NBER WORKING PAPER SERIES

SHARED ANALYST COVERAGE:
UNIFYING MOMENTUM SPILLOVER EFFECTS

Usman Ali
David Hirshleifer

Working Paper 25201
http://www.nber.org/papers/w25201

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
October 2018

We thank John Campbell, Kent Daniel, Danling Jiang, Abhiroop Mukherjee, Lin Sun, and Siew Hong Teoh for very helpful comments and suggestions and Marcin Kacperczyk for making broker merger data publicly available. The views expressed herein are those of the author and do not necessarily reflect the views of the National Bureau of Economic Research.

Shared Analyst Coverage: Unifying Momentum Spillover Effects
Usman Ali and David Hirshleifer
NBER Working Paper No. 25201
October 2018
JEL No. D03,G02,G11,G12,G14,G4

ABSTRACT

Identifying stock connections by shared analyst coverage, we find that a connected-stock (CS) momentum factor generates a monthly alpha of 1.68% (t = 9.67). In spanning regressions, the alphas of industry, geographic, customer, customer/supplier industry, single- to multi-segment, and technology momentum factors are insignificant/negative after controlling for CS momentum. Similar results hold in cross-sectional regressions and in developed international markets. Sell-side analysts incorporate news about linked stocks sluggishly. These effects are stronger for complex/indirect linkages, and when sentiment is high. These results indicate that previously documented momentum spillover effects represent a *unified phenomenon* that is captured by shared analyst coverage.

Usman Ali
MIG Capital
Portfolio Manager
Newport Beach, CA 92660
UAli@migcap.com

David Hirshleifer
The Paul Merage School of Business
University of California, Irvine
4291 Pereira Drive
Irvine, CA 92697
and NBER
david.h@uci.edu

1. Introduction

If investors in a firm, or analysts covering that firm, have limited attention, then the price of the firm may react sluggishly to the arrival of relevant news about other firms. This suggests that firms that have fundamental similarities or fundamental linkages will have *momentum spillovers*, wherein past return of one firm predicts the returns of firms that are linked to it or similar to it. Using a variety of proxies for interfirm linkage or relatedness, various papers have verified such spillovers.[1] This literature documents lead-lag relationships among stocks belonging to the same industry (Moskowitz and Grinblatt 1999), firms that share the same geographic location (Parsons, Sabbatucci, and Titman 2016), firms that are linked along the supply chain (Cohen and Frazzini 2008 and Menzly and Ozbas 2010), firms with similar technologies (Lee, Ma, and Wang 2016), and single- and multi-segment firms operating in similar segments (Cohen and Lou 2012).

These findings raise two interesting questions. The first is whether these seemingly distinct findings can be unified by a sufficiently strong measure of firm linkage or relatedness. If so, this has advantages both for gaining a deeper understanding of the exact drivers of the effects, and for future empirical tests that might want to control for momentum spillovers in a parsimonious way. The second is whether the effect is exacerbated by the complexity of firm linkages, and more generally, whether forces that expedite transfer of information would be expected to weaken or strengthen the effect.

In this paper, we propose that the momentum spillover effects documented in past literature are aspects of a *unified phenomenon* that is captured by shared analyst coverage. In other words, we suggest that there is really just a single momentum spillover effect. For several reasons, shared analyst coverage is a useful proxy for fundamental linkages between firms and for relatedness of firms, and, therefore, it can be useful for probing more deeply into the sources of momentum spillover effects. First, Lee, Ma, and Wang (2016) document that analysts cover economically similar or related stocks—the fundamentals of analyst co-covered stocks are highly correlated. Furthermore, they show that analyst linkages explain the cross-sectional variation in firm returns and fundamentals better than traditional industry linkages. This suggests that shared analyst coverage may offer a stronger measure of fundamental linkages than proxies in the existing momentum spillovers literature.

[1] Throughout this paper, we use the terms linked firms, related firms, and peer firms interchangeably. These measures can capture either direct economic relationships between firms (e.g., customer and supplier firms) or other types of fundamental similarities.

Second, analyst linkages uniquely identify linked firm pairs, in contrast with most previous studies that aggregate stocks into buckets. For example, viewing firms that are in the same industry or geographic location aggregates related firms into large groups, rather than identifying specific pairs. Firms in the same industry or geographic location, for example, are not all equally related to each other. Studies that do identify firm-specific linkages have relatively small cross-sections and are limited to linkages along very specific dimensions. For instance, Cohen and Frazzini (2008) use data on sales to principal customers to identify firm linkages, and Cohen and Lou (2012) study conglomerate firms linked to single-segment firms. In contrast, analyst coverage peers are available for the majority of publicly traded firms throughout the globe.

Third, analyst data is available in real time, so analyst linked peers can be identified in a more timely fashion compared to most previously studied methods of identifying related firms.[2, 3]

Finally, since the number of shared analysts of a pair of firms is not a binary variable (in contrast, e.g., with whether two firms are in the same industry), the degree of linkage can be measured in a more refined way by using the number of shared analysts as a measure of the strength of the relationship.

Based on these points, we hypothesize that interfirm linkages will be stronger when identified using shared analyst coverage; and that analyst-identified linkages can be used to provide insights about the sources of the effects.

If shared analyst coverage does identify the fundamental relatedness of firms, then it may also help identify momentum spillovers. When news about one firm causes it to have a high return, for example, this information may be relevant for another linked firm. If analysts or the linked firm's investors are slow to react to this information, the linked firm will experience a high return with a lag. Furthermore, if shared analyst coverage identifies fundamental relatedness more accurately than other measures, such spillover effects may be stronger than when other such measures are used.

This further conclusion, however, is not the only possibility, because shared analysts may help expedite the transfer of information. If shared analysts update their opinions of connected stocks without delay in response to the arrival of relevant information, this could cause such information to be

[2] For instance, Cohen and Frazzini (2008) and Cohen and Lou (2012) use data from annual filings to identify related firms and Menzly and Ozbas (2010) use input-output data from Bureau of Economic Analysis (BEA), which is updated infrequently, to identify related firms.

[3] Analyst data also does not suffer from any look-ahead bias unlike geographic location data (COMPUSTAT only reports the location of the latest headquarters of each firm).

impounded so rapidly that a lead-lag relationship is not identifiable in monthly return tests. Consistent with this idea, Parsons, Sabbatucci, and Titman (2016) motivate their study of geographic connections by arguing that analysts tend to specialize by industry and not by geographic location so common information is reflected more slowly among geographic peers. There is also some evidence in support of a similar idea that common mutual fund ownership accelerates the impounding of information across related stocks. Cohen and Frazzini (2008) document that common mutual fund ownership of customer and supplier firms weakens customer to supplier return predictability.

On the other hand, in principle, expedited impounding of information across stocks could *strengthen* empirical findings of momentum spillovers. Suppose that in the absence of shared analysts certain kinds of information are impounded across linked stocks with lags of a year or more. For standard econometric reasons, holding constant the size of the effect, cross-sectional predictability is much harder to identify empirically at long lags than at short lags. This is because at longer lags there is more time for unrelated information to arrive, so the signal-to-noise ratio is lower. Indeed, for this reason we focus on predictability at horizons of up to a year.

So there are three possible hypotheses about whether analyst linkages are associated empirically with stronger return predictability than other linkage measures (in monthly tests with horizons of up to a year). First is that the effect will be stronger because analyst linkages identify fundamental relationships more sharply. Second is that the effect will be weaker because analyst linkages expedite information flow, causing news to be impounded in less than a month. Third is that the effect will be stronger (given our one-month to one-year prediction horizon) because analyst linkages expedite information flow, causing news to be impounded within a year instead of taking longer than a year.

We first verify a basic premise underlying the first hypothesis that analyst linkages help identify fundamental relationships, and that they do so more strongly than other proxies for firm linkages from past literature. We find that firm fundamentals (sales and profit growth) are strongly correlated with current and lagged fundamentals of analyst linked peer firms. Furthermore, these correlations are much higher than the corresponding correlations using other linkage proxies. This lends support to the premise of Hypothesis 1.

Turning to the return implications of the hypotheses, we find that analyst linkages are associated with extremely strong momentum spillovers—much stronger than in past literature. This evidence is consistent with the first and third hypotheses, and strongly opposes the second hypothesis. In our tests, we first link each stock to a portfolio of stocks that are also covered by analysts who cover that particular stock. We then sort stocks into quintiles based on past one-month return on the connected-stock (CS) portfolio and find a strong monotonic relationship between past CS return and future stock returns. A value-weighted long-short portfolio that is long top- and short bottom-quintile stocks generates a five-factor (market, size, value, momentum, and short-term reversal factors) alpha of 1.19% per month (t = 6.71). This portfolio continues to generate positive returns over the subsequent 11 months—its cumulative return increases to 3.21% one year after portfolio formation. We obtain significantly stronger results for equal-weighted portfolios. The equal-weighted long-short portfolio generates an alpha of 2.10% per month (t = 11.88), and a cumulative 12-month return of 6.68%.

We then compare analyst-identified momentum spillovers with previously documented momentum spillover effects. To this end, we perform both spanning regression tests and cross-sectional regression tests. The seven cross-asset momentum anomalies that we consider are industry momentum, geographic momentum, customer momentum, customer industry momentum, supplier industry momentum, single- to multi-segment firm momentum, and technology momentum.

For spanning tests, we construct long-short factor portfolios by sorting stocks into quintiles based upon each characteristic and independently based upon market capitalization. The CS momentum factor yields the highest monthly alpha of 1.68% (t = 9.67). Strikingly, the alphas of all seven cross-asset momentum factors become insignificant or turn negative once the CS momentum factor is added to the spanning regressions. In contrast, these seven cross-asset momentum factors do not explain the performance of the CS momentum factor; its alpha remains large and highly significant. These results indicate that previously studied cross-asset momentum effects are spanned by CS momentum and standard factors. In other words, there is really just one momentum spillover effect, which is captured by shared analysts as a proxy for linkage. So one of our main contributions is that we provide some structure to the "zoo" of cross-asset momentum factors proposed in the literature. We show that these factors do not "really provide independent information about average returns" (Cochrane 2011). This is also in the spirit of a literature, starting with Fama and French (1993), that attempts to capture a broad set of anomalies with only a few factors.

The results are very similar in cross-sectional tests. In Fama-Macbeth regressions using the entire cross-section, the coefficients of many of the other cross-asset momentum variables become insignificant once past CS return is added as an explanatory variable. Although one-month industry, customer, single- to multi-segment, and technology momentum variables remain statistically significant, their economic magnitudes are reduced substantially. For example, the coefficient on past one-month industry return decreases by 69% once past CS return is added to the regression. A one-standard deviation increase in past industry return predicts an increase of only 12 basis points while a one-standard deviation increase in past CS return predicts an increase of 64 basis points in future stock return.

It is well-known that Fama-Macbeth regressions can place undue weight on small and illiquid stocks, making results hard to interpret. When our sample is restricted to large stocks (market capitalization above NYSE median), the results are even stronger. All other cross-asset momentum variables become insignificant while the coefficient on past CS return remains economically very large and highly significant.

We also find that past 12-month (skipping the most recent month) CS return subsumes the predictive power of past 12-month industry and geographic return variables. However, the predictive power of longer-term lags of CS return is limited to smaller stocks. In regressions limited to large stocks, longer-term lags of CS, industry, and geographic return are all insignificant.

To evaluate the robustness of our conclusions, and to mitigate data mining concerns we also test whether the CS momentum effect is present in international markets, and whether it subsumes other effects in these markets. In developed international markets that have reasonably large cross-sections of liquid stocks, we find very strong results. Industry momentum is profitable in 6 of the 11 international markets in the sample. In spanning regressions, in all but one of these countries, the alpha of the industry momentum strategy becomes statistically and economically insignificant once CS momentum is controlled for. In contrast, the CS momentum strategy generates large and significant (at the 1% level) alphas in 10 of the 11 countries even after controlling for industry momentum.

To probe more deeply into the sources of momentum spillovers, we explore how quickly analysts apply news about firms they cover to other firms that they cover. One possibility is that analysts swiftly incorporate news about related firms into their forecasts, but that investors are sluggish in impounding the information contained in analyst forecasts. In other words, news cross firms quickly at the analyst level, so that the slow-down is in investors reacting to the analysts.

An alternative possibility is that in forming forecasts, shared analysts are slow to carry information across the firms that they cover. Even though we would expect the presence of a shared analyst to expedite information flow from news about one firm to forecasts about another linked firm, the reaction may still be slower than it should be. (Such delays could result from either analyst irrationality or agency problems.)[4]

So to test whether shared analysts are slow to carry fundamental news across firms, we regress change in analyst earnings forecast revisions on forecast revisions of linked stocks in the previous month. We find that there is predictability, and that the effect is much stronger when linkages are identified using shared analysts than using other measures of linkage from past literature. In other words, past revisions of analyst-linked firms have a much stronger ability to predict future revisions than do past revisions of firms whose linkages are defined in other ways. These results suggest that analysts have some kind of a processing bias or constraint, such as limited attention or overconfidence, that causes them to transfer information sluggishly. We do not, however, rule out the possibility that this sluggishness is induced by agency issues. The stronger predictability when linkages are defined by shared analyst coverage may reflect (consistent with Hypothesis 1) that firms that are linked by shared analysts have stronger fundamental linkages. Any general tendency of analysts to react sluggishly will be more important for firms which are genuinely related, so that there is more relevant information to be transferred across firms.

If momentum spillovers are driven by limited analyst or investor attention, then we expect them to be stronger when attention and cognitive processing is more costly. This is likely to be the case when firm linkages are more complex. For example, updating is a harder problem when there is a greater number of linked firms whose news needs to be monitored and evaluated. So one way of measuring the complexity is the number of linkages a firm has to other firms.[5] In the theoretical literature on networks, this is known as the *degree centrality* of the firm. This literature also considers the idea that the centrality of a firm can be viewed as an iterative concept. In our context, this would reflect the idea that updating information about a firm is more complex if the firms it is linked to are also complex. For example, suppose that news about firms C_1, C_2, C_3, … C_n and so forth matters for the fundamentals of firm B, which in turn are relevant for the focal firm A. Then updating by investors in firm A is harder if *firm B* has many links to

[4] As a reminder, even if shared analysts expedite the flow of information across firms, momentum spillovers could be larger when there are shared analysts, for the reasons given in Hypotheses 1 and 3. As in Hypothesis 1, the firms with shared analysts may have stronger fundamental relationships, so there is more room for spillover. As in Hypothesis 3, expediting information flow could cause spillovers to happen rapidly enough to be observable in our 1-month to 1-year forecasting window.

[5] This argument is related to, though distinct from, the argument and finding of Hirshleifer, Lim and Teoh (2009) that investors process earnings news more sluggishly on days with a greater number of earnings announcements, since processing more announcements is a more challenging task.

other firms (i.e., *n* is large), because this requires monitoring a larger number of B's neighbors. This process can be iterated any number of steps. If this is done without limit, it turns out that the resulting measure of network centrality is called *eigenvector centrality* (see, e.g., Jackson 2008). In our context, the eigenvector centrality of a firm in the network of analyst linkages is therefore another measure of the complexity of updating. We find that higher levels of both degree centrality and eigenvector centrality measures are associated with a stronger lead-lag relationship between connected stocks.

If firm A is connected to B, and B is connected to C, then A is indirectly linked to C. This suggests that that C's lagged return may predict A's return, though the effect may be diluted if second-order linkages are weaker than direct ones. On the other hand, the set of indirect linkages is larger and more complex than the set of direct ones, which makes it more costly for investors to monitor and impound indirect information signals. This could strengthen spillover effects for second-order linkages. Furthermore, the direct linkages used in our main tests are unlikely to capture all fundamental linkages between stocks, especially for stocks that are covered by only a few analysts. This also suggests that for such stocks, there will be strong indirect spillovers. In this case, it is especially likely that firm C is fundamentally connected to firm A, and the two are not covered by a shared analyst (because they have few followers). So any common news is even less likely to be reflected into the forecasts of firms A and C in a timely fashion. We find strong evidence of indirect spillovers among low analyst coverage stocks, which is consistent with the idea that complexity delays the market's impounding of information.

Research in psychology suggests that negative mood causes people to be careful and critical in their judgments, and that positive mood promotes less critical evaluation. We therefore test whether momentum spillover effects are greater in periods when investor sentiment is high, based on the idea that at such times investors may not monitor as carefully news about linked firms. In time-series regressions of CS momentum five-factor alphas on the previous month's sentiment index of Baker and Wurgler (2006), the effect is large and highly significant. A one standard deviation increase in sentiment is associated with an increase of 63 basis points in the CS momentum alpha in the next month (t = 4.54).

Finally, we show that our results are robust to alternative industry and geographic classifications. Specifically, we find very similar results using Fama-French 12, 17, and 30 industry classifications and the text-based industry classification of Hoberg and Phillips (2010, 2015, and 2016). Our results are also robust to using a state-level definition of geographic momentum. In another robustness test, we divide our sample into two equal halves and show that the main results hold in both sub-samples. Importantly, CS momentum generates an economically large alpha of 1.13% per month (t = 4.48), whereas only two of the previously studied cross-asset momentum strategies have statistically significant (though economically small) alphas in the more recent sample.

Our paper is not the first to examine leads and lags in the returns of linked firms. A large literature finds that information about related companies is incorporated into stock prices with a delay, resulting in what we call momentum spillovers. Moskowitz and Grinblatt (1999) find that past industry return forecasts future stock returns, even after controlling for stock-level momentum. Cohen and Frazzini (2008) identify economically related firms using data on firms' principal customers. They find that past customer return forecasts future returns of supplier firms after controlling for industry and cross-industry momentum effects. Another way to identify customer and supplier industries is to use data on flow of goods to and from industries. Using this approach, Menzly and Ozbas (2010) find that past customer and supplier industry returns forecast future stock returns in a larger cross-section relative to the one studied by Cohen and Frazzini (2008). Cohen and Lou (2012) use operating segment data to show that single-segment firm returns lead the returns of multi-segment firms operating in the same industries. Parsons, Sabbatucci, and Titman (2016) document geographic momentum—past return of neighboring stocks forecasts future stock returns after controlling for industry momentum. Related to the notion of industry relatedness is technological relatedness. In a very recent paper, Lee et al. (2017) find return predictability across technology-linked firms.

A basic theme of many of these papers is that investors are subject to limited attention, and therefore do not process value-relevant information about related firms in a timely fashion. Some of the papers provide evidence consistent with this hypothesis by showing that variation in attention forecasts variation in return predictability. For example, Cohen and Frazzini (2008) show that common ownership of customer and supplier stocks by mutual funds weakens the customer-supplier return predictability. Such findings are broadly consistent with a theoretical literature on how limited investor attention or cognitive processing can cause delayed stock price responses to information (Hong and Stein (1999), Hirshleifer and Teoh (2003), Peng and Xiong (2006), Hirshleifer, Lim and Teoh (2013)).

An emerging literature documents that shared analyst coverage of firms is associated with greater contemporaneous return correlations (Anton and Polk (2014), Rebello, and Xu (2014), Lee, Ma, and Wang (2016)). Lee, Ma, and Wang (2016) also examine various approaches to peer firm identification such as GICS industry classification, Yahoo Finance peers, and common search based peers. They find that analyst co-coverage peers explain the cross-sectional variation in contemporaneous firm returns and fundamentals much better than GICS based peers. Our paper differs from these in examining the effect of shared analyst coverage on future stock returns, and the relation to previously documented momentum spillover effects.

Israelsen (2016) finds that common analyst coverage leads to excess comovement. He also briefly examines whether trading strategies based on past return of peer firms can generate abnormal returns. Unlike this paper, he does not find statistically significant abnormal returns to long-short strategies that buy (short) stocks with high (low) past peer return.[6] He does find that a strategy that combines short-term reversal and peer momentum generates a statistically significant alpha. In contrast, the measure studied in this paper generates highly significant alphas for the strategies studied in Israelsen (2016) even without combing them with short-term reversal. In our robustness section, we also show that our measure subsumes the predictive ability of Israelsen's (2016) measure.

Using shared mutual fund ownership as a proxy for stock linkage, Anton and Polk (2014) use the return of connected stocks as a measure of price impact from mutual fund trading. They find that return on a connected-stock portfolio *negatively* forecasts future returns even after controlling for the short-term reversal effect. Our results are that past return on a portfolio of stocks connected through common analyst coverage *positively* forecasts future returns.

In an independent and contemporaneously written working paper, Petzev (2017) also finds a lead-lag relationship between analyst co-covered stocks. He uses a narrower definition of analyst co-coverage, and the return predictability that he documents is somewhat weaker than the results of this paper.[7] More importantly, he does not link his findings to previously studied momentum spillover effects. For example, our paper differs in showing that these effects are subsumed by our CS momentum effect, which is one of our paper's key contributions. Our paper also differs in providing international evidence of the CS momentum effect, in examining the effects of complex and higher-order linkages, and in examining the predictive power of CS momentum at different lags.

[6] The *t*-statistics are below 1.28 for all five high minus low peer return strategies in Table 10 of Israelsen (2016), and one of the strategies has a negative alpha.

[7] On average, the connected portfolio in Petzev (2017) consists of only 37 stocks, as compared with 86 stocks in this paper's connected portfolio.

2. Data

The US sample used in this paper consists of all common stocks listed on NYSE, NASDAQ, and NYSE MKT (formerly AMEX) from the CRSP database. We use the IBES detail file to identify stocks related through shared analyst coverage. At the end of each month, we define two stocks as "connected" if at least one analyst covers both stocks. A stock is considered to be covered by an analyst if the analyst issues at least one FY1 or FY2 earnings forecast for the stock over the past 12 months. The US sample starts in 1983:12—the first month for which one year of historical IBES detail data is available—and ends in 2015:12. We exclude stocks with price below $5 at the end of prior month from the return predictability tests to ensure that the results are not driven by small, illiquid stocks.

Accounting, geographic location, and segment data are from COMPUSTAT. We follow the standard convention and assume that COMPUSTAT data for fiscal years ending in year *t-1* becomes available at the end of June of year *t*. Data on customer-supplier links is from Andrea Frazzini's website and is available through 2006:05. Following Cohen and Frazzini (2008), we lag the customer-supplier links data by six months to ensure that the data is publicly available before portfolio formation. We use the annual input-output data from Bureau of Economic Analysis (BEA) to calculate customer and supplier industry returns. Specifically, we use the annual data for years 1982, 1987, 1992, 1997, 2002, 2007, and 2012 to determine the flow of goods to and from industries and assume that this flow remains constant for the in-between years. We lag the data by one year since the data becomes publicly available 11 months after the end of the reference year. Stocks are assigned to BEA industries using their historical NAICS codes and BEA NAICS-industry mapping tables. The sample for customer and supplier industry variables starts in 1986:07 due to availability of historical NAICS codes.

We use Google patent data provided by Kogan et al. (2017) to identify technology linkages among firms. Following Lee et al. (2017), we exclude financial stocks from the analysis and assume that the patent data becomes publicly available six months after the end of the year in which the patent is granted. The patent data is available through 2010 so the sample for tests including technology linked variables ends in 2012:06. Finally, we obtain factor returns from Ken French's website.

Table 1 provides some summary statistics for the connected-stock portfolios. On average, each stock is connected to 86 other stocks through shared analyst coverage. Also, only 39% of the connected stocks belong to the same Fama-French industry and only 5% belong to the same geographic county. Table 1 also shows that stocks in our universe have higher market capitalizations relative to the average stock since analysts tend to cover larger stocks. On average, our sample covers 98% of the total stock universe in terms of market capitalization and 77% in terms of number of stocks.

3. Results

We next turn to the main results of the paper. We first verify whether analyst co-covered stocks are fundamentally related. We then document the return predictability of our momentum measure and its ability to subsume known effects. Finally, we try to pin down the source of momentum spillovers by examining the effects of the complexity of linkages and of analyst behavior.

3.1. Fundamental Linkages

We first test the basic premise underlying Hypothesis 1 that firms linked through shared analyst coverage are fundamentally similar to each other. Specifically, we regress firms' annual sales and profitability growth measures on the average growth measures of their peer firms (analyst coverage peers and peer firms studied in previous literature).[8] All regressions include year fixed effects and size and book-to-market as controls; for brevity, the coefficients on these controls are not reported. To ensure that the growth variables for all firms are measured over the same horizon, we only include firms with December fiscal year ends. For ease of interpretation, all independent variables are cross-sectionally standardized to have zero mean and unit variance.

Table 2 presents the results. The first eight columns of Panel A show that there is a strong contemporaneous relationship between firm and peer firm sales growth for most peer firm measures. Consistent with Hypothesis 1, analyst connected-stock (CS) sales growth has the strongest relationship; a one-standard deviation increase in CS sales growth is associated with an increase of 11.2% in firm sales growth. The economic magnitudes of the other peer firm measures from past literature are much smaller. For instance, according to the regression in Column 2, a one-standard deviation increase in industry sales growth is associated with an increase of 3.6% in firm sales growth, which is about one-third the size of the CS sales growth coefficient. In the last eight columns of Panel A, the dependent variable is one-year ahead

[8] We calculate the average growth variables of peer firms using the same methodology as used in our return predictability results (see Table 4 for details). For example, connected-stock (CS) sales growth is calculated as the weighted average sales growth of analyst peers using the weights in Equation 1.

sales growth. The results show that CS sales growth is a strong predictor of future firm sales growth, while almost all of the other peer firm growth measures are not significant. Finally, Panel B shows that the same conclusions hold when fundamental performance is measured as profitability growth instead of sales growth.[9] In untabulated results, we also find that higher frequency CS profit growth, as measured by quarterly standardized unexpected earnings (SUE), is also a very strong predictor of future SUE even after controlling for lagged SUE over the past four quarters.

These results strongly suggest that firm and analyst peer firm fundamentals are related, and that analyst linked peers are economically much more similar to each other than the peers identified in previous studies. This lends support to the premise of Hypothesis 1.

3.2. The CS Momentum Effect

We next turn to the return predictability tests. The main variable studied in this paper is the past return on a connected-stock portfolio. Specifically, at the end of each month, for each stock *i*, we calculate its connected-stock (CS) portfolio return as the weighted average return of all stocks linked to it during the month:

$$CS\ RET_{it} = \frac{1}{\sum_{j=1}^{N} n_{ij}} \sum_{j=1}^{N} n_{ij} Ret_{jt} \,, \tag{1}$$

where Ret_{jt} is the return of stock *j* during month t, n_{ij} is the number of analysts who cover both stocks *i* and *j*, and *N* is the total number of stocks connected to stock *i* during the month. Stocks that are co-covered by a greater number of analysts are more likely to be similar to each other so they get a higher weight.

We then examine the relationship between past CS RET and future stock returns. Specifically, at the end of each month, we rank stocks into quintiles based on CS RET and calculate value- and equal-weighted returns of these quintile portfolios in the next month. These portfolios are rebalanced at the end of each month.

Table 3 reports the average returns, four- and five-factor alphas, and factor loadings of these portfolios. The four-factor model includes market, size, value, and momentum factors and the five-factor

[9] The results of Table 2 are robust to alternative measures of fundamental performance such as asset turnover and the level of profitability.

model includes the short-term reversal factor as an additional factor. There is a strong, monotonic relationship between quintile rank and future returns and alphas. The long-short portfolio which is long top-quintile and short bottom-quintile stocks generates highly significant four-factor alphas of 0.89% (value-weighted) and 1.81% (equal-weighted) per month, and both long and short legs of the portfolios generate large alphas. For value-weighted portfolios, return predictability is about twice as strong on the short side compared to the long side and for equal-weighted portfolios, it is 38% higher for the short portfolio.

Adding the short-term reversal factor to the regressions increases the magnitudes of the alphas since past month's CS return is highly correlated with stock's own return. The long-short strategy generates a value-weighted five-factor alpha of 1.19% (t = 6.71) and an equal-weighted alpha of 2.10% (t = 11.88) per month. In untabulated results, we find that the alphas of the long-short strategies are larger for decile sorts. For example, the five-factor alphas are 1.52% and 2.67% per month for value- and equal-weighted portfolios, respectively.

Figure 1 plots the cumulative returns of the value- and equal-weighted long-short portfolios over the next 12 months. Although the portfolios generate the highest return in month $t + 1$, they continue to drift upwards for the remainder of the year; the one-year cumulative return is 3.21% and 6.68% for value- and equal-weighted portfolios, respectively. Once again, predictability is stronger for the equal-weighted strategy, which is consistent with the hypothesis that smaller stocks are more prone to mispricing because of limits to arbitrage and because less information is available for smaller stocks.

Having verified that connected-stock return forecasts future returns, we next examine how connected-stock momentum is related to previously documented cross-asset momentum effects. We use both spanning tests and cross-sectional regressions for this analysis.

3.3. Spanning Tests

In this section, we present the results of time-series regressions of returns of CS momentum and various other cross-asset momentum strategies. To construct factor portfolios, we first rank stocks into quintiles at the end of each month based on the characteristic of interest (e.g., CS RET). We also independently divide stocks into large and small size groups based on whether their market capitalization is above or below the NYSE median market capitalization at the end of the month. We then calculate the value-weighted returns of the 10 (5 x 2) resulting portfolios during the next month and the long-short factor return as

$$\frac{1}{2}\left(RET_{small}^{5}+RET_{large}^{5}\right)-\frac{1}{2}\left(RET_{small}^{1}+RET_{large}^{1}\right), \tag{2}$$

where RET_{small}^{q} is the value-weighted average return of small cap stocks in characteristic quintile q and RET_{large}^{q} is the value-weighted average return of large cap stocks in quintile q in month $t+1$.[10]

We construct eight factors using this methodology. We construct the CS momentum factor by sorting stocks on past CS RET, as calculated in Equation 1. To form industry momentum portfolios, we classify stocks into industries based on Fama and French 49-industry classification (excluding the residual industry 'other') using SIC codes, and for each stock *i*, we calculate its industry return as the value-weighted average return of all stocks besides stock *i* in the same industry.[11] We then form the industry momentum factor by ranking stocks into quintiles based on their industry return in the previous month. For geographic momentum factor, we rank stocks into quintiles based on the average return in the previous month of all other stocks headquartered in the same county.[12] We construct the customer momentum factor by sorting stocks based on past month's equal-weighted average return of the firm's principal customers (Cohen and Frazzini 2008). We also construct customer and supplier *industry* momentum factors by ranking stocks based on past month's customer and supplier industry return, respectively. For each BEA industry, its customer (supplier) industry return is calculated as the weighted average return of all the industries that buy from (supply to) that industry. The flow of goods to and from industries are used as portfolio weights (Menzly and Ozbas 2010).

We construct the complicated firm momentum factor by sorting all multi-segment firms into quintiles based on the weighted average return of related single-segment firms using the percentage of sales belonging to each segment within the conglomerate as weights (Cohen and Lou 2012). Finally, we compute the technology momentum factor by sorting stocks into quintiles based on past month's

[10] We have also repeated the tests of this section by forming factor portfolios using two size groups and three cross-asset momentum groups like Fama and French (1993). Results are very similar—the CS momentum factor subsumes the return predicting ability of the other cross-asset momentum factors, but not vice versa.

[11] We exclude own stock return to ensure that industry momentum is not contaminated by short-term reversal. Industry momentum (raw) returns are slightly smaller if own stock return is included in past industry return calculation.

[12] Following Parsons, Sabbatucci, and Titman (2016), we rank stocks based on equal-weighted (instead of value-weighted) average return of neighboring stocks to make our results comparable to theirs. The returns of the geographic momentum strategy are weaker if stocks are ranked based on value-weighted average return of neighboring stocks.

weighted average return of their technology-linked stocks, where linked stocks are weighted by pairwise technology closeness. Specifically, technology closeness between firms *i* and *j* is defined as

$$TECH_{ij} = \frac{T_i T_j'}{(T_i T_i')^{1/2}(T_j T_j')^{1/2}},$$

where $T_i = (s_1, s_2, \ldots, s_k, \ldots, s_{427})$ is a vector of the firm's patent activity and the k^{th} element, s_k, is the average share of the firm's patents in technology class *k* out of the firm's total number of patents granted over the rolling past five years (Lee et al. 2017).

Panel A of Table 4 presents the average returns and alphas of these factors. The second and third columns show that all eight factors have positive and significant alphas after controlling for MKT, SMB, HML, UMD, and short-term reversal factors.[13] CS momentum factor is the most profitable with a five-factor alpha of 1.68% per month, almost twice the size of industry momentum alpha, and has the highest statistical significance (t = 9.67). Geographic momentum factor has the smallest alphas and technology momentum factor alphas have the lowest statistical significance. In Columns 4 and 5, we add the CS momentum factor as an additional explanatory variable in the four- and five-factor regressions. Remarkably, the alphas of all other cross-asset momentum factors become small and insignificant. In fact, industry, geographic, and customer industry, and technology momentum four-factor alphas are negative and statistically significant. Only customer momentum factor has positive alphas but they are not statistically significant. These results clearly suggest that the returns of all other cross-asset momentum strategies can be explained by their loadings on the CS momentum factor.[14]

In Panel B of Table 4, we regress CS momentum factor returns on the four (five) factors plus each of the seven other cross-asset momentum factors individually. None of these factors can explain the returns of CS momentum factor as its alpha remains economically large and statistically significant at 1% level in all of the regressions. In Column 1, the alphas of CS momentum factor are between 0.65% and 1.11% per month and in Column 2, they range from 1.10% to 2.24% per month.[15] While industry

[13] Adding a liquidity factor (Pastor and Stambaugh 2003) or using Fama-French five factor model augmented with momentum, short-term reversal, and liquidity factors has no effect on the conclusions of this section.
[14] We have also run regressions with only CS momentum factor as the explanatory variable and the results are very similar—all seven cross-asset momentum factors have insignificant or negative alphas.
[15] Regressions of CS momentum factor returns on four (and five) factors and Customer momentum factor have large alphas because the sample for Customer momentum factor ends in 2006:06 and the CS momentum strategy was more profitable in the earlier part of the sample period.

momentum factor can explain a large fraction of the returns of CS momentum factor, the alphas are still economically large 0.65% and 1.10% per month in Columns 1 and 2, respectively.

Finally, we test whether a factor which combines all seven of the previously studied firm linkage measures can explain the CS momentum effect. To construct this factor, we first cross-sectionally standardize each of the seven variables to have zero mean and unit variance. We then calculate the average of these standardized variables and construct a long-short factor by ranking stocks based on this variable and market capitalization, as described in Equation (2).[16] The last row of Panel B of Table 4 shows that the alpha of CS Momentum factor remains large and significant even after controlling for this combined factor. This result indicates that the CS momentum effect cannot be simply explained by combining the known effects into a more powerful measure.

Our results suggest very substantial return predictability even after controlling for known anomalies. After hedging out exposure to common risk factors, the CS momentum factor has a t-statistic of 9.67. This implies a Sharpe ratio of 1.71 over the 1984-2015 sample period. We have examined a comprehensive list of anomalies proposed in the literature and studied by Hirshleifer, Daniel, and Sun (2017). The Sharpe ratios of all these anomalies are significantly below 1.71 over the same sample period.

3.4. Fama-MacBeth Regressions

We next run Fama-MacBeth regressions of one-month ahead stock returns on past returns of portfolios of related stocks described in the last sub-section. We also include controls for book-to-market, size, past one-month return, and past 12-month (skipping the most recent month) stock return in all of the regressions but do not report their coefficients for brevity. We estimate two sets of regressions, one for the entire cross-section and one for large capitalization stocks (market capitalization above NYSE median market capitalization) since regressions with all stocks are dominated by small stocks which are numerous but make up a tiny fraction of the total stock market capitalization.

Table 5 presents the results of these regressions; Columns 1-22 present the results for all stocks and Columns 1a-22a present the results for large stocks. Columns 1, 1a, 2, and 2a show that both past

[16] To maximize the sample, if data on any of the variables is unavailable for a stock in a given month, we calculate the average of the remaining variables.

one-month CS and industry return are individually strong predictors of future returns in both samples, consistent with the spanning tests in the previous section.

In Column 3, once both are included in the same regression, the predictive power of industry return decreases substantially by 69%, while the coefficient on CS return does not decrease much. In terms of the economic magnitudes of the effects, a one-standard deviation increase in past CS return predicts an increase of 64 basis points while a one-standard deviation increase in past industry return predicts an increase of only 12 basis points in future stock return according to regression 3.

Column 3a shows that the decline in predictive power of industry return is even stronger for large cap stocks—the coefficient on past industry return becomes tiny and insignificant when past CS return is added to the regression. These results once again suggest that almost all of the return predictability of past industry return can be explained by the past return of analyst linked stocks, especially for large stocks.

While most of the previous cross-asset momentum studies have focused on one-month lagged returns as predictors, some studies also examine longer horizon lags. Columns 4 and 5 of Table 5 show that CS and industry return over the past 12 months (skipping the most recent month) are individually statistically strong predictors of future returns. However, consistent with past studies (e.g., Moskowitz and Grinblatt 1999), the economic magnitude of the long-horizon effects is rather modest. A one-standard deviation increase in CS RET (t-12, t-2) predicts an increase of only 0.16% in future return and a one-standard deviation increase in Industry RET (t-12, t-2) predicts an increase of only 0.14% in future return. Column 6 shows that CS RET (t-12, t-2) subsumes the predictive power of Industry RET (t-12, t-2) once both are included in the same regression. Columns 4a-6a show that long-horizon past cross-asset returns do not predict returns among large stocks, but past one-month CS return remains a strong predictor.

Columns 7-10 and 7a-10a of Table 5 examine geographic momentum. The results once again suggest that the predictability of past (short- and long-horizon) return of neighboring stocks is subsumed by past CS return as the coefficients on one-month and 12-month geographic return variables become insignificant once CS return variables are added to the regressions. The next seven columns examine return predictability along the supply chain. Columns 11, 11a, 12, and 12a show that past return of firm's principal customers is a strong predictor in both the samples, but its predictability is largely subsumed by past CS return—the coefficient on past customer return decreases by almost one half in regression 12 and becomes insignificant in regression 12a once CS return is added to the regressions. Columns 13-17 and 13a-17a show that the same result holds for past customer and supplier *industry* returns; while both of them are really strong predictors of future returns on their own in both samples, their coefficients become tiny and insignificant once we control for past CS return.

Columns 18, 18a, 19, and 19a examine the return predictability from single- to multi-segment firms. In Column 19, including past CS return greatly reduces the predictive power of past return of single-segment firms—the coefficient decreases by almost 60%. A one standard-deviation increase in CS RET predicts an increase of 54 basis points while a one standard-deviation increase in Single-Segment RET predicts an increase of only 12 basis points in future return according to the regression in Column 19. Once again, this effect is stronger among large stocks as the coefficient on Single-Segment RET becomes small and insignificant in Column 19a.

Finally, columns 20, 20a, 21, and 21a show the results of regressions including past return of technology linked firms. Regressions 20 and 21, which include large and small cap stocks, show that including past CS return reduces the predictive power of past return of technology linked firms by almost 60%. In terms of the economic magnitudes, a one standard-deviation increase in CS RET predicts an increase of 58 basis points while a one standard-deviation increase in Technology Linked RET predicts an increase of only 12 basis points in future return according regression 21. Column 20a shows that among large cap stocks Technology Linked RET is a very weak predictor of future returns even without including CS RET in the regression. Once CS RET is included as an explanatory variable, Technology Linked RET loses its weak significance in Column 21a.

In regressions 22 and 22a, we include all of the above predictors in the regressions.[17] The results show that past one-month CS return remains a highly significant predictor even after simultaneously controlling for all of the previously documented cross-asset momentum effects. None of the other cross-asset momentum variables are significant in regressions 22 and 22a.

All in all, the cross-sectional regression tests confirm the findings from the spanning tests. Past CS return is a strong predictor of future returns and it largely subsumes the predictive power of other cross-asset momentum anomalies, especially among large capitalization stocks.[18]

---

[17] We do not include past customer return as a predictor because the resulting cross-section becomes extremely small to give any meaningful results.

[18] We have also repeated the tests of this section using market-capitalization-weighted regressions to minimize the effect of small firms. Only past CS return is a significant predictor in these regressions and all other cross-asset momentum variables become insignificant once CS return is included as a predictor.

3.5. International Tests

In order to verify the robustness of our conclusions and to address any data mining concerns, we next test whether similar patterns show up in international markets. A major advantage of using analyst co-coverage to identify related firms is that such relationships can be identified for the vast majority of stocks globally.

Due to lack of availability of data on other linkages, we focus on return predictability arising from analyst and industry linkages. The sample for international tests includes the major developed markets in the S&P Global BMI Index. Analyst forecast data is from IBES Global Detail File and country-level market, size, value, and momentum factor returns are from AQR's data library. Following the methodology described on Ken French's website, we also construct a short-term reversal factor for each country by sorting stocks based on size and past one-month return. Stock return and market capitalization data are from S&P Capital IQ. All returns are in USD. The sample for each country begins in the first month in which there are at least 50 stocks in the S&P BMI Index belonging to that country that have analyst forecast data available and ends in 2015:12 for all countries. Table 6 lists the countries along with the sample start dates.

Similar to the US tests, we define two stocks as connected if at least one analyst covers both stocks. At the end of each month for each stock, we calculate CS RET as the weighted average return of all stocks connected to it during that month, as described in Equation 1. We then rank stocks in each country into two groups based on their market capitalization, and within each group we rank the stocks into quintiles based on CS RET.[19] We then calculate CS momentum factors for each country as described in Equation 2.

For industry momentum portfolios, we assign stocks to sectors based on their GICS codes. Using a broader sector classification ensures that the industry portfolios include a sufficient number of stocks to be meaningful. At the end of each month, we rank stocks in each country into two size groups, and within each size group into quintiles based on one-month industry return. For each stock, its industry return is calculated as the value-weighted average return of all other stocks in the same industry. We then compute industry momentum factor returns for each country as described in Equation 2.

[19] Since many countries have small cross-sections (especially in the early years of the sample), we use dependent sorts to ensure that the portfolios are well diversified.

Table 6 presents the results of time-series regressions of CS and industry momentum factor returns.[20] Column 2 shows that the industry momentum factor generates a positive and significant five-factor alpha in six out of the 11 countries. However, in all but one of these countries, the alpha becomes both economically and statistically insignificant once the CS momentum factor is added to the regressions in Column 3. For instance, industry momentum has a highly significant five-factor alpha of 0.67% per month in the Japan, but the alpha decreases to an insignificant 0.15% per month after controlling for CS momentum. The alpha remains statistically significant in the UK after controlling for CS momentum, but its economic magnitude decreases substantially from 1.21% to 0.36% per month. Industry momentum five-factor alphas are also weakly significant (at 10% level) in three countries, but these alphas lose their weak significance once the CS momentum factor is added to the regressions in Column 3. These results clearly show that the returns of the industry momentum factor can be completely explained by the CS momentum factor in international markets as well.

In sharp contrast, Column 6 of Table 6 shows that CS momentum factors generate significant (at 1% level) alphas even after controlling for industry momentum factors in 10 of the 11 countries. Notably, CS momentum generates economically large returns in Hong Kong, Sweden, Italy, and Spain where industry momentum returns are weak. CS momentum is also much more profitable; the average five-factor alpha of CS momentum factor is 1.15% per month compared to 0.69% per month for industry momentum factor. CS momentum factor alpha is also significant in Australia but becomes insignificant once industry momentum is controlled for.

3.6. Mechanism

We next probe more deeply the mechanism underlying the lead-lag relationship. More complex judgments require greater attention and cognitive processing. This suggests that sluggish reactions to news about linked firms will be greater when there is a greater number of linked firms whose news needs to be monitored and evaluated. So we hypothesize that if the lead-lag relationship between connected stocks is being driven by investors' limited ability to process information, it should be stronger if the connected portfolio is more difficult to process.

[20] For brevity, we only report five-factor alphas.

To test this hypothesis, we use two measures of complexity. The first is the number of stocks that a particular stock is connected to in the network of analyst linkages. In the network theory literature, this is referred to as degree centrality. The second is the eigenvector centrality measure in the network of analyst linkages. As discussed in the introduction, this reflects the fact that in principle an investor should recognize indirect linkages, as when firm C affects firm B which in turn affects firm A; and reflects the fact that such relationships could be iterated any number of steps. It is likely that if a stock is connected to a lot of different stocks, the information about related firms will be incorporated into prices more slowly as investors will need to examine a large number of related firms. Similarly, if a stock is linked to other stocks that are more complex (and those stocks in turn are linked to other stocks that are more complex—in principle ad infinitum), that makes it harder for investors in the stock to incorporate information rapidly and completely.

To capture the effect of complexity, we add interaction terms between our complexity measures and CS Return as predictors in our regression tests. A problem with this testing approach is that firms that are covered by a lot of analysts will have connected portfolios that consist of more firms. Since analyst coverage is highly correlated with firm size, such a test will get confounded with the relationship between firm size and the strength of lead-lag effect. Eigenvector centrality is also highly correlated with firm size. To address this, we control for the interactions between firm size and CS Return and between analyst coverage and CS Return in our regression tests. (The regression also includes controls for past one-month return, past 12-month return, size, and book-to-market.)

Table 7 presents the results. Consistent with the idea that information diffuses slowly among stocks with little analyst coverage, we find that the return predictability of CS Return decreases with analyst coverage in regression 1. Moreover, the coefficient on the interaction term #Connections*CS Return is positive and significant (t = 4.00). This result is consistent with the hypothesis that investors have greater difficulty extracting information when it is associated with a large number of related firms. Column 2 shows that the interaction term between eigenvector centrality and CS Return is also positive and significant (t = 5.08). This is consistent with the hypothesis that it is hard for investors to impound indirect effects when the firm is situated in a highly connected part of the analyst-linkage network, so that the firms it is connected to are highly connected, and so on iteratively.

We next examine whether more complex indirect linkages predict returns. If firm A is connected to B, and B is connected to C, then A is indirectly linked to C. This suggests that firm C's lagged return may also predict firm A's return. This effect may be diluted if indirect linkages are weaker than direct ones. On the other hand, since there are more paths from C to A than from B to A, the monitoring and computational costs to investors of determining out how news about C affects A are higher. This could strengthen the effects of limited attention. Moreover, firms that are covered by a few analysts are connected to a smaller set of stocks according to our measure of connectedness. For these firms, the direct connections examined so far may not capture all of the fundamental linkages that they have with other firms. In the example above, if stocks A and C are related but not linked directly because A is followed by a few analysts, the return predictability from C to A is likely to be strong, and may even be stronger than from B to A because A and B share common analysts whose forecast revisions are likely to help impound the relevant information in news about B into the price of A; whereas A and C do not have any common analysts.

To test for indirect momentum spillovers, we examine the predictive power of CS Return Level 2, which is computed as

$$CS\ RET2_{it} = \frac{1}{\sum_{j=1}^{N} n_{ij}} \sum_{j=1}^{N} n_{ij} CS\ RET_{jt}. \tag{3}$$

We also divide our sample into two groups based on analyst coverage. Columns 4-7 of Table 7 present the results of this analysis. Columns 4 and 5 show that among stocks with low analyst coverage, both CS Return and CS Return Level 2 are individually strong predictors of future returns. When both are included in the same regression in Column 6, CS Return Level 2 has much stronger predictive power. A one standard deviation increase in CS Return Level 2 predicts an increase of 72 basis points (t = 7.39) in future return, while the same increase in CS Return predicts an increase of only 15 basis points (t = 2.94).[21, 22] In Column 7, the sample is stocks with high analyst coverage. The results show that CS Return Level 2 is an insignificant predictor among high analyst coverage stocks which suggests that the direct linkages capture most of fundamental linkages for firms that are covered by many analysts. Overall, these results are consistent with limited investor attention as the source of underreaction.

We next examine how quickly analysts incorporate news about related firms into their forecasts. One possibility that is potentially consistent with our results so far is that analysts react swiftly to news about related firms, but that investors are sluggish in impounding the information contained in analyst

[21] We have also examined the return predictive power of CS Return Level 3, but it is not statistically significant after controlling for the first two levels of CS Return, which suggests that the first two levels capture most of the linkages for low analyst coverage stocks.

[22] We find very similar results when split the sample based on market capitalization instead of analyst coverage, which is not surprising since size is highly correlated with analyst coverage.

forecasts. Another possibility is that analysts themselves are slow to carry information across firms they cover due to a behavioral bias or constraint. Moreover, if it is more difficult for analysts to extract information from firms that are linked through shared analyst coverage, then this information should predict their future forecasts more strongly than the information contained in other linkages. To test these hypotheses, we repeat the tests of Table 5 except that we use analyst forecast revisions of the current fiscal year earnings instead of stock returns.

Table 8 presents the results. All of the regressions include past one-month and past 12-month (skipping the most recent month) return, size, and book-to-market ratio as control variables, but their coefficients are not reported for brevity. The dependent variable is one-month ahead percentage change in consensus annual earnings forecast of the stock. Column 1 shows that the average forecast revision of stocks in the same industry (Industry FR) is a very strong predictor of future revisions, consistent with previous studies.

In Column 2, we add analyst connected-stock forecast revision (CS FR) as an additional explanatory variable. For each stock, CS FR is calculated as the weighted average forecast revision in the previous month of all stocks that are linked to that particular stock through shared analyst coverage using the same weights as in Equation 1. The coefficient on Industry FR halves once CS FR is added to the regression while the coefficient on CS FR is much larger and highly significant (t = 23.25). A one standard-deviation increase in CS FR predicts an increase of 86 basis points while a one standard-deviation increase in Industry FR predicts an increase of much smaller 36 basis points in next month's consensus forecast revision of the stock according to the regression in Column 2.

Columns 3 and 4 of Table 8 show that CS FR is a much stronger predictor of future revisions than the past average forecast revision of stocks in the same geographic location (Geographic FR) and that adding CS FR as an explanatory variable reduces the predictability of Geographic FR by half. Columns 5-10 show that similar results hold for linkages along the supply chain. In fact, after controlling for CS FR, the coefficients on customer industry and supplier industry forecast revisions become economically small and statistically insignificant. Columns 11 and 12 show that even for conglomerate firms, CS FR is a significantly stronger predictor than revisions of single-segment firms (Single-Segment FR) operating in the same segments; a one standard-deviation increase in CS FR predicts an increase of 89 basis points while a one standard-deviation increase in Single-Segment FR predicts an increase of only 20 basis points in future revisions according to the regression in Column 12. Finally, columns 13 and 14 show that CS FR is a much stronger predictor of future revisions compared to past revisions of technology-linked firms; a one standard-deviation increase in CS FR predicts an increase of 86 basis points while a one standard-deviation increase in Technology Linked FR predicts an increase of only 15 basis points in future revisions according to the regression in Column 14.

These results suggest that the return lead-lag relationship that we document is at least partially driven by sluggish analyst forecasting behavior.[23] In order to identify more sharply the effect of analyst behavior on the lead-lag relationships, we have also examined the effects of exogenous changes in stock linkages due to broker mergers. Unfortunately, the sample size is too small for us to detect any return predictability either before or after changes in these linkages. Only about 1600 stock pairs become disconnected due to broker mergers, which is a negligible fraction of the total stock pairs used in our main tests. We do, however, find strong contemporaneous correlation in returns for these stock pairs both before and after they become disconnected, which is consistent with the hypothesis that an exogenous change in coverage does not affect the underlying fundamentals of the connected firms.

The psychology literature suggests that mood valence affects how carefully people process information to form judgements. Specifically, studies report that good mood tends to promote the use of simplifying heuristics in decision making (see the reviews of Bless, Schwarz, and Kemmelmeier (1996) and Isen (2000)). Furthermore, negative mood is associated with people engaging in detailed analysis, whereas good mood is associated with less critical modes of information processing (Schwarz (1990), Petty, Gleicher, and Baker (1991), and Sinclair and Mark (1995)). In our context, this suggests that during periods of high sentiment investors may be less careful about monitoring and evaluating news about linked firms. This in turn suggests that momentum spillover effects are likely to be greater when investor sentiment is high. To test this idea, we regress the time-series of CS momentum five-factor alphas (intercept + residual) on previous month's sentiment index of Baker and Wurgler (2006). We find that a one standard deviation increase in sentiment predicts an increase of 63 basis points in CS momentum alpha in the next month (t = 4.54).

[23] It might seem surprising that the same analysts who are able to identify economically related firms are not skilled enough to update their forecasts to reflect common information about related firms in a timely fashion. However, several papers have documented inefficient forecasting behaviors by analysts, and have offered explanations in terms of biases, constraints, or agency problems. For example, forecast revisions of a stock are very strong predictors of subsequent forecast revisions of the same stock. If analysts underreact to news about the *same* firm, it is very plausible that they might underreact to news about a firm that is merely *related*.

3.7. Robustness

We next perform a series of checks to verify the robustness of our conclusions. We first show that our results are robust to a number of alternative industry classifications. In the first three rows of Panel A of Table 9, we construct industry momentum factors using Fama-French 12, 17, and 30 industry classifications. The results show that all three of these industry momentum factors lie inside the span of CS momentum factor—the alphas are insignificant. In contrast, the CS momentum factor has positive and significant (at the 1% level) alphas after controlling for these alternative industry momentum factors.

The next row examines the text-based industry classification developed by Hoberg and Phillips (2010, 2015, and 2016). This methodology constructs a set of peers for each firm by comparing the business description section of the firm's 10-K with those of other firms and it also assigns a similarity score to each peer. To construct text-based industry momentum portfolios, we rank stocks into quintiles based on similarity score-weighted average return of peer firms in the last month. Data on text-based industry classification is available from Gerard Hoberg's website for the period from 1997:07 to 2015:06. Table 9 shows that text-based industry momentum is also subsumed by CS momentum but not vice versa—CS momentum factor generates an alpha of 0.58% per month even after controlling for Text-based industry momentum factor, while Text-based industry momentum factor has a negative alpha of -0.08% per month after controlling for CS momentum.

We next examine whether our results are robust to an alternative definition of geographic momentum.[24] Specifically, for each stock, we calculate its neighboring stocks' return as the average return of all other stocks headquartered in the same state (instead of county) as that particular stock. Panel A of Table 9 shows that using this alternative definition does not affect the earlier conclusion.

In Panel B of Table 9, we divide our sample into two equal halves and conduct the tests of Table 4 in each sub-sample.[25] The first row shows that although the predictability of CS momentum has declined in recent years, CS momentum factor yields an economically large five-factor alpha of 1.13% per month (t = 4.48) from 2000-2015. The next six rows show that the results of Table 4 also show up in the two sub-samples. Almost all of the other cross-asset momentum factors have negative or insignificant alphas once

[24] Parsons, Sabbatucci, and Titman (2016) use BEA defined Economic Areas to calculate geographic momentum. However, BEA has stopped providing zip code to Economic Area mapping so we are unable to use their exact measure of geographic momentum.

[25] We do not examine customer momentum in Table 9 since data on customer-supplier links is not available post 2006:06.

the CS momentum factor is added to the spanning regressions. The only exception is industry momentum in the first half of the sample—its alpha remains significant even after controlling for CS momentum but the alpha decreases substantially by 63%.

In contrast, the CS momentum factor yields large alphas (all significant at the 1% level) even after controlling for other cross-asset momentum factors in both sub-samples. Also, strikingly, while CS momentum generates a large alpha, all but two of the other cross-asset momentum factors have insignificant and small alphas in the more recent sub-sample even without controlling for CS momentum.

Finally, we compare our connected-stock measure with the one studied by Israelsen (2016). We limit our analysis to the largest 10% of stocks so the tests are conducted on the same sample that is studied by Israelsen. In Panel A of Table 10, we rank stocks into quintiles based on CS return and construct a value-weighted long-short CS momentum factor which is long top- and short bottom-quintile stocks. We also construct a similar long-short factor based on the measure studied by Israelsen. Consistent with the evidence in Israelsen (2016), his factor generates an insignificant return. Moreover, once the CS momentum effect is controlled for, the alpha of Israelsen's momentum factor turns negative. In contrast, CS momentum factor generates a positive and significant alpha of 0.31% per month even after controlling for Israelsen's momentum factor.

Panel B of Table 10 shows that the same conclusions hold in cross-sectional regression tests. The first two columns show that CS return is a strong predictor and it subsumes the predictive ability of Israelsen's measure. In the last 2 columns, we exclude the set of stocks for which Israelsen finds the greatest predictability (past winners with lowest peer return and past losers with highest peer return). This has no effect on our result.

4. Conclusion

If two firms are economically connected or have similar economic fundamentals, news about one is relevant for the other. If investors in or analysts of a firm underreact to relevant information about a linked firm, there will be cross-firm return predictability, which we call momentum spillovers. Past research has documented such spillovers with an array of proxies for interfirm linkage or relatedness, such as common industry, common geographical location, supply chain links, technology links, and similar firm divisions.

We show that these spillover effects are actually a unified phenomenon that is captured by shared analyst coverage. In motivation of our tests, we provide reasons why shared analyst coverage could be associated with either stronger or weaker momentum spillovers. On the one hand, such spillovers are driven by fundamental relatedness of firms. Other things equal, a sharper identification of relatedness should lead to stronger effects. On the other hand, shared analysts may help expedite the impounding of information between linked firms. If so, this could cause any lead-lag relationship to be at too high a frequency to be detectable in monthly return tests. Finally, expedited impounding of information across stocks could make momentum spillovers *more detectible*, if, in the absence of shared analysts, lags in the impounding of information are very long (e.g., longer than a year), since predictability of a given size is statistically harder to detect at long lags.

We first show that analyst linkages do in fact identify fundamental relationships, as reflected in stronger cross-firm correlations in current and lagged sales and profit growth. Furthermore, we find that the returns of stocks with shared analyst coverage have a strong and highly significant lead-lag relationship. A long-short trading strategy based on this relationship yields monthly value- and equal-weighted five-factor alphas of 1.19% and 2.10%, respectively.

We find that previously-studied industry, geographic, customer, customer industry, supplier industry, single- to multi-segment firm, and technology cross-asset momentum effects are subsumed by our CS momentum effect. In spanning regressions, the alphas of these cross-asset momentum strategies become insignificant or turn negative once CS momentum effect is controlled for. We find similar results using cross-sectional regressions, and in a large sample of international markets.

To further explore the source of this effect, we examine whether the forecasts of shared analysts react rapidly in impounding information across firms. We find that analysts, like market prices, react sluggishly. Past earnings forecast revisions of analyst-linked firms are strong predictors of future revisions of the firm, and this predictability is much stronger when linkages are identified using shared analysts than linkages used in previous literature.

We also test whether greater complexity of a firm's analyst linkages to other firms, and more generally of the firm's position in the network of analyst linkages between firms, retards the flow of information to that firm. We find that this is the case—the return predictability is significantly higher for firms that are linked to a greater number of firms, and for firms that have higher eigenvector centrality in the network of analyst linkages. We also find that second-order, indirect linkages also predict returns strongly, especially among low analyst coverage stocks, which is consistent with limited investor attention as the source of underreaction. We further find, consistent with the psychological hypothesis that positive mood is associated with less critical consideration in forming judgments, that momentum spillover effects are substantially stronger during periods of high market sentiment.

Overall, our findings suggest several conclusions. First, there is basically only one momentum spillover effect, and it is well captured by analyst linkages. There are strong indications that analyst linkages proxy for fundamental linkage, which offers a plausible explanation for the effect. Second, although we do not rule out the possibility that shared analysts expedite the flow of information across firms, even the forecasts of shared analysts underreact, which highlights a surprising limitation in the ability or willingness of analysts to process information effectively. Third, analyst connection as a proxy for firm linkages provides an excellent research tool for studying information flow across firms, because of its strong identification of fundamental linkages, its strong and parsimonious identification of momentum spillovers, and by its availability for large samples of firms in many countries, and its ability to identify pairwise linkages rather than by broad aggregates of firms. This last point may have value for future research into network effects, since analyst linkages could be used to map out the entire network of firm connections. Finally, as a practical matter, using analyst coverage to identify momentum spillovers leads to a simple and profitable strategy—one that is much more profitable than those constructed based on past measures of firm linkage. In fact, the CS momentum factor generates a Sharpe ratio of 1.71, after hedging out exposure to standard risk factors, which is much larger than that of any other anomaly that we are aware of over a similar sample period.

References

Anton, M., Polk, C., 2014, Connected Stocks, Journal of Finance 69, 1099-1127.

Baker, M., Wurgler, J., 2006, Investor sentiment and the cross-section of stock returns, Journal of Finance 61(4), 1645-1680.

Bless, H., Schwarz, N., Kemmelmeier, M., 1996, Mood and stereotyping: The impact of moods on the use of general knowledge structures, European Review of Social Psychology 7, 63-93.

Cochrane, J. H., 2011, Presidential address: Discount rates, Journal of Finance, 66 (4), 1047-1108.

Cohen, L., Frazzini, A., 2008, Economic links and predictable returns, Journal of Finance 63 (4), 1977-2011.

Cohen, L., Lou, D., 2012, Complicated firms, Journal of Financial Economics 104, 383-400.

Daniel, K., Hirshleifer, D., Lin, S., 2017, Short and long horizon behavioral factors, Working paper, Columbia University.

Fama, E., MacBeth, J., 1973, Risk, return and equilibrium: empirical tests, Journal of Political Economy 81, 607-636.

Fama, E., French, K., 1993, Common risk factors in the returns on stocks and bonds, Journal of Financial Economics 33, 3-56.

Hirshleifer, D., Teoh, S. H., 2003, Limited attention, information disclosure, and financial reporting, Journal of Accounting and Economics 36 (1), 337-386.

Hirshleifer, D., Lim, S. S., Teoh, S. H., 2011, Limited investor attention and stock market misreactions to accounting information, Review of Asset Pricing Studies 1 (1), 35-73.

Hoberg, G., Phillips, G., 2010, Product market synergies and competition in mergers and acquisitions: A text-based analysis, Review of Financial Studies 23 (10), 3773-3811.

Hoberg, G., Phillips, G., 2015, Text-based industry momentum, Working paper, University of Southern California.

Hoberg, G., Phillips, G., 2016, Text-based network industries and endogenous product differentiation, Journal of Political Economy 125 (5), 1423-1465.

Hong, H., Stein, J., 1999, A unified theory of underreaction, momentum trading, and overreaction in asset markets, Journal of Finance 54, 2143-2184.

Isen, A., 2000, Positive affect and decision making, in M. Lewis and J. Haviland-Jones, eds.: Handbook of Emotion, Guilford, NY.

Israelsen, R., 2016, Does common analyst coverage explain excess comovement?, Journal of Financial and Quantitative Analysis 51 (4), 1193-1229.

Jackson, M. O., 2008, Social and Economic Networks, Princeton University Press, Princeton, NJ.

Kogan, L., Papanikolaou, D., Seru, A., Stoffman, N., 2017, Technological innovation, resource allocation, and growth, Quarterly Journal of Economics 132 (2), 410-431.

Lee, C., Sun, S., Wang, R., Zhang, R., 2017, Technological links and predictable returns, Journal of Financial Economics, Forthcoming.

Lee, C., Ma, P., Wang, C., 2016, The search for peer firms: When do crowds provide wisdom?, Working paper, Stanford University.

Menzly, L., Ozbas, O., 2010, Market segmentation and cross-predictability of returns, Journal of Finance 65, 1555-1580.

Moskowitz, T., Grinblatt, M., 1999, Do industries explain momentum?, Journal of Finance 54, 1249-1290.

Muslu, V., Rebello, M., Xu, Y., 2014, Sell-side analyst research and stock comovement, Journal of Accounting Research 52 (4), 911-954.

Parsons, C., Sabbatucci, R., Titman, S., 2016, Geographic momentum, Working paper, University of California San Diego.

Pastor, L., Stambaugh, R., 2003, Liquidity risk and expected stock returns, Journal of Political Economy 111, 642-685.

Peng, L., Xiong, W., 2006, Investor attention, overconfidence and category learning, Journal of Financial Economics 80 (3), 563-602.

Petty, R. E., Gleicher, F., Baker, S. M., 1991, Multiple roles for affect in persuasion, in J. Forgas, ed.: it Emotion and Social Judgments, Pergamon, Oxford.

Petzev, I., 2017, Information diffusion in analyst portfolios, Working paper, University of Zurich.

Schwarz, N., 1990, Feelings as information. Informational and motivational functions of affective states, in R. Sorrentino and E.T. Higgins, eds.: Handbook of Motivation and Cognition, Guilford Press, NY.

Sinclair, R. C., Mark, M. M., 1995, The effects of mood state on judgmental accuracy: Processing strategy as a mechanism, Cognition and Emotion 9, 417-438.

Figure 1: Cumulative Returns

This figure plots the cumulative returns over the 12 month period after formation of the value- and equal-weighted long-short portfolios described in the caption of Table2.

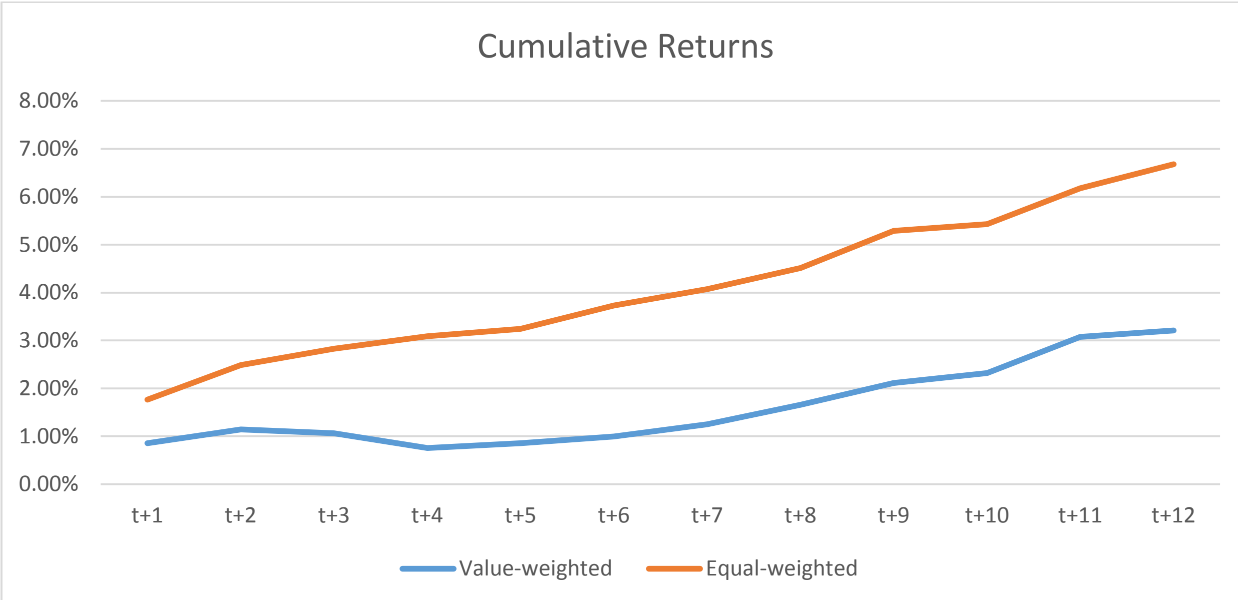

Table 1: Summary Statistics

This table reports summary statistics for the sample used in this paper. The sample period is 1984:01 to 2015:12. The sample includes common stocks listed on NYSE, AMEX, and NYSE MKT and excludes stocks with price <$5. Each month, the connected-stock portfolio of each stock is defined as the set of all stocks that are also covered by the analysts who cover that particular stock. A stock is considered to be covered by an analyst if the analyst issues at least one FY1 or FY2 earnings forecast for the stock over the past 12 months. Each month, stocks are assigned to industries using Fama-French 49-industry classification based on their SIC codes and to geographic counties based on the location of their headquarters. The first five rows of Panel A report the time-series averages of monthly cross-sectional minimum, median, mean, maximum, and standard deviation of the respective variables. "All stocks" refers to all common stocks listed in NYSE, NASDAQ, and NYSE MKT with month end price >$5. The last two rows of Panel A report the time-series minimum, median, mean, maximum, and standard deviation of the % of all stock universe covered by the sample used in this paper. Panel B reports the average number of focal firms per month and their average market capitalization for the eight momentum measures studied in this paper.

Panel A

	Min	Median	Mean	Max	Std. Dev.
# connected stocks	1	71	86	368	62.09
% connected stocks in same industry	0	0.35	0.39	1	0.29
% connected stocks in same geographic location	0	0.01	0.05	0.88	0.09
Universe market capitalization	9.56	540.92	3,291.96	277,636.93	12,609.05
All stocks market capitalization	4.30	376.15	2,729.93	277,636.93	11,464.09
% of total number of stocks covered	0.52	0.78	0.77	0.91	0.08
% of total market capitalization covered	0.89	0.98	0.98	1.00	0.02

Panel B

	Avg. # Focal Firms	Avg. Focal Firm Size
CS Momentum	3,010	3,291.96
Industry Momentum	2,960	3,264.46
Geographic Momentum	2,619	3,552.58
Customer Momentum	232	1,546.08
Supplier Industry Momentum	2,647	3,435.48
Customer Industry Momentum	2,636	3,444.17
Complicated Firm Momentum	671	5,833.59
Technology Momentum	972	4,879.11

Table 2: Fundamental Linkages

This table reports the results of panel regressions. Sales growth(t) is calculated as Sales per share$_t$ /Sales per share$_{t-1}$ -1. Profit growth is calculated as (Profit$_t$ - Profit$_{t-1}$)/average(Assets$_t$, Assets$_{t-1}$), where Profit is measured as operating income before depreciation (COMPUSTAT data item OIBDP). Profit growth is scaled by average assets since Profit is negative for many firm years in the sample. CS Sales growth is calculated the weighted average Sales growth of analyst linked peers, using the weights in Equation 1. Industry Sales growth is measured as the market capitalization weighted average Sales growth of all other firms in the same Fama-French 49 industry. Geographic Sales growth is the average Sales growth of all other firms headquartered in the same county. Customer Sales growth is the average Sales growth of the firm's principal customers. Customer (Supplier) Industry Sales growth is the weighted average Sales growth of all the industries that buy from (supply to) that stock's industry. The flow of goods to and from industries are used as weights. Single-Segment Sales growth is the weighted average Sales growth of single-segment firms operating in the same segments as the conglomerate firm. Technology Linked Sales growth is the weighted average Sales growth of technologically similar firms, using technological closeness as weights. Peer firm Profit growth measures are calculated similarly. The sample is limited to firms with December fiscal year ends. All variables are measured at the end of each calendar year and are winsorized at 1% and 99% levels. Independent variables are cross-sectionally standardized to have zero mean and unit variance. All regressions include year fixed effects and size and book-to-market ratio as control variables. *t*-statistics based on standard errors clustered by year are shown below coefficient estimates.

Panel A	Dependent variable: Sales growth (t)								Dependent variable: Sales growth (t+1)							
CS Sales growth (t)	0.112	0.102	0.113	0.112	0.090	0.091	0.075	0.113	0.021	0.024	0.021	-0.001	0.015	0.017	0.014	0.024
	(4.70)	(4.83)	(4.65)	(3.88)	(4.58)	(4.84)	(7.12)	(4.47)	(3.27)	(3.74)	(3.16)	(-0.11)	(2.40)	(2.71)	(2.67)	(3.07)
Industry Sales growth (t)		0.036								-0.006						
		(5.32)								(-1.40)						
Geo. Sales growth (t)			0.012								0.007					
			(2.06)								(1.84)					
Customer Sales growth (t)				0.038								0.009				
				(3.38)								(0.63)				
Supplier Ind. Sales growth (t)					0.045								0.005			
					(6.19)								(0.78)			
Customer Ind. Sales growth (t)						0.041								-0.008		
						(4.82)								(-1.32)		
Single-Segment Sales growth (t)							0.001								-0.004	
							(0.19)								(-1.19)	
Tech. Linked Sales growth (t)								0.008								0.010
								(0.97)								(2.22)
Sales growth (t)									0.065	0.064	0.065	0.071	0.057	0.058	0.053	0.035
									(8.66)	(8.95)	(8.53)	(4.01)	(8.84)	(8.91)	(8.56)	(3.73)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Avg. R^2	0.112	0.114	0.112	0.141	0.109	0.109	0.082	0.113	0.107	0.107	0.107	0.121	0.103	0.103	0.081	0.095
# stocks	65,018	64,266	60,309	2,657	57,619	57,619	15,766	20,418	58,300	57,636	54,122	2,400	51,390	51,390	14,467	19,131

Panel B	Dependent variable: Profit growth (t)								Dependent variable: Profit growth (t+1)							
CS Profit growth (t)	0.018	0.017	0.018	0.026	0.018	0.018	0.014	0.017	0.003	0.003	0.003	0.004	0.003	0.003	0.002	0.002
	(14.35)	(15.20)	(14.10)	(6.73)	(15.75)	(15.85)	(10.64)	(11.02)	(3.03)	(3.65)	(2.77)	(1.68)	(3.02)	(3.02)	(1.52)	(2.10)
Industry Profit growth (t)		0.003								-0.001						
		(3.92)								(-0.98)						
Geo. Profit growth (t)			0.001								0.000					
			(2.85)								(0.83)					
Customer Profit growth (t)				0.007								-0.001				
				(5.02)								(-0.59)				
Supplier Ind. Profit growth (t)					0.003								-0.001			
					(4.96)								(-1.07)			
Customer Ind. Profit growth (t)						0.004								0.000		
						(4.33)								(0.25)		
Single-Segment Profit growth (t)							0.003								0.002	
							(4.72)								(2.75)	
Tech. Linked Profit growth (t)								0.005								0.002
								(4.50)								(1.11)
Profit growth (t)									-0.002	-0.002	-0.002	-0.005	-0.002	-0.002	-0.003	-0.003
									(-1.07)	(-1.08)	(-0.95)	(-1.35)	(-1.06)	(-1.11)	(1.96)	(-1.89)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Avg. R^2	0.088	0.090	0.089	0.148	0.088	0.088	0.119	0.094	0.019	0.019	0.019	0.035	0.018	0.018	0.042	0.029
# stocks	64,647	63,892	59,950	2,605	57,252	57,252	15,498	20,522	57,865	57,199	53,701	2,347	51,117	51,117	14,178	19,256

Table 3: Quintile Portfolio Returns and Alphas

This table reports the returns, four- and five-factor (four-factor and short-term reversal factor) alphas, and factor loadings of quintile portfolios. The sample period is 1984:01 to 2015:12. The sample includes common stocks listed on NYSE, AMEX, and NYSE MKT that are covered by analysts. Each month, stocks are ranked into quintile portfolios based on CS RET, as calculated in Equation 1, and value- and equal-weighted return in the next month of each portfolio is calculated. Market, size, value, momentum, and short-term reversal factor returns are from Ken French's website. Stocks with price < $5 at the end of previous month are excluded from the analysis. *t*-statistics are shown below coefficient estimates.

				Value-Weighted				
Quintile	Excess Ret	4-factor Alpha	5-factor Alpha	Mkt-Rf	SMB	HML	UMD	ST Reversal
1	0.05	-0.61	-0.77	1.00	0.10	-0.08	-0.00	0.76
	(0.17)	(-3.49)	(-7.30)	(34.18)	(2.06)	(-1.46)	(-0.15)	(22.48)
2	0.70	0.01	-0.05	0.99	-0.09	0.01	0.06	0.29
	(2.80)	(0.15)	(-0.52)	(44.86)	(-2.88)	(0.21)	(2.76)	(7.42)
3	0.70	0.03	0.03	0.97	-0.08	0.14	0.02	0.02
	(3.10)	(0.42)	(0.35)	(42.21)	(-2.41)	(3.92)	(0.99)	(0.75)
4	0.87	0.24	0.30	1.01	-0.05	0.01	-0.01	-0.28
	(3.75)	(2.57)	(3.76)	(46.78)	(-1.86)	(0.18)	(-0.39)	(-8.17)
5	0.91	0.28	0.42	1.09	0.17	-0.04	-0.04	-0.67
	(3.42)	(1.89)	(3.80)	(39.28)	(5.20)	(-0.73)	(-1.25)	(-15.36)
5-1	0.86	0.89	1.19	0.09	0.07	0.04	-0.04	-1.45
	(2.98)	(2.99)	(6.71)	(2.06)	(1.22)	(0.47)	(-0.71)	(-22.09)

				Equal-Weighted				
Quintile	Excess Ret	4-factor Alpha	5-factor Alpha	Mkt-Rf	SMB	HML	UMD	ST Reversal
1	-0.36	-1.05	-1.21	1.01	0.67	0.03	-0.05	0.75
	(-1.03)	(-6.46)	(-11.65)	(39.96)	(10.95)	(0.59)	(-1.51)	(17.21)
2	0.47	-0.23	-0.29	0.99	0.57	0.20	-0.04	0.33
	(1.66)	(-2.69)	(-4.12)	(48.54)	(10.54)	(5.59)	(-1.96)	(7.65)
3	0.82	0.15	0.14	0.96	0.53	0.29	-0.07	0.08
	(3.20)	(2.12)	(1.83)	(42.71)	(10.42)	(6.94)	(-2.98)	(1.74)
4	1.07	0.39	0.43	1.02	0.59	0.25	-0.07	-0.19
	(4.09)	(4.98)	(6.03)	(48.83)	(13.34)	(6.31)	(-2.92)	(-5.03)
5	1.41	0.76	0.89	1.08	0.85	0.11	-0.10	-0.65
	(4.66)	(5.11)	(8.93)	(43.02)	(14.94)	(2.60)	(-3.33)	(-14.97)
5-1	1.76	1.81	2.10	0.07	0.18	0.08	-0.06	-1.41
	(6.23)	(6.15)	(11.88)	(1.65)	(1.74)	(1.09)	(-1.02)	(-17.80)

Table 4: Long-Short Factor Returns and Alphas

This table reports the mean returns and alphas of CS momentum, industry momentum, geographic momentum, customer momentum, supplier industry momentum, customer industry momentum, complicated firm momentum, and technology momentum factors. The calculation of these factors is described in Section 3.1. The sample includes common stocks listed on NYSE, AMEX, and NYSE MKT. The sample period for customer momentum factor is from 1984:01 to 2006:06 due to availability of data on customer-supplier links. The sample period for customer and supplier industry momentum factors is from 1986:07 to 2015:12 due to availability of historical NAICS codes. The sample period for technological momentum factor is from 1984:01 to 2012:06 due to availability of Kogan et al. (2017) patent data. The sample period for all other tests is from 1984:01 to 2015:12. Market, size, value, momentum, and short-term reversal factor returns are from Ken French's website. In Panel A, 4-factor + CS Momentum Factor Alpha is the alpha from time-series regression of portfolio returns on MKT, SMB, HML, UMD, and CS momentum factors. In Panel A, 5-factor + CS Momentum Factor Alpha is the alpha from time-series regression of portfolio returns on MKT, SMB, HML, UMD, short-term reversal, and CS momentum factors. The dependent variable in the regressions in Panel B is the return of CS momentum factor. Column 1 of Panel B reports the alphas of CS momentum factor from regressions of its return on MKT, SMB, HML, UMD, and the cross-asset momentum factor from the corresponding row. Column 2 of Panel B reports the alphas of CS momentum factor from regressions of its return on MKT, SMB, HML, UMD, short-term reversal, and the cross-asset momentum factor from the corresponding row. The combined momentum factor in Panel B is constructed by ranking stocks based on average values of the seven cross-asset momentum variables, as described in Equation (2). Stocks with price <$5 at the end of previous month are excluded from the tests. *t*-statistics are shown below coefficient estimates.

Panel A

	Mean Return	4-factor Alpha	5-factor Alpha	4-factor + CS Momentum Factor Alpha	5-factor + CS Momentum Factor Alpha
	(1)	(2)	(3)	(4)	(5)
CS Momentum Factor	1.33	1.38	1.68		
	(4.70)	(4.65)	(9.67)		
Industry Momentum Factor	0.64	0.64	0.85	-0.24	-0.04
	(3.06)	(2.92)	(5.13)	(-2.06)	(-0.27)
Geographic Momentum Factor	0.31	0.31	0.43	-0.23	-0.23
	(2.23)	(2.47)	(3.91)	(-2.46)	(-2.34)
Customer Momentum Factor	1.15	0.97	1.29	0.43	0.74
	(3.44)	(2.47)	(3.62)	(1.09)	(1.79)
Supplier Industry Momentum Factor	0.58	0.55	0.71	-0.26	-0.12
	(2.54)	(2.24)	(3.98)	(-1.73)	(-0.79)
Customer Industry Momentum Factor	0.40	0.45	0.62	-0.42	-0.10
	(1.73)	(1.94)	(3.84)	(-2.86)	(-0.71)
Complicated Firm Momentum Factor	0.42	0.40	0.54	-0.18	0.02
	(2.56)	(2.25)	(4.38)	(-1.41)	(0.17)
Technology Momentum Factor	0.55	0.50	0.72	-0.52	-0.60
	(2.06)	(1.89)	(3.24)	(-2.90)	(-2.82)

Panel B

	4-factor + Alpha of CS Momentum Factor	5-factor + Alpha of CS Momentum Factor
	(1)	(2)
Industry Momentum Factor	0.65	1.10
	(3.77)	(6.92)
Geographic Momentum Factor	0.87	1.31
	(4.53)	(9.94)
Customer Momentum Factor	1.11	2.24
	(3.07)	(10.82)
Supplier Industry Momentum Factor	0.80	1.26
	(4.02)	(7.86)
Customer Industry Momentum Factor	0.90	1.29
	(4.66)	(8.12)
Complicated Firm Momentum Factor	0.87	1.41
	(4.46)	(8.99)
Technology Momentum Factor	1.05	1.51
	(5.03)	(10.37)
Combined Momentum Factor	0.62	0.90
	(4.85)	(6.93)

Table 5: Fama-MacBeth Regressions

This table reports the results of cross-sectional regressions. The dependent variable is monthly stock return. CS RET is the weighted average return in the previous month of stocks that are connected through shared analyst coverage, as described in Equation 1. CS RET(t-12,t-2) is the weighted average past 12-month (skipping the most recent month) return of stocks that are connected through shared analyst coverage using the same weights as in Equation 1. Industry RET is past month's value-weighted average return of all other stocks in the same Fama-French 49 industry. Industry RET(t-12,t-2) is calculated as cumulative monthly industry return (excluding own stock return) from months t-12 through t-2. Geographic RET is the average return in the previous month of all other stocks headquartered in the same county. Geographic RET(t-12,t-2) is calculated as cumulative monthly geographic return (excluding own stock return) from months t-12 through t-2. Customer RET is the equal-weighted average return of the firm's customers in the previous month. The sample period for regressions with Customer RET is from 1984:01 to 2006:06 due to availability of customer-supplier links. Customer (Supplier) Industry RET is the weighted average return in the previous month of all the industries that buy from (supply to) that stock's industry. The flow of goods to and from industries are used as portfolio weights. The sample period for regressions with customer and supplier industry returns is from 1986:07 to 2015:12 due to availability of historical NAICS codes. Single-Segment RET is the weighted average return in the previous month of single-segment firms operating in the same segments as the conglomerate firm. Tech. Linked RET is the weighted average return of technologically similar firms in the previous month. Stock returns are weighted by technological closeness. The sample period for regressions with Tech. Linked RET is from 1984:01 to 2012:06 due to availability of Kogan et al. (2017) patent data. The sample period for all other tests is from 1984:01 to 2015:12. Control variables include past one-month return, past 12-month return (excluding the most recent month), log of market capitalization, and log of book-to-market ratio. Stocks with price <$5 at the end of previous month are excluded from the regressions. In columns 1-22, the sample includes all stocks and in columns 1a-22a, the sample includes large stocks (stocks with market cap above NYSE median) only. Independent variables are winsorized at 1% and 99% levels. *t*-statistics are shown below coefficient estimates.

	All Stocks																					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
CS RET	0.180		0.165	0.181		0.164		0.176		0.176		0.199		0.166		0.165	0.162		0.158		0.152	0.128
	(11.46)		(11.34)	(12.71)		(12.42)		(11.25)		(12.36)		(6.70)		(10.85)		(10.79)	(10.93)		(9.70)		(8.09)	(5.64)
Industry RET		0.109	0.034		0.115	0.041																0.003
		(8.05)	(3.17)		(8.81)	(3.81)																(0.19)
CS RET (t-12,t-2)				0.009		0.007				0.009												0.008
				(2.52)		(2.23)				(2.38)												(1.46)
Industry RET (t-12,t-2)					0.011	0.005																0.005
					(2.86)	(1.87)																(1.22)
Geographic RET							0.022	0.008	0.019	0.005												0.013
							(4.33)	(1.93)	(4.16)	(1.36)												(1.28)
Geographic RET(t-12,t-2)									0.002	0.002												-0.001
									(2.26)	(1.68)												(-0.22)
Customer RET											0.041	0.022										
											(4.02)	(2.34)										
Supplier Ind. RET													0.153	0.030			0.024					-0.013
													(4.66)	(1.08)			(0.80)					(-0.35)
Customer Ind. RET															0.149	0.033	0.020					0.047
															(5.32)	(1.48)	(0.90)					(1.30)
Single-Segment RET																		0.080	0.034			0.020
																		(6.98)	(3.51)			(1.25)
Tech. Linked RET																				0.092	0.039	0.008
																				(5.11)	(2.69)	(0.46)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Avg. R^2	0.049	0.045	0.052	0.055	0.050	0.059	0.040	0.050	0.041	0.056	0.044	0.056	0.044	0.052	0.043	0.051	0.054	0.046	0.054	0.049	0.057	0.084
Avg. # stocks	2,662	2,631	2,631	2,661	2,613	2,613	2,506	2,506	2,354	2,354	212	212	2,549	2,549	2,549	2,549	2,549	654	654	942	942	257

	Large Stocks																					
	(1a)	(2a)	(3a)	(4a)	(5a)	(6a)	(7a)	(8a)	(9a)	(10a)	(11a)	(12a)	(13a)	(14a)	(15a)	(16a)	(17a)	(18a)	(19a)	(20a)	(21a)	(22a)
CS RET	0.151		0.145	0.161		0.153		0.148		0.155		0.178		0.142		0.137	0.137		0.156		0.138	0.111
	(7.41)		(7.31)	(8.39)		(8.17)		(7.31)		(8.16)		(2.90)		(6.80)		(6.59)	(6.77)		(7.46)		(5.50)	(3.93)
Industry RET		0.078	0.007		0.089	0.011																-0.026
		(5.26)	(0.55)		(6.19)	(0.97)																(-1.48)
CS RET (t-12,t-2)				0.003		0.002				0.002												0.005
				(0.58)		(0.41)				(0.32)												(0.75)
Industry RET (t-12,t-2)					0.005	0.002																0.002
					(1.29)	(0.77)																(0.59)
Geographic RET							0.016	0.006	0.015	0.004												-0.000
							(2.46)	(1.13)	(2.57)	(0.79)												(-0.01)
Geographic RET(t-12,t-2)									0.002	0.002												-0.002
									(1.33)	(1.30)												(-0.84)
Customer RET											0.039	0.030										
											(2.22)	(1.65)										
Supplier Ind. RET													0.082	-0.014			-0.014					0.007
													(2.48)	(-0.48)			(-0.42)					(0.16)
Customer Ind. RET															0.095	0.006	0.009					0.036
															(3.24)	(0.23)	(0.32)					(0.89)
Single-Segment RET																		0.055	0.010			0.017
																		(4.29)	(0.92)			(0.99)
Tech. Linked RET																				0.036	-0.019	0.003
																				(1.67)	(-1.00)	(0.14)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Avg. R^2	0.078	0.072	0.082	0.090	0.081	0.097	0.065	0.080	0.065	0.091	0.102	0.134	0.073	0.086	0.072	0.085	0.090	0.067	0.079	0.076	0.090	0.124
Avg. # stocks	899	889	889	899	887	887	859	859	836	836	53	53	843	843	843	843	843	321	321	399	399	149

Table 6: International Tests

This table reports the mean returns and alphas of CS momentum and industry momentum factors for 11 international markets. The calculation of these factors is described in Section 3.3. The sample includes the major developed markets in the S&P Global BMI Index. Analyst forecast data is from IBES Global Detail File and country-level market, size, value, and momentum factor returns are from AQR's data library. Short term reversal factor is constructed using the methodology described on Ken French's website. Stock return and market capitalization data are from S&P Capital IQ. All returns are in USD. The sample for each country begins in the first month in which there are at least 50 stocks in the S&P BMI Index for that country that have analyst forecast data available and ends in 2015:12 for all countries. Columns 1 and 4 (2 and 5) report the mean returns (5-factor alphas) of industry momentum and CS momentum factors, respectively. Column 3 reports the alphas from regressions of the industry momentum factor on the five factors and the CS momentum factor. Column 6 reports the alphas from regressions of the CS momentum factor on the five factors and the industry momentum factor. *t*-statistics are shown below coefficient estimates.

	Sample start date	Industry Momentum			CS Momentum		
		(1)	(2)	(3)	(4)	(5)	(6)
		Mean Return	5-factor Alpha	5-factor + CS Momentum Factor Alpha	Mean Return	5-factor Alpha	5-factor + Industry Momentum Factor Alpha
Japan	8/1989	0.29	0.67	0.15	0.41	1.01	0.63
		(1.61)	(3.96)	(0.96)	(1.82)	(5.96)	(4.19)
UK	8/1989	0.95	1.21	0.36	1.39	1.74	1.19
		(4.81)	(7.14)	(2.09)	(5.46)	(10.57)	(7.57)
France	6/1990	0.73	0.94	0.21	1.14	1.44	0.99
		(3.24)	(4.57)	(1.10)	(3.94)	(7.42)	(5.50)
Germany	6/1990	0.71	0.73	0.10	1.23	1.43	1.13
		(2.72)	(2.74)	(0.41)	(3.95)	(5.18)	(4.69)
Australia	6/1990	0.75	0.38	0.17	0.62	0.46	0.30
		(3.10)	(1.68)	(0.81)	(2.30)	(2.07)	(1.50)
Hong Kong	6/1993	0.38	0.35	0.10	1.03	0.90	0.80
		(1.23)	(1.14)	(0.33)	(2.91)	(2.97)	(2.73)
Switzerland	6/1995	0.89	0.90	0.35	1.35	1.44	1.07
		(3.22)	(3.36)	(1.31)	(4.19)	(4.84)	(3.87)
Netherlands	7/1995	0.77	0.75	0.26	1.26	1.22	0.94
		(2.35)	(2.27)	(0.77)	(3.37)	(4.14)	(3.41)
Sweden	6/1996	0.41	0.52	0.08	0.88	0.98	0.77
		(1.28)	(1.55)	(0.23)	(2.42)	(3.10)	(2.72)
Italy	1/1997	0.66	0.49	0.16	1.00	0.83	0.65
		(2.24)	(1.73)	(0.61)	(3.08)	(3.13)	(2.61)
Spain	6/1997	0.70	0.63	0.20	1.27	1.24	1.02
		(2.24)	(1.91)	(0.68)	(3.60)	(3.60)	(3.13)

Table 7: Linkage Complexity

This table reports the results of a cross-sectional regression in which the dependent variable is monthly stock return. CS RET is the weighted average return in the previous month of stocks that are connected through shared analyst coverage, as described in Equation 1. CS RET2 is the weighted average CS RET in the previous month of stocks that are connected through shared analyst coverage, as described in Equation 3. #Connections is the number of unique stocks that a stock is linked to through shared analyst coverage at the end of previous month. EV Centrality is the percentile rank of eigenvector centrality of the stock in the network of analyst linkages measured at the end of previous month. Size is log of market capitalization. Analyst Coverage is the number of analysts that cover the stock. In Columns 4-7, the stocks are divided into two groups each month based on analyst coverage. In Columns 4-6, the sample consists of low analyst coverage stocks. In Column 7, the sample consists of high analyst coverage stocks. The sample period is from 1984:01 to 2015:12. Other control variables include past one-month return, past 12-month return (excluding the most recent month), and log of book-to-market ratio. Stocks with price <$5 at the end of previous month are excluded from the regressions. Non-discrete independent variables are winsorized at 1% and 99% levels. *t*-statistics are shown below coefficient estimates.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CS RET	0.308	0.301	0.298	0.179		0.037	0.221
	(9.36)	(9.23)	(9.30)	(14.21)		(2.94)	(6.33)
CS RET2					0.294	0.247	-0.035
					(12.92)	(7.39)	(-0.58)
#Connections*CS RET	0.001		0.000				
	(4.00)		(0.33)				
EV Centrality*CS RET		0.002	0.002				
		(5.08)	(3.11)				
Size*CS RET	-0.029	-0.032	-0.031				
	(-4.55)	(-4.97)	(-4.82)				
Analyst Coverage*CS RET	-0.003	-0.001	-0.002				
	(-1.97)	(-0.96)	(-1.12)				
#Connections	-0.000		0.000				
	(-0.51)		(0.76)				
EV Centrality		-0.000	-0.000				
		(-0.75)	(-1.24)				
Size	0.000	0.000	0.000				
	(0.31)	(0.53)	(0.50)				
Analyst Coverage	0.000	0.000	0.000				
	(0.50)	(0.58)	(0.27)				
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Avg. R^2	0.056	0.058	0.061	0.037	0.040	0.041	0.073
Avg. # stocks	2,662	2,662	2,662	1,339	1,339	1,339	1,323

Table 8: Analyst Forecast Revisions

This table reports the results of cross-sectional regressions in which the dependent variable is monthly percentage forecast revision. Percentage forecast revision (FR) is calculated as (Consensus forecast$_t$ - Consensus forecast$_{t-1}$)/maximum (0.01, |Consensus forecast$_{t-1}$|), where Consensus forecast is the average analyst forecast of FY1 earnings. FR is winsorized at 1% and 99% levels to minimize the effect of outliers. CS FR is the weighted average FR of connected stocks in the previous month calculated using the weights in Equation 1. Industry FR is the average FR in the previous month of stocks in the same Fama-French 49 industry. Geographic FR is the average FR in the previous month of stocks headquartered in the same county. Customer FR is the average FR in the previous month of the firm's principal customers. The sample for regressions with Customer FR is from 1984:01 to 2006:06 due to availability of customer-supplier links. Customer (Supplier) Industry FR is the weighted average of the industry forecast revisions of all the industries that buy from (supply to) that stock's industry. The flow of goods to and from industries are used as weights. The sample period for regressions with customer and supplier industry FR is from 1986:07 to 2015:12 due to availability of historical NAICS codes. Single-Segment FR is the weighted average FR in the previous month of single-segment firms operating in the same segments as the conglomerate firm. Tech. Linked FR is the weighted average FR of technologically similar firms in the previous month. Linked firms' forecast revisions are weighted by technological closeness. The sample period for regressions with Tech. Linked FR is from 1984:01 to 2012:06 due to availability of Kogan et al. (2017) patent data. The sample period for all other tests is from 1984:01 to 2015:12. Control variables include past one-month return, past 12-month return (excluding the most recent month), log of market capitalization, and log of book-to-market ratio. Stocks with price <$5 at the end of previous month are excluded from the regressions. Independent variables are winsorized at 1% and 99% levels. *t*-statistics are shown below coefficient estimates.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
CS FR		0.315		0.313		0.249		0.300		0.300		0.345		0.320
		(23.25)		(22.96)		(6.34)		(21.50)		(21.42)		(18.69)		(17.03)
Industry FR	0.298	0.145	0.293	0.142	0.263	0.145	0.288	0.149	0.290	0.150	0.159	0.062	0.185	0.076
	(22.57)	(13.54)	(21.99)	(13.26)	(7.59)	(4.05)	(21.77)	(13.10)	(20.88)	(13.05)	(10.38)	(4.14)	(13.92)	(5.81)
FR (t-1)	0.226	0.221	0.223	0.219	0.214	0.211	0.223	0.218	0.223	0.218	0.251	0.244	0.254	0.248
	(32.05)	(31.86)	(31.63)	(31.52)	(15.86)	(15.59)	(30.38)	(30.23)	(30.37)	(30.22)	(25.59)	(25.02)	(27.37)	(27.13)
Geographic FR			0.022	0.010										
			(4.28)	(1.98)										
Customer FR					0.051	0.043								
					(3.03)	(2.62)								
Supplier Ind. FR							0.113	0.039						
							(4.50)	(1.65)						
Customer Ind. FR									0.119	0.044				
									(4.23)	(1.62)				
Single-Segment FR											0.117	0.065		
											(6.94)	(4.02)		
Tech. Linked FR													0.123	0.062
													(7.34)	(4.03)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Avg. R^2	0.101	0.105	0.101	0.104	0.128	0.133	0.098	0.101	0.099	0.102	0.123	0.129	0.123	0.127
Avg. # stocks	2,507	2,507	2,467	2,467	194	194	2,434	2,434	2,434	2,434	616	616	894	894

Table 9: Robustness Tests

This table provides robustness tests. Panel A performs the tests of Table 4 for alternative industry and geographic momentum factors. In Panel B, the sample is divided into two equal halves and the tests of Table 4 are performed on each sub-sample. Text-based industry data is available from 1997:07 to 2015:06. 5-factor + CS Momentum Factor Alpha is the alpha from time-series regression of the cross-asset momentum factor return on MKT, SMB, HML, UMD, short-term reversal and CS momentum factors. 5-factor + Alpha of CS Momentum Factor is the alpha from time-series regression of the CS momentum factor return on MKT, SMB, HML, UMD, short-term reversal, and the cross-asset momentum factor from the corresponding row. *t*-statistics are shown below coefficient estimates.

Panel A

	5-factor + CS Momentum Factor Alpha	5-factor + Alpha of CS Momentum Factor
	(1)	(2)
FF 12 Industry Momentum	-0.18	1.23
	(-1.19)	(8.60)
FF 17 Industry Momentum	0.01	1.27
	(0.09)	(7.45)
FF 30 Industry Momentum	0.03	1.09
	(0.26)	(7.59)
Text-Based Industry Momentum	-0.08	0.58
	(-0.67)	(3.93)
State Level Geo. Momentum	-0.15	1.31
	(-1.26)	(9.13)

Panel B

	1984-1999			2000-2015		
	5-factor Alpha	5-factor + CS Momentum Factor Alpha	5-factor + Alpha of CS Momentum Factor	5-factor Alpha	5-factor + CS Momentum Factor Alpha	5-factor + Alpha of CS Momentum Factor
	(1)	(2)	(3)	(4)	(5)	(6)
CS Momentum Factor	2.19			1.13		
	(10.98)			(4.48)		
Industry Momentum Factor	1.46	0.54	1.39	0.36	-0.31	0.86
	(8.22)	(2.33)	(3.90)	(1.53)	(-1.83)	(4.95)
Geographic Momentum Factor	0.44	-0.17	1.83	0.37	-0.17	0.80
	(3.44)	(-1.42)	(10.10)	(2.22)	(-1.25)	(4.47)
Supplier Industry Momentum Factor	0.94	0.01	1.78	0.50	-0.11	0.85
	(3.74)	(0.02)	(7.05)	(1.91)	(-0.62)	(4.17)
Customer Industry Momentum Factor	0.83	-0.03	1.82	0.44	-0.10	0.86
	(3.50)	(-0.10)	(7.50)	(2.09)	(-0.55)	(4.04)
Complicated Firm Momentum Factor	0.67	0.35	2.03	0.28	-0.17	0.95
	(4.37)	(1.72)	(10.11)	(1.55)	(-1.09)	(4.48)
Technology Momentum Factor	1.11	-0.44	1.64	0.08	-0.87	1.28
	(4.41)	(-1.59)	(10.43)	(0.25)	(-2.93)	(5.53)

Table 10: Comparison with Israelsen (2016)

This table compares the predictability of the CS momentum measure with the peer momentum measure of Israelsen (2016). The sample in each month consists of the largest 10% stocks. In Panel A, stocks are ranked into quintiles based on CS RET (Israelsen peer return) and a value-weighted long-short portfolio is formed which is long top- and short bottom-quintile stocks. 6-factor + CS Momentum Factor Alpha is the alpha from time-series regression of Israelsen Momentum Factor return on MKT, SMB, HML, UMD, short-term reversal, liquidity, and CS momentum factors. 6-factor + Alpha of CS Momentum Factor is the alpha from time-series regression of the CS momentum factor return on MKT, SMB, HML, UMD, short-term reversal, liquidity, and Israelsen Momentum factors. Panel B shows the results of cross-sectional regressions in which the dependent variable is one-month ahead return and the independent variables include past month CS return and Israelsen peer return. Control variables include past one-month return, past 12-month return (excluding the most recent month), log of market capitalization, and log of book-to-market ratio. In columns 3 and 4 of Panel B, the set of stocks for which Israelsen finds statistically significant return predictability are excluded from the regressions. These include stocks in the lowest past one-month stock return quintile and the highest peer return quintile, and the highest past one-month stock return quintile and the lowest peer return quintile. Independent variables are winsorized at 1% and 99% levels. *t*-statistics are shown below coefficient estimates.

Panel A: Long-Short Factors

Israelsen Momentum Factor		CS Momentum Factor	
Mean Return	6-factor + CS Momentum Factor Alpha	Mean Return	6-factor + Israelsen Momentum Factor Alpha
0.37	-0.07	0.62	0.31
(1.54)	(-0.81)	(2.09)	(3.04)

Panel B: Fama-MacBeth Regressions

	(1)	(2)	(3)	(4)
CS RET	0.131	0.131	0.134	0.136
	(6.21)	(4.68)	(6.28)	(4.81)
Israelsen Peer Return		-0.002		-0.003
		(-0.13)		(-0.21)
Controls	Yes	Yes	Yes	Yes
Avg. R^2	0.090	0.092	0.091	0.093
Avg. # stocks	510	510	493	493