownership. The sample excludes stocks with market capitalizations below the 20th NYSE percentile. $r_{composite}$ represents returns in related industries, and is calculated as the average of $r_{supplier}$ and $r_{customer}$. Analyst coverage for a stock in a given month is measured as the number of analysts who have made an EPS forecast for the stock within the last twelve months (column 1) or the number of analysts who have made an EPS forecast for the stock in that month (column 2). Institutional ownership is measured as the percentage of outstanding shares owned by institutions (column 3). Stocks are ranked into five quintiles based on analyst coverage and institutional ownership. All return variables are in excess of the risk-free rate. t-statistics are reported in parentheses. Standard errors assume independence across monthly regressions. ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, or 10% level, respectively.

	(1)	(2)	(3)
Constant	0.009**	0.009**	0.010**
	(2.46)	(2.39)	(2.60)
$r_{composite,t-1}$ x $Rank_{t-1}$ (1st Quintile - Low)	0.250***	0.229***	0.242***
	(4.22)	(3.87)	(3.81)
$r_{composite,t-1}$ x $Rank_{t-1}$ (2nd Quintile)	0.223***	0.214***	0.213***
	(3.77)	(3.80)	(3.67)
$r_{composite,t-1}$ x $Rank_{t-1}$ (3rd Quintile)	0.187***	0.213***	0.202***
	(3.15)	(3.58)	(3.62)
$r_{composite,t-1}$ x $Rank_{t-1}$ (4th Quintile)	0.123**	0.137**	0.149***
	(2.18)	(2.29)	(2.73)
$r_{composite,t-1}$ x $Rank_{t-1}$ (5th Quintile - High)	0.100	0.096	0.110**
	(1.62)	(1.64)	(1.99)
R^2	0.018	0.017	0.017
T	281	281	303

Table IA.IV

Institutional Ownership and Cross-Predictability Effects

This table presents time-series averages of coefficient estimates from monthly cross-sectional regressions of stock returns on lagged related industry returns interacted with lagged institutional ownership. $r_{composite}$ represents returns in related industries, and is calculated as the average of $r_{supplier}$ and $r_{customer}$. Institutional ownership is measured as the percentage of outstanding shares owned by institutions. Stocks are ranked into five quintiles based on institutional ownership. All return variables are in excess of the risk-free rate. t-statistics are reported in parentheses. Standard errors are heteroskedasticity consistent and adjusted for clustering at the year-quarter level. ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, or 10% level, respectively.

	(1)
Constant	0.008*
	(1.89)
$r_{composite,t-1}$ *x Rank* $_{t-1}$ *(1st Quintile - Low)*	0.380***
	(5.11)
$r_{composite,t-1}$ *x Rank* $_{t-1}$ *(2nd Quintile)*	0.317***
	(4.90)
$r_{composite,t-1}$ *x Rank* $_{t-1}$ *(3rd Quintile)*	0.244***
	(4.12)
$r_{composite,t-1}$ *x Rank* $_{t-1}$ *(4th Quintile)*	0.177***
	(2.96)
$r_{composite,t-1}$ *x Rank* $_{t-1}$ *(5th Quintile - High)*	0.067
	(1.12)
R^2	0.012
T	303

Table IA.V

Self-Financing Trading Strategies

This table reports the mean and standard deviation of monthly excess returns on value-weighted portfolios of industries formed on the basis of related industry returns in the previous month (reported figures are annualized). Stocks with market capitalizations below the 20^{th} NYSE percentile are excluded from industry portfolios. Industries are sorted into five bins at the beginning of each month according to returns in related industries in the previous month. Self-financing trading strategies reported in the last column consist of buying the high (5) portfolio (top quintile) and selling the low (1) portfolio (bottom quintile).

Panel A: Industries Sorted on $r_{supplier,t-1}$

	Low (1)	(2)	(3)	(4)	High (5)	H - L
Mean return	0.027	0.053	0.051	0.087	0.093	0.066
Standard deviation	0.159	0.176	0.176	0.178	0.164	0.112
Sharpe ratio	0.169	0.302	0.292	0.490	0.564	0.587

Panel B: Industries Sorted on $r_{customer,t-1}$

	Low (1)	(2)	(3)	(4)	High (5)	H - L
Mean return	0.018	0.052	0.059	0.067	0.083	0.065
Standard deviation	0.178	0.165	0.154	0.167	0.185	0.136
Sharpe ratio	0.099	0.316	0.380	0.400	0.448	0.480

Panel C: Industries Sorted on $r_{composite,t-1}$

	Low (1)	(2)	(3)	(4)	High (5)	H - L
Mean return	0.012	0.041	0.063	0.073	0.090	0.078
Standard deviation	0.170	0.165	0.166	0.177	0.170	0.131
Sharpe ratio	0.072	0.246	0.381	0.413	0.531	0.592

Table IA.VI
Alternative Formation and Holding Periods

This table reports the monthly profitability of self-financing trading strategies formulated on the basis of lagged returns in related industries with various formation and holding periods (reported figures are annualized). For each trading strategy considered, industries are sorted at the beginning of each month into five bins according to their previous J-month related industry returns. The trading strategy then buys the high (5) portfolio (comprised of industries with previous J-month related industry returns in the top quintile), sells the low (1) portfolio (comprised of industries with previous J-month related industry returns in the bottom quintile) and holds the position for K months. As a result, the strategy holds in any given month a series of K portfolios that are selected in that month and as far back as K-1 months prior. t-statistics are reported in parentheses.

Panel A: Supplier Strategy

J	K = 1	3	6	12
1	0.073	0.035	0.016	0.017
	(4.27)	(3.23)	(1.91)	(2.70)
3	0.062	0.034	0.015	0.017
	(3.70)	(2.52)	(1.40)	(2.03)
6	0.032	0.015	0.017	0.015
	(1.91)	(1.03)	(1.27)	(1.38)
12	0.053	0.040	0.032	0.019
	(3.05)	(2.54)	(2.12)	(1.35)

Panel B: Customer Strategy

J	K = 1	3	6	12
1	0.070	0.021	0.016	0.016
	(3.37)	(1.60)	(1.53)	(2.07)
3	0.035	0.017	0.015	0.019
	(1.69)	(1.04)	(1.12)	(1.81)
6	0.037	0.033	0.037	0.028
	(1.74)	(1.68)	(2.10)	(1.87)
12	0.063	0.050	0.034	0.023
	(2.74)	(2.35)	(1.68)	(1.23)

Panel C: Composite Strategy

J	K = 1	3	6	12
1	0.087	0.041	0.020	0.021
	(4.26)	(3.23)	(2.04)	(2.89)
3	0.059	0.027	0.012	0.023
	(2.89)	(1.63)	(0.94)	(2.39)
6	0.052	0.026	0.026	0.027
	(2.39)	(1.41)	(1.64)	(2.06)
12	0.054	0.041	0.027	0.021
	(2.72)	(2.22)	(1.53)	(1.27)

Table IA.VII

BEA Industries

This table lists the industries in the 1987 Benchmark Input-Output Survey of the Bureau of Economic Analysis.

BEA Industry	Industry Name
1+2	Livestock and livestock products, and other agricultural products
3	Forestry and fishery products
4	Agricultural, forestry, and fishery services
5+6	Metallic ores mining
7	Coal mining
8	Crude petroleum and natural gas
9+10	Nonmetallic minerals mining
11+12	Construction
13	Ordnance and accessories
14	Food and kindred products
15	Tobacco products
16	Broad and narrow fabrics, yarn and thread mills
17	Miscellaneous textile goods and floor coverings
18	Apparel
19	Miscellaneous fabricated textile products
20+21	Lumber and wood products
22	Household furniture and fixtures
23	Non-household furniture and fixtures
24	Paper and allied products, except containers
25	Paperboard containers and boxes
26	Newspapers and periodicals, and other printing and publishing
27	Industrial and other chemicals, and agricultural fertilizers and chemicals
28	Plastics and synthetic materials
29	Drugs, and cleaning and toilet preparations
30	Paints and allied products
31	Petroleum refining and related products
32	Rubber and miscellaneous plastics products
33+34	Footwear, leather, and leather products
35	Glass and glass products
36	Stone and clay products
37	Primary iron and steel manufacturing
38	Primary nonferrous metals manufacturing
39	Metal containers
40	Heating, plumbing, and fabricated structural metal products
41	Screw machine products and stampings
42	Other fabricated metal products
43	Engines and turbines
44	Farm machinery
45	Construction and mining machinery
46	Materials handling machinery and equipment
47	Metalworking machinery and equipment
48	Special industry machinery and equipment

BEA Industry	Industry Name
49	General industrial machinery and equipment
50	Miscellaneous machinery, except electrical
51	Computer and office equipment
52	Service industry machinery
53	Electrical industrial equipment and apparatus
54	Household appliances
55	Electric lighting and wiring equipment
56	Audio, video, and communication equipment
57	Electronic components and accessories
58	Miscellaneous electrical machinery and supplies
59	Motor vehicles, truck and bus bodies, trailers, and motor vehicles parts
60	Aircraft and parts
61	Other transportation equipment
62	Scientific and controlling instruments
63	Ophthalmic and photographic equipment
64	Miscellaneous manufacturing
65	Railroads, motor freight, water and air transportation, pipelines
66	Communications, except radio and TV
67	Radio and TV broadcasting
68	Electric services, gas distribution, water and sanitary services
69	Retail and wholesale
70	Finance and insurance
71	Owner-occupied dwellings, real estate and royalties
72	Hotels and lodging places, personal and repair services except auto
73	Computer, legal, engineering, and accounting services, and advertising
74	Eating and drinking places
75	Automotive repair and services
76	Amusements
77	Health, educational and social services, and membership organizations

Table IA.VIII

BEA Industry - SIC Code Dictionary

BEA Industry	SIC Code
1+2	100-299
3	800-849, 860-919, 930-999
4	700-739, 750-799, 850-859, 920-929
5+6	1000-1079, 1090-1099
7	1200-1239, 1250-1299
8	1300-1379, 1390-1399
9+10	1400-1479, 1490-1499
11+12	1080-1089, 1240-1249, 1380-1389, 1480-1489, 1500-1799, 6550-6559
13	3480-3489, 3761, 3795
14	2000-2099, 5460-5469
15	2100-2199
16	2200-2249, 2260-2269, 2280-2289
17	2270-2279, 2290-2299
18	2250-2259, 2300-2389
19	2390-2399
20+21	2400-2499
22	2500-2519
23	2520-2599
24	2600-2649, 2660-2699
25	2650-2659
26	2700-2799
27	2800-2819, 2860-2899
28	2820-2829
29	2830-2849
30	2850-2859
31	2900-2999
32	3000-3099
33+34	3100-3199
35	3200-3229
36	3230-3299
37	3300-3329, 3390-3399, 3462
38	3330-3389, 3460-3461, 3463-3469
39	3400-3419
40	3430-3449
41	3450-3469
42	3420-3429, 3470-3479, 3490-3499
43	3500-3519
44	3520-3529
45	3530-3533
46	3534-3539
47	3540-3549
48	3550-3559
49	3560-3569
50	3590-3599
51	3570-3579

BEA Industry	SIC Code
52	3580-3589
53	3600-3629
54	3630-3639
55	3640-3649
56	3650-3669
57	3670-3679
58	3680-3699
59	3700-3715, 3717-3719
60	3720-3729, 3760, 3762-3769
61	3716, 3730-3759, 3770-3794, 3796-3799
62	3800-3849
63	3850-3899
64	3900-3999
65	4000-4299, 4400-4799
66	4800-4829, 4840-4899
67	4830-4839
68	4900-4999
69	5000-5459, 5470-5799, 5900-5999
70	6000-6499, 6700-6731, 6733-6799
71	6500-6549, 6560-6599
72	7000-7099, 7200-7299, 7600-7689
73	7300-7399, 7690-7699, 8100-8199, 8700-8732, 8734-8799
74	5800-5899
75	7500-7599
76	7800-7999
77	740-749, 6732, 8000-8099, 8200-8499, 8600-8699, 8733, 8800-8999