Production Complementarity and Information Transmission Across Industries

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Abstract

Economic theory suggests that production complementarity is an important driver of sectoral co-movements and business cycle fluctuations. We operationalize this concept using a measure of production complementarity proximity (*COMPL*) between any two companies. We show firms from different industries but are closely aligned in *COMPL* exhibit strong co-movement in their operating, investing, and financing activities, as well as quarterly earnings revisions and monthly returns. We further document a lead-lag effect in their returns, such that a long-short strategy based on recent *COMPL* peer returns yields a monthly 6-factor alpha of 122 basis points. This inter-industry momentum spillover effect is not explained by other network-based mechanisms, such as shared analyst coverage. We conclude information transmission takes place along complementarity networks, but stock prices do not update instantaneously.

JEL Classifications: E60, G10, G14, M20, M21

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1. Introduction

A striking feature of production networks is that industries (or firms) producing distinct intermediate inputs to the same output can form complementary relationships. Entities that share some production complementarities are called complementors, and the production decisions of these entities are textbook examples of strategic complementarity from game theory. For example, batteries and processor chips are complementary goods because of their common usage in the production of smartphones. Breakthroughs in battery technology will likely increase demand for more powerful processor chips, just as breakthroughs in processor chips will likely increase demand for more durable batteries. In this setting, producers of batteries and producers of processor chips are complementors, even though (a) they belong to different industries, and (b) they have no direct customer-supplier relationship with each other. Economic theory predicts that a positive (negative) shock affecting one entity in a complementarity network bodes well (poorly) for other entities along the same complementarity network.

Economists have long posited that such networks play an important role in the transmission of shocks across the economy. For example, macroeconomists use this theory to model the aggregation and propagation of more granular shocks (Conley and Dupor, 2003; Jones, 2011; Baqaee and Farhi, 2019; Elliott and Golub, 2022). In particular, Atalay (2017) estimates a multi-industry general equilibrium model in which goods produced by different industries complement one another as inputs in the production process of downstream industries. In this framework, Atalay (2017) shows sectoral shocks can explain more than half of the variation in aggregate output growth for the economy as a whole. Much of the power in the model derives not from direct customer-supplier links, but from second-moment linkages in which shocks to complementor industries reinforce each other. A key stylized fact from this literature is that production complementarity can be an important driver of sectoral co-movements and business cycle fluctuations.

This study examines the capital market implications of production complementarity. Our analysis proceeds in two stages. First, we develop a measure of complementarity proximity (*COMPL*) between any two companies. Intuitively, *COMPL* captures the extent to which the outputs of any two firms are used as complementary inputs in the same downstream production process. Next, for each "focal firm" (i.e., a firm of primary research interest), we use *COMPL* to identify a set of complementor peers. In identifying these complementors, we drop any peer firm that is in the same SIC 4-digit industry as the focal firm ("horizontal" peers), as well as any firm with a material customer-supplier relationship with the focal firm ("vertical" peers). These procedures ensure that the set of identified complementors does not include any direct competitors, customers, or suppliers. They also ensure that our subsequent analyses are sharply focused on information transfers of an inter-industry nature that are not due to direct customer-supplier linkages.[1]

Our first set of tests investigates the usefulness of *COMPL* as a measure of economic linkage between firms. Theory suggests that the economic fortunes of complementor firms should wax and wane together, even if they are not from the same industry. We conduct a series of tests to evaluate the extent to which firms with high *COMPL* scores experience correlated shocks in various dimensions of their businesses. To the extent that these firms are economically linked, we expect to find a positive co-movement in the level of their fundamental activities over time.

Our results show that this is the case. Using seven measures of fundamental business activity, we find firms that are close to each other in terms of *COMPL* exhibit strong co-movement in their annual operating (profitability, sales growth), investing (capital expenditures, R&D, and patent-related innovation measures), and financing (market leverage, external financing) activities. These results hold after controlling for industry-wide co-movements as well as firm and year fixed effects. We also find

[1] Our correlation results, both contemporaneous and lagged, are uniformly stronger if we include firms from the same industry or firms with a direct customer-supplier relationship in the set of complementor peers. However, to cleanly isolate inter-industry spillover effects that are not due to customer-supplier links, we opt to eliminate all firms with a direct vertical or horizontal relationship with the focal firm.

a positive correlation in the monthly stock returns and quarterly analyst earnings forecast revisions between the focal firms and their complementors, after controlling for firm size, book-to-market, the firm's own lagged monthly returns, and medium-term price momentum.

Further analyses show a peer firm's complementarity closeness (*COMPL*) is positively associated with the degree of co-movement in company fundamentals. We find the strongest positive correlation for *Strong Complementors* (peer firms ranked above 98% by *COMPL*). These positive correlations are still detectable, but become weaker, for *Medium Complementors* (peer firms ranked between 98% and 96% by *COMPL*) and *Weak Complementors* (peer firms ranked between 96% and 94% by *COMPL*). This pattern of gradually weaker results as we increase complementarity proximity is observed for all seven measures of business activity, as well as for quarterly earnings revisions and monthly stock returns.[2]

Together, these findings show that a production complementor based algorithm can identify peer firms from different industries that are linked economically. To our knowledge, these are among the first pieces of micro-level evidence on the importance of inter-corporate connectedness between firms from different industries that do not share direct customer-supplier relations. The granularity of this data (firm-level observations at relatively high frequencies) allows us to confirm a long-standing prediction from macro- and micro-economic theory about how shocks propagate across industries and business sectors. Our evidence shows that these inter-industry linkages are pervasive in the cross-section of publicly traded companies.

In the second stage of our analyses, we investigate the lead-lag relationship in stock returns among complementors. Having established complementors as closely linked firms that reside in different industries, we now evaluate the speed with which shocks propagate along complementarity networks.

[2] We find the same complementarity distance related decay in correlations whether peer firms are weighted equally, by their *COMPL* scores, or by a variety of size-related metrics (i.e., asset value, market capitalization, log of asset value, and log of market capitalization).

While neoclassic theory predicts that asset prices are quickly updated to reflect all publicly available information, recent empirical studies report striking lead-lag patterns in the returns of economically linked firms. Starting with early work by Cohen and Frazzini (2008), who document a significant return lead-lag relationship between customer firms and their suppliers, a large body of literature now reports similar patterns between the returns of firms that share some form of fundamental commonality. Collectively, this is referred to as a "momentum spillover effect".[3] We examine the return lead-lag pattern among complementor firms.

This part of our investigation is motivated by two observations. First, complementors typically share little, if any, common analyst coverage. This is because most financial analysts focus on one sector and/or a few closely related industries. By construction, our complementor firms come from different industries, so that although they are economically linked, they are not typically covered by the same analysts. Ali and Hirshleifer (2020; AH) show that firms with shared analyst coverage exhibit an exceptionally strong lead-lag effect in returns. After controlling for shared analyst coverage, AH find the other momentum spillover effects become insignificant, leading them to conclude that "momentum spillover effects are a unified phenomenon captured by shared analyst coverage (p.649)". We are interested in understanding whether AH's claim about shared analyst coverage applies to firms that are in the same complementarity network but have no direct industry or customer-supplier linkages.

A second reason for examining the momentum spillover effect among complementors is the subtle nature of this economic linkage. The prevailing explanation for these lead-lag return patterns is that investors have limited attention and do not fully appreciate the price implications of the fundamental

[3] Studies that report a momentum spillover effect among economically-linked firms have examined many kinds of linkages: firms in the same industry (Moskowitz and Grinblatt, 1999), text-based industry peers (Hoberg and Phillips, 2018), firms that share the same geographic location (Parsons, Sabbatucci, and Titman, 2020), customer-supplier relationships (Cohen and Frazzini, 2008; Menzly and Ozbas, 2010), firms with similar technological expertise (Lee et al., 2019), single- and multi-segment firms operating in the same industries (Cohen and Lou, 2012), U.S. multinationals with different foreign operations (Huang, 2015), and shared analyst coverage (Ali and Hirshleifer, 2020).

connection between linked firms.[4] Prior studies show that the delayed price reaction is stronger for focal firms with less media attention and analyst coverage (e.g., Lee et al., 2019) and for past return patterns that are less likely to attract investor attention (Huang et al., 2022). By these metrics, the complementor relationship may be one of the strongest, yet least appreciated, economic linkages between publicly traded firms. Complementors are not from the same industry and their relationships are not as visible or salient as customer-supplier links, industry links, or geographic links. These firms are typically not covered by focal firm analysts and this economic linkage is not readily discernible from the focal company's financial reports. To the extent that limited investor attention is an important driver of momentum spillover effects, we predict a significant lead-lag return pattern among complementor firms.

We measure the degree of production complementarity between firms using the industry-level Input-Output (IO) table from the Bureau of Economic Analysis (BEA) and each firm's reported segment information.[5] Specifically, for each firm i and time period t, we construct an "output flow" vector $OF_{it} = (O_{it1}, O_{it2}, \dots, O_{itn}, \dots, O_{itN})$, where each element O_{itn} describes the proportion of firm i sales used by industry n. We then define the production complementarity score between any two firms i and j as the cosine similarity of their output flow vectors, i.e., $COMPL_{ijt} = \frac{(OF_{it}OF_{jt}^{'})}{(OF_{it}OF_{it}^{'})^{1/2}(OF_{jt}OF_{jt}^{'})^{1/2}}$. Similar measures have been used to estimate the pairwise distance between firms in other contexts, but our application of this procedure to estimate production complementarity proximity between firms is,

[4] For example, Cohen and Frazzini (2008) argue that the customer-supplier return predictability is due to investors' ignorance of customer-supplier links. Similarly, Moskowitz and Grinblatt (1999) and Hou (2007) suggest that investors tend to overlook common industry shocks, and Huang (2015) posits a lack of appreciation for information that originates from foreign sources. In each case, the sluggish price adjustment is attributed to investors' failure to understand or be fully attentive to, the nature of the underlying economic linkage.

[5] We construct *COMPL* by combining industry-level exposure data (from BEA) and firm-level data on sales to different industries (from the Compustat Historical Industry Segment database). As a result, the quality of the firm-level partitions is constrained by the granularity of the disclosed segment information. For multi-segment firms (firms that operate in multiple industries), we weigh each of the industry-level exposures by the fraction of the firm-sales that comes from a given industry. For single-segment firms, the firm-level output flows are assumed to be the same as those of its industry. Section 3 explains *COMPL* construction in more detail.

to our knowledge, novel to the literature.[6] To reduce noise from the inclusion of peer firms with relatively weakly correlated outputs, we further impose a minimum threshold requirement for the complementarity score. Specifically, we report results for *Strong* complementors (the top 2% of complementor pairs in the network, as ranked by *COMPL*), *Medium* complementors (next 2% as ranked by *COMPL*) and *Weak* complementors (the third 2% as ranked by *COMPL*).

Our results show that complementors' lagged returns have significant predictive power for focal firm returns. Specifically, a portfolio that goes long in the focal firms whose complementors (defined as the top 2% *COMPL* related firms) performed best in the prior month and goes short in the focal firms whose complementors performed worst in the prior month, yields an equal-weighted return of 130 basis points (t = 6.01) per month. The analogous value-weighted portfolio yields hedged returns of 92 basis points (t = 3.97) per month. Controlling for common risk factors has little effect. For example, the 6-factor alpha is 122 basis points (t = 5.95) for the equal-weighted strategy, and 68 basis points (t = 3.04) for the value-weighted strategy.[7] The economic magnitude of these returns is striking, given that the lead firms are in different industries from the lag firms. We refer to this return predictability effect as "complementor momentum."

We find that the magnitude of the complementor momentum effect is a function of *COMPL*: as complementarity distance increases, the predictive power of *COMPLRET* for focal firm returns declines. For example, while the 3-factor alpha for the *Strong* complementor group is 1.34% per month, the corresponding alphas for the *Medium* and *Weak* complementors are 0.58% (t = 2.88) and 0.50% (t =

[6] The original cosine similarity measure developed by Jaffe (1986) has been used to estimate the distance between firms in terms of technological expertise (Bloom, Schankerman, and Van Reenen, 2013; Lee et al., 2019), as well as the textual similarity of their business descriptions (Hoberg and Phillips, 2016) and financial statements (Brown, Ma, and Tucker, 2023). Brown and Tucker (2011) apply a similar technique to measure year-over-year changes in each firm's management discussion analysis (MD&A) disclosure. Other studies also used BEA data to examine economic linkages between segments of a given firm (e.g., Lemelin, 1982; Fan and Lang, 2000). Our *COMPL* variable differs from variables in these prior studies in that it is constructed to capture the *output complementarity distance* between firms from different industries.

[7] The 6-factor risk model we use adds a momentum factor (Carhart, 1997) to the 5-factor model in Fama and French (2015).

2.74), respectively. While both are still significantly positive, the predictive powers of the *Medium* and *Weak* complementors are reliably less than the predictive power of the *Strong* complementors.[8]

We conduct a battery of tests to ensure we have not rediscovered a previously documented network effect. As noted earlier, we exclude firms from the same industry in constructing complementor portfolios. To further ensure this effect is not driven by industry momentum, we incorporate past industry returns in cross-sectional regressions. In addition, we also explicitly control for lagged supplier and customer returns (Cohen and Frazzini, 2008; Menzly and Ozbas, 2010), pseudo-conglomerate returns (Cohen and Lou, 2012), and technology-peer returns (Lee et al., 2019). We find our main results remain robust in all these tests, both statistically and economically.[9]

Ali and Hirshleifer (2020; hereafter AH) argue that analyst co-coverage subsumes other proxies for fundamental linkage across firms. To better understand how complementor momentum is related to their finding, we perform two standard asset pricing tests. First, we run a time-series spanning test that adds AH's co-coverage factor to the five Fama and French (2015) factors and the Carhart (1997) momentum factor. We find that the magnitude of the monthly alphas from the complementor strategy remains both economically and statistically significant. Second, we run a series of cross-sectional Fama-Macbeth regressions, with the AH momentum variable included as a regressor. Again, we find that the complementor factor continues to predict focal firm returns.

To further shed light on the role of analysts in the price discovery process, we subdivide complementor firms into two groups: one that shares at least one common analyst with the focal firm,

[8] Summarizing the theory behind inter-industry complementarity, Shea (2002) asserts that "complementarities do not merely imply that A should comove with B; they imply that the amount of co-movement between A and B should depend on the degree of linkage between A and B." In support of this assertion, Conley and Dupor (2003) show that cross-sector productivity covariance is higher for sectors with higher production complementarity.

[9] Menzly and Ozbas (2010; hereafter MO) warrants additional attention as they also use BEA data and report a lead-lag return relationship. In the context of their study, the BEA data is used to identify customer-supplier connections, not complementor relationships. To be sure that we did not rediscover the common customer effect from MO, we performed a 5x5 portfolio double-sort, on complementor returns and lagged customer returns (computed using the same methodology as MO). Our results, reported in Internet Appendix Table IA10, show that in each of the five quintiles of lagged customer returns, the long-short hedged *COMPL* portfolio delivers positive and significant returns (with t-stats from 4.8 to 11.2). These findings further confirm the complementor effect is distinct from the customer-supplier effect reported by MO.

and another that has no shared coverage. We find that when complementors come exclusively from the second group (i.e., when they have no co-coverage with the focal firm), the complementor strategy still predicts returns (monthly alpha =1.17; t =5.99), again indicating this is not a rediscovery of the AH effect. The predictive power of this non co-coverage group is significant in months t, $t+1$, and $t+2$. Interestingly, the co-coverage group (i.e., the complementors with some co-coverage) exhibits an even higher correlation with focal firm returns in months t and $t+1$, but has no ability to predict returns beyond month $t+1$. Overall, these findings suggest the existence of shared analyst coverage helps to facilitate a faster integration of news from complementors into focal firm returns.

We also conduct a battery of cross-sectional tests to shed light on the underlying reasons for the gradual diffusion of value-relevant information along the production complementarity network. First, we show the lead-lag effect is stronger for focal firms with higher "degree centrality" in the network (i.e., they are linked to more complementors). Second, we show return predictability is stronger for focal firms that are more likely to be overlooked by investors (i.e., smaller firms, firms with lower analyst coverage, or firms with lower institutional ownership). Third, we document a stronger effect for focal firms that are associated with higher arbitrage costs (i.e., higher idiosyncratic return volatility). Together, our findings are broadly consistent with a sluggish price response process that is more pronounced when: (a) the complementary linkage is stronger; (b) the focal firm is more central in the network; (c) the focal firm receives less attention; and (d) the focal firm is more difficult to arbitrage.

As a final test, we provide direct evidence of information transmission between complementor firms using a patent announcement setting. Every Tuesday, the U.S. Patent Office publishes newly granted patents and Kogan et al. (2017) find substantial stock trading around the day when a firm's patent issuance is announced. For each focal firm patent announcement date, we calculate the cumulative abnormal return (*Patent CAR*) around a two-day window. We then examine the extent of news transmission by regressing peer firms' average monthly return on the focal firm's average *Patent*

CAR in a month. Our results show a strongly positive relation between focal firm short-window returns due to patent announcements and same-month returns among its complementors (*COMPLRET*). Grouping complementors by their *COMPL* score (*Strong, Medium, Weak*), we find a monotonically decreasing relation in their response to *Patent CAR*. Moreover, we find that *Patent CAR* reliably predicts the next-month returns of the complementors in the *Strong COMPL* groups, but has no predictive power for the returns of the *Medium* and *Weak* groups. This additional test is novel to the momentum spillover literature and provides direct evidence that: (a) economic shocks are being transmitted along complementor networks, and (b) the economic impact of a firm-level shock is not fully incorporated into complementor prices instantaneously.

The remainder of the paper is organized as follows. Section 2 lays out the background for the setting we examine in the paper. Section 3 describes the data and variables. Section 4 presents our main results as well as robustness tests. Section 5 explores the underlying mechanism behind our results and rules out risk-based explanations. Section 6 concludes.

2. Background

Our paper builds on and contributes to several strands of existing literature. First, we add to a growing body of work on the implications of production complementarity among firms or sectors, and the broader literature that studies production networks. Interest in production networks, especially the complementarity construct, has been growing in the economics literature. Macroeconomists, in particular, have adopted complementarity concepts to help explain the granular origin of aggregate shocks (Acemoglu et al., 2012; Acemoglu et al., 2017; Conley and Dupor, 2003; Jones, 2011; Baqaee and Farhi, 2019; Elliott and Golub, 2022). The pioneering work of Jovanovic (1987) shows that sufficiently strong forms of strategic complementarity among agents are required if one wants to obtain aggregate shocks from micro shocks. Later works using sector-level aggregates provide empirical support for Jovanovic (1987)'s theoretical argument. Notable studies such as Shea (2002), Conley and

Dupor (2003), and Atalay (2017) confirm: (a) the existence of a strong co-movement in the outputs of sectors that have overlapping customer sectors, and (b) production complementarity plays an important role in the propagation of individual sectoral shocks across the aggregate economy.

Durlauf (1993) studies the implications of production complementarity in macroeconomic growth models by analyzing the evolution of a countable set of industries over time. In his model, technological complementarities create intertemporal linkages between the production functions of each sector. An interesting implication of this model is that the growth of leading sectors can cause a shift to a high aggregate production equilibrium for the economy as a whole. Jones (2011) further develops the growth implications of production complementarity in a theory of "weak links": just as a chain is only as strong as its weakest link, problems along a production chain can sharply reduce output across the entire complementarity network. In his model, these forces amplify distortions to the allocation of resources and contribute to large income differences across countries.

Two recent microeconomic studies also provide supporting evidence on the role of production complementarity in transmitting economic shocks. Boehm et al. (2019) utilize the exogenous disruption of production in Japan caused by the March 2011 Tohoku earthquake and tsunami as a natural experiment. They find that as imports from Japan for intermediate inputs to the Japanese affiliates in the US decreased sharply, non-Japanese imported complementary inputs also fell nearly proportionately, demonstrating that the shock in Japan has quickly propagated to other non-Japanese firms through production complementarity. Barrot and Sauvagnat (2016) provide similar evidence by demonstrating that natural disasters in the US hitting certain suppliers have large spillover effects on other suppliers to the same firm that were otherwise untouched by the disasters.

Our paper provides highly granular supporting evidence for these theories by documenting a strong co-movement in the operating, investment, and financing activities of complementor firms. Our evidence shows that news shocks propagate along production complementarity networks across firms in different industries, leading to a positive correlation in the quarterly earnings forecast revisions and monthly stock returns of complementor firms. These return correlations are stronger for firms that are closer in complementarity proximity, further validating our *COMPL* variable as a meaningful measure of economic distance between seemingly unrelated firms.

Our paper also contributes to a large body of literature that examines investors' inefficient belief updating in the context of new information. Tversky and Kahneman (1974) and Daniel, Hirshleifer, and Subrahmanyam (1998), among others, suggest that investors may overweigh their own prior beliefs and underweight observable public signals. Thus, investors may have lagged responses to the information contained in value-relevant public price signals. Models featuring limited attention investors (e.g., Merton, 1987; Hong and Stein, 1999; Hirshleifer and Teoh, 2003; and Peng and Xiong, 2006) predict that delayed information recognition due to investors' limited attention can give rise to return predictability patterns that are difficult to explain with traditional asset pricing models. These theoretical works have inspired a growing set of empirical studies.[10] Particularly noteworthy are recent studies that document a lead-lag return relation between firms that have close economic affinities of varying forms.[11]

Our paper can be framed in terms of this literature, and we contribute to it by showing that investors under-react to information from production complementors, an economic linkage with deep theoretical underpinnings. We further provide evidence that the main driver of this effect is a form of investor inattention or sluggish adjustment to value-relevant information along the complementarity network. The effect is stronger for firms that receive less investor attention and are more costly to arbitrage. Shared analyst coverage is relatively rare among our complementor firms (which are from different

[10] Exemplary studies include Barber and Odean (2008); Dellavigna and Pollet (2009); Hong, Torous, and Valkanov (2007); Hou (2007); Huberman and Regev (2001); Menzly and Ozbas (2010).

[11] See, for example, Cohen and Frazzini (2008); Cohen and Lou (2012); Hou, van Dijk, and Zhang (2012); Aobdia, Caskey, and Ozel (2014); Li, Richardson, and Tuna (2014); Li (2015); Huang (2015); Lee, Ma, and Wang (2015); Cao, Chordia, and Lin (2016); Hoberg and Phillips (2018); Lee, Sun, Wang, and Zhang (2019); Parsons, Sabbatucci, and Titman (2020); Ali and Hirshleifer (2020).

industries by construction), but where it exists, common coverage improves the price adjustment process, leading to shorter momentum spillover effects. This last finding suggests that common analyst coverage plays two, potentially offsetting, roles in the transmission of information between firms: (1) it helps to identify more subtle forms of economic linkage between two firms (as per Ali and Hirshleifer, 2020), and (2) it helps to facilitate the price discovery of new information between firms, thus reducing the momentum spillover effect.

3. Data and Variables

We use a series of Benchmark Input-Output Surveys of the Bureau of Economic Analysis to identify product complementary relationships (see Fan and Lang, 2000; Aobdia, 2014). BEA Surveys provide a detailed picture of the interdependent structure of the U.S. economy by assigning gross output to industry accounts and by reporting the amount of inter-industry flows of goods and services in the Use Table. The industry linkages are reported at both the sector level (around 70 IO industries) and the detail level (around 400 IO Industries, with the exact number varying slightly across years). We rely on the detail level data to identify a firm's industry membership. BEA Surveys are published roughly once every five years to coincide with the Economic Census conducted by the U.S. Census Bureau. We draw on nine different surveys (1967, 1972, 1977, 1982, 1987, 1992, 1997, 2002, and 2007) on a rolling basis to measure complementary relations. Here, the "year" label indicates the first year for each survey. For example, the "2007 version" of BEA IO table covers data from 2007 to 2012 and was not publicly available until December 2013.

For the first part of our analysis, when testing for contemporaneous co-movement in firms' underlying fundamentals and stock returns, we use data from a given survey until a new snapshot is provided by the following survey. That is, we use data from the 1977 Survey between 1977 and 1981, the 1982 Survey between 1982 and 1986, and so on. For the second part of our analysis, when investigating lead-lag return patterns, we delay the use of any data from a given survey until the survey is publicly released – i.e., 1974, 1979, 1984, 1991, 1994, 1997, 2002, 2007, and 2013. For example, the "2007 version" of the BEA IO table covered data from 2007 to 2012 and was released in 2013. To avoid peek-ahead bias, we use the "2007 version" for 2014 and forward.

We begin by computing an *industry-level* complementarity measure. From the IO table, we extract a measure of the degree to which two industries' outputs are going to a common clientele. Specifically, we use O_{akt} to denote the proportion of industry *a*'s output that is supplying industry *k* at time *t*. There are around 400 different industries at the most granular level of the IO table, and we construct a vector of the output flow for each industry *a* at time *t* as: $OI_{at} = \left(O_{a1t,} \, O_{a2t,} \ldots, O_{aNt}\right)$. The level of overlap in the output flow between any two industries, *a* and *b,* can then be calculated as the cosine similarity of their output flow vectors,

$$IND\_COMPL_{abt} = \frac{(OI_{at}OI_{bt}^{'})}{(OI_{at}OI_{at}^{'})^{1/2}(OI_{bt}OI_{bt}^{'})^{1/2}} \tag{1}$$

To extend this analysis from the industry level to the firm level, we utilize the Compustat Historical Industry Segment database.[12] For a single-segment firm *i*, the firm level output flow OF_{it} is the same as the industry-level output flow vector OI_{nt}, where *n* is its industry membership. For a multi-segment firm, we compute its output flow vector as a weighted average of its segment industry's output flow vectors, using its segment sales as weight. That is, for a multi-segment firm *i*, $OF_{it} = \sum_{n=1}^{N} sales\_share_{int} * OI_{nt}$, where $sales\_share_{int}$ is firm *i*'s segment sales of industry *n* out of total firm-level sales and OI_{nt} is the output flow vector of industry *n*.

For any two firms *i* and *j* at time *t*, we then calculate a pairwise production complementarity score as the cosine similarity of their output flow vectors,

[12] Starting from 1976, all firms are required by Statement of Financial Accounting Standards (SFAS) No.14 (Financial reporting for segments of a business enterprise, 1976) and No.131 (Reporting desegregated information about a business enterprise, 1998) to report relevant financial information of any industry segment that comprises more than 10% of a firm's total consolidated annual sales. We exclude firms that do not have data available in the Compustat Segment database. On average 4.02% of Compustat firms do not have data in the Compustat Segment Database. The proportion of missing firms in each industry range from a high of 15.3% (Coal Mining) to a low of 0% (Legal Service, Membership Organizations, and Miscellaneous Services).

$$COMPL_{ijt} = \frac{(OF_{it}OF_{jt}^{'})}{(OF_{it}OF_{it}^{'})^{1/2}(OF_{jt}OF_{jt}^{'})^{1/2}} \tag{2}$$

where OF_{it} is a vector of firm *i*'s output flow as defined above. Note that this production complementarity measure ranges between zero and one, depending on the degree of overlap in downstream industry space, and is symmetric in firm ordering (i.e., $COMPL_{ijt} = COMPL_{jit}$).

Our design of *COMPL* reflects our interest in evaluating production complementarity as a conduit for inter-industry news transmission. Two prior studies featured variables that are related to *COMPL*. First, Lemelin (1982) used the correlation coefficient across the industry input structure between any two industries to measure industry-level relatedness. Second, Fan and Lang (2000) proposed two industry-level relatedness measures which they call "vertical relatedness" and "(industry) complementarity." Compared to the variables in these studies, *COMPL* is unique in that it alone measures the output complementarity distance between pairs of firms. We further sharpen the economic interpretation of this variable by removing from the set of potential complementors any same-industry firm and any firm with a direct customer-supplier relationship with the focal firm.[13]

The construction of production complementarity may be illustrated using a numerical example. For simplicity, assume there are in total three BEA IO industries (IO_A, IO_B, IO_C) and two firms (F_1, F_2). Most of F_1's revenue (80%) belongs to industry IO_A, with the rest (20%) coming from IO_B. All of F_2's revenue belongs to IO_c. At the industry level, assume that 60% of IO_A's outputs are consumed by itself (i.e., by the same industry), with the rest being equally consumed by IO_B and IO_C (20% each). The distribution of IO_A's outputs can be represented using a vector: (0.6, 0.2, 0.2). Similarly, assume the output flow vectors of IO_B and IO_C are (0.1, 0.5, 0.4) and (0.1, 0.2, 0.7), respectively. Then the conglomerate F_1's output flow vector is a combination of IO_A and IO_B's output vectors, using its share

[13] The year-by-year pairwise complementarity scores we developed are available for download at: *https://sites.google.com/view/complementarity-link?usp=sharing.*

of sales as weight: $OF_1 = (0.5, 0.26, 0.24)$. For the standalone firm F_2, its output flow vector is the same as IO_C: $OF_2 = (0.1, 0.2, 0.7)$. Following the formula above, the production complementarity between F_1 and F_2 is $COMPL_{12} = 0.60$.

In Figure 1, we provide a case study featuring two firms: Cummins Inc. (NYSE: CMI; SIC 3510) and Magna International (NYSE: MGA; SIC 3714). Although these firms are in different industries, their pairwise production complementarity score is high ($COMPL_{ijt} = 0.85$). On reflection, it is perhaps not surprising, as Magna produces key components for the transmission and driveshaft of many vehicles that feature Cummins' engines.

To provide further intuition on the nature of production complementarity linkages across a broader set of firms and industries, Appendix B presents information on ten focal firms, along with four or five of their major complementors.[14] We provide industry codes and brief business descriptions for each focal firm, and offer a suggested rationale for each pairwise complementarity relation. The key takeaway from this table is that well-known firms from different industries can be closely linked through complementarity networks, even though such linkages may not come readily to mind when identifying peers through other means.

Having developed a continuous production complementarity measure for any pair of firms each year, we then eliminate peers from the same 4-digit SIC industry group as the focal firm.[15] We also eliminate peer firms that are either a material customer or material supplier of the focal firm, based on the Compustat Segment database (Cohen and Frazzini, 2008). For any given focal firm, the remaining

[14] The 10 large focal firms were chosen to represent a diverse range of industries, including IT, healthcare, automotive, semiconductor, mining, steel, and others. For each focal firm, we report 4 or 5 major complementors. We chose these complementors based on the following criteria: (a) it must rank among the top 2% of complementary peers by *COMPL* score, (b) it is a large cap (relatively visible) firm, and (c) it comes from a different industry from the other selected complementors. This last criterion helps to ensure the table reflects the broad range of industries represented in each focal firm's strong (top 2%) complementors.

[15] In Internet Appendix Table IA2 and IA3, we further exclude: (a) peer firms that belong to the same Fama-French 17 or 48 industry or sector, or (b) peer firms in the same textual-based industry (Hoberg and Phillips, 2016). Our results are robust to these perturbations.

peers with a non-zero production complementarity score can still be quite large. In our baseline analysis, to focus on firms with a sufficiently high level of complementarity, we keep only those in the 99th and 98th percentile (the top 2%) as ranked by their *COMPL* score (we call these *Strong Complementors*). In more detailed analyses, we also report results for firms in the 97th and 96th percentile (*Medium Complementors*) and firms in the 95th and 94th percentile (*Weak Complementors).*[16] Finally, to exclude sparely connected firms, we require a focal firm to have at least 3 complementor peers. Varying this minimum cutoff from 1 to 5 firms makes little difference to our results.

We define complementor return (*COMPLRET*) as the equal-weighted average monthly return of the portfolio of complementary firms in our network. We also use the same equal-weighting scheme to compute the average fundamental variables for our complementor firms. We report the equal-weighting results for parsimony, because the industry peer portfolios are also equal-weighted. All of our findings are robust to the use other weighting schemes, such as: (a) the *COMPL* score between focal firm and its complementors, (b) total assets, (c) the log of total assets, (d) market value, and (e) the log of market value.

Our main sample consists of firms at the intersection of the Compustat Historical Industry Segments and CRSP. We focus the analysis on common stocks (CRSP share codes 10 and 11) and exclude financial firms (firms with a one-digit SIC code of six). To ensure the relevant financial information is publicly available, we impose at least a six-month gap between the fiscal-year end month and the portfolio formation date. To reduce the impact of micro-cap stocks, we further exclude from our sample those stocks priced below one dollar a share at the beginning of the holding period.[17] Finally,

[16] Our choice of a 2% cutoff corresponds to prior studies of information transmission between peer firms, such as Hoberg and Phillips (2016, 2018). Note that a top-2% cutoff produces a network granularity comparable to that of the 3-digit SIC code (i.e., it results in each focal firm having roughly 80 complementor peers). We also compare results for *Strong*, *Medium*, and *Weak* complementors, to help gauge how quickly network effects diminish beyond the top 2% of ranked firms.
[17] In Internet Appendix Table IA1, we further restrict our tests to more liquid focal firms. First, we limit our focal firms to stocks that are priced above five dollars per share (rather than one dollar per share). Second, we narrowly examine the results for the top 500 focal firms in terms of market capitalization at the beginning of the holding period. The Internet Appendix shows that our main results are robust to these perturbations.

we also require firms to have non-missing market equity from CRSP, and non-negative book equity at the end of the previous fiscal year from Compustat. The final sample consists of 1,002, 682 firm-month observations spanning July 1978 to June 2018.

Table 1 presents descriptive statistics for our sample firms. On average, we have 2,799 focal firms per year, ranging from a low of 1,185 firms in 1977 to a high of 4,919 firms in 1998. These focal firms have an average of 103 complementors each. The pairwise product complementarity score (*COMPL*) has an average value of 0.20 with a standard deviation of 0.25, indicating that the focal firms in our sample generally share some measure of production complementarity with the firms that we have identified as their complementors.

4. Empirical Results

4.1 Fundamentals co-movement

We begin by examining the degree of co-movement in the fundamentals of production complementor firms. We examine a set of firm-level fundamentals: economic performance measured by *ROA* (return on assets) and sales growth, financial policy in terms of market leverage and external financing, and real activities in terms of capital expenditures and innovation activities. More specifically, we estimate a firm-level panel regression in the form of:

$$Fundamental_{it} = \beta_1 Fundamental_{it}^{Complementors} + \beta_2 Fundamental_{it}^{Industry} + \gamma_i + \delta_t + \varepsilon_{it} \quad (3)$$

where $Fundamental_{it}$ is the fundamental variable for focal firm i. The average fundamental of complementors, $Fundamental_{it}^{Complementors}$, is calculated as the equal-weighted average of complementors' corresponding fundamental variable (analogous to our approach in calculating complementor returns). We also control for industry level average of the fundamental variable $Fundamental_{it}^{Industry}$, calculated as the simple arithmetic average of firms in the same industry. We standardized $Fundamental_{it}^{Complementors}$

and $Fundamental_{it}^{Industry}$ to have a mean of zero and a standard deviation of one, so that their coefficients can be directly compared. Firm and year fixed effects are included, and standard errors are clustered by firm for robustness.

We examine fundamental co-movement among complementors for three types of business activities: (a) operating performance, (b) financing activities, and (c) investment and innovation activities. We posit that annual changes in the fundamental activities of the complementor firms will be positively correlated with changes in the focal firms, even after controlling for the focal firm's own industry peers. For operating performance, we measure each firm's return-on-asset (*ROA*) and growth in sales (*Sales Growth*). For financing activities, we measure each firm's market leverage (*Leverage*) and net new financing ratio (*External Financing*). For investment and innovation activities, we measure each firm's capital expenditure (*CapEx*), research and development expense (*R&D*), and the log of one plus the citation-weighted-patent numbers (*Citation-weighted-patents*). See Appendix A for variable construction details.

Table 2 Panel A presents the results of these tests. Not surprisingly, focal firm fundamentals co-move strongly with their same industry peers (i.e., 4-digit SIC). More importantly, focal firms also display a strong contemporaneous co-movement with their complementors from other industries. We find a statistically significant positive relation on the *Strong Complementors* variable (peer firms in the top 2% as ranked by *COMPL*) for all seven fundamental activities. In terms of their economic magnitude, the coefficients on the complementor variable are roughly 1/4 to 3/4 the size of the corresponding coefficients on the industry peers, which seems reasonable considering complementors are in different industries from the focal firms. Note that the R^2s are quite high: on average, these models explain more than half of the annual change in focal firm *ROA*, *Leverage*, *CapEx*, *R&D*, and *Citation-weighted-patents*.

As a placebo test, we also created a *Random Complementor* portfolio by randomly selecting 2% of the firms from our complementarity network sample in a given year. As reported in Table 2 Panel B, we find the business fundamentals of the *Random Complementors* are not significantly correlated with those of the focal firms. The last row of Panel B reports a formal test of differences in the estimated coefficients. These results show *Strong Complementors* co-move more strongly with focal firms than *Random Complementors.* Across the seven fundamental activity measures, the difference between *Strong vs. Random* peers is most pronounced for *Sales Growth* (t = 11.72) and *CapEx* (t = 10.86), and least pronounced for *External Financing* (t = 2.84).

We further investigate how complementarity intensity (i.e., *COMPL*) affects the degree of co-movement among complementor firms. Summarizing the theory behind interindustry complementarity, Shea (2002) asserts that "complementarities do not merely imply that A should comove with B; they imply that the amount of co-movement between A and B should depend on the degree of linkage between A and B." In support of this assertion, Conley and Dupor (2003) show that cross-sector productivity covariance is higher for sectors with higher production complementarity. Analogously, if our results are driven by economic proximity between firms, firms closer in the network should exhibit greater co-movement in fundamentals.

To test this conjecture, we construct three complementor peer groups based on their *COMPL* scores. In addition to using peer firms ranked in the top 2% by their production complementarity score (this is the group we call *Strong Complementors* in Panel A), we also consider a group of *Medium Complementors* (firms in the 97 and 96 percentiles as ranked by *COMPL*) and *Weak Complementors* (firms in the 95 and 94 percentiles as ranked by *COMPL*). Table 2 Panel C reports the co-movement in company fundamentals when firms from all three complementor groups are included in the same regression. Looking across the first row, *Strong Complementors* exhibit positive co-movement with the focal firm across all seven fundamental metrics. Looking across the second row, all seven coefficients for the *Medium Complementors* are again positive, although two are insignificant. Looking at the third row, six of the seven coefficients for the *Weak Complementors* are positive, but only three are statistically significant. These findings suggest that the co-movement in company fundamentals dissipates as *COMPL* distance increases.

The magnitudes of the estimated coefficients convey the same story. Coefficients for the *Strong Complementor* group (in row 1) are generally two to four times larger than the coefficients for the other two groups (rows 2 and 3). At the bottom of Panel C, we report a test of the differences in coefficients between *Strong Complementors* and the other two groups. These results show *Strong* complementors have reliably more positive coefficients than either the *Medium* or the *Weak* group. However, the co-movement results become weaker as we move away from the top 2% *COMPL* firms. We find that *Medium Complementors* generally, but not always, have more positive coefficients than the *Weak Complementors*. Taken together, these results show that (a) the correlation in company fundamentals decreases as the complementarity distance between firms increases, and (b) the usefulness of *COMPL* as a measure of economic distance fades quickly beyond the top 2 to 6% of ranked firms.[18]

In sum, our firm-level evidence confirms and extends the evidence from macroeconomics on the role of complementarity networks. Using detailed capital market data, we show granular economic shocks can propagate across the economy along such networks. We also establish *COMPL* as a credible measure of economic distance between firms from different industries. These results set the stage for a more detailed analysis of the speed of information transmission along complementor networks, which we undertake in the next section.

[18] Our results are based on an equal weighting of peer firms. We chose equal weighting to ensure complementor firms are weighted the same way as the peer firms in the *Industry Peer Average* control variable. However, all our results, including the gradual fading of the correlation in company fundamentals beyond the top 2-4% of *COMPL* firms, show up clearly when we use other weighting schemes, such as weighting firms by: *COMPL*, total assets, log of total assets, market capitalization, and log of market capitalization. These results are available upon request.

4.2 Stock returns and production complementarity

We now focus on the stock market reaction to news shocks along production complementarity networks. To perform these analyses, we use higher frequency (quarterly and monthly) data. In Table 3, we examine the contemporaneous co-movement in monthly stock returns and quarterly analyst forecast revisions. In Tables 4 through 8 we study the pattern of lead-lag returns among complementor firms. Table 9 examines how stock market shocks originating from a patent grant to the focal firm propagate across the stock returns of complementors, industry peers, and technology peers.

4.2.1 Contemporaneous response in the stock market

Table 3 documents the co-movement in stock returns and earnings forecast revisions between focal firms and their peer firms. In Panel A, we report the results of monthly Fama-MacBeth return regressions where the standard errors are Newey-West adjusted for heteroskedasticity and autocorrelation. The dependent variable is either the focal firm's monthly return *RET* (columns 1-6), or the firm's excess return over its industry return *RET-INDRET* (columns 7-8). The independent variable of primary interest is the average complementors' return in the same period ($COMPLRET_t$). In columns 5 to 8, we add the concurrent industry average return (*INDRET*). Other control variables include firm size (*SIZE*), book-to-market ratio (*BM*), the focal firm's own lagged monthly return (RET_{t-1}), and medium-term price momentum (*MOM*). We find a significant and positive co-movement between the focal firm's stock return and its complementors' average return in the same month. In all eight specifications, the coefficient on *Strong COMPLRET* is positive and significant (*t*-statistic from 11.47 to 17.43). Furthermore, consistent with Table 2 results, the co-movement in monthly returns drops as complementarity distance increases. While the coefficient on the *Medium* and the *Weak* complementor returns are also positive, their magnitudes are generally only one-third to one-eighth that of the coefficients for *Strong Complementors* (column 6 or 8).

We also examine how analysts' quarterly earnings (*EPS*) forecast revisions are correlated among complementors. Having observed a positive co-movement in their annual *ROA* and sales growth, we expect their quarterly *EPS* revisions to also exhibit some co-movement. Table 3 Panel B shows that this is indeed the case. Overall, we find the quarterly *EPS* revisions of the focal firm are correlated with the analyst forecast revisions of its complementors, above and beyond the information contained in same-industry peers. We no longer observe any co-movement pattern when we use the *Medium* or *Weak Complementors*, again demonstrating that the degree of complementarity affects the degree of co-movement.

Taken together, Table 2 and 3 results offer a coherent set of evidence that focal firms and their complementors are affected by similar economic shocks. These shocks result in a highly significant level of co-movements in their fundamental performance metrics. We observe this co-movement at the annual, quarterly, and even monthly levels. In short, production complementors are highly economically linked firms that reside in different industries. In the next section, we examine whether these relatively subtle economic linkages result in lead-lag return patterns.

4.2.2 Lead-lag effect

Table 4 reports the performance of a complementor momentum strategy for the 1978-2018 period. Panel A provides the baseline portfolio return results. To construct this table, we sort all focal firms into deciles at the beginning of each month, based on the return of their complementors in the previous month. The decile portfolios are then rebalanced monthly to maintain either equal (EW) or value (VW) weights. The last two rows in the table report the average monthly returns to a long-short portfolio (L/S) that buys the firms in the top 10% as ranked by their complementor returns in the past month and sells short firms in the bottom 10%. Our results show that an equal-weighted hedge portfolio yields average monthly returns of 130 basis points (t = 6.01), or roughly 15.6% per year. The corresponding value-weighted hedged return is 92 basis points per month (t = 3.97), or about 11.2% per year. In the next five columns, we control for other known risk factors. The same L/S strategy delivers *CAPM* abnormal returns of 1.31% (0.97%) per month in equal- (value-) weighted portfolios. The Fama and French (1993) three-factor abnormal returns for this strategy are 1.34% (0.93%) per month in equal- (value-) weighted implementations. Augmenting this model by adding the stock's own price momentum (Carhart, 1997) has limited effects, as the four-factor alpha remains 1.16% (0.75%) per month in equal- (value-) weighted portfolios. Finally, we adjust returns using the Fama and French (2015) five-factor model (5-factor), and also conduct a test using the five-factor model plus the momentum factor (6-factor). We find the strategy continues to earn positive 5-factor and 6-factor monthly abnormal returns of 1.34% (0.79%) and 1.22% (0.68%), respectively, in equal- (value-) weighted portfolios. These results show high (low) complementor momentum stocks earn high (low) subsequent returns, even after controlling for common risk factors.

In Panel B of Table 4, we report the portfolio alphas as well as the factor loadings on each of the Fama-French five factors and the Carhart momentum factor (*MOM*). The L/S hedge portfolio has a significant positive loading on *MOM*. Evidently, this strategy works well when momentum firms outperform. It has no significant exposure to market beta (*MKT*), firm size (*SMB*), or book-to-market (*HML*), and its exposure to *RMW* and *CMA* seems to vary depending on whether the portfolio is equal- or value-weighted. Overall, the strategy earns significant monthly alphas even after controlling for all these exposures.

4.2.3 Ali and Hirshleifer (2020) common analyst linkage

Ali and Hirshleifer (2020) argue that common analyst coverage is a superior proxy for the economic linkage between firms and report a strong momentum spillover effect when focal firms are sorted on the recent returns of their co-covered peer firms. A key implication of their findings is that new information or common economic shocks are transmitted along networks of firms that share common analyst coverage. In this subsection, we conduct several analyses to better understand the interaction between the production complementarity linkage and the common analyst linkage.

In the first analysis, we exclude peer firms simultaneously covered by shared analysts in the construction of a production complementary network (among complementary peers, only 4.75% have co-coverage with the focal firm). This analysis ensures the complementor firms we use for the *COMPL* strategy exclude any common coverage firms from Ali and Hirshleifer (2020). Panel A of Table 5 shows that the portfolio alphas are only slightly weaker under this more stringent definition of complementors. Specifically, the average equal- (value-) weighted monthly hedge returns drop 2 (16) bps to 128 (76) bps. Across the factor models, all results remain statistically significant at the 1% level. Evidently, production complementary linkages provide predictive power beyond analyst co-coverage.

Second, we examine how the predictive power of *COMPL* varies as a function of whether the complementary peers are covered (or not covered) by a common analyst. To conduct this analysis, we first separate all complementary peer firms into two groups depending on whether each peer shares an analyst with the focal firm. We then construct complementor momentum signals for each of the two groups. At the end of each month, we separately rank and assign firms into decile portfolios based on the returns to a portfolio of their within-group complementors. We then hold this portfolio for up to 3 months and calculate the factor alpha from the time-series regression of portfolio returns in a five-factor model at the end of each month (from t to $t+3$).

The results are reported in Panel B of Table 5. The first column of Panel B (column label t) shows the focal firm's return has a strong contemporaneous correlation with both peer groups. Perhaps not surprisingly, the group of complementors that also share at least one common analyst displays a stronger contemporaneous correlation. This finding suggests that either (a) co-coverage by analysts is a sign of closer inter-firm linkages, or (b) co-coverage accelerates price discovery between pairs of complementor firms. The first-month lead-lag alpha (labeled $t+1$) is slightly larger for complementors that do not share common analysts (the N group), suggesting that the month *t+1* returns to a *COMPL* strategy are stronger when the lead firm is not connected with the lag firm through analyst coverage. Specifically, we see that the complementor strategy for the group with no shared analysts (row N) returns a five-factor alpha of 1.29 (t = 6.45), and for the group with shared analysts (row O) returns a five-factor alpha of 1.17 (t = 4.58).

Even more interesting is the performance of the two strategies in months *t+2* and *t+3*. Starting from month *t+2*, the alphas of the O group become statistically insignificant from zero. In contrast, the monthly alpha to production complementary peers that are not covered by a common analyst (the N group) remains sizable (51 bps larger than the alpha from co-covered complementary peers) and significantly different from zero at the 5% level. We observe a similar, although diminished, pattern in month *t+3*. In the last column of Panel B, we calculate the percentage of price drift for each group, defined as the returns that are not realized in the contemporaneous month (t) as a percentage of the accumulated returns from t to *t+3*. We find that the price drift for complementarity peers not covered by a common analyst (the N group) is 34.03%, while the price drift for co-covered complementarity peers (the O group) is only 12.89%. In other words, the delayed price adjustment for a focal firm without co-covered complementors, as a percentage of total news, is more than twice as large when a focal firm shares at least one analyst with its complementors.

These findings have two implications for the momentum spillover literature. First, *COMPL* is a novel inter-firm linkage not spanned by prior momentum spillover variables, including analyst co-coverage. Second, we show that shared analyst coverage in fact speeds up the rate of information transmission along *COMPL* networks. Evidently, when investors or analysts do not pay enough attention to these linkages, information transmission occurs with a lag. However, the presence of at least one shared analyst increases the speed of news transmission and reduces the momentum effect.

In Table 5 Panel C, we conduct a series of spanning tests to further examine whether returns from a *COMPL* strategy can be fully explained by the common analyst momentum from Ali and Hirshleifer (2020). To construct this panel, we rank stocks into quintiles at the end of each month based on the lag returns of connected firms through common analyst coverage. 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:

$$0.5 * \left(RET^5_{small} + RET^5_{large}\right) - 0.5 * \left(RET^1_{small} + RET^1_{large}\right)$$

where $RET^5_{small(Large)}$ is the value-weighted average return of small (large) cap stocks in characteristic quintile q.

Panel C of Table 5 presents the results of time-series regressions of the returns of complementor momentum after adding the common analyst momentum factor as an additional explanatory variable in the five- and six-factor regressions. We find that controlling for common analyst momentum reduces the alpha of the *COMPL* strategy, but this strategy still produces sizable and statistically significant alphas of 71 to 75 basis points per month. These results show both the power of the common analyst momentum variable (Ali and Hirshleifer, 2020) and the incremental usefulness of *COMPL* in return prediction.

4.2.4 Predictability beyond one month

We also examine the long-run return pattern of the complementor momentum effect. If returns to the *COMPL* strategy reflect investor overreaction to the news from complementor firms, we should observe some return reversal over a longer holding period. Conversely, if the effect we document is primarily an underreaction to the news that affects focal firms' fundamental value, we should see little return reversal in the future. In Figure 2, we plot the cumulative return of the *COMPLRET* hedge portfolio in the 12 months after portfolio formation. Consistent with the latter hypothesis, we observe a modest upward drift through month 12 for an equal-weighted portfolio and month 11 for a value-weighted portfolio. The returns of equal- (value-) weighted portfolios accumulate to 455 (218) basis points in 12 months after the portfolio formation. Moreover, in unreported analyses, we find no return reversals in even longer periods. Overall, the evidence reveals a mechanism of delayed updating of focal firm prices to complementor information and not an overreaction phenomenon.

4.3 Cross-sectional analysis

4.3.1 Baseline Fama-Macbeth regression results

In this section, we use Fama-Macbeth regressions to test for the return predictability of complementors after controlling for a number of other variables nominated by the literature. To ensure the robustness of the results, we follow the suggestion of Hou, Xue, and Zhang (2020) and use both ordinary least squares (shown in Table 6 Panel A) and weighted least squares with the market equity as the weights (shown in Panel B) in the Fama and MacBeth (1973) cross-sectional regressions. Specifically, in Table 6, the dependent variable of columns 1 to 3 is the focal firm's raw return in month t (RET_t). The independent variable of interest is the average return of the focal firm's complementors in month $t\text{-}1$ ($COMPLRET_{t-1}$). To further control for industry momentum, we also include the industry return of the focal firm in month $t\text{-}1$ ($INDRET_{t-1}$) as an independent variable (Cohen and Lou, 2012; Moskowitz and Grinblatt, 1999). Other control variables include lagged size, book-to-market, lagged focal firm return RET_{t-1} (Jegadeesh and Titman, 1993) and medium-term price momentum *MOM* (Chan, Jegadeesh, and Lakonishok, 1996). All explanatory variables are based on the last non-missing available observation for each month t and are assigned to deciles ranging from zero to one. Cross-sectional regressions are run each calendar month, and the time-series standard errors are Newey-West (1987) adjusted for heteroskedasticity and autocorrelation.

Table 6 columns 1 to 3 in Panel A and B report the baseline results. Consistent with the time-series portfolio-based tests, $COMPLRET_{t-1}$ remains a strong predictor of next month's focal firm return in all three specifications. Controlling for standard variables (Panel A column 3) and using the equal-weighted OLS, the coefficient on $COMPLRET_{t-1}$ is 0.969 with a *t-statistic* of 6.37, indicating that the average monthly alpha spread of the focal firms in the top and bottom deciles is 96.9 basis points. Results are similar with weighted least squares in Panel B of Table 6, as the coefficient on $COMPLRET_{t-1}$ is 0.902 with a *t-statistic* of 6.37. The coefficients on other control variables are consistent with prior literature and omitted for brevity. In column 4 of both panels, we report results using the firm's industry-adjusted return (calculated as the difference between a focal firm's return and its contemporaneous industry return) as the dependent variable. Moskowitz and Grinblatt (1999) show industry momentum is a short-lived effect strongest in the month immediately after portfolio formation. By subtracting industry return from focal firm return, we purge any predictability from monthly industry-wide autocorrelation in returns. Column 4 results show that the magnitude of the coefficient for $COMPLRET_{t-1}$ is slightly smaller with industry-adjusted returns. However, the implied monthly alpha continues to be economically significant in both the FM-OLS (0.803; *t-statistic* of 6.46) and the FM-WLS (0.730; *t-statistic* of 6.66) specifications. Note also that the coefficient on lagged industry returns, $INDRET_{t-1}$, decreases in both significance and magnitude. Together, these results show the predictive power of $COMPLRET_{t-1}$ comes from delayed processing of firm-level news rather than from industry-wide return continuation (see Cohen and Lou (2012) for an expanded discussion of this argument).

4.3.2 Controlling for other economic links

Using Fama-Macbeth regressions, we further account for effects from other economic links that are well established in the literature. Columns 5-8 of Table 6 examines the incremental usefulness of complementor momentum after controlling for various other links. Specifically, we control for similar link-based momentum factors such as supplier and customer returns (Menzly and Ozbas, 2010; column 5), pseudo-conglomerate returns (Cohen and Lou, 2012; column 6), technology-linked returns (Lee, Sun, Wang, Zhang, 2019; column 7) and common analyst returns (Ali and Hirshleifer, 2020; column 8). In each case, we find the coefficient for $COMPLRET_{t-1}$ remains statistically significant and economically sizeable, indicating that the sluggish diffusion of information along complementarity networks is not subsumed by other well-documented inter-firm links in previous literature.

5. Underlying Mechanisms and Robustness Tests

In this section, we conduct several empirical analyses to better understand the underlying mechanisms driving our main finding. Overall, our results provide support for the delayed updating of focal firm prices to fundamental information transmitted through the production complementarity network. We further explore the cross-sectional sensitivity of our main results to various characteristics associated with: (a) the intensity of production complementarity, (b) the degree centrality of a firm in the complementarity network, (c) the extent to which investors might be attentive to information transmitted through production complementarity network, and (d) the costs that investors face if they attempt to arbitrage the mispricing. We also examine stock price reactions around earnings announcement to provide direct evidence that it is mispricing rather than risks that drives our results.

5.1 Intensity of production complementarity

In Table 7 Panel A, we conduct Fama-Macbeth regressions using Strong, Medium, and Weak return signals. Specifically, we regress the raw returns of the focal firm on the lagged returns of the *Strong*, *Medium,* and *Weak* complementors (see columns 1, 2, and 3, respectively). These tests show both the economic magnitude of the coefficients and their statistical significance decline as we move from *Strong* to *Weak* complementors. The coefficient on *Strong Complementor* is 1.221, with a *t-statistics* of 7.35, compared with the coefficient on *Weak Complementor* of 0.389. Note also that the returns from all three groups significantly predict the focal firm's returns at the 5% confidence level. In column 4, we run a pooled regression with *Strong*, *Medium*, and *Weak Complementor* returns simultaneously and find these results still hold. In Table 7, Panel B, we replicate our main tests in Table

4 and estimate the hedged portfolio returns based on *Medium Complementors* or *Weak Complementors*. The monthly average excess returns and 3-factor model adjusted abnormal returns exhibit a gradual decline but remain significant when we use the *Medium* or *Weak* complementor signal. The monthly hedged return of 48 basis points for the *Weak Complementor* group is roughly 37% of the returns from the baseline hedged portfolio using *Strong Complementors*. Overall, these results are consistent with our hypothesis that the lead-lag effect along the production complementary network is attributable to the co-movement in underlying fundamentals: when we observe a tighter relation in terms of the firms' economic fundamentals, we also observe a stronger lead-lag relation in return.

5.2 Degree centrality in the complementarity network

In this subsection, we examine how production network centrality affects complementor momentum. We measure production network centrality by the number of stocks that a particular stock is connected to in the complementary network (i.e., a stock's "degree centrality"). If a stock is connected to many other stocks in the network, information from the adjacent stocks would be incorporated more slowly into the focal firm's price. Intuitively, this effect arises because when a focal firm has a higher degree of centrality investors need to monitor or consider a larger set of related firms. Following this intuition, we expect the delayed price reaction to be more pronounced when the focal firm has a greater number of linked firms.[19]

[19] Ahern (2013) argues that industries in more central positions within an input-output network are riskier, because they have greater exposure to sectoral shocks that transmit from one industry to another. Consistent with this argument, his empirical findings show that centrally positioned industries earn higher average returns. Like Ahern (2013), we are interested in how the greater sectoral exposure of centrally position firms affect their stock prices. However, our focus differs from Ahern (2013) in that we are studying how network centrality affects the speed of price adjustment, not the average returns earned by these firms. In his study, network centrality leads to higher risk and thus higher average returns. In our study, network centrality leads to greater informational friction and thus slower price adjustment. The two findings are not incompatible. The increased exposure to sectoral shocks could potentially make these focal firms riskier. These cross-sectoral exposures can also make it more difficult for investors to keep track of all relevant shocks from related peer firms, leading to a stronger complementor momentum effect. Our results show a slower price adjustment process among centrally positioned firms, but we do not speak to their average returns.

The results in column 1 of Table 8 show that complementor momentum is indeed stronger for focal firms with a higher number of complementors. In this table, *HighPeerNum* equals one if the number of complementary peers of a focal firm is above the sample median in a given year. The estimated coefficient on the key interaction variable ($COMPLRET_{t-1}$* *HighPeerNum*) shows that highly networked focal firms (those firms with a high degree of centrality) exhibit a complementor momentum effect that is roughly twice that of other firms.

5.3 Investors' limited attention

If complementor momentum is due to investor inattention, we should observe a stronger effect for focal firms that are subject to less investor monitoring. We adopt three measures of investor attention commonly used in prior literature: firm size, analyst coverage, and institutional ownership (e.g., Cohen and Frazzini, 2008; Hirshleifer, Hsu, and Li, 2013; Hou, 2007; Jiang, Qian, and Yao, 2016; Menzly and Ozbas, 2010). Larger firms, firms with higher analyst coverage, and firms with more institutional ownership are generally regarded as receiving more attention from investors, and if investor under-reaction drives our result, these firms should exhibit a less sluggish price reaction to the information contained in complementors' returns.

To test this prediction, we construct an indicator variable (*Larger_Size*) that equals one if a focal firm's market capitalization is above the third quartile of the sample in a given month, and zero otherwise. Similarly, we capture the analyst coverage effect using an indicator variable (*More_Analyst*) that equals one if the number of analysts following a focal firm at the end of the previous month is above the third quartile in the sample, and zero otherwise. We also construct an indicator variable (*Higher_InstitOwn*) that equals one if the institutional ownership at the end of the previous fiscal year is above the sample median. Results of the tests are reported in columns 2-4 of Table 8. Consistent with the limited attention explanation, the coefficient estimates on these three interaction terms are all negative and statistically significant, indicating that the complementor momentum effect is more muted among firms with higher investor attention. These results lend further support to our hypothesis that the lead-lag effect is driven by investors' inattention to fundamental news transmitted along production complementary networks.

5.4 Cost of arbitrage

Investors may be less able or willing to fully incorporate new information into prices when the focal firm is associated with higher arbitrage costs (Beneish, Lee, and Nichols, 2015; Hirshleifer, Lim, and Teoh, 2011). Wurgler and Zhuravskaya (2002) argue that arbitrageurs' demand for a stock is inversely related to its arbitrage cost, as measured by the idiosyncratic volatility of its returns. Analogously, if complementor momentum is a form of slow price reaction to fundamental news, the effect should be more pronounced for firms with higher idiosyncratic volatility. To test this conjecture, we compute idiosyncratic volatility as the standard deviation of the residuals from a regression of daily stock returns in the previous month on the Fama and French (1993) factors. We then construct an indicator variable (*More_IdioVol*) that equals one if the idiosyncratic volatility at the end of the previous fiscal year is above the sample median, and zero otherwise. As reported in Table 8 column 5, the estimated coefficient on the interaction term $COMPLRET_{t-1}$**More_IdioVol* is strongly positive and statistically significant, indicating that arbitrage costs likely contribute to the magnitude of the complementor momentum effect.

5.5 Evidence on shock transmission across stocks

As a final test, we investigate information transmission from focal firms to their complementor peers using a patent announcement setting (Kogan et al., 2017). Every Tuesday, the U.S. Patent Office publishes newly granted patents and Kogan et al. (2017) find substantially higher trading volume around the day when a firm's patent is published. They further construct a measure of the market value of the patents, based on the stock market reaction, or short-window cumulative abnormal returns (*CAR*), around the announcement date. The publication date for a given patent is not known in advance, either by the focal firm or by its investors. The timing of these events is also exogenous with respect to daily market conditions and news shocks from the firm's customers/suppliers. Therefore, we should be able to use the announcement date return in a patent publication setting to examine shock transmission from the focal firm to its peer firms. To perform this test, we obtain the publication date for each patent from Kogan et al. (2017)'s patent database. For each patent publication, we compute the focal firm *CAR* around a 2-day event window (day *t* and day *t+1*). If there is more than one patent publication for a given firm-month, we sum up the individual *CAR*s to derive a "*Patent CAR*" variable for that focal firm. Intuitively, *Patent CAR* is a measure of the market value of the focal firm's approved patent(s) in a given month. We then examine whether, and how quickly, the news contained in "*Patent CAR*" is transmitted to other peer firms.

In Table 9 we present the results of this analysis for contemporaneous return transmission (month *t*) as well as one-month forward return transmission (month *t+1*). In Panel A, we find a strongly positive relation between focal firm short-window returns and same-month returns among its complementors (*COMPLRET*), industry peers (*INDRET*), and technology peers (*TECHRET*). Dividing the complementor returns into three groups based on their *COMPL* distance (*Strong, Medium, Weak*), we find a monotonic relation in terms of their response to the focal firm patent issuance shock – Strong complementors exhibit the most positive return correlation, followed by the Medium group and then the Weak group. These results further validate the notion that *COMPL* is a sound measure of the economic distance between a focal firm and its complementors. We find an even stronger positive correlation among industry and technology peers. This is perhaps unsurprising, as industry and technology affinities are more salient and likely to be more closely monitored by analysts and investors.

We find a striking result when examining shock transmission in the following month (month *t+1*): the short-window focal firm return (*Patent CAR*) significantly predicts the next-month returns of *Strong* complementors, but not the returns of the *Medium* and *Weak* complementors (see Table 9 Panel B).

The month *t+1* effects for industry peers and technology peers are also insignificant or marginally significant, suggesting a relatively complete same-month response to the focal firm shock among industry and technology peers. We note that the return signal featured in our main tests (*COMPLRET*) is more comprehensive, in that it summarizes all the news affecting the complementor firms, not just patent news. However, this additional test is novel in the literature and provides direct evidence that economic shocks are indeed being transmitted along complementor networks.

5.6 Robustness tests

In the Internet Appendix, we present the findings of a host of additional robustness tests. First, we impose more stringent restrictions on firms' market capitalization to prevent a microcap bias (Table IA1) and find the results still hold. Second, we exclude peer firms that belong to the same Fama-French 17 or 48 sector (Table IA2), or peer firms in the same textual-based industry from Hoberg and Phillips (2016) (Table IA3) and find our results remain robust. Third, we change the threshold for the minimum number of complementor peers. In our main tests, we keep a focal firm if it has 3 or more complementor peers; in Table IA4, we show our results are robust when the minimum threshold changes to 1, 2, 4, or 5 complementor peers. Fourth, we examine the sensitivity of the results to the "age" of the production complementarity mapping (Table IA5). Our results show that the effect declines slightly with "stale" *COMPL* mappings but is still significant even when we use three-year-old *COMPL* data. Fifth, we employ the method in Burt and Hrdlicka (2021) to rule out any bias arising from correlated alphas between linked firms due to common factor shocks. Our results show that sorting on the idiosyncratic returns of complementor firms yields essentially the same return predictability patterns as sorting on raw returns (Table IA6). Sixth, we examine whether *COMPLRET* can predict future standardized unexpected earnings (*SUE)*, defined as the unexpected earnings (year-over-year change in quarterly earnings before extraordinary items) scaled by the standard deviation of unexpected earnings over the eight preceding quarters. Our results show that *COMPLRET* has strong predictability power for future

SUE even after including a variety of lagged control variables (Table IA7). Seventh, we examine stock returns around subsequent earnings announcements and find that the return spread from complementor strategy on a day during an earnings announcement window is more than two times higher than on non-announcement days (Table IA8). This evidence is difficult to square with standard risk models and points toward investor underreaction as a more likely explanation. Eighth, we use focal firms' disclosed information on major customers, rather than BEA's Input-Output table, to construct the complementarity network.[20] Because most firms do not list *any* major customers, this alternative approach greatly restricts the number of complementors we are able to identify. Nevertheless, we still find a strong lead-lag return relationship between these complementors and the focal firm (Table IA9). Ninth, as discussed earlier, we report portfolio returns from a double sort on our variable and the Menzly and Ozbas (2010) lagged customer return variable and find that our variable has strong incremental power to predict returns in every quintile of the lagged customer return (Table IA10).

Finally, we examine the robustness of our results to the inclusion of indirect network effects. Our *COMPL* variable is a measure of direct network complementarity. However, higher orders of indirect effect exist in IO matrices and may be important. For example, although industry A and industry B may not share any common customers, firms in industry A may still be indirectly complementary to firms in industry B if some of both A and B's customers have industry C as a common customer. The chain of input–output relations among industries thus gives rise to an indirect effect, which can be neatly computed using a Leontief inverse transformation (see ten Raa, 2006).[21] Internet Appendix Table IA11 reports a replication of our key results using a *Combined Complementors* variable developed from Leontief inverse transformed IO matrices to account for combined effects from both direct and indirect complementors derived in the BEA Input-Output table. When we examine fundamental variables, the

[20] Firms are required to report material customers in their annual reports, and we use the disclosed customer information from Compustat to identify a group of alternative complementor firms. For this test, we define a complementor as a firm from a different industry that has at least one major customer in common with the focal firm.

[21] This is one of several excellent suggestions provided by our referee, to whom we owe a great debt of gratitude.

coefficients on the *Combined Complementors* variable are positive and mostly significant (except for R&D), indicating that it can still identify peer firms with contemporaneous co-movements of the focal firm. However, the coefficient value and statistical significance are weaker compared with our baseline case when we only use direct complementarity information from the BEA IO table. Furthermore, when we construct long-short hedge portfolios based on the *Combined Complementors'* past month average returns, we no longer find any statistically significant excess returns or alphas when constructing value-weighted portfolios. We conclude that for most applications, the set of complementors derived from using only direct network relationships is likely to suffice.

6. Conclusions

Firms along the same production network can develop a complementary relationship because they supply an overlapping set of customers. A growing literature in economics demonstrates the micro and macro implications of such production complementarity. Our study extends this analysis by demonstrating the implications of production networks for firm-level fundamental analysis and asset pricing. To our knowledge, this is the first paper that documents these capital market implications.

We find that firms co-move strongly with their complementor peer firms in terms of economic fundamentals related to operating, investing, and financial activities. We further show that news shocks, including news about focal firm patent approvals, travel along complementor networks. By construction, these complementor firms have neither "vertical" nor "horizontal" linkages with the focal firm. Therefore, our results suggest a new way to identify economically linked peer firms that are not disclosed in focal firm financial reports. As a practical matter, our evidence suggests that the efficacy of *COMPL* as a measure of economic distance gradually dissipates as we move below the top 2% of ranked firms. We think this is something future researchers should consider when using this algorithm in their projects.

Furthermore, we find a robust lead-lag relationship between the stock returns of the complementors and the focal firm. The economic magnitude of this lead-lag effect is substantial, with a hedged portfolio constructed based on the price signals of the complementors producing a monthly excess return of 130 basis points or 15.6% on an annual basis. This complementor momentum effect is robust after controlling for a variety of predictive variables, including firm size, book-to-market, short-term reversal, and medium-term price momentum. It is distinct from, and cannot be explained by, previously documented lead-lag effects among economically linked firms, such as industry momentum, customer-supplier momentum, technology momentum, or momentum from common analyst coverage.

In the cross-section, we show *COMPL* is a meaningful measure of economic distance between firms from different industries. Specifically, we find that firms whose pairwise *COMPL* scores are higher (i.e., are more closely aligned in terms of production complementarity) exhibit stronger same-month return correlations, as well as stronger lead-lag return patterns. This pattern appears in our main tests, as well as in an announcement-based event study of shock transmission from focal firm patent publications to peer firm returns.

We further provide evidence that the main driver of this effect is a form of investor inattention or sluggish adjustment to value-relevant information along the complementarity network. The effect is strongest for firms that receive less investor attention and are more costly to arbitrage. Shared analyst coverage is relatively rare among complementor firms (which are from different industries by construction), but where it exists, common coverage improves the price adjustment process. This last finding suggests that common analyst coverage plays two, potentially offsetting, roles in the transmission of information between firms: (1) it helps to identify more subtle forms of economic linkage between two firms (as per Ali and Hirshleifer, 2020), and (2) it helps to facilitate price discovery of new information between firms, thus reducing the momentum spillover effect.

Overall, we show that production complementarity networks play an important role in the transmission of information across publicly listed firms. Our hope is that these findings will stimulate further research into the capital market implications of production complementarity. In particular, the network connections that we have identified should help researchers trace the propagation of specific granular shocks across the cross-section of stocks. In such applications, the ability to identify and isolate idiosyncratic shocks becomes important. Recent work by Gabaix and Koijen (2023) appears particularly promising in this regard. To facilitate this and other future research, we have compiled a database of our complementarity distance measure (*COMPL*), which is available for download (https://sites.google.com/view/complementarity-link?usp=sharing). We look forward to future research along these lines.

Appendix A. Variable Definitions

Variables	Definitions
COMPL	$COMPL_{ijt}$ denotes the production complementarity between firm *i* and *j* at year *t*, calculated as the cosine similarity of their output flow vectors, $COMPL_{ijt} = \frac{(OF_{it}OF_{jt}^{'})}{(OF_{it}OF_{it}^{'})^{1/2}(OF_{jt}OF_{jt}^{'})^{1/2}}$ where $OF_{it} = (O_{it1}, O_{it2}, \dots, O_{itN})$ is a vector of firm *i*'s output flow among the detailed-level IO industries.
COMPLRET	The equal-weighted average stock returns of complementors.
RET	Stock monthly raw return.
INDRET	Industry returns, defined as value-weighted average industry returns following Moskowitz and Grinblatt (1999). Specifically, for each month, we construct 20 industry portfolios using CRSP two-digit SIC codes and calculate value-weighted average returns within each industry as industry returns.
INDMOM	Medium-term Industry peer value-weighted average price momentum, defined as a focal firm's *INDRET* for the last 12 months except for the past one month.
SIZE	Firm size, defined as the natural log of market equity.
BM	Book-to-market ratio, calculated as book equity divided by market value at the end of the fiscal year.
RET_{t-1}	Lagged stock return, or short-term return reversal, defined as the firm's stock return at month *t-1*.
MOM	Medium-term price momentum, calculated as the firm's stock return over the previous 12 months, excluding the most recent month.
ROA	Income before extraordinary items divided by lagged total assets.
Sales Growth	The change in logged sales of the current year over the last year.
Leverage	The total book value of debt divided by the sum of total book value of debt and the market value of common stock.
External Financing	The sum of net equity issuance and net debt issuance, divided by lagged total assets.
CapEx	The capital expenditures on PPE, excluding amounts arising from acquisitions, scaled by lagged total assets.
R&D	R&D expenses scaled by lagged total assets.
Citation-weighted-patents	The log of 1 plus the number of citation-weighted patents applied in a given year.
Consensus EPS Revisions	The change of the market consensus (median) of analysts' *EPS* forecast.
CUSRET	Customer industry momentum, defined as the returns from a portfolio of the focal firm's customer industries, constructed following Menzly and Ozbas (2010).
SUPRET	Supplier industry momentum, defined as the returns from a portfolio of the focal firm's supplier industries, constructed following Menzly and Ozbas (2010).
PCRET	Returns from pseudo conglomerate portfolios, constructed following Cohen and Lou (2012).
TECHRET	The average returns of the focal firm's technological peers, constructed following Lee, Sun, Wang and Zhang (2019).
CARET	The average return of firms that are connected through common analyst coverage with the focal firm, constructed following Ali and Hirshleifer (2020).
HighPeerNum	An indicator variable that equals one if the number of complementary peers of a focal firm is above the sample median in a given year, and zero otherwise.
Larger_Size	An indicator variable that takes the value of 1 if a focal firm is above the third quartile in a given month in terms of the log value of market capitalization, and zero otherwise.

More_Analyst	An indicator variable that takes the value of 1 if the number of analysts following a focal firm at the end of the previous month is above the third quartile in the sample, and zero otherwise.
Higher_InstitOwn	An indicator variable that takes the value of 1 if the institutional holding at the end of the previous fiscal-year end is above the sample median, and zero otherwise.
More_IdioVol	An indicator variable that takes the value of 1 if the idiosyncratic volatility at the end of the previous fiscal year is above the sample median, and zero otherwise. *IdioVol* is the standard deviation of the residuals from a regression of daily stock returns in the previous month on the Fama and French (1993) factors (at least ten daily returns required).

Appendix B. Examples of Focal Firms and Their Complementors

Focal Firms (SIC Industry)	Top Large Complementors (SIC Industry)	Nature of Complementarity
Focal Firm 1: Alphabet Inc. **SIC Industry:** Services-Computer Programming, Data Processing (7370)	AT&T Inc.; US Cellular Corp (*Radiotelephone Communications, 4812*)	Alphabet's technological infrastructure and digital services can complement carriers' telecommunications offerings, serving a common base of businesses that require integrated digital solutions and connectivity services.
	Symbol Technologies *(Computer Peripheral Equipment, 3577)*	They complement each other by providing integrated technology solutions to retail businesses and logistics companies, where Alphabet offers digital platforms and cloud services, and Symbol Technologies provides barcode and RFID technology.
	Omnicom Group Inc. *(Services-Advertising Agencies, 7311)*	They have a complementary relationship as both cater to businesses needing digital advertising and marketing services, with Alphabet providing the technological platform and Omnicom offering specialized marketing and communication expertise.
	S&P Global Inc. *(Credit Reporting Services, 7323)*	Both companies serve businesses requiring analytical tools and data insights, with Alphabet providing technological infrastructure and S&P Global offering financial and market data.
Focal Firm 2: Cisco Systems, Inc. **SIC Industry:** Computer Communications Equipment (3576)	Oracle Corp *(Services-Computer Programming, Data Processing, 7370)*	Oracle provides database and cloud services, which complement Cisco's networking solutions for shared customers in sectors like finance and healthcare, enhancing overall IT infrastructure.
	Microsoft Corporation *(Services-Computer Programming, Data Processing, 7370)*	Microsoft's cloud services and software products complement Cisco's networking hardware for shared customers, particularly in enterprise IT environments.
	Verizon Communications Inc. *(Radiotelephone Communications, 4812)*	Telecommunications services can complement Cisco's networking hardware and services by providing the necessary connectivity solutions for enterprises, enhancing overall communication and network infrastructure.
	Citrix Systems Inc. *(Services-Prepackaged Software, 7372)*	Citrix's virtualization and networking solutions complement Cisco's offerings, enhancing network and application delivery for shared customers, particularly in remote work environments.
	VMware, Inc. *(Services-Computer Integrated Systems Design, 7373)*	VMware's virtualization and cloud services complement Cisco's networking and security solutions for shared customers, particularly in the creation of efficient and secure IT infrastructures.
Focal Firm 3: Johnson & Johnson	Becton Dickinson *(Surgical & Medical Instruments & Apparatus, 3841)*	J&J's surgical products and BD's medical technology products are used together in hospitals and clinics

SIC Industry: Pharmaceutical Preparations (2834)	Stryker Corp *(Orthopedic, Prosthetic & Surgical Appliances & Supplies, 3842)*	Johnson & Johnson's medical devices and Stryker's orthopedic products are often used together in surgical procedures, serving the same healthcare providers.
	3M Co *(Converted Paper & Paperboard Prods, 2670)*	Johnson & Johnson's surgical products and wound care items complement 3M's medical supplies such as medical tapes, dressings, sterilization products, and infection prevention solutions.
	Medtronic PLC *(Electromedical & Electrotherapeutic Apparatus, 3845)*	J&J's medical devices and Medtronic's technology complement each other in surgical and chronic disease management applications, serving the same healthcare institutions.
	OPKO Health Inc. *(Services-Medical Laboratories, 8071)*	Johnson & Johnson's broad range of healthcare products can complement OPKO Health's diagnostic technologies and pharmaceuticals in shared healthcare provider settings.
Focal Firm 4: Nvidia Corp **SIC Industry:** Semiconductors & Related Devices, 3674	NetApp Inc. *(Computer Storage Devices, 3572)*	Nvidia's GPUs are crucial in AI and machine learning, while NetApp specializes in data management. Both can complement each other in sectors like AI data analysis, where robust data storage and processing power are needed.
	SanDisk Corp *(Computer Storage Devices, 3572)*	SanDisk provides memory storage solutions, complementing Nvidia's high-speed data processing in environments needing large-scale data storage, like in advanced computing systems.
	Trimble Inc. *(Measuring & Controlling Devices, 3829)*	Nvidia's technology in AI and GPUs can complement Trimble's solutions in GPS, laser, optical and inertial positioning technologies used in surveying, construction, agriculture, and other fields, especially in the context of data processing and analysis.
	Panasonic Holdings Corp *(Electronic & Other Electrical Equipment, No Computer Equip, 3600)*	Panasonic's diverse electronic products can be complemented by Nvidia's GPU technology, especially in areas like automotive electronics, where advanced processing power is beneficial.
	Blue Coat Systems Inc *(Services-Computer Programming, Data Processing, etc., 7370)*	Nvidia Corp and Blue Coat Systems are complementary because Nvidia's advanced GPU and AI technology can complement Blue Coat's cybersecurity solutions, benefiting common customers in sectors like technology, finance, and healthcare that require robust data processing and secure network environments.
Focal Firm 5: Cummins Inc. **SIC Industry:** Engines & Turbines (3510)	Aptiv plc *(Motor Vehicle Parts & Accessories, 3714)*	Aptiv focuses on automotive technology, especially advanced safety, connectivity, and mobility solutions, complementing Cummins' engine in the automotive industry.
	Magna International Inc *(Motor Vehicle Parts & Accessories, 3714)*	Magna International specializes in automotive manufacturing, offering body exteriors, powertrains, and electronic systems, complementing Cummins' engine in the automotive industry.

	Goodyear Tire & Rubber Co *(Tires & Inner Tubes, 3011)*	Goodyear is a renowned tire manufacturer. Their products can complement Cummins' engines in the automotive sector, particularly in heavy vehicles like trucks and buses, where both high-quality tires and efficient engines are crucial.
	Illinois Tool Works *(General Industrial Machinery & Equipment, 3560)*	Illinois Tool Works produces a wide range of industrial products and equipment. There's potential synergy in combining their industrial tools and solutions with Cummins' power generation products for customers in industries like construction, agriculture, and manufacturing.
	Openlane Inc. *(Services-Business Services, 7389)*	Openlane provides online auction services for automotive dealers. While not directly product-related, there could be complementary benefits in terms of vehicle lifecycle management and remarketing services for vehicles equipped with Cummins engines.
Focal Firm 6: Oracle Corp **SIC Industry:** Services-Prepackaged Software (7372)	Accenture PLC *(Services-Management Consulting Services, 8742)*	Oracle's enterprise software products can be integrated into the solutions Accenture develops for its clients, particularly in digital transformation projects.
	Seagate Technology Holdings *(Computer Storage Devices, 3572)*	Seagate's products can complement Oracle's database and cloud solutions by providing the physical data storage infrastructure necessary for Oracle's systems, beneficial for customers needing comprehensive data management solutions.
	Netgear Inc *(Telephone & Telegraph Apparatus, 3661)*	Netgear provides networking equipment for home and business use. Oracle's cloud solutions could be complemented by Netgear's networking hardware, offering a more complete infrastructure setup for small to medium-sized businesses.
	Micron Technology Inc *(Semiconductors & Related Devices, 3674)*	Micron is a leader in memory and storage solutions. Their products could complement Oracle's database technologies, offering enhanced performance for applications that require fast and large-scale memory solutions, like big data analytics.
	Keysight Technologies Inc *(Instruments for Measuring & Testing of Electricity & Electrical Signals, 3825)*	Specializing in electronic design and test instrumentation, Keysight's technologies can be used alongside Oracle's software products in the development and testing of electronics, benefiting customers in sectors like telecommunications and industrial electronics.
Focal Firm 7: Medtronic Plc **SIC Industry:** Electromedical & Electrotherapeutic Apparatus (3845)	Johnson & Johnson; Pfizer Inc. *(Pharmaceutical Preparations, 2834)*	Johnson & Johnson or Pfizer's focus is on pharmaceuticals, while Medtronic's is on medical devices. The medications developed by Johnson & Johnson or Pfizer could be used in conjunction with Medtronic's devices for treatments, benefiting common customers such as hospitals and clinics.
	3M Co *(Converted Paper & Paperboard Prods, 2670)*	3M's medical supplies and technologies can complement Medtronic's devices in surgical, dental, orthopedic, and other healthcare settings.

	<u>Laboratory Corp Of Amer</u> *(Services-Medical Laboratories, 8071)*	Laboratory Corp provides clinical laboratory services. There could be complementary use cases where LabCorp's diagnostic tests and Medtronic's medical devices are used together for patient treatment planning.
	<u>Quest Diagnostics Inc</u> *(Services-Medical Laboratories, 8071)*	Quest Diagnostics offers diagnostic testing services. Medtronic's devices for monitoring and treatment could be used in tandem with diagnostic information provided by Quest to offer comprehensive patient care.
Focal Firm 8: RTX Corporation **SIC Industry:** Aircraft Engines & Engine Parts (3724)	<u>Trimble Inc.</u> *(Measuring & Controlling Devices, 3829)*	Trimble's advanced navigation and surveying (e.g., GPS, laser, inertial positioning) technologies could complement RTX's aerospace engine and system products in joint end-user applications, such as precision agriculture or construction.
	<u>B/E Aerospace Inc.</u> (Public Bldg & Related Furniture, 2531)	RTX Corporation, through its aerospace systems and engines, and B/E Aerospace Inc., which specializes in aircraft cabin interior products, complement each other by offering different components to the aircraft constructions.
	<u>ITT INC</u> *(Search, Detection, Navigation, Guidance, Aeronautical Sys, 3812)*	ITT Inc.'s engineered components, like connectors and energy absorption devices, can complement RTX Corp's aerospace engines and systems for the common customers in the aerospace industry.
	<u>Precision Castparts Corp</u> *(Aircraft Parts & Auxiliary Equipment, 3728)*	Precision Castparts Corp produces critical metal components and castings for use in the aerospace and defense industries, complementing RTX Corp’s products of aerospace engines and defense systems.
	<u>Crane Co</u> *(Miscellaneous Fabricated Metal Products, 3490)*	Crane Co's specialized industrial products, such as fluid handling systems and electronics, could complement RTX Corp's aerospace and defense technologies by providing essential sub-components that enhance the functionality and efficiency of RTX's systems.
Focal Firm 9: Nucor Corp **SIC Industry:** Steel Works, Blast Furnaces & Rolling Mills (Coke Ovens) (3312)	<u>Texas Industries Inc.</u> *(Cement, Hydraulic, 3241)*	Texas Industries was a supplier of heavy construction materials, including cement and aggregates. They are complementary in construction, where steel from Nucor and materials from Texas Industries could be used in tandem for infrastructure projects.
	<u>Fastenal Co</u> *(Wholesale-Durable Goods, 5000)*	Fastenal provides industrial supplies, fasteners, tools, and materials. Nucor's steel products can serve as essential raw materials for Fastenal's customers, enabling the manufacture of a diverse range of industrial and construction products.
	<u>Kennametal Inc.</u> *(Metalworking Machinery & Equipment, 3540)*	Kennametal specializes in tooling solutions for manufacturing sectors. The steel products from Nucor could be used in the production of Kennametal's tooling solutions by their shared customers in manufacturing sectors.
	<u>Watsco Inc.</u> *(Wholesale-Hardware & Plumbing & Heating Equipment & Supplies, 5070)*	Nucor is a manufacturer of steel and steel products, whereas Watsco is the largest distributor of air conditioning, heating, and refrigeration equipment.

		The steel produced by Nucor could be used in the manufacturing of HVAC systems that Watsco distributes.
	ARMCO Metals Holdings Inc. *(Rolling Drawing & Extruding Of Nonferrous Metals, 3350)*	They are complementary in the metals industry because while Nucor produces a broad range of standard steel products, ATI specializes in advanced specialty materials and complex components, catering to interconnected needs from their shared customers.
Focal Firm 10: Occidental Petroleum Corp **SIC Industry:** Crude Petroleum & Natural Gas (1311)	Magellan Midstream; MPLX LP *(Pipe Lines (No Natural Gas), 4610)*	Magellan Midstream and MPLX specialize in the transportation, storage, and distribution of petroleum products. There's a complementary relationship with Occidental, where Occidental's production could be transported and stored by Magellan's or MPLX's infrastructure.
	Quanta Services *(Electrical Work, 1731)*	Quanta's expertise in designing and building energy infrastructure complements Occidental's supply of oil and gas, ensuring efficient project implementation and dependable energy utilization for their shared customers.
	TC Energy *(Natural Gas Transmission, 4922)*	TC Energy's extensive network for transporting and storing energy resources efficiently supports Occidental's oil and gas production, ensuring a streamlined and reliable supply chain for energy consumers.
	Headwaters Incorporated *(Concrete Products, Except Block & Brick, 3272)*	Headwaters' construction materials and energy technologies can enhance infrastructure development and efficiency, while Occidental's oil and gas production ensures a reliable supply of energy resources, together offering a more integrated and efficient solution to their shared customers.

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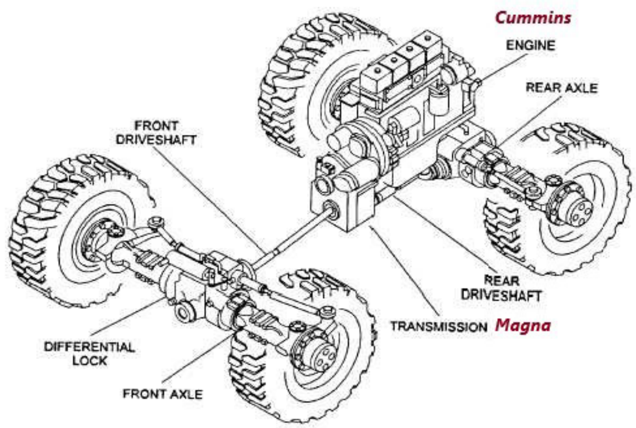

Fig. 1. Product Complementarities between Cummins Inc. and Magna International Inc.

This figure depicts the product complementary nature of Cummins Inc. (NYSE: CMI) and Magna International Inc. (NYSE: MGA). Cummins Inc. (SIC Code: 3510) is a manufacturer of internal combustion engines used in construction machinery and heavy trucks. Magna International (SIC Code: 3714) is a producer of vehicle parts and accessories. Although these two firms are in different industries, their pairwise production complementarity score is high:

$$COMPL_{ijt} = \frac{(OF_{it}OF_{jt}^{'})}{(OF_{it}OF_{it}^{'})^{1/2}(OF_{jt}OF_{jt}^{'})^{1/2}} = 0.85.$$

On reflection, it is perhaps not surprising, as Magna produces key components for the transmission and driveshaft of many vehicles that feature Cummins' engines. Our results show that this close affinity in terms of their production complementarity is an important economic linkage for the firms, even though they operate in different industries and are not a supplier or a customer to each other.

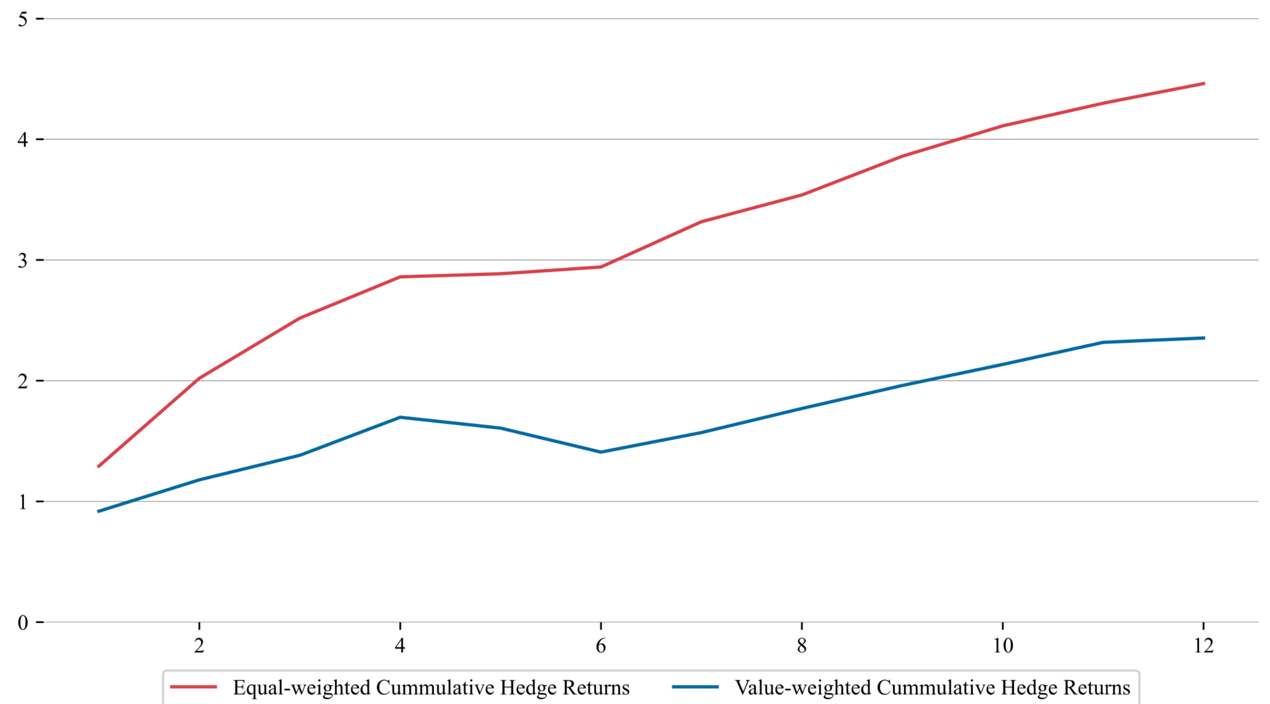

Fig. 2. Hedge Portfolio Performance Persistence

This figure shows the cumulative returns of the hedge portfolio in the 12 months after portfolio formation. At the beginning of every calendar month, all firms are ranked in ascending order on the basis of the return of a portfolio of its complementors at the end of the previous month. The ranked stocks are assigned to one of ten decile portfolios. All stocks are either equal-weighted (red) or value-weighted (blue) within each portfolio, and the portfolios are rebalanced every calendar month to maintain equal or value weights. The hedge portfolio is a zero-cost portfolio that buys the top decile and sells short the bottom decile. The sample excludes financial firms (with a one-digit SIC code of six) and stocks with a price of less than $1 at portfolio formation.

Table 1. Summary Statistics

This table presents summary statistics for the key variables used in the cross-sectional regressions. The sample includes all NYSE/AMEX/NASDAQ-listed securities with share codes 10 or 11 that are contained in the CRSP/Compustat merged data file. Financial firms (i.e., firms with a one-digit SIC code of six) and stocks with price less than $1 at portfolio formation are excluded. All variable definitions are in Appendix A.

	Mean	**Sd**	**Q1**	**Med**	**Q3**
Sample Description					
# of focal firms per year	2,799	810	2,488	2,601	3,015
Average # of complementors per firm	103	134	13	42	153
Key Variables					
COMPL	0.20	0.25	0.02	0.09	0.32
RET	0.01	0.15	-0.07	0.01	0.08
COMPLRET	0.01	0.07	-0.03	0.01	0.05
INDRET	0.01	0.05	-0.02	0.01	0.04
SIZE	5.20	2.10	3.60	5.08	6.67
BM	0.67	0.59	0.28	0.52	0.88
RET_{t-1}	0.01	0.15	-0.07	0.00	0.08
MOM	0.17	0.60	-0.19	0.07	0.37
INDMOM	0.12	0.20	0.01	0.12	0.24

Table 2. Co-movement in Operating Performance & Other Fundamentals

This table presents a series of panel regressions on the co-movement between focal firms and their peers in terms of operating performance and other fundamental metrics. In each regression, the dependent variable is a fundamental metric of the focal firm. In Panel A, we report contemporaneous co-movements between the focal firm, *Strong Complementors* (firm in the 99th and 98th percentile as ranked by their complementarity score, *COMPL*) and *Industry Peers* (based on 4-digit SIC). Each regressor is computed as the equal-weight average of the fundamental metric across a given group of peer firms. The fundamental metrics we examine are annual measures of: *ROA*, *Sales Growth*, *Leverage*, *External Financing, CapEx*, *R&D*, and *Citation-weighted-patents*. In Panel B, we repeat this analysis while adding a set of *Random* peers (2% of the firms in the network, randomly selected). We also report the differences in the estimated coefficients between the *Strong Complementors* vs. *Random Complementors*, as well as the *t*-statistics associated with these differences. In Panel C, we replace the *Random* peer group with a group of *Medium Complementors* (firms in the 97th and 96th percentiles as ranked by *COMPL*) and *Weak Complementors* (firms in the 95th and 94th percentiles as ranked by *COMPL*). We also report the differences in the estimated coefficients between the *Strong Complementors* vs. either the *Medium* or *Weak* complementors. In each analysis, we include firm and year fixed effects and report *t*-statistics in parentheses. Standard errors are adjusted for clustering by firm. All variables are winsorized at 1% and 99% levels and are standardized with a mean of zero and a standard deviation of one. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

Panel A. Co-movement in Operating Performance and other Fundamentals

Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ROA	*Sales Growth*	*Leverage*	*External Financing*	*CapEx*	*R&D*	*Citation-weighted-patents*
Strong Complementors	0.032***	0.060***	0.051***	0.018***	0.060***	0.036***	0.030***
	(6.44)	(15.40)	(9.32)	(4.12)	(11.34)	(5.00)	(5.01)
Industry Peers Average	0.043***	0.113***	0.183***	0.049***	0.170***	0.150***	0.072***
	(7.41)	(26.56)	(22.98)	(8.75)	(20.97)	(10.90)	(8.20)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	108,661	107,905	104,301	94,088	107,464	108,898	108,898
R^2	0.552	0.225	0.701	0.298	0.532	0.770	0.752

Panel B. Co-movement in Fundamentals, including Random Complementors as Placebo

Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ROA	*Sales Growth*	*Leverage*	*External Financing*	*CapEx*	*R&D*	*Citation-weighted-patents*
Strong Complementors	0.032***	0.060***	0.051***	0.018***	0.060***	0.036***	0.030***
	(6.44)	(15.40)	(9.31)	(4.12)	(11.34)	(5.00)	(5.01)
Random Complementors	0.001	-0.001	-0.003	0.002	-0.002	-0.002	-0.002
	(0.25)	(-0.29)	(-1.53)	(0.56)	(-0.93)	(-1.13)	(-1.27)
Industry Peers Average	0.043***	0.113***	0.183***	0.049***	0.170***	0.150***	0.072***
	(7.41)	(26.56)	(22.96)	(8.76)	(20.97)	(10.89)	(8.20)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	108,661	107,905	104,301	94,088	107464	108,898	108,898
R^2	0.552	0.225	0.701	0.298	0.532	0.770	0.752
Strong vs. Random	**0.031*** **	**0.061*** **	**0.054*** **	**0.016*** **	**0.062*** **	**0.038*** **	**0.032*** **
Coeff. Difference	(4.86)	(11.72)	(9.28)	(2.84)	(10.86)	(5.13)	(5.17)

Panel C: Co-movement between Focal Firms and Strong, Medium, and Weak Complementors

Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ROA	*Sales Growth*	*Leverage*	*External Financing*	*CapEx*	*R&D*	*Citation-weighted-patents*
Strong Complementors	0.030***	0.056***	0.047***	0.018***	0.059***	0.032***	0.028***
	(6.03)	(14.38)	(8.75)	(4.08)	(11.08)	(4.54)	(4.62)
Medium Complementors	0.018***	0.015***	0.010***	0.005	0.008**	0.014***	0.003
	(5.16)	(4.26)	(2.76)	(1.50)	(2.17)	(3.51)	(0.80)
Weak Complementors	0.004	0.014***	0.011***	0.008*	-0.001	0.002	0.005
	(1.18)	(4.15)	(3.08)	(1.92)	(-0.17)	(0.55)	(1.34)
Industry Peers Average	0.041***	0.110***	0.182***	0.048***	0.169***	0.149***	0.072***
	(7.15)	(26.05)	(22.87)	(8.60)	(20.96)	(10.77)	(8.20)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	108,661	107,905	104,301	94,088	107,464	108,898	108,898
R^2	0.552	0.226	0.701	0.298	0.532	0.770	0.752
Strong vs. Medium	**0.012** **	**0.041*** **	**0.037*** **	**0.013** **	**0.051*** **	**0.018** **	**0.025*** **
Coeff. Difference	(1.98)	(7.81)	(5.71)	(2.35)	(7.88)	(2.22)	(3.51)
Strong vs. Weak	**0.026*** **	**0.042*** **	**0.036*** **	**0.010* **	**0.060*** **	**0.030*** **	**0.023*** **
Coeff. Difference	(4.32)	(8.15)	(5.58)	(1.65)	(7.49)	(3.79)	(3.23)

Table 3. Co-movement in Stock Returns and Earnings Forecast Revisions

This table reports the co-movement in monthly stock returns and quarterly analysts' (EPS) forecast revisions between focal firms and their peers. In Panel A, we report results of monthly Fama-MacBeth return regressions. The dependent variable is either the focal firm's monthly return *RET* (columns 1-6), or the firm's excess return over its industry return *RET-INDRET* (columns 7-8). The main independent variables of interests, *Strong (Medium/Weak)* $COMPLRET_t$, are the average strong (medium/weak) complementors' return in the same period. In columns 5-8, we add the concurrent industry average return (*INDRET*). Other control variables include firm size (*SIZE*), book-to-market ratio (*BM*), the focal firm's own lagged monthly return (RET_{t-1}), and medium-term price momentum (*MOM*). Standard errors are Newey-West adjusted for heteroskedasticity and autocorrelation. We report the differences in the estimated coefficients between *Strong* $COMPLRET_t$ vs. either *Medium* or *Weak* $COMPLRET_t$. In Panel B, we report co-movements in quarterly EPS revisions between focal firms and their peers. We measure EPS consensus revisions using the change in the median forecast. *Strong (Medium/Weak) Complementors* is the equal-weighted average of the consensus EPS revisions across complementor peers. *Industry Peers Average* is the equal-weighted average of the consensus EPS revisions across industry peers. We include firm and quarter fixed effects, and *t*-statistics are reported in parentheses. Standard errors are adjusted for clustering by firm. We also report the differences in the estimated coefficients between the *Strong Complementors* vs. either the *Medium* or *Weak* complementors. All variables are winsorized at 1% and 99% and are standardized with a mean of zero and a standard deviation of one. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

Panel A: Co-movement in Monthly Stock Returns

Dependent Variable	(1) RET_t	(2) RET_t	(3) RET_t	(4) RET_t	(5) RET_t	(6) RET_t	(7) RET_t - $INDRET_t$	(8) RET_t - $INDRET_t$
Strong $COMPLRET_t$	5.464***	4.632***	4.329***	3.658***	4.038***	3.431***	2.200***	1.865***
	(16.07)	(15.93)	(17.43)	(17.19)	(16.83)	(16.60)	(12.13)	(11.47)
Medium $COMPLRET_t$		1.417***		1.171***		1.082***		0.339***
		(10.01)		(9.20)		(8.75)		(3.36)
Weak $COMPLRET_t$		1.130***		0.887***		0.780***		0.231**
		(8.75)		(7.45)		(6.73)		(2.11)
$INDRET_t$					1.080***	1.014***	0.537***	0.506***
					(9.04)	(8.93)	(3.62)	(3.41)
Controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes
N	989,165	989,165	989,165	989,165	989,165	989,165	989,165	989,165
R^2	0.015	0.019	0.050	0.053	0.052	0.056	0.041	0.043
Strong vs. Medium		**3.22*** **		**2.49*** **		**2.35*** **		**1.53*** **
Coeff. Difference		(9.94)		(10.03)		(9.75)		(7.97)
Strong vs. Weak		**3.50*** **		**2.77*** **		**2.65*** **		**1.63*** **
Coeff. Difference		(11.01)		(11.36)		(11.19)		(8.34)

Panel B: Co-movement in Quarterly Consensus EPS Forecast Revisions

Dependent Variable	(1)	(2)
	Consensus EPS Revisions	*Consensus EPS Revisions*
Strong Complementors	0.007***	0.007***
	(4.69)	(4.67)
Medium Complementors		-0.001
		(-0.76)
Weak Complementors		0.000
		(0.05)
Industry Peers Average	0.031***	0.031***
	(9.00)	(9.00)
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	173,494	173,494
R^2	0.092	0.092

Strong vs. Medium		**0.008*** **
Coeff. Difference		(4.14)
Strong vs. Weak		**0.007*** **
Coeff. Difference		(3.63)

Table 4. Complementor Momentum Strategy, Abnormal Returns

This table reports abnormal returns for a complementor momentum strategy. To construct this table, firms are ranked and assigned into decile portfolios at the beginning of every calendar month, based on the prior-month return to a portfolio of their *Strong Complementors* (*COMPLRET*). All stocks are equal- (value-) weighted within a given portfolio, and the portfolios are rebalanced every calendar month to maintain equal (value) weights. All non-financial stocks with stock price greater than $1 at portfolio formation are included. Excess return is the raw return of the portfolio over the risk-free rate. Alpha is the intercept from a regression of monthly excess return on factor returns. Factor returns are from the Kenneth French Data Library, and factor models include: the CAPM model; the Fama-French (1993) three-factor model; a four-factor model (Fama-French three factors and Carhart (1997)'s momentum factor), Fama-French (2015) five-factor model, and six-factor model (Fama-French five factors and momentum factor). L/S is the alpha of a zero-cost portfolio that holds the top 10% stocks ranked by average complementors returns (*COMPLRET*) and sells the bottom 10%. Panel B reports the alpha and the risk factor loadings, where the benchmark is a six-factor model (Fama-French five-factor + momentum factor).

Panel A: Baseline Portfolio Returns

	Excess Return (%)	CAPM Alpha (%)	3-Factors Alpha (%)	4-Factors Alpha (%)	5-Factors Alpha (%)	6-Factors Alpha (%)
1(Low)	0.08	-0.72	-0.77	-0.55	-0.55	-0.42
	(0.27)	(-3.99)	(-5.35)	(-4.07)	(-3.76)	(-3.03)
2	0.30	-0.51	-0.51	-0.33	-0.25	-0.15
	(1.00)	(-2.98)	(-4.06)	(-2.76)	(-1.98)	(-1.22)
3	0.39	-0.40	-0.44	-0.25	-0.23	-0.11
	(1.34)	(-2.36)	(-3.34)	(-1.97)	(-1.74)	(-0.90)
4	0.47	-0.28	-0.33	-0.19	-0.19	-0.11
	(1.71)	(-1.90)	(-2.92)	(-1.74)	(-1.64)	(-0.93)
5	0.65	-0.10	-0.20	-0.04	-0.12	-0.02
	(2.35)	(-0.67)	(-1.78)	(-0.40)	(-1.10)	(-0.20)
6	0.54	-0.18	-0.26	-0.14	-0.21	-0.14
	(2.04)	(-1.24)	(-2.43)	(-1.40)	(-1.99)	(-1.31)
7	0.95	0.22	0.16	0.23	0.20	0.25
	(3.49)	(1.40)	(1.35)	(1.97)	(1.74)	(2.15)
8	1.01	0.26	0.19	0.31	0.28	0.36
	(3.61)	(1.62)	(1.64)	(2.82)	(2.43)	(3.25)
9	1.22	0.45	0.40	0.52	0.64	0.70
	(4.02)	(2.33)	(2.97)	(3.89)	(4.86)	(5.37)
10(High)	1.38	0.59	0.57	0.61	0.79	0.80
	(4.33)	(2.82)	(3.71)	(3.87)	(5.31)	(5.29)
L/S	1.30	1.31	1.34	1.16	1.34	1.22
(EW)	(6.01)	(4.74)	(6.37)	(5.59)	(6.45)	(5.95)

L/S	0.92	0.97	0.93	0.75	0.79	0.68
(VW)	(3.97)	(4.50)	(4.26)	(3.45)	(3.51)	(3.04)

Panel B: Risk Factor Loadings

	Alpha (%)	MKT	SMB	HML	RMW	CMA	MOM
1(Low)	-0.42	1.00	0.81	-0.07	-0.24	-0.11	-0.24
	(-3.03)	(29.69)	(16.37)	(-1.07)	(-3.83)	(-1.17)	(-7.60)
10(High)	0.80	0.96	0.90	-0.23	-0.57	0.30	-0.01
	(5.29)	(26.04)	(16.56)	(-3.22)	(-8.15)	(2.89)	(-0.21)
L/S	1.22	-0.04	0.09	-0.16	-0.33	0.41	0.23
(EW)	(5.95)	(-0.79)	(1.19)	(-1.65)	(-3.43)	(2.93)	(4.97)
L/S	0.68	-0.01	0.11	0.09	0.12	0.17	0.19
(VW)	(3.04)	(-0.18)	(1.33)	(0.89)	(1.19)	(1.15)	(3.87)

Table 5. Incremental Information Beyond Common Analyst Coverage

This table presents a series of tests that examine the incremental information in complementor momentum after controlling for the common analyst effect documented in Ali and Hirshleifer (2020). In Panel A, we exclude all complementors that are simultaneously covered by common analysts when constructing complementor momentum and report equal- and value-weighted hedge portfolio returns. In Panel B, we separate all production complementors into two groups by whether the peers are covered by common analysts or not and construct complementor momentums for each group. At the end of each month, we separately rank and assign firms into decile portfolios based on the contemporaneous returns to a portfolio of their within-group complementors. We then hold this portfolio for 3 months and calculate the factor alpha from the time-series regression of portfolio returns in a five-factor model at the end of each month (from *t* to *t+3*). All stocks are equal weighted within a given portfolio. In the last column, "Percentage of Price Drift (%)" is defined as the returns that are not realized in the contemporaneous month (*t*) as a percentage of the accumulated returns from *t* to *t+3*. *"O/N"* is the alpha of a zero-cost portfolio that buys the hedge portfolio *covered by common analysts group (O)* and shorts the hedge portfolio *Not covered by common analysts group (N)*. In Panel C, we report returns to the complementor strategy after adding common analyst (CA) momentum factor as an additional explanatory variable to the standard five- or six-factor model. In both Panel A and C, L/S is the alpha of a zero-cost portfolio that holds the top 10% stocks ranked by complementor momentum and sells short the bottom 10%.

Panel A: Abnormal Returns after Excluding Complementors covered by at least One Common Analyst

	Excess Return (%)	CAPM Alpha (%)	3-Factors Alpha (%)	4-Factors Alpha (%)	5-Factors Alpha (%)	6-Factors Alpha (%)
1	0.07	-0.73	-0.76	-0.55	-0.54	-0.42
(Low)	(0.22)	(-4.09)	(-5.49)	(-4.19)	(-3.89)	(-3.13)
10	1.35	0.56	0.54	0.56	0.76	0.75
(High)	(4.25)	(2.70)	(3.71)	(3.78)	(5.35)	(5.27)
L/S	1.28	1.30	1.31	1.11	1.30	1.17
(EW)	(6.37)	(4.71)	(6.46)	(5.61)	(6.54)	(5.99)
L/S	0.76	0.78	0.71	0.58	0.63	0.54
(VW)	(3.37)	(3.75)	(3.45)	(2.76)	(2.95)	(2.54)

Panel B: Price Discovery for Complementors Covered and not Covered by a Common Analyst

	t	*t+1*	*t+2*	*t+3*	Percentage of Price Drift (%)
Not covered by a	4.13	1.29	0.49	0.35	34.03%
common analyst (N)	(17.43)	(6.45)	(2.29)	(1.63)	
Covered by a common	7.91	1.17	-0.02	0.02	12.89%
analyst (O)	(27.46)	(4.58)	(-0.09)	(0.07)	
O/N (Long O and Short N)	3.78	-0.12	-0.51	-0.33	
	(10.13)	(-0.37)	(-1.65)	(-0.92)	

Panel C: Spanning Tests

	5-Factors + CA Momentum Factor Alpha (%)	6-Factors + CA Momentum Factor Alpha (%)
1	-0.18	-0.35
(Low)	(-1.45)	(-2.78)
10	0.57	0.36
(High)	(4.24)	(2.54)
L/S	0.75	0.71
(EW)	(4.07)	(3.75)

Table 6. Fama-MacBeth Regressions

This table reports results of the Fama-MacBeth return forecasting regressions. The dependent variable is either the focal firm's monthly return *RET* (columns 1-3, 5-8), or the firm's excess return over its industry return *RET-INDRET* (column 4). In columns 3 and 4, we add the lagged industry average returns (*INDRET*). In column 5, we add the lagged returns from portfolios of both the focal firm's suppliers (*SUPPRET*) and customers (*CUSTRET*). These portfolios are constructed following Menzly and Ozbas (2010). In column 6, a portfolio of pseudo conglomerate returns (*PCRET*) is added based on Cohen and Lou (2012). In column 7, a portfolio of technology-linked firms' returns (*TECHRET*) is added following Lee, Sun, Wang and Zhang (2019). In column 8, we also add the lagged average return of firms that are connected through common analyst coverage (*CARET*) following Ali and Hirshleifer (2020). The control variables include firm size (*SIZE*), book-to-market ratio (*BM*), the firm's own lagged monthly return (RET_{t-1}), and medium-term price momentum (*MOM*). We use ordinary least squares cross-sectional regressions in Panel A and weighted least squares with market equity as the weights in Panel B. All variables are defined in Appendix A. The sample sizes for different columns vary by data availability. All explanatory variables are assigned to deciles ranging from 0 to 1. Cross-sectional regressions are run every calendar month, and the standard errors are Newey-West adjusted for heteroskedasticity and autocorrelation. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

Panel A: Ordinary Least Squares (Equal-Weighted) Fama-Macbeth

*Dependent Variable *100*	(1) RET_t	(2) RET_t	(3) RET_t	(4) RET_t - $INDRET_t$	(5) RET_t	(6) RET_t	(7) RET_t	(8) RET_t
$COMPLRET_{t-1}$	1.267***	1.221***	0.969***	0.803***	1.059***	0.616***	0.799***	0.733***
	(5.72)	(7.35)	(6.37)	(6.46)	(7.00)	(4.60)	(5.24)	(4.93)
$INDRET_{t-1}$			1.176***	0.603***				
			(8.58)	(4.16)				
$CUSRET_{t-1}$					0.592***			
					(4.03)			
$SUPRET_{t-1}$					0.626***			
					(3.87)			
$PCRET_{t-1}$						0.959***		
						(6.82)		
$TECHRET_{t-1}$							0.527**	
							(2.32)	
$CARET_{t-1}$								1.909***
								(8.94)
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,002,682	1,002,682	1,002,682	1,002,682	843,463	205,126	244,508	640,427
R^2	0.005	0.034	0.037	0.030	0.046	0.066	0.060	0.053

Panel B: Weighted Least Square (Size-Weighted) Fama-Macbeth

*Dependent Variable *100*	(1) RET_t	(2) RET_t	(3) RET_t	(4) RET_t - $INDRET_t$	(5) RET_t	(6) RET_t	(7) RET_t	(8) RET_t
$COMPLRET_{t-1}$	1.174***	1.137***	0.902***	0.730***	0.991***	0.537***	0.763***	0.638***
	(5.33)	(7.30)	(6.37)	(6.66)	(6.99)	(4.57)	(5.17)	(4.63)
$INDRET_{t-1}$			1.054***	0.480***				
			(7.65)	(3.53)				
$CUSRET_{t-1}$					0.498***			
					(3.42)			
$SUPRET_{t-1}$					0.585***			
					(3.60)			
$PCRET_{t-1}$						0.852***		
						(6.30)		
$TECHRET_{t-1}$							0.465**	
							(2.07)	
$CA\ RET_{t-1}$								1.882***
								(8.67)
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,002,682	1,002,682	1,002,682	1,002,682	843,463	205,126	244,508	640,427
R^2	0.007	0.041	0.044	0.034	0.054	0.070	0.066	0.058

Table 7. Intensity of Production Complementarity

This table reports how expected returns vary by the intensity of production complementarity. For a focal firm, strong complementor returns (*Strong* $COMPLRET_{t-1}$) are the equal-weighted average returns of complementors in the 99th and 98th percentile as ranked by their complementarity score, *COMPL*. Medium complementor returns (*Medium* $COMPLRET_{t-1}$) are the equal-weighted average returns of complementors in the 97th and 96th percentile as ranked by their complementarity score. Weak complementor returns (*Weak* $COMPLRET_{t-1}$) are the equal-weighted average returns of complementors in the 95th and 94th percentile as ranked by their complementarity score. All columns include *SIZE, BM,* RET_{t-1}, and *MOM* as controls. In Panel A, we report the results from Fama-MacBeth return forecasting regressions. The time-series standard errors are Newey-West adjusted for heteroskedasticity and autocorrelation. Fama-MacBeth *t-statistics* are reported below the coefficient estimates. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively. We report the differences in the estimated coefficients between *Strong* $COMPLRET_{t-1}$ vs. either *Medium* or *Weak* $COMPLRET_{t-1}$. In Panel B, we replicate our main tests in Table 4 and estimate the hedged portfolio returns based on *Medium complementors* or *Weak complementors*. Returns and alphas are in monthly percent, and *t-statistics* are shown in parentheses below the coefficient estimates.

Panel A: Fama-Macbeth Regressions

Dependent Variable **100*	(1) RET_t	(2) RET_t	(3) RET_t	(4) RET_t
Strong $COMPLRET_{t-1}$	1.221***			1.036***
	(7.35)			(6.03)
Medium $COMPLRET_{t-1}$		0.429***		0.170
		(3.34)		(1.25)
Weak $COMPLRET_{t-1}$			0.389***	0.266**
			(3.40)	(2.23)
Controls	Yes	Yes	Yes	Yes
N	1,002,682	935,514	909,078	766,330
R^2	0.034	0.035	0.034	0.041

Strong vs. Medium				**0.866***
Coeff. Difference				(3.39)
Strong vs. Weak				**0.770***
Coeff. Difference				(3.11)

Panel B: Portfolio Returns

Decile	**Strong**		**Medium**		**Weak**	
	Excess Returns (%)	3-Factors Alpha (%)	Excess Returns (%)	3-Factors Alpha (%)	Excess Returns (%)	3-Factors Alpha (%)
1	0.08	-0.77	0.44	-0.37	0.45	-0.39
(Low)	(0.27)	(-5.35)	(1.42)	(-2.41)	(1.58)	(-2.93)
10	1.38	0.57	1.06	0.21	0.93	0.11
(High)	(4.33)	(3.71)	(3.52)	(1.62)	(3.19)	(0.86)
L/S (EW)	1.30	1.34	0.62	0.58	0.48	0.50
	(6.01)	(6.37)	(3.59)	(2.88)	(2.93)	(2.74)

Table 8. Production Complementarity Characteristics, Limited Attention, and Cost of Arbitrage

This table reports the results of a series of cross-sectional analyses designed to evaluate the sensitivity of complementor momentum to proxies of limited attention and arbitrage costs. The tests are Fama-MacBeth return forecasting regressions where the dependent variable is the monthly stock return (*RET*). Explanatory variables include the lagged complementor returns ($COMPLRET_{t-1}$), assigned to deciles ranging from 0 to 1, plus a number of interaction terms. *HighPeerNum* equals one if the number of complementary peers of a focal firm is above the sample median in a given year. *Larger_Size* equals one if a focal firm is above the third quartile in a given month in terms of the log value of market capitalization, and zero otherwise. *More_Analyst* equals one if the number of analysts following a focal firm at the end of the previous month is above the third quartile in the sample, and zero otherwise. *Higher_InstitOwn* equals one if the institutional holding at the end of the previous fiscal-year is above the sample median. *More_IdioVol* equals one if the idiosyncratic volatility at the end of the previous fiscal year is above the sample median. *IdioVol* is the standard deviation of the residuals from a regression of daily stock returns in the previous month on the Fama and French (1993) factors (at least ten daily returns required). Control variables include *SIZE, BM,* RET_{t-1}, and *MOM*. The sample excludes financial firms (with a one-digit SIC code=6) and stocks with price less than one dollar at portfolio formation. Cross-sectional regressions are run every month and the time-series standard errors are Newey-West adjusted. Fama-MacBeth *t*-statistics are reported below the coefficient estimates. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

Dependent Variable *100	(1) RET_t	(2) RET_t	(3) RET_t	(4) RET_t	(5) RET_t
$COMPLRET_{t-1}$	0.828***	1.543***	1.299***	1.503***	1.013***
	(5.04)	(7.90)	(7.37)	(7.30)	(7.39)
$COMPLRET_{t-1}$* *HighPeerNum*	0.816***				
	(3.14)				
$COMPLRET_{t-1}$* *Larger_Size*		-0.656***			
		(-4.23)			
$COMPLRET_{t-1}$* *More_Analyst*			-0.313**		
			(-2.34)		
$COMPLRET_{t-1}$* *Higher_InstitOwn*				-0.575***	
				(-3.73)	
$COMPLRET_{t-1}$* *More_IdioVol*					0.419***
					(2.59)
Controls	Yes	Yes	Yes	Yes	Yes
N	1,002,682	1,002,682	1,002,682	1,002,682	1,002,682
R^2	0.038	0.030	0.035	0.036	0.037

Table 9. Patent Shocks and Complementor Returns

This table reports how patent-induced stock price shocks to a focal firm transmit to complementors, industry peers, and technology peers. The key variable, $CAR_{[0,1]}$, is the sum of a focal firm's cumulative abnormal returns around 2-day windows (day *t* and day *t+1*) of patent issuance dates in a month. In columns 1 - 3, the dependent variable is strong, medium and weak complementor return. Strong complementor returns are the equal-weighted average returns of complementors in the 99th and 98th percentile as ranked by their complementarity score, COMPL. Medium complementor returns are the equal-weighted average returns of complementors in the 97th and 96th percentile as ranked by their complementarity score. Weak complementor returns are the equal-weighted average returns of complementors in the 95th and 94th percentile as ranked by their complementarity score. The dependent variable is either industry average returns, *INDRET*, in column 4 or technological peers returns in column 5. In Panel A, we focus on the stock market reaction of peer firms in the contemporaneous month. In Panel B, we focus on the stock market reaction of peer firms in the subsequent month. The control variables include *SIZE, BM,* and *MOM*. All variables are defined in Appendix A. Both firm fixed effects and month fixed effects are included. Standard errors are double-clustered by both firm and month. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

Panel A: Patent Shock Transmission in the Contemporaneous Month

	$COMPLRET_t$			$INDRET_t$	$TECHRET_t$
	(1)	(2)	(3)	(4)	(5)
	Strong	*Medium*	*Weak*		
$CAR_{[0,1]}$	0.046***	0.027***	0.024***	0.050***	0.057***
	(8.51)	(5.84)	(6.56)	(10.44)	(11.28)
Controls	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	106,358	90,400	86,514	106,358	78,762
R^2	0.631	0.667	0.727	0.755	0.864

Panel B: Patent Shock Transmission in the Subsequent Month

	$COMPLRET_{t+1}$			$INDRET_{t+1}$	$TECHRET_{t+1}$
	(1)	(2)	(3)	(4)	(5)
	Strong	*Medium*	*Weak*		
$CAR_{[0,1]}$	0.018***	0.004	0.005	0.008*	0.007
	(3.49)	(1.01)	(1.63)	(1.66)	(1.30)
Controls	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	103,362	88,056	84,276	103,362	76,446
R^2	0.629	0.664	0.726	0.751	0.861