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 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.

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I Introduction

Since Jegadeesh and Titman (1993) (JT) reported the momentum anomaly, a large literature documented the magnitude of momentum, its pervasiveness in many settings,[1] and its potential explanations. Jegadeesh and Titman (2001) and Jegadeesh and Titman (2011) document momentum's continued robustness in more recent years. Yet scholars continue to disagree regarding the causes of momentum. In their recent review, Jegadeesh and Titman (2011) 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 to momentum.

Using Textual Network Industry Classifications (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) (MG). However, MG's conclusion that industry momentum matters was called into ques-

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

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tion by Grundy and Martin (2001) (GM), who show that industry momentum using SIC–code–based peers is not robust to the bid–ask bounce, and to lagging the portfolio formation period by one 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 GM 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 five 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 industry classifications are roughly 25% to 40% more informative than SIC codes regarding 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 was not widely distributed during our sample and the first paper illustrating TNIC peers (Hoberg and Phillips (2010a)) was published late in our sample.[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 one to two months. In contrast, and consistent with inattention and slow moving information, analogous shocks to less visible TNIC peers take up to twelve 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

[2]Publication dates of academic articles pertaining to predictable stock returns are relevant, as Mclean and Pontiff (2014) find evidence that anomalies attenuate after such publication, perhaps due to increased attention.

are similarly shocked.

Relatedly, under the inattention hypothesis, a further prediction is that systematic shocks, which are highly visible by definition, should decay more quickly than idiosyncratic shocks, which are localized and less visible. Alternative risk–based theories would predict that returns should be more linked to systematic 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 only exist 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 their portfolios. 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 if momentum is related to the breadth of various peer shocks. We define broad shocks as those that impact a larger set of related firms that are more 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 classification generate strong momentum returns, as do TNIC peers that are calibrated to be as fine as the SIC–3 network. We also find and report that broader TNIC peers, calibrated to be as coarse as the 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]

We examine various momentum horizon variables to further assess the findings of JT and MG. Using the standard one–year momentum horizon, we find that the less visible TNIC peer momentum variables are substantially more significant than are SIC–based peers or own–firm momentum variables in standard Fama–Macbeth return regressions. Moreover, the economic magnitude of TNIC peer momentum variables is considerably larger. Our results are strong both for the six month horizon and for the subsequent six 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) (GM) show that industry momentum for SIC–code–based peers is not robust to the bid–ask bounce, and to lagging the portfolio formation period by one month. To underscore this point, Jegadeesh and Titman

[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 in order 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 also 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).

(2011) highlight GM's findings in their recent review and conclude that industry momentum cannot explain the momentum anomaly. They however do conclude that momentum profits likely "arise because of a delayed reaction to firm–specific information". 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 re–test 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.

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, Shleifer, and Vishny (1998). However, we further predict that the specific mechanism driving inattention momentum is less visible industry links through which large price shocks need to propagate.

Hypothesis H1: Industry momentum arises from underreaction to shocks to groups of peer firms with less–visible economic links.

Hypothesis H2: Past returns of less visible industry peers will be stronger than the past returns of highly visible peers in simultaneous regressions predicting future returns. Momentum profits from less visible peer shocks should also be economically larger than shocks to highly visible peers.

Hypothesis H3: Momentum profits should be largest following idiosyncratic shocks to peers, as fewer investors likely pay attention to such localized shocks.

Profits should be smaller following more visible systematic shocks.

Hypotheses H1 to H3 are direct implications of inattention to economic shocks to economically related firms. We test hypotheses H1 to H3 using horizons up to one year. Our use of less visible TNIC peers and highly visible SIC peers that measure 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 SEC Edgar website 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 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 Service (WRDS) SEC Analytics product to map each SEC CIK to its COMPUSTAT gvkey on a historical basis. We require that each firm has a valid link from the 10–K CIK to the CRSP/Compustat merged database, and it must also have a valid CRSP permno in order to remain in our database. Our focus is therefore on publicly traded firms in the CRSP database. Our primary database of monthly firm returns is thus based on the CRSP monthly returns database. Because our 10–K data begins 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 December 2012. We also exclude observations from our returns database if their stock price is less than one dollar to avoid drawing inferences from penny stocks.

A Asset Pricing Variables

We construct size and book to market ratio variables following Davis, Fama, and French (2000) and Fama and French (1992). Market size is the natural log of the CRSP market cap. Following the lag convention in the literature, we use size variables from each June, and apply them to the monthly panel to use to predict returns in the following one 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 the accounting variables from fiscal years ending in each calendar year (see Davis, Fama, and French (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 one year window beginning in July of the following year until June one year later.

For each firm, we compute the own–firm momentum variable as the stock return during the eleven 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 one–month reversal effect. Because industry momentum variables do not experience the one–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 industry momentum variables are not susceptible to the Grundy and Martin (2001) critique).

After requiring that adequate data exist to compute the aforementioned asset pricing control variables, and requiring valid return data in CRSP and also 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 the related firms generate comovement, and more interesting, if the shocks disseminate slowly and thus entail prolonged return predictability. We consider industry returns using both text–based network industry classification (TNIC) peers and SIC code based peers at different levels of aggregation.

1 Text–Based Industry Momentum Variables

We consider simultaneously–measured monthly returns of product market peers. For text–based industries, we consider the textual network industry classification (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 3–digit SIC code. We use this level of granularity as this 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 that are more idiosyncratic in nature. We briefly note that results later in this article will illustrate that indeed 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 paper and in the Internet Appendix (available at www.jfqa.org) Table A5 for example, that this prediction is strongly upheld in the data.

2 SIC–Based Industry Momentum Variables

For traditional SIC–based industry momentum returns, we follow the existing 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–48 industries, which are indeed considerably more coarse than are our TNIC–3 industries, which are calibrated to three digit SIC codes.

To ensure that these differences between our chosen SIC–based and TNIC–based portfolios do not strongly impact our results, we examine robustness to a basket of 8 variations on how we compute SIC–based momentum variables. In Internet Appendix (available at www.jfqa.org) Table A1, for example, we consider four levels of SIC granularity: (1) 20 industries from Moskowitz and Grinblatt (1999) that are constructed from SIC codes, (2) the Fama-French-48 industries that are also derived from SIC codes, (3) two–digit SIC codes, and (4) three–digit SIC codes.

C Industry Disparity

We also 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 one 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–a–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 the highly visible links, leaving fewer alternative channels for information dissemination for these links.

D Systematic and Idiosyncratic Risk

We also 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, HML, SMB, and UMD.[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 supporting evidence that TNIC peers were indeed less visible than SIC peers during our sample. Because share turnover is a direct consequence of

[4]We thank Ken French for providing the daily factor returns on his website.

attention (see Gervais, Kaniel, and Mingelgrin (2001) for example), we examine the relationship 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 code peers or TNIC peers experienced the highest quintile of sample–wide returns in the given month. The upper graph 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 quite modest. However, this unconditional result is primarily due to the fact that high–quintile stock returns to SIC code peers and TNIC peers are highly correlated, as both classifications contain many of the same firms.

[Insert Figure 1 Here]

The lower graph 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 analogous SIC peer returns are near zero (in the 40th to the 60th percentile) and vice–a–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 two months later. In contrast, when TNIC peers are uniquely shocked (solid line), turnover does not immediately increase at $t = 0$. Instead, turnover increases in 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 indeed being less visible than SIC peers. Later in this study, we show additional evidence that TNIC peers are less visible than SIC–based 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 relationship between focal firm returns and the returns of various peers. We examine co–movement 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. Table 1 presents summary statistics for our firm–month observations from July 1997 to December 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 is due to the fact that these peer return variables are averages, which reduces the level of variation relative to that of individual firms.

[Insert Table 1 Here]

Panel D of Table 1 reports Pearson correlations. Not surprisingly, the book to market ratio and the firm size variables are not highly correlated with any of the momentum variables. The table also shows that own–firm returns are 40.2% correlated with the return of TNIC–3 peers, and 32.5% correlated with SIC–based Fama–French–48 (FF–48) peers. The TNIC–3 and FF–48 peers are also 62.2% mutually correlated, indicating that they also have some common information. Despite the information overlap, our later tests will show that both have distinct signals, and TNIC–3 momentum is stronger than FF–48 momentum.

Our short–term tests involve assessing the extent to which focal firm monthly returns comove with TNIC–3 and FF–48 peer returns, and also whether information in these variables disseminates gradually. We consider Fama–MacBeth regressions where the dependent variable is the month t return of the focal firm. In simultaneous return tests, we consider specifications in which the return of the TNIC–3 peers and FF–48 peers is the key 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 $t-2$.

[Insert Table 2 Here]

Panel A of Table 2 displays the results. All RHS variables are standardized to have unit standard deviation prior to 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 does the SIC–based Fama–French–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) through (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 both in coefficient magnitudes and also in significance levels going out all six months. In particular, FF–49 momentum becomes negative and insignificant after three months. Internet Appendix (available at www.jfqa.org) Table A2 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 two month horizons and beyond. Our findings broadly are consistent with TNIC peers being stronger, potentially due to 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 text–based peer returns contribute information over and above SIC–based variables.

We use as our baseline specification the following two industry variables: TNIC–3 industry momentum and SIC–based peers using the Fama–French–48 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, 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 relationship with ex–post own firm returns using various lags. This test assesses whether lagged monthly returns from more versus less visible product market peers both predict monthly ex–post focal firm returns.

We consider standard Fama–MacBeth regressions where the dependent variable is the own–firm month t excess stock return. In addition to the book to market and size control, we consider four variables based on past returns. For own–firm returns, we include returns from the past one–month, which relate to the one–month reversal anomaly and also include returns over the 11 month period beginning in month $t-12$ and ending in month $t-2$. For industry returns, we include the return of FF–48 peers and the return of TNIC–3 peers 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). We separately consider the most recent own–firm month (known as the reversal variable).

As discussed earlier, our FF–48 industry momentum variables are value weighted, and TNIC–3 industry momentum variables are equal weighted. We use these 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 strongly conclude that Hou (2007) cannot explain TNIC momentum.

Our paper focuses 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 sample column, we report the sample used in each regression: the entire sample or the subsample that ends prior to the 2008–2009 crisis period. All RHS variables are standardized prior to running the regressions for ease of comparison.

[Insert Table 3 Here]

We test the baseline industry momentum hypothesis in Table 3 for the entire sample (Panel A) and for the sample ending in December 2007, 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 based 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 TNIC momentum variables are the most impactful industry momentum variables in both samples. These findings, when considered along with the results of the last 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.

[Insert Table 4 Here]

We also split the yearly momentum variables into two half–year periods. We examine these splits so as to examine the relative decay rate of momentum. The regressions are similar to those in Table 3, except that we divide the momentum variables into one component from the most recent six months ($t-1$ to $t-6$) and a separate component form the previous six months ($t-7$ to $t-12$). In the sample column, we note that we consider the entire sample, and the sample that ends prior to the 2008–2009 crisis period.

The results show that industry TNIC momentum persists into the longer monthly period $t-7$ to $t-12$, while the FF–48 industry past returns and the own firm past returns only matter for the first six months. These findings give strong support to the interpretation that the information contained in TNIC peers is less visible to market participations, supporting the explanation of slow industry dissemination.

A Bid–Ask Bounce, Vertical Links and Simultaneous Returns

We consider three robustness tests that use the same baseline specifications in Table 3, although each with one change meant consider different robustness tests. Panel A of Table 3 examines robustness to the bid–ask bounce critique as in Grundy and Martin (2001). For this test, we thus divide each industry momentum variable into two parts: an 11 month term ($t-2$ to $t-12$) and a one month term ($t-1$).

Two existing 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 if 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 should be highly distinct.

Panel B of Table 3 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 IO–table vertical peer returns, we use the 1997 and 2002 Input–Output tables given that we predict returns from July 1997 and forward. We then compute the average returns separately for both upstream industries and downstream industries for the same two return windows. We then compute the average of the upstream and downstream peer returns for both return windows. We then reconsider the regressions in Table 3 with these four additional control variables included (two horizons, two types of vertical links).

Lastly, Panel C of Table 3 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).

[Insert Table 5 Here]

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 the 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 four vertical link variables. We also note that we are able to replicate the main results in both of these previous studies. For example, the shock to customers is positive and significant in most specifications. We also find that the IO Table vertical return is positive and significant at the shorter one–month horizon.

We note that we standardize all RHS variables in the regressions to have a zero mean and a unit variance prior to 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 the potential of shocks to horizontal peers to explain momentum far exceeds that of the vertical peer shocks. This statement is particularly true for the less visible TNIC peer links.

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

B Various Horizons

We consider variations in the horizon of the momentum variables. In particular, we consider three–month, six–month, twelve month, 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 one 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 shorter–lived.

[Insert Table 6 Here]

The independent variables in our regressions are standardized prior to running the regressions and the coefficients are interpretable. The six–month economic impact of FF–48 peer peers (monthly return of 0.004 per unit of sigma) is only half that of the TNIC–3 peers at the same horizon (0.008). Moreover, the TNIC–3 returns continue to accumulate returns with a total summed coefficient of 0.013 over the one 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 that includes the financial crisis, and the shorter sample that ends in 2007. This is expected under our hypothesis that 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 like "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 are those affecting only a small region of the space around a firm, and broader peer shocks affect wide swaths of space around a firm. This question is particularly interesting because a theory of systematic risk would predict that only broad shocks affecting many firms should be priced. If this was not the case, then the peer shocks would be easy to diversify and in equilibrium, investors would not demand risk premia for investing in firms exposed to diversifiable shocks.

On the other hand, the inattention hypothesis predicts that shocks to local product market peers should be more important. A key reason is that broader shocks affecting large numbers of firms should be more visible, and hence would be 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.

[Insert Table 7 Here]

In Table 7, we consider peers positioned in the product market in different distance–bands around a given focal firm. For example, we consider 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 four–digit SIC code, and firms at this level of proximity are thus 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 three–digit SIC code, but are not in the same four–digit SIC code. Intuitively, peers in this second group are somewhat broader in the product market space than peers in the first band. We consider a third band that includes firms that are as proximate in the TNIC industry space as are two–digit SIC pairs (4.52%), but not as proximate as three–digit SIC pairs (2.03%). Finally, our broadest band includes firms that are as proximate in the TNIC industry space as are one–digit SIC pairs (15.8%), but not as proximate as two–digit SIC pairs (4.52%).

We consider shocks to these distance–based peer groups as competing RHS variables in our standard Fama–MacBeth 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 of Table 7. The table shows that shocks to product market peers drive momentum only when the peers are local. The inner band is highly significant in predicting ex–post returns, as is the second band. However, both of the broader bands are not statistically significant.

We conclude that peers located in the product market space with similar proximity as 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 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 factors plus momentum (UMD), and we then tabulate the total contribution of systematic risk projections to each firm's monthly return.

We then compute peer momentum variables using our standard averaging approach. We define the idiosyncratic component as the raw peer return minus the systematic peer return component.

[Insert Table 8 Here]

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 the two horizons, the near–term horizon of $t-1$ to $t-6$ and a longer term horizon of $t-7$ to $t-12$. Panel A of Table 8 presents results for the full sample and Panel B of Table 8 for the subsample that excludes the financial crisis.

The Table shows that, for long–term momentum for the $t-7$ to $t-12$ horizon in columns three and four, only idiosyncratic peer shocks matter. Even for the shorter six month horizon in columns one and two, the idiosyncratic component (highly significant at the 1% level in all four specifications) strongly dominates the systematic component (only significant in two of the specifications at the 5% level and insignificant in the other two). These results reinforce our earlier findings as discussed in Internet Appendix (available at www.jfqa.org) Table A3, 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 one year. We conclude that the industry momentum anomaly is likely due to more localized idiosyncratic peer shocks affecting a smaller fraction of the 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 would be attentive 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 yet 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 two sets of peers. We thus compute "disparity" as one minus the total sales of firms that are in the intersection of TNIC–3 peers and SIC–3 peer groups divided by the total 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 a longer term horizon of $t-7$ to $t-12$. We rerun this model for firms in different quintiles based on their industry disparity. In Panels A and B, we consider the full sample and the sample that excludes the financial crisis years, respectively. Our hypothesis is that momentum variables should be stronger in high disparity quintiles and weaker in low disparity quintiles.

[Insert Table 9 Here]

The results in both panels for the longer $t-7$ to $t-12$ horizon strongly support the conclusion 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 much smaller magnitudes 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 the short horizon is further consistent with a visibility interpretation, as it indicates that return shocks disseminate most slowly and most intensively when visibility (as measured by disparity) is lowest. Indeed a slower speed 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 longer–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 three groups: (1) firms that are TNIC–3 peers but not SIC–3 peers, (2) firms that are SIC–3 peers but not TNIC–3 peers, and (3) 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 one–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 should 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 should be strongest for the high disparity quintile.

[Insert Table 10 Here]

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. Interestingly, we also find that the "both TNIC and SIC peer group" performs well, and produces positive and significant momentum returns. This suggests that the presence of a less visible link is more important than the absence of a highly visible link when predicting momentum returns. This suggests that a firm that is both a SIC and a TNIC peer likely has an ultra–strong economic link to the firm. As investors are likely inattentive to the TNIC link, they would 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) to (6) for the full sample and (7) to (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 of the quintiles except for the highest disparity quintile. In contrast, the both TNIC and SIC peer group predicts momentum returns in all of the quintiles. This variable is slightly stronger in low to middle disparity quintiles, where the existence of peers that are in both classifications is more common (given the definition of disparity). In all, the findings here 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 (A) invest long in the highest quintile firms and (B) 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 a 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

[5] We thank Ken French for providing factor data on his website.

statistically and economically distinct from zero.

[Insert Table 11 Here]

In Panel A of Table 11, we compute the zero cost portfolios only based 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) and (2), we consider the full sample from July 1997 to December 2012, and 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 four specifications. Economically, we observe predictable returns in the range of 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 to be in the range of 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 level of disparity 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 of Table 11, 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 lack of robustness to including the UMD factor. We conclude overall that the calendar time tests produce results that are similar to our baseline Fama–MacBeth regressions.

Internet Appendix (available at www.jfqa.org) Table A6 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 only find that 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 its ability to produce predictable returns outside the crisis, and also the extent to which each portfolio under–performs during the financial crisis. This question is not only interesting 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 indeed does or does not explain momentum.

[Insert Figure 2 Here]

We first report in Figure 2 the cumulative abnormal monthly returns for the four momentum strategies we highlighted in Table 11 during our 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 the UMD factor in order to 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 some after 2000 and 2001. This flattening of returns is consistent with returns attributable to both 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 th 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 high disparity momentum

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

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 three years, is not strong enough to ultimately 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 continue 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 explanation rooted in inattention.

We conclude that although individual firms that had high returns prior to the crisis did not perform well, that 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 in 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.

[Insert Figure 3 Here]

In Figure 3, we report analogous cumulative abnormal returns for the four 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 was true for equal weighted results, the high disparity TNIC–3 momentum portfolio only has a small impact from the crisis, and quickly recovers. This strategy, even value weighted, continues to accumulate high returns during the last part of our sample.

I Attention from Professional Investors

We now further examine the link between our central results and visibility using an approach from Cohen and Frazzini (2008) (CF), 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 specifically to the economic link between the pair of stocks. The authors 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 will be strongest in subsamples where horizontal TNIC–3 pairs are not jointly held by mutual funds.

We use the CRSP Survivor–Bias Free US Mutual Fund database[7] to compute

[7] We use the data selection algorithm used in Kacperczyk, Sialm, and Zheng (2007) to limit attention to diversified equity funds as our goal is to exclude non–actively managed index funds.

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 zero). 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.

[Insert Table 12 Here]

Table 12 displays the results of Fama–MacBeth 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 one–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 one standard deviation higher level of this variable outperform control firms by twelve percentage points per year. For the monthly periods of $t-7$ to $t-12$, we also find that the TNIC industry return is significant for the two quintiles of low common ownership. In the highest quintile of joint ownership for the nearby month periods $t-1$ 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 the quintiles, and these results are also robust to dropping the financial crisis period in Panel B of Table 12. 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 if mutual funds recognize the links between firms that are present in the TNIC network. We examine if 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, that 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 two metrics of joint ownership, one based on portfolio weights and the other based on non–zero ownership. In both cases, the first step is, for each fund in each year, identify all pairwise permutations of the stocks held in its portfolio. For example, a fund holding 5 stocks would have $\frac{5^2-2}{2} = 10$ permutations. For each permutation, we also compute the product weight $pw_{i,j,t} = w_{i,t} * w_{j,t}$, where $w_{i,t}$ and $w_{j,t}$ are the fraction of the fund's wealth in stock i and j in year t (although fund's report holdings quarterly, we only consider 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 zero otherwise. The former metric is thus a value–weighted overlap metric, whereas the other is an ownership weighted metric. We then regress these overlap matrics on a dummy indicating whether stocks i and j are in the same SIC–3 code industry and whether then are in the same TNIC–3 industry.

[Insert Table 13 Here]

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 of Table 13. 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.

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 Internet Appendix (available at www.jfqa.org) Table A4, we repeat this test for our TNIC–based one 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 much more strongly predict momentum returns 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 are significantly stronger than the random peers at the 1% level.

Hou (2007) documents that the well–known result that large firm stock returns lead those of smaller firms is primarily due to within–industry return predictability. We examine if our results can be explained by Hou (2007) using subsample tests in Table A5 of the Internet Appendix. Ex–ante, we should not expect our results to be related to Hou (2007) because we are addressing the long–term momentum anomaly (12 months), whereas the lead–lag anomaly is short–term in nature (one month or less). Nevertheless, Table A5 shows that our results (A) are robust to using the subsample of above–median market capitalization firms, and (B) to only including firms in the largest tercile based on firm size. In contrast, FF–49 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–49 momentum is related to the lead–lag anomaly.

We additionally examine in Table A7 of the Internet Appendix if 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, Shleifer, and Vishny (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) (GM) 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 GM 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 paper provides evidence that industry momentum is in fact important, and slow propagation of information across less visible economic links plays a strong role.

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.

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.

Mclean, 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.

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.

Table 1: Summary Statistics

Summary statistics are reported for our sample of 805,090 observations based on monthly return data from July 1997 to December 2012. Observations are required to be in CRSP, COMPUSTAT, and our 10–K database. Consistent with existing studies, observations must have a one 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 one dollar. One observation is one firm in one month. The 11 month firm momentum variable measures past returns from month t–2 to t–11, again consistent with the literature. We also include a one–month firm momentum variable. The industry momentum variables (FF–48 using value weighted peers in Panel B) and (TNIC–3 using equal weighted peers in Panel C) are from month 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). Panel D displays Pearson correlation coefficients for one–month return variables.

Variable	Mean	Std. Dev.	Minimum	Median	Maximum
Panel A: Data from the Existing Literature					
Monthly Return	0.009	0.172	-0.981	0.002	9.374
Log B/M Ratio	-7.577	0.931	-16.164	-7.496	-1.223
Log Market Cap	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

Panel D: Pearson Correlations

Row	Variable	Month t Own-Firm Return	Log Book to Market Ratio	Log Mkt Capital-ization	Month $t-1$ Own-Firm Return	Month $t-1$ FF–48 Industry Return
(1)	B/M Ratio	0.024				
(2)	Log Mkt Cap	-0.012	-0.308			
(3)	Month $t-1$ Own-Firm Return	0.010	0.026	-0.022		
(4)	Month $t-1$ FF–48 Return	0.076	0.012	-0.012	0.325	
(5)	Month $t-1$ TNIC–3 Return	0.083	0.015	-0.017	0.402	0.622

Table 2: Return Comovement

Fama–MacBeth regressions with own–firm monthly stock return as the dependent variable. One observation is one firm from July 1997 to December 2012. The independent variables include the text–based return benchmark (excluding the firm itself), and the Fama–French–49 (SIC–based) return 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 month $t-12$ to $t-2$). We consider industry peer variables that are simultaneously measured with the focal firm return (month t returns), as well as various lags ranging from one 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 SIC–3. The FF–48 peer returns are value–weighted and the TNIC–3 returns are equal weighted. All RHS variables are standardized to have a standard deviation of one for ease of comparison and interpretation. All standard errors are adjusted using Newey–West with two lags.

Row	TNIC–3 t Return	TNIC–3 $t-1$ Return	TNIC–3 $t-2$ Return	TNIC–3 $t-3$ Return	TNIC–3 $t-4$ Return	TNIC–3 $t-5$ Return	TNIC–3 $t-6$ Return	FF–48 t Return	FF–48 $t-1$ Return	FF–48 $t-2$ Return	FF–48 $t-3$ Return	FF–48 $t-4$ Return	FF–48 $t-5$ Return	FF–48 $t-6$ Return	RSQ / # Obs.
(1)	0.036							0.021							0.070
	(33.03)							(24.07)							805,090
(2)	0.042														0.064
	(37.39)														805,090
(3)								0.034							0.046
								(34.78)							805,090
(4)	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
(5)	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
(6)		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
(7)		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

Table 3: Fama MacBeth Return Regressions (Various 1-Year Momentum Variables)

Fama–MacBeth 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. The key variables include 10–K Based TNIC–3 momentum, FF–48 (SIC–based) based 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), and 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 peers are based on value–weighted peers. In both cases, the firm itself is excluded from the average. In the sample column, we note that we consider the entire sample, and the sample that ends prior to the 2008–2009 crisis period. All RHS variables are standardized prior to running the regression for ease of comparison. All standard errors are adjusted using Newey–West with two lags.

Row	Sample	t-1 to t-12 TNIC–3 Industry Past Return	t-1 to t-12 FF–48 Industry Past Return	t-1 Own Firm Past Return	t-2 to t-12 Own Firm Past Return	Log Market Capital-ization	Log Book to Market Ratio	R^2	# Months/ # Obs.
				Panel A: All Months 7/97 to 12/12					
(1)	All Months			-0.004	0.001	-0.000	0.002	0.035	186
				(-3.19)	(0.52)	(-0.35)	(1.57)		805,090
(2)	All Months	0.008				-0.000	0.002	0.031	186
		(3.07)				(-0.27)	(1.99)		805,090
(3)	All Months		0.005			-0.000	0.002	0.026	186
			(2.60)			(-0.18)	(1.66)		805,090
(4)	All Months		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
(5)	All Months	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: Pre–Crisis Months 7/97 to 12/07					
(6)	Pre-2008			-0.003	0.004	-0.001	0.003	0.037	126
				(-2.33)	(2.16)	(-0.74)	(1.43)		591,241
(7)	Pre-2008	0.011				-0.001	0.003	0.037	126
		(3.55)				(-0.67)	(1.89)		591,241
(8)	Pre-2008		0.007			-0.001	0.003	0.030	126
			(2.73)			(-0.59)	(1.49)		591,241
(9)	Pre-2008		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
(10)	Pre-2008	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

Table 4: Fama MacBeth Return Regressions (Split Half-Year Variables)

Fama–MacBeth 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. The key variables include 10–K Based TNIC–3 momentum, Fama–French–48 (SIC–based) 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 six months ($t-1$ to $t-6$) and a separate component form the previous six months ($t-7$ to $t-12$). TNIC–3 industry momentum variables are based on equal–weighted peers and FF–48 peers are based on value–weighted peers. In both cases, the firm itself is excluded from the average. In the sample column, we note that we consider the entire sample, and the sample that ends prior to the 2008–2009 crisis period. All RHS variables are standardized prior to running the regression for ease of comparison. All standard errors are adjusted using Newey–West with two lags.

Row	Sample	t-1 to t-6 TNIC–3 Industry Past Ret.	t-7 to t-12 TNIC–3 Industry Past Ret.	t-1 to t-6 FF–48 Industry Past Ret.	t-7 to t-12 FF–48 Industry Past Ret.	t-1 Own Firm Past Ret.	t-2 to t-6 Own Firm Past Ret.	t-7 to t-12 Own Firm Past Ret.	Log Market Capital-ization	Log Book to Market Ratio	R^2	# Months/ # Obs.
					Panel A: All Months 7/97 to 12/12							
(1)	All Months					-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
(2)	All Months	0.008	0.004						-0.000	0.002	0.036	186
		(3.74)	(2.28)						(-0.33)	(2.19)		805,090
(3)	All Months			0.006	0.002				-0.000	0.002	0.030	186
				(3.97)	(0.89)				(-0.21)	(1.85)		805,090
(4)	All Months			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
(5)	All Months	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: Pre–Crisis Months 7/97 to 12/07							
(6)	Pre-2008					-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
(7)	Pre-2008	0.011	0.005						-0.001	0.003	0.043	126
		(4.21)	(2.39)						(-0.73)	(2.08)		591,241
(8)	Pre-2008			0.007	0.002				-0.001	0.002	0.033	126
				(4.22)	(1.10)				(-0.62)	(1.58)		591,241
(9)	Pre-2008			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
(10)	Pre-2008	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

Table 5: Fama MacBeth Return Regressions (Bid–Ask Bounce, Vertical Links and Simultaneous Returns)

Fama–MacBeth 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. We consider three robustness tests that use the same baseline specifications in Table 3, although each with one change meant to zoom in on a particular issue of robustness. Panel A examines robustness to the bid–ask bounce critique as in Grundy and Martin (2001). Hence we divide each industry momentum variable into two parts: an 11 month term ($t-2$ to $t-12$) and a one 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). 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 Input–Output tables given that we predict returns from July 1997 and forward. Panel C examines robustness to including controls for simultaneous TNIC–3 and Fama–French–48 industry 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 prior to the 2008–2009 crisis period. All RHS variables are standardized prior to running the regression for ease of comparison. All standard errors are adjusted using Newey–West with two lags.

Panel A: Robustness to Bid–Ask Bounce

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

Panel B: Robustness to Vertical Economic Links

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

Panel C: Robustness to Simultaneous Returns

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

Table 6: Fama MacBeth Return Regressions (Various Momentum Horizons)

Fama–MacBeth 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. The key variables include own–firm momentum, Fama–French–48 (SIC–based) momentum, and 10–K Based TNIC–3 momentum. We consider momentum horizons that range from month $t-1$ to $t-6$ for short horizons and month $t-13$ to $t-24$ for longer horizons. TNIC–3 industry momentum variables are based on equal–weighted peers and FF–48 peers 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. In the sample column, we note that we consider the entire sample, and the sample that that ends prior to the 2008–2009 crisis period. All RHS variables are standardized prior to running the regression for ease of comparison. All standard errors are adjusted using Newey–West with two lags.

Row	Sample & Duration	TNIC–3 Industry Past Return	FF–48 Industry Past Return	Own Firm Past Return	Log Market Capital- ization	Log Book to Market Ratio	R^2	# Months/ # Obs.
			Panel A: All Months 7/97 to 12/12					
(1)	All Months: months 1-6 momentum	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
(2)	All Months: months 7-12 momentum	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
(3)	All Months: months 13-24 momentu	-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: Pre–Crisis Months 7/97 to 12/07					
(4)	Pre-2008: months 1-6 momentum	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
(5)	Pre-2008: months 7-12 momentum	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
(6)	Pre-2008: months 13-24 momentum	-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

Table 7: Fama MacBeth Return Regressions (Industry Breadth)

Fama–MacBeth 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. We compute TNIC momentum using various granularities as noted in the first column: TNIC–4 (analogous to 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, FF–48 momentum, size, and book to market. We also note that we consider the entire sample, and the sample that ends prior to the 2008–2009 crisis period as noted in the first column. All RHS variables are standardized prior to running the regression for ease of comparison. All standard errors are adjusted using Newey–West with two lags.

Row	Sample	t-1 to t-12 TNIC-4 Industry Past Ret.	t-1 to t-12 TNIC-(3-4) Industry Past Ret.	t-1 to t-12 TNIC-(2-3) Industry Past Ret.	t-1 to t-12 TNIC-(1-2) Industry Past Ret.	t-2 to t-12 Own Firm Industry Past Ret.	t-1 to t-12 FF–48 Industry Past Ret.	t-1 Own Firm Industry Past Ret.	Log Mkt Capital-ization	Log Book to Market Ratio	R^2	# Months/ # Obs.
						Panel A: All Months 7/97 to 12/12						
(1)	All Months	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
(2)	All Months	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
(3)	All Months	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: Pre–Crisis Months 7/97 to 12/07						
(4)	Pre-2008	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
(5)	Pre-2008	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
(6)	Pre-2008	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

Table 8: Fama MacBeth Return Regressions (Idiosyncratic and Systematic Risk)

Fama–MacBeth 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. To compute the systematic portion, we first regress (for each month) daily stock returns for each firm onto the three Fama French 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. 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 (Panel A) and the sample that ends prior to the 2008–2009 crisis period (Panel B). All RHS variables are standardized prior to running the regression for ease of comparison. All standard errors are adjusted using Newey–West with two lags.

Row	Sample	Idiosyn. t-1 to t-6 TNIC–3 Industry Past Return	Systematic t-1 to t-6 TNIC–3 Industry Past Return	Idiosyn. t-7 to t-12 TNIC–3 Industry Past Return	Systematic t-7 to t-12 TNIC–3 Industry Past Return	Log Market Capital-ization	Log Book to Market Ratio	R^2	# Months/ # Obs.
				Panel A: All Months 7/97 to 12/12					
(1)	All Months	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
(2)	All Months	0.006		0.003		-0.000	0.002	0.027	186
		(4.13)		(3.36)		(-0.13)	(2.14)		805,090
(3)	All Months		0.001		0.000	-0.000	0.002	0.029	186
			(0.44)		(0.11)	(-0.33)	(1.53)		805,090
				Panel B: Pre–Crisis Months 7/97 to 12/07					
(4)	All Months	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
(5)	All Months	0.008		0.004		-0.001	0.003	0.032	126
		(4.39)		(3.13)		(-0.55)	(2.06)		591,241
(6)	All Months		0.002		-0.000	-0.001	0.002	0.034	126
			(1.11)		(-0.27)	(-0.67)	(1.41)		591,241

Table 9: Fama MacBeth Return Regressions (High and Low Industry Disparity)

Fama–MacBeth regressions with the monthly stock return as the dependent variable. A key variable we use to subsample the data is industry disparity, which is one minus the total sales of firms in the intersection of TNIC–3 and 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 the 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. The key variables include 10–K Based TNIC–3 momentum measured over the past 6 months and also 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 (Panel A) and the sample that ends prior to the 2008–2009 crisis period (Panel B). All RHS variables are standardized prior to running the regression for ease of comparison. All standard errors are adjusted using Newey–West with two lags.

Row	Sample	t-1 to t-6 TNIC–3 Industry Past Return	t-7 to t-12 TNIC–3 Industry Past Return	Log Market Capital-ization	Log Book to Market Ratio	R^2	# Months/ # Obs.
				Panel A: All Months 7/97 to 12/12			
(1)	Low Disparity	0.006	0.001	-0.000	0.001	0.041	186
		(2.52)	(0.32)	(-0.14)	(1.25)		160,576
(2)	Quintile 2	0.009	0.004	-0.001	0.001	0.063	186
		(2.55)	(1.56)	(-0.70)	(0.70)		162,396
(3)	Quintile 3	0.008	0.004	-0.001	0.002	0.051	186
		(2.54)	(1.55)	(-0.73)	(2.06)		161,957
(4)	Quintile 4	0.010	0.005	-0.001	0.002	0.038	186
		(4.55)	(2.35)	(-0.64)	(1.45)		160,600
(5)	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: Pre–Crisis Months 7/97 to 12/07			
(6)	Low Disparity	0.007	0.001	-0.000	0.002	0.043	126
		(4.06)	(0.68)	(-0.03)	(1.73)		118,136
(7)	Quintile 2	0.014	0.004	-0.002	0.001	0.069	126
		(3.40)	(1.32)	(-1.19)	(0.83)		119,180
(8)	Quintile 3	0.011	0.005	-0.002	0.003	0.060	126
		(3.18)	(1.72)	(-0.89)	(1.69)		118,780
(9)	Quintile 4	0.012	0.006	-0.002	0.003	0.042	126
		(4.43)	(2.73)	(-0.91)	(1.93)		118,104
(10)	High Disparity	0.011	0.006	-0.002	0.004	0.027	126
		(5.11)	(3.71)	(-1.16)	(3.42)		117,041

Table 10: Fama–MacBeth Return Regressions (Various Peer Groups)

Fama–MacBeth regressions with the monthly stock return as the dependent variable. We subsample the data regarding whether or not peers are only TNIC–3 peers, only SIC–3 peers, or are peers according to both classifications. We then compute equal–weighted average returns for the peers in each group to thus construct three industry momentum variables. The independent variables are all measured ex–ante using the lag structure given by Fama and French. 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 (Panel A) and the sample that ends prior to the 2008–2009 crisis period (Panel B). All RHS variables are standardized prior to running the regression for ease of comparison. All standard errors are adjusted using Newey–West with two lags.

Row	Sample	t-1 to t-12 TNIC–3 Only Peers Past Return	t-1 to t-12 SIC–3 Only Peers Past Return	t-1 to t-12 Both TNIC & SIC Past Return	Log Market Capital-ization	Log Book to Market Ratio	R^2	# Months/ # Obs.
				Panel A: All Months 7/97 to 12/12				
(1)	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
(2)	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
(3)	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
(4)	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
(5)	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
(6)	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: Pre–Crisis Months 7/97 to 12/07				
(7)	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
(8)	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
(9)	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
(10)	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
(11)	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
(12)	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

Table 11: Calendar–Time Portfolios (Equal Weighted BJS Alpha Tests)

We report 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: TNIC–3 momentum (Panels A and B), Fama–French–49 (SIC–based) momentum (Panel C), and own momentum (Panel D). 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 (one minus the total sales of all firms in the intersection of TNIC–3 and 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 one year measurement period for past returns as noted in the first column. For own firm momentum, we skip the most recent month following the existing 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 twelve 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.

Row	Sample / Horizon	Alpha	MKT	HML	SMB	UMD	Sharpe Ratios	R^2	Obs.
	Panel A: 10-K Based TNIC–3 Momentum (High Disparity Quintile), long/short quintiles								
(1)	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		
(2)	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		
(3)	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		
(4)	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, long/short quintiles								
(5)	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		
(6)	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		
(7)	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		
(8)	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, long/short quintiles								
(9)	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		
(10)	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		
(11)	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		
(12)	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, long/short quintiles								
(13)	All Months	0.010	-0.470	-0.323	0.097		0.399	0.106	186
	t-1 to t-12 Momentum	(2.08)	(-4.38)	(-2.13)	(0.66)		0.540		
(14)	All Months	0.003	0.058	0.044	-0.145	1.157	0.399	0.895	186
	t-1 to t-12 Momentum	(1.96)	(1.46)	(0.82)	(-2.85)	(36.87)	0.512		
(15)	Pre-2008	0.016	-0.511	-0.253	0.157		0.653	0.082	126
	t-1 to t-12 Momentum	(2.52)	(-3.11)	(-1.17)	(0.92)		0.810		
(16)	Pre-2008	0.003	0.014	0.006	-0.181	1.224	0.653	0.886	126
	t-1 to t-12 Momentum	(1.42)	(0.24)	(0.08)	(-2.93)	(29.16)	0.466		

Table 12: Fama MacBeth Return Regressions (High versus Low Mutual Fund Common Ownership of Linked Peers)

Fama–MacBeth regressions with the monthly stock return as the dependent variable. 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 the given pair divided by the number of mutual funds that own the peer firm (when no funds own the peer, this is set to zero). Hence this number is bounded in the interval [0,1]. We then compute the average of this quantity over each firm's 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 CRSP Survivor–Bias Free US 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 (2007). The independent variables are all measured ex–ante using the lag structure given by Fama and French. The key variables include 10–K Based TNIC–3 momentum. We consider the entire sample (Panel A) and the sample that ends prior to the 2008–2009 crisis period (Panel B). All RHS variables are standardized prior to running the regression for ease of comparison. All standard errors are adjusted using Newey–West with two lags.

Row	Sample	t-1 to t-6 TNIC–3 Industry Past Return	t-7 to t-12 TNIC–3 Industry Past Return	Log Market Capital-ization	Log Book to Market Ratio	R^2	# Months/ # Obs.
			Panel A: All Months 7/97 to 12/12				
(1)	Less Jointly Owned	0.009	0.005	-0.001	0.004	0.026	186
		(4.84)	(3.54)	(-0.37)	(3.40)		167,196
(2)	Quintile 2	0.009	0.004	-0.001	0.003	0.031	186
		(5.63)	(2.50)	(-0.74)	(2.44)		157,592
(3)	Quintile 3	0.008	0.002	-0.001	0.002	0.039	186
		(4.43)	(1.22)	(-0.37)	(1.51)		162,405
(4)	Quintile 4	0.006	0.001	-0.001	0.000	0.046	186
		(3.14)	(0.59)	(-1.00)	(0.36)		162,469
(5)	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: Pre–Crisis Months 7/97 to 12/07				
(6)	Less Jointly Owned	0.009	0.008	-0.002	0.004	0.028	126
		(4.47)	(3.88)	(-1.02)	(2.76)		124,137
(7)	Quintile 2	0.010	0.004	-0.002	0.004	0.035	126
		(4.85)	(2.44)	(-1.15)	(2.22)		114,476
(8)	Quintile 3	0.010	0.004	-0.000	0.003	0.041	126
		(4.68)	(2.27)	(-0.14)	(1.86)		119,298
(9)	Quintile 4	0.007	0.003	-0.001	0.001	0.049	126
		(3.26)	(1.49)	(-0.42)	(0.71)		119,368
(10)	More Jointly Owned	0.004	0.002	-0.001	0.001	0.072	126
		(1.87)	(0.88)	(-0.54)	(0.50)		119,269

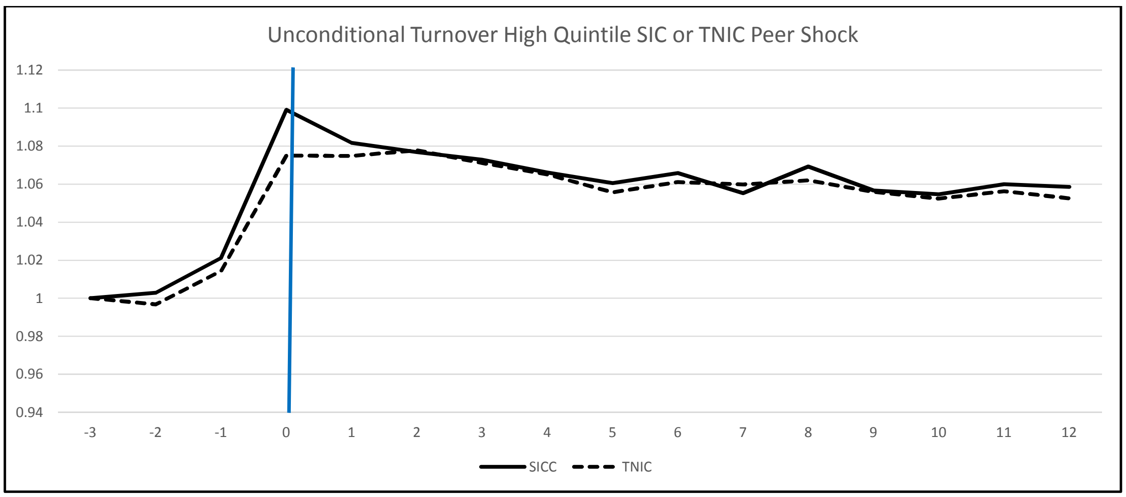
Table 13: Mutual Fund Ownership Regressions

Panel data regressions with firm–pair–year joint ownership metrics as the dependent variable. We consider two metrics of joint ownership, one based on portfolio weights and the other based on non–zero ownership. In both cases, the first step is, for each fund in each year, identify all pairwise permutations of the stocks held in its portfolio. For example, a fund holding 5 stocks would have $\frac{5^2-2}{2} = 10$ permutations. For each permutation, we also compute the product weight $pw_{i,j,t} = w_{i,t} * w_{j,t}$, where $w_{i,t}$ and $w_{j,t}$ are the fraction of the fund's wealth in stock i and j in year t (although fund's report holdings quarterly, we only consider 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 zero otherwise. The former metric is thus a value–weighted overlap metric, whereas the other is an ownership weighted metric. We then regress these overlap matrics on a dummy indicating whether stocks i and j are in the same 3–digit SIC code industry and whether then are in the same TNIC–3 industry (where the TNIC–3 networks is calibrated to be exactly as granular as the SIC–3 network). We also include controls for the natural log of the CRSP market capitalization for stock i and stock j, denoted as Log Size 1 and Log Size 2 below. Finally, we consider firm and year fixed effects as noted, and all standard errors are clustered by firm.

Row	Dependent Variable	Sample	Same SIC–3	Same TNIC–3	Log Size 1	Log Size 2	R^2	Fixed Effects	Obs (000s)
				Panel A: Sector Funds					
(1)	Portfolio Weight Overlap	Sector Funds	6.046	3.521	0.981	1.504	0.130	Firm and Year	8,294
			(12.91)	(22.42)	(14.88)	(28.08)			
(2)	NonZero Ownership Overlap	Sector Funds	2.397	1.279	0.653	0.623	0.250	Firm and Year	8,294
			(17.85)	(28.46)	(22.22)	(46.29)			
(3)	Portfolio Weight Overlap	Sector Funds	6.183	3.412	1.460	1.460	0.087	Year	8,294
			(12.57)	(19.57)	(27.83)	(28.86)			
(4)	NonZero Ownership Overlap	Sector Funds	2.720	1.329	0.596	0.596	0.198	Year	8,294
			(18.47)	(26.88)	(44.48)	(45.84)			
				Panel B: Diversified Funds					
(5)	Portfolio Weight Overlap	Non-Sector Funds	0.195	1.424	0.509	0.795	0.059	Firm and Year	159,363
			(5.24)	(15.81)	(20.62)	(24.28)			
(6)	NonZero Ownership Overlap	Non-Sector Funds	0.580	3.727	4.123	4.115	0.209	Firm and Year	159,363
			(6.15)	(27.48)	(21.20)	(55.69)			
(7)	Portfolio Weight Overlap	Non-Sector Funds	0.161	1.505	0.820	0.820	0.037	Year	159,363
			(3.00)	(13.66)	(25.10)	(24.36)			
(8)	NonZero Ownership Overlap	Non-Sector Funds	-0.032	3.990	4.270	4.270	0.348	Year	159,363
			(-0.22)	(24.67)	(115.76)	(55.32)			

Figure 1: Turnover Following Return Shocks

Event study graph of own–firm average turnover surrounding months when the firm's SIC or TNIC peers have returns in the highest quintile. The upper figure shows unconditional average turnover rates around month zero (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 very similar because having SIC peers with returns in the highest quintile is highly correlated with having TNIC peer returns that are in the highest quintile. Hence the bottom figure is more informative. Here we plot turnover surrounding a month when the SIC peers have a return in the highest quintile, but at the same time, TNIC peers only have returns between the 40th and 60th percentile (average returns). Analogously, we plot results for the case when TNIC peers have high qunitile returns and the SIC peers have returns in the 40th to 60th percentile. This lower plot thus allows us to show more uniquely how turnover evolves when one peer group is uniquely shocked.



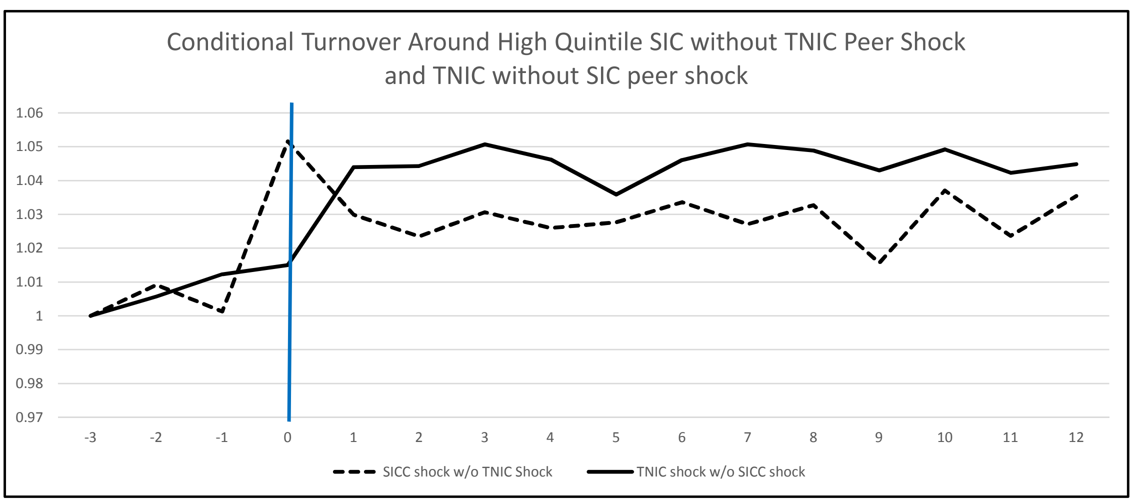


Figure 2: Equal Weighted Cumulative Portfolio Returns

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 and French factors, and compute the abnormal return as the intercept plus the residuals. The graph displays the arithmetically cumulated abnormal returns over our sample. We consider own–firm momentum, Fama–French–48 (SIC–based) industry momentum, and 10–K based TNIC–3 industry momentum. Past returns are computed based on the window month t–1 to t–12 (except for own–firm momentum which is based on t–2 to t–12 due to the well–known one–month reversal). TNIC–3 portfolios are based on a granularity equal to three–digit SIC codes. The TNIC and SIC returns are computed using equal–weighted averages of peers.

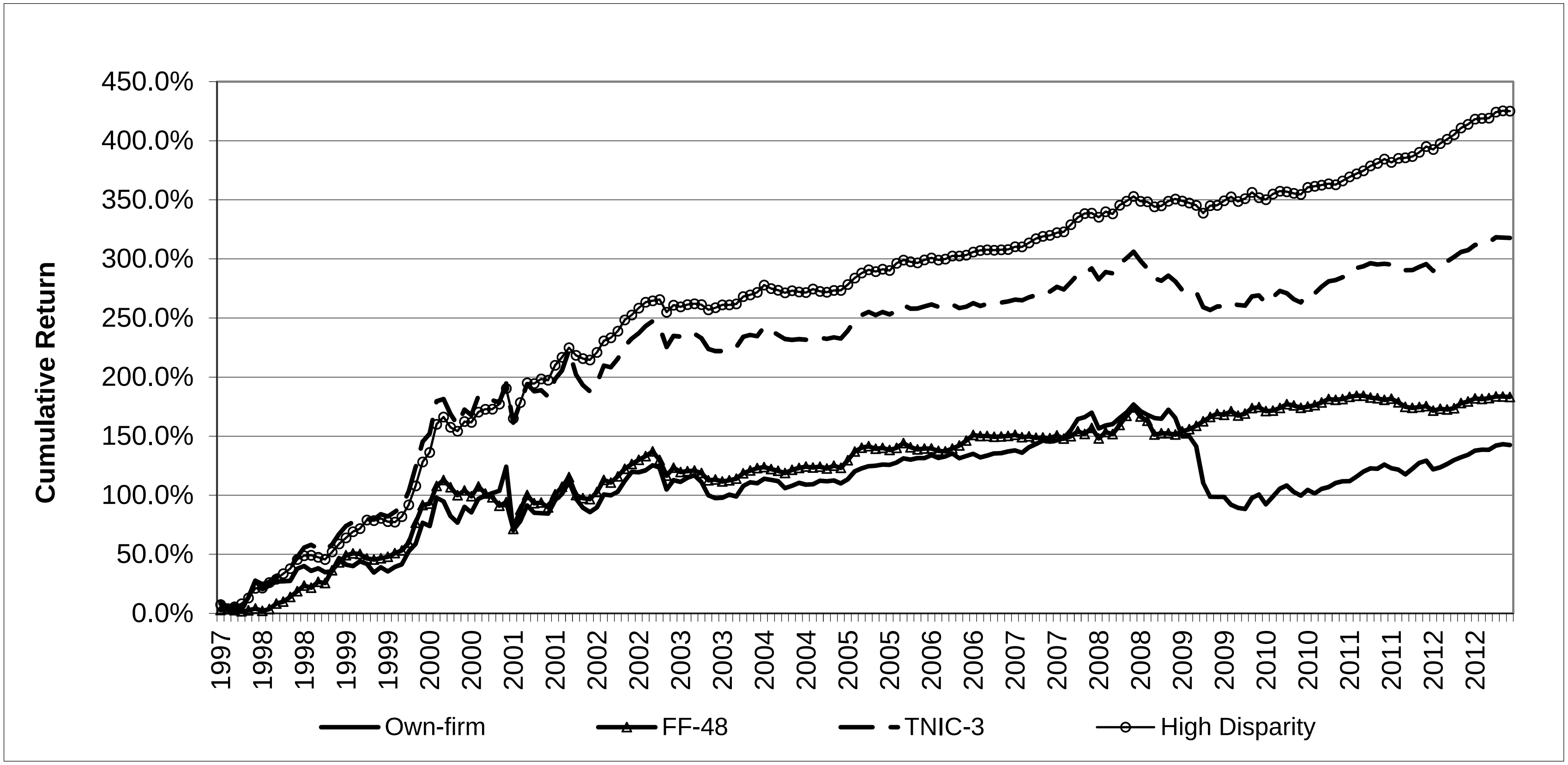


Figure 3: Value Weighted Cumulative Portfolio Returns

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 and French factors, and compute the abnormal return as the intercept plus the residuals. The graph displays the arithmetically cumulated abnormal returns over our sample. We consider own–firm momentum, Fama–French–48 (SIC–based) industry momentum, and 10–K based TNIC–3 industry momentum. Past returns are computed based on the window month t–1 to t–12 (except for own–firm momentum which is based on t–2 to t–12 due to the well–known one–month reversal). TNIC–3 portfolios are based on a granularity equal to three–digit SIC codes. The TNIC and SIC returns are computed using equal–weighted averages of peers.