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Shared analyst coverage: Unifying momentum spillover effects[☆]

Usman Ali[a], David Hirshleifer[b,*]

[a] MIG Capital, 660 Newport Center Drive Suite 1300, Newport Beach, CA 92660, USA
[b] University of California, Merage School of Business, 4291 Pereira Drive, SB2, Suite 406, Irvine, CA 92697, USA

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ABSTRACT

Identifying firm connections by shared analyst coverage, we find that a connected-firm (CF) 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 CF momentum. Similar results hold in cross-sectional regressions and in developed international markets. Sell-side analysts incorporate news about linked firms sluggishly. These effects are stronger for complex and indirect linkages. Consistent with limited investor attention, these results indicate that momentum spillover effects are a unified phenomenon that is captured by shared analyst coverage.

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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 the past return of one firm predicts the returns of firms that are linked to it or are similar to it. Using a variety of proxies for interfirm linkage or relatedness, various papers have verified such spillovers.[1] This literature shows lead-lag relations among stocks belonging to the same industry (Moskowitz and Grinblatt, 1999), firms that share the same geographic location (Parsons et al., 2016), firms that are linked along the supply chain (Cohen and Frazzini, 2008; Menzly and Ozbas, 2010), firms with similar technologies (Lee et al., 2016), and single- and multi-segment firms operating in the same industries (Cohen and Lou, 2012).

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* Corresponding author.
E-mail address: david.h@uci.edu (D. Hirshleifer).

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

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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 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. There is no reason why limited investor attention to news about related firms would be restricted to a particular type of firm relatedness, such as industry, geography, or supply-chain linkage. Hence the limited attention hypothesis suggests that it may be possible to empirically unify these seemingly distinct findings.

In particular, we expect news about a related firm to be more important if the fundamental linkage is stronger. Such strong linkage implies that there is more relevant news for investors to underreact to. Therefore the limited attention hypothesis implies that, other things equal, the stronger the fundamental linkage, the stronger the momentum spillover. This suggests that a sufficiently strong measure of firm linkage or relatedness can potentially unify known findings.

For three reasons, we expect shared analyst coverage to be a strong and versatile proxy for fundamental linkages between firms and for relatedness of firms. Hence shared analyst coverage may help identify momentum spillover effects more strongly and can be a tool for probing more deeply into their sources.

The first reason is that the job of analysts is to impound all information relevant for fundamentals, including information about related firms, such as customers and suppliers, competitors, and so forth. This in turn suggests that, owing to complementarities in the generation of information about related firms, analysts are more likely to co-cover firms that are fundamentally related. We therefore expect analyst co-coverage to be a unified proxy for economic linkages between firms and for fundamental relatedness of firms.

Consistent with this idea, Lee et al. (2016) show 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.

The second reason is that 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. Hence an advantage of analyst peers relative to peers in previous studies that identify firm-specific linkages is that analyst peers are available for the majority of publicly traded firms throughout the globe.[2] Because of different reporting requirements in different countries, customer-supplier and single- to multiple-segment links are not available for international companies from standard data sources. We are also unaware of any database that identifies technology links for a large number of international companies.

Third and 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 relation. To capture this, we weight each linked firm by the number of common analysts it has with the focal firm. Such linkage-strength weighting analysis analyses cannot be done for previously studied spillover effects based upon industry and geographic peers, though it could be done for other firm-specific linkage measures.

Based on these points, we hypothesize that interfirm linkages are stronger when identified using shared analyst coverage and 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 firms without delay in response to the arrival of relevant information, this could cause such information to be impounded so rapidly that a lead-lag relation is not identifiable in monthly return tests. Consistent with this idea, Parsons et al. (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

[2] Also, compared to linkages such as customer-supplier links that are identified from annual financial statements, analyst links can be identified in a more timely fashion. Analyst data also does not suffer from any look-ahead bias, in contrast with geographic location data (Compustat only reports the location of the latest headquarters of each firm).

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) show that common mutual fund ownership of customer and supplier firms weakens customer-to-supplier return predictability.

It is also possible that some analyst connections are random in the sense that they do not identify fundamental relations between firms. Thus, in principle our analyst linkage approach could lead to weaker spillover effects than the linkages studied in past literature based on common industry, common product market, and so forth.

There are two possible hypotheses about whether analyst linkages are associated empirically with stronger return predictability than other linkage measures. First is that the effect will be stronger because analyst linkages identify fundamental relations 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, or because many analyst links are random and do not identify fundamental relations between firms.

We first verify a basic premise underlying the first hypothesis, which we call Hypothesis 1, that analyst linkages help identify fundamental relations and 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 hypothesis 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-firm (CF) portfolio and find a strong monotonic relation between past CF 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 even 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 CF 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 CF momentum factor is added to the spanning regressions. In contrast, these seven cross-asset momentum factors do not explain the performance of the CF momentum factor; its alpha remains large and highly significant. These results indicate that previously studied cross-asset momentum effects are dominated by CF momentum. In other words, there is really just one momentum spillover effect, which is captured by shared analysts as a proxy for linkage. Therefore 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), which attempts to capture a broad set of anomalies with only a few factors.

Our 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 CF 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 CF 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 CF 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 CF return remains economically very large and highly significant.

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

In an alternative test, we divide previously studied links into links in which there is also a shared analyst connection and those in which there is not. We find that the predictive power when previously studied links overlap with analyst connections is about three times as great as when such links are not associated with an analyst connection. We also find that analyst links that do not overlap with previously studied links have strong predictive power, which shows that analyst links identify important cross-firm relatedness that is not captured by previous measures. Overall, these results suggest that analyst co-coverage identifies fundamental relatedness in an integrated way by picking up linkages that previous measures miss and by identifying the strongest linkages from the set of previously studied linkages.

To evaluate the robustness of our conclusions, and to mitigate data mining concerns, we also test whether the CF 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 CF momentum is controlled for. In contrast, the CF 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 investors are sluggish in impounding the information contained in analyst forecasts. In other words, news crosses firms quickly at the analyst level, so the delay 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.)[3]

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 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 may have some kind of a processing bias or constraint, such as limited attention or overconfidence, that causes them to transfer information sluggishly. Alternatively, this sluggishness could be driven by agency issues. In either case, the stronger predictability when linkages are defined by shared analyst coverage is consistent with the possibility (Hypothesis 1) that firms linked by shared analysts have stronger fundamental linkages. Any general tendency of analysts to react sluggishly will be more important for firms that 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.[4] In the theoretical literature on networks, this is known as the degree centrality of the firm.

This literature also considers the centrality of a firm 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. Updating by investors in firm A is harder if firm B has many links to 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, 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 relation 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 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). Therefore 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.

To test whether common analysts expedite information flow between co-covered stocks, we examine breaks in

[3] As a reminder, even if shared analysts expedite the flow of information across firms, momentum spillovers could be larger when there are shared analysts. As discussed in Hypothesis 1, the firms with shared analysts may have stronger fundamental relations, so there is more room for spillover.

[4] This argument is related to, though distinct from, the argument and finding of Hirshleifer et al. (2011) 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.

links going back in time. Suppose that A and B are linked in the current period but are unlinked in a recent prior period because either A or B had no analyst coverage. If investor reliance on sluggish analyst forecast revisions is not the only source of lead-lag relations (and if fundamental linkages are reasonably stable over short periods of time), then we still expect to find cross-firm return predictability for A and B in the prior period. We find that this is indeed the case. Moreover, the return predictability is higher in prior periods, which is consistent with the idea that common analyst coverage expedites the information flow between connected firms. Overall, our results suggest that both analyst and investor sluggishness may contribute to the lead-lag relations we show.

We also show that past return on analyst-linked firms strongly predicts future fundamentals of the focal firm. This, along with our result that the CF momentum effect lasts for up to one year and does not reverse afterwards, strongly suggests that CF momentum is driven by underreaction, not overreaction or liquidity effects.

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 time periods and show that the main results hold in both subsamples. Importantly, CF 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 links 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 than 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 et al. (2016) show 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 recent paper, Lee et al. (2019) 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 (Hirshleifer and Teoh, 2003; Peng and Xiong, 2006; Hirshleifer et al., 2011).

An emerging literature shows that shared analyst coverage of firms is associated with greater contemporaneous return correlations (Anton and Polk, 2014; Muslu et al., 2014; Lee et al., 2016; Kaustia and Rantala, 2018). Lee et al. (2016) also examine various approaches to peer firm identification such as Global Industry Classification Standard (GICS), 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. Kaustia and Rantala (2015) find that firms are more likely to split their stock if their analyst peers have done so recently. 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.[5] He does find that a strategy that combines short-term reversal and peer momentum generates a statistically significant alpha. In contrast, the strategies studied in this paper generate highly significant alphas even without combining them with short-term reversal. In our robustness section, we also show that our measure subsumes the predictive ability of Israelsen's (2016) measure.

Our paper differs from previous studies on analyst co-coverage in a number of important ways. First, we focus on return predictability rather than contemporaneous relations. Second, by using the information in the entire network of analyst connections, we can show much stronger relations between firms, and hence stronger return predictability, than the specialized predictability results of Israelsen (2016). Third, we show that for half of the stocks, second-level indirect connections also contain important information that dominates the information in direct connections. We also examine the effects of network complexity by showing how degree and eigenvector centrality of the network of analyst connections affect

[5] 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.

return predictability. Finally, we provide some structure to the "zoo" of momentum spillover effects in previous literature by showing that they are all captured by analyst co-coverage spillover effect.

The finding that a large number of momentum spillover effects are all captured by shared analyst coverage suggests that these effects share a common causal explanation, which is that information is transmitted sluggishly across firms that are fundamentally related. Specifically, it is not important for momentum spillovers whether the fundamental relatedness derives from customer-supplier links, technology links, and so forth. This can be useful for theoretical work. Any model that is specific to just one type of fundamental relatedness would almost surely be incorrect since any source of analyst co-coverage works. We argue that limited attention offers an integrated explanation. This is corroborated by our findings that complex linkages, which require greater cognitive processing, generate stronger return predictability.

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 relation between analyst co-covered stocks. He uses a narrower definition of analyst co-coverage, and the return predictability that he shows is somewhat weaker than the results of this paper.[6] 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 CF momentum effect, which is one of our paper's key contributions. Our paper also differs in providing international evidence of the CF momentum effect, in examining the effects of complex and higher-order linkages, and in examining the predictive power of CF momentum at different lags.

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 Center for Research in Security Prices (CRSP) database. We use the Institutional Brokers Estimate System (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 December 1983—the first month for which one year of historical IBES detail data are available—and ends in December 2015. 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 are from Andrea Frazzini's website and are available through May 2006. Following Cohen and Frazzini (2008), we lag the customer-supplier links data by six months to ensure that the data are publicly available before portfolio formation. We use the annual input-output data from the 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 become publicly available 11 months after the end of the reference year. Stocks are assigned to BEA industries using their historical North American Industry Classification System (NAICS) codes and BEA NAICS-industry mapping tables. The sample for customer and supplier industry variables starts in July 1986 due to the 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. (2019), we exclude financial stocks from the analysis and assume that the patent data become publicly available six months after the end of the year in which the patent is granted. The patent data are available through 2010, so the sample for tests including technology-linked variables ends in June 2012. Finally, we obtain factor returns from Ken French's website.

Table 1 provides some summary statistics for the CF portfolios. On average, each stock is connected to 86 other stocks through shared analyst coverage. About half of these linkages overlap with previously studied links. This is consistent with our conjecture that analysts are more likely to co-cover firms that are economically related. 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 show 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

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

Table 1
Summary statistics.
This table reports summary statistics. The sample period is January 1984 to December 2015. The sample includes common stocks listed on NYSE, Amex, and NYSE Mkt and excludes stocks with price <\$5. Each month, the CF 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. Previous links in the second row refers to links identified through common industry, geographic, customer-supplier, technology, or single- to multiple-segment links. The first four 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 percentage of all stock universe covered by the sample used in this paper. Panel B reports the average number of analyst covered 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 firms	1	71	86	368	62.09
% connected firms that overlap with previous links	0	0.48	0.47	1	0.28
Universe market capitalization	9.56	540.92	3291.96	277,636.93	12,609.05
All stocks market capitalization	4.30	376.15	2729.93	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
CF momentum	3010	3291.96
Industry momentum	2960	3264.46
Geographic momentum	2619	3552.58
Customer momentum	232	1546.08
Supplier industry momentum	2647	3435.48
Customer industry momentum	2636	3444.17
Complicated firm momentum	671	5833.59
Technology momentum	972	4879.11

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).[7] 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 relation between firm and peer firm sales growth for most peer firm measures. Consistent with Hypothesis 1, analyst CF sales growth has the strongest relation; a one standard deviation increase in CF sales growth is associated with 5.1% higher 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 2.6% in firm sales growth, which is about 60% the size of the CF sales growth coefficient. In the last eight columns of Panel A, the dependent variable is one-year-ahead sales growth. The results show that CF sales growth is a strong predictor of future firm sales growth, while 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.[8] In untabulated results, we also find that higher frequency CF 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 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 CF momentum effect

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

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

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

[7] 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, CF sales growth is calculated as the weighted average sales growth of analyst peers using the weights in Eq. (1) below.

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

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. CF sales growth is calculated the weighted average Sales growth of analyst-linked peers, using the weights in Eq. (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 the 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 ($t+1$)							
CF sales growth (t)	0.051	0.044	0.052	0.061	0.041	0.042	0.038	0.048	0.011	0.012	0.011	0.001	0.010	0.011	0.007	0.013
	(4.97)	(4.34)	(4.80)	(4.35)	(4.92)	(5.04)	(8.12)	(4.51)	(3.17)	(3.25)	(3.08)	(0.13)	(2.65)	(2.87)	(2.71)	(2.93)
Industry sales growth (t)		0.026								−0.002						
		(5.30)								(−0.45)						
Geo. sales growth (t)			0.004								0.002					
			(1.64)								(1.66)					
Customer sales growth (t)				0.030								−0.007				
				(3.33)								(−0.69)				
Supplier ind. sales growth (t)					0.026								−0.002			
					(4.71)								(−0.50)			
Customer ind. sales growth (t)						0.023								−0.006		
						(4.11)								(−1.59)		
Single-segment sales growth (t)							0.002								−0.001	
							(0.68)								(−0.44)	
Tech. linked sales growth (t)								0.006								0.005
								(0.99)								(1.29)
Sales growth (t)									0.035	0.035	0.035	0.042	0.030	0.030	0.032	0.017
									(7.87)	(8.22)	(7.67)	(5.48)	(6.82)	(6.86)	(8.51)	(2.82)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.088	0.092	0.087	0.121	0.085	0.084	0.077	0.084	0.086	0.086	0.085	0.096	0.080	0.081	0.083	0.074
# observations	65,018	64,266	60,309	2657	57,619	57,619	15,766	20,418	58,300	57,636	54,122	2400	51,390	51,390	14,467	19,131

Panel B	Dependent variable: Profit growth (t)								Dependent variable: Profit growth ($t+1$)							
CF 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
Adj. 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
# observations	64,647	63,892	59,950	2605	57,252	57,252	15,498	20,522	57,865	57,199	53,701	2347	51,117	51,117	14,178	19,256

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 examine the relation between past CF RET and future stock returns. At the end of each month, we rank stocks into quintiles based on CF 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 model includes the short-term reversal factor as an additional factor. There is a strong, monotonic relation between quintile rank and future returns and alphas. The long-short portfolio that 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

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 January 1984 to December 2015. 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 CF RET, as calculated in Eq. (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)

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 CF 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.

Fig. 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.

It is possible that the monthly predictability that we show reflects a liquidity effect, wherein common information gets incorporated into the prices of large and liquid stocks sooner than into prices of small and illiquid stocks (Hou, 2007). To address this possibility, we divide the analyst-linked peers of each stock into two size groups based on NYSE median market capitalization breakpoint and test whether the average return of small connected firms predicts returns of large focal firms. We find that a long-short value-weighted portfolio of large capitalization stocks constructed by sorting them into quintiles based on one-month lagged small capitalization CF return generates a five-factor alpha of 0.76% ($t = 4.69$).[9] We also show later in the paper that momentum spillovers are strong even in the largest 10% of the stocks, so it is highly unlikely that liquidity is the main driver of our results.

[9] In untabulated results, we find predictability at daily frequency as well. Lagged one-day CF return strongly predicts focal firm returns. The predictability is especially strong in the first four weeks and lasts for about one year. While a part of this effect almost certainly arises from liquidity effects as common information gets incorporated into prices of illiquid stocks with some delay, we also find that lagged one-day return of small capitalization analyst peers predicts large capitalization focal firm returns, suggesting that liquidity is not the full explanation. Also, liquidity and nonsynchronous trading effects cannot explain why the predictability lasts so long. It may seem surprising that enough corrective news arrives at a daily frequency to result in substantial cross-firm return predictability. However, in general, when a stock is valued incorrectly, under Bayesian or quasi-Bayesian updating, it is the early pieces of corrective information that tend to cause the largest corrections.

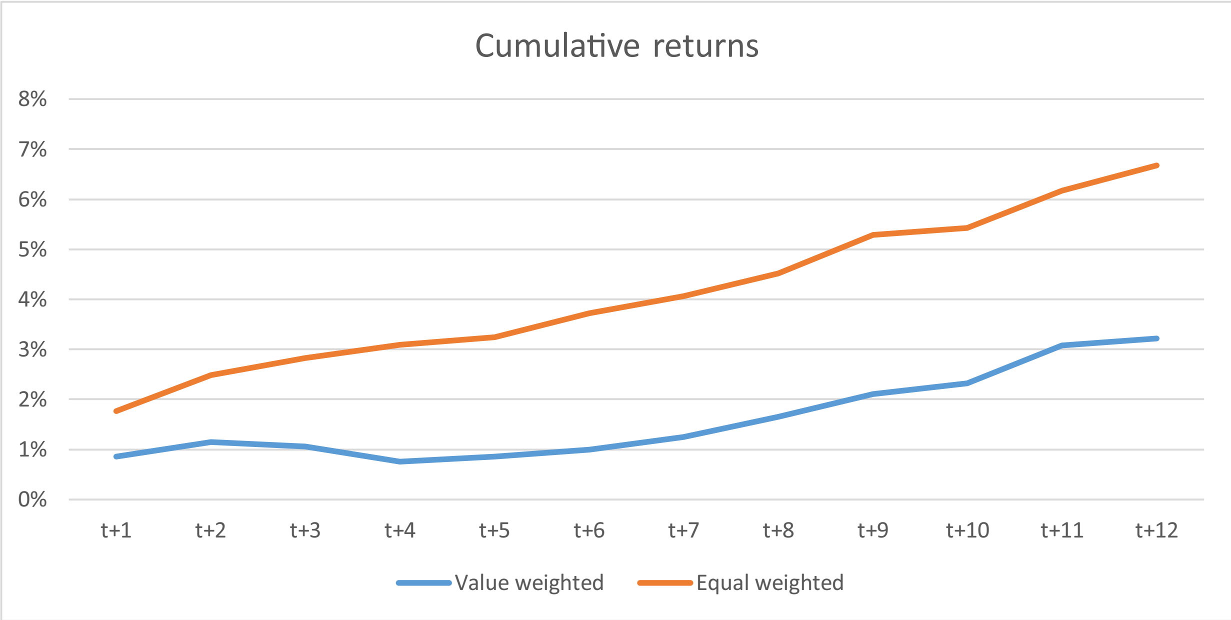

Fig. 1. Cumulative returns.
This figure plots the cumulative returns over the 12-month period after formation of the value- and equal-weighted long-short portfolios described in Table 3's caption. The sample period is January 1984 to December 2015. The sample includes common stocks listed on NYSE, Amex, and NYSE Mkt and excludes stocks with price <\$5.

Another possible explanation of our results is contagion of nonfundamental sentiment. For example, overoptimistic sentiment about a connected firm might infect the focal firm. However, this explanation is opposed by our findings that the CF momentum effect does not reverse in the long-run and past CF return strongly predicts focal firm fundamentals.

Having verified that CF return forecasts future returns, we next examine how CF 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 CF 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., CF 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 (5×2) resulting portfolios during the next month and the long-short factor return as

$$\frac{1}{2}\left(RET^{5}_{small} + RET^{5}_{large}\right) - \frac{1}{2}\left(RET^{1}_{small} + RET^{1}_{large}\right), \qquad (2)$$

where RET^{q}_{small} is the value-weighted average return of small cap stocks in characteristic quintile q and RET^{q}_{large} 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 CF momentum factor by sorting stocks on past CF RET, as calculated in Eq. (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 Standard Industrial Classification (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

[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 CF 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 et al. (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.

(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 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

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

where $T_i = (s_1, s_2, \ldots, s_k, \ldots, s_{427})$ is a vector of the firm's patent activity and the kth 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., 2019).[13]

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.[14] CF 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 CF 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.[15] Only the 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 CF momentum factor.[16]

In Panel B of Table 4, we regress CF 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 CF 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 CF 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.[17] While industry momentum factor can explain a large fraction of the returns of CF momentum factor, the alphas are still economically large 0.65% and 1.10% per month in columns 1 and 2, respectively.

We also test whether a factor that combines all seven of the previously studied firm linkage measures can explain the CF 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 Eq. (2).[18] The last row of Panel B in Table 4 shows that the alpha of CF momentum factor remains large and significant even after controlling for this combined factor. This result indicates that the CF momentum effect cannot be simply explained by combining the known effects into a more powerful measure.

Finally, in the last column of Panel B, we examine the incremental reduction in CF momentum factor alpha by adding the other seven cross-asset momentum factors one by one (along with the five factors) to the spanning regressions. The sample period for this test is from July 1986 to June 2006 due to the availability of data on all other factors. The five-factor alpha of CF momentum is 2.30% ($t = 10.58$) over this period. Adding the industry momentum factor to spanning regressions reduces this alpha to 1.48%, and adding all seven factors reduces the alpha to 1.08% ($t = 5.76$), so these seven factors reduce CF momentum factor alpha by about one-half.

Our results suggest very substantial return predictability even after controlling for known anomalies. After hedging out exposure to five common risk factors, the CF momentum factor has a t-statistic of 9.67. This implies an information ratio of 1.71 over the 1984–2015 sample

[13] When constructing the seven previously studied momentum factors, we do not restrict the cross-section to analyst covered stocks. This is only to ensure that our tests are comparable to those in previous papers. All of our results hold if we restrict the cross-section to analyst covered stocks.

[14] 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.

[15] It might at first seem surprising that some of the other factors generate negative incremental alphas after controlling for CF momentum. However, this can be econometrically reasonable if the effects of different linkages are not equally strong. For example, suppose hypothetically that industry linkages are associated with weaker (positive) predictability than other types of linkages and analysts co-cover firms in the same industry (along with other strongly linked firms). Consider a multivariate regression that uses linked firm returns based on analyst links and based on industry links. Then we may see a negative coefficient on industry links because the coefficient on our analyst linkage measure captures the effects of linkages more strongly than the predictability associated with industry linkages.

[16] We have also run regressions with only CF momentum factor as the explanatory variable, and the results are very similar—all seven cross-asset momentum factors have insignificant or negative alphas.

[17] Regressions of CF momentum factor returns on four (and five) factors and Customer momentum factor have large alphas because the sample for Customer momentum factor ends in June 2006 and the CF momentum strategy was more profitable in the earlier part of the sample period.

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

Table 4
Long-short factor returns and alphas.

This table reports the mean returns and alphas of CF 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 January 1984 to June 2006 due to the availability of data on customer-supplier links. The sample period for customer and supplier industry momentum factors is from July 1986 to December 2015 due to the availability of historical NAICS codes. The sample period for technological momentum factor is from January 1984 to June 2012 due to the availability of Kogan et al. (2017) patent data. The sample period for all other tests is from January 1984 to December 2015. Market, size, value, momentum, and short-term reversal factor returns are from Ken French's website. In Panel A, 4-factor + CF momentum factor alpha is the alpha from the time-series regression of portfolio returns on MKT, SMB, HML, UMD, and CF momentum factors. In Panel A, 5-factor + CF momentum factor alpha is the alpha from the time-series regression of portfolio returns on MKT, SMB, HML, UMD, short-term reversal, and CF momentum factors. The dependent variable in the regressions in Panel B is the return of the CF momentum factor. Column 1 of Panel B reports the alphas of the CF 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 the CF momentum factor from regressions of its return on the 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 Eq. (2). Column 3 of Panel B reports the incremental alphas of the CF momentum factor after adding the seven other cross-asset factors one-by-one to the five-factor regressions. The sample for this test is July 1986 to June 2006 due to the availability of the data on all factors. 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 (1)	4-factor alpha (2)	5-factor alpha (3)	4-factor + CF momentum factor alpha (4)	5-factor + CF momentum factor alpha (5)
CF 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 CF momentum factor (1)	5-factor + Alpha of CF momentum factor (2)	Incremental alpha of CF momentum factor (3)
Industry momentum factor	0.65	1.10	1.48
	(3.77)	(6.92)	(5.41)
Geographic momentum factor	0.87	1.31	1.22
	(4.53)	(9.94)	(5.95)
Customer momentum factor	1.11	2.24	1.21
	(3.07)	(10.82)	(5.65)
Supplier industry momentum factor	0.80	1.26	1.21
	(4.02)	(7.86)	(5.59)
Customer industry momentum factor	0.90	1.29	1.20
	(4.66)	(8.12)	(5.62)
Complicated firm momentum factor	0.87	1.41	1.11
	(4.46)	(8.99)	(5.27)
Technology momentum factor	1.05	1.51	1.08
	(5.03)	(10.37)	(5.76)
Combined momentum factor	0.62	0.90	
	(4.85)	(6.93)	

period. We have examined a comprehensive list of anomalies proposed in the literature and studied by Daniel et al. (2019). The information/Sharpe ratios of all these anomalies are considerably below 1.71 over the same sample period.

The one-month CF momentum strategy generates a monthly return of 133 basis points and has a turnover of 313% per month. This implies a break-even transaction cost of 42.5 basis points, which is considerably higher than the average transaction costs in the US reported by

Frazzini et al. (2015). This suggests that in our sample the one-month strategy was profitably tradable by a large arbitrageur despite its high turnover. The 12-month CF momentum strategy generates a monthly return of 90 basis points with a turnover of 119%. Therefore, net of transaction cost of approximately 20 basis points (as estimated by Frazzini et al., 2015), both strategies have similar net returns.

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 preceding 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 we 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. Small stocks 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 one-month CF 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 CF return does not decrease much. In terms of the economic magnitudes of the effects, a one standard deviation increase in past CF 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 in column 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 CF 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 CF 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 CF 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 CF 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 CF return remains a strong predictor.

In untabulated results, we have also examined lags of CF return beyond one year but did not find any evidence of return predictability. For instance, CF return (t-36, t-13) has a t-statistic of 0.21, and CF return (t-60, t-13) has a t-statistic of 0.87. Taken together, these regressions tests and the evidence in Fig. 1 show that CF momentum spillovers last for one year and do not reverse in years two through five.

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 CF return as the coefficients on 1-month and 12-month geographic return variables become insignificant once CF return variables are added to the regressions.

It is interesting that all of the momentum spillover effects, including CF momentum, are strongest at the one-month horizon. This is also true of many underreaction effects documented in the literature such as Post Earnings Announcement Drift (PEAD) and the forecast revision and recommendation revision anomalies. This suggests that although the market is not perfectly efficient, it reacts quickly enough to news to start the process of correcting underreaction within a month.

The next seven columns of Table 5 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 CF return—the coefficient on past customer return decreases by almost one-half in regression in column 12 and becomes insignificant in regression in column 12a once CF 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 CF return.

Columns 18, 18a, 19, and 19a examine the return predictability from single- to multi-segment firms. In column 19, including past CF 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 CF 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 in columns 20 and 21, which include large and small cap stocks, show that including past CF return reduces the predictive power of past return of

Table 5

Fama-MacBeth regressions.

This table reports the results of cross-sectional regressions. The dependent variable is the monthly stock return. CF RET is the weighted average return in the previous month of stocks that are connected through shared analyst coverage, as described in Eq. (1). CF 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 Eq. (1). Industry RET is the 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 the 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 the 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 January 1984 to June 2006 due to the 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 July 1986 to December 2015 due to the 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 January 1984 to June 2012 due to the availability of Kogan et al. (2017) patent data. The sample period for all other tests is from January 1984 to December 2015. Control variables include the past 1-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 the 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)
CF 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)
CF 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	2662	2631	2631	2661	2613	2613	2506	2506	2354	2354	212	212	2549	2549	2549	2549	2549	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)
CF 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)
CF 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

technology-linked firms by almost 60%. In terms of the economic magnitudes, a one standard deviation increase in CF 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 in column 21. Column 20a shows that among large cap stocks Technology-linked RET is a very weak predictor of future returns even without including

Table 6

Analyst connections versus all other connections combined.

This table reports the results of cross-sectional regressions. The dependent variable is the monthly stock return. All link RET EW (VW) is the equal-weighted (value-weighted) return in previous month of all stocks that are linked to the focal firm through common industry, geographic, customer-supplier, technology, or single- to multiple-segment links but are not linked through common analysts. All link overlap RET EW (VW) is the equal-weighted (value-weighted) return in the previous month of all stocks that are linked to the focal firm through common industry, geographic, customer-supplier, technology, or single- to multiple-segment links and are also linked through common analysts. CF unique RET is the weighted average return in previous month, as defined in Eq. (1), of all stocks that are linked to the focal firm through shared analyst coverage but are not linked through common industry, geographic, customer-supplier, technology, or single- to multiple-segment links. CF Overlap RET is the weighted average return in the previous month, as defined in Eq. (1), of all stocks that are linked to the focal firm through shared analyst coverage and through common industry, geographic, customer-supplier, technology, or single- to multiple-segment links. The sample period is from January 1984 to December 2015. Control variables include the past 1-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. The sample in columns 3, 4, and 6 includes large stocks (stocks with market cap above NYSE median) only. Independent variables are winsorized at the 1% and 99% levels. *t*-statistics are shown below coefficient estimates.

	Dependent variable: Return (*t*)					
	(1)	(2)	(3)	(4)	(5)	(6)
All link RET VW	0.057		0.024			
	(4.71)		(1.89)			
All link overlap RET VW	0.089		0.090			
	(11.54)		(6.75)			
All link RET EW		0.094		0.024		
		(5.17)		(1.28)		
All link overlap RET EW		0.103		0.105		
		(11.67)		(7.54)		
CF unique RET					0.056	0.048
					(7.07)	(4.16)
CF overlap RET					0.103	0.098
					(11.53)	(7.54)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Avg. R^2	0.049	0.053	0.081	0.085	0.050	0.079
Avg. # stocks	2581	2581	895	895	2490	889

CF RET in the regression. Once CF RET is included as an explanatory variable, Technology-linked RET loses its weak significance in Column 21a.

In regressions in columns 22 and 22a, we include all of the above predictors in the regressions.[19] The results show that past one-month CF 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 in columns 22 and 22a. In the Online Appendix, we show that CF return $(t-12,t-2)$ also makes long-horizon customer industry, supplier industry, and single-segment return variables insignificant.

In regressions including both large and small capitalization stocks, some of the previous cross-asset momentum variables remain statistically significant after controlling for CF momentum, but their magnitudes are substantially reduced. For stocks with low analyst coverage, the CF portfolio is small by construction and therefore may not capture all of the fundamental connections that are important to the focal firm. In untabulated results, we find that if we restrict the sample to stocks that are covered by at least four analysts, all of the previous cross-asset momentum variables become statistically insignificant after controlling for CF momentum.

Overall, the cross-sectional regression tests confirm the findings from the spanning tests. Past CF return is a strong predictor of future returns, and it largely subsumes the predictive power of other cross-asset momentum anomalies and completely so among large capitalization and medium to high analyst coverage stocks.[20]

We next examine the combined predictability of all previously studied linked stocks that are not linked through shared analyst coverage. In these tests we cannot use customer and supplier industry links. Since each industry is linked to a large number of other industries through upstream and downstream links, the number of linked stocks includes almost all stocks. This coupled with the fact that the CF portfolio consists of only 86 stocks on average means that the portfolio of all linked stocks that do not have an analyst connection will be very similar to the market portfolio. Therefore we use five previously studied forms of linkage (industry, geographic, customer-supplier, technology, and single to multiple segment) for this test. Our tests do not lose any information by excluding customer and supplier industry links because in our sample, both customer and supplier industry momentum strategies are spanned by own-industry momentum.

Each focal firm in our sample is linked to 397 unique stocks on average through at least one of these five links. Of these 397 stocks, 41 are also linked through shared analyst coverage. In Table 6, we divide these linked stocks into two groups—All link is the set of 356 stocks that are not

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

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

linked through shared analyst coverage, and All link overlap is the set of 41 stocks that are also linked through shared analyst coverage. For robustness, we examine the return predictive ability of both equal- and value-weighted returns of these two portfolios.[21]

Column 1 of Table 6 shows that stocks linked through previously studied linkages that also have an analyst connection have higher predictive power. A one standard deviation increase in All link overlap value-weighted return predicts an increase of 0.43% in future return, while a one standard deviation increase in All link value-weighted return predicts an increase of only 0.15% in future return. Column 2 shows that the same result holds for equal-weighted linked stock portfolios. In columns 3 and 4, we limit the sample to large capitalization stocks. These results show that only linked stocks that also have an analyst connection are statistically significant predictors of future return among large capitalization stocks, which is consistent with the results in Panel B of Table 5. These results suggest that analyst links identify the subset of previously studied links that have the greatest predictive ability.

We next divide analyst connected firms into two groups based on whether they are also linked through the five previously studied links or not. In Table 6, CF unique is the set of stocks linked through analyst co-coverage that are not linked through any of the five previously studied connections, and CF overlap is the set of stocks that are also linked through at least one of the five previously studied connections. Columns 5 and 6 show that while CF overlap return has greater predictive power in both full and large capitalization samples, CF unique return is also a very strong predictor in both samples.

Overall, the results in Table 6 suggest two conclusions. First, even within the set of previously studied links, analyst links can identify the subset of stocks that are most strongly related to the focal firm. Second, analyst links identify many important connections that are not captured by previously studied links.

3.5. International tests

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 relations can be identified for the vast majority of stocks globally.

Due to the 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 are 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 December 2015 for all countries. Table 7 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 CF RET as the weighted average return of all stocks connected to it during that month, as described in Eq. (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 CF RET.[22] We then calculate CF momentum factors for each country as described in Eq. (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 Eq. (2).

Table 7 presents the results of time-series regressions of CF and industry momentum factor returns.[23] Column 2 shows that the industry momentum factor generates a positive and significant five-factor alpha in 6 out of the 11 countries. However, in all but one of these countries, the alpha becomes both economically and statistically insignificant once the CF 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 CF momentum. The alpha remains statistically significant in the UK after controlling for CF 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 CF 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 CF momentum factor in international markets as well.

In sharp contrast, column 6 of Table 7 shows that CF momentum factors generate significant (at 1% level) alphas even after controlling for industry momentum factors in 10 of the 11 countries. Notably, CF momentum generates economically large returns in Hong Kong, Sweden, Italy, and Spain, where industry momentum returns are weak. CF momentum is also much more profitable; the average

[21] Since a given focal firm can be connected to some firms only by links other than shared analysts, and to other firms by common analysts, there are firm-month observations that include both situations.

[22] 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.

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

Table 7
International tests.
This table reports the mean returns and alphas of CF 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 are from IBES Global Detail File and country-level market, size, value, and momentum factor returns are from AQR's data library. The 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 December 2015 for all countries. Global ex US factors are weighted averages of country-level factors, where each country's lagged total market cap is used as weights. Columns 1 and 4 (2 and 5) report the mean returns (five-factor alphas) of industry momentum and CF momentum factors, respectively. Column 3 reports the alphas from regressions of the industry momentum factor on the five factors and the CF momentum factor. Column 6 reports the alphas from regressions of the CF momentum factor on the five factors and the industry momentum factor. *t*-statistics are shown below coefficient estimates.

	Sample start date	Industry momentum			CF momentum		
		(1) Mean return	(2) 5-factor alpha	(3) 5-factor + CF momentum factor alpha	(4) Mean return	(5) 5-factor alpha	(6) 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)
Global ex US	8/1989	0.65	0.92	0.20	0.92	1.38	0.78
		(5.43)	(8.35)	(1.86)	(5.35)	(12.28)	(6.23)

five-factor alpha of CF momentum factor is 1.15% per month compared to 0.69% per month for industry momentum factor. CF momentum factor alpha is also significant in Australia but becomes insignificant once industry momentum is controlled for.

In the last row of Table 7, we construct Global ex US CF and industry momentum strategies, where each country is weighted by its lagged total market capitalization. The Global ex US industry momentum factor generates a highly significant alpha of 0.92% per month ($t = 8.35$), but this alpha decreases to a marginally insignificant 0.20% after controlling for CF momentum. Meanwhile, CF momentum generates an alpha of 0.78% per month ($t = 6.23$) even after controlling for industry momentum.

3.6. Mechanism

We next probe more deeply the mechanism underlying the lead-lag relation. 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. Hence we hypothesize that if the lead-lag relation between connected stocks is driven by investors' limited ability to process information, it should be stronger if the connected portfolio is more difficult to process.

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 relations could be iterated any number of steps. It is likely that if a stock is connected to many 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), it makes it harder for investors in the stock to incorporate information rapidly and completely.

Table 8
Linkage complexity.
This table reports the results of a cross-sectional regression in which the dependent variable is the monthly stock return. CF RET is the weighted average return in the previous month of stocks that are connected through shared analyst coverage, as described in Eq. (1). CF RET2 is the weighted average CF RET in the previous month of stocks that are connected through shared analyst coverage, as described in Eq. (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. CF 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 Eq. (1). CF RET2(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 Eq. (3). In columns 4–7, the stocks are divided into two groups each month based on analyst coverage. In columns 4–7, the sample consists of low analyst coverage stocks. In column 8, the sample consists of high analyst coverage stocks. The sample period is from January 1984 to December 2015. Other control variables include the past 1-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. Independent variables are winsorized at the 1% and 99% levels. t-statistics are shown below coefficient estimates.

	Dependent variable: Return (t)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CF RET	0.308	0.301	0.298	0.179		0.037	0.037	0.221
	(9.36)	(9.23)	(9.30)	(14.21)		(2.94)	(2.96)	(6.33)
CF RET2					0.294	0.247	0.246	−0.035
					(12.92)	(7.39)	(8.33)	(−0.58)
#Connections*CF RET	0.001		0.000					
	(4.00)		(0.33)					
EV centrality*CF RET		0.002	0.002					
		(5.08)	(3.11)					
Size*CF RET	−0.029	−0.032	−0.031					
	(−4.55)	(−4.97)	(−4.82)					
Analyst coverage*CF 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)					
CF RET(t-12,t-2)							0.006	
							(1.48)	
CF RET2(t-12,t-2)							0.011	
							(1.81)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Avg. R^2	0.056	0.058	0.061	0.037	0.040	0.041	0.046	0.073
Avg. # stocks	2662	2662	2662	1339	1339	1339	1338	1323

To capture the effect of complexity, we add interaction terms between our complexity measures and CF return as predictors in our regression tests. A potential confound for this test is that firms covered by many analysts will have connected portfolios that consist of more firms. Since analyst coverage is highly correlated with firm size, such a test will be confounded with the relation 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 CF return and between analyst coverage and CF return in our regression tests. (The regressions also include controls for past one-month return, past 12-month return, size, and book to market.)

Table 8 presents the results. Consistent with the idea that information diffuses slowly among stocks with little analyst coverage, we find that the return predictability of CF return decreases with analyst coverage in the regression in column 1. Moreover, the coefficient on the interaction term #Connections*CF return is positive and significant ($t = 4.00$). This result is consistent with the hypothesis that investors have greater difficulty extracting information when the firm is fundamentally linked to a large number of related firms. Column 2 shows that the interaction term between eigenvector centrality and CF 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.[24] Another closely related centrality measure is diffusion centrality, as introduced by Banerjee et al. (2013). In untabulated results, we find that the predictability of CF return increases substantially and significantly with diffusion centrality as well.

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

[24] These results are robust to including the interaction term between CF return and lagged idiosyncratic volatility of the CF portfolio as a control variable, so the effect of connectedness here does not just derive from the fact that CF return has a higher signal-to-noise ratio when the CF portfolio consists of a larger number of stocks.

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 CF return level 2, which is computed as

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

We also divide our sample into two groups based on analyst coverage. Columns 4–8 of Table 8 present the results of this analysis. Columns 4 and 5 show that among stocks with low analyst coverage, both CF return and CF return level 2 are individually strong predictors of future returns. When both are included in the same regression in column 6, CF return level 2 has much stronger predictive power. A one standard deviation increase in CF return level 2 predicts an increase of 72 basis points ($t = 7.39$) in future return, while the same increase in CF return predicts an increase of only 15 basis points ($t = 2.94$).[25,26] In column 7, we find that CF return (t-12, t-2) has an insignificant coefficient, and CF return level 2 (t-12, t-2) has a bigger and weakly significant coefficient. This is consistent with the idea that since level 2 linkages are indirect and complex, their predictability should last longer. In column 8, the sample is stocks with high analyst coverage. The results show that CF return level 2 is an insignificant predictor among high analyst coverage stocks that 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 investors are sluggish in impounding the information contained in analyst forecasts. Another possibility is that analysts themselves are slow to carry information across firms they cover due to a behavioral bias or constraint. Moreover, since analyst links identify fundamental relations more sharply than previously studied measures, past revisions of analyst peers may predict future focal firm revisions more strongly owing to a greater amount of relevant information to be transferred across firms. To test these hypotheses, we repeat the tests of Table 5 except we use analyst forecast revisions of the current fiscal year earnings instead of stock returns.

Table 9 presents the results. All of the regressions include past 1-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 the 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 CF forecast revision (CF FR) as an additional explanatory variable. For each stock, CF 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 Eq. (1). The coefficient on Industry FR halves once CF FR is added to the regression, while the coefficient on CF FR is much larger and highly significant ($t = 23.25$). A one standard deviation increase in CF 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 9 show that CF 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 adding CF 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 CF 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, CF 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 CF 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 CF FR is a much stronger predictor of future revisions compared to past revisions of technology-linked firms; a one standard deviation increase in CF 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.

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

[26] 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.

Table 9
Analyst forecast revisions.
This table reports the results of cross-sectional regressions in which the dependent variable is the monthly percentage forecast revision. The percentage forecast revision (FR) is calculated as (Consensus forecast_t – Consensus $\text{forecast}_{t\text{-}1}$)/maximum (0.01, |Consensus $\text{forecast}_{t\text{-}1}$|), where Consensus forecast is the average analyst forecast of FY1 earnings. FR is winsorized at the 1% and 99% levels to minimize the effect of outliers. CF FR is the weighted average FR of connected firms in the previous month, calculated using the weights in Eq. (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 January 1984 to June 2006 due to the 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 July 1986 to December 2015 due to the 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 January 1984 to June 2012 due to the availability of Kogan et al. (2017) patent data. The sample period for all other tests is from January 1984 to December 2015. Control variables include the past 1-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 the 1% and 99% levels. *t*-statistics are shown below coefficient estimates.

	Dependent variable: Forecast revision (*t*)													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
CF 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	2507	2507	2467	2467	194	194	2434	2434	2434	2434	616	616	894	894

These results suggest that the return lead-lag relation that we show may at least partially be driven by sluggish analyst forecasting behavior. In other words, while the contemporaneous correlation between focal and CF forecast revisions is large and significant, analyst reaction is incomplete, as evidenced by the strong lead-lag relationship between forecast revisions. It might seem surprising that the same analysts who can 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. 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.

Previous studies have offered explanations for inefficient analyst behavior in terms of biases, constraints, or agency problems. For example, the models of Trueman (1994) and Prendergast and Stole (1996) suggest that to maximize short-term reputation, agents such as analysts may engage in herding and/or be sluggish in updating their behaviors such as revising earnings forecasts. Analysts tend to issue overly optimistic forecasts to increase trading revenue and to appease management at covered firms. Such behavior can contribute to analyst underreaction to negative news about connected firms. Also, the empirical finding of a walkdown to beatable analyst forecasts (Richardson et al., 2004) suggests that other agency problems may also reduce the responsiveness of forecasts to news. Another possibility is that it takes time to write up an analyst report, making it hard for an analyst who is covering two linked firms to simultaneously update forecasts about both of them (so if A and B are linked and news about B arrives, the analyst is likely to update B's forecast first because the news is most relevant to B, and only afterwards get to updating A's forecast to reflect the common information).

To identify more sharply the effect of analyst behavior on the lead-lag relations, 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

Table 10
Do analysts expedite information flow?
This table reports the results of cross-sectional regressions. The dependent variable is monthly stock return. CF-no coverage (CF-no coverage1) is the set of stocks that are linked to the focal firm in month t-1 through shared analyst coverage but are unlinked in month t-7 (t-13) because either the focal firm or the linked firm had no analyst coverage in month t-7 (t-13). CF-no coverage return variables are standardized each month to have zero mean and unit variance. The sample period is from January 1984 to December 2015. Control variables include the past 1-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 the 1% and 99% levels. t-statistics are shown below coefficient estimates.

	(1)	(2)	(3)	(4)
	Dependent variable			
	RET(t-6)	RET(t)	RET(t-12)	RET(t)
CF-no coverage RET(t-7)	0.0025			
	(6.15)			
CF-no coverage RET(t-1)		0.0016		
		(3.84)		
CF-no coverage1 RET(t-13)			0.0026	
			(6.71)	
CF-no coverage1 RET(t-1)				0.0018
				(5.37)
Controls	Yes	Yes	Yes	Yes
Avg. R^2	0.050	0.047	0.048	0.045
Avg. # stocks	1211	1211	1453	1453

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.

To test whether analysts expedite information flow between connected stocks, we examine breaks in links going back in time. Suppose that stocks A and B are connected in month t-1 and either A or B does not have any analyst coverage in month t-7, so they are unlinked in month t-7. Since fundamental linkages are unlikely to change over relatively short periods of time, we expect to find return predictability from A to B (and vice versa) in the prior period as well if the lead-lag relation derives at least in part from direct bias in investor perceptions of fundamentals rather than from investor reliance upon analyst underreaction. (Since there are no common analysts in the prior period, this return predictability cannot be attributed to analyst sluggishness.)

For this test, at the end of each month t-1, we start with all analyst-linked pairs of stocks. We then construct a subset of these linked firms that are unlinked six months ago because either the focal firm or the linked firm had no analyst coverage six month ago. We call this subset CF-no coverage. We then regress Return (t-6) on CF-no coverage return (t-7) and separately regress Return (t) on CF-no coverage return (t-1) and compare the two coefficients. In other words, we examine the return predictive ability of the same portfolio, CF-no coverage, during months in which the focal firm is linked to CF-no coverage stocks and during months in which the focal firm is not linked to CF-no coverage stocks.

Table 10 presents these results. We standardize the independent variables to have zero mean and unit variance each month for ease of comparisons across regressions. The first regression shows that CF-no coverage return is a strong predictor of returns during the months in which the focal firm is not connected to CF-no coverage stocks. A one standard deviation increase in CF-no coverage return (t-7) predicts an increase of 25 basis points ($t = 6.15$) in focal firm return in month t-6. The magnitude and the statistical significance of the effect is remarkable given that the CF-no coverage portfolio consists of only 2.6 stocks on average. Consistent with the hypothesis that common analysts expedite the information flow between connected firms, column 2 shows the return predictability is weaker during months in which the focal firm and CF-no coverage firms share common analysts. The difference between the two coefficients is an economically meaningful 9.6 basis points per month ($t = 1.75$).[27]

In columns 3 and 4, we repeat these tests except that we examine stocks that are linked in month t-1 but are unlinked 12 months ago, instead of 6 months ago, because of no analyst coverage on either focal or linked firm. We find very similar results. The return predictability is 8.6 basis points ($t = 1.69$) higher during months in which the focal firm is not connected to CF-no coverage stocks.

We next examine how variation in the number of shared analysts affects our results. As before, there are two competing hypotheses. On the one hand, a larger number of common analysts should expedite information flow between connected firms and therefore reduce return predictability, all else equal. On the other hand, more common analysts might indicate a stronger relation between firm fundamentals, which should increase return predictability, all else equal.

To test this idea, we divide the CF portfolio into two groups based on the number of common analysts. On average, about 70% of the linked stocks in our sample only have one analyst in common. To maximize the sample size, we start by dividing connected firms into two groups

[27] We do not control for CF return in any of the regressions. Including CF return (t-1) unfairly penalizes CF-no coverage return (t-1) since CF-no coverage stocks are a subset of the CF portfolio, and including it makes the difference between regression 1 and 2 coefficients larger and highly significant. In regression 1, including CF return (t-7) has little effect on CF-no coverage return (t-7) coefficient—it remains large and highly significant.

Table 11
Variation in number of shared analysts.

This table reports the results of cross-sectional regressions. The dependent variable is the monthly stock return. Each month, the CF portfolio of each focal firm is divided into two groups based on the number of common analysts. CF RET 1 comm. analyst (CF RET >1 comm. analyst) is the weighted average return in the previous month, as defined in Eq. (1), of all stocks that are linked to the focal firm through only one (more than one) common analyst. CF RET >4 comm. Analyst is the weighted average return in the previous month, as defined in Eq. (1), of all stocks that are linked to the focal firm through at least five common analysts. In column 5, stocks are ranked each month into quintiles based on analyst coverage, and the sample is restricted to focal and linked firms that belong to the same analyst coverage quintile in that particular month. The sample period is from January 1984 to December 2015. Control variables include the past 1-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 the 1% and 99% levels. *t*-statistics are shown below coefficient estimates.

	Dependent variable: Return (*t*)				
	(1)	(2)	(3)	(4)	(5)
CF RET	0.103	0.103	0.087	0.092	0.051
1 comm. analyst	(6.85)	(7.35)	(4.56)	(4.94)	(6.47)
CF RET	0.091	0.093			0.058
>1 comm. analyst	(12.68)	(13.62)			(11.28)
CF RET (*t*-12,*t*-2)		0.004		0.001	0.002
1 comm. analyst		(1.23)		(0.13)	(0.92)
CF RET (*t*-12,*t*-2)		0.006			0.005
>1 comm. analyst		(3.08)			(3.40)
CF RET			0.078	0.079	
>4 comm. analyst			(10.77)	(11.31)	
CF RET (*t*-12,*t*-2)				0.006	
>4 comm. analyst				(2.86)	
Controls	Yes	Yes	Yes	Yes	Yes
Avg. R^2	0.059	0.067	0.071	0.082	0.061
Avg. # stocks	2205	2203	1254	1253	1806

based on whether they share only one common analyst or more than one common analyst with the focal firm. We then compare the return predictive power of these two groups of connected firms. (Since a given focal firm can be connected to some firms by one common analyst and other firms by multiple common analysts, there are firm-month observations of CF return for both situations.) Table 11 presents the results. Column 1 shows that past one-month CF return is a stronger predictor when the connected firms share at least two analysts with the focal firm. A one standard deviation increase in CF >1 common analyst return predicts an increase of 48 basis points ($t = 12.68$), while the same increase in CF 1 common analyst return predicts an increase of 34 basis points ($t = 6.85$) in future return. (Since the CF portfolio with at least two common analysts is less diversified, its standard deviation is much larger.) The difference between the two (standardized) coefficients is also significant ($t = 2.42$). Column 2 shows that CF return (t - 12, t - 2) is only statistically significant when there are at least two common analysts. In other words, longer-term lags of CF return only predict returns when there are more common analysts. In untabulated results, we find, consistent with previous results, that lagged CF return beyond one year does not significantly predict returns regardless of the number of common analysts.

In columns 3 and 4, we compare the return predictive ability of connected firms that share only one analyst to those that share at least five analysts with the focal firm. We find very similar results. A one standard deviation increase in CF > 4 common analyst return predicts an increase of 47 basis points ($t = 10.77$), while the same increase in CF 1 common analyst return predicts an increase of 27 basis points ($t = 4.56$) in future return. We next limit the sample to focal and connected firms than belong to the same analyst coverage quintile to ensure that differences in analyst coverage are not driving these results. Column 5 shows that this does not affect any of the conclusions.

These results suggest that firms that share more analysts are fundamentally more similar to each other. In untabulated results, we have verified that this is true. For instance, a one standard deviation increase in CF sales growth is associated with a 3.3% higher increase in focal firm sales growth when there are at least two common analysts versus only one common analyst. We also find that while the contemporaneous correlation between forecast revisions of focal firm and connected firms is much larger when there are more common analysts (suggesting substantial related information being impounded), the correlation between focal firm forecast revision and lagged CF forecast revision is also higher when there are more common analysts (suggesting substantial sluggishness in the impounding of information). In other words, firms with more shared analysts have more fundamental relatedness that needs to be impounded across firms. There is more information to potentially underreact to, and indeed our finding is that the total forecast underreaction is greater when the fundamental relation between connected firms is stronger.[28]

[28] Suppose that analysts of the focal stock always underreact by a fixed percentage to all fundamental news, regardless of whether it is firm specific or derives from the connected firm. This assumption is consistent with the post-earnings announcement drift anomaly and with the general finding that forecast revisions are positively autocorrelated. Then, just like any other news that is relevant for the focal firm, the focal firm will underreact to news derived from linked firms. The stronger the fundamental linkage, the bigger the news for the focal firm (i.e., the stronger its correct reaction should be to the linked firm's news). A general fixed percentage underreaction to fundamental news implies a larger total underreaction

To try to isolate the effect of increase in analyst co-coverage, we have considered tests that seek to minimize variation in the fundamental relatedness between linked stocks as we vary the number of common analysts. Unfortunately, we find that either the measures of fundamental relations (such as overlap with previously studied linkages and historical correlations between firm fundamentals) are poor ex-ante measures of fundamental linkages (i.e., they are poor predictors of realized fundamental relations) or the resulting sample sizes as too small to run a powerful test.

3.7. Fundamentals and stock returns

The return predictability results presented so far indirectly suggest that past return of CF portfolio contains information about future focal firm fundamentals since the effects last for about one year and do not reverse. We nonetheless directly test whether CF return predicts fundamentals. In Panel A of Table 12, we regress future earnings and sales growth on 1-month and 12-month lagged CF return. All regressions include size, book to market, 1-month and 12-month lagged returns, and four lags of the dependent variable as controls, but their coefficients are not reported for brevity. Both 1-month and 12-month lagged CF return are strong predictors of future sales and earnings growth, and the effect of 12-month lagged CF return is much stronger. This does not contradict our previous finding that 1-month CF return is a much stronger predictor of future focal firm return than 12-month CF return. Since lagged CF return beyond one month has been public information for longer than one-month lagged CF return, a large part of the information contained in the former is already reflected into stock prices before month *t*.

It is also interesting to examine whether lagged fundamentals of connected firms predict future returns of focal firms. Also, while CF return contains information about concurrent fundamentals of connected firms, it also reflects market expectations of future fundamentals of connected firms (and hence of future fundamentals of focal firm since focal and connected firm fundamentals are highly correlated). Therefore, the component of CF return that is orthogonal to CF fundamentals might contain incremental information about focal firm return.

We test these ideas in Panel B, Table 12. In column 1, we regress focal firm return in month *t* on average CF quarterly earnings growth over the past four quarters for which earnings were announced before month *t* and on 12-month CF return orthogonal to CF quarterly earnings growth.[29] We find a weakly significant coefficient ($t = 1.86$) on average CF quarterly earnings growth, suggesting that most of the return predictability of CF return arises from its component that is orthogonal to CF fundamentals, as measured by earnings growth. In column 2, we use average quarterly revenue growth instead of earnings growth as a measure of fundamentals and find even weaker predictability—the coefficient on CF revenue growth is close to zero and insignificant. These results indicate that the market reacts relatively quickly to tangible information contained in CF fundamentals, which is easier to process but is slow to react to intangible CF return, which requires greater cognitive processing.

Analyst forecast revisions of upcoming fiscal year's earnings are another, and perhaps a better, measure of fundamentals since they also contain information about fiscal quarters for which earnings are yet to be announced. Moreover, forecast revisions can be measured at a monthly frequency unlike fundamental measures, computed from annual or quarterly filings. Columns 3 and 4 in Panel B of Table 12 show that CF forecast revision (FR) and CF return orthogonal to CF FR both predict future return for both 1 and 12-month lags even after controlling for focal firm FR, but intangible CF return is a stronger predictor.

Table 9 indicates that lagged CF FR strongly predicts future focal firm FR. This suggests that the return predictive power of CF FR documented in columns 3 and 4 in Panel B of Table 12 might simply derive from lagged CF FR being correlated with FR, which in turn is highly correlated with stock return. To test this, we regress monthly return orthogonal to contemporaneous forecast revision of the stock on lagged CF FR and CF return in columns 5 and 6 of Panel B of Table 12. The coefficients on 1 and 12-month lagged CF FR are now insignificant, which suggests that investors respond quickly to revisions when they occur. However, as before, the coefficients on lagged CF return are highly significant. This suggests that investors underreact substantially to intangible CF return, which in turn suggests that sluggish analyst behavior alone does not explain the momentum spillovers that we show.

The results in the preceding sections help us draw some further conclusions. First, the fact that CF return is related to future focal firm fundamentals coupled with our result that CF momentum does not reverse suggests that CF momentum is driven by underreaction (e.g., owing to limited investor attention) and not by overreaction or liquidity effects.

Second, both analysts and investors likely contribute to this underreaction. The results on analyst forecast revisions show that analysts react sluggishly to news about connected firms, and this may contribute to the return lead-lag relation we show since connected-stock forecast revisions strongly predict focal firm revisions, which in turn are highly correlated with stock returns.[30] We also find that lagged CF return predicts focal firm return even after controlling for sluggishness in analyst forecasts, which suggests that investors independently underreact to news about linked firms. The results in Table 10, in which we examine links going back in time before analyst coverage, provide further evidence that investors underreact to news about linked firms. (Since there are no common analysts,

(i.e., Total underreaction = Percentage underreaction * Size of the news). Even if Percentage underreaction is decreasing in number of analysts, it is possible that Total underreaction increases.

[29] We control for focal firm lagged fundamentals in all regressions in Panel B of Table 12. Other control variables include size, book to market, and 1-month and 12-month lagged returns. The coefficients on control variables are not reported for brevity.

[30] We cannot draw a conclusion about causality since analysts and investors could independently underreact to news arrival.

Table 12
Fundamentals and stock returns.
Panel A reports the results of panel regressions in which the dependent variable is quarterly earnings or revenue growth. Earnings growth in quarter q is calculated as (earnings per share_q - earnings per share_{q-4})/(standard deviation of (earnings per share_q - earnings per share_{q-4}) over the past eight quarters). Revenue growth is calculated similarly. The sample is restricted to firms with fiscal quarter ends in March, June, September, and December. Control variables include the past 1-month return, past 12-month return (excluding the most recent month), log of market capitalization, log of book-to-market ratio, and four quarterly lags of the dependent variable. Independent variables are cross-sectionally standardized each quarter to have zero mean and unit variance and are winsorized at the 1% and 99% levels. Year-quarter fixed effects are included in all regressions. The sample period is from January 1984 to December 2015. *t*-statistics are shown below coefficient estimates. Panel B reports the results of cross-sectional regressions in which the dependent variable is the monthly stock return. In columns 5 and 6, the dependent variable is the monthly stock return orthogonal to contemporaneous forecast revision of the stock. Avg. CF earnings (revenue) growth(t-12,t-1) is the weighted average earnings (revenue) growth during the quarters for which earnings were announced between months t-12 and t-1, calculated using the weight in Eq. (1). CF FR(t-1) is the weighted average forecast revision of connected firms in the previous month, calculated using the weights in Eq. (1). CF FR(t-12, t-1) is the weighted average of the 12-month average forecast revision of connected firms, calculated using the weights in Eq. (1). The sample period is from January 1984 to December 2015. Control variables in all regressions include the past 1-month return, past 12-month return (excluding the most recent month), log of market capitalization, and log of book-to-market ratio. Additional control variables include focal firm Avg. earnings growth(t-12,t-1) in column 1, focal firm Avg. revenue growth(t-12,t-1) in column 2, focal firm FR(t-1) in columns 3 and 5, and focal firm FR(t-12,t-1) in columns 4 and 6. Stocks with price <$5 at the end of previous month are excluded from the regressions. Independent variables are winsorized at the 1% and 99% levels. *t*-statistics are shown below coefficient estimates.

Panel A: Predicting fundamentals

	Dependent variable			
	Earnings growth (t,t+2)	Earnings growth (t,t+2)	Revenue growth (t,t+2)	Revenue growth (t,t+2)
CF RET(t-1)	0.028	0.015	0.025	0.016
	(5.39)	(3.04)	(4.06)	(2.57)
CF RET(t-12,t-1)		0.039		0.025
		(6.91)		(3.89)
Controls	Yes	Yes	Yes	Yes
Adj. R^2	0.359	0.360	0.634	0.636
# observations	281,772	281,772	281,772	281,772

Panel B: Using CF fundamentals to predict returns

	(1)	(2)	(3)	(4)	(5)	(6)
Avg. CF earnings growth(t-12,t-1)	0.002					
	(1.86)					
CF RET(t-12,t-1) orthogonal to Avg. CF earnings growth(t-12,t-1)	0.023					
	(6.05)					
Avg. CF revenue growth(t-12,t-1)		0.000				
		(0.52)				
CF RET(t-12,t-1) orthogonal to Avg. CF revenue growth(t-12,t-1)		0.023				
		(6.09)				
CF FR(t-1)			0.061		0.010	
			(2.78)		(0.45)	
CF RET(t-1) orthogonal to CF FR(t-1)			0.184		0.186	
			(11.88)		(11.98)	
CF FR(t-12,t-1)				0.058		0.022
				(1.99)		(0.77)
CF RET(t-12,t-1) orthogonal to CF FR(t-12,t-1)				0.025		0.024
				(5.75)		(5.62)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Avg. R^2	0.053	0.053	0.056	0.059	0.057	0.059
Avg. # stocks	2453	2453	2564	2273	2536	2259

the predictability cannot be driven by sluggish analyst behavior.) Finally, the results in Table 10 suggest that the presence of common analysts does help expedite the information flow between connected firms since predictability is lower during months in which stocks are linked.

3.8. 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 13, 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 CF momentum factor—the alphas are insignificant. In contrast, the CF 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 are available from Gerard Hoberg's website for the period from July 1997 to June 2015. Table 13 shows

Table 13
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 subsample. Text-based industry data are available from July 1997 to June 2015. The 5-factor + CF 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 CF momentum factors. The 5-factor + Alpha of CF momentum factor is the alpha from time-series regression of the CF 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: Alternative industry and geographic definitions

	5-factor + CF momentum factor alpha (1)	5-factor + Alpha of CF momentum factor (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: Subsample analysis

	1984–1999			2000–2015		
	5-factor alpha (1)	5-factor + CF momentum factor alpha (2)	5-factor + Alpha of CF momentum factor (3)	5-factor alpha (4)	5-factor + CF momentum factor alpha (5)	5-factor + Alpha of CF momentum factor (6)
CF 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)

that text-based industry momentum is also subsumed by CF momentum but not vice versa—CF 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 CF momentum.

We next examine whether our results are robust to an alternative definition of geographic momentum.[31] 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 13 shows that using this alternative definition does not affect the earlier conclusion.

In Panel B of Table 13, we divide our sample into two equal halves and conduct the tests of Table 4 in each subperiod.[32] The first row shows that although the predictability of CF momentum has declined in recent years, the CF momentum factor yields an economically large five-factor alpha of 1.13% per month ($t = 4.48$) from 2000 to 2015. The next six rows show that the results of Table 4 also show up in the two subsamples. Almost all of the other cross-asset momentum factors have negative or insignificant alphas once the CF 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 CF momentum, but the alpha decreases substantially—by 63%.

[31] Parsons et al. (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.

[32] We do not examine customer momentum in Table 13 since data on customer-supplier links is not available post June 2006.

Table 14
Comparison with Israelsen (2016).
This table compares the predictability of the CF 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 CF RET (Israelsen peer return) and a value-weighted long-short portfolio is formed that is long top- and short bottom-quintile stocks. The 6-factor + CF 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 CF momentum factors. The 6-factor + Alpha of CF momentum factor is the alpha from time-series regression of the CF 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 the one-month ahead return and the independent variables include past month CF return and Israelsen peer return. Control variables include the past 1-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 the 1% and 99% levels. *t*-statistics are shown below coefficient estimates.

Panel A: Long-short factors

Israelsen momentum factor		CF momentum factor	
Mean return	6-factor + CF 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)
CF 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

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

Finally, we compare our CF 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 14, we rank stocks into quintiles based on CF return and construct a value-weighted long-short CF momentum factor that 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 CF momentum effect is controlled for, the alpha of Israelsen's momentum factor turns negative. In contrast, CF 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 14 shows that the same conclusions hold in cross-sectional regression tests. The first two columns show that CF 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 shown 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 relation to be at too high a frequency to be detectable in monthly return tests.

We first show that analyst linkages do in fact identify fundamental relations, 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 relation. A long-short trading strategy based on this relation 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 CF momentum effect. In spanning regressions, the alphas of these cross-asset momentum strategies become insignificant or turn negative once CF 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.

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, while 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, as well as 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 CF momentum factor generates an information 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.

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