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Institutional Ownership and Return Predictability Across Economically Unrelated Stocks

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Keywords
institutional ownership, return predictability, anomalies, institutional trading

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Comments

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Keywords: Return predictability; anomalies; institutional ownership; institutional trading

JEL Classifications: G12; G14

The finance literature has documented that some stocks lead other stocks in returns (lead-lag cross-autocorrelation) in several different contexts, including from large to small firms within the same industry, between customer-supplier linked firms and industries, from more actively to less actively traded stocks, from high to low institutional ownership stocks, and from easy-to-analyze firms to complicated firms.[1] In all of these cases, the explanation for the lead-lag effect is slow information diffusion, often among economically linked firms and industries.[2]

This paper documents a new type of return predictability that is distinct from previous studies. We investigate whether common institutional ownership (that is, the same institution holding multiple stocks) is related to return predictability between the stocks of otherwise economically unrelated firms.[3] More specifically, can the historical return relations between economically unrelated stocks that have common institutional owners be used to predict the subsequent returns of a stock?

Our central idea is that after observing abnormal returns for one stock in his portfolio, an institutional investor is likely to revisit his investment decisions and re-optimize his entire portfolio, which can cause him to buy or sell stocks that are unrelated to the stock whose returns motivate the portfolio changes. For example, some institutional investors have limits on how much of their portfolios can be invested in a single stock, requiring them to sell a stock whose value rises above a certain level and reallocate the funds to other stocks in their portfolios.[4] Previous theoretical (e.g.,

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[1] These phenomena are documented in Cen, Ling, Chen, Dasgupta, and Gao (2013), Hou (2007), Lo and MacKinlay (1990), Cohen and Frazzini (2008), Huang and Kale (2013), Menzly and Ozbas (2010), Chordia and Swaminathan (2000), Badrinath, Kale, and Noe (1995), and Cohen and Lou (2012), respectively.

[2] Other examples of lead-lag effects caused by slow information diffusion include studies showing return predictability from high analyst coverage to low analyst coverage stocks (Brennan, Jegadeesh, and Swaminathan, 1993), from low friction stocks to high friction stocks (Hou and Moskowitz, 2005), from illiquid large stocks to smaller stocks (Chordia, Sarkar, and Subrahmanyam, 2011), from globally accessible stocks to inaccessible stocks (Bae, Ozoguz, Tan, and Wirjanto, 2012), and from industries to the market (Hong, Torous, and Valkanov, 2007).

[3] Since all firms are exposed to market shocks and macroeconomic factors such as GDP growth and inflation, they are all economically related in the broadest sense. Our definition of "economically unrelated" specifically focuses on links between firms' cash flows that could lead to information transfers between stocks, rather than common macroeconomic fundamentals that drive all stocks' returns.

[4] In a related vein, Covrig, Fontaine, Jimenez-Garces, and Seasholes (2009) and Hau and Rey (2009) examine the portfolio rebalancing effect of institutions. Another example of how price changes in some stocks may

Basak and Pavlova, 2013, and Cont and Wagalath, 2014) and empirical work (e.g., Anton and Polk, 2012) finds that institutional portfolio readjustments can lead to higher return correlations among the stocks held by an institution. When capital is slow moving (Duffie 2010) or readjustments take place periodically (e.g., weekly) rather than instantaneously, the collective actions of institutional investors can give rise to price pressures and subsequent short-term return predictability (see Section 1 for discussion of related literature).[5] We exclude economically linked firms from our analysis in order to shut down the classic cash flow links between firms, allowing a clearer focus on the role of common institutional ownership.

Our empirical design begins with identifying pairs of stocks that are from different industries and whose industries have no supplier-customer links ("unrelated stocks"). Following Menzly and Ozbas (2010) and Huang and Kale (2013), we identify supplier-customer links from the Bureau of Economic Analysis (BEA) Benchmark Input-Output Surveys. To verify that the stocks in each pair are not economically related, we also examine the correlation between their earnings surprises. The economically unrelated stock pairs have low earnings surprise correlations in general (average 0.017), and our results are robust to excluding stock pairs with significant earnings surprise correlations.

For each pair of unrelated stocks, we examine the history of how one stock's cumulative abnormal return relates to the second, economically unrelated stock's cumulative abnormal return over a subsequent week.[6] We use cumulative abnormal returns rather than raw returns in order to remove market-wide effects. We apply the coefficient estimates from a historical regression to the

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induce institutional trading in other stocks is provided by Hau and Lai (2012), who find evidence consistent with mutual funds that have high exposure to financial stocks engaging in asset fire sales of non-financial stocks during the 2007 financial crisis. Similarly, Broner, Gelos, and Reinhart (2006) document how fund trading can propagate financial crises.

[5] Chakrabarty, Moulton, and Trzcinka's (2015) model shows that rationally optimizing portfolio managers weigh the cost of readjustment (including price pressures) against the cost of being away from their desired portfolio allocations. Thus the mere existence of price pressures does not necessarily keep institutional investors from trading.

[6] For brevity, we often refer to cumulative abnormal returns as simply "returns"; all of our analyses are based on cumulative abnormal returns, as defined in Appendix A. Details of the return prediction methodology are contained in Section 2.4.

first stock's recent performance, in order to predict the second stock's future weekly cumulative abnormal return. We then aggregate multiple return predictions (based on different economically unrelated stocks) for each stock and sort the stocks into industry-neutral portfolios based on their average predicted returns.[7]

We find strong weekly return predictability from economically unrelated stocks. During the 1980 to 2010 sample period, the industry-neutral long-short hedge portfolio, which is long (short) the stocks with the highest (lowest) predicted returns, earns an average of over 19 basis points per week (with a *t*-statistic above five), implying an annualized average return of nearly 10%. This return predictability arises exclusively from the pairs of stocks in which there are common institutional owners. When we forecast returns using only pairs of unrelated stocks that do not share common institutional owners, we find insignificant return predictability.

We examine numerous alternative explanations and find that our results are distinct from previously documented return predictability. Our results are not explained by industry or supplier-customer linkages between firms, as we exclude all such economically related stock pairs from our analysis. Industry and sector rotation do not explain our results, since our strategy employs industry-neutral portfolios. Our findings are not explained by previously documented lead-lag relations arising from slow information diffusion, including from large to small firms, more actively traded to less actively traded stocks, high institutional ownership to low institutional ownership stocks, and high analyst coverage to low analyst coverage stocks. Our documented predictability is also distinct from well-known return anomalies including size effects, book-to-market effects, weekly and monthly return reversals, long-run reversals, price momentum, earnings momentum, liquidity effects, and trading volume effects. Our results are not due to nonsynchronous trading or seasonality. Our sample includes only stocks with share prices not less than $5 at the end of the prior quarter, and the return predictability results are qualitatively unchanged when we use only

[7] Note that this is not a pairs trading strategy, although pairs of economically unrelated stocks are used to predict returns.

stocks that trade every day in the previous 12 months. Overall, we find a novel, highly robust link between common institutional ownership and return predictability for economically unrelated stocks.

To investigate the mechanism through which common institutional ownership is associated with return predictability among economically unrelated stocks, we analyze changes in quarterly institutional holdings. We find that institutions accumulate more of stocks in the highest predicted-return quintile than in the lowest predicted-return quintile, linking return predictability to institutional portfolio changes. We also explore the mechanics of the return signals arising from the economically unrelated stock pairs and find patterns consistent with cross-stock reallocations within institutions.

The remainder of the paper is organized as follows. Section 1 describes related literature on institutional investors and stock returns. Section 2 presents the data and our methodology for constructing return predictions and forming portfolios. Section 3 presents the main results on return predictability among economically unrelated stocks with and without common institutional owners. Section 4 investigates other possible explanations for return predictability in economically unrelated stock pairs. Section 5 examines how the predictability relates to changes in institutional holdings. Section 6 discusses additional analyses and robustness checks, and Section 7 concludes. Appendix A contains variable definitions. Appendix B provides a detailed example of how return predictions are determined using a specific pair of unrelated stocks.

1. Relation to literature on institutional investors and stock returns

Our paper builds on and contributes to recent literature on how institutional ownership may affect stock return variance or correlations. Greenwood and Thesmar (2011) show that “fragile” stocks (i.e., stocks with high percentages held by a few institutions) have high volatility. Anton and Polk (2012) show that the degree of common institutional ownership forecasts cross-sectional variation in return correlation, and Bartram, Griffin, Lim, and Ng (2013) show that foreign ownership linkage is an important driver of the covariation of returns for stocks in different countries. These studies suggest that simply by investing in multiple stocks, institutional investors may affect the contemporaneous return correlations between stocks.[8] In addition, capital can be slow moving as Duffie (2010) suggests. Institutions may re-adjust their portfolios periodically (for example, weekly) rather than instantaneously. In this case, common institutional ownership could affect not only contemporaneous return correlations but also cross-autocorrelations of stocks they hold. Our study focuses on the unexamined question of whether common institutional investment is associated with lead-lag return predictability across different stocks. By examining the return predictability of economically unrelated stocks owned by the same institution, our study focuses on common institutional ownership in the absence of information links between firms.

Our paper is also related to, but distinct from, recent papers that emphasize fund flows as a mechanism that creates price pressure. Coval and Stafford (2007) find that funds experiencing large outflows create price pressures on stocks held in common by distressed funds, while Jotikasthira, Lundblad, and Ramadorai (2012) document fire sale effects in emerging markets. Frazzini and Lamont (2008) find that mutual fund flows negatively predict future long-term returns, while Lou (2012) finds that the mutual fund flow-driven return effect can partially explain stock price momentum. While these papers focus on how capital inflows and outflows induce trading that in turn affects stock prices, our paper investigates a different mechanism: the reallocation of institutional investors' capital from some stocks to others, which occurs whenever institutional investors adjust their portfolios, not only when large inflows or outflows occur.

This work contributes to our understanding of how institutional trading may affect returns. Previous empirical papers have documented that mutual fund herding may move the price of small stocks in subsequent quarters (Wermers, 1999; Sias, 2004). There are generally three explanations

[8] Similarly, the accounting literature documents evidence of institutional ownership affecting stock returns around earnings announcements (e.g., Potter, 1992; Bartov, Radhakrishnan, and Krinsky, 2000).

offered for why institutional trading may affect subsequent stock returns (Sias, Starks, and Titman, 2006). One is that institutions uncover private information about individual stocks and reveal it through their trading, leading to permanent price effects (e.g., Easley and O'Hara, 1987; Kyle, 1985; Boehmer and Kelley, 2009). A second explanation for a permanent price effect from institutional trades is that investors view stocks as imperfect substitutes and their long-term supply and demand curves are not perfectly elastic. Thus the non-institutional traders who are on the other side of aggregate institutional trades demand lower (higher) prices to buy (sell) stocks (e.g., Shleifer, 1986; Bagwell, 1991; Lynch and Mendenhall, 1997; Greenwood, 2005). The third explanation implies a temporary price effect from institutional trading. Institutional trading may affect stock prices if it pushes liquidity providers away from their preferred inventory position (e.g., Stoll, 1978; Grossman and Miller, 1988) or if there is slow movement of investment capital to trading opportunities (Duffie, 2010). We find that the return predictability from unrelated stocks is a temporary price effect, yielding the highest return in the first week after portfolio formation and then reversing in the following weeks. This pattern suggests that the return predictability arises primarily because aggregate trading from institutional portfolio adjustments results in temporary price pressures, rather than because institutions are trading on superior information or long-term supply and demand curves for non-institutional traders are elastic.

2. Data and methodology

Our analysis uses stock return data from the Center for Research in Security Prices (CRSP), earnings announcement and accounting data from Compustat, analyst forecast data from the Institutional Brokers' Estimate System (I/B/E/S) from Thomson Reuters, 13F institutional holdings data from Thomson Reuters, and information on customer-supplier industry links from the Bureau of Economic Analysis (BEA) Benchmark Input-Output Surveys.[9] Our sample period is January 1980 to December 2010; we start our sample in 1980 because that is when the institutional holdings data begin. We begin with the universe of all common stocks (CRSP share codes 10 and 11) listed on NYSE, AMEX, and NASDAQ, and apply the following screens to create our sample of weekly observations: the share price at the end of the previous quarter must be greater than or equal to $5; the firm must be present in Compustat data for at least the prior two years; and the most recent earnings announcement must be regular and on time (i.e., the firm makes four quarterly earnings announcements each year and has earnings announced during the three-month period after the end of each fiscal quarter). In Appendix A we provide a description of all variables used in our empirical analyses.

2.1 Economically unrelated stock pairs

Pairs of economically unrelated stocks are the focus of this study. Each stock whose return we are interested in predicting ("target stock") is matched with multiple economically unrelated stocks ("unrelated stocks") as follows. For each target stock in our sample each week, we identify all other stocks that do not have the same Fama-French 30 industry classification. We then determine the industry code for each stock and retain only those stocks (unrelated stocks) that are from industries that show zero dollar value of inputs/outputs between them and the industry of the target stock in the most recent BEA survey.[10] We thus make sure that we are considering only stock pairs that have no industry or cash flow links between them. We recognize that despite these precautions, there still could be some more subtle economic relations between any two firms, so in

[9] The BEA data are publicly available at http://www.bea.gov/industry/index.htm. In using the BEA data we follow Menzly and Ozbas (2010), who point out that the BEA surveys provide a more complete picture in identifying economically related stocks than the Compustat customer information database used in Menzly and Ozbas (2004) and Cohen and Frazzini (2008).

[10] We use BEA's standard make and use tables at the detailed level, which identify 484, 496, 537, 542, 498, 498, 511, and 537 industries in the surveys from 1967, 1972, 1977, 1982, 1987, 1992, 1997, and 2002, respectively. The BEA survey uses Standard Industry Codes (SIC) prior to 1997 and North American Industry Classification System (NAICS) codes from 1997 on. We merge SIC and NAICS codes as in Menzly and Ozbas (2010).

our robustness checks we exclude any stock pairs that have significant unexpected earnings correlations over our sample period (see Section 6.3).

2.2 Institutional ownership

We count the number of common institutional owners and the number of significant common institutional owners for each pair of economically unrelated stocks using the quarterly 13F institutional holdings data. Common institutional owners are defined as the same institutional investor holding positions in two stocks as of the prior quarter-end. Because we expect that any return predictability connected to institutional trading should be stronger when institutions have larger common holdings, we further categorize common institutional ownership as "significant" if an institution holds more of each stock than the median institutional holder of that stock. For example, if the median institutional holding in stock A is 0.4% of shares outstanding and the median institutional holding in stock B is 0.1%, we define an institution that holds more than 0.4% of stock A and more than 0.1% of stock B as a significant common owner.

For our main analyses, we identify a stock pair as having common institutional ownership if it has common institutional owners on all of the prior 20 quarter-ends, while a stock pair would have no common institutional ownership if it has no common institutional investor in any of the prior 20 quarter-ends.[11] Similarly, a pair of stocks would have no significant common institutional owners if there is no significant common institutional investor in any of the past 20 quarter-ends.

2.3 Sample descriptive statistics

Table 1 presents descriptive statistics for the stocks in our sample. Our sample comprises 13,109 stocks. Panel A of Table 1 shows that institutions hold 41.2% of a firm's outstanding stock

[11] Results are robust to determining common ownership based on institutional holdings as of only the prior quarter-end, as in Anton and Polk (2012), rather than over the prior 20 quarters. We focus on the prior 20 quarters for our main analyses because our predicted returns are based on a trailing five-year regression analysis, as described in Section 2.4 below.

on average, and the average firm has 93 institutional investors. Panel B provides some basic statistics about the pairs of economically unrelated stocks. On average there are 215 unrelated-stock pairs for each target stock.[12] Of the average 215 economically unrelated pairs of stocks, 188 have significant common institutional investors and 206 have common institutional investors. We note the small number of economically unrelated pairs that have no significant common institutional owners (an average of 20) or no common institutional owners (an average of 10); in our robustness checks we verify that the small number of pairs in these categories does not drive our results. On average there are 10 significant common institutional investors per stock pair and 27 common institutional investors per stock pair. The prevalence and variation of institutional ownership make this a promising sample in which to examine the link between institutional ownership and return predictability.

[Table 1 here]

2.4 Return prediction and portfolio formation methodology

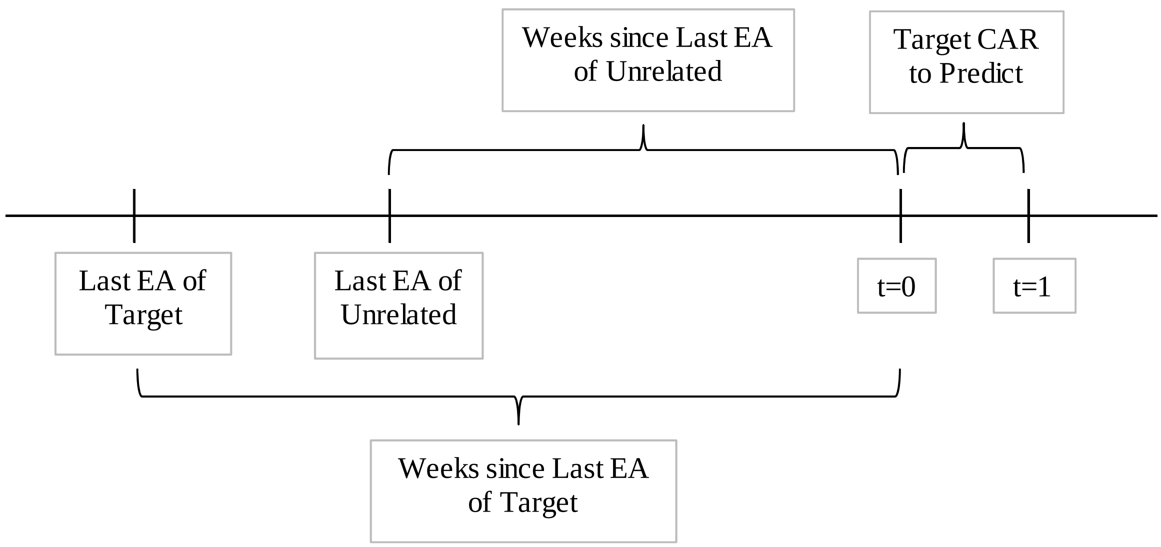
The underlying mechanism we envision is that information about a specific economically unrelated stock affects investment decisions in the target stock because the portfolio manager re-optimizes his entire portfolio, trading many stocks (including the target stock), not just the one whose price has changed. To determine which stock in an unrelated stock pair is the target stock (whose return is being predicted) and which is the unrelated stock (whose return is used to predict the target's return), we determine which stock has had a more recent earnings announcement.[13] The stock with the most recent earnings announcement date is designated the unrelated stock and used to predict the return of the target stock.

[12] In our robustness checks we test whether predictability is significantly affected by the number of economically unrelated pairs available.

[13] Other information events, such as dividend payout announcements, merger and acquisition announcements, and idiosyncratic firm news, do not occur with enough regularity to facilitate broad analysis. Note that in this exercise we are not exploiting the information transfers among firms within the same industry, because we explicitly exclude stock pairs from the same or related industries.

To illustrate our return prediction methodology, consider one target stock and one unrelated stock in a particular week. We count the number of full weeks since the unrelated stock's last earnings announcement and the number of full weeks since the target stock's last earnings announcement; see Figure 1.

Figure 1: Timing for return prediction methodology



We then search the previous five years to find occasions when the unrelated stock was exactly the same number of weeks past its most recent earnings announcement and the target stock's last earnings announcement was at least one week prior to the unrelated stock's.[14] For each occasion in the last five years, we calculate the unrelated stock's average cumulative abnormal return (CAR) over its post-earnings-announcement weeks until the week of interest.[15] We also calculate the CAR for the target stock over the subsequent week.

We regress the target stock's subsequent-week CAR on the average CAR of the unrelated stock over the previous weeks since the unrelated stock's earnings announcement. We use data

[14] In using five years of earnings history we follow the literature on earnings releases and anomalies (e.g., Foster, Olsen, and Shevlin, 1984). The target stock is not allowed to have more than 12 post-earnings-announcement weeks because firms generally announce their quarterly earnings every three months.
[15] We require at least three years of earnings announcement date history and at least 10 valid occasions to estimate the regression for a stock pair. Since firms generally time their earnings announcements similarly across quarters and years, we typically find an adequate number of valid occasions.

from all eligible historical periods to run the regression and obtain the coefficients. We apply the coefficients from the historical regression to the average CAR for the unrelated stock over its current post-earnings-announcement weeks to predict the target stock's return for the next week. Appendix B contains a detailed example of the prediction methodology for one pair of economically unrelated stocks.

For each target stock, we calculate the predicted CAR for the next week based on each of its unrelated stocks. We calculate the target stock's average predicted CAR for the next week as the mean of the predictions from all of its unrelated stocks.[16] Note that since the predicted return and the stock returns used to predict it are all cumulative abnormal returns, market-wide effects are already removed.

Finally, we form industry-neutral quintile portfolios based on the target stocks' predicted returns, to prevent our results from being driven by industry rotation.[17] We repeat this procedure for all stocks each week to form weekly quintiles based on predicted weekly returns.

Table 2 presents descriptive statistics for the quintile portfolios, which form the basis for our tests. We calculate simple averages of firm-level characteristics for stocks within each quintile and then report time-series averages of each quintile's characteristics from January 1980 to December 2010. Panel A shows that there are variations across the predicted-return portfolios in terms of the component stocks' size, book-to-market, lagged returns, volatility, liquidity, and trading volume. For example, the predicted-CAR-sorted portfolios are monotonically decreasing in book-to-market and increasing in price momentum over the previous year (Return month t-12 to

[16] We also consider the weighted mean of the predictions from unrelated stocks where weights are based on the precisions of predicted values. The results are qualitatively similar to those based on the simple average.
[17] To form industry-neutral quintile portfolios, we identify all of the target stocks by their Fama-French 30 industries, and within each industry we sort the target stocks into five groups (each containing 20% of the stocks in that industry): Group 1 contains the target stocks with the lowest predicted returns for the following week, and Group 5 contains the target stocks with the highest predicted returns for the following week. We then form industry-neutral portfolios by combining the target stocks in Group 1 from all 30 of the Fama-French industries into a single Quintile 1 portfolio, and similarly with the remaining four groups to form the five industry-neutral predicted-return portfolios.

t-2). Therefore in addition to investigating the potential relation of return predictability to common institutional ownership, we examine other previously documented explanations for return predictability, such as size, book-to-market, momentum, reversals, and liquidity, in Section 4. Panel B shows that return autocorrelations are generally small in each of the quintile portfolios.

[Table 2 here]

3. Return predictability and common institutional ownership

Table 3 presents our core results on return predictability from economically unrelated stock pairs, using all economically unrelated stock pairs to predict returns. We report the value-weighted weekly excess return (ER) and value-weighted alphas from Capital Asset Pricing Model (CAPM), Fama-French three-factor (FF3), and Fama-French-Carhart four-factor (FFC4) regressions for each portfolio (Fama and French, 1993; Carhart, 1997).[18] The excess returns and alphas are reported in percent; for example, the excess return of 0.020 for Quintile 1 represents 2.0 basis points per week. Quintile 1 (5) is an industry-neutral portfolio containing stocks with the lowest (highest) predicted returns, and the bottom row tests the return difference between Quintile 5 and Quintile 1 (Q5-Q1 spread), the classic long-short portfolio. We find strong return predictability in this long-short portfolio, with weekly excess return and Fama-French-Carhart alpha both over 19 basis points and *t*-statistics of 5.3 and 5.7, respectively.[19]

[18] All results are qualitatively similar when returns are equal-weighted rather than value-weighted. We use value-weights rather than equal-weights in the calculation of daily portfolio returns for the following three reasons: (1) equal-weighting of daily returns leads to portfolio returns that may be overstated because of the so-called "bid-ask bounce effect" (see Blume and Stambaugh, 1983; and Canina, Michaely, Thaler, and Womack, 1998); (2) equal-weighting of daily returns essentially assumes daily rebalancing of portfolios, which could further overstate the economic magnitude of the returns: and, (3) value-weighting of daily returns better captures the economic significance of the covariance implied returns because equal-weighting of returns over-represents smaller firms. Value-weighting may bias against finding any evidence of abnormal returns, since stocks with larger market capitalization are more likely to be informationally efficient -- including efficiency in the incorporation of information from the early announcers.

[19] Factor loadings from the four-factor Fama-French-Carhart regressions are reported in the Internet Appendix.

[Table 3 here]

Figure 2 graphs annual long-short portfolio returns and Sharpe ratios over the 31-year period. The long-short hedge portfolio annual return is calculated as the average weekly excess return times the number of weeks in the year. The Sharpe ratio divides the annual excess return by the annualized standard deviation of weekly returns. The annual return is positive in all but three years of the sample period and notably remains positive even during the financial crisis in 2007-2009.

[Figure 2 here]

We next calculate predicted returns using subsets of the economically unrelated stock pairs. In Panel A of Table 4, we calculate predicted returns for each stock first using only stock pairs that have significant common institutional owners, and then using only stock pairs that have no significant common institutional owners. Panel A compares the weekly return performance of each set of predicted return quintile portfolios. Portfolios formed based on predicted returns from stocks with significant common institutional owners (the first four columns) show strong predictability: The excess return difference in the long-short portfolio is 19.8 basis points per week with a *t*-statistic of 4.8. In contrast, portfolios formed using only predicted returns from stocks with no significant common institutional owners (the middle four columns) show insignificant return spreads in the long-short portfolio: spreads of less than five basis points per week with *t*-statistics just over one. The final four columns show that the difference between the long-short portfolio returns using stock pairs with versus without significant common institutional owners is also significant. The excess return difference is estimated at 15.5 basis points, risk-adjusted alphas are of similar magnitude, and all are significant. Panel B shows that basing return predictions on stock pairs with common institutional owners yields similar results. The difference between long-short portfolio returns based on stock pairs with versus without common institutional owners is 16.5 basis points in excess return with a *t*-statistic of 2.2. All of these results support our conjecture that return predictability among economically unrelated stocks is related to common institutional ownership.

[Table 4 here]

We extend our analysis of one-week return predictability with versus without significant common institutional investors by calculating the weekly Fama-French-Carhart 4-factor alpha for each portfolio and the long-short portfolio strategy from one week to twelve weeks after portfolio formation. Figure 3 shows that the first-week alpha is much higher for the long-short strategy based on stock pairs with significant common institutional investors, as in Table 4, Panel A. The abnormal returns dissipate quickly and are reversed in the following weeks, leading to cumulative average weekly returns near zero for the longer holding periods, consistent with institutional investors' trading patterns creating temporary price pressures (e.g., Stoll, 1978; Grossman and Miller, 1988; Duffie, 2010). The timing of the reversals over the following several weeks is consistent with that of other reversals documented in the literature (e.g., Cohen and Lou, 2012; Coval and Stafford, 2010).

[Figure 3 here]

4. Alternative explanations for return predictability

In this section we examine whether our findings on the link between common institutional ownership and return predictability could simply be a manifestation of other factors that are already known to be related to return predictability.

Table 5 examines lead-lag effects. Return predictability is known to be related to the relative size of firms, with large-firm returns leading small-firm returns (e.g., Lo and MacKinlay, 1990; and Hou, 2007). Panel A shows that our predictability results are significant when predicted returns are calculated based on stock pairs in which the target firm is from a larger or equal size decile than the economically unrelated stock used to predict its return (left panel) and when the target firm is smaller (right panel).[20] Cohen and Lou (2012) find that the returns of stand-alone firms, which operate in only one industry, can be used to predict the returns of conglomerates, which are involved in multiple industries but are assigned a single SIC code that reflects the firm's main industry segment. To verify that our results are not driven by the presence of conglomerates, we run our analysis using stock pairs in which all of the stocks are stand-alone firms and, separately, all of the stocks are conglomerates.[21] Panel B shows that our results are robust to excluding conglomerates.

Chordia and Swaminathan (2000) find a lead-lag effect from more actively traded stocks to less actively traded stocks. Panel C shows that our predictability results are significant when predicted returns are calculated separately based on stock pairs in which the target firm is from a larger or equal NYSE/AMEX volume decile than the economically unrelated stock (left panel) and when the target firm is from a smaller volume decile (right panel). Panel D presents analogous results using pairs of NASDAQ stocks.

Badrinath, Kale, and Noe (1995) find that stocks with high institutional ownership lead the returns of stocks with low institutional ownership. Panel E shows that our predictability results are significant when predicted returns are calculated separately based on stock pairs in which the target firm has higher or equal decile institutional ownership than the economically unrelated stock (left panel) and when the target firm has lower decile institutional ownership (right panel).

Brennan, Jegadeesh, and Swaminathan (1993) find return predictability from stocks with high analyst coverage to stocks with low analyst coverage. Panel F shows that our results are robust to using stock pairs in which the target firm has higher or equal (left panel) or lower (right panel)

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[20] Hou (2007) shows that the lead-lag effect from large firms to small firms is mainly driven by intra-industry effects; since we exclude firm pairs within the same industry, our findings are not a contradiction of his.

[21] We thank Dong Lou for sharing his list of conglomerates and stand-alone firms.

analyst coverage than the unrelated stock. In short, none of the previously documented lead-lag relationships explain our results.

[Table 5 here]

We next conduct double portfolio sorts in Table 6 to examine whether other documented return anomalies can explain our results. Previous literature has documented return anomalies due to size and book-to-market (Fama and French, 1992), past 1-week returns (Lehmann, 1990), past 1-month returns (Jegadeesh, 1990), past 12-month returns up until the prior month (Jegadeesh and Titman, 1993), earnings surprise (Chan, Jegadeesh, and Lakonishok, 1996; Sadka, 2006), illiquidity (Amihud, 2002), and trading volume (Chordia and Swaminathan, 2000). A natural question is whether our results could be due to one of these well-documented effects rather than institutional ownership per se (for example, we know from Table 2 that our predicted-CAR-sorted portfolios are monotonically decreasing in book-to-market and increasing in prior-year price momentum). Thus our interest in these double sorts is whether we find predictability (significant Quintile 5 minus Quintile 1 differences) within secondary sorts on each of these stock characteristics.

Table 6 reports double sorting results in which we conduct independent, industry-neutral sorts on predicted CARs and firm size, book-to-market equity, weekly return reversals, monthly return reversals, momentum, long-run return reversals, earnings momentum, liquidity, and NYSE/AMEX trading volume and turnover. We find that our return predictability is robust to all of these secondary portfolio sorts. In particular, our results are not driven by weekly or monthly return reversal or momentum effects. For brevity, we report only the top and bottom predictability quintiles and their differences in Table 6; full results are reported in the internet appendix.

[Table 6 here]

Next we conduct Fama-MacBeth (1973) cross-sectional regressions to test whether the return predictability arising from economically unrelated stocks remains significant in a multivariate setting that includes explanatory variables previously linked to return predictability.

Table 7 presents the results of the time-series average of Fama-MacBeth regression coefficients (and *t*-statistics) when we regress stocks' weekly excess returns on the previously predicted CARs. In particular, we use each stock's predicted-return quintile number (5=highest predicted return, 1=lowest) as the first explanatory variable, and we include other known explanatory factors as control variables in alternate specifications. In specifications (1) and (2), the predicted CARs are based on all economically unrelated stock pairs. The coefficient on the predicted CAR is positive and highly significant, showing that the predictability documented in this paper is not subsumed by return reversals, price momentum, earnings momentum, or other firm characteristics including market capitalization, book-to-market equity, operating accruals, net stock issuance, idiosyncratic volatility, or Amihud illiquidity.

In specifications (3) and (4), the predicted CARs are based on only economically unrelated stock pairs with significant common institutional owners. The coefficients on predicted CAR remain positive and highly significant. In contrast, the coefficients on predicted CAR are insignificant in specifications (5) and (6), where the predicted CARs are based on pairs with no significant common institutional owners. Taken together, the results in Tables 5, 6, and 7 confirm that the return predictability is driven by stock pairs with significant common institutional owners and is not subsumed by other documented sources of predictability.

[Table 7 here]

5. Institutional portfolio changes and return predictability

In this section, we analyze institutional portfolio changes to see whether they are consistent with our notion of how common institutional ownership is related to return predictability between economically unrelated stocks. We examine the changes in quarterly institutional holdings of stocks in the high versus low predicted return quintiles. We posit that institutions increase their holdings more in stocks that rank in the highest predicted return quintile (Quintile 5) than stocks in the lowest predicted return quintile (Quintile 1). Quintile portfolios are formed weekly, but institutional holdings are reported only quarterly, so we focus on stocks that are consistently ranked in the same quintile throughout the calendar quarter. Table 8 presents the change in percentage institutional ownership for stocks consistently ranked in each predicted return quintile during the same calendar quarter.

[Table 8 here]

Panel A of Table 8 presents the results for stocks that are in the same quintile portfolio for at least 75% of the weeks in the quarter. Panel B takes an alternative definition of consistently, based on stocks that are in the same quintile portfolio for at least 50% of the weeks in the quarter. Overall, the results show that institutional investor ownership increases more for stocks with the highest predicted returns (Quintile 5) than for those with the lowest predicted returns (Quintile 1). For example, Panel A shows that the average change in percentage institutional ownership is more than one percentage point greater for Quintile 5 than for Quintile 1 stocks, and the difference is significant. This evidence is consistent with the notion that institutional trading activity induces the return predictability among economically unrelated stocks.

6. Additional analyses and robustness checks

6.1 Positive versus negative predicted returns

The intuition behind our empirical set-up is that after observing the return on one stock he owns, a portfolio manager decides to buy or sell a different, economically unrelated stock. If he wants to buy, he could either buy more of a stock he already owns or buy another stock, but if he wants to sell, his choices are likely limited to stocks he already owns. Thus stocks may experience more selling rather than buying pressures from owners who reallocate from their other portfolio holdings. Based on this intuition, we might expect the return predictability to be stronger for stocks when the signals from the economically unrelated stocks suggest selling (i.e., a negative predicted return).

In Table 9, we predict returns separately for stocks using only the signals from economically unrelated stocks with significant common institutional investors that predict a negative return versus only signals that predict a positive return. As we are using only a subset of the available signals (positive or negative) for each stock, we expect the resulting predicted return for each stock to be noisier and the Quintile 5 minus Quintile 1 spread within each subset to be less significant.

[Table 9 here]

Panel A shows some predictability when we use only the negative signals, but we find no predictability when we use only the positive signals. Using only pairs predicting negative returns, the Quintile 5 minus Quintile 1 spread after controlling for Fama-French and Fama-French-Carhart factors is significant. In contrast, using only pairs predicting positive returns, none of the Quintile 5 minus Quintile 1 differences are significant. These subset results are consistent with our expectation that return predictability is stronger for stocks when the signals from the economically unrelated stocks suggest selling (i.e., a negative predicted return).

In Panel B we investigate the negative-predicted-return signals in more detail, bearing in mind that the more finely we separate the subsets the harder it is to see any predictability within the subset. Negative-predicted-return signals can arise in two ways. First is an unrelated-stock-loss channel. After one stock's price declines, institutional investors may sell another stock in order to reduce their equity exposure (similar to Kodres and Pritsker, 2002) or to meet liquidity demands (Coval and Stafford, 2007). In our empirical set-up, such cases arise when two stocks have a positive historical correlation and the unrelated stock has a negative recent return. Second is a return-chasing channel. After one stock's price rises, in order to increase their investment in that stock institutional investors may sell another stock (Bohn and Tesar, 1996). In our setting, this happens when two stocks have a negative historical correlation and the unrelated stock has a positive recent return. Panel B presents the results separately for the unrelated-stock-loss and return-chasing channels. We find some support for the unrelated-stock loss channel (Fama-French and Fama-French-Carhart Q5-Q1 spreads are significant) and less support for the return-chasing channel (only Fama-French Q5-Q1 spread is significant).

6.2 Seasonality

Previous literature suggests that institutional investors are more concerned about readjusting their portfolios at certain times of the year, such as at quarter-ends and month-ends (e.g., Lakonishok, Shleifer, Thaler, and Vishny, 1991; Moulton, 2005). In our context, we thus expect to see stronger predictability arising at quarter- and month-ends, and a natural question is whether all of the predictability is driven by the last week of the month or quarter. In Panel A of Table 10 we separate out the last week in each calendar quarter, and in Panel B we separate out the last week in each month. We find larger Quintile 5 minus Quintile 1 return differences in the end-of-quarter and end-of-month weeks than other weeks, although the non-end-of-quarter and non-end-of-month differences remain significant. The higher predictability in quarter-end and month-end weeks is consistent with increased portfolio adjustments at those calendar intervals.

[Table 10 here]

6.3 Narrower definition of economically unrelated stocks

Even though the stock pairs we identify have no direct cash flow links (since they are from different industries that have zero dollar value in the standard BEA make-use tables at the detailed level), it is possible that they could have some more subtle economic links that our methodology does not capture. To account for this possibility, we examine the correlations between unexpected earnings for each pair of economically unrelated stocks over our entire sample period. As Panel A of Table 11 shows, the average correlation is only 0.017. About 9.5% of the stock pairs in our sample exhibit significant correlations between their unexpected earnings. In Panel B of Table 11, we exclude all stock pairs that have significant correlations between their unexpected earnings, calculate predicted returns, and repeat our quintile sorts. The Quintile 5 minus Quintile 1 return differences range from 17.2 to 20.4 basis points and remain statistically significant, suggesting that our results are not driven by some more subtle economic link between the stocks in each pair.

[Table 11 here]

6.4 Simulation exercise

To verify that our main results on the link between return predictability and institutional ownership are not driven by the small number of economically unrelated stock pairs with no significant common (or no common) institutional investors, we perform simulation exercises as follows. For each target firm, we count the number of stock pairs with no significant common (no common) institutional investors, randomly draw the same number of pairs from among the pairs with significant common (common) institutional investors to predict returns, and form quintile portfolios. We run 1000 simulations, and the results, reported in Table 12, show that long-short portfolio excess returns and alphas from these matched-number-of-pairs strategies remain significantly positive and are more than double the returns for the strategy based on stock pairs with no significant common (no common) institutional investors (reported in Table 4).

[Table 12 here]

6.5 Other robustness checks

We conduct two additional tests to confirm the robustness of our results (results are in internet appendix). To verify that our predictability findings are not due to non-synchronous trading, we restrict stocks to those that have traded every day in the prior 12 months, which yields identical inference. To determine whether the predictability is driven by stocks that have the most (or fewest) economically unrelated stock pairs, we perform a double sort, with the secondary sort on the number of stock pairs used to predict the target stock's return. We find strong and significant predictability across all of the secondary sorts, showing that the predictability is not driven by stocks with the most or fewest pairs.

7. Conclusion

In this study we document a new type of lead-lag return predictability that yields weekly long-short portfolio returns of over 19 basis points. This predictability is distinct from previously documented lead-lag effects driven by slow information diffusion, as we focus on economically unrelated stock pairs (stocks from different industries with no supplier-customer links). We find that stock pairs with common institutional investors can be used to predict subsequent returns, while stock pairs without common institutional investors yield insignificant predictability. The predictability is reversed in subsequent weeks, consistent with temporary price pressures and the general pattern of institutional trading. The predictability is not explained by any previously identified factors and is consistent with optimizing behavior of institutional portfolio managers. Overall, the picture that emerges suggests that by adjusting their portfolios in systematic ways, institutional investors themselves affect stock returns and covariances and thus can induce return predictability. That said, our main interest is in documenting a new type of lead-lag return predictability, and we cannot unequivocally establish the direction of causality in our study.

We limit our study to economically unrelated stocks in order to focus on the role of common institutional investment, shutting down the cash flow links between firms that may lead to information spillovers affecting trading. Including pairs of stocks from the same or related industries should strengthen the predictability results and may be of more interest to practitioners. Similarly, one could allow industry concentration in the portfolios, to pick up possible industry or sector rotation effects, rather than constructing industry-neutral predicted return portfolios, as we do in this study.

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Appendix A: Brief definitions and sources of main variables

This table briefly defines the main variables used in the empirical analyses. The data sources are:

(i) CRSP: Center for Research in Security Prices database

(ii) Compustat: North America Annual and Quarterly database

(iii) I/B/E/S: Institutional Brokers' Estimate System database from Thomson Reuters

(iv) 13F: Institutional Holdings database from Thomson Reuters

(v) BEA: Bureau of Economic Analysis Benchmark Input-Output Accounts

(vi) Estimated: Estimated by the authors

Panel A: Stock characteristics

Variable Name	Description	Source
Price	Price at end of previous quarter.	CRSP
Market capitalization	Price times shares outstanding, at end of previous quarter.	CRSP
Book-to-market equity	Annual book value of equity divided by market value of equity, at end of previous quarter.	Compustat
Idiosyncratic volatility	Idiosyncratic volatility calculated from daily Fama-French three-factor regression residuals over a one-year period, at end of previous month (Ang, Hodrick, Xing, and Zhang, 2006).	CRSP, estimated
Amihud illiquidity	Average of daily absolute value of return divided by dollar volume over a one-month period, at end of previous month, scaled by 10^6 (Amihud, 2002).	CRSP, estimated
NYSE/AMEX volume	NYSE/AMEX share trading volume (in thousands), at end of previous month.	CRSP
NYSE/AMEX turnover	NYSE/AMEX share turnover (in percent), at end of previous month.	CRSP
NASDAQ volume	NASDAQ share trading volume (in thousands), at end of previous month.	CRSP
NASDAQ turnover	NASDAQ share turnover (in percent), at end of previous month.	CRSP

Earnings surprise	Standardized unexpected earnings (SUE) based on seasonal random walk model with drift, at end of previous quarter (as in Chan, Jegadeesh, and Lakonishok, 1996; Sadka, 2006).	Compustat, estimated
Operating accruals	The change in current assets excluding cash and short-term investments, minus the change in current liabilities excluding short-term debt and taxes payable, minus the change of depreciation and amortization at end of previous quarter (as in Sloan, 1996).	Compustat
Net stock issuance	The log level change in split-adjusted shares outstanding, at end of previous month (as in Fama and French, 2008).	CRSP

Panel B: Stock returns

Variable Name	Description	Source
Cumulative abnormal return (CAR)	Daily abnormal return is calculated as the daily holding period return (RET) minus the value-weighted market index return (VWRET); weekly cumulative abnormal return (CAR) is the compounded daily abnormal returns over one week. If there are weeks with fewer than five trading days (because of holidays), we scale the CAR by dividing by the number of trading days and multiplying by five.	CRSP, estimated
Return week t-1	Weekly holding period return (compounded daily returns as of the end of previous week t-1).	CRSP
Return month t-1	Monthly holding period return at end of previous month t-1.	CRSP
Return month t-12 to t-2	Past 11-month cumulative returns from t-12 to t-2.	CRSP
Return month t-60 to t-13	Past 48-month cumulative returns from t-60 to t-13.	CRSP

Panel C: Institutional ownership

Variable Name	Description	Source
Institutional ownership %	Shares held by 13F institutions divided by total shares outstanding, at end of previous quarter.	13F and CRSP
# Institutional investors	Number of institutional investors in a stock as of previous quarter-end.	13F
# Common institutional investors	Number of institutional investors holding both stocks in a pair as of previous quarter-end.	13F, estimated
# Significant common institutional investors	Number of institutional investors holding more than the median institutional holder of both stocks in a pair as of previous quarter-end.	13F, estimated

Appendix B: Example of stock prediction methodology

We provide an example using one weekly observation date for a target stock and an economically unrelated stock. Our strategy is to first identify the current position of the two stocks relative to their most recent earnings announcement dates, then identify similar patterns in the historical sequence of earnings announcements, and finally use the two stocks' historical abnormal return relationship to predict one-week-forward CAR for the target stock.

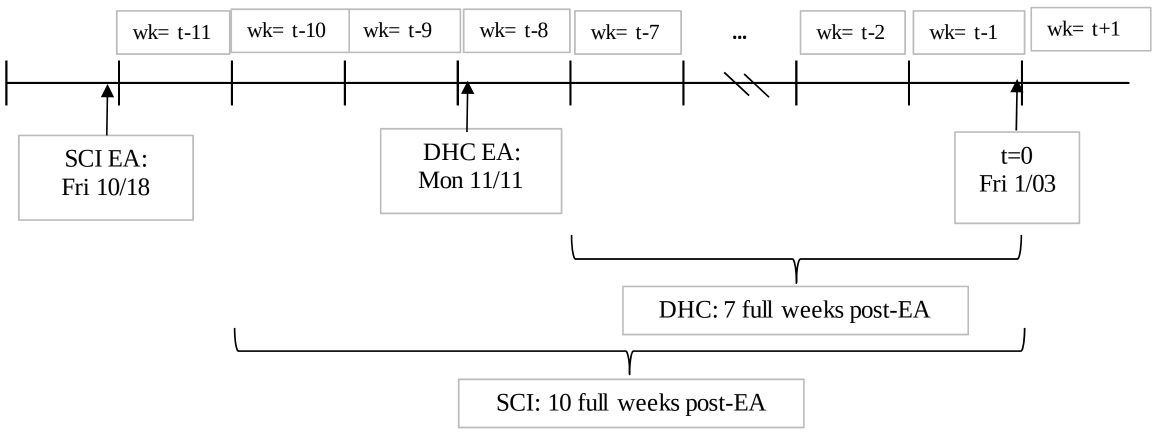
The example target stock is Service Corp International (SCI), which is classified as NAICS code 812210, funeral homes and funeral services. The example unrelated stock is Driver Harris Corp. (DHC), which is classified as NAICS code 331422, copper wire drawing.[22] On Friday, January 3, 1997, we conduct the following exercise to predict SCI's return for the following week (01/06/1997 to 01/10/1997).

1. Identify the last earnings announcement date for each firm, and confirm that the unrelated stock (DHC) had the more recent earnings announcement. SCI's last earnings announcement was on 10/18/1996 (for the fiscal quarter 1996Q3), and DHC's last earnings announcement was on 11/11/1996 (for the fiscal quarter 1996Q3). To align weekly intervals across firms and over time, we designate as the first post-announcement week the full week starting from Monday after the second trading day following the earnings announcement.[23] In this case, DHC's first post-announcement week is from 11/18/1996 to 11/22/1996, and SCI's first post-announcement week is from 10/28/1996 to 11/01/1996, so we find that there have been seven full weeks between DHC's earnings announcement and today, and ten full weeks between SCI's earnings announcement and today; see Figure 4.

[22] SCI's database identifiers are PERMNO = 51625, GVKEY = 009611, SIC code = 7261, and Fama-French 30-industry code = 22 (Personal and Business Services). DHC's database identifiers are PERMNO = 31376, GVKEY = 004083, SIC code = 3356, and Fama-French 30-industry code = 12 (Steel Works).

[23] The two days immediately following the earnings announcement are excluded to minimize the influence of immediate announcement reactions. If the market is closed on Monday, we use the next trading day.

Figure 4: SCI (Target) and DHC (Unrelated) Current period



2. Search the previous five years (for the fiscal quarters from 1991Q3 to 1996Q2) for occasions on which DHC was seven full weeks post earnings announcement and SCI was at least eight full weeks (but not more than 12 full weeks) post earnings announcement; that is, the target's post-announcement period must be longer than its unrelated stock's post-announcement period. There may be up to 20 such occasions in the previous five years, depending on how the two firms' earnings announcement dates fell relative to each other in each quarter. [24] In this example, we find 10 occasions that satisfy the criteria (01/03/1992, 07/10/1992, 10/09/1992, 07/16/1993, 10/22/1993, 07/22/1994, 07/07/1995, 09/22/1995, 07/05/1996, and 09/27/1996).
3. For each of the 10 valid occasions (with seven weeks since the DHC earnings announcement and eight to 12 weeks since the SCI earnings announcement[25]), calculate the cumulative abnormal return (CAR) for the unrelated stock (DHC) for each of the seven weeks since its earnings announcement and the unrelated stock's average CAR over the

[24] We refer to these situations as "occasions" rather than "events" to avoid confusion with the customary references to earnings announcements themselves as "events."
[25] In this example, the 10 occasions that meet the criteria have 10, 10, 11, 11, 12, 12, 10, 9, 10, and 9 weeks since the SCI earnings announcements dates, respectively.

seven weeks, and calculate the CAR for the target stock (SCI) in the subsequent week (i.e., the eighth week after the unrelated stock's earnings announcement).

4. Using the CARs for all of the 10 valid occasions in the past five years, regress the target stock SCI's subsequent-week CAR on the average CAR for its unrelated stock DHC over its seven post-earnings-announcement weeks. This regression is estimated with an intercept, as follows:

$$CAR_{s+1}^{Target} = \alpha + \beta CAR_{s-7,s-1}^{Unrelated} + \varepsilon , \quad (1)$$

where the subscript *s* refers to each of the 10 historical occasions.

5. Calculate the average CAR for DHC over the seven-week post-announcement period ending on 01/03/1997, our weekly observation date. Use the regression coefficients from equation (1) to calculate the predicted value for SCI's CAR in the subsequent week, from 01/06/1997 to 01/10/1997. The predicted CAR for the target stock SCI is calculated as:

$$PredictedCAR_{t+1}^{Target} = \hat{\alpha} + \hat{\beta} CAR_{t-7,t-1}^{Unrelated} , \qquad (2)$$

where the subscript *t* refers to the point in time at which the target stock's return is being predicted, and $\hat{\alpha}$ and $\hat{\beta}$ are the coefficient estimates from equation (1).

Table 1: Sample descriptive statistics

The sample consists of common stocks traded on NYSE/AMEX/NASDAQ from 1980 to 2010. Panel A reports descriptive statistics for the 13,109 stocks in the sample. Cross-sectional statistics of each stock characteristic are calculated at the end of each quarter, and time series averages of the mean and 25th, 50th, and 75th percentile values over the 124 quarters are reported in Panel A. Panel B presents descriptive statistics for the pairs of economically unrelated stocks. *Number of pairs* is the number of economically unrelated pairs; *Common institutional investors* are defined as the same institution holding both stocks in a stock pair at the end of the prior quarter; *Significant common institutional investors* hold more than the median institutional holder of each stock in the pair. Cross-sectional statistics are calculated across all economically unrelated pairs of stocks in each week, and time-series averages of the mean and 25th, 50th, and 75th percentile values over the 1617 weeks are reported in Panel B.

Panel A: Quarterly stock characteristics

	Mean	25th Percentile	50th Percentile	75th Percentile
Price ($)	36.37	10.86	18.76	30.65
Market capitalization ($ million)	2,118.6	92.0	289.9	1,056.6
Book-to-market ratio	0.78	0.41	0.68	1.01
Cumulative monthly return, months t-12 to t-1 (%)	22.7	-7.9	12.0	37.5
Cumulative monthly return, months t-60 to t-13 (%)	115.9	11.8	66.2	146.0
Institutional ownership (%)	41.2	21.2	41.5	60.3
Number of institutional investors	93	20	50	112

Panel B: Weekly pairs of economically unrelated stocks

	Mean	25th Percentile	50th Percentile	75th Percentile
Number of pairs	215	85	175	312
Number of pairs with				
- significant common institutional investors	188	71	151	274
- common institutional investors	206	79	166	299
- no significant common institutional investors	20	5	11	22
- no common institutional investors	10	2	6	11
Significant common institutional investors per stock pair	10	2	6	13
Common institutional investors per stock pair	27	7	17	34

Table 2: Portfolio characteristics

In every week, stocks are sorted into five industry-neutral portfolios based on predicted cumulative abnormal returns (CARs) using information from stocks in unrelated industries. Portfolio characteristics are calculated as the simple averages of firm-level characteristics. Panel A reports the time-series average of each quintile's characteristics over the sample period, 1980-2010, with all characteristics calculated as of the end of the previous month. Panel B shows weekly portfolio return autocorrelations; *Rho_n* refers to the order-n autocorrelation.

Panel A: Portfolio characteristics

Quintile	Size ($mn)	Book-to-Mkt	Return (%) week t-1	Return (%) month t-12 to t-2	Idiosyncratic Volatility (%)
1 (Low)	1,574	0.90	1.53	13.22	2.66
2	2,731	0.83	1.48	14.95	2.26
3	3,070	0.79	1.45	18.20	2.22
4	2,667	0.75	1.45	22.70	2.33
5 (High)	1,621	0.72	1.54	35.56	2.77

Quintile	Amihud Illiquidity ($x10^6$)	NYSE/AMEX Volume (shares, 000)	NYSE/AMEX Turnover	NASDAQ Volume (shares, 000)	NASDAQ Turnover
1 (Low)	2.29	12,214	9.36	6,442	5.86
2	1.54	13,379	8.93	7,901	5.70
3	1.34	13,587	9.00	8,687	5.83
4	1.24	12,631	9.41	8,925	6.09
5 (High)	1.31	11,256	10.67	8,112	6.54

Panel B: Portfolio weekly return autocorrelations

Quintile	Rho_1	Rho_2	Rho_3	Rho_4	Rho_8
1 (Low)	0.002	0.047	-0.071	-0.004	0.008
2	-0.028	0.067	-0.053	-0.017	-0.002
3	-0.023	0.035	-0.066	-0.019	-0.019
4	-0.047	0.054	-0.038	-0.013	-0.019
5 (High)	-0.032	0.026	-0.016	0.009	-0.015

Table 3: Return predictability among economically unrelated stock pairs

This table reports the weekly excess returns and alphas (in percent) of industry-neutral portfolios of stocks sorted based on predicted cumulative abnormal returns (CARs) from all economically unrelated stock pairs. Quintile 1 has the lowest predicted CARs, while quintile 5 has the highest. For each quintile of stocks, we report the value-weighted excess return above the risk-free rate (*ER*), and the value-weighted alpha from CAPM (*CAPM*), Fama-French three-factor (*FF3*), and Fama-French-Carhart four-factor (*FFC4*) regressions. The average number of stocks in each portfolio is reported under *# Stocks*. The row labeled Q5-Q1 shows the difference between Quintile 5 and Quintile 1. *t*-statistics are reported in parentheses below the coefficient estimates.

Quintile	ER	CAPM	FF3	FFC4	# Stocks
1 (Low)	0.020	-0.106	-0.129	-0.119	356
	(0.3)	*(-4.5)*	*(-5.7)*	*(-5.3)*	
2	0.064	-0.054	-0.057	-0.054	368
	(1.1)	*(-3.0)*	*(-3.2)*	*(-3.1)*	
3	0.114	-0.004	-0.003	-0.001	368
	(2.0)	*(-0.2)*	*(-0.2)*	*(-0.1)*	
4	0.172	0.044	0.047	0.044	368
	(2.8)	*(2.6)*	*(2.8)*	*(2.6)*	
5 (High)	0.211	0.070	0.077	0.076	380
	(3.1)	*(3.1)*	*(3.6)*	*(3.5)*	
Q5 - Q1	0.191	0.176	0.206	0.195	
	(5.3)	*(4.9)*	*(6.0)*	*(5.7)*	

Table 4: Return predictability with and without common institutional owners

This table reports the weekly excess returns and alphas (in percent) of industry-neutral portfolios of stocks sorted based on predicted cumulative abnormal returns (CARs) from economically unrelated stock pairs. Quintile 1 has the lowest predicted CARs, while quintile 5 has the highest. For each quintile of stocks, we report the value-weighted excess return above the risk-free rate (*ER*), and the value-weighted alpha from CAPM (*CAPM*), Fama-French three-factor (*FF3*), and Fama-French-Carhart four-factor (*FFC4*) regressions. The average number of stocks in each portfolio is reported under *# Stocks*. The row labeled Q5-Q1 shows the difference between Quintile 5 and Quintile 1. *t*-statistics are reported in parentheses below the coefficient estimates. Each panel reports the predictability results using subsets of the economically unrelated stock pairs to predict returns. Panel A reports predictability results using economically unrelated stock pairs with at least one significant common institutional owner (*With Significant Common Institutional Owners*) versus without any significant common institutional owners (*Without Significant Common Institutional Owners*), and the difference, where significant common institutional ownership is defined as an institution holding more of each stock than the median institutional holder of each stock. Panel B reports the predictability results using stock pairs with and without common institutional owners (*With Common Institutional Owners* and *Without Common Institutional Owners*, respectively).

Panel A: Stock pairs with versus without significant common institutional owners

	With Significant Common Institutional Owners				Without Significant Common Institutional Owners				With - Without Difference			
Quintile	ER	CAPM	FF3	FFC4	ER	CAPM	FF3	FFC4	ER	CAPM	FF3	FFC4
1 (Low)	0.023	-0.116	-0.140	-0.131	0.118	-0.025	-0.035	-0.035	-0.096	-0.091	-0.105	-0.096
	(0.3)	*(-4.2)*	*(-5.5)*	*(-5.1)*	*(1.6)*	*(-0.8)*	*(-1.1)*	*(-1.1)*	*(-2.4)*	*(-2.3)*	*(-2.7)*	*(-2.5)*
2	0.072	-0.056	-0.060	-0.058	0.130	-0.001	-0.014	-0.012	-0.058	-0.054	-0.047	-0.046
	(1.2)	*(-2.8)*	*(-3.1)*	*(-3.0)*	*(1.9)*	*(-0.1)*	*(-0.5)*	*(-0.5)*	*(-1.8)*	*(-1.7)*	*(-1.5)*	*(-1.5)*
3	0.132	0.001	-0.003	-0.002	0.135	0.001	-0.014	-0.011	-0.003	0.001	0.011	0.009
	(2.1)	*(0.1)*	*(-0.2)*	*(-0.1)*	*(2.0)*	*(0.0)*	*(-0.5)*	*(-0.4)*	*(-0.1)*	*(0.0)*	*(0.3)*	*(0.3)*
4	0.192	0.052	0.052	0.052	0.160	0.024	0.014	0.012	0.031	0.028	0.038	0.039
	(2.9)	*(2.9)*	*(2.9)*	*(2.8)*	*(2.3)*	*(0.9)*	*(0.5)*	*(0.4)*	*(1.0)*	*(0.9)*	*(1.2)*	*(1.3)*
5 (High)	0.220	0.064	0.071	0.071	0.161	0.013	0.007	0.005	0.059	0.051	0.064	0.066
	(2.9)	*(2.5)*	*(2.9)*	*(2.9)*	*(2.2)*	*(0.5)*	*(0.3)*	*(0.2)*	*(1.8)*	*(1.6)*	*(2.0)*	*(2.1)*
Q5 - Q1	0.198	0.180	0.211	0.202	0.043	0.039	0.042	0.040	0.155	0.142	0.169	0.162
	(4.8)	*(4.4)*	*(5.5)*	*(5.3)*	*(1.2)*	*(1.0)*	*(1.1)*	*(1.1)*	*(3.0)*	*(2.8)*	*(3.4)*	*(3.3)*

Panel B: Stock pairs with versus without common institutional owners

	With Common Institutional Owners				Without Common Institutional Owners				With - Without Difference			
Quintile	ER	CAPM	FF3	FFC4	ER	CAPM	FF3	FFC4	ER	CAPM	FF3	FFC4
1 (Low)	0.010	-0.119	-0.138	-0.132	0.159	0.048	0.034	0.023	-0.149	-0.168	-0.172	-0.155
	(0.2)	*(-4.7)*	*(-5.7)*	*(-5.4)*	*(2.1)*	*(0.9)*	*(0.6)*	*(0.4)*	*(-2.5)*	*(-2.8)*	*(-2.9)*	*(-2.6)*
2	0.069	-0.052	-0.057	-0.056	0.125	0.013	0.006	0.001	-0.056	-0.066	-0.063	-0.057
	(1.1)	*(-2.7)*	*(-3.0)*	*(-2.9)*	*(1.7)*	*(0.3)*	*(0.1)*	*(0.0)*	*(-1.0)*	*(-1.2)*	*(-1.2)*	*(-1.1)*
3	0.126	0.003	-0.001	0.002	0.135	0.027	0.022	0.011	-0.009	-0.024	-0.023	-0.009
	(2.0)	*(0.1)*	*(-0.0)*	*(0.1)*	*(1.8)*	*(0.5)*	*(0.4)*	*(0.2)*	*(-0.2)*	*(-0.4)*	*(-0.4)*	*(-0.2)*
4	0.193	0.059	0.057	0.056	0.132	0.018	0.016	-0.001	0.060	0.041	0.041	0.057
	(2.9)	*(3.3)*	*(3.2)*	*(3.2)*	*(1.9)*	*(0.4)*	*(0.4)*	*(-0.0)*	*(1.2)*	*(0.9)*	*(0.9)*	*(1.2)*
5 (High)	0.211	0.062	0.067	0.067	0.195	0.065	0.059	0.048	0.016	-0.004	0.007	0.019
	(2.8)	*(2.4)*	*(2.8)*	*(2.8)*	*(2.5)*	*(1.4)*	*(1.3)*	*(1.0)*	*(0.3)*	*(-0.1)*	*(0.2)*	*(0.4)*
Q5 - Q1	0.201	0.181	0.205	0.199	0.036	0.017	0.026	0.025	0.165	0.164	0.180	0.174
	(5.0)	*(4.7)*	*(5.5)*	*(5.3)*	*(0.5)*	*(0.3)*	*(0.4)*	*(0.4)*	*(2.2)*	*(2.2)*	*(2.4)*	*(2.3)*

Table 5: Return predictability and lead-lag effects

This table reports the weekly excess returns and alphas (in percent) of industry-neutral portfolios of stocks sorted based on predicted cumulative abnormal returns (CARs) from economically unrelated stock pairs. Quintile 1 has the lowest predicted CARs, while quintile 5 has the highest. For each quintile of stocks, we report the value-weighted excess return above the risk-free rate (*ER*) and value-weighted alpha from a Fama-French-Carhart four-factor regression (*FFC4*) in each quintile. The row labeled Q5-Q1 shows the difference between quintile 5 and quintile 1. *t*-statistics are reported in parentheses below the coefficient estimates. Panel A reports results using only stock pairs in which the target firm is from an equal or larger size decile than the economically unrelated firm (on the left) and using only stock pairs in which the target firm is from a smaller size decile than the economically unrelated firm (on the right). Panels B, C, D, E, and F report analogous results using only stock pairs in which the stocks are standalone versus conglomerates, or from different NYSE/AMEX trading volume deciles, NASDAQ trading volume deciles, institutional ownership deciles, and analyst coverage deciles, respectively.

Panel A: Size of target firm versus economically unrelated firm

Target stock >= economically unrelated stock					**Target stock < economically unrelated stock**			
Quintile	ER	FFC4	# Stocks		Quintile	ER	FFC4	# Stocks
1 (Low)	0.018	-0.118	354		1 (Low)	0.095	-0.053	329
	(0.3)	*(-5.2)*				*(1.5)*	*(-3.1)*	
2	0.066	-0.053	366		2	0.114	-0.025	341
	(1.2)	*(-2.9)*				*(2.0)*	*(-1.5)*	
3	0.125	0.011	366		3	0.135	-0.009	341
	(2.2)	*(0.6)*				*(2.3)*	*(-0.6)*	
4	0.161	0.033	366		4	0.168	0.025	341
	(2.6)	*(2.0)*				*(2.8)*	*(1.6)*	
5 (High)	0.216	0.079	378		5 (High)	0.198	0.046	353
	(3.1)	*(3.5)*				*(2.9)*	*(2.7)*	
Q5 - Q1	0.198	0.196			Q5 - Q1	0.104	0.100	
	(5.3)	*(5.6)*				*(4.4)*	*(4.5)*	

Panel B: Standalone firms versus conglomerates

Both stocks in pair from standalone firms					**Both stocks in pair from conglomerate firms**			
Quintile	ER	FFC4	# Stocks		Quintile	ER	FFC4	# Stocks
1 (Low)	-0.010	-0.113	170		1 (Low)	0.018	-0.093	85
	(-0.2)	*(-3.5)*				*(0.3)*	*(-2.7)*	
2	0.040	-0.045	181		2	0.077	-0.014	97
	(0.7)	*(-1.7)*				*(1.2)*	*(-0.5)*	
3	0.102	0.012	181		3	0.113	0.014	97
	(1.6)	*(0.4)*				*(1.8)*	*(0.5)*	
4	0.145	0.055	181		4	0.137	0.028	97
	(2.1)	*(1.9)*				*(2.1)*	*(1.1)*	
5 (High)	0.202	0.119	193		5 (High)	0.160	0.041	109
	(2.6)	*(3.3)*				*(2.3)*	*(1.4)*	
Q5 - Q1	0.212	0.232			Q5 - Q1	0.142	0.134	
	(4.0)	*(4.7)*				*(3.1)*	*(3.0)*	

Panel C: NYSE/AMEX Volume of target stock versus economically unrelated stock							
Target stock >= economically unrelated stock				Target stock < economically unrelated stock			
Quintile	ER	FFC4	# Stocks	Quintile	ER	FFC4	# Stocks
1 (Low)	0.036	-0.104	198	1 (Low)	0.073	-0.071	177
	(0.6)	*(-4.3)*			*(1.3)*	*(-3.3)*	
2	0.055	-0.071	210	2	0.111	-0.028	189
	(1.0)	*(-3.4)*			*(2.0)*	*(-1.4)*	
3	0.100	-0.023	210	3	0.132	-0.009	189
	(1.8)	*(-1.3)*			*(2.4)*	*(-0.4)*	
4	0.162	0.034	210	4	0.143	0.004	189
	(2.8)	*(1.8)*			*(2.5)*	*(0.2)*	
5 (High)	0.201	0.061	222	5 (High)	0.194	0.042	201
	(3.1)	*(2.8)*			*(3.2)*	*(2.0)*	
Q5 - Q1	0.165	0.165		Q5 - Q1	0.122	0.113	
	(4.7)	*(4.9)*			*(5.4)*	*(5.1)*	

Panel D: Nasdaq Volume of target stock versus economically unrelated stock							
Target stock >= economically unrelated stock				Target stock < economically unrelated stock			
Quintile	ER	FFC4	# Stocks	Quintile	ER	FFC4	# Stocks
1 (Low)	0.053	-0.060	154	1 (Low)	0.120	-0.022	131
	(0.6)	*(-1.5)*			*(1.7)*	*(-0.8)*	
2	0.147	0.061	165	2	0.124	-0.018	141
	(1.8)	*(1.5)*			*(2.0)*	*(-0.8)*	
3	0.176	0.081	165	3	0.170	0.032	141
	(2.2)	*(1.9)*			*(2.8)*	*(1.4)*	
4	0.284	0.192	165	4	0.194	0.051	141
	(3.3)	*(4.5)*			*(3.0)*	*(2.1)*	
5 (High)	0.208	0.105	176	5 (High)	0.227	0.071	153
	(2.2)	*(2.3)*			*(3.1)*	*(2.9)*	
Q5 - Q1	0.158	0.165		Q5 - Q1	0.106	0.093	
	(2.6)	*(2.8)*			*(3.3)*	*(2.9)*	

Panel E: Institutional ownership of target stock versus economically unrelated stock

Target stock >= economically unrelated stock				Target stock < economically unrelated stock			
Quintile	ER	FFC4	# Stocks	Quintile	ER	FFC4	# Stocks
1 (Low)	0.036	-0.109	349	1 (Low)	0.074	-0.069	289
	(0.6)	*(-4.8)*			*(1.2)*	*(-2.7)*	
2	0.063	-0.062	361	2	0.071	-0.048	301
	(1.1)	*(-3.5)*			*(1.2)*	*(-2.3)*	
3	0.132	0.010	361	3	0.099	-0.014	301
	(2.3)	*(0.6)*			*(1.8)*	*(-0.6)*	
4	0.176	0.046	361	4	0.170	0.040	301
	(2.9)	*(2.7)*			*(2.8)*	*(2.0)*	
5 (High)	0.202	0.059	373	5 (High)	0.225	0.086	313
	(2.9)	*(2.7)*			*(3.4)*	*(3.6)*	
Q5 - Q1	0.166	0.169		Q5 - Q1	0.151	0.155	
	(4.5)	*(4.8)*			*(3.9)*	*(4.1)*	

Panel F: Analyst coverage of target stock versus economically unrelated stock

Target stock >= economically unrelated stock				Target stock < economically unrelated stock			
Quintile	ER	FFC4	# Stocks	Quintile	ER	FFC4	# Stocks
1 (Low)	0.026	-0.101	273	1 (Low)	0.045	-0.073	267
	(0.4)	*(-4.9)*			*(0.8)*	*(-3.8)*	
2	0.047	-0.057	286	2	0.082	-0.026	279
	(0.9)	*(-3.5)*			*(1.6)*	*(-1.5)*	
3	0.111	0.006	285	3	0.126	0.012	279
	(2.1)	*(0.4)*			*(2.4)*	*(0.7)*	
4	0.141	0.029	286	4	0.145	0.022	279
	(2.5)	*(1.9)*			*(2.6)*	*(1.3)*	
5 (High)	0.206	0.073	297	5 (High)	0.169	0.032	291
	(3.3)	*(3.8)*			*(2.8)*	*(1.9)*	
Q5 - Q1	0.181	0.174		Q5 - Q1	0.125	0.105	
	(5.5)	*(5.6)*			*(4.4)*	*(3.9)*	

Table 6: Return predictability and characteristic-based explanations

This table reports the weekly excess return in percent for portfolios based on double sorts of predicted cumulative abnormal returns (CARs) and other characteristics. For each characteristic, we form 25 portfolios by independent industry-neutral sorts on predicted CAR and the firm characteristic. The portfolios are formed and rebalanced weekly. We report value-weighted excess returns above risk-free rate for each of the 25 portfolios. The row labeled Q5-Q1 shows the difference in estimate for quintile 5 minus quintile 1, with the *t* -statistic in parentheses below the difference. Earnings surprise is measured by three-day abnormal returns for the earnings announcement within the past 60 days of portfolio formation. Market capitalization, book-to-market ratio, and past returns are as of the month prior to portfolio formation.

Pred. CAR	**Market Capitalization (Size) Quintile**				
Quintile	1 (Small)	2	3	4	5 (Big)
1 (Low)	0.130	0.106	0.097	0.096	0.017
5 (High)	0.286	0.264	0.192	0.179	0.227
Q5 - Q1	0.155	0.158	0.091	0.079	0.211
	(4.6)	*(4.7)*	*(2.9)*	*(2.3)*	*(4.8)*

Pred. CAR	**Book-to-Market (Growth vs Value) Quintile**				
Quintile	1 (Growth)	2	3	4	5 (Value)
1 (Low)	0.018	0.015	0.051	-0.027	0.147
5 (High)	0.208	0.191	0.251	0.196	0.318
Q5 - Q1	0.189	0.174	0.203	0.228	0.172
	(3.5)	*(3.3)*	*(4.0)*	*(3.8)*	*(3.4)*

Pred. CAR	**Past 1-wk Return (Weekly Reversal) Quintile**				
Quintile	1 (Loser)	2	3	4	5 (Winner)
1 (Low)	0.393	0.140	0.037	-0.090	-0.251
5 (High)	0.664	0.353	0.198	0.129	-0.099
Q5 - Q1	0.269	0.213	0.154	0.224	0.153
	(4.4)	*(4.0)*	*(2.9)*	*(4.2)*	*(2.7)*

Pred. CAR	**Past 1-mo Return (Monthly Reversal) Quintile**				
Quintile	1 (Loser)	2	3	4	5 (Winner)
1 (Low)	0.080	0.104	0.075	-0.026	-0.032
5 (High)	0.195	0.286	0.209	0.208	0.218
Q5 - Q1	0.113	0.174	0.139	0.234	0.251
	(1.8)	*(3.1)*	*(2.5)*	*(4.4)*	*(4.8)*

Pred. CAR	**Past 12-2 month (Momentum) Return Quintile**				
Quintile	1 (Loser)	2	3	4	5 (Winner)
1 (Low)	-0.034	0.060	0.050	0.023	0.131
5 (High)	0.058	0.143	0.185	0.198	0.301
Q5 - Q1	0.089	0.082	0.139	0.175	0.169
	(1.4)	*(1.4)*	*(2.6)*	*(3.4)*	*(3.4)*

Pred. CAR Quintile	Past 60-13 month (Long Run Reversal) Return Quintile				
	1 (Loser)	2	3	4	5 (Winner)
1 (Low)	0.143	0.068	-0.014	-0.040	0.025
5 (High)	0.223	0.246	0.274	0.252	0.193
Q5 - Q1	0.084	0.174	0.281	0.293	0.170
	(1.4)	*(3.2)*	*(5.0)*	*(5.0)*	*(2.8)*

Pred. CAR Quintile	Earnings Surprise (Earnings Momentum) Quintile				
	1 (Bad)	2	3	4	5 (Good)
1 (Low)	0.036	-0.014	-0.006	0.093	0.127
5 (High)	0.151	0.137	0.289	0.223	0.242
Q5 - Q1	0.118	0.155	0.292	0.131	0.116
	(1.9)	*(2.7)*	*(5.2)*	*(2.5)*	*(2.2)*

Pred. CAR Quintile	Amihud Illiquidity Quintile				
	1 (Low)	2	3	4	5 (High)
1 (Low)	0.024	0.052	0.109	0.078	0.080
5 (High)	0.224	0.174	0.192	0.266	0.281
Q5 - Q1	0.198	0.124	0.079	0.181	0.205
	(4.3)	*(3.3)*	*(2.3)*	*(5.4)*	*(5.4)*

Pred. CAR Quintile	NYSE/AMEX Trading Volume Quintile				
	1 (Low)	2	3	4	5 (High)
1 (Low)	0.103	0.051	0.080	0.050	0.016
5 (High)	0.258	0.202	0.222	0.221	0.206
Q5 - Q1	0.144	0.145	0.139	0.177	0.184
	(3.2)	*(4.0)*	*(3.7)*	*(4.3)*	*(4.0)*

Pred. CAR Quintile	NYSE/AMEX Turnover Quintile				
	1 (Low)	2	3	4	5 (High)
1 (Low)	0.002	-0.033	0.023	0.066	0.059
5 (High)	0.220	0.248	0.225	0.142	0.236
Q5 - Q1	0.206	0.290	0.196	0.074	0.173
	(3.2)	*(5.0)*	*(3.9)*	*(1.4)*	*(3.0)*

Table 7: Fama-MacBeth regressions of return predictability with controls

This table reports results from Fama-MacBeth regressions of stocks' realized excess returns in week t+1 on sets of explanatory variables. The predicted cumulative abnormal return (*Predicted CAR*) is the stock's quintile rank calculated based on all pairs of economically unrelated stocks in columns (1) and (2), based on pairs of economically unrelated stocks with significant common institutional owners in columns (3) and (4), and based on pairs of economically unrelated stocks without significant common institutional owners in columns (5) and (6). *Return week t-1*, *Return month t-1*, and *Return month t-60 to t-13* control for weekly, monthly, and long-term return reversals. *Return month t-12 to t-2* and *Earnings surprise* control for price momentum and earnings momentum. The remaining explanatory variables control for other stock characteristics known to be related to return predictability. All explanatory variables are defined in Appendix A. *t*-statistics (in parentheses) are based on Newey-West standard errors.

	(1)	(2)	(3)	(4)	(5)	(6)
Predicted CAR: all pairs	0.0003	0.0003				
	(8.2)	*(10.7)*				
Predicted CAR: pairs with significant common institutional owners			0.0004	0.0003		
			(7.1)	*(8.4)*		
Predicted CAR: pairs without significant common institutional owners					0.0000	-0.0031
					(0.1)	*(-1.0)*
Return week t-1		-0.0671		-0.0587		-0.0636
		(-29.6)		*(-23.0)*		*(-22.7)*
Return month t-1		-0.0039		-0.0013		-0.0026
		(-4.0)		*(-1.1)*		*(-2.1)*
Return month t-60 to t-13		-0.0002		-0.0001		-0.0001
		(-2.7)		*(-2.2)*		*(-0.8)*
Return month t-12 to t-2		0.0010		0.0007		0.0013
		(2.5)		*(1.5)*		*(2.9)*
Earnings surprise		0.0001		0.0001		0.0001
		(5.3)		*(3.0)*		*(3.6)*
Market capitalization		0.0000		0.0000		0.0000
		(-3.1)		*(0.2)*		*(0.6)*
Book-to-market equity		0.0001		0.0000		0.0000
		(0.3)		*(-0.1)*		*(0.0)*
Operating accruals		-0.0022		-0.0026		-0.0055
		(-3.2)		*(-3.1)*		*(-3.8)*
Net stock issuance		-0.0031		-0.0028		-0.0015
		(-5.5)		*(-4.9)*		*(-1.4)*
Idiosyncratic volatility		0.0044		0.0090		0.0114
		(0.2)		*(0.4)*		*(0.5)*
Amihud illiquidity		0.0001		0.0000		0.0000
		(1.9)		*(0.0)*		*(0.4)*
Intercept	0.0010	0.0008	0.0007	0.0003	0.0020	0.0250
	(1.7)	*(1.6)*	*(1.0)*	*(0.6)*	*(1.9)*	*(1.2)*
Average # of stocks per week	1838	1288	1743	1245	1361	1064
Average adjusted R^2	0.001	0.045	0.001	0.044	0.001	0.045

Table 8: Predicted returns and changes in institutional holdings

This table reports the quarterly changes in institutional holdings of portfolios sorted based on predicted cumulative abnormal returns (CARs), where each quintile contains only those stocks that are consistently ranked in the same quintile throughout the quarter. In Panel A we select stocks that are ranked in a given quintile for at least 75% of the weeks in a quarter, and in Panel B we select stocks that are ranked in a given quintile for at least 50% of the weeks in the quarter. Quintile 1 has the lowest predicted CARs, while quintile 5 has the highest. For each quintile of stocks, we report the change in percentage insitutional ownership over the same quarter.The row labeled Q5-Q1 shows the difference between quintile 5 and quintile 1, followed by the *t* -statistic, signed rank statistic, and the p-values for each test in parentheses.

Panel A: Change in institutional holdings for stocks in same quintile for at least 75% of weeks in quarter

Quintile	Change in Percentage Institutional Ownership (%)
1 (Low)	-0.2437
2	0.2088
3	0.0824
4	0.6765
5 (High)	0.9531
Q5 - Q1	1.2394
t-statistic	2.91
(p-value)	*(0.00)*
signed rank statistic	1.58.E+03
(p-value)	*(0.00)*

Panel B: Change in institutional holdings for stocks in same quintile for at least 50% of weeks in quarter

Quintile	Change in Percentage Institutional Ownership (%)
1 (Low)	0.1987
2	0.2770
3	0.2529
4	0.3099
5 (High)	0.4422
Q5 - Q1	0.2434
t-statistic	8.79
(p-value)	*(0.00)*
signed rank statistic	2.94.E+03
(p-value)	*(0.00)*

Table 9: Return predictability from positive versus negative predicted-return pairs

This table reports the weekly excess returns and alphas (in percent) of industry-neutral portfolios of stocks sorted based on predicted cumulative abnormal returns (CARs) from economically unrelated stock pairs that have significant common institutional owners for the period 1980-2010. Quintile 1 has the lowest predicted CARs, while quintile 5 has the highest. For each quintile of stocks, we report the value-weighted excess return above the risk-free rate (*ER*), and the value-weighted alpha from CAPM (*CAPM*), Fama-French three-factor (*FF3*), and Fama-French-Carhart four-factor (*FFC4*) regressions.The row labeled Q5-Q1 shows the difference between quintile 5 and quintile 1. *t*-statistics are reported in parentheses below the coefficient estimates. Panel A reports predictability results using only stock pairs for which the predicted return is negative (*Pairs Predicting Negative Returns*) versus only stock pairs predicting positive returns (*Pairs Predicting Positive Returns*), and the difference. Panel B reports the predictability results using only stock pairs predicting negative returns, further dividing them into negative predictions arising from the *Unrelated-Stock-Loss* channel (positive historical correlation with negative recent return on the unrelated stock) and from the *Return-Chasing* channel (negative historical correlation with positive recent return on the unrelated stock).

Panel A: Predictions based on stock pairs predicting only negative versus only positive returns

	Pairs Predicting Negative Returns				Pairs Predicting Positive Returns				Negative - Positive Difference			
Quintile	ER	CAPM	FF3	FFC4	ER	CAPM	FF3	FFC4	ER	CAPM	FF3	FFC4
1 (Low)	0.111	-0.066	-0.081	-0.070	0.101	-0.021	-0.018	-0.019	0.010	-0.045	-0.063	-0.051
	(1.2)	*(-1.7)*	*(-2.6)*	*(-2.3)*	*(1.7)*	*(-1.2)*	*(-1.1)*	*(-1.2)*	*(0.2)*	*(-0.9)*	*(-1.6)*	*(-1.3)*
2	0.133	-0.023	-0.038	-0.033	0.149	0.010	0.009	0.004	-0.016	-0.033	-0.046	-0.036
	(1.7)	*(-0.8)*	*(-1.5)*	*(-1.3)*	*(2.2)*	*(0.6)*	*(0.5)*	*(0.2)*	*(-0.5)*	*(-1.0)*	*(-1.6)*	*(-1.2)*
3	0.114	-0.037	-0.045	-0.042	0.155	0.004	-0.006	0.001	-0.041	-0.041	-0.039	-0.043
	(1.6)	*(-1.7)*	*(-2.2)*	*(-2.1)*	*(2.1)*	*(0.2)*	*(-0.3)*	*(0.0)*	*(-1.8)*	*(-1.8)*	*(-1.7)*	*(-1.9)*
4	0.103	-0.038	-0.041	-0.042	0.173	0.014	0.010	0.013	-0.071	-0.052	-0.051	-0.055
	(1.5)	*(-2.2)*	*(-2.4)*	*(-2.4)*	*(2.2)*	*(0.5)*	*(0.4)*	*(0.5)*	*(-2.1)*	*(-1.6)*	*(-1.7)*	*(-1.9)*
5 (High)	0.140	0.013	0.019	0.016	0.165	-0.015	-0.025	-0.014	-0.025	0.028	0.044	0.030
	(2.3)	*(0.8)*	*(1.3)*	*(1.1)*	*(1.8)*	*(-0.4)*	*(-0.7)*	*(-0.4)*	*(-0.5)*	*(0.6)*	*(1.1)*	*(0.7)*
Q5 - Q1	0.029	0.080	0.100	0.086	0.065	0.006	-0.006	0.006	-0.036	0.073	0.107	0.081
	(0.5)	*(1.7)*	*(2.6)*	*(2.3)*	*(1.1)*	*(0.1)*	*(-0.2)*	*(0.1)*	*(-0.3)*	*(0.8)*	*(1.4)*	*(1.1)*

Panel B: Predictions based on stock pairs predicting only negative returns, comparison of "Unrelated-Stock-Loss" vs "Return-Chasing" channels

	Pairs Predicting Negative Returns due to "Unrelated-Stock-Loss" channel				Pairs Predicting Negative Returns due to "Return-Chasing" channel				"Unrelated-Stock-Loss" - "Return Chasing" Difference			
Quintile	ER	CAPM	FF3	FFC4	ER	CAPM	FF3	FFC4	ER	CAPM	FF3	FFC4
1 (Low)	0.108	-0.063	-0.084	-0.074	0.142	-0.031	-0.047	-0.037	-0.034	-0.032	-0.038	-0.037
	(1.2)	*(-1.7)*	*(-2.8)*	*(-2.5)*	*(1.6)*	*(-0.9)*	*(-1.5)*	*(-1.2)*	*(-1.3)*	*(-1.2)*	*(-1.4)*	*(-1.4)*
2	0.088	-0.068	-0.085	-0.080	0.124	-0.033	-0.050	-0.041	-0.036	-0.035	-0.035	-0.039
	(1.1)	*(-2.4)*	*(-3.3)*	*(-3.1)*	*(1.6)*	*(-1.1)*	*(-1.9)*	*(-1.5)*	*(-1.4)*	*(-1.4)*	*(-1.4)*	*(-1.6)*
3	0.136	-0.011	-0.018	-0.015	0.112	-0.035	-0.043	-0.044	0.024	0.025	0.025	0.029
	(1.9)	*(-0.5)*	*(-0.9)*	*(-0.8)*	*(1.6)*	*(-1.7)*	*(-2.2)*	*(-2.2)*	*(1.1)*	*(1.1)*	*(1.1)*	*(1.3)*
4	0.107	-0.032	-0.033	-0.034	0.100	-0.040	-0.040	-0.040	0.006	0.008	0.007	0.006
	(1.6)	*(-2.0)*	*(-2.1)*	*(-2.1)*	*(1.5)*	*(-2.4)*	*(-2.4)*	*(-2.3)*	*(0.4)*	*(0.5)*	*(0.4)*	*(0.3)*
5 (High)	0.143	0.015	0.022	0.018	0.146	0.020	0.026	0.022	-0.003	-0.005	-0.004	-0.004
	(2.3)	*(0.9)*	*(1.5)*	*(1.2)*	*(2.4)*	*(1.2)*	*(1.7)*	*(1.5)*	*(-0.3)*	*(-0.6)*	*(-0.5)*	*(-0.4)*
Q5 - Q1	0.036	0.078	0.106	0.092	0.004	0.051	0.072	0.059	0.031	0.027	0.033	0.033
	(0.7)	*(1.7)*	*(2.8)*	*(2.5)*	*(0.1)*	*(1.1)*	*(2.0)*	*(1.6)*	*(1.1)*	*(0.9)*	*(1.2)*	*(1.2)*

Table 10: Seasonality of quarter-end and month-end weeks versus other weeks

This table reports the weekly excess returns and alphas (in percent) of industry-neutral portfolios of stocks sorted based on predicted cumulative abnormal returns (CARs) from economically unrelated stock pairs, separating the last week of each calendar quarter (Panel A) and month (Panel B) from other weeks. Last week of the calendar quarter (month) is defined as the week containing the last trading day of the calendar quarter (month). Quintile 1 has the lowest predicted CARs, while quintile 5 has the highest. For each quintile of stocks, we report the value-weighted excess return above the risk-free rate (*ER*) and the value-weighted alphas from CAPM (*CAPM*), the Fama-French three-factor model (*FF3*), and the Fama-French-Carhart four-factor model (*FFC4*). The average number of stocks in each portfolio is reported under *# Stocks*. The row labeled Q5-Q1 shows the difference between quintile 5 and quintile 1. *t*-statistics are reported in parentheses below the coefficient estimates.

Panel A: Calendar quarters

Last week						All other weeks					
Quintile	ER	CAPM	FF3	FFC4	# Stocks	Quintile	ER	CAPM	FF3	FFC4	# Stocks
1 (Low)	0.174	0.004	-0.114	-0.077	421	1 (Low)	0.094	-0.015	-0.050	-0.027	349
	(0.9)	*(0.1)*	*(-2.3)*	*(-1.7)*			*(1.5)*	*(-0.5)*	*(-3.0)*	*(-1.8)*	
2	0.249	0.085	-0.014	0.016	433	2	0.129	0.023	-0.010	0.005	361
	(1.4)	*(1.2)*	*(-0.3)*	*(0.4)*			*(2.2)*	*(1.0)*	*(-0.7)*	*(0.4)*	
3	0.341	0.176	0.081	0.102	433	3	0.156	0.049	0.019	0.033	361
	(1.9)	*(2.7)*	*(2.1)*	*(2.8)*			*(2.7)*	*(2.2)*	*(1.4)*	*(2.6)*	
4	0.368	0.197	0.088	0.109	433	4	0.187	0.075	0.049	0.063	361
	(1.9)	*(2.8)*	*(2.3)*	*(3.0)*			*(3.0)*	*(3.2)*	*(3.6)*	*(4.8)*	
5 (High)	0.472	0.288	0.153	0.170	445	5 (High)	0.218	0.093	0.078	0.089	372
	(2.3)	*(3.3)*	*(3.3)*	*(3.7)*			*(3.1)*	*(3.3)*	*(5.3)*	*(6.2)*	
Q5 - Q1	0.298	0.283	0.267	0.247		Q5 - Q1	0.123	0.108	0.128	0.116	
	(5.2)	*(5.1)*	*(5.2)*	*(4.9)*			*(6.0)*	*(5.6)*	*(7.1)*	*(6.6)*	

Panel B: Calendar months

Last week						All other weeks					
Quintile	ER	CAPM	FF3	FFC4	# Stocks	Quintile	ER	CAPM	FF3	FFC4	# Stocks
1 (Low)	0.401	-0.085	-0.099	-0.111	347	1 (Low)	-0.095	-0.108	-0.132	-0.120	359
	(3.2)	*(-1.6)*	*(-1.9)*	*(-2.1)*			*(-1.3)*	*(-4.1)*	*(-5.3)*	*(-4.9)*	
2	0.377	-0.089	-0.090	-0.101	358	2	-0.031	-0.042	-0.047	-0.043	371
	(3.2)	*(-2.4)*	*(-2.4)*	*(-2.7)*			*(-0.5)*	*(-2.1)*	*(-2.4)*	*(-2.2)*	
3	0.436	-0.037	-0.047	-0.039	359	3	0.017	0.005	0.008	0.008	371
	(3.7)	*(-1.0)*	*(-1.3)*	*(-1.1)*			*(0.3)*	*(0.3)*	*(0.4)*	*(0.4)*	
4	0.553	0.023	0.008	0.015	358	4	0.057	0.044	0.050	0.046	371
	(4.2)	*(0.6)*	*(0.2)*	*(0.4)*			*(0.8)*	*(2.3)*	*(2.7)*	*(2.5)*	
5 (High)	0.653	0.073	0.077	0.082	370	5 (High)	0.077	0.064	0.073	0.071	382
	(4.4)	*(1.5)*	*(1.6)*	*(1.7)*			*(1.0)*	*(2.5)*	*(3.0)*	*(2.9)*	
Q5 - Q1	0.252	0.158	0.175	0.193		Q5 - Q1	0.173	0.171	0.205	0.191	
	(3.2)	*(2.0)*	*(2.3)*	*(2.5)*			*(4.3)*	*(4.3)*	*(5.4)*	*(5.1)*	

Table 11: Stock pairs without correlated earnings surprises

We estimate each stock's quarterly unexpected earnings (earnings surprise) using a seasonal random walk model with drift (Chan et al., 1996; Sadka, 2006) and then calculate time-series correlations of unexpected earnings using all available observations. To reduce estimation error, we require at least 12 observations to estimate correlations. Panel A presents descriptive statistics for the time-series correlations of earnings surprises for the economically unrelated stock pairs used in the main analysis. Panel B reports the weekly excess returns and alphas (in percent) of industry-neutral portfolios of stocks sorted based on predicted cumulative abnormal returns (CARs) from economically unrelated stock pairs, excluding stock pairs whose time-series correlations are significant at the 5% level (approximately 9.5% of the stock pairs). Quintile 1 has the lowest predicted CARs, while quintile 5 has the highest. For each quintile of stocks, we report the value-weighted excess return above the risk-free rate (*ER*) and the value-weighted alphas from CAPM (*CAPM*), the Fama-French three-factor model (*FF3*), and the Fama-French-Carhart four-factor model (*FFC4*). The average number of stocks in each portfolio is reported under *# Stocks*. The row labeled Q5-Q1 shows the difference between quintile 5 and quintile 1. *t*-statistics are reported in parentheses below the coefficient estimates.

Panel A: Distribution of time-series correlations of earnings surprises for economically unrelated stock pairs

	Mean	25^{th} P'tile	Median	75^{th} P'tile
Correlation	0.017	-0.144	0.012	0.177
t-statistic	0.10	-0.65	0.05	0.80
p-value	0.48	0.20	0.48	0.75

Panel B: Return predictability excluding stock pairs with correlations significant at 5% level of significance

Quintile	ER	CAPM	FF3	FFC4	# Stocks
1 (Low)	0.020	-0.106	-0.130	-0.119	356
	(0.3)	*(-4.4)*	*(-5.7)*	*(-5.3)*	
2	0.070	-0.047	-0.049	-0.045	368
	(1.2)	*(-2.6)*	*(-2.8)*	*(-2.6)*	
3	0.108	-0.010	-0.009	-0.007	368
	(1.9)	*(-0.6)*	*(-0.5)*	*(-0.4)*	
4	0.175	0.047	0.050	0.046	368
	(2.9)	*(2.8)*	*(3.0)*	*(2.8)*	
5 (High)	0.207	0.067	0.074	0.071	380
	(3.0)	*(3.0)*	*(3.3)*	*(3.2)*	
Q5 - Q1	0.188	0.172	0.204	0.191	
	(5.0)	*(4.7)*	*(5.8)*	*(5.4)*	

Table 12: Simulation using matching number of stock pairs

This table reports the weekly excess returns and alphas (in percent) of industry-neutral portfolios of stocks sorted based on predicted cumulative abnormal returns (CARs) from economically unrelated stock pairs, based on a simulation that randomly draws the same number of stock pairs that have significant common institutional investors (in Panel A) or common institutional investors (in Panel B) as the number of stock pairs with no significant common institutional investors (Panel A) or no common institutional investors (Panel B). Each simulation is run 1000 times, and average excess returns and alphas are reported in the table. Quintile 1 has the lowest predicted CARs, while quintile 5 has the highest. For each quintile of stocks, we report the value-weighted excess return above the risk-free rate (*ER*) and the value-weighted alphas from CAPM (*CAPM*), the Fama-French three-factor model (*FF3*), and the Fama-French-Carhart four-factor model (FFC4). The row labeled Q5-Q1 shows the difference between quintile 5 and quintile 1. *t*-statistics are reported in parentheses below the coefficient estimates.

Panel A: Significant common institutional investors

Quintile	ER	CAPM	FF3	FFC4
1 (Low)	0.068	-0.066	-0.084	-0.076
	(1.1)	*(-4.7)*	*(-6.4)*	*(-5.9)*
2	0.091	-0.033	-0.034	-0.034
	(1.6)	*(-2.8)*	*(-3.1)*	*(-3.0)*
3	0.122	-0.002	0.003	0.001
	(2.2)	*(-0.1)*	*(0.2)*	*(0.1)*
4	0.151	0.020	0.025	0.022
	(2.6)	*(1.9)*	*(2.4)*	*(2.1)*
5 (High)	0.182	0.038	0.041	0.039
	(2.8)	*(2.7)*	*(2.9)*	*(2.8)*
Q5 - Q1	0.114	0.105	0.125	0.115
	(5.2)	*(4.9)*	*(6.1)*	*(5.6)*

Panel B: Common institutional investors

Quintile	ER	CAPM	FF3	FFC4
1 (Low)	0.077	-0.058	-0.074	-0.067
	(1.3)	*(-4.8)*	*(-6.7)*	*(-6.1)*
2	0.095	-0.030	-0.031	-0.030
	(1.7)	*(-2.7)*	*(-3.0)*	*(-2.9)*
3	0.122	-0.002	0.002	0.001
	(2.2)	*(-0.2)*	*(0.2)*	*(0.1)*
4	0.147	0.017	0.022	0.019
	(2.5)	*(1.7)*	*(2.2)*	*(1.9)*
5 (High)	0.175	0.032	0.032	0.030
	(2.7)	*(2.6)*	*(2.6)*	*(2.5)*
Q5 - Q1	0.098	0.090	0.107	0.097
	(5.5)	*(5.2)*	*(6.4)*	*(5.9)*

Figure 2: Annual long-short portfolio returns and Sharpe ratios

This figure shows the annual excess return and Sharpe ratio each year from the strategy of going long the quintile portfolio with the highest predicted CAR (Quintile 5) and short the quintile portfolio with the lowest predicted CAR (Quintile 1). The long-short hedge portfolio annual return is calculated as the average weekly return multiplied by the number of weeks in the year. The annual Sharpe ratio is calculated as the annual return divided by the annual standard deviation of returns, which equals the standard deviation of weekly returns multiplied by the square root of the number of weeks in the year.

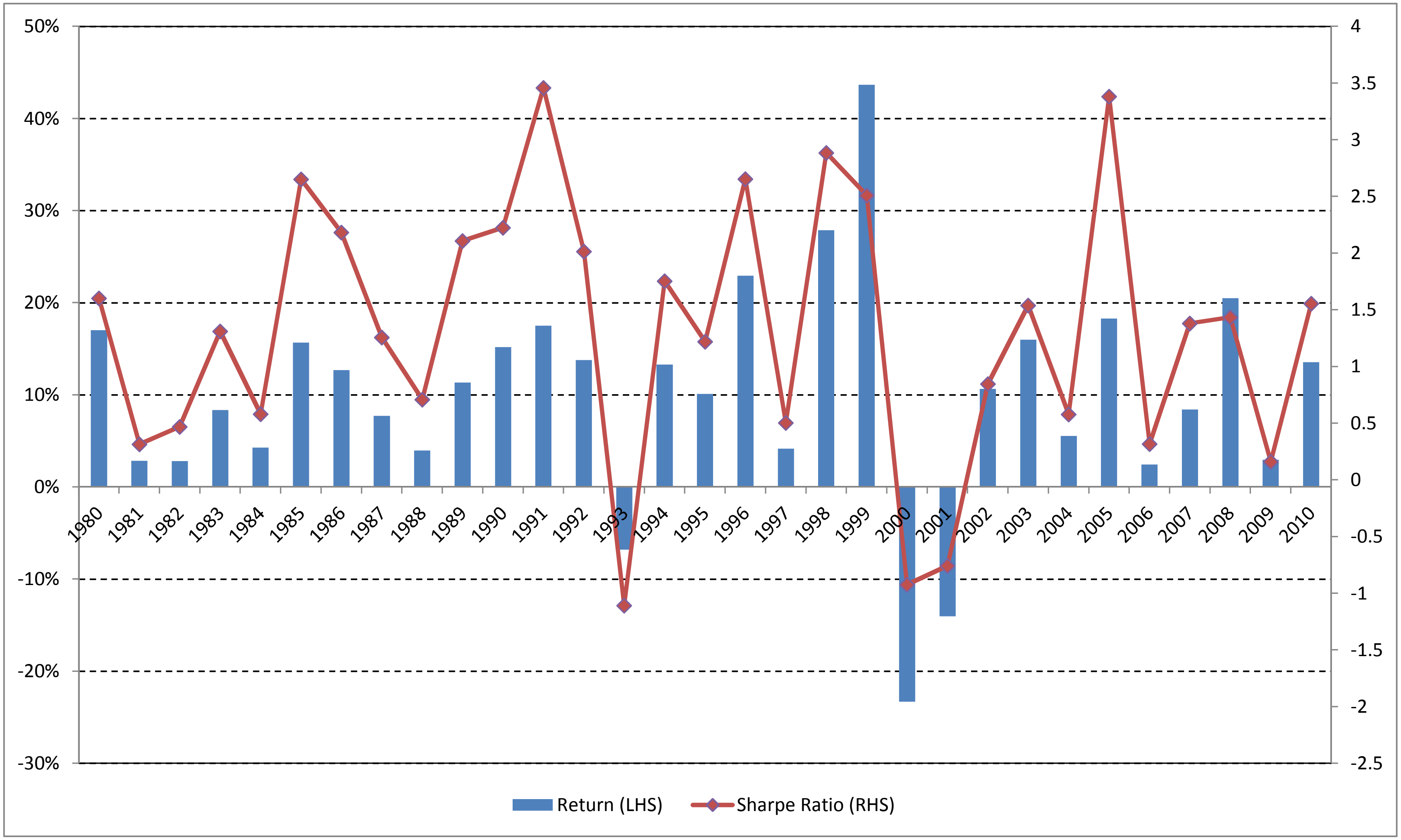


Figure 3: Long-short portfolio returns by week, with versus without significant common institutional investors

This figure shows the Fama-French-Carhart four-factor alpha from the strategy of going long the quintile portfolio with the highest predicted CAR (Quintile 5) and short the quintile portfolio with the lowest predicted CAR (Quintile 1), holding the portfolio from one week to 12 weeks after portfolio formation, where predicted returns are based on either stock pairs with significant common institutional owners (*With Significant Common Inst'l Owners*) or stock pairs without significant common institutional owners (*No Significant Common Inst'l Owners*).