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Text-Based Industry Momentum

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Abstract

We test the hypothesis that low-visibility shocks to text-based network industry peers can explain industry momentum. We consider industry peer firms identified through 10-K product text and focus on economic peer links that do not share common Standard Industrial Classification (SIC) codes. Shocks to less visible peers generate economically large momentum profits and are stronger than own-firm momentum variables. More visible traditional SIC-based peers generate only small, short-lived momentum profits. Our findings are consistent with momentum profits arising partially from inattention to economic links of less visible industry peers.

I. Introduction

Since Jegadeesh and Titman (1993) reported the momentum anomaly, a large literature has documented the magnitude of momentum, its pervasiveness in many settings,[1] and its potential explanations. Jegadeesh and Titman (2001), (2011) document the continued robustness of momentum in more recent years. Yet scholars continue to disagree about the causes of momentum. In their recent review, (Jegadeesh and Titman (2011), p. 507) state that "financial economists are far from reaching a consensus on what generates momentum profits, making this an interesting area for future research." We focus on the importance of horizontal industry links between firms with varying degrees of visibility to investors and momentum.

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[1]Rouwenhorst (1998), (1999) further shows that momentum exists around the world, and Gebhardt, Hvidkjaer, and Swaminathan (2005) show that it spills over into bond markets.

Using the text-based network industry classification (TNIC) (Hoberg and Phillips (2016)) to identify peer firms, our first central finding is that industry momentum profits are highly robust and substantially larger than previously documented. Industry momentum was first documented by Moskowitz and Grinblatt (1999). However, Moskowitz and Grinblatt's conclusion that industry momentum matters is called into question by Grundy and Martin (2001), who show that industry momentum using peers based on Standard Industrial Classification (SIC) codes is not robust to the bid–ask bounce and to lagging the portfolio formation period by 1 month. We document that industry momentum is substantially more important for less visible text-based industry peer firms, and this stronger form of industry momentum is highly robust to the issues raised by the Grundy and Martin critique.

Recently, Hong and Stein (1999) and Barberis, Shleifer, and Vishny (1998) suggest that inattention or slow-moving information might also be a key driver of momentum. Our second central finding is that inattention to shocks to less visible industry peers can explain these large industry momentum profits.

We note 5 key results that support our conclusion that inattention is likely a central explanation for the industry momentum we document. First, the economic magnitudes are too large to be explained by simple differences in the information content of industry classifications. For example, Hoberg and Phillips (2016) find that TNIC is roughly 25% to 40% more informative than SIC codes in their ability to explain a battery of variables in cross section. These gains are much smaller than the 100% to 200% improvements in momentum profits we document here.

Second, we find that industry momentum profits are stronger following shocks to specific peers that are less visible to the investment community. SIC peers are widely reported in financial databases, financial reports, regulatory disclosures, and online data resources. However, TNIC peer data were not widely distributed during our sample period, and the first paper focusing on TNIC peers (Hoberg and Phillips (2010)) was published late in our sample period.[2] Because TNIC and SIC both capture horizontal relatedness, we consider TNIC peers that are not SIC peers to examine the role of visibility. We predict and find that shocks to TNIC peers that are not SIC peers, and shocks in product markets where SIC and TNIC peers disagree (high disparity), generate the strongest momentum returns.

Third, we find that the timing of momentum profits due to shocks to SIC peer firms versus less visible TNIC peer firms is fundamentally different. Stock return shocks to SIC peers transmit to the focal firm in 1 to 2 months. In contrast, and consistent with inattention and slow-moving information, analogous shocks to less visible TNIC peers take up to 12 months to transmit. We also find that own-firm share turnover increases only with significant lags when TNIC peers have high stock returns, whereas share turnover increases immediately when SIC peers are similarly shocked.

[2]Publication dates of academic articles pertaining to predictable stock returns are relevant, as McLean and Pontiff (2016) find evidence that anomalies attenuate after such publication, perhaps because of increased attention.

Under the inattention hypothesis, a related prediction is that systematic shocks, which are highly visible by definition, will decay more quickly than idiosyncratic shocks, which are localized and less visible. Alternative risk-based theories predict that returns will be linked more to systematic shocks than to idiosyncratic shocks. We find that only idiosyncratic shocks transmit slowly and generate industry momentum. These findings are consistent with inattention and not systematic risk-based explanations.

Fourth, in a direct test of inattention to economic links motivated by Cohen and Frazzini (2008), we find that longer term industry momentum profits exist only when mutual funds on average do not jointly own economically linked firms. This implies profits are largest where there is little institutional attention to the given economic links. Our results suggest that momentum is stronger when fewer professional investors (mutual fund managers) are paying attention to our less visible economically linked firms, as they are not in the portfolios of professional investors. Supporting the conclusion that information about TNIC-related firms is less visible to the market, we find that sector funds are more likely to own pairs of firms that are in the same SIC code but are less likely to own pairs of TNIC peer firms.

Fifth, we find that momentum profits are driven by economic links that are relatively local in the product market network. The spatial nature of TNIC industries allows us to examine whether momentum is related to the breadth of various peer shocks. We define broad shocks as those that affect a large set of related firms that are distant in the product market space, whereas localized shocks affect only a small number of proximate firms. We find that local TNIC peers calibrated to be as fine as the SIC 4-digit (SIC-4) classification generate strong momentum returns, as do TNIC peers that are calibrated to be as fine as the SIC 3-digit (SIC-3) network. We also find and report that broader TNIC peers, calibrated to be as coarse as the SIC 2-digit (SIC-2) industry network, still generate significant industry momentum profits, albeit at a lower magnitude. Our results suggest that only 2% to 5% of all firm pairs are needed to explain industry momentum, consistent with momentum being idiosyncratic and localized in the product market.

Our results thus support the following interpretation of momentum profit cycles. Initially, the market underreacts to large shocks to economically linked firms. This underreaction is more severe when the economic links are less visible. Furthermore, the time required for shocks to transmit is substantially longer.

Our findings indicate that industry momentum profits have high Sharpe ratios, as they can be easily diversified despite their high returns. These findings cannot be explained by a systematic risk explanation and overall are consistent with inattention driving at least part of industry momentum profits.[3]

[3]Systematic risk models, which require transparency for equilibrium pricing, predict that links with more visibility should generate stronger risk premia. Investors need to be aware of risk loadings to price them in equilibrium. Risk models also require that systematic shocks are pervasive and difficult to diversify. In conflict with these predictions, we instead find that less visible links matter more than highly visible links, and we find that momentum is most priced when shocks are localized, unrelated to risk factors, and thus easier to diversify. Griffin, Ji, and Martin (2003) also suggest that systematic risk likely cannot explain momentum through a different test (the absence of a business-cycle effect).

We examine various momentum horizon variables to further assess the findings of Jegadeesh and Titman (1993) and Moskowitz and Grinblatt (1999). Using the standard 1-year momentum horizon, we find that the less visible TNIC peer momentum variables are substantially more significant than are SIC peers or own-firm momentum variables in standard Fama–MacBeth (1973) return regressions. Moreover, the economic magnitude of TNIC peer momentum variables is considerably larger. Our results are strong for both the 6-month horizon and the subsequent 6-month period from months $t+7$ to $t+12$.

Our findings run counter to recent conclusions on industry momentum in the literature, as Grundy and Martin (2001) show that industry momentum for SIC peers is not robust to the bid–ask bounce and to lagging the portfolio formation period by 1 month. To underscore this point, Jegadeesh and Titman (2011) highlight Grundy and Martin's findings in their review and conclude that industry momentum cannot explain the momentum anomaly. However, they do conclude that momentum profits likely "arise because of a delayed reaction to firm-specific information" (Jegadeesh and Titman (2011), p. 497). The conclusion in the literature that industry momentum matters little is thus based on using highly visible traditional SIC-based industry links. We show that this long–standing conclusion is reversed when less visible text-based industry links are used to retest the industry momentum hypothesis.

Recent work by Cohen and Frazzini (2008) and Menzley and Ozbas (2010) suggests that inattention also plays a role in generating predictable returns following shocks to vertically linked firms. We focus on shocks to horizontally linked firms and not to vertically linked firms, and our objective is to address the industry momentum literature. Controls for shocks to vertically linked firms do not materially affect our results. Furthermore, only shocks to our less visible horizontal industry peers, and not vertical peers, can explain own-firm momentum. The finding that vertical and horizontal peers contain distinct information is expected as horizontal economic links overlap little with vertical links, as reported in Hoberg and Phillips (2016).

Our results are consistent with the momentum literature in terms of the duration of momentum profits being roughly 12 months. These long horizons explain why our results are not driven by the existing short-horizon finding that large firm returns lead small firm returns especially within industry (see Hou (2007)). Moreover, our results are robust to controlling for lagged return variables used in Hou (2007), including lagged return variables based on larger firms.

This article is organized as follows: Section II presents hypotheses motivated by the theoretical models of Hong and Stein (1999) and Barberis et al. (1998). Section III describes our data and methods. Section IV presents initial evidence on the relation between share turnover and company visibility. Section V presents summary statistics and results regarding comovement and short-term lagged information dissemination. Section VI considers long-term momentum. Section VII considers mutual fund ownership and whether common ownership of economically linked firms reduces momentum profits through a visibility channel as in Cohen and Frazzini (2008). Section VIII provides our robustness tests. Section IX concludes.

II. Hypotheses

In this section, we formalize our predictions through three central hypotheses. Our predictions match those of the theoretical models by Hong and Stein (1999) and Barberis et al. (1998). However, we further predict that the specific mechanism driving inattention momentum is the presence of less visible industry links through which large price shocks need to propagate.

Hypothesis 1. Industry momentum arises from underreaction to shocks to groups of peer firms with less visible economic links.

Hypothesis 2. Past returns of less visible industry peers are stronger than past returns of highly visible peers in simultaneous regressions predicting future returns. Momentum profits from less visible peer shocks are also economically larger than profits from highly visible peer shocks.

Hypothesis 3. Momentum profits are largest following idiosyncratic shocks to peers, as fewer investors likely pay attention to such localized shocks. Profits are smaller following more visible systematic shocks.

Hypotheses 1–3 are direct implications of the inattention to economic shocks to economically related firms. We test Hypotheses 1–3 using horizons up to 1 year. Our use of less visible TNIC peers and highly visible SIC peers that measures the same fundamental concept of industry relatedness, but with different levels of visibility to investors, provides a way to examine these hypotheses.

III. Data and Methods

The methodology we use to extract 10-K text follows Hoberg and Phillips (2016). The first step is to use Web crawling and text parsing algorithms to construct a database of business descriptions from 10-K annual filings from the U.S. Securities and Exchange Commission (SEC) Electronic Data Gathering, Analysis, and Retrieval (EDGAR) Web site from 1996 to 2011. We search the EDGAR database for filings that appear as "10-K," "10-K405," "10-KSB," or "10-KSB40." The business descriptions appear as Item 1 or Item 1A in most 10-Ks. The document is then processed using the programming language APL to extract the business description text and the company identifier, CIK. Business descriptions are legally required to be accurate, as Item 101 of Regulation S-K requires firms to describe the significant products they offer, and these descriptions must be updated and representative of the current fiscal year of the 10-K.

We use the Wharton Research Data Services (WRDS) SEC Analytics product to map each SEC Central Index Key (CIK) to its Compustat Global Company Key (GVKEY) on a historical basis. We require that each firm has a valid link from the 10-K CIK to the Center for Research in Security Prices (CRSP)/Compustat merged database as well as a valid CRSP permno (permanent number) to remain in our database. Our focus is therefore on publicly traded firms in the CRSP database, and the CRSP monthly returns database is our primary database. Because our 10-K data begin with fiscal years ending in 1996, after using the lag structure advocated in Davis, Fama, and French (2000), our starting point is the CRSP monthly returns database beginning in July 1997 and ending in Dec. 2012. We exclude observations from our returns database if their stock price is less than $1 to avoid drawing inferences from penny stocks.

A. Asset Pricing Variables

We construct size and book-to-market ratio variables following Davis et al. (2000) and Fama and French (1992). Market size is the natural log of the CRSP market capitalization. Following the lag convention in the literature, we use size variables from each June and apply them to the monthly panel to predict returns in the following 1-year interval from July to June.

The book-to-market ratio is based on CRSP and Compustat variables. The numerator, the book value of equity, is based on accounting variables from fiscal years ending in each calendar year (see Davis et al. (2000) for details). We divide each book value of equity by the CRSP market value of equity prevailing at the end of December of the given calendar year. We then compute the log book-to-market ratio as the natural log of the book value of equity from Compustat divided by the CRSP market value of equity. Following standard lags used in the literature, this value is then applied to the monthly panel to predict returns for the 1-year window beginning in July of the following year until June 1 year later.

For each firm, we compute the own-firm momentum variable as the stock return during the 11-month period beginning in month $t-12$ relative to the given monthly observation to be predicted, and ending in month $t-2$. This lag structure that avoids month $t-1$ is intended to avoid contamination from microstructure effects, such as the well-known 1-month reversal effect. Because industry momentum variables do not experience the 1-month reversal effect, we compute our baseline industry momentum variables as the average return of the given firm's industry peers over the complete window from $t-12$ to $t-1$. For robustness, we also consider industry momentum variables measured from $t-12$ to $t-2$ and show that our results are robust (indicating that TNIC momentum variables are not susceptible to the Grundy and Martin (2001) critique).

After requiring adequate data to compute the aforementioned asset pricing control variables, and requiring valid return data in CRSP and a valid link to 10-K data from EDGAR, our final sample has 805,090 observations.

B. Industry Momentum Variables

The variables we focus on are based on the return of peer firms residing in related product markets relative to a given firm (henceforth, the focal firm). The central question is whether shocks to related firms generate comovement and, more interesting, whether the shocks disseminate slowly and thus entail prolonged return predictability. We consider industry returns using both TNIC peers and SIC peers at different levels of aggregation.

1. TNIC Momentum Variables

We consider simultaneously measured monthly returns of product market peers. For text-based industries, we consider the TNIC of Hoberg and Phillips (2016). In particular, we compute the equal-weighted average of the simultaneous monthly stock returns of TNIC industry peers (excluding the focal firm itself). We use the TNIC-3 network, which is calibrated to have a granularity to be comparable with SIC-3 code. We use this level of granularity as it is the standard granularity used in the literature, but also to be consistent with our theoretical prediction that the impact of low visibility is likely to be stronger in more localized regions of the product market space, which are more idiosyncratic in nature. We briefly note that results later in this article illustrate that broader classifications, such as TNIC levels of granularity that are matched to SIC-2 industries, do not contain any additional marginal information beyond our baseline method.

We compute ex ante TNIC peers returns using both equal-weighted and value-weighted averages. However, we focus on equal weighting as this method is consistent with visibility playing an important role. We hypothesize that large peers are likely subject to high attention, and shocks to large peers are priced appropriately with little underreaction and thus little industry momentum. Hence, shocks to smaller peers should more strongly predict focal-firm returns under this hypothesis. Our results, presented later, confirm this prediction.

It is further important to note that the choice of using ex ante equal- versus value-weighted peer average returns does not preclude our momentum variables predicting ex post returns using portfolios that are either equal or value weighted. Our central prediction is that by looking at more peers, even smaller peers, we can better predict the impact of shocks on a focal firm, even a large focal firm. We note that in tests reported throughout this article and in Table A5 of the Supplementary Material, for example, this prediction is strongly upheld in the data.

2. SIC-Based Industry Momentum Variables

For traditional SIC-based industry momentum returns, we follow the literature to ensure consistency. Hence, the methods we use to compute our SIC-based momentum variables differ on two dimensions from how we compute our TNIC-based momentum variables. In particular, following Moskowitz and Grinblatt (1999), we consider highly coarse SIC-based classifications and we value weight industry peers when computing SIC-based industry momentum variables. In our main specification, we use Fama–French (1997) 48 (FF-48) industries, which are indeed considerably more coarse than are our TNIC-3 industries, which are calibrated to SIC-3 codes.

To ensure that these differences between our chosen SIC- and TNIC-based portfolios do not strongly affect our results, we examine robustness to a basket of 8 variations on how we compute SIC-based momentum variables. In Table A1 of the Supplementary Material, for example, we consider 4 levels of SIC granularity: i) 20 industries from Moskowitz and Grinblatt (1999) that are constructed from SIC codes, ii) the FF-48 industries that are also derived from SIC codes, iii) SIC-2 codes, and iv) SIC-3 codes.

C. Industry Disparity

We consider more refined subsamples based on the data structures generated by text-based industries. In particular, we consider "disparity," which we define as the extent to which a given focal firm's less visible TNIC peers disagree with highly visible SIC peers. In particular, disparity is equal to 1 minus the ratio of total sales of peers in the intersection of TNIC-3 and SIC-3 industry peer groups, divided by the total combined sales of peers in the union of TNIC-3 and SIC-3 peer groups overall. The use of sales weights is based on the assumption that the price of a focal firm is more likely to be influenced by larger rivals than smaller rivals.

A firm in an industry with a high degree of disparity is thus in an industry with a large number of big TNIC-3 peers that are not SIC-3 peers and vice versa. Our prediction is that the dissemination of information should be particularly lagged when disparity is high, as this would indicate that less visible links are not replicated by highly visible links, leaving fewer alternative channels to disseminate information for these links.

D. Systematic and Idiosyncratic Risk

We consider whether shocks to peers are idiosyncratic or systematic in nature. We thus begin with a simple decomposition of any firm's monthly return into a systematic and an idiosyncratic component. We use daily stock return data to implement this decomposition for each monthly stock return of each firm in each month. Using daily excess stock returns as the dependent variable, we regress these returns onto the daily stock returns of the market factor, high minus low market-to-book (HML), small minus big (SMB), and up minus down momentum (UMD) factors.[4]

The predicted value from this regression is the systematic return. We use the geometric return formulation to aggregate the systematic daily returns to a database of monthly systematic stock returns for each firm in each month. We define the idiosyncratic component of returns as the monthly excess stock return minus the systematic excess stock return in the same month. We thus have excess stock returns, systematic stock returns, and idiosyncratic stock returns for each firm in each month.

IV. Industry Peer Returns and Share Turnover

We begin by providing evidence that TNIC peers were indeed less visible than SIC peers during our sample period. Because share turnover is a direct consequence of attention (see, e.g., Gervais, Kaniel, and Mingelgrin (2001)), we examine the relation between share turnover and industry peer returns. Figure 1 plots average levels of turnover (trading volume scaled by shares outstanding) surrounding months during which either SIC peers or TNIC peers experienced the highest quintile of samplewide returns in the given month. Graph A shows that although SIC peers have a stronger jump in turnover around the time of the shock consistent with greater attention to these economic links, the difference between TNIC and SIC peers in this graph is modest. However, this unconditional result is primarily because high-quintile stock returns to SIC peers and TNIC peers are highly correlated, as both classifications contain many of the same firms.

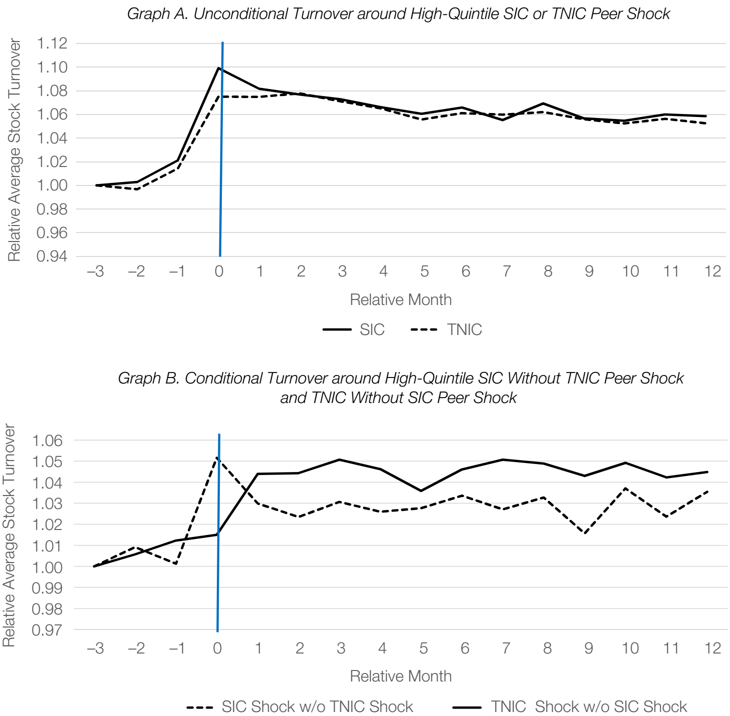
Graph B in Figure 1 separates the effects of TNIC and SIC peers and is more informative. This graph displays turnover when TNIC peer returns are in the highest quintile and SIC peer returns are near 0 (in the 40th to 60th percentiles) and

[4]We thank Kenneth French for providing the daily factor returns on his Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

FIGURE 1

Turnover Following Return Shocks

Figure 1 is the event-study graph of own-firm average turnover surrounding months when the firm's Standard Industrial Classification (SIC) or text-based network industry classification (TNIC) peers have returns in the highest quintile. Graph A shows unconditional average turnover rates around month 0 (date of high peer return). All results are scaled so that the first month in the event study has unit turnover. We note that the unconditional results for SIC and TNIC are similar because having SIC peers with returns in the highest quintile is highly correlated with having TNIC peer returns in the highest quintile. Hence, Graph B is more informative. Here, we plot turnover surrounding a month when SIC peers have returns in the highest quintile while TNIC peers have returns between the 40th and 60th percentiles (average returns). Analogously, we plot results when TNIC peers have high-quintile returns and SIC peers have returns in the 40th to 60th percentiles. Graph B thus allows us to show more how turnover evolves when one peer group is uniquely shocked.



vice versa. This separation allows us to examine how turnover evolves when one group of peers is shocked but not the other. We find that when SIC peers are shocked and TNIC peers are not (dotted line), turnover increases immediately at time $t=0$ and then reverts to a stable level 2 months later. In contrast, when TNIC peers are uniquely shocked (solid line), turnover does not immediately increase at $t=0$. Instead, turnover increases the month after the shock and then exhibits no reversion. These results suggest that large stock return shocks to TNIC peers generate lagged and prolonged increases in visibility consistent with TNIC peers being less visible than SIC peers. Later in this article, we provide additional evidence that TNIC peers are less visible than SIC peers based on common mutual fund ownership of linked peers.

V. Return Comovement

In this section, we present summary statistics and examine the short-term relation between the focal firm's returns and various peers' returns. We examine comovement of stocks before turning to momentum to establish that the peers identified using the text-based methods we develop are indeed relevant in understanding linked firms. Panels A–C of Table 1 present summary statistics for monthly returns using different industry definitions our firm–month observations from July 1997 to Dec. 2012. The average monthly return in our sample is 0.9% with a standard deviation of 17.2%. The average monthly return of our various peer groups is analogous, but the standard deviation of these variables is lower (7.0% and 9.4%). This result occurs because these peer return variables are averages, which reduces the level of variation relative to that of individual firms.

Panel D of Table 1 reports Pearson correlations. It is not surprising that the book-to-market ratio and firm size variables are not highly correlated with

TABLE 1
Summary Statistics

Table 1 reports summary statistics for our sample of 805,090 observations based on monthly return data from July 1997 to Dec. 2012. Observations are required to be in the Center for Research in Security Prices (CRSP), Compustat, and our 10-K database. Consistent with existing studies, observations must have a 1-year history of past stock return data to compute momentum variables, and must have a stock price in the preceding month that is greater than $1. One observation is 1 firm in 1 month, and basic asset pricing variables are displayed in Panel A (see Section III.A for descriptions). The 11-month firm momentum variable measures past returns from months $t-2$ to $t-11$, again consistent with the literature. We also include a 1-month firm momentum variable. The industry momentum variables (FF-48 (Fama–French (1992) 48 industries) using value-weighted peers in Panel B and TNIC-3 (text-based network industry classification) using equal-weighted peers in Panel C) are from months $t-1$ to $t-12$ and are based on corresponding averages for the given industry classifications, but all industry returns exclude the firm itself as this form of momentum is reflected in the own-momentum variable. Industry momentum variables do not separate out the first month following convention in the literature (although our results are robust to doing so). See Section III.B for descriptions of the industry momentum variables. Panel D displays Pearson correlation coefficients for 1-month return variables.

Variable	Mean	Std. Dev.	Minimum	Median	Maximum
Panel A. Data from the Literature					
Monthly return	0.009	0.172	−0.981	0.002	9.374
Log book-to-market ratio	−7.577	0.931	−16.164	−7.496	−1.223
Log market capitalization	12.664	2.009	6.233	12.575	20.121
Month $t-1$ past return	0.012	0.172	−0.878	0.003	13.495
Month $t-2$ to $t-12$ past return	0.158	0.811	−0.989	0.050	98.571
Panel B. Data from FF-48 Industries					
Month $t-1$ past return	0.008	0.070	−0.437	0.011	0.622
Month $t-1$ to $t-3$ past return	0.027	0.126	−0.684	0.033	1.141
Month $t-1$ to $t-6$ past return	0.059	0.182	−0.770	0.059	1.806
Month $t-1$ to $t-12$ past return	0.158	0.315	−0.715	0.133	6.018
Panel C. Data from 10-K-Based-TNIC-3 Industries					
Month $t-1$ past return	0.012	0.094	−0.780	0.012	9.374
Month $t-1$ to $t-3$ past return	0.038	0.189	−0.952	0.034	10.202
Month $t-1$ to $t-6$ past return	0.075	0.291	−0.995	0.054	16.692
Month $t-1$ to $t-12$ past return	0.157	0.461	−0.997	0.097	26.500

Variable	Month t Own-Firm Return	Log Book-to-Market Ratio	Log Market Capitalization	Month $t-1$ Own-Firm Return	Month $t-1$ FF-48 Industry Return
Panel D. Pearson Correlations					
Log book-to-market ratio	0.024				
Log market capitalization	−0.012	−0.308			
Month $t-1$ own-firm return	0.010	0.026	−0.022		
Month $t-1$ FF-48 return	0.076	0.012	−0.012	0.325	
Month $t-1$ TNIC-3 return	0.083	0.015	−0.017	0.402	0.622

any of the momentum variables. The table also shows that own-firm returns are 40.2% correlated with TNIC-3 peer returns and 32.5% correlated with SIC-based FF-48 peer returns. The TNIC-3 and FF-48 peer returns are also 62.2% mutually correlated, indicating they have some common information. Despite the information overlap, our later tests show that both have distinct signals, and TNIC-3 momentum is stronger than FF-48 momentum.

Our short-term tests assess the extent to which focal-firm monthly returns comove with TNIC-3 and FF-48 peer returns, and whether information in these variables disseminates gradually. We consider Fama–MacBeth (1973) regressions where the dependent variable is the month t focal-firm return. In simultaneous return tests, we consider specifications in which TNIC-3 and FF-48 peer returns is the key right-hand side (RHS) variable. We also include controls for the log book-to-market ratio, log firm size, and lagged own-firm return from both $t-1$ and month $t-12$ to $t-2$.

Panel A of Table 2 displays the results. All RHS variables are standardized to have unit standard deviation before running the regressions so that coefficient magnitudes can be directly compared. When included together in row 1, we find that the TNIC-3 peer returns generate larger price impact (coefficient = 0.036) than do the SIC-based FF-48 peer returns (coefficient = 0.021). A 1-standard-deviation shift in TNIC-3 peers implies a return impact of 3.6% on the focal firm. In rows 2–7, we run analogous regressions with the individual lags for TNIC and SIC going out 6 months each. Thus, there are 12 lagged RHS variables in addition to controls for log book-to-market, log market capitalization, and own-firm month $t-2$ to $t-12$ momentum (not reported to conserve space).

The results show that TNIC beats FF-48 in both coefficient magnitudes and significance levels going out all 6 months. In particular, FF-48 momentum becomes negative and insignificant after 3 months. Table A2 of the Supplementary Material further shows that information disseminates more slowly when industries have high disparity. Table A3 shows, based on a decomposition of returns into systematic and idiosyncratic parts, that idiosyncratic peer shocks disseminate slowly and remain highly significant in 2-month horizons and beyond. Our findings are broadly consistent with TNIC peers being stronger, potentially because of the effects of inattention.

VI. Industry Momentum

We consider momentum variables with varying horizons and test the hypothesis that momentum might be partially explained by the slow dissemination of shocks to product market peers. Our initial tests explore whether less visible TNIC peer returns contribute information above SIC peer returns.

We use as our baseline specification the following 2 industry variables: TNIC-3 industry momentum and SIC-based FF-48 peer industries. In our main tests, we use TNIC-3 returns constructed using equal weighting, as our hypothesis is that shocks to smaller firms are more susceptible to inattention and hence their impact on peers is less likely to be priced efficiently. In robustness tests, we also consider value-weighted peers. We focus on ex ante monthly returns of TNIC and SIC peers as independent variables, and we examine their relation with ex post

TABLE 2
Return Comovement

Table 2 reports Fama–MacBeth (1973) regressions with own-firm monthly stock return as the dependent variable. One observation is 1 firm from July 1997 to Dec. 2012. The independent variables include the text-based network industry classification (TNIC-3) return benchmark (excluding the firm itself) and the Fama–French 48-industry (based on Standard Industrial Classification (SIC)) return (FF-48) benchmark (also excluding the firm itself). Although we do not report them to conserve space, we also include controls for log book-to-market ratio, log size, a dummy for negative book-to-market ratio stocks, and a control for momentum (defined as the own-firm 11-month lagged return from months $t-12$ to $t-2$). All industry momentum variables are defined in Section III.B. We consider industry peer variables that are simultaneously measured with the focal firm return (month t returns), as well as various lags ranging from 1 month ($t-1$) to 6 months ($t-6$) as noted in the column headers. The table displays results for our baseline specification based on FF-48 and a TNIC-3 network calibrated to be as granular as 3-digit SIC. The FF-48 peer returns are value weighted and the TNIC-3 returns are equal weighted. All right-hand-side variables are standardized to have a standard deviation of 1 for ease of comparison and interpretation. All standard errors are adjusted using Newey–West (1987) with 2 lags. t-statistics are reported in parentheses.

TNIC-3 Returns							FF-48 Returns							
t	$t-1$	$t-2$	$t-3$	$t-4$	$t-5$	$t-6$	t	$t-1$	$t-2$	$t-3$	$t-4$	$t-5$	$t-6$	R^2 / No. of Obs.
0.036							0.021							0.070
(33.03)							(24.07)							805,090
0.042														0.064
(37.39)														805,090
							0.034							0.046
							(34.78)							805,090
0.032	0.005	0.002	0.002				0.020	0.000	−0.000	0.001				0.076
(34.22)	(7.94)	(3.83)	(3.83)				(24.24)	(0.38)	(−0.20)	(1.42)				776,209
0.030	0.005	0.002	0.002	0.001	0.001	0.001	0.019	0.000	0.000	0.001	0.000	−0.001	−0.001	0.079
(33.26)	(8.41)	(3.77)	(4.08)	(2.11)	(1.93)	(2.24)	(22.43)	(0.34)	(0.27)	(1.45)	(0.34)	(−1.15)	(−1.19)	745,852
	0.008	0.004	0.003					0.002	−0.000	0.001				0.050
	(6.59)	(3.10)	(2.96)					(1.65)	(−0.05)	(1.49)				776,209
	0.007	0.003	0.003	0.002	0.001	0.002		0.001	−0.001	0.002	−0.000	−0.000	−0.000	0.060
	(7.30)	(3.44)	(3.83)	(2.11)	(1.13)	(1.97)		(1.19)	(−0.50)	(1.53)	(−0.05)	(−0.28)	(−0.30)	745,852

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own-firm returns using various lags. This test assesses whether lagged monthly returns from more versus less visible product market peers predict monthly ex post focal-firm returns.

We consider standard Fama–MacBeth (1973) regressions where the dependent variable is the own-firm month t excess stock return. In addition to book-to-market and size controls, we consider 4 variables based on past returns. For own-firm returns, we include returns from the past 1 month, which relate to the 1-month reversal anomaly, and returns over the 11-month period beginning in month $t-12$ and ending in month $t-2$. For industry returns, we include FF-48 and TNIC-3 peer returns for months $t-12$ to $t-1$. Both industry momentum variables are based on the past return window $t-1$ to $t-12$, whereas the own-firm momentum variable skips the most recent month (consistent with other studies).

As discussed earlier, our FF-48 industry momentum variables are value weighted, and TNIC-3 industry momentum variables are equal weighted. We use different weighting mechanisms because these momentum variables are likely driven by potentially different mechanisms, as each is stronger using a diametrically opposite specification. We advocate that TNIC momentum is likely driven by inattention and underreaction to the shocks of less visible peers. In contrast, some evidence we find suggests that SIC-based momentum is shorter lived and is only significant for smaller firms when their larger SIC-based peers are shocked. This suggests that SIC-based momentum might be driven by the industry lead–lag anomaly reported in Hou (2007). Because, in contrast, TNIC momentum is long-lived, and is highly robust for both small- and large-capitalization firms, a battery of tests leads us to conclude that Hou cannot explain TNIC momentum.

We focus on TNIC momentum. Throughout our study, we include complete controls for, and comparisons to, SIC-based momentum to illustrate that TNIC and SIC-based momentum variables are fundamentally distinct. In the column headers, we report the sample used in each regression: the entire sample or the subsample that ends before the 2008–2009 crisis period. All RHS variables are standardized before running the regressions for ease of comparison. We test the baseline industry momentum hypothesis in Table 3 for the entire sample (Panel A) and for the sample ending in Dec. 2007 (Panel B), which excludes the financial crisis and the subsequent recovery period. The results for the longer horizon momentum variables illustrate that when own-firm and FF-48 momentum variables are included alone, they are both generally significant. However, when they are included alongside the less visible TNIC-3 peers, both lose a material amount of their predictive power and are either insignificant or only marginally significant. Also relevant is the fact that TNIC-3 momentum is highly significant in both samples, and it does not lose much of its significance when FF-48 or own-firm momentum variables are included. We conclude that the TNIC momentum variables have the greatest impact in both samples. These findings, when considered with the results of the previous section, support the conclusion that shocks to related product market links that are less visible can explain a large fraction of the industry momentum anomaly.

In Table 4, we split the yearly momentum variables into 2 half-year periods. We examine these splits to examine the relative decay rate of momentum. The regressions are similar to those in Table 3, except that we divide the momentum

TABLE 3

Fama–MacBeth Return Regressions: Various 1-Year Momentum Variables

Table 3 reports Fama–MacBeth (1973) regressions with the monthly stock return as the dependent variable. The independent variables are all measured ex ante using the lag structure given by Fama and French (1992). All industry momentum variables are defined in Section III.B. The key variables include 10-K-based text-based network industry classification (TNIC-3) momentum, Fama–French 48-industry (FF-48) (based on Standard Industrial Classification (SIC)) momentum, and own-firm momentum. Both industry momentum variables are based on the past return window $t-1$ to $t-12$, and the own-firm momentum variable skips the most recent month (consistent with other studies); we separately consider the most recent month (known as the reversal variable). TNIC-3 industry momentum variables are based on equal-weighted peers and FF-48 momentum variables are based on value-weighted peers. In both cases, the firm itself is excluded from the average. We consider the entire sample in Panel A, and the sample that ends before the 2008–2009 crisis period in Panel B. All right-hand-side variables are standardized before running the regression for ease of comparison. All standard errors are adjusted using Newey–West (1987) with 2 lags. t-statistics are reported in parentheses.

Industry Past Return		Own-Firm Past Return					
TNIC-3 $t-1$ to $t-12$	FF-48 $t-1$ to $t-12$	$t-1$	$t-2$ to $t-12$	Log Market Capitalization	Log Book-to-Market Ratio	R^2	No. of Months/ No. of Obs.
Panel A. All Months: July 1997 to Dec. 2012							
		−0.004	0.001	−0.000	0.002	0.035	186
		(−3.19)	(0.52)	(−0.35)	(1.57)		805,090
0.008				−0.000	0.002	0.031	186
(3.07)				(−0.27)	(1.99)		805,090
	0.005			−0.000	0.002	0.026	186
	(2.60)			(−0.18)	(1.66)		805,090
	0.006	−0.004	0.001	−0.000	0.002	0.041	186
	(2.84)	(−3.54)	(0.28)	(−0.30)	(1.88)		805,090
0.008	0.003	−0.004	−0.000	−0.000	0.002	0.047	186
(4.36)	(1.65)	(−4.26)	(−0.18)	(−0.35)	(2.30)		805,090
Panel B. Precrisis Months (Pre-2008): July 1997 to Dec. 2007							
		−0.003	0.004	−0.001	0.003	0.037	126
		(−2.33)	(2.16)	(−0.74)	(1.43)		591,241
0.011				−0.001	0.003	0.037	126
(3.55)				(−0.67)	(1.89)		591,241
	0.007			−0.001	0.003	0.030	126
	(2.73)			(−0.59)	(1.49)		591,241
	0.006	−0.004	0.004	−0.001	0.003	0.044	126
	(2.74)	(−2.66)	(2.03)	(−0.70)	(1.71)		591,241
0.009	0.003	−0.004	0.002	−0.001	0.003	0.050	126
(4.15)	(1.56)	(−3.40)	(1.36)	(−0.73)	(2.17)		591,241

variables into one component from the most recent 6 months ($t-1$ to $t-6$) and a separate component from the previous 6 months ($t-7$ to $t-12$). In the columns, we consider the entire sample and the sample that ends before the 2008–2009 crisis period.

The results show that industry TNIC momentum persists into the longer monthly period $t-7$ to $t-12$, whereas the FF-48 industry past returns and the own-firm past returns matter only for the first 6 months. These findings strongly suggest that the information contained in TNIC peer returns is less visible to market participants, supporting the explanation of slow industry dissemination.

A. Bid–Ask Bounce, Vertical Links, and Simultaneous Returns

In Table 5, we consider three robustness tests to the base line specification of Table 3. Panel A examines robustness to the bid–ask bounce critique, as in Grundy and Martin (2001). For this test, we divide each industry momentum variable into two parts: an 11-month term ($t-2$ to $t-12$) and a 1-month term ($t-1$).

TABLE 4

Fama–MacBeth Return Regressions: Split Half-Year Variables

Table 4 reports Fama–MacBeth (1973) regressions with the monthly stock return as the dependent variable. The independent variables are all measured ex ante using the lag structure given by Fama and French (1992). All industry momentum variables are defined in Section III.B. The key variables include 10-K-based text-based network industry classification (TNIC-3) momentum, Fama–French 48-industry (FF-48) (based on Standard Industrial Classification (SIC)) momentum, and own-firm momentum. The regressions are similar to those in Table 3, except that we divide the momentum variables into one component from the most recent 6 months ($t-1$ to $t-6$) and a separate component from the previous 6 months ($t-7$ to $t-12$). TNIC-3 industry momentum variables are based on equal-weighted peers and FF-48 momentum variables are based on value-weighted peers. In both cases, the firm itself is excluded from the average. We consider the entire sample in Panel A, and the sample that ends before the 2008–2009 crisis period in Panel B. All right-hand-side variables are standardized before running the regression for ease of comparison. All standard errors are adjusted using Newey–West (1987) with 2 lags. t-statistics are reported in parentheses.

Industry Past Return											
TNIC-3		FF-48		Own-Firm Past Return							
$t-1$ to $t-6$	$t-7$ to $t-12$	$t-1$ to $t-6$	$t-7$ to $t-12$	$t-1$	$t-2$ to $t-6$	$t-7$ to $t-12$	Log Market Capitalization	Log Book-to-Market Ratio	R^2	No. of Months/ No. of Obs.	
Panel A. All Months: July 1997 to Dec. 2012											
				−0.004	0.001	0.002	−0.001	0.002	0.040	186	
				(−3.38)	(0.28)	(1.15)	(−0.52)	(1.58)		805,090	
0.008	0.004						−0.000	0.002	0.036	186	
(3.74)	(2.28)						(−0.33)	(2.19)		805,090	
		0.006	0.002				−0.000	0.002	0.030	186	
		(3.97)	(0.89)				(−0.21)	(1.85)		805,090	
		0.007	0.001	−0.004	−0.000	0.002	−0.001	0.002	0.049	186	
		(4.62)	(0.71)	(−3.99)	(−0.04)	(1.09)	(−0.49)	(2.09)		805,090	
0.008	0.004	0.003	−0.000	−0.005	−0.001	0.001	−0.001	0.002	0.056	186	
(5.29)	(2.88)	(2.98)	(−0.20)	(−4.97)	(−0.65)	(0.74)	(−0.54)	(2.58)		805,090	
Panel B. Precrisis Months (Pre-2008): July 1997 to Dec. 2007											
				−0.003	0.003	0.003	−0.002	0.002	0.043	126	
				(−2.49)	(1.54)	(1.76)	(−0.89)	(1.46)		591,241	
0.011	0.005						−0.001	0.003	0.043	126	
(4.21)	(2.39)						(−0.73)	(2.08)		591,241	
		0.007	0.002				−0.001	0.002	0.033	126	
		(4.22)	(1.10)				(−0.62)	(1.58)		591,241	
		0.007	0.001	−0.004	0.002	0.003	−0.002	0.003	0.051	126	
		(4.86)	(0.83)	(−3.01)	(1.30)	(1.73)	(−0.86)	(1.83)		591,241	
0.010	0.004	0.004	−0.000	−0.005	0.001	0.002	−0.002	0.003	0.059	126	
(4.98)	(2.73)	(3.31)	(−0.34)	(−4.02)	(0.55)	(1.37)	(−0.89)	(2.37)		591,241	

Two studies document that shocks to vertical peers can also predict future returns. Cohen and Frazzini (2008) consider vertical links using disclosed customer links from the Compustat segment tapes, and Menzley and Ozbas (2010) consider both upstream and downstream vertical links using the input–output tables from the Bureau of Economic Analysis. Our objective is to examine whether information in our horizontal links is distinct from information in these vertical links. Because Hoberg and Phillips (2016) document that TNIC links overlap very little with vertical links, we predict that information in both sets of links will be highly distinct.

Panel B of Table 5 examines robustness to shocks to vertically linked firms following Cohen and Frazzini (2008) (vertical links using customer links) and Menzley and Ozbas (2010) (vertical links using the input–output tables). We follow the procedures used in both studies to compute the respective vertical-peer shocks. For customer links, we use the Compustat segment files, and we lag information on major customers 6 months to avoid look-ahead bias. For the

TABLE 5

Fama–MacBeth Return Regressions: Bid–Ask Bounce, Vertical Links, and Simultaneous Returns

Table 5 reports Fama–MacBeth (1973) regressions with the monthly stock return as the dependent variable. The independent variables are all measured ex ante using the lag structure given by Fama and French (1992). All industry momentum variables are defined in Section III.B. We consider 3 robustness tests that use the same baseline specifications in Table 3, although each with one change meant to zoom in on a particular robustness issue. Panel A examines robustness to the bid–ask bounce critique as in Grundy and Martin (2001). Hence, we divide each industry momentum variable into 2 parts: an 11-month term ($t-2$ to $t-12$) and a 1-month term ($t-1$). Panel B examines robustness to shocks to vertically linked firms following Cohen and Frazzini (2008) (vertical links using customer links) and Menzley and Ozbas (2010) (vertical links using the input–output tables (IO tables)). We follow the procedures used in both studies to compute the respective vertical-peer shocks. For customer links, we use the Compustat segment files, and we lag information on major customers 6 months to avoid look-ahead bias. For IO table vertical-peer returns, we use the 1997 and 2002 IO tables given that we predict returns from July 1997 forward. Panel C examines robustness to including controls for simultaneous text-based network industry classification (TNIC-3) and Fama–French 48-industry (FF-48) returns measured in the same period as the dependent variable (month t). In the sample column, we note that we consider the entire sample, and the sample that ends before the 2008–2009 crisis period. All right-hand-side variables are standardized before running the regression for ease of comparison. All standard errors are adjusted using Newey–West (1987) with 2 lags. t-statistics are reported in parentheses.

Panel A. Robustness to Bid–Ask Bounce

	Past Return					
	$t-2$ to $t-11$		$t-2$ to $t-12$	$t-1$		
	Industry			Industry		
Sample	TNIC-3	FF-48	Own Firm	TNIC-3	FF-48	Own Firm
All	0.005 (2.85)		0.000 (0.04)	0.010 (7.99)		−0.005 (−5.35)
All		0.002 (1.15)	0.001 (0.39)		0.012 (6.86)	−0.005 (−4.66)
All	0.006 (3.95)	−0.001 (−0.59)	0.000 (0.06)	0.008 (8.41)	0.008 (5.34)	−0.005 (−5.70)
Pre-2008	0.007 (3.15)		0.002 (1.64)	0.011 (7.33)		−0.005 (−4.30)
Pre-2008		0.003 (1.60)	0.004 (2.17)		0.014 (6.72)	−0.004 (−3.59)
Pre-2008	0.007 (3.83)	−0.001 (−0.53)	0.002 (1.67)	0.009 (7.65)	0.009 (5.34)	−0.005 (−4.57)

Panel B. Robustness to Vertical Economic Links

	Past Return					
	Industry		Vertical			
	$t-1$ to $t-12$		$t-2$ to $t-12$		$t-1$	
Sample	TNIC-3	FF-48	Customer	IO Table	Customer	IO Table
All	0.008 (4.64)	0.003 (1.94)	0.001 (1.73)	−0.004 (−1.56)	0.001 (1.96)	0.006 (2.17)
Pre-2008	0.009 (4.26)	0.003 (1.96)	0.001 (2.17)	−0.003 (−1.34)	0.001 (1.50)	0.007 (2.60)

Panel C. Robustness to Simultaneous Returns

	Past Return				Industry Return	
	Industry		Own Firm		Simultaneous	
	$t-1$ to $t-12$					
Sample	TNIC-3	FF-48	$t-2$ to $t-12$	$t-1$	TNIC-3	FF-48
All	0.014 (6.37)	0.003 (0.86)	−0.001 (−0.27)	−0.005 (−5.75)	0.034 (35.24)	0.021 (22.86)
Pre-2008	0.013 (4.98)	0.000 (0.18)	0.002 (1.25)	−0.005 (−4.66)	0.034 (28.15)	0.018 (17.30)

input–output table vertical-peer returns, we use the 1997 and 2002 input–output tables given that we predict returns from July 1997 forward. Second, we compute the average returns separately for both upstream and downstream industries for the same 2 return windows. Third, we compute the average of the upstream and downstream peer returns for both return windows. We then reconsider the regressions in Table 3 including these 4 additional control variables (2 horizons, 2 types of vertical links).

Panel C of Table 5 examines robustness to including controls for simultaneous TNIC-3 and FF-48 monthly industry returns measured in the same period as the dependent variable (month t).

Panel A of Table 5 shows that our results are robust to the bid–ask bounce critique. Our TNIC past industry return measured from $t-2$ to $t-12$ remains highly significant. However, the table also shows, consistent with Grundy and Martin (2001), that SIC-based FF-48 momentum generally loses significance in this specification.

Panel B of Table 5 shows that our TNIC-3 past return variables are also highly robust to including the 4 vertical link variables. We are able to replicate the main results in both Cohen and Frazzini (2008) and Menzley and Ozbas (2010). For example, the shock to customers is positive and significant in most specifications. We also find that the input–output table vertical return is positive and significant at the shorter 1-month horizon.

We standardize all RHS variables in the regressions to have a 0 mean and a unit variance before running the regressions in Table 5. Hence, the coefficients can be compared and conclusions can be drawn regarding relative economic magnitudes. The table shows that the coefficients for TNIC-3 momentum are nearly a full order of magnitude larger than the vertical-peer coefficients for the long horizon, which is the standard horizon used to assess momentum. We conclude that shocks to both vertical and horizontal firms can independently predict returns, although shocks to horizontal peers are far more likely to explain momentum than are shocks to vertical peers. This statement is particularly true for the less visible TNIC peer links.

Finally, Panel C of Table 5 shows that our TNIC industry past return remains significant when including simultaneous TNIC-3 and FF-48 returns.

B. Various Horizons

We consider various horizons of the momentum variables. In particular, we consider 3-, 6-, 12-, and 24-month past returns. Panel A of Table 6 displays results for the full sample and shows that TNIC momentum is highly significant even at longer horizons up to 1 year. In contrast, FF-48 momentum is not significant beyond the 6-month horizon. The results for the FF-48 peers overall are smaller in magnitude and more short-lived.

The independent variables in our regressions are standardized before running the regressions, and the coefficients are interpretable. The 6-month economic impact of FF-48 peer peers (monthly return of 0.004 per sigma unit) is only half that of TNIC-3 peers at the same horizon (0.008). Moreover, TNIC-3 returns continue to accumulate returns, with a total summed coefficient of 0.013 over the 1-year horizon. FF-48 coefficients do not accumulate beyond 0.005. These findings suggest that the market more efficiently prices shocks to more visible peers. Our results are also robust during the broader sample, which includes the financial crisis, and the shorter sample, which ends in 2007. This is expected

TABLE 6

Fama–MacBeth Return Regressions: Various Momentum Horizons

Table 6 reports Fama–MacBeth (1973) regressions with the monthly stock return as the dependent variable. The independent variables are all measured ex ante using the lag structure given by Fama and French (1992). All industry momentum variables are defined in Section III.B. The key variables include own-firm momentum, Fama–French 48-industry (FF-48) (based on Standard Industrial Classification (SIC)) momentum, and 10-K-based text-based network industry classification (TNIC-3) momentum. We consider momentum horizons that range from months $t-1$ to $t-6$ for short horizons and months $t-13$ to $t-24$ for longer horizons. TNIC-3 industry momentum variables are based on equal-weighted peers and FF-48 momentum variables are based on value-weighted peers. In both cases, the firm itself is excluded from the average. We also include controls for size and book-to-market. We consider the entire sample in Panel A, and the sample that ends before the 2008–2009 crisis period in Panel B. All right-hand-side variables are standardized before running the regression for ease of comparison. All standard errors are adjusted using Newey–West (1987) with 2 lags. t-statistics are reported in parentheses.

	Past Return						
	Industry						
Momentum Duration	TNIC-3	FF-48	Own Firm	Log Market Capitalization	Log Book-to-Market Ratio	R^2	No. of Months/ No. of Obs.
Panel A. All Months: July 1997 to Dec. 2012							
Months 1–6	0.008	0.004	−0.001	−0.001	0.002	0.039	186
	(4.58)	(3.41)	(−0.56)	(−0.46)	(2.13)		805,090
Months 7–12	0.005	0.001	0.001	−0.001	0.002	0.033	186
	(2.93)	(0.40)	(0.88)	(−0.42)	(1.76)		805,090
Months 13–24	−0.002	−0.001	−0.002	−0.000	0.001	0.030	186
	(−1.17)	(−0.44)	(−2.04)	(−0.33)	(0.70)		762,400
Panel B. Precrisis Months (Pre-2008): July 1997 to Dec. 2007							
Months 1–6	0.010	0.005	0.001	−0.001	0.003	0.043	126
	(4.41)	(3.81)	(0.87)	(−0.82)	(1.93)		591,241
Months 7–12	0.006	0.001	0.002	−0.002	0.002	0.036	126
	(3.02)	(0.60)	(1.45)	(−0.77)	(1.54)		591,241
Months 13–24	−0.001	−0.000	−0.002	−0.001	0.001	0.036	126
	(−0.37)	(−0.24)	(−1.60)	(−0.77)	(0.57)		556,149

under our hypothesis that states momentum is due to inattention and not systematic risk.

C. Product Market Breadth

Does momentum arise from shocks to more localized peers in the product market space (we refer to such shocks as “local”) or broader shocks affecting larger numbers of product market peers (we refer to such shocks as “broad”)? We note the use of terms such as “local” and “broad” are intended to have a spatial interpretation as the TNIC industry classification can be viewed as a product market space shaped as a high dimensional sphere (see Hoberg and Phillips (2016)). Local peer shocks affect only a small region of the space around a firm, and broad peer shocks affect wide swaths of space around a firm. This question is particularly interesting because a theory of systematic risk predicts that only broad shocks affecting many firms will be priced. If this is not the case, peer shocks would be easy to diversify, and in equilibrium, investors would not demand risk premia for investing in firms exposed to diversifiable shocks.

In contrast, the inattention hypothesis states that shocks to local product market peers are be more important. A key reason is that broad shocks that affect large numbers of firms are more visible and hence are less susceptible to inattention–driven anomalies. In contrast, local product market shocks are not as visible and are more idiosyncratic, and hence, the inattention hypothesis predicts larger momentum returns.

In Table 7, we consider peers positioned in the product market in different distance bands around a given focal firm. For example, our first distance band includes the most local peers, defined as peers with textual cosine similarity to a given focal firm that is in the highest 1.05% of all pairwise similarities. This threshold is equally as granular as firms appearing in the same SIC-4 code, and thus firms in this band are highly similar. Our second distance band includes firms that are not in the 1.05% most similar peers but are in the 2.03% most similar peers. This threshold is analogous to firms that are in the same SIC-3 code but are not in the same SIC-4 code. Intuitively, peers in this second group are broader in the product market space than peers in the first band. Our third distance band includes firms that are as proximate in the TNIC industry space as are SIC-2 pairs (4.52%) but not as proximate as SIC-3 pairs (2.03%). Finally, our broadest distance band includes firms that are as proximate in the TNIC industry space as are SIC-1 pairs (15.8%) but not as proximate as SIC-2 pairs (4.52%).

We consider shocks to these distance-based peer groups as competing RHS variables in our standard Fama–MacBeth (1973) setting. All momentum variables are based on peer returns using the standard 12-month horizon from $t-12$ to $t-1$. As before, we consider the full sample in Panel A of Table 7, and a sample that excludes the financial crisis period in Panel B. The table shows that shocks to product market peers drive momentum only when the peers are local. The inner

TABLE 7

Fama–MacBeth Return Regressions: Industry Breadth

Table 7 reports Fama–MacBeth (1973) regressions with the monthly stock return as the dependent variable. The independent variables are all measured ex ante using the lag structure given by Fama and French (1992). All industry momentum variables are defined in Section III.B. We compute text-based network industry classification (TNIC) momentum using various granularities as noted in the first column: TNIC-4 (analogous to 4-digit Standard Industrial Classification (SIC-4)), TNIC-(3-4) (analogous to being in SIC-3 but not SIC-4), TNIC-(2-3) (analogous to being in SIC-2 but not SIC-3), and TNIC-(1-2) (analogous to being in SIC-1 but not SIC-2). We consider the past 12-month returns for each. Industry momentum variables are based on the equal-weighted average past returns of rival firms in each industry where the firm itself is excluded from the average. We also include controls for own-firm momentum, Fama–French 48-industry (FF-48) momentum, size, and book-to-market. We consider the entire sample in Panel A, and the sample that ends before the 2008–2009 crisis period in Panel B. All right-hand-side variables are standardized before running the regression for ease of comparison. All standard errors are adjusted using Newey–West (1987) with 2 lags. t-statistics are reported in parentheses.

Industry Past Return										
$t-1$ to $t-12$				$t-2$ to $t-12$	$t-1$ to $t-12$	$t-1$				
TNIC-4	TNIC-(3-4)	TNIC-(2-3)	TNIC-(1-2)	Own Firm	FF-48	Own Firm	Log Market Capitalization	Log Book-to-Market Ratio	R^2	No. of Months/ No. of Obs.
Panel A. All Months: July 1997 to Dec. 2012										
0.005	0.004	0.001	−0.001			−0.004	−0.000	0.002	0.044	186
(4.79)	(4.09)	(0.75)	(−0.32)			(−4.23)	(−0.26)	(2.29)		805,090
0.005	0.004	0.001	−0.001	−0.001	0.008	−0.004	−0.000	0.002	0.051	186
(6.05)	(4.36)	(0.54)	(−0.22)	(−0.23)	(1.56)	(−4.47)	(−0.39)	(2.56)		805,090
0.005	0.004			−0.001	0.009	−0.004	−0.001	0.002	0.047	186
(5.51)	(3.08)			(−0.24)	(1.64)	(−4.26)	(−0.39)	(2.25)		805,090
Panel B. Precrisis Months (Pre-2008): July 1997 to Dec. 2007										
0.006	0.005	0.002	−0.002			−0.004	−0.001	0.003	0.050	126
(5.11)	(4.52)	(1.36)	(−0.59)			(−3.51)	(−0.62)	(2.32)		591,241
0.006	0.005	0.001	−0.001	0.002	0.002	−0.004	−0.001	0.003	0.055	126
(5.71)	(4.43)	(0.98)	(−0.47)	(1.30)	(1.51)	(−3.62)	(−0.74)	(2.51)		591,241
0.006	0.005			0.002	0.002	−0.004	−0.001	0.003	0.051	126
(5.02)	(3.06)			(1.29)	(1.54)	(−3.39)	(−0.77)	(2.11)		591,241

band is highly significant in predicting ex post returns, as is the second band. However, neither of the broader bands is statistically significant.

We conclude that peers located in the product market space with proximity similar to SIC-4 and SIC-3 peers (analogous to the 2% most similar firm pairs among all pairs) generate long-term momentum. This finding is not consistent with an explanation for momentum based on systematic risk, as shocks to peers that are this local should be relatively easy to diversify. Our results thus favor the visibility and inattention hypothesis for industry momentum.

D. Idiosyncratic and Systematic Risk

In this section, we decompose our momentum variables into a component that is due to systematic risk and a component that is due to idiosyncratic risk. We use the decomposition methods discussed in Section III.D. We use projections of daily stock returns onto the daily Fama–French (1992) factors plus momentum (UMD) and then tabulate the total contribution of systematic risk projections to each firm's monthly return. Next, we compute peer momentum variables using our standard averaging approach. Finally, we define the idiosyncratic component as the raw peer return minus the systematic peer return component.

Table 8 displays results for our standard asset pricing regressions, with both the TNIC-3 idiosyncratic peer return and the systematic peer return as RHS variables. We consider 2 horizons: the near-term horizon of $t-1$ to $t-6$ and a longer term horizon of $t-7$ to $t-12$. Panel A presents results for the full sample and Panel B for the subsample that excludes the financial crisis.

Table 8 shows that for long-term momentum for the $t-7$ to $t-12$ horizon in columns 3 and 4, only idiosyncratic peer shocks matter. Even for the shorter 6-month horizon in columns 1 and 2, the idiosyncratic component (highly significant at the 1% level in all 4 specifications) strongly dominates the systematic component (significant in only 2 of the specifications at the 5% level and insignificant in the other 2 specifications). These results reinforce our earlier findings as discussed in Table A3 of the Supplementary Material, but in a more stark, long-horizon fashion. Whereas systematic peer returns do create some modest return predictability lasting 1–2 months, they create no return predictability beyond this horizon. Idiosyncratic returns generate predictability for at least 1 year. We conclude that the industry momentum anomaly is likely due to more localized idiosyncratic peer shocks affecting a smaller fraction of firms in the economy, which is also consistent with a low-visibility interpretation given that fewer investors pay attention any specific localized shock and more investors pay attention to larger and more systematic shocks.

E. TNIC and SIC Disparity

In this section, we consider how firms that are in the TNIC network, but are not in the same SIC code, might drive our results. We note that for some firms, these peers are highly concordant, and for others, TNIC-3 peers differ substantially from SIC-3 peers. Under the inattention hypothesis, we expect long-term momentum returns to be sharpest for firms that have high disparity across the 2 sets of peers. We thus compute "disparity" as 1 minus the total sales of firms that are at the intersection of TNIC-3 peers and SIC-3 peer groups divided by the total

TABLE 8

Fama–MacBeth Return Regressions: Idiosyncratic and Systematic Risk

Table 8 reports Fama–MacBeth (1973) regressions with the monthly stock return as the dependent variable. The independent variables include momentum variables based on the systematic and idiosyncratic portions of the text-based return benchmark. Industry momentum variables are defined in Section III.B. To compute the systematic portion, we first regress (for each month) daily stock returns for each firm onto the 3 Fama and French (1992) factors and the momentum factor. The projection from this regression (excluding the projection from the intercept) is the systematic portion of a firm's daily return. These are then aggregated to monthly observations, and we compute the value-weighted average of these systematic returns over each firm's text-based peers to get the systematic peer return. The idiosyncratic peer return is the raw text-based peer return minus the systematic peer return. Text-based network industry classification (TNIC-3) momentum variables are based on the equal-weighted average past returns of rival firms in each TNIC industry where the firm itself is excluded from the average. We also include controls for size and book-to-market. We consider the entire sample in Panel A, and the sample that ends before the 2008–2009 crisis period in Panel B. All right-hand-side variables are standardized before running the regression for ease of comparison. All standard errors are adjusted using Newey–West (1987) with 2 lags. t-statistics are reported in parentheses.

TNIC-3 Industry Past Return							
$t-1$ to $t-6$		$t-7$ to $t-12$					
Idiosyncratic	Systematic	Idiosyncratic	Systematic	Log Market Capitalization	Log Book-to-Market Ratio	R^2	No. of Months/ No. of Obs.
Panel A. All Months: July 1997 to Dec. 2012							
0.007	0.004	0.004	0.002	−0.000	0.002	0.041	186
(4.39)	(1.97)	(3.05)	(1.40)	(−0.37)	(2.28)		805,090
0.006		0.003		−0.000	0.002	0.027	186
(4.13)		(3.36)		(−0.13)	(2.14)		805,090
	0.001		0.000	−0.000	0.002	0.029	186
	(0.44)		(0.11)	(−0.33)	(1.53)		805,090
Panel B. Precrisis Months: July 1997 to Dec. 2007							
0.009	0.006	0.005	0.002	−0.001	0.003	0.047	126
(4.91)	(2.69)	(3.49)	(1.17)	(−0.72)	(2.26)		591,241
0.008		0.004		−0.001	0.003	0.032	126
(4.39)		(3.13)		(−0.55)	(2.06)		591,241
	0.002		−0.000	−0.001	0.002	0.034	126
	(1.11)		(−0.27)	(−0.67)	(1.41)		591,241

sales of firms in the union of TNIC-3 and SIC-3 peers. This variable is bounded in the range [0, 1], and a high value indicates that an investor relying on SIC-3 classifications would miss a large fraction of information about product market peers. Hence, we hypothesize that firms with high disparity are more susceptible to momentum under the hypothesis that momentum is driven by inattention and less visible economic links.

Our main specification in Table 3 focuses on momentum for both the near-term horizon of $t-1$ to $t-6$ and the longer term horizon of $t-7$ to $t-12$. In Table 9, we rerun this model for firms in different quintiles based on their industry disparity. Panel A presents results for the full sample and Panel B for the subsample that excludes the financial crisis. Our hypothesis is that momentum variables are stronger in high-disparity quintiles and weaker in low-disparity quintiles.

The results in both panels for the longer $t-7$ to $t-12$ horizon strongly support the hypothesis that momentum is stronger for firms with more TNIC rather than SIC-based industry peers. The long-horizon momentum variable is positive and significant at the 1% level and highly economically significant in high-disparity quintiles. In contrast, it has a much smaller magnitude and is not significant in the low-disparity quintile. We observe similar but less striking sorts by disparity for the shorter $t-1$ to $t-6$ horizon. The fact that the longer horizon sorts by disparity more than does the short horizon is further consistent with a visibility interpretation, as it indicates that return shocks disseminate most slowly

TABLE 9

Fama–MacBeth Return Regressions: High- and Low-Industry Disparity

Table 9 reports Fama–MacBeth (1973) regressions with the monthly stock return as the dependent variable. All industry momentum variables are defined in Section III.B. A key variable we use to subsample the data is industry disparity, which is 1 minus the total sales of firms in the intersection of text-based network industry classification (TNIC-3) and 3-digit Standard Industrial Classification (SIC-3) peers divided by the total sales of firms in the union of TNIC-3 and SIC-3 peers. This quantity measures how similar TNIC-3 and SIC-3 are for a given firm. As noted in the first column, we run the stock return regressions for subsamples based on quintiles of disparity, where quintiles are formed separately in each month. The independent variables are all measured ex ante using the lag structure given by Fama and French (1992). The key variables include 10-K-based TNIC-3 momentum measured over the past 6 months and the preceding 6 months. TNIC-3 momentum variables are based on the equal-weighted average past returns of rival firms in each TNIC industry where the firm itself is excluded from the average. We also include controls for size and book-to-market. We consider the entire sample in Panel A, and the sample that ends before the 2008–2009 crisis period in Panel B. All right-hand-side variables are standardized before running the regression for ease of comparison. All standard errors are adjusted using Newey–West (1987) with 2 lags. t-statistics are reported in parentheses.

	TNIC-3 Industry Past Return					
Sample	$t-1$ to $t-6$	$t-7$ to $t-12$	Log Market Capitalization	Log Book-to-Market Ratio	R^2	No. of Months/ No. of Obs.
Panel A. All Months: July 1997 to Dec. 2012						
Low disparity	0.006	0.001	−0.000	0.001	0.041	186
	(2.52)	(0.32)	(−0.14)	(1.25)		160,576
Quintile 2	0.009	0.004	−0.001	0.001	0.063	186
	(2.55)	(1.56)	(−0.70)	(0.70)		162,396
Quintile 3	0.008	0.004	−0.001	0.002	0.051	186
	(2.54)	(1.55)	(−0.73)	(2.06)		161,957
Quintile 4	0.010	0.005	−0.001	0.002	0.038	186
	(4.55)	(2.35)	(−0.64)	(1.45)		160,600
High disparity	0.010	0.006	−0.001	0.004	0.025	186
	(5.92)	(4.68)	(−0.48)	(4.24)		159,561
Panel B. Precrisis Months: July 1997 to Dec. 2007						
Low disparity	0.007	0.001	−0.000	0.002	0.043	126
	(4.06)	(0.68)	(−0.03)	(1.73)		118,136
Quintile 2	0.014	0.004	−0.002	0.001	0.069	126
	(3.40)	(1.32)	(−1.19)	(0.83)		119,180
Quintile 3	0.011	0.005	−0.002	0.003	0.060	126
	(3.18)	(1.72)	(−0.89)	(1.69)		118,780
Quintile 4	0.012	0.006	−0.002	0.003	0.042	126
	(4.43)	(2.73)	(−0.91)	(1.93)		118,104
High disparity	0.011	0.006	−0.002	0.004	0.027	126
	(5.11)	(3.71)	(−1.16)	(3.42)		117,041

and most intensively when visibility (as measured by disparity) is lowest. Indeed, a slower rate of dissemination is particularly consistent with behavioral hypotheses such as visibility.

We conclude that when firms have proximate peers that are less visible to investors, they experience greater long-horizon industry momentum returns. This result is hard to square with a risk-based explanation but supports slow information dissemination and a role for the visibility of economic links. In particular, TNIC peers were less visible to investors during our sample period, indicating that firms with higher disparity thus are more exposed to anomalies relating to low visibility.

F. Partitioning TNIC and SIC Peers

In this section, we consider whether the past returns of various peer groups separately predict momentum returns. We focus on 3 groups: i) firms that are TNIC-3 peers but not SIC-3 peers, ii) firms that are SIC-3 peers but not

TNIC-3 peers, and iii) firms that are both TNIC-3 and SIC-3 peers. For each group of peers, we compute the average past-month $t-12$ to $t-1$ return for the peer group and the previous 1-month return variable for the peer group. Our prediction is that momentum returns relating to peers that have a less visible text-based economic link will be stronger than for those that only have a highly visible SIC-3 link. We also compare these results across disparity quintiles to reinforce our expectation that results will be strongest for the high-disparity quintile.

The results are displayed in Table 10. We find strong and consistent evidence in row 1 that TNIC-only peers outperform SIC-only peers in predicting future momentum returns. The SIC-3-only coefficient is insignificantly negative, and the TNIC-3-only coefficient is positive and significant at the 1% level for the $t-12$ to $t-1$ past-return horizon. This suggests that the presence of a less visible link is

TABLE 10

Fama–MacBeth Return Regressions: Various Peer Groups

Table 10 reports Fama–MacBeth (1973) regressions with the monthly stock return as the dependent variable. All industry momentum variables are defined in Section III.B. We subsample the data regarding whether peers are only text-based network industry classification (TNIC-3) peers, only 3-digit Standard Industrial Classification (SIC-3) peers, or peers according to both classifications. We then compute equal-weighted average returns for the peers in each group to construct 3 industry momentum variables. The independent variables are all measured ex ante using the lag structure given by Fama and French (1992). We consider the past 12-month returns for each momentum variable. Momentum variables for each peer group are based on the equal-weighted average past returns of rival firms in each peer group where the focal firm itself is always excluded from the average. We also include controls for size and book to market. We consider the entire sample in Panel A, and the sample that ends before the 2008–2009 crisis period in Panel B. All right-hand-side variables are standardized before running the regression for ease of comparison. All standard errors are adjusted using Newey–West (1987) with 2 lags. t-statistics are reported in parentheses.

	$t-1$ to $t-12$ Past Return						
Sample	TNIC-3 Only	SIC-3 Only	Both TNIC and SIC	Log Market Capitalization	Log Book-to-Market Ratio	R^2	No. of Months/ No. of Obs.
Panel A. All Months: July 1997 to Dec. 2012							
All months	0.005	−0.000	0.004	−0.000	0.002	0.031	186
	(3.15)	(−0.57)	(2.75)	(−0.28)	(1.93)		805,090
Low disparity	−0.001	0.000	0.005	0.000	0.001	0.037	186
	(−0.49)	(0.21)	(2.06)	(0.15)	(1.20)		160,576
Quintile 2	0.002	−0.002	0.008	−0.001	0.001	0.055	186
	(0.82)	(−1.96)	(2.60)	(−0.60)	(0.61)		162,396
Quintile 3	0.003	−0.001	0.006	−0.001	0.003	0.046	186
	(1.41)	(−1.33)	(2.42)	(−0.58)	(1.77)		161,957
Quintile 4	0.006	0.000	0.005	−0.001	0.002	0.035	186
	(3.15)	(0.39)	(3.43)	(−0.60)	(1.45)		160,600
High disparity	0.008	0.002	0.003	−0.001	0.003	0.024	186
	(5.57)	(2.52)	(2.68)	(−0.62)	(4.02)		159,561
Panel B. Precrisis Months: July 1997 to Dec. 2007							
All months	0.012	−0.001	0.010	−0.001	0.003	0.037	126
	(3.10)	(−0.46)	(3.32)	(−0.69)	(1.80)		591,241
Low disparity	0.000	−0.001	0.005	0.000	0.002	0.041	126
	(0.28)	(−0.44)	(3.30)	(0.18)	(1.68)		118,136
Quintile 2	0.005	−0.005	0.020	−0.001	0.002	0.060	126
	(0.85)	(−1.79)	(3.66)	(−1.15)	(0.81)		119,180
Quintile 3	0.011	−0.004	0.015	−0.001	0.003	0.054	126
	(2.02)	(−1.58)	(2.63)	(−0.75)	(1.36)		118,780
Quintile 4	0.007	0.000	0.005	−0.002	0.003	0.039	126
	(3.02)	(0.16)	(3.27)	(−0.81)	(1.89)		118,104
High disparity	0.010	0.003	0.003	−0.002	0.004	0.026	126
	(4.43)	(2.74)	(2.37)	(−1.29)	(3.24)		117,041

more important than the absence of a highly visible link when predicting momentum returns. Interestingly, we also find that the both-TNIC-and-SIC peer group performs well and produces positive and significant momentum returns. This suggests that a firm that is both an SIC and a TNIC peer has a strong economic link to the firm. As investors are likely inattentive to the TNIC link, they should underreact to the large momentum returns that flow through such ultra-strong peers as they would not be aware that these peers are stronger than standard SIC-only peers. These findings are robust both in the full sample and in the pre-2008 sample.

Table 10 also displays results separately for firms by industry disparity quintiles in rows 2–6 for the full sample and 7–12 for the pre-2008 sample. The table shows strong and nearly monotonic sorting of the TNIC-only coefficient, which becomes very large in the high-disparity quintile. We also observe that the FF-48-only peers do not predict momentum returns in a material way in any quintile except the highest disparity quintile. In contrast, the both-TNIC-and-SIC peer group predicts momentum returns in all quintiles. This variable is slightly stronger in low- to middle-disparity quintiles, where peers that are in both classifications is more common (given the definition of disparity). In all, the findings support our conclusion that momentum due to less visible peers predicts strong momentum profits, whereas highly visible peers do not.

G. Calendar-Time Portfolios

We next consider whether our results are robust to calendar-time portfolio methods. For a given momentum variable (TNIC-3 based, FF-48 based, or own firm based), we first sort firms into quintiles based on the given variable separately in each month. For all industry momentum returns, we focus on the standard horizon of $t-1$ to $t-12$. For own-firm momentum, consistent with the literature, we focus on the 11-month horizon from $t-2$ to $t-12$.

We then compute the returns of equal-weighted portfolios that i) invest long in the highest quintile firms and ii) invest short in the lowest quintile firms. We thus have a consistent way of computing the returns of zero-cost portfolios for any momentum variable. In the second stage, we regress the returns of our zero-cost portfolios on the market factor, HML, SMB, and, in some specifications, the UMD factor.[5] Our primary test is whether the intercept (which we refer to as "alpha") is statistically and economically distinct from 0.

In Panel A of Table 11, we compute the zero-cost portfolios based only on the subsample of firms in the high-disparity quintile. We expect predictable returns to be particularly high in this subsample, and we focus on TNIC-3 momentum as the momentum sort variable. In rows 1–2, we consider the full sample from July 1997 to Dec. 2012; row 1 omits the UMD factor whereas row 2 includes the UMD factor. We note that the alpha is statistically significant with a t-statistic that exceeds 5.0 in all 4 specifications. Economically, we observe predictable returns that range from 1.9% to 2.3% per month for the full sample, and 1.8% to 2.7% for the sample that excludes the financial crisis. We find Sharpe ratios that range

[5]We thank Kenneth French for providing factor data on his Web site.

TABLE 11

Calendar-Time Portfolios: Equal-Weighted Black–Jensen–Scholes (BJS) Alpha Test

Table 11 reports ordinary least squares (OLS) coefficients and factor loadings based on calendar-time zero-investment portfolios investing long in positive momentum stocks and short in negative momentum stocks. All portfolios are equal weighted. The portfolios are constructed from varying definitions of momentum: text-based network industry classification (TNIC-3) momentum (Panels A and B), Fama–French 48-industry (FF-48) (based on Standard Industrial Classification (SIC)) momentum (Panel C), and own momentum (Panel D). All industry momentum variables are defined in Section III.B. All tests are based on the full sample except Panel A, which is based on portfolios of stocks in the highest quintile of industry disparity (1 minus the total sales of all firms in the intersection of TNIC-3 and 3-digit SIC (SIC-3) peer groups, divided by the total sales of firms in the union of the given firm's TNIC-3 and SIC-3 industries). We consider a 1-year measurement period for past returns as noted in the first column. For own-firm momentum, we skip the most recent month, following the literature. Zero-investment calendar-time portfolios are constructed by first sorting firms into quintiles based on the given momentum variables in each month. We then compute equal-weighted average returns of firms in the highest quintile and subtract the equal-weighted returns of firms in the lowest quintile. Annualized Sharpe ratios are computed as the square root of 12 times the monthly mean divided by the monthly standard deviation. We report the Sharpe ratio of the raw return (top) and the residual return (bottom) for each specification. t-statistics are reported in parentheses.

Sample/ Horizon	Alpha	MKT	HML	SMB	UMD	Sharpe Ratios	R^2	No. of Obs.
Panel A. 10-K Based TNIC-3 Momentum (High-Disparity Quintile)								
All months	0.023	−0.259	−0.280	0.530		1.432	0.195	186
$t-1$ to $t-12$ momentum	(6.18)	(−3.28)	(−2.50)	(4.91)		1.603		
All months	0.019	0.039	−0.073	0.393	0.653	1.432	0.613	186
$t-1$ to $t-12$ momentum	(7.29)	(0.66)	(−0.92)	(5.20)	(13.99)	1.908		
Pre-2008	0.027	−0.333	−0.272	0.638		1.424	0.242	126
$t-1$ to $t-12$ momentum	(5.22)	(−2.54)	(−1.57)	(4.67)		1.680		
Pre-2008	0.018	0.025	−0.095	0.407	0.835	1.424	0.722	126
$t-1$ to $t-12$ momentum	(5.68)	(0.29)	(−0.90)	(4.81)	(14.46)	1.868		
Panel B. 10-K-Based TNIC-3 Momentum								
All months	0.017	−0.386	−0.285	0.611		0.777	0.146	186
$t-1$ to $t-12$ momentum	(3.30)	(−3.50)	(−1.82)	(4.05)		0.857		
All months	0.011	0.099	0.051	0.389	1.062	0.777	0.746	186
$t-1$ to $t-12$ momentum	(3.73)	(1.53)	(0.59)	(4.68)	(20.69)	0.975		
Pre-2008	0.024	−0.597	−0.380	0.678		0.898	0.192	126
$t-1$ to $t-12$ momentum	(3.39)	(−3.28)	(−1.58)	(3.57)		1.091		
Pre-2008	0.011	−0.045	−0.107	0.322	1.288	0.898	0.825	126
$t-1$ to $t-12$ momentum	(3.14)	(−0.50)	(−0.95)	(3.57)	(20.92)	1.033		
Panel C. FF-48 Momentum								
All months	0.010	−0.151	−0.247	0.410		0.649	0.132	186
$t-1$ to $t-12$ momentum	(2.68)	(−1.92)	(−2.22)	(3.82)		0.695		
All months	0.006	0.126	−0.055	0.283	0.605	0.649	0.525	186
$t-1$ to $t-12$ momentum	(2.24)	(2.02)	(−0.65)	(3.54)	(12.23)	0.587		
Pre-2008	0.013	−0.271	−0.264	0.439		0.700	0.156	126
$t-1$ to $t-12$ momentum	(2.56)	(−2.11)	(−1.56)	(3.28)		0.824		
Pre-2008	0.004	0.092	−0.085	0.206	0.846	0.700	0.729	126
$t-1$ to $t-12$ momentum	(1.37)	(1.20)	(−0.88)	(2.65)	(16.00)	0.452		
Panel D. Own Momentum								
All months	0.010	−0.470	−0.323	0.097		0.399	0.106	186
$t-2$ to $t-12$ momentum	(2.08)	(−4.38)	(−2.13)	(0.66)		0.540		
All months	0.003	0.058	0.044	−0.145	1.157	0.399	0.895	186
$t-2$ to $t-12$ momentum	(1.96)	(1.46)	(0.82)	(−2.85)	(36.87)	0.512		
Pre-2008	0.016	−0.511	−0.253	0.157		0.653	0.082	126
$t-2$ to $t-12$ momentum	(2.52)	(−3.11)	(−1.17)	(0.92)		0.810		
Pre-2008	0.003	0.014	0.006	−0.181	1.224	0.653	0.886	126
$t-2$ to $t-12$ momentum	(1.42)	(0.24)	(0.08)	(−2.93)	(29.16)	0.466		

from 1.4 to 1.9 depending on the specification. These results are economically large and imply annualized returns between 21.6% and 32.4%.

In Panel B of Table 11, we ignore the disparity level and form the long and short portfolios using the entire cross-sectional sample. We continue to observe positive TNIC-3 momentum alphas that are significant at the 1% level. In this case, the results are stronger when we exclude the UMD factor as compared to when we include it. It is unclear whether the UMD factor should be considered in these tests given that the objective is to assess momentum return magnitudes without double counting. Regardless, our results are highly significant with or without the UMD control.

When we consider FF-48 momentum in Panel C of Table 11, and own-firm momentum in Panel D, the results are weaker. FF-48 momentum is statistically significant but the economic size of the alpha is lower as are the Sharpe ratios. For own-firm momentum, Sharpe ratios are lower still. For both FF-48 and own-firm momentum, we observe a lack of robustness to including the UMD factor. We conclude that the calendar-time tests produce results that are similar to our baseline Fama–MacBeth (1973) regressions.

Table A6 of the Supplementary Material presents analogous results for value-weighted portfolios. As noted earlier, value-weighted tests impose a much higher bar as larger stocks are much more actively arbitraged. For these stringent tests, we find that only TNIC-3 momentum in high-disparity industries remains highly significant. t-statistics generally remain above 3.0, especially when UMD is excluded, and results remain economically large. For example, in both samples we find that annualized returns exceed 20% in both samples, and Sharpe ratios are higher than 0.81. These economic magnitudes are very large, particularly for value-weighted portfolios where few anomalies are comparable.

H. Time Series and the Financial Crisis

In this section, we examine the time-series performance of various momentum strategies during the financial crisis. The objective is to examine the consistency of each strategy in producing predictable returns outside the crisis, and the extent to which each portfolio underperforms during the financial crisis. This question is interesting not only from an informational perspective, but also from a theoretical perspective. For example, a finding that momentum performs poorly during the crisis, in itself, can be viewed as evidence supporting the systematic risk factor hypothesis for the momentum anomaly. This result would suggest that investors were "right" to demand a risk premium for investing in these stocks.

To the contrary, evidence that momentum does not perform differentially during the crisis might be more consistent with behavioral or market inefficiency hypotheses. It is noteworthy that our calendar-time portfolios are balanced on the long and short legs, so even if the market performed poorly, there is no mechanistic prediction regarding how our momentum portfolios should perform in the crisis if systematic risk does or does not explain momentum.

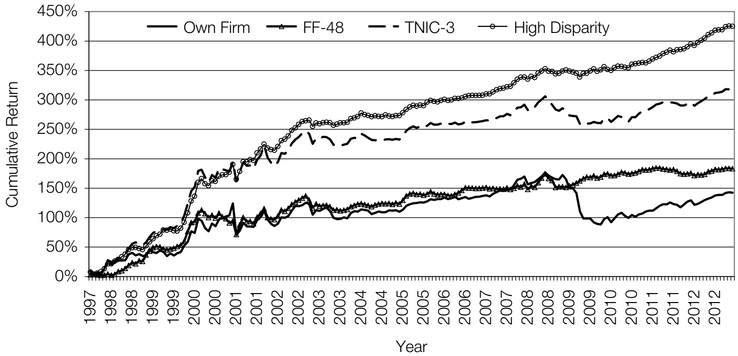
We first show in Figure 2 the cumulative abnormal monthly returns for the 4 momentum strategies highlighted in Table 11 during the entire sample period.[6] In this figure, portfolio returns are equal weighted (we consider value-weighted returns next). We also note that the cumulative abnormal returns in Figure 2 are adjusted for the market factor, HML, and SMB. However, we do not control for

[6]In a given month, the cumulative abnormal return is the cumulative (alpha plus the monthly residual) from the regressions in Table 11.

FIGURE 2

Equal-Weighted Cumulative Portfolio Returns

Figure 2 shows arithmetic cumulative abnormal returns (HML, SMB, MKT adjusted) of zero-investment, equal-weighted, calendar-time momentum portfolios based on varying definitions of momentum. Calendar-time portfolios are constructed by first sorting firms into quintiles in each month based on the given momentum variables. We then compute equal-weighted average returns of firms in the highest quintile and subtract the equal-weighted returns of firms in the lowest quintile. The result is a zero-investment portfolio capturing the return differential across the extreme quintiles. We then regress each portfolio on the 3 Fama–French (1992) factors and compute the abnormal return as the intercept plus the residuals. Figure 2 displays the arithmetically cumulated abnormal returns over our sample. We consider own-firm momentum, Fama–French 48-industry (FF-48) (based on Standard Industrial Classification (SIC)) momentum, and 10-K-based text-based network industry classification (TNIC-3) momentum. Past returns are computed based on the window of months $t-1$ to $t-12$ (except for own-firm momentum, which is based on $t-2$ to $t-12$ due to the well-known 1-month reversal). TNIC-3 portfolios are based on a granularity equal to 3-digit SIC (SIC-3) codes. The TNIC and SIC returns are computed using equal-weighted averages of peers.



the UMD factor so that we can report the full magnitude of each momentum variable.

Figure 2 shows that own-firm momentum is the weakest strategy, followed by FF-48 industry momentum. Also interesting is that both of these strategies did better in the earlier part of our sample, but returns flattened after 2000 and 2001. This flattening of returns is consistent with returns being highly visible and hence generating lower returns, particularly after the publication of Moskowitz and Grinblatt (1999). We also observe that own-firm momentum performed particularly poorly during the 2008 financial crisis. In contrast, returns attributable to TNIC industry momentum continued to accumulate strongly during the entire sample, even in later years. These persistent returns, which had minimal disruption even during the crisis period, are consistent with TNIC peers being less visible to investors, and are consistent with the inattention hypothesis.

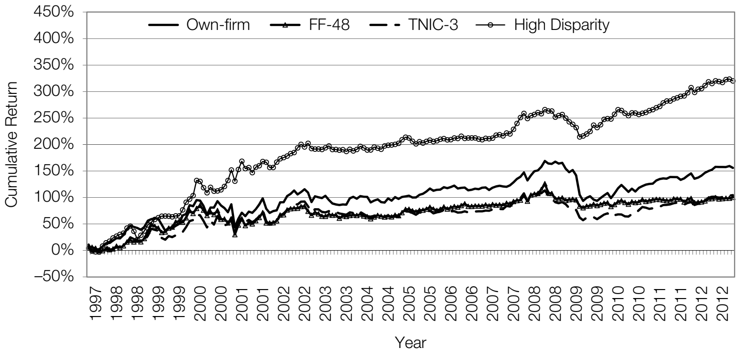
Perhaps most striking is the differential performance of the high-disparity momentum strategy during the financial crisis period as compared to other momentum strategies. For own-firm momentum, we observe a substantial drop in cumulative returns in late 2008 and early 2009. The ensuing recovery, even after 3 years, is not strong enough to recover the losses. For the high-disparity TNIC-3 industry momentum strategy, we observe essentially no drop, as the strategy continued to accumulate gains even in the crisis. By the end of our sample, the cumulative returns continued to reach new highs. These results, which are not sensitive to the state of the economy, are hard to square with a risk-based interpretation of our results. In contrast, they are consistent with an inattention explanation.

We conclude that although individual firms that had high returns before the crisis did not perform well, when the momentum anomaly is measured in the most informative way (text-based peers with high disparity), we observe very little in the way of poor performance during the crisis. These results are consistent with industry momentum being driven at least in part by slow dissemination of information around shocks to less visible industry peers.

In Figure 3, we show analogous cumulative abnormal returns for the 4 momentum strategies, but this time we consider value-weighted returns. We expect and find that the economic magnitude of all strategies declines when we use value weights instead of equal weights. We also observe that all strategies have at least some impact from the financial crisis. However, as is true for the equal-weighted results, the high-disparity TNIC-3 momentum portfolio suffers only a small impact from the crisis and quickly recovers. This strategy, even when value weighted, continues to accumulate high returns during the last part of our sample.

FIGURE 3
Value-Weighted Cumulative Portfolio Returns

Figure 3 shows arithmetic cumulative abnormal returns (HML, SMB, MKT adjusted) of zero-investment, value-weighted, calendar-time momentum portfolios based on varying definitions of momentum. Calendar-time portfolios are constructed by first sorting firms into quintiles in each month based on the given momentum variables. We then compute value-weighted average returns of firms in the highest quintile and subtract the value-weighted returns of firms in the lowest quintile. The result is a zero-investment portfolio capturing the return differential across the extreme quintiles. We then regress each portfolio on the 3 Fama–French (1992) factors and compute the abnormal return as the intercept plus the residuals. Figure 3 displays the arithmetically cumulated abnormal returns over our sample. We consider own-firm momentum, Fama–French 48-industry (FF-48) (based on Standard Industrial Classification (SIC)) momentum, and 10-K-based text-based network industry classification (TNIC-3) momentum. Past returns are computed based on the window of months $t-1$ to $t-12$ (except for own-firm momentum, which is based on $t-2$ to $t-12$ due to the well-known 1-month reversal). TNIC-3 portfolios are based on a granularity equal to 3-digit SIC (SIC-3) codes. The TNIC and SIC returns are computed using equal-weighted averages of peers.



I. Attention from Professional Investors

We now examine the link between our central results and visibility using an approach from Cohen and Frazzini (2008), who consider the extent to which economically linked firm pairs are jointly held in mutual fund portfolios. Such joint ownership measures the degree of institutional attention to the economic link between the pair of stocks. Cohen and Frazzini show that mutual fund joint ownership reduces return predictability associated with vertical customer–supplier economic links. We consider joint ownership of horizontally linked TNIC-3 pairs. Under the inattention hypothesis, we expect our momentum variables to be strongest in subsamples where horizontal TNIC-3 pairs are not jointly held by mutual funds.

We use the CRSP Survivor-Bias-Free U.S. Mutual Fund database[7] to compute common ownership for each linked pair of TNIC firms as the number of mutual funds that hold both the focal firm and the peer firm divided by the total number of mutual funds that own the peer firm (when no funds own the peer, the overall quantity is set to 0). We then compute the average of this quantity over each firm's TNIC rivals to obtain our firm-level measure of joint ownership for any given focal firm's TNIC industry in each month. Firms with high joint ownership are in product markets where there is high institutional attention to economic shocks that might affect firms in the TNIC industry. Momentum should be weaker for such firms.

Table 12 displays the results of Fama–MacBeth (1973) regressions with the monthly stock return as the dependent variable. As noted in the first column, we run these regressions separately for quintile subsamples based on the above-mentioned TNIC-level mutual fund joint ownership, where quintiles are formed separately in each month. The table shows that both the coefficient and the magnitude of our TNIC-3 1-year momentum variable is strongly linked to the level of joint mutual fund ownership. For the lowest quintile of joint ownership for the lagged 6-month return, TNIC momentum is highly significant, with a t-statistic of 4.84 and an economically large coefficient magnitude of 0.009, indicating that firms with a 1-standard-deviation higher level of this variable outperform control firms by 12 percentage points per year. For the monthly periods of $t-7$ to $t-12$, we find that the TNIC industry return is significant for the 2 quintiles of low common ownership. In the highest quintile of joint ownership for the nearby monthly periods of $t-1$ to $t-6$, the TNIC momentum variable is not statistically significant and its coefficient drops to just 0.002. We also observe a strictly monotonic pattern across quintiles, and these results are robust to dropping the financial crisis period in Panel B. These results strongly support the conclusion that investor attention to linked firms, especially attention from institutional investors, plays a role in determining when momentum returns are large and when they are not.

VII. Mutual Fund Ownership

In our last set of tests, we consider whether mutual funds recognize the links between firms that are present in the TNIC network. We examine whether sector funds in particular own firms in the TNIC network or just focus on common SIC codes. If mutual funds are more likely to focus on firms with common SIC codes versus shared TNIC links, this would lend credence to our proposition that the information in the TNIC network is less visible.

We thus conduct panel data regressions with firm–pair–year joint ownership metrics as the dependent variable. We consider 2 metrics of joint ownership: one based on portfolio weights and the other based on nonzero ownership. In

[7]We use the data selection algorithm in Kacperczyk, Sialm, and Zheng (2005) to limit attention to diversified equity funds as our goal is to exclude non-actively managed index funds.

TABLE 12

Fama–MacBeth Return Regressions:
High versus Low Mutual Fund Common Ownership of Linked Peers

Table 12 reports Fama–MacBeth (1973) regressions with the monthly stock return as the dependent variable. All industry momentum variables are defined in Section III.B. A key variable we use to subsample the data is mutual fund common ownership, which is based on Cohen and Frazzini (2008). We first compute this quantity at the level of linked economic peers. The fraction of common ownership for a given peer is equal to the number of mutual funds that hold both the focal firm and the peer firm in a given pair divided by the number of mutual funds that own the peer firm (when no funds own the peer, this is set to 0). Hence, this number is bounded in the interval [0,1]. We then compute the average of this quantity over each firm's text-based network industry classification (TNIC) rivals to obtain a direct measure of joint ownership of a given focal firm's TNIC industry. Firms with high common ownership are in industries where there is likely a high level of attention to economic shocks that might affect the pairs of firms in the TNIC industry. Hence, anomalies that require low attention should not exist when there is a high level of joint ownership. As noted in the first column, we run the stock return regressions for subsamples based on quintiles of mutual fund joint ownership, where quintiles are formed separately in each month. Our mutual fund ownership metrics are based on the Center for Research in Security Prices (CRSP) Survivor-Bias-Free U.S. Mutual Fund database. We limit attention to diversified equity funds (our goal is to exclude non-actively managed index funds) by following the sequential data selection algorithm used in Kacperczyk, Sialm, and Zheng (2005). The independent variables are all measured ex ante using the lag structure given by Fama and French (1992). The key variables include 10-K-based TNIC-3 momentum. We consider the entire sample in Panel A, and the sample that ends before the 2008–2009 crisis period in Panel B. All right-hand-side variables are standardized before running the regression for ease of comparison. All standard errors are adjusted using Newey–West (1987) with 2 lags. t-statistics are reported in parentheses.

	TNIC-3 Industry Past Return					
Sample	$t-1$ to $t-6$	$t-7$ to $t-12$	Log Market Capitalization	Log Book-to-Market Ratio	R^2	No. of Months/ No. of Obs.
Panel A. All Months: July 1997 to Dec. 2012						
Less jointly owned	0.009	0.005	−0.001	0.004	0.026	186
	(4.84)	(3.54)	(−0.37)	(3.40)		167,196
Quintile 2	0.009	0.004	−0.001	0.003	0.031	186
	(5.63)	(2.50)	(−0.74)	(2.44)		157,592
Quintile 3	0.008	0.002	−0.001	0.002	0.039	186
	(4.43)	(1.22)	(−0.37)	(1.51)		162,405
Quintile 4	0.006	0.001	−0.001	0.000	0.046	186
	(3.14)	(0.59)	(−1.00)	(0.36)		162,469
More jointly owned	0.002	0.001	−0.002	0.000	0.064	186
	(1.41)	(0.55)	(−1.42)	(0.41)		162,357
Panel B. Precrisis Months: July 1997 to Dec. 2007						
Less jointly owned	0.009	0.008	−0.002	0.004	0.028	126
	(4.47)	(3.88)	(−1.02)	(2.76)		124,137
Quintile 2	0.010	0.004	−0.002	0.004	0.035	126
	(4.85)	(2.44)	(−1.15)	(2.22)		114,476
Quintile 3	0.010	0.004	−0.000	0.003	0.041	126
	(4.68)	(2.27)	(−0.14)	(1.86)		119,298
Quintile 4	0.007	0.003	−0.001	0.001	0.049	126
	(3.26)	(1.49)	(−0.42)	(0.71)		119,368
More jointly owned	0.004	0.002	−0.001	0.001	0.072	126
	(1.87)	(0.88)	(−0.54)	(0.50)		119,269

both cases, the first step is, for each fund in each year, to identify all pairwise permutations of the stocks held in its portfolio. For example, a fund holding 5 stocks would have $(5^2-2)/2 = 10$ permutations. For each permutation, we also compute the product weight $pw_{i,j,t} = w_{i,t} \times w_{j,t}$, where $w_{i,t}$ and $w_{j,t}$ are the fraction of the fund's wealth in stock i and j in year t (because funds report holdings quarterly, we consider only the last quarter in each year to reduce the size of our database).

The second step is to sum $pw_{i,j,t}$ across all funds in a given year to obtain the total product weight $tpw_{i,j,t}$ for stocks i and j, which is our dependent variable PORTFOLIO_WEIGHT_OVERLAP in our panel regressions.

To compute the alternative metric NONZERO_OWNERSHIP_OVERLAP, we repeat the calculation but replace $pw_{i,j,t}$ with unity if the given fund owns a positive amount of stocks i and j, and 0 otherwise. PORTFOLIO_WEIGHT_OVERLAP is thus a value-weighted overlap metric, and NONZERO_OWNERSHIP_OVERLAP is an ownership-weighted metric. We then regress these overlap metrics on a dummy indicating whether stocks i and j are in the same SIC-3 code industry and whether they are in the same TNIC-3 industry.

The results in Panel A of Table 13 show that sector funds are more likely to hold stocks that share common SIC codes versus holding stocks with common TNIC industry membership. This is the opposite for diversified funds as shown in Panel B. Our conclusion is that given sector mutual funds are more likely to focus on firms with common SIC codes versus shared TNIC links, this lends credence to the proposition that the information in the TNIC network is less visible and reinforces our earlier results that industry momentum is caused by firms with less visible economic links.

TABLE 13
Mutual Fund Ownership Regressions

Table 13 reports panel data regressions with firm–pair–year joint ownership metrics as the dependent variable. We consider 2 metrics of joint ownership: one based on portfolio weights and the other based on nonzero ownership. In both cases, the first step is, for each fund in each year, to identify all pairwise permutations of the stocks held in its portfolio. For example, a fund holding 5 stocks would have $(5^2-2)/2=10$ permutations. For each permutation, we also compute the product weight $pw_{i,j,t}=w_{i,t}\times w_{j,t}$, where $w_{i,t}$ and $w_{j,t}$ are the fraction of the fund's wealth in stock i and j in year t (because funds report holdings quarterly, we consider only the last quarter in each year to reduce the size of our database). The second step is to sum $pw_{i,j,t}$ across all funds in a given year to obtain the total product weight $tpw_{i,j,t}$ for stocks i and j, which is our dependent variable PORTFOLIO_WEIGHT_OVERLAP in our panel regressions. To compute the alternative metric NONZERO_OWNERSHIP_OVERLAP, we repeat the calculation but replace $pw_{i,j,t}$ with unity if the given fund owns a positive amount of stocks i and j, and 0 otherwise. The former metric is thus a value-weighted overlap metric, whereas the other is an ownership-weighted metric. We then regress these overlap metrics on a dummy indicating whether stocks i and j are in the same 3-digit Standard Industrial Classification (SIC-3) code industry (SAME_SIC_3) and whether they are in the same text-based network industry classification (TNIC-3) industry (SAME_TNIC_3) (where the TNIC-3 network is calibrated to be exactly as granular as the 3-digit Standard Industrial Classification (SIC-3) network). We also include controls for the natural log of the Center for Research in Security Prices (CRSP) market capitalization for stock i and stock j, denoted as LOG_SIZE_1 and LOG_SIZE_2. Finally, we consider firm and year fixed effects as noted, and all standard errors are clustered by firm. t-statistics are reported in parentheses.

Dependent Variable	SAME_SIC_3	SAME_TNIC_3	LOG_SIZE_1	LOG_SIZE_2	R^2	Fixed Effects	No. of Obs. (000s)
Panel A. Sector Funds							
PORTFOLIO_WEIGHT_OVERLAP	6.046 (12.91)	3.521 (22.42)	0.981 (14.88)	1.504 (28.08)	0.130	Firm and year	8,294
NONZERO_OWNERSHIP_OVERLAP	2.397 (17.85)	1.279 (28.46)	0.653 (22.22)	0.623 (46.29)	0.250	Firm and year	8,294
PORTFOLIO_WEIGHT_OVERLAP	6.183 (12.57)	3.412 (19.57)	1.460 (27.83)	1.460 (28.86)	0.087	Year	8,294
NONZERO_OWNERSHIP_OVERLAP	2.720 (18.47)	1.329 (26.88)	0.596 (44.48)	0.596 (45.84)	0.198	Year	8,294
Panel B. Diversified Nonsector Funds							
PORTFOLIO_WEIGHT_OVERLAP	0.195 (5.24)	1.424 (15.81)	0.509 (20.62)	0.795 (24.28)	0.059	Firm and year	159,363
NONZERO_OWNERSHIP_OVERLAP	0.580 (6.15)	3.727 (27.48)	4.123 (21.20)	4.115 (55.69)	0.209	Firm and year	159,363
PORTFOLIO_WEIGHT_OVERLAP	0.161 (3.00)	1.505 (13.66)	0.820 (25.10)	0.820 (24.36)	0.037	Year	159,363
NONZERO_OWNERSHIP_OVERLAP	−0.032 (−0.22)	3.990 (24.67)	4.270 (115.76)	4.270 (55.32)	0.348	Year	159,363

VIII. Robustness

Moskowitz and Grinblatt (1999) consider a random industry portfolio test to reinforce their conclusion that actual economic links between firms in the same industry explain their results. In Table A4 of the Supplementary Material, we repeat this test for our TNIC-based 1-year momentum variables. In particular, we form for each firm a random industry portfolio containing firms that had nearly the same past return as its actual set of industry peers. Each random portfolio also contains the same number of random peers as the firm's actual TNIC industry. We predict that actual industry peers will predict momentum returns much more strongly than will the random industry portfolios. We find that this is indeed the case, and the momentum results for actual industry peers are economically much larger and significantly stronger than the random peers at the 1% level.

Hou (2007) documents that the well-known result that the stock returns of large firms lead those of small firms is primarily due to within-industry return predictability. We examine whether our results can be explained by Hou using subsample tests in Table A5 of the Supplementary Material. Ex ante, we should not expect our results to be related to Hou because we are addressing the long-term momentum anomaly (12 months), whereas the lead–lag anomaly is short term in nature (1 month or less). Nevertheless, Table A5 shows that our results are robust to i) using the subsample of above-median market capitalization firms and ii) including only firms in the largest tercile based on firm size. In contrast, FF-48 momentum loses its significance even in the above-median market capitalization sample. Overall we conclude that our TNIC-3 momentum results are indeed distinct from the short-term lead–lag anomaly. However, it we cannot rule out that FF-48 momentum is related to the lead–lag anomaly.

We additionally examine in Table A7 of the Supplementary Material whether our results are stronger when past returns are positive or negative. Hou (2007) finds stronger results when past returns are negative, consistent with the lead–lag anomaly being related to short-sale constraints. We find that our results are significant for both positive and negative past returns, and moreover are stronger when past returns are positive. This further suggests that our results are distinct from the lead–lag anomaly.

IX. Conclusions

We find that industry momentum is linked to shocks to less visible industry peer firms. We examine industry peers based on new text-based industry peer firms as well as traditional SIC-based peers. Both peer groups capture horizontal industry relatedness. The peer groups differ in that SIC-based peers were highly visible to investors in our sample, and text-based peers, which were not widely distributed during our sample, were less visible. We find that shocks to less visible text-based peers produce long-lived momentum profits that are economically large in magnitude. In contrast, more visible SIC-based industry peers produce only short-lived momentum with modest profits.

These findings support the hypothesis that industry momentum can be explained by inattention to less visible economic links, supporting theories by Hong and Stein (1999) and Barberis et al. (1998). Our finding that industry-based economic links are important to understanding momentum runs counter to prevailing views in the literature, as Grundy and Martin (2001) show that industry momentum based on traditional SIC codes is not robust to the bid–ask bounce. Jegadeesh and Titman (2011) reinforce this finding in their recent review. Our results are robust to the Grundy and Martin critique.

Our findings suggest that the earlier reports of weak industry momentum profits are likely explained by the fact that industry momentum was tested using the more visible SIC-based industry peers. Our inattention hypothesis predicts that this is not an ideal setting for testing industry momentum. Reexamining industry momentum using less visible text-based industry peers, we find that industry momentum is strong, and momentum profits become substantially larger in economic magnitude.

Additional tests further support the role of low visibility. When a firm's most visible peers disagree with its less visible peers, momentum profits are stronger. Results are also stronger when mutual funds do not jointly own the economically linked firms in a given TNIC industry, illustrating that inattention from professional investors is a specific channel. We also find that momentum arises from narrow idiosyncratic peer shocks, which are likely subjected to less attention than are broad systematic peer shocks. Overall, our article provides evidence that industry momentum is in fact important, and slow propagation of information across less visible economic links plays a strong role.

Supplementary Material

Supplementary Material for this article is available at https://doi.org/10.1017/S0022109018000479.

References

Barberis, N.; A. Shleifer; and R. Vishny. "A Model of Investor Sentiment." *Journal of Financial Economics*, 49 (1998), 307–343.

Cohen, L., and A. Frazzini. "Economic Links and Predictable Returns." *Journal of Finance*, 63 (2008), 1977–2011.

Davis, J.; E. Fama; and K. French. "Characteristics, Covariances, and Average Returns: 1929–1997." *Journal of Finance*, 55 (2000), 389–406.

Fama, E., and K. French. "The Cross-Section of Expected Stock Returns." *Journal of Finance*, 47 (1992), 427–465.

Fama, E., and K. French. "Industry Costs of Equity." *Journal of Financial Economics*, 43 (1997), 153–193.

Fama, E., and J. D. MacBeth. "Risk, Return, and Equilibrium: Empirical Tests." *Journal of Political Economy*, 81 (1973), 607–636.

Gebhardt, W.; S. Hvidkjaer; and B. Swaminathan. "Stock and Bond Market Interaction: Does Momentum Spill Over?" *Journal of Financial Economics*, 75 (2005), 651–690.

Gervais, S.; R. Kaniel; and D. Mingelgrin. "The High-Volume Return Premium." *Journal of Finance*, 56 (2001), 877–919.

Griffin, J.; X. Ji; and J. Martin. "Momentum Investing and Business Cycle Risk: Evidence from Pole to Pole." *Journal of Finance*, 58 (2003), 2515–2547.

Grundy, B., and J. Martin. "Understanding the Nature of the Risks and the Source of the Rewards to Momentum Investing." *Review of Financial Studies*, 14 (2001), 29–78.

Hoberg, G., and G. Phillips. "Product Market Synergies and Competition in Mergers and Acquisitions: A Text-Based Analysis." *Review of Financial Studies*, 23 (2010), 3773–3811.

Hoberg, G., and G. Phillips. "Text-Based Network Industry Classifications and Endogenous Product Differentiation." *Journal of Political Economy*, 124 (2016), 1423–1465.
Hong, H., and J. Stein. "A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets." *Journal of Finance*, 54 (1999), 2134–2184.
Hou, K. "Industry Information Diffusion and the Lead-Lag Effect in Stock Returns." *Review of Financial Studies*, 20 (2007), 1113–1138.
Jegadeesh, N., and S. Titman. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *Journal of Finance*, 48 (1993), 65–91.
Jegadeesh, N., and S. Titman. "Profitability of Momentum Strategies: An Evaluation of Alternative Explanations." *Journal of Finance*, 56 (2001), 699–720.
Jegadeesh, N., and S. Titman. "Momentum." *Annual Review of Financial Economics*, 3 (2011), 493–509.
Kacperczyk, M.; C. Sialm; and L. Zheng. "On the Industry Concentration of Actively Managed Equity Mutual Funds." *Journal of Finance*, 60 (2005), 1983–2011.
McLean, R. D., and J. Pontiff. "Does Academic Research Destroy Stock Return Predictability." *Journal of Finance*, 71 (2016), 5–32.
Menzley, L., and O. Ozbas. "Market Segmentation and Cross-Predictability of Returns." *Journal of Finance*, 65 (2010), 1555–1580.
Moskowitz, T., and M. Grinblatt. "Do Industries Explain Momentum." *Journal of Finance*, 54 (1999), 1249–1290.
Newey, W. K., and K. D. West. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica*, 55 (1987), 703–708.
Rouwenhorst, G. "International Momentum Strategies." *Journal of Finance*, 53 (1998), 267–284.
Rouwenhorst, G. "Local Return Factors and Turnover in Emerging Stock Markets." *Journal of Finance*, 54 (1999), 1439–1464.