Social Ties and Predictable Returns*

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JEL Codes: G14, D85
Keywords: social networks, slow information diffusion, return predictability, machine learning

Preliminary, please do not circulate

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1 Introduction

Extensive theoretical and empirical literature studying how investor attention affects information processing suggests that limited attention can lead to market underreactions to value-relevant news.[1] The underreaction-based mechanism explains predictable returns in firms connected by shared economic links such as industry, location, and analyst coverage (e.g., Moskowitz and Grinblatt, 1999; DellaVigna and Pollet, 2007; Cohen and Frazzini, 2008; Ali and Hirshleifer, 2020; Parsons et al., 2020). More recently, a growing body of literature highlights the interconnected nature of firms in the economy (e.g., Acemoglu et al., 2012; Bailey et al., 2018a) and shows that economic exchanges between regions are positively associated with the intensity of social connections (e.g., Breschi and Lenzi, 2016; Cohen et al., 2017; Bailey et al., 2021).

Motivated by the recent studies, in this paper we explore a new dimension of cross-firm linkages based on social connections between regions in which the firms are located. We posit that the fundamentals of firms located in regions with strong social ties tend to comove more strongly. If investors are inattentive to this fundamental linkage, asset prices would not be able to timely reflect such information. As information diffuses slowly across the population of investors, the returns of firms located in socially connected regions can help predict the future stock returns and performance of related firms.

We empirically measure the social ties of two firms using Facebook's Social Connectedness Index (SCI) between the firms' headquarters counties (see Bailey et al., 2018a). SCI measures the relative social connectedness between geographies and is defined as the number of Facebook friendship connections between users in two counties relative to the product of the counties' populations. As the world's largest online social networking service, Facebook's enormous scale and coverage (over 258 million active users in the United States as of 2020) and the relative representatives of its user body makes SCI a unique measure of the real-world geographic structure of U.S. social networks at population scale.[2]

We first show that a substantial component of industry momentum (e.g., Moskowitz and Grinblatt, 1999; Hoberg and Phillips, 2018) is attributable to the returns of socially connected industry peers. The contemporaneous comovement between the returns of a stock and its highly connected industry peers are 84% higher than with returns of peers with low connectedness. Similarly, the one-month-ahead return predictability based on returns of highly connected industry peer firms is 92% higher than that based on returns of industry peers with low connectedness. This suggests that social connectedness between industry firms contains incremental information about

[1] See, for example, Hong and Stein (1999), Huberman and Regev (2001), Hirshleifer and Teoh (2003), Hou and Moskowitz (2005), Peng and Xiong (2006), Hirshleifer et al. (2009), and DellaVigna and Pollet (2009).

[2] See, Bailey et al. (2018a), Kuchler et al. (2020a), and Kuchler et al. (2020b) for further discussion on these points.

the fundamental economic linkages across the firms.

Motivated by this preliminary finding, we combine the information embedded in social ties between firms' locations and their industry connections and propose a novel measure of social peer firm returns (*SPFRET*). Specifically, we define *SPFRET* as the SCI-weighted returns of a firm's same-industry peers. By construction, this measure gives more weight to the returns of a firm's industry peers headquartered in socially connected regions.

We next explore the relevance of the information in *SPFRET* and the extent that the information is fully incorporated into securities' prices. We first conduct portfolio analysis and construct a long-short portfolio sorted by *SPFRET*. We show that this portfolio generates a highly significant Fama and French (2015) five-factor adjusted returns of 157 basis points (equal weighted) and 84 basis points (value weighted) in the following month. The result remains robust when we examine two-way sorted portfolios by *SPFRET* and industry returns. The results suggest that *SPFRET* contains highly relevant information about focal stock returns that has not been fully incorporated by stock prices.

We then investigate the underlying economic mechanisms of our findings by exploring a number of cross-firm linkages that our measure may capture. We show that roughly 35% of the return predictability of social peer firm returns is attributable to the lead-lag effects based on known economic connections among firms such as industry momentum, the "complicated firm" effect (Cohen and Frazzini, 2008), and economic linkages based on the flow of the labor force. However, even after accounting for these economic linkages, the *SPFRET*-based strategy still generates an abnormal return of over 54 basis points per month. These findings suggest that social peer firms' returns contain important information regarding the fundamentals of focal firms in a way that is not fully incorporated into prices or explained by existing factors.

Consistent with these findings, we further show that predictability remains strong when we include a comprehensive list of firm characteristics that are known to predict returns in Fama and MacBeth (1973) regressions. Our results are not subsumed by other cross-firm lead-lag effects such as industry momentum (e.g., Moskowitz and Grinblatt, 1999; Hoberg and Phillips, 2018), geographic lead-lag effects (e.g., Parsons et al., 2020), customer-supplier lead-lag effects (e.g., Cohen and Frazzini, 2008), lead-lag effects based on technological similarity (Lee et al., 2019), the complicated firm effect (Cohen and Lou, 2012), lead-lag control based on labor flows across locations, or shared analyst coverage (Ali and Hirshleifer, 2020).[3] Even after accounting for all the lead-lag relationships, the firms with the highest *SPFRET* outperform those with the lowest *SPFRET* by 42 basis points in the next month.

[3]In all of our cross-sectional regression specifications, we include lag one-month return, size, book-to-market ratio, momentum, illiquidity, idiosyncratic volatility, skewness, and co-skewness.

To assess the relative importance of *SPFRET* compare to the other predictors, we follow Gu et al. (2020) and apply machine learning techniques (PLS) to form a composite measure that aggregates the predictive information of all return predictors. We show that *SPFRET* contributes substantially to the predictive power of the composite measure and is among the most important lead-lag return predictors. Economically, a long-short portfolio created in 1994 using the composite measure yields a cumulative return as of 2019 that is 86.4 percentage points higher than an alternative portfolio that does not utilize the information in *SPFRET*.

To gain insights into what market frictions drive the return predictability of SPFRET, we explore how firm characteristics influence the strength of the predictability. If the documented return predictability is due to investor inattention to value-relevant information from socially connected peer firm returns, we should expect stronger predictability for focal firms that are less visible to investors. Consistent with this, we find that return predictability results are stronger for smaller firms, firms with low institutional ownership, and firms with low analyst coverage—precisely those firms that receive little investor attention. Similarly, our results show that information from social peer firms impound more quickly into prices for firms that are located in an industry cluster, consistent with the finding of Engelberg et al. (2018) that analysts tend to cover stocks inside industry clusters and firms located away from industry clusters are likely to receive less investor attention.

In addition, we investigate the return predictability of social peer firms in the long run and find that return predictability may last up to 12 months with no evidence of return reversals. The evidence further confirms that the return predictability is driven by underreaction.

We then explore the nature of the information that social peer firm returns convey. We show that firms with the highest past cumulative social peer firm returns (*SPFMOM*) have, on average, standardized unexpected earnings (*SUE*) that are 5.5 percentage points higher in the next quarter than those with the lowest *SPFMOM* (or 3.9% of the standard deviation of *SUE*). We find strong evidence that this predictability persists for at least a year. Similarly, sell-side analysts substantially underestimate future earnings of firms with high social peer firm returns, by 5.1 percentage points (or 5.8% of the standard deviation of the forecast error) for the next quarter. Furthermore, social peer firm returns positively predict focal firms' future earnings announcement returns. The findings further confirms that social peer returns contains important information regarding a firm's future earnings that has been ignored by the market participants.

Our paper is closely related to recent studies suggesting that firms that share similar locations or business footprints tend to have correlated performance or returns (e.g., Pirinsky and Wang, 2006; Parsons et al., 2020; Jin and Li, 2020). Other papers have shown that firms' locations are associated with the firms' fundamentals such as growth and profitability (Dougal et al., 2015;

Huang, 2015; Dougal et al., 2018; Smajlbegovic, 2019), stock returns (Korniotis and Kumar, 2013; Tuzel and Zhang, 2017), and borrowing costs (Hasan et al., 2017). Also using the Facebook data, Kuchler et al. (2020a) find that an area's social proximity to the institutional capital is positively related to the valuation and stock liquidity of firms located in that area. Our unique insight is that social connectedness across regions captures a substantial component of economic ties of firms that is not explained by local economic conditions or physical proximity.

We also contribute to the understanding of how networks shape economic relationships. In social finance literature, the evidence often indicates that the primary role of social networks is to increase recognition or transmit information (e.g., Cohen et al., 2008; Hwang and Kim, 2009; Hochberg et al., 2007; Pool et al., 2012, 2015; Heimer, 2016; Kuchler et al., 2020a). While previous research documents that firms can be connected through customer-supplier relationships or co-location (e.g., Cohen and Frazzini, 2008; Pirinsky and Wang, 2006; Parsons et al., 2020), our results suggest that the effect of social connections can also be important in a way that is neither localized nor limited to customer-supplier relations.[4]

Finally, this paper adds to the extensive literature that studies return predictability in financial markets (see McLean and Pontiff, 2016; Harvey, 2017, for recent meta studies). More specifically, several papers document lead-lag patterns that are difficult to explain using the efficient market hypothesis (e.g., Jegadeesh and Titman, 1993; Moskowitz and Grinblatt, 1999; Hou, 2007; Hoberg and Phillips, 2018; Lee et al., 2019; Ali and Hirshleifer, 2020; Parsons et al., 2020; Jin and Li, 2020). Consistent with these studies, our results suggest that investors and financial analysts fail to fully identify the economic links between firms. Further, we show that our results are not explained by the previously documented lead-lag effects.

The rest of the paper is organized as follows. In Section 2, we provide a detailed description of the data used in this study. In Section 3, we discuss the return predictability results. In Section 4, we analyze whether social peer firm returns capture earnings-related information about the focal firm and whether market participants fully incorporate this information. Section 5 concludes.

2 Data and Variable Definitions

Our sample includes all common stocks traded on the NYSE, AMEX, and NASDAQ exchanges, covering the period from July 1963 through December 2019. The Center for Research in Security Prices (CRSP) provides the daily and monthly return and volume data. The accounting variables, including earnings, are obtained from the CRSP-Compustat merged database. Analyst earnings forecasts and institutional ownership data are from the Institutional Brokers' Estimate System

[4]Another strand of literature studies how shocks are propagated through within-firm networks (e.g., Giroud and Mueller, 2019).

(I/B/E/S) database and Thomson Reuters institutional (13F) holdings database, respectively. Data on the Fama-French five-factor and the Fama-French 48-industry classification are obtained from Kenneth French's data library. We eliminate stocks with a price per share less than \$5 or more than \$1,000. We require a minimum of 24 monthly observations for variables created using monthly data and 15 daily observations for those created using daily data. Unless otherwise stated, all variables are measured as of the end of the portfolio formation month (i.e., month t). The variables and the corresponding definitions are summarized in Table A1.

2.1 Key Variables

We follow Bailey et al. (2018a) and measure social connectedness between two U.S. counties using Facebook's *Social Connectedness Index* (*SCI*). The measure is the total number of Facebook friendship links between two U.S. counties (as of April 2016), divided by the product of the populations of the two counties. As the world's largest online social networking service, Facebook's scale and the relative representativeness of its user body make SCI a comprehensive measure of the geographic structure of the U.S. social networks.[5]

Figure 1 plots heat maps of social connectedness, measured with SCI, for Cook County, IL, in Panel A, and Bartholomew, IN, in Panel B. The focal counties are colored in red and darker colors indicate higher social connectedness to the focal counties. Although the two focal counties are located in two adjacent states, the maps show differences in their relative connectedness to other regions. Cook County, which includes the city of Chicago, is strongly connected to nearby counties as well as to counties in the southern states along the Mississippi River. The pattern has been documented by Bailey et al. (2018a) and Kuchler et al. (2020a) and is attributed to the large-scale migration of African Americans from southern states to northern industrial cities during the Great Migration of 1916–1970.[6] Bartholomew County is strongly connected to nearby counties in the state of Indiana, counties in the neighboring state of Illinois, and counties in distant states such as Kentucky, Tennessee, North Dakota, Texas, and Florida. Hence, these plots show that there are substantial differences between the geographic proximity and the social connectedness across regions in the United States. These differences will help us identify the incremental information that social ties contain that is different from the effects of physical proximity.

[Insert Figure 1 here]

[5]Facebook had more than 2.1 billion monthly active users globally and 239 million active users in the United States and Canada as of 2017. This represents 68% of the adult population and 79% of online adults in the United States (Duggan et al., 2016). Facebook usage rates among U.S.-based online adults were relatively constant across various demographics and locations. Bailey et al. (2018a,b, 2019a,b,c, 2021); Kuchler et al. (2020a,b), and Rehbein et al. (2020) provide evidence that friendships observed on Facebook are a good proxy for real-world connections.

[6]Bailey et al. (2018a) show that social connections across regions are persistent and argue that SCI is a reasonable proxy for historical social connectedness between regions.

Our main variable of interest is the social peer firm return (*SPFRET*). For a given firm i and for a given month t, *SPFRET* is the average returns of i's same-industry peer firms that are located outside of the focal firm's headquarters states, weighted by the SCI between the headquarters locations of firm i and j. Formally, *SPFRET* is given by

$$SPFRET_{i,t} \equiv \frac{\sum_{j \in I_i, j \notin S_i} SCI_{i,j} RET_{j,t}}{\sum_{j \in I_i} SCI_{i,j}},$$

where I_i is the Fama-French 48-industry (FF48) to which firm i belongs, and S_i is the state where firm i's headquarters are located.[7] We exclude peer firms from the same state as the focal firm, thus alleviating the concerns that our results are driven by firms in close geographic proximity (e.g., Parsons et al., 2020). For our long-run prediction analysis, we also consider *INDMOM*, the long-run version of *SPFMOM*, by compounding the variable from month $t-11$ to $t-1$.

We illustrates the construction of *SPFRET* in Figure 1 Panel C, in which the focal firm is Cummins Incorporated (ticker: CMI). CMI is headquarterd in Bartholomew county. The firm belongs to the machinery industry (FF48 code Mach) and manufactures engines and filtration and power generation products. Figure 1 plots the heat maps of SCI for Bartholomew county, showing only the counties with the headquarters presence of firms in the machinery industry, whereas counties without the presence of such firms are presented in dark grey. Examples of CMI's industry peers include Caterpillar (ticker: CAT), Clarcor (ticker: CLC), and Stanley Black & Decker (ticker: SWK), located in Peoria, IL, Williamson, TN, and Hartford, CT, respectively.[8]

When calculating *SPFRET*, the firms headquartered in counties with higher SCI with Bartholomew County receive higher weights. As a result, CAT and CLC have corresponding weights of 3.44% and 4.32%, respectively, due to the higher SCIs between their headquarters counties and Bartholomew County, whereas the weight on SWK is only 0.57%, due to the low SCI between Williamson and Bartholomew Counties. The SCI-based weighting of industry peers is distinctly different from the value-based weights of 13.66%, 0.83%, and 4.32% for CAT, CLC, and SWK, respectively. Hence, the *SPFRET* measure gives more weight to the returns of a firm's in-

[7] We obtain firm headquarters location data from the "Augmented 10-X Header Data" for the period between 1994 and 2018, supplemented by data parsed from 10-Q and 10-K filings on SEC's Edgar database for 2019. For observations prior to 1994, for which firms' electronic filings are unavailable, we follow Parsons et al. (2020) and use the first available headquarters location in a firm's post-1994 SEC filings. As argued by Parsons et al. (2020), such measurement error would only create noise and bias against finding significant results. We thank Bill McDonald for providing the pre-1998 data through the Notre Dame Software Repository for Accounting and Finance (SRAF).

[8] Caterpillar designs, develops, engineers, manufactures, markets, and sells machinery, engines, financial products, and insurance to customers via a worldwide dealer network. It is the world's largest construction equipment manufacturer. CLARCOR, Inc. manufactures engine filtration and industrial/environmental filtration systems. Stanley Black & Decker, Inc. manufactures industrial tools and household hardware, and provides security products. The weights are measured as of April 2016.

dustry peers from socially connected regions, which captures a dimension of the linkages between firms and their industry peers that is different from those reflected in a value- or equally-weighted industry portfolio.

2.2 Controls

Lead-Lag Return Predictors We control for a list of variables that previous studies have shown to have cross-firm return predictability. The data are available for the entire sample period from July 1963 through December 2019 unless otherwise mentioned.

For a given stock and for a given month t, we define *INDRET* as the month-t equal-weighted average return of stocks from the same industry as the focal stock (see Moskowitz and Grinblatt, 1999). *TNICRET*, available starting July 1989, is the equal-weighted stock return of peer firms identified through 10-K product text (Hoberg and Phillips, 2018). *GEORET* is the month t equal-weighted average return of all stocks from the same economic area (EA) as the focal stock, excluding same-industry stocks (Parsons et al., 2020). *CFRET*, available since January 1982, is the month t weighted average return of stocks that share at least one analyst with the focal stock over the previous 12 months, where weights are the number of shared analysts between stocks.

CRET, available starting December 1976, is the equal-weighted average stock return of the main customers of the focal firm, where a six-month gap is required between the fiscal year-end of the supplier and stock returns (Cohen and Frazzini, 2008). *TECHRET*, available between July 1963 and July 2012, is the weighted average stock return of technology-linked peer firms, where the weights are the technological closeness between the peer firm and the focal firm, determined by the similarities between patent distributions across different technology categories (Lee et al., 2019).[9] *CONGRET* is the pseudo-conglomerate return, defined as the sales-weighted return of (value-weighted) single-segment firm portfolios, formed for each segment in which a conglomerate firm operates (Cohen and Lou, 2012); data is obtained from the Compustat segment files and starts from July 1977.

We also consider a potential lead-lag effects driven by cross-firm labor flows. The job-to-job (J2J) flow statistics, available quarterly from the U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) database, provide estimates of worker flows across jobs and across different geographic labor markets by worker and firm characteristics (see Hyatt et al., 2014; Hahn et al., 2017). We track the within-industry labor flows between firms' headquarters locations for

[9]The economic area-ZIP Code link file is obtained from Riccardo Sabbatucci's website. The textual network industry relatedness classification (TNIC) for individual firms are obtained from the online data library of Gerard Hoberg and Gordon Phillips. Customer-supplier firm links are obtained through the Linking Suite by WRDS. We thank Usman Ali and Stephen Teng Sun for providing their data on technological overlap among firms.

each industry and define *J2JRET* as the labor flow intensity-weighted industry peer returns.[10]

For our long-run prediction analysis, we also consider the long-run versions of the above variables (i.e., *INDMOM, GEOMOM, CFMOM, CMOM, TECHMOM, CONGMOM, TNICMOM*, and *J2JMOM*), by compounding the variable from month $t-11$ to $t-1$. Following Ali and Hirshleifer (2020), *CFMOM* is calculated as the coverage-weighted average of cumulative returns of analyst-coverage-connected stocks from month $t-11$ to $t-1$.

Other Controls We also control for a stock's own characteristics that the literature has shown to predict returns. The variables are measured as of the end of month t unless otherwise stated and are described below.

RET is the monthly stock return, adjusted for delisting to avoid survivorship bias (Shumway, 1997). We estimate firm size (*SIZE*) and book-to-market ratio (*BMKT*) following Fama and French (1992). *MOM* is obtained by compounding *RET* from month $t-11$ to $t-1$ (Jegadeesh and Titman, 1993). *IVOL* is the monthly idiosyncratic volatility, computed as the standard deviation of the daily residuals obtained by regressing the stock return on the Fama and French (1992) three factors over the previous month (Ang et al., 2006). *ILLIQ* is Amihud's illiquidity (Amihud, 2002), defined as the average daily ratio of the absolute stock return to the dollar trading volume within the previous month. *MAX* is the maximum daily stock return realized over the previous month (Bali et al., 2011). *SKEW* is the sample skewness of the daily stock returns from the previous month (Bali and Hovakimian, 2009). *COSKEW* is the stock's monthly coskewness, following (Harvey and Siddique, 2000).

2.3 Summary Statistics

Table 1 presents the time-series averages of cross-sectional statistics (Panel A) and correlations (Panel B) of the main variables in our analyses. All variables except RET_{t+1} are measured at the end of month t. Summary statistics shown in Panel A are consistent with earlier studies such as Ali and Hirshleifer (2020).

Panel B shows that *SPFRET* is highly correlated with *CFRET* of Ali and Hirshleifer (2020), with a coefficient of 0.47. This may be because the firms that share analyst coverage are likely to be in

[10] For a given industry, we define the directional labor migration probability from state i to state j as the labor flow from i to j (relative to the number of employees in j) divided by the sum of i's relative labor outflows. We then define the (two-way) labor flow intensity between states i and j, $J2J$, as the average of the labor migration probabilities from i to j and from j to i. We average the quarterly values to annual frequencies to reduce seasonality effects. $J2JRET$ is then the $J2J$-weighted industry peer firm returns (excluding same-state peers) where monthly returns between July of year t and June of $t+1$ are matched to the $J2J$ of year $t-1$. The LEHD data are available since year 2000, and the $J2J$ measures are persistent, with an annual AR(1) coefficient of 0.93. Given the persistence, we backfill the observations prior to 2000 with the corresponding value as of year 2000. To the extent that we use this as a control variable, the backfilling would only bias against finding results for our main variable of interest, *SPFRET*.

the same industry. Furthermore, the average cross-sectional correlation between *SPFRET* and *INDRET* is considerable, at 0.64. This is likely due to the construction of *SPFRET*, which relies on the SCI-weighted, same-industry firm returns. Given the finding that industry momentum strongly predicts a stock's future returns (e.g., Moskowitz and Grinblatt, 1999; Hoberg and Phillips, 2018), we first conduct preliminary analysis in the next subsection to gain insight into the extent to which social ties between firms are associated with the return predictability of industry momentum.

[Insert Table 1 here]

2.4 Social Ties and Industry Momentum: Preliminary Analysis

We evaluate the extent to which industry momentum (Moskowitz and Grinblatt, 1999) is attributable to the social connectedness between the locations of a firm and its industry peers.

We first sort a firm's same-industry peer firms into tercile portfolios based on the SCIs between the headquarters locations of the peer firms and the focal firm. Next, for each of the high-, medium-, and low-tercile portfolios, we measure the corresponding equal- and value-weighted industry peer returns and denote them $INDRET_{HIGH_SCI}$, $INDRET_{MED_SCI}$, and $INDRET_{LOW_SCI}$. Our procedure essentially allows us to decompose industry returns into three components based on the strengths of social ties between the focal firm and its industry peers.

We then use these SCI-based industry returns to explain focal stock returns based on the following regression:

$$\begin{aligned} RET_{t+s} = \alpha + \beta_1 INDRET_{HIGH_SCI,i,t} + \beta_2 INDRET_{MED_SCI,i,t} \\ + \beta_3 INDRET_{LOW_SCI,i,t} + \epsilon_{i,t+s}, \end{aligned} \tag{1}$$

where $s = 0$ for contemporaneous regression and $s = 1$ for one-month-ahead regression. We estimate the regression with the Fama-MacBeth method, in which we standardize the independent variables following Kelly et al. (2019) and Gu et al. (2020).[11]

Table 2 reports the result of the regression analyses. Columns 1 and 3 correspond to contemporaneous regressions, with equal- and value-weighted industry returns, respectively. It shows that $INDRET_{HIGH_SCI}$ has substantial explanatory power for the contemporaneous focal stock returns. Specifically, an increase of one (from the lowest to the highest) in the equal-weighted $INDRET_{HIGH_SCI}$ is associated with an increase in a stock's contemporaneous returns by a substan-

[11] Specifically, the variables are ranked cross-sectionally period-by-period from lowest to highest and the ranks are then scaled into the $[0, 1]$ interval. This nonparametric transformation allows the analysis to focus on the ordering of the variables as opposed to magnitudes, which makes the estimates less sensitive to the effect of outliers (Kelly et al., 2019; Freyberger et al., 2020). Missing values are imputed by the cross-sectional median. We report t-statistics with standard errors based on Newey and West (1994) adjustments in parentheses.

tial 424 basis points per month. For the value-weighted $INDRET_{HIGH_SCI}$, the corresponding increase is also large, at 321 basis points. These coefficients of $INDRET_{MID_SCI}$ and $INDRET_{LOW_SCI}$ are significantly lower, suggesting that industry momentum is considerably weaker when the variable is constructed with the returns of the less socially connected industry peers. For example, column 1 shows that the coefficient of $INDRET_{LOW_SCI}$ is 2.301, suggesting that an increase of one in $INDRET_{LOW_SCI}$ is associated with a 230 basis point increase in the stock's returns, or only 54% of the effect of $INDRET_{HIGH_SCI}$. The results suggest that industry momentum reflects strong comovements among firms, and the effects are more pronounced for those located in places with strong social ties.

In columns 2 and 4, we explore the relationship between SCI-sorted industry returns and the one-month-ahead focal stock returns. We find that all three SCI-sorted industry portfolios have power to predict future returns, consistent with the industry momentum literature (see Moskowitz and Grinblatt, 1999). More importantly, the coefficient of $INDRET_{HIGH_SCI}$ is significantly larger than that of $INDRET_{LOW_SCI}$, indicating that the past returns of the highly connected industry peers exhibit stronger return predictability than those of the less connected peers. Hence the analysis suggests that a considerable portion of the strong predictive power of industry momentum is associated with the social ties between firms' locations.

Hence in the subsequent analysis, we directly analyze the SCI-weighted industry returns and focus on *SPFRET* as our key variable of interest. We directly control for industry momentum and other return predictors in our regression analysis.

[Insert Table **2** here]

3 Social Ties and Return Predictions

A growing body of literature shows that social ties between regions foster economic interactions (e.g., Cohen et al., 2017; Bailey et al., 2018b), suggesting that social ties can potentially serve as a proxy for the strength of economic links between firms located in these regions. This is consistent with our preliminary findings in Section 2.4. In this section, we formally examine whether returns of social peer firms can explain and predict the returns of focal firms.

We begin our analysis with portfolio analyses, showing that a long-short portfolio sorted by *SPFRET* produces significant abnormal returns. We then conduct spanning tests to investigate the extent to which the abnormal returns can be explained by existing economic mechanisms. Next, we present Fama-MacBeth regression analysis to formally control for a comprehensive set of return predictors identified in previous studies and assess the relative importance of the predictors in a composite predictor that summarizes all return predictors using machine learning techniques.

We also analyze the heterogeneity of our results to gain further insight on the market frictions that might drive the predictability. Lastly, we present a set of robustness checks.

3.1 Portfolio Analysis

We first perform portfolio analysis and investigate the returns to a long-short portfolio sorted by *SPFRET*. Specifically, for each month, we sort our sample firms into deciles based on *SPFRET*. We then hold the portfolios for a month and calculate returns for each portfolio and the return differential between the portfolios with the highest and the lowest *SPFRET*.

Table 3, Panel A reports the results of the univariate portfolio analysis. The first row in each panel shows the raw returns for equal-weighted portfolios. To ensure that our results are not driven by risk factors, we also report the Fama-French five-factor alphas (FF5) for equal-weighted portfolios in the second row. The third and fourth rows in each panel report the raw returns and FF5 alphas for value-weighted portfolios, respectively. We find that SPFRET-sorted long-short portfolio produces economically large and highly significant excess returns. For example, the FF5 alpha is 157 basis points per month (t = 7.06) for equal-weighted portfolio and 84 basis points (t = 5.22) for the value-weighted portfolio.

[Insert Table 3 here]

Figure 2 presents the average monthly long-short portfolio alpha over time. Panel A shows that a positive alpha exists for most of the years in our sample. Given that *SPFRET* is highly correlated with industry momentum, we examine the incremental return predictability of *SPFRET* by examining the abnormal returns of portfolios sorted by $SPFRET_{\perp}$ (after controlling for industry momentum). Panel B shows that the $SPFRET_{\perp}$-based portfolios also consistently produce positive returns. This suggests that *SPFRET* captures additional information that is distinct from the average industry momentum effects.

Panel A also shows that the abnormal returns for the post-2000 period tend to be somewhat smaller. One reason for this is that industry momentum is substantially weaker and becomes insignificant post 2000 (Ali and Hirshleifer, 2020). In contrast, Panel B shows that, after filtering out the industry returns, the $SPFRET_{\perp}$-based abnormal returns perform reasonably well in more recent periods, again confirming the relevance of the incremental information contained in the social peer firm returns.

[Insert Figure 2 here]

Next, we conduct two-way sorted portfolio analysis to further isolate the effect of *SPFRET* from the effects of industry momentum. At the end of each month, stocks are first sorted into

quintiles based on *INDRET*. Then, within each *INDRET* quintile, stocks are further sorted into quintiles based on *SPFRET*. We calculate the returns for each of the 25 portfolios in the month that follows, along with the returns of five high-minus-low portfolios based on *SPFRET* for each *INDRET* quintile.

We report the results of a bivariate portfolio sort with equal-weighted and value-weighted Fama and French (2015) abnormal returns in Table 3, Panels B and C, respectively. The final rows in both panels report the average alphas for the *SPFRET* quintiles. The high-minus-low average alpha in Panel B is 56 basis points per month with a t-statistic of 7.38 whereas the economic magnitude under value-weight is 39 basis points with a t-statistic of 4.84, as reported in Panel C. Hence, the bivariate sort results further confirm that *SPFRET* has economically large return predictability that is above and beyond the effect of the traditional industry momentum of Moskowitz and Grinblatt (1999).

3.2 Identifying Underlying Channels with Spanning Tests

In this subsection, we conduct a portfolio spanning test to provide insight into the potential underlying economic linkages that drive *SPFRET*'s return predictability. The portfolio spanning test can also help confirm that the return predictability is not driven by other well-documented lead-lag relationships documented in the existing literature.

Specifically, we follow Ali and Hirshleifer (2020) and estimate the following time-series regression:

$$RET_{SPFRET,i,t} = \alpha + \beta F_{i,t} + \epsilon_{i,t}, \tag{2}$$

where RET_{SPFRET} is the value-weighted long-short portfolio returns constructed in Section 3.1. F represents a vector of long-short portfolios. We consider the Fama-French five-factor (Fama and French, 2015) returns and the returns of portfolios based on firms' economic linkages as identified by previous studies. To ensure that the coefficients are comparable across different columns, we require that return information exists for all the portfolios considered in our test.

Table 4 reports the results for a sample period in which all portfolios under our consideration have valid return data to facilitate the comparison across different specifications. Column 1 is the baseline specification with a constant and the Fama-French five-factors as the explanatory variables. The column shows that the coefficient on the constant, which captures the Fama-French five-factor alpha of the *SPFRET*-based portfolio strategy, is 92 basis points per month and is significant at the 1% level. The result is consistent with the portfolio analysis that we show in Table 3.

Next, we gradually include additional long-short portfolios one at a time to examine the extent that the alpha of a *SPFRET* portfolio can be explained by other lead-lag effects. We first

consider the industry momentum strategy based on the FF 48 industry (i.e., *INDRET*) in column 2. Industry momentum is highly relevant as *SPFRET* is constructed using firms from the same industry. Indeed, we find that the *SPFRET* strategy loads highly positively on the industry momentum portfolio. However, after controlling for *INDRET*, the alpha of *SPFRET* is 77 bps per month and remains significant at the 1% level.

We next include the geographic momentum documented in Parsons et al. (2020). Column 3 shows that the coefficient of *GEORET* is insignificant, suggesting that geographic momentum is not a significant contributor to the alpha of *SPFRET*. This may be because we exclude industry peers that are headquartered in the focal firm's headquarters county when constructing the *SPFRET* variable.

We also consider a new channel, which is the labor flows between firms' headquarters locations, as a possible contributor to our findings. Column 4 shows that the labor flow-based industry peer firm returns, *J2JRET*, explains an economically meaningful portion of the returns to the *SPFRET*-based portfolio. However, the *SPFRET* alpha remains robust, at 60 basis points.

Cohen and Lou (2012) document that a conglomerate firm's returns can be predicted by the return of its industry segments. While it is unclear how this effect can directly explain our results, we nonetheless consider it as an additional control. Again, as reported in column 5, we find that our portfolio loads on *CONGRET* positively and significantly, but our alpha remains highly significant.

In column 6, we additionally include the lead-lag effect due to the customer-supplier relationship (Cohen and Frazzini, 2008). It is possible that firms located in socially connected areas are more likely to form customer-supplier relationships. The *SPFRET* alpha remains highly significant (54 basis points per month).

In column 7, we further include lead-lag effect due to product market similarities (see Hoberg and Phillips, 2018, for more detail). We find that the *SPFRET* portfolio loads significantly on both industry return portfolios. However, the alpha of the *SPFRET* portfolio remains highly significant, at 51 basis points.

We also add the lead-lag effect due to technological similarity between firms (Lee et al., 2019), as Bailey et al. (2018a) find evidence consistent with social connectedness facilitating technological spillover across regions. As reported in column 8, although the coefficient on the *TECHRET* portfolio is positive, the variable does not fully subsume the alpha of the *SPFRET* portfolio. Overall, this result indicates that the most relevant lead-lag effects to the *SPFRET* portfolio are industry momentum, labor flow-based industry peer firm returns, and the lead-lag effect due to the product market similarity. After such stringent control, our alpha remains both economically as well as statistically significant at 51 basis points per month.

[Insert Table 4 here]

Figure 3 further illustrates the relative contributions of the economic linkage-based variables, using coefficient estimates from the last column of Table 4 and the average returns of the corresponding long-short portfolios. The figure shows that, among the largest contributors of the *SPFRET* portfolio excess returns, industry returns explain close to 16 basis points and *J2JRET* explains roughly 6 basis points. The contribution from the other factors are relatively small, all below 5 basis points. More important, even after accounting for the economic linkages documented in the existing literature, the *SPFRET* portfolio still generates a substantial incremental alpha, which is not only higher than the contribution from each of the individual long-short portfolios but is also greater than the contribution from the sum of the contribution of the risk factors and other lead-lag relationships.

[Insert Figure 3 here]

In sum, the spanning tests show that social connectedness between firm locations corresponds to important economic ties across firms such as industry or product similarity, labor flow, customer-supplier links, and technology similarity. But our social tie–based peer firm measure also captures a substantial amount of cross-firm linkages that existing measures do not account for. Our results therefore suggest that the linkages across firms can be complex and nuanced and that these linkages have not been fully understood by the market participants or incorporated into prices.

3.3 Fama-MacBeth Regression Analysis

Our portfolio sorting analyses and spanning tests show that a long-short portfolio based on social peer firm returns generates strongly abnormal returns that are not subsumed by the abnormal returns obtained by sorting on alternative variables. In this subsection, we conduct further analysis using Fama-MacBeth regression, which allows us to examine whether social peer firm returns predict future stock returns at the stock level while accounting for a comprehensive set of controls.

We estimate the following regression:

$$RET_{i,t+1} = \alpha + \beta SPFRET_{i,t} + \gamma X_{i,t} + \epsilon_{i,t+1}, \tag{3}$$

where $RET_{i,t+1}$ is the one-month-ahead firm return and *SPFRET* is the social peer firm returns. X is a vector of control variables that includes short-term industry momentum (*INDRET*), the geographic lead-lag effect (*GEORET*), the shared analyst coverage lead-lag effect (*CFRET*), the

customer-supplier lead-lag effect (*CRET*), the technological spillover effect (*TECHRET*), the complicated firm effect (*CONGRET*), the labor market lead-lag effect (*J2JRET*), and the text-based industry momentum (*TNICRET*). We also include a battery of well-known cross-sectional predictive variables, including *RET*, *SIZE*, *BMKT*, *BM*, *MOM*, *IVOL*, *ILLIQ*, *MAX*, *SKEW*, and *COSKEW*. As before, we standardize the independent variables following Gu et al. (2020) and Kelly et al. (2019).

Table 5 reports the results of Fama-MacBeth regressions. In column 1, we only include *SPFRET* and a vector of return predictability controls. We find that *SPFRET* is positive and significant at the 1% level. Moving from the lowest to the highest *SPFRET* leads to a 1.4% higher average return in the following month. Next, we gradually include additional lead-lag controls in columns 2 through 9.

In columns 2, we include the industry momentum effect documented in Moskowitz and Grinblatt (1999). As expected, the industry momentum variables are highly significant and their inclusion attenuates the effect of *SPFRET* to some extent, due to the strong positive correlation between these variables. Nevertheless, the coefficient of *SPFRET* remains large and highly significant, at 0.787, with a *t*-statistic of 7.669.

Column 3 additionally controls for the geographic lead-lag effects and shows that the coefficient of *GEORET* is positive and highly significant, consistent with Parsons et al. (2020). More importantly, the coefficient of *SPFRET* remains very similar to the corresponding value in column 2, suggesting that the geographic lead-lag effects does not contribute significantly to the effect of *SPFRET*.

In column 4, we add a control for the labor flow–based return predictor that we propose and shows that *J2JRET* is positive and significant. Consistent with the spanning test, we find that *J2JRET* slightly weakens the predictive power of *SPFRET*. However, the coefficient of *SPFRET* remains highly significant both economically and statistically.

Similarly, in columns 5 through 8, we further control for the "complicated firm" effect (Cohen and Lou, 2012) by including *CRET*, the customer-supplier effect (Cohen and Frazzini, 2008), the product market similarity effect (Hoberg and Phillips, 2018) (*TNICRET*), and the effect of technological linkage (Lee et al., 2019) (*TECHRET*), respectively. We show that these variables have positive coefficients, consistent with the previous findings, but these controls do not significantly affect the economic magnitude and the statistical significance of *SPFRET*.

Finally, we control for *CFRET*, which is a proxy for the analyst lead-lag effect. This variable is known to explain many other lead-lag effects in the literature (Ali and Hirshleifer, 2020). Column 9 shows that the return predictability of *SPFRET* remains strong and economically meaningful even after including this control. To further ensure the validity of these key empirical analyses, we present a comprehensive set of robustness tests in subsection 3.6.

In sum, our results show that *SPFRET* continues to significantly predict next month's return despite including a comprehensive set of predictive variables associated with specific economic linkages across firms. The economic magnitude of *SPFRET* is substantial. Firms with the highest *SPFRET* outperform firms with the lowest *SPFRET* by 41.7 basis points in the following month. This set of results is consistent with the analyses presented in Table 4, supporting the notion that industry peer firms located in socially proximate areas contain important information about the focal firm that is not fully incorporated into the focal firm's stock prices.

The comprehensive set of economic linkages that we consider partially explains the predictability of *SPFRET*, suggesting that social ties between firms' headquarters locations capture some of these known economic linkages. More importantly, our results also show that these economic linkages do not fully explain the predictability of *SPFRET*. Hence, our evidence suggests that the cross-firm linkages are multifaceted and that our social tie–based peer returns help provide incremental information regarding some of these nuanced linkages.

[Insert Table 5 here]

3.4 Relative Importance in the Composite Return Predictor

So far we have shown that our main variable, *SPFRET*, can significantly predict one-month-ahead focal stock returns in a way that is incremental to the 18 other predictors used in the literature. In this section, we assess the extent to which our variable can help enhance the joint return predictability of all the existing predictors using a machine learning approach. That is, we follow Kelly et al. (2019) and Gu et al. (2020) and evaluate the incremental contribution of *SPFRET* relative to a composite predictor that aggregates all 19 individual predictors (included in equation (3).

Specifically, starting with July 1994, each month, we train a partial least square regression (PLS) model using all the data available up to that point.[12] We generate a composite predictor that combines all 19 variables. Then, for each training set, we obtain the in-sample R^2s from the full PLS model and from a restricted model omitting one of the nine key cross-firm lead-lag return predictors (namely, *SPFRET*, *INDRET*, *GEORET*, *J2JRET*, *CONGRET*, *CRET*, *TNICRET*, *TECHRET*, and *CFRET*). For each omitted variable, we calculate the R^2 difference between the full model and the restricted model.[13] We then define the relative importance of the variable as the corresponding R^2 difference divided by the sum of the R^2 differences associated with each of the five predictors.

[12] *TNICRET* data starts in July 1989, and the length of the initial training period is five years. We employ a five fold cross-validation procedure to determine the number of PLS components for each training set.

[13] We follow Kelly et al. (2019) and Gu et al. (2020) and use the coefficient estimates obtained from the complete model to compute R^2 for the restricted model.

Figure 4 presents the monthly average relative importance of the nine cross-firm lead-lag return predictors for the full sample period of 1994–2019. It shows that, among the predictors, *SPFRET* contributes substantially to the predictive power of the composite predictor, with a relative importance of 18% for the full sample period.[14] In particular, *SPFRET* is more important than *INDRET*, with the relative importance of *SPFRET* exceeding that of *INDRET* by 7.9%. In sum, our analysis shows that *SPFRET* substantially improves the predictive power of the PLS-based composite return predictor, beyond the variables analyzed in the prior literature.

[Insert Figure 4 here]

To illustrate the economic magnitude of *SPFRET*'s contribution to the composite predictor, we follow Gu et al. (2020) and compare the performance of portfolios based on the composite predictor that includes information from all 19 predictive variables (i.e., full model predictor) and an alternative composite predictor, "No SPFRET", that excludes *SPFRET*. Each month, we sort stocks into deciles based on the two predictors respectively and obtain the one-month-ahead value-weighted returns of the corresponding portfolios. We then compute the cumulative log returns over the period of August 1994 through December 2019.

Figure 5 presents the cumulative log returns of portfolios based on the full model predictor (in orange) and the "No SPFRET" predictor (in blue). Panel A plots the returns to the long-short portfolios and shows that portfolio based on the composite predictor substantially outperforms the alternative "No SPFRET" portfolio, by 86.4 percentage points at the end of 2019. Panel B plots the returns of the long- and the short-legs separately and shows that the full model composite predictor outperforms the "No SPFRET" predictor for both the long and the short legs. Hence, the result suggests that *SPFRET* contains additional information that helps enhance the predictive power of the existing cross-sectional predictors in an economically meaningful way.

[Insert Figure 5 here]

3.5 Heterogeneity in Return Predictability

Our analysis has so far established that social ties between industry peer firm locations capture important linkages between firms. Even so, these linkages would not necessarily result in return predictability if the linkages are well understood by investors and timely reflected in stock prices. Therefore in this subsection, we conduct additional analysis to provide insight into the underlying market frictions that may contribute to the failure to incorporate such information. We do so by

[14] The nine key predictors contribute to 42% of the R^2 differences in the complete model, whereas the remaining ten own-stock characteristics together contribute 58%.

exploring differences in a firm's information environment and the firm's headquarters location relative to industry cluster areas.

Information Environment One explanation for the return predictability that we document is slow information diffusion (e.g., Hong and Stein, 1999), due to investors' limited cognitive resources (e.g., Hirshleifer and Teoh, 2003; Peng and Xiong, 2006). The limited attention mechanism further predicts that the predictability should be stronger for firms with poor information environments. Thus, we examine how our results vary across firms with different information environments using three common proxies in the literature: firm size, analyst coverage, and institutional ownership.

We estimate the following Fama and MacBeth (1973) regression:

$$RET_{i,t+1} = \alpha + \beta_1 SPFRET_{i,t} + \beta_2 SPFRET_{i,t} \times High + \beta_3 High + \gamma X_{i,t} + \epsilon_{i,t+1}, \tag{4}$$

where $SPFRET$ is the social peer firm returns, and $High$ is an indicator variable for a subsample based on a firm characteristics of interest.[15] At the end of month t, we sort all common stocks into two subsamples based on the cross-sectional mean of size, institutional ownership, and analyst coverage.[16] The $High$ indicator equals one if the measure of the firm's information environment is higher than the value of the breakpoint.

Table 6, column 1 reports the result based on the size split. We find that the return predictability is mainly driven by firms with low market capitalization. Column 2 reports the result based on the institutional ownership split. We find that return predictability is much stronger among the low institutional ownership group. Similarly, we find that return predictability only exists in the low analyst coverage group in column 3.

Taken together, these results support the slow information diffusion hypothesis and suggest that a firm's visibility to its investors influences the speed at which information about the firm's peer returns are incorporated into the firm's stock prices.

[Insert Table 6 here]

Firms in Industry Cluster Areas The next hypothesis is motivated by Engelberg et al. (2018) that firms located inside industry clusters are watched more closely by analysts and other market participants. As a result, social peer firm information is more timely impounded into these firms.

[15] We also include *INDRET, GEORET, CRET, TECHRET, CONGRET, TNICRET, J2JRET, CFRET*, and the other basic controls.

[16] For size sorting, we use NYSE breakpoints.

Therefore the hypothesis predicts that the return predictability of *SPFRET* would be stronger for firms located outside of industry clusters.

We first define a county as an industry cluster county if the county is ranked among the top 20% or 10% in the market capitalization for a given Fama-French 48 industry. We then define an indicator variable, *OUTCLS*, as one if a firm's headquarters is located in one of the industry cluster counties and zero otherwise. We conduct the following Fama-MacBeth regression to explore whether the out-of-cluster focal firms react to *SPFRET* differently from the in-cluster focal firms:

$$RET_{i,t+s} = \alpha + \beta_1 SPFRET_{i,t} + \beta_2 SPFRET_{i,t} \times OUTCLS + \beta_3 OUTCLS + \gamma X_{i,t} + \epsilon_{i,t+1}, \quad (5)$$

where s is either 0 or 1, as we explore both the contemporaneous and the predictive relationships.

These results are reported in Table 7. The first two columns define industry cluster counties using the top 20% of counties, and the next two columns define top 10% of counties as industry cluster counties. We find that under both definitions, out-of-cluster focal firm have low contemporaneous return correlations with *SPFRET*. On the other hand, *SPFRET* strongly and positively predicts the one-month-ahead off-cluster firm returns. The weaker contemporaneous relation and stronger predictive relation suggest that stock prices of firms located outside of industry centers are slow to incorporate important information in social peer firm returns.

[Insert Table 7 here]

3.6 Robustness

We have shown that *SPFRET* strongly predicts the one-month-ahead stock returns. In this subsection, we present a battery of robustness checks, based on the full model of the Fama-MacBeth specification as in Table 5. Table A2 presents the results, with column 1 the same as column 9 of Table 5 to facilitate the comparison.

Panel Regressions with Time Fixed Effects In column 2, we use a panel regression to examine the predictive relationship instead of the Fama-MacBeth regression specification. We also double-cluster the standard errors by month and by stock. Pástor et al. (2017) argue that an OLS regression specification with time fixed effects weighs each cross-section differently whereas the Fama-MacBeth method uses equal weightings. Thus, our panel regression analysis ensures that our results are robust under this alternative weighting scheme. The coefficient of *SPFRET* is highly significant, and the magnitude is also large, at 0.65, which is even higher than the coefficient obtained from the Fama-MacBeth specification.

Controlling for Value-Weighted Industry Returns In our main analysis, we control for the equal-weighted industry returns (*INDRET*) because the variable is highly correlated with our main variable, *SPFRET*, with a coefficient of 63.8%. The correlation between *SPFRET* and the value-weighted *INDRET*, on the other hand, is 52.8%. Hence the equal-weighted *INDRET* serves as a more stringent control and allows the report of more conservative results. Column 3 presents the results when value-weighted *INDRET* are used instead. The coefficient on *SPFRET* is now substantially larger, both in magnitude and in statistical significance, compared to column 1, and *INDRET* becomes insignificant. This comparison confirms that our main findings are robust to the construction of *INDRET*.

Alternative SCI Measures One concern regarding the use of *SPFRET* is that the measure is based on Facebook's SCI as of 2016. We believe that SCI serves as a useful proxy that reflects stable historical social ties between regions. As shown in Bailey et al. (2018a), the Facebook SCI measure can be mapped to labor migration patterns dating back to the 1930s, suggesting that the SCI measure closely corresponds to historical social connections between regions. Nevertheless, there is a legitimate concern that traders may not have been able to use this measure in real time prior to 2016 and thus may not have been able to incorporate the specific signal. There is also a concern that SCI between counties are determined endogenously. For example, the presence of highly economically related firms could lead to higher social connectedness between firms' headquarters locations.

To address these concerns, we assess whether traders could use an alternative measure of social ties between two locations. As shown in Bailey et al. (2018a), the Facebook SCI is highly negatively correlated with geographic distance. Hence we use geographic proximity as an alternative proxy for social ties between regions and define $SPFRET_{DIST}$ as the inverse distance–weighted industry peer firm returns. Thus, the alternative *SPFRET* measure relies on the historically available information and is less likely to be subject to the reverse causality concern.

We examine whether this proxy can also have significant power in predicting future returns. Column 4 shows that $SPFRET_{DIST}$ also significantly predicts future returns, with a comparable coefficient of 0.500.[17] We therefore conclude that social tie–based peer firm returns provide valuable information for return predictions in real time.

In column 5, we show that our results are robust to using a ZIP code–based SCI measure, which defines geographic regions more granularly. In column 6, we show that our result is ro-

[17] When we include both *SPFRET* and $SPFRET_{DIST}$ in the same regression, *SPFRET* remains highly significant and comparable to its coefficient in column 1, whereas $SPFRET_{DIST}$ becomes insignificant. This is consistent with the finding of Kuchler et al. (2020a) that SCI is a richer proxy for the underlying social connectedness between two locations than physical distance.

bust to an alternative industry classification that is based on TNIC (Hoberg and Phillips, 2018). While the economic magnitude is slightly lower than in column 1, it remains highly statistically significant.

Alternative Standardization Our main regression analysis follows Gu et al. (2020) and uses ranked independent variables that are scaled to the $[0, 1]$ interval to alleviate the influences of potential outliers. In column 7 of A2, we show that our results are robust under an alternative standardization procedure in which independent variables are demeaned and then divided by the variable's standard deviation. The coefficient on *SPFRET* is 0.109 and is statistically significant. Note that the coefficient in column 8 is not directly comparable with those from the other columns because of the scale differences. We therefore compare the economic magnitude of coefficients by looking at the return differences predicted by a *SPFRET* increase of 10% to 90%. The resulting return difference is 36 basis points based on the coefficient estimates in column 7, qualitatively similar to the corresponding value of 44 basis points for column 1.

Orthogonalized *SPFRET* We have so far directly controlled for 18 other return predictors in the regression analysis. To further address the concern that the coefficient of *SPFRET* may be influenced by its correlations with these other variables, we conduct an additional test using orthogonalized *SPFRET* as the main independent variable. We define $SPFRET_{\perp}$ as the regression residual of *SPFRET* on all the other 18 independent variables (including the basic controls) and report the result based on this variable in column 8. The economic magnitude of the coefficient drops to some extent, consistent with our prior results that part of the effect of *SPFRET* is attributable to labor flow and other economic linkages documented in the literature. However, our results remain highly statistically significant and economically meaningful, at 0.265, confirming that the incremental information in *SPFRET* remains relevant.

Controlling for Economic Presence In column 9, we investigate whether the predictability of *SPFRET* can be explained by firms' economic presences in socially connected locations. We follow Garcia and Norli (2012) and Bernile et al. (2015) to extract the frequency of states in firms' 10-K filings. We exclude peer firms that are headquartered in a state in which the focal firm has an economic presence. This exercise is highly conservative, as it eliminates 28% of peer firms. We find that even under this very restrictive specification, *SPFRET* still delivers considerable predictive power.

In-State v.s. Out-of-State Peers We also delve deeper into the construction of *SPFRET* and evaluate the predictive power of two alternative variables. Our main measure *SPFRET* excludes returns of same-state peers, alleviating the concerns that our results are driven by geographic proximity (e.g., Parsons et al., 2020). To directly account for the returns of same-state industry peers, we define $SPFRET_{STATE}$ as the SCI-weighted returns of same-state industry peers as the focal firm. Table A3, column 1, presents the results. We find that the coefficient of *SPFRET* remains highly significant and comparable to the corresponding coefficients in Table 5. The coefficient on $SPFRET_{STATE}$ is also positive and significant, although somewhat smaller than *SPFRET*. This result further confirms that our results are not driven solely by the return predictability of geographically proximate industry firms.

Returns of Firms From Other Industries Similarly, to examine whether returns from socially connected firms from other industries exhibit predictive power, we define *NPFRET* as the SCI-weighted returns of firms from other industries. Table A3, column 2 presents the results and shows that *SPFRET* remains robust, whereas *NPFRET* is insignificant. This suggest that the power of *SPFRET* mostly comes from industry-based fundamental linkages between firms.

4 Predictability in the Long Run

In this section, we test whether the returns of social peer firms can predict stock returns in longer horizons. We also examine the types of the fundamental information about focal firms that social peer firms' returns contain. In addition, we investigate the extent to which investors and analysts fail to incorporate such information into their expectations.

4.1 Predicting Long-Run Returns

As shown in subsection 3.5, our evidence is consistent with investors' underreaction to fundamental information (e.g., Hirshleifer and Teoh, 2003; Peng and Xiong, 2006). However, the same set of results can also be consistent with investors overreacting to information from socially connected firms (e.g., De Bondt and Thaler, 1985; Daniel et al., 1998). Therefore, we analyze the return predictability over longer horizons to help us differentiate these two hypotheses. If the predictability is a result of investors' underreaction, we should not observe a reversal in the long run, whereas the overreaction-based mechanism would imply long-run reversals.

For long-horizon analysis, we consider both *SPFRET* and the cumulative version of social peer firm returns, *SPFMOM*, following previous studies (e.g., Moskowitz and Grinblatt, 1999; Parsons et al., 2020; Ali and Hirshleifer, 2020). *SPFMOM* is also likely to reflect longer-run fundamental information more accurately than the monthly *SPFRET* as the latter tends to be noisier. Table 8

reports the long-horizon return predictability results using an calendar time portfolio approach following Jegadeesh and Titman (1993). Panel A presents the raw return of the equal-weighted calendar time portfolios, and Panel B presents the FF5 alphas. Both *SPFRET* and *SPFMOM* generate high return predictability in the first three months (67 basis points based on *SPFRET* and 58 basis points based on *SPFMOM* per month). These results are not affected when we control for the Fama and French (2015) five factors. The strength of predictability remains significant in months 4–6, generating a return differential of 24.7 and 39.4 basis points, respectively. The effect of *SPFRET* remains significant for months 7–12, and both variables lose their significance in generating excess returns after the first twelve months.[18] Panel B examines the FF5 alphas and shows results that are very similar to those presented in Panel A. Panels C and D present the raw return and the Fama and French (2015) five factor alpha for value-weighted portfolios. The patterns are similar to those presented in Panels A and B. In particular, we find that both *SPFRET* and *SPFMOM* can strongly predict returns in the short run and there is no evidence for long-run reversals.

Overall, the findings show that the return predictability of social peer firm returns lasts for up to one year and the lack of reversal provides further support to the underreaction-based explanations.

[Insert Table **8** here]

4.2 Predicting Future Earnings Surprises

We next investigate the nature of the information that social peer firm returns capture and consider whether such information help predict a firm's future earnings. We estimate panel regressions in the following form:

$$SUE_{i,t+s} = \alpha + \beta_1 SPFRET_{i,t} + \beta_2 SPFMOM_{i,t} + \gamma X_{i,t} + \epsilon_{i,t+1}, \tag{6}$$

where *SUE* represents the standardized unexpected earnings (constructed following Bernard and Thomas (1990) and Mendenhall (1991)).[19] *SPFRET* and *SPFMOM* are social peer firm returns and momentum, respectively. X is a vector of control variables identical to those used in Table **8**, along

[18] We conduct the these analyses using the orthogonalized versions of *SPFRET* and *SPFMOM*, after controlling for all other variables in Panel A of Table A4. The results are similar to those obtained by using raw *SPFRET* and *SPFMOM*.

[19] We calculate the unexpected earnings (UE) of stock i in calender quarter q of an earnings announcement as $UE_{i,q} = EPS_{i,q} - EPS_{i,q-4}$, where $EPS_{i,q}$ and $EPS_{i,q-4}$ are the stock's basic earnings per share (EPS) excluding extraordinary items in quarters q and $q-4$ respectively. EPS is adjusted for stock splits and reverse splits through division by the Compustat item AJEXQ, the quarterly cumulative adjustment factor. Standardized unexpected earnings in quarter q ($SUE_{i,q}$) is defined as $UE_{i,q}$ scaled by its standard deviation over the past eight quarters, with a minimum of four UE observations available.

with month fixed effects.

In Table 9, Panel A, we examine *SUE* in quarters 1–4 following the portfolio formation month. We find that *SPFMOM* shows strong power in predicting future SUEs. Specifically, an increase from the lowest *SPFMOM* to the highest leads to a 5.5 percentage point increase in the following quarter's SUE, which equals 3.9% of the average cross-sectional standard deviation of SUE.

Overall, this result indicates that social peer firm returns are positively associated with future earnings growth, confirming that social peer firm returns contain valuable information about firms' fundamentals.

4.3 Do Investors Incorporate Information on Social Ties?

Last, we investigate the extent to which market participants incorporate information regarding the performance of social peer firms.

We first focus on a very important information provider in the financial market, the financial analyst. In a frictionless market in which analysts are fully aware of information about socially-connected industry peers, such information should have been incorporated into their earnings forecasts. On the other hand, if social peer firm return information has not been fully incorporated by financial analysts, then social peer firm returns would be able to predict future analyst forecast errors.

Similarly, if marginal investors of a stock are fully aware of the peers' information and correctly price the focal stock's prices, social peer firm returns would not be able to forecast future earnings announcement returns. But if social peer firm information has not been fully incorporated by prices, then the peer returns would be able to forecast future earnings announcement returns. Therefore, we next examine whether social peer firm returns can predict future analyst forecast errors and earnings announcement returns.

Analyst Forecast Errors Financial analysts obtain and communicate information about the firms they follow and serve as crucial information intermediaries between firms and investors. Therefore, focusing on the information set of this class of sophisticated players in the financial market helps us to gain insight into the extent to which peer firm information is incorporated by market professionals.

Specifically, we analyze whether analysts have incorporated the peer firm information into their earnings forecasts by examining their forecast errors. Following DellaVigna and Pollet (2009), we regress forecast errors onto peer firm returns using the following panel regression:

$$FE_{i,t+s} = \alpha + \beta_1 SPFRET_{i,t} + \beta_2 SPFMOM_{i,t} + \gamma X_{i,t} + \epsilon_{i,t+1}, \tag{7}$$

where FE is the analyst forecast error.[20] We consider forecast errors in quarters $t+1$ to $t+4$. *SPFRET* and *SPFMOM* are social peer firm returns and social peer firm momentum, respectively. X is a vector of control variables identical to those used in Table 8, along with month fixed effects. Standard errors are clustered by month and firm.

Our results, reported in Table 9, Panel B, show that *SPFMOM* can predict forecast errors over the following year. While *SPFRET* is positively associated with forecast errors, it is not statistically significantly. These results suggest that even professional market participants such as sell-side analysts are sluggish in incorporating the information of social peer firms into their earnings forecasts, with a substantial delay of up to one year.

Announcement Returns An alternative method to assess whether relevant fundamental information of social peer firms has been incorporated by investors is to examine future earnings announcement returns. If investors fail to consider such information in a timely manner, such underreaction would be corrected upon future earnings announcements. Hence, we expect that social peer firms' returns would positively predict focal firms' earnings announcement returns in the future.

To examine this hypothesis, we conduct a panel regression in the following form:

$$CAR_{i,t+s} = \alpha + \beta_1 SPFRET_{i,t} + \beta_2 SPFMOM_{i,t} + \gamma X_{i,t} + \epsilon_{i,t+1}, \tag{8}$$

where the dependent variable CAR is the market-adjusted cumulative abnormal returns computed for three-day windows around earnings announcements in the next four quarters. *SPFRET* and *SPFMOM* are social peer firm returns and social peer firm momentum, respectively. X is a vector of control variables identical to those used in Table 8, along with month fixed effects. Standard errors are clustered by month and firm.

Our results are reported in Table 9, Panel C. We find that both *SPFRET* and *SPFMOM* are strongly related to earnings announcement returns in the following quarter. In fact, *SPFMOM* can predict earnings announcement CAR in four quarters. In terms of the economic magnitude, companies with the highest *SPFMOM* (*SPFRET*) have 25 (15) basis points higher returns in the following quarter's CAR compared with those with the lowest *SPFMOM* (*SPFRET*).

We conduct robustness checks of results in Section 4 with $SPFRET_{\perp}$ and $SPFMOM_{\perp}$, the ver-

[20] Forecast errors are defined as the difference between the announced earnings for that quarter and analyst consensus forecast (i.e., the median forecast), scaled by the stock price five trading days before the earnings announcement date. We adjust actuals, forecasts, and prices for stock splits and reverse splits through scaling them by the item CFACSHR—the cumulative adjustment factor from the daily CRSP file. We only use the forecasts for the next quarter and within 90 days of the earnings announcement date. If an analyst makes multiple forecasts within this time window, we use the latest forecast.

sions of *SPFRET* and *SPFMOM* that are orthogonalized to the other predictive variables. Table A4 presents the results and shows that our findings are robust.

Taken together, our results suggest that the strong return predictability of social peer returns on focal firm returns that we document in Section 3 are due to the fundamental linkages between the firms that have not been fully recognized by market participants.

5 Conclusion

This paper proposes a new dimension of cross-firm linkages that is based on social connections between the regions in which the firms are located. We show that a novel measure of same-industry social peer returns (*SPFRET*) strongly predicts the returns of focal firms. A long-short portfolio based on *SPFRET* generates a highly significant Fama and French (2015) monthly alpha of 157 basis points (equal weighted) and 84 basis points (value weighted).

Investigating the underlying economic mechanisms, we show that only 39% of the long-short portfolio alpha can be explained by economic connections that have been documented in previous studies (such as industry momentum, technology similarity, and labor flows across regions), leaving unexplained a substantial abnormal return of over 50 basis points per month. The result remains robust when we examine two-way sorted portfolios by *SPFRET* and industry returns as well as with Fama and MacBeth (1973) regression analysis, in which we control for 18 other lead-lag return predictors or stock characteristics established in previous studies. *SPFRET* is among the most important contributors to the power of a PLS-based composite predictor that aggregates the effects of all 18 individual predictors.

Consistent with investor inattention generating sluggish price adjustments, our results are stronger for firms with low visibility (measured by market capitalization, institutional ownership, or low analyst coverage), as well as for firms located outside of industry cluster counties. Furthermore, the predictability of *SPFRET* lasts for up to one year and does not reverse in the long run. In addition, social peer firm returns help predict focal firms' future earnings, analyst forecast errors, and future earnings announcement returns.

Our findings suggest that social ties across regions offer a new way to capture important fundamental economic linkages across firms that has not been fully incorporated by stock prices. The social connection–based linkage measure can be useful for future studies that try to uncover the way in which firms are related to each other, how innovations disseminate, how shocks propagate across firms, and, more broadly, what influences economic exchanges and labor mobility across regions.

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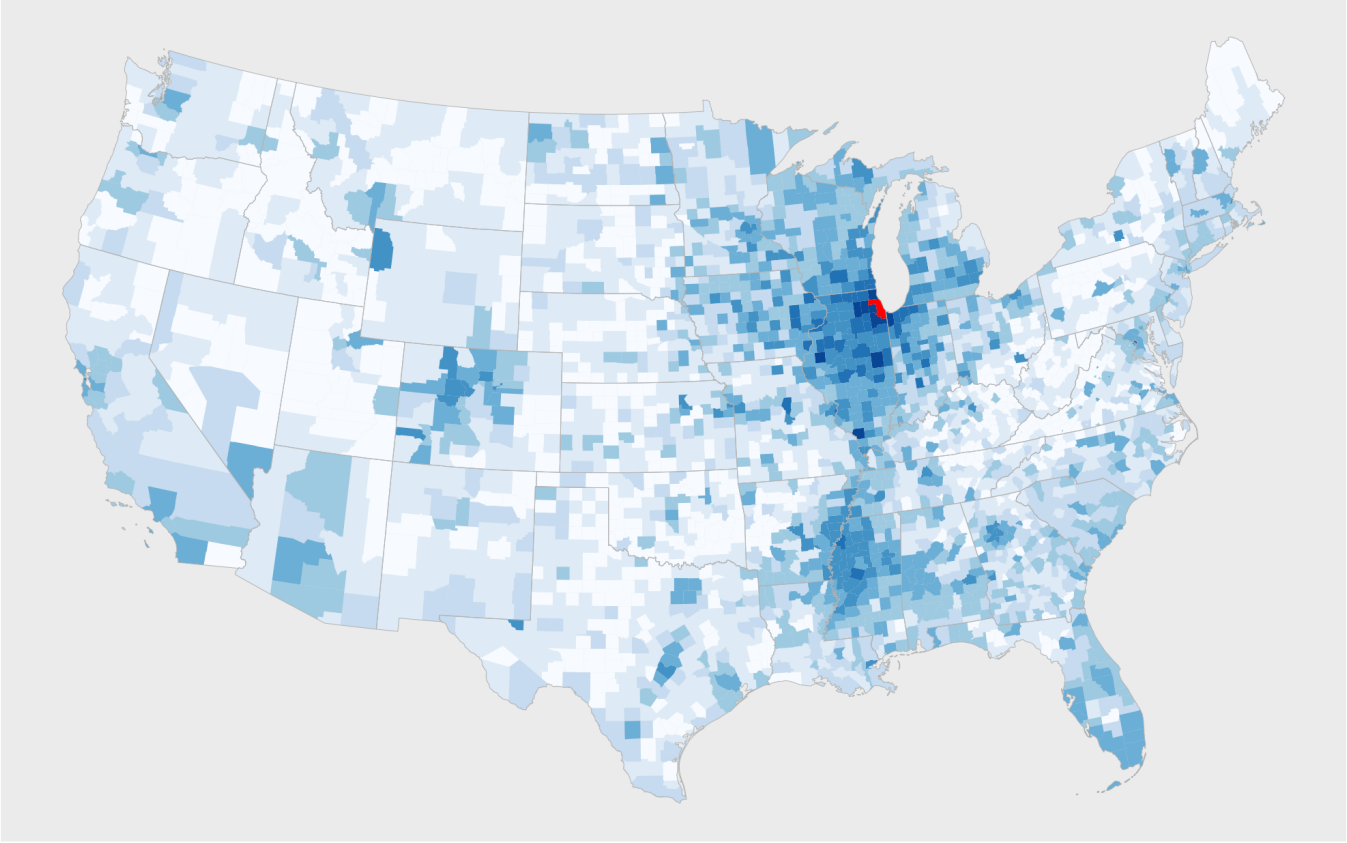
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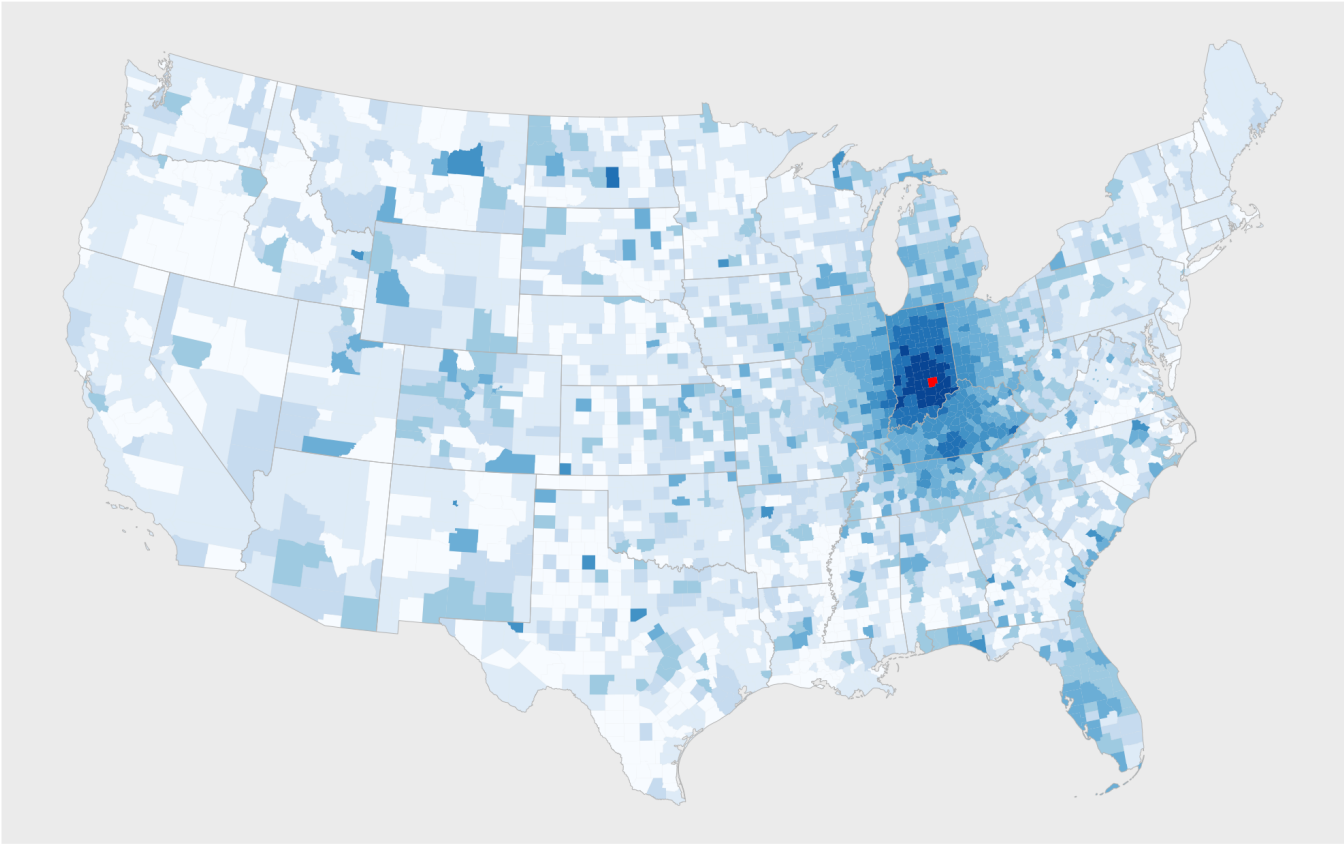
Figure 1: Examples of Social Connectedness

This figure shows county-level heat maps of the social connectedness to Cook County, IL, in Panel A, and Bartholomew County, IN, in Panel B. The focal counties are in red and darker colors indicate higher social connectedness to the focal counties. Panel C The figure presents CMI's headquarters county, Bartholomew County, IN, and the locations of CMI's industry peers, with dark blue indicating higher social connectedness to Bartholomew County. Examples of the industry peer firms include Caterpillar (ticker: CAT), Clarcor (ticker: CLC), and Stanley Black & Decker (ticker: SWK), located in Peoria, IL, Williamson, TN, and Hartford, CT, respectively. Counties without any peer firms' presence are presented in dark grey.

Panel A: Social Connectedness to Cook County, IL



Panel B: Social Connectedness to Bartholomew County, IN



Panel C: Social Connectedness to Bartholomew County, IN, and the Presence of "Machinery" Firms

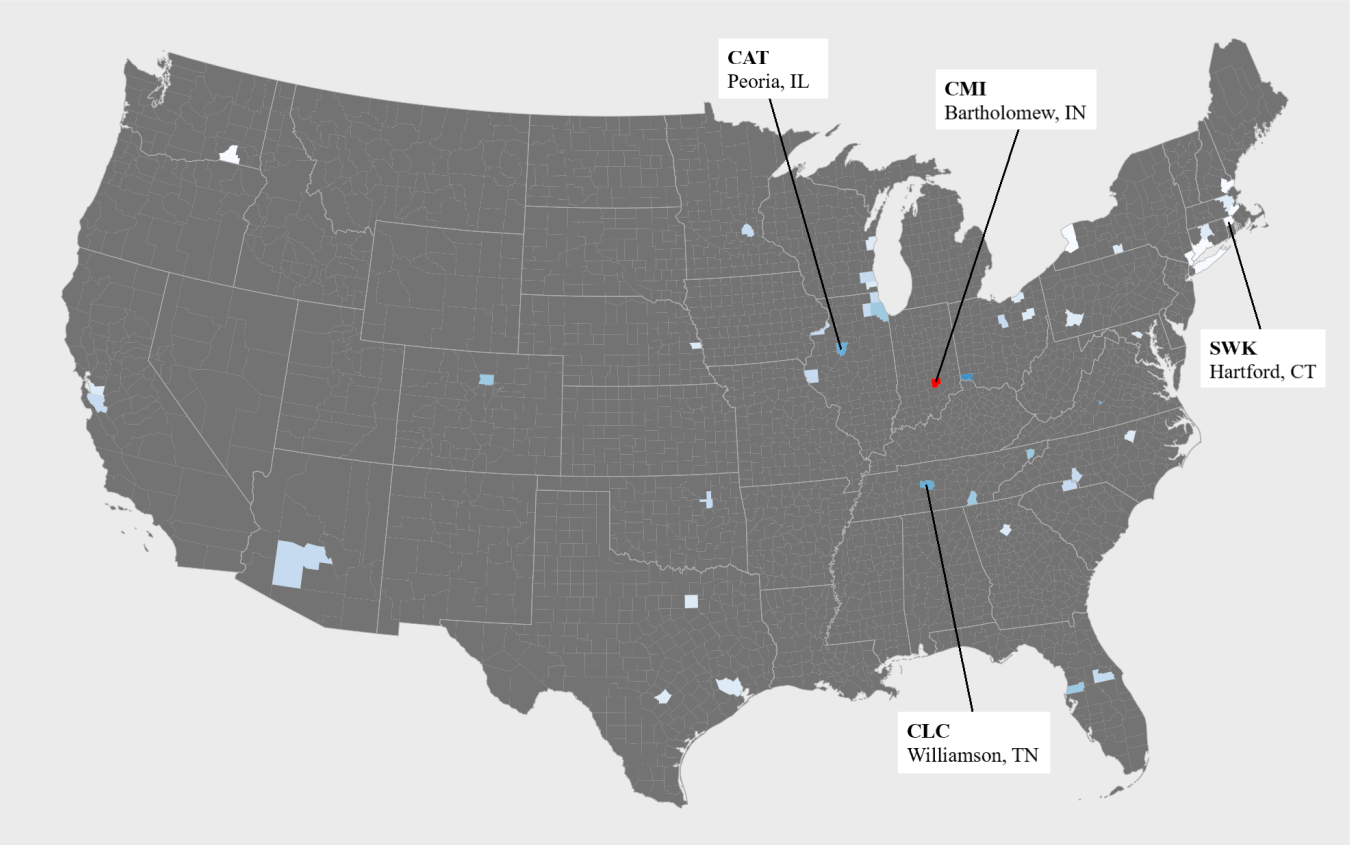


Figure 2: Average Monthly Alpha of Long Short Portfolio Over Time

The figure depicts the time series of monthly average Fama-French five-factor (FF5) alphas for long-short (LS) portfolios based on *SPFRET* (Panel A) and $SPFRET_{\perp}$ (Panel B), computed for each year in our sample. *SPFRET* is the SCI-weighted average return of stocks from the same Fama-French 48-industry as the focal stock but from a different state. $SPFRET_{\perp}$ is the abnormal return generated from a panel regression of *SPFRET* on the equal-weighted industry return, using all available stock-month observations prior to the portfolio formation month (i.e., month t) and month fixed effects. At the end of each month from July 1963 through November 2019, all common stocks are sorted into deciles based on either *SPFRET* (the left panel) or $SPFRET_{\perp}$ (the right panel). Then, next month's value-weighted return of the decile-1 portfolio is subtracted from that of the decile-10 portfolio to calculate the return of the LS portfolio for the following month. Monthly LS abnormal returns are then calculated using the FF5 model. Each bar in the figure shows the average monthly abnormal return for the year that it represents. All returns are in percentages.

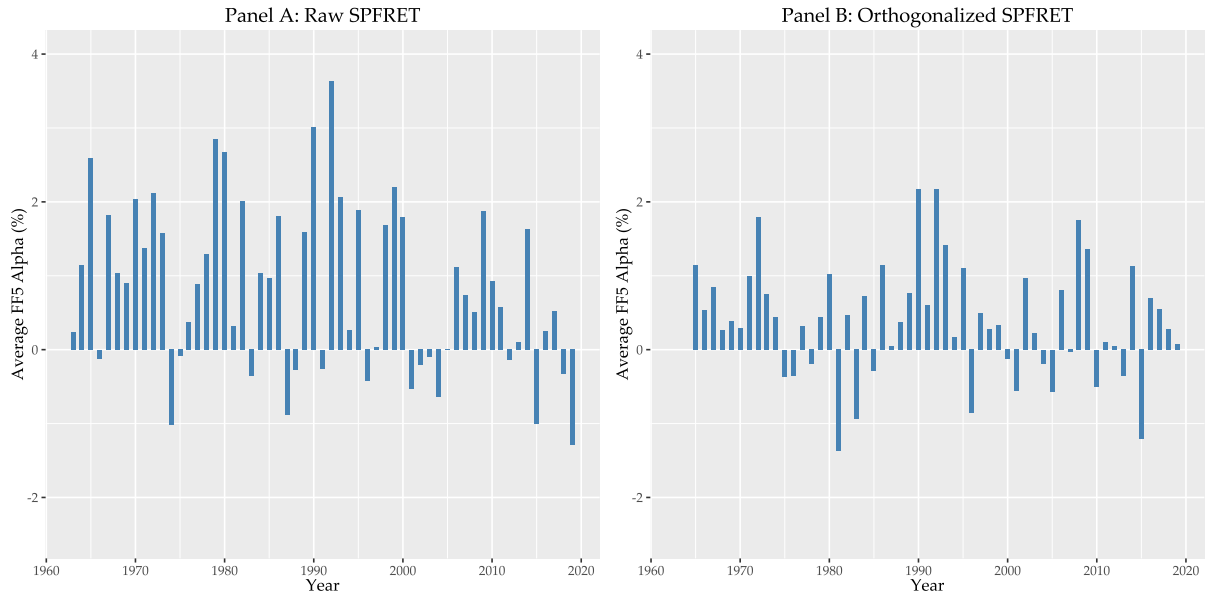


Figure 3: Decomposing *SPFRET* Portfolio Returns

The figure decomposes the average return of the *SPFRET*-sorted value-weighted LS portfolio into its various components. Each bar shows the amount of the average return that is explained by the variable(s) indicated below it. *INDRET* represents the contribution of *INDRET*, the equal-weighted Fama-French 48-industry return. *GEORET* represents the contribution of geographic momentum. *CONGRET* represents the contribution from the complicated firm effect. *CRET* represents the contribution from the customer return. *J2JRET* represents the contribution from the return predictability based on job-to-job movement across states. *TNICRET* represents the contribution of the text-based industry return of Hoberg and Phillips (2018). *TECHRET* represents the contribution of the technological spillover effect. *FF5* represents the combined contribution of the Fama-French five factors. The last bar shows the alpha, the portion of the average return not explained by variables shown in the plot. Red indicates negative values.

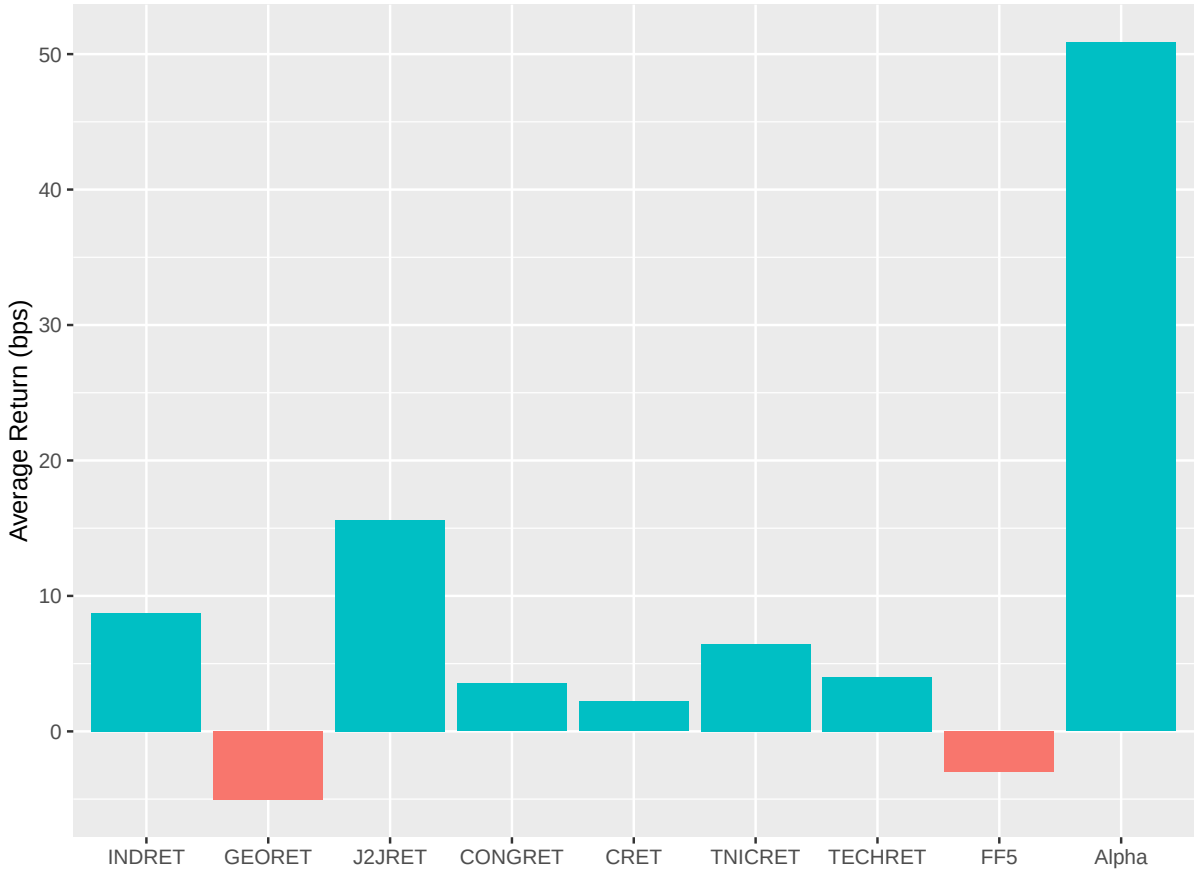


Figure 4: Relative Variable Importance

The figure depicts the relative importance of lead-lag predictors (*SPFRET*, *INDRET*, *GEORET*, *CFRET*, *CRET*, *TECHRET*, *TNICRET*, *J2JRET*, and *CONGRET*) in a partial least squares (PLS) model that uses these predictors along with all the other controls (i.e., *INDMOM*, *RET*, *MOM*, *SIZE*, *BM*, *BMKT*, *ILLIQ*, *SKEW*, *COSKEW* and *MAX*). Starting from July 1994, a new PLS model is trained each month using all the data available up to that point. For each training set, the difference between the full-model R^2 and the R^2 obtained by dropping one of the nine predictors while keeping the coefficient estimates for the rest of the predictors fixed. These marginal changes in R^2 are then normalized so that their sum equals one. The relative variable importance in each panel is then calculated by taking the average over the normalized values over all the training sets. *CFRET* refers to shared analyst coverage returns. *SPFRET* refers to social peer firm returns. *INDRET* is the industry return. *CRET* is the customer return. *GEORET* is the geographic momentum. *TECHRET* is the technology-linked firm return. *TNICRET* is the text-based industry return. *J2JRET* is the job flow–based return. *CONGRET* is the pseudo-conglomerate return.

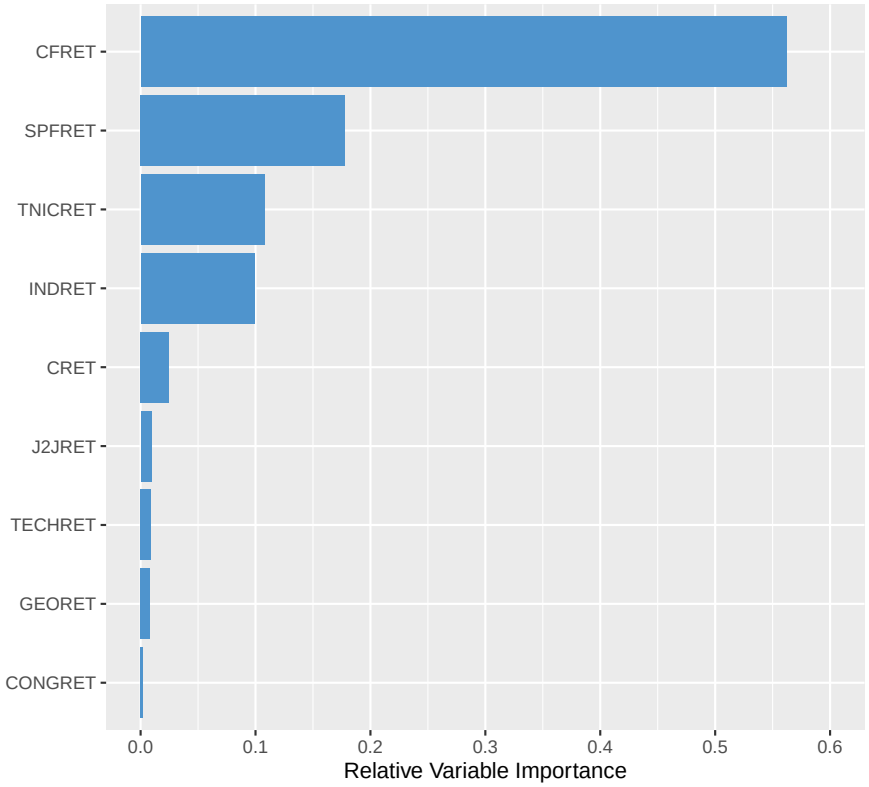
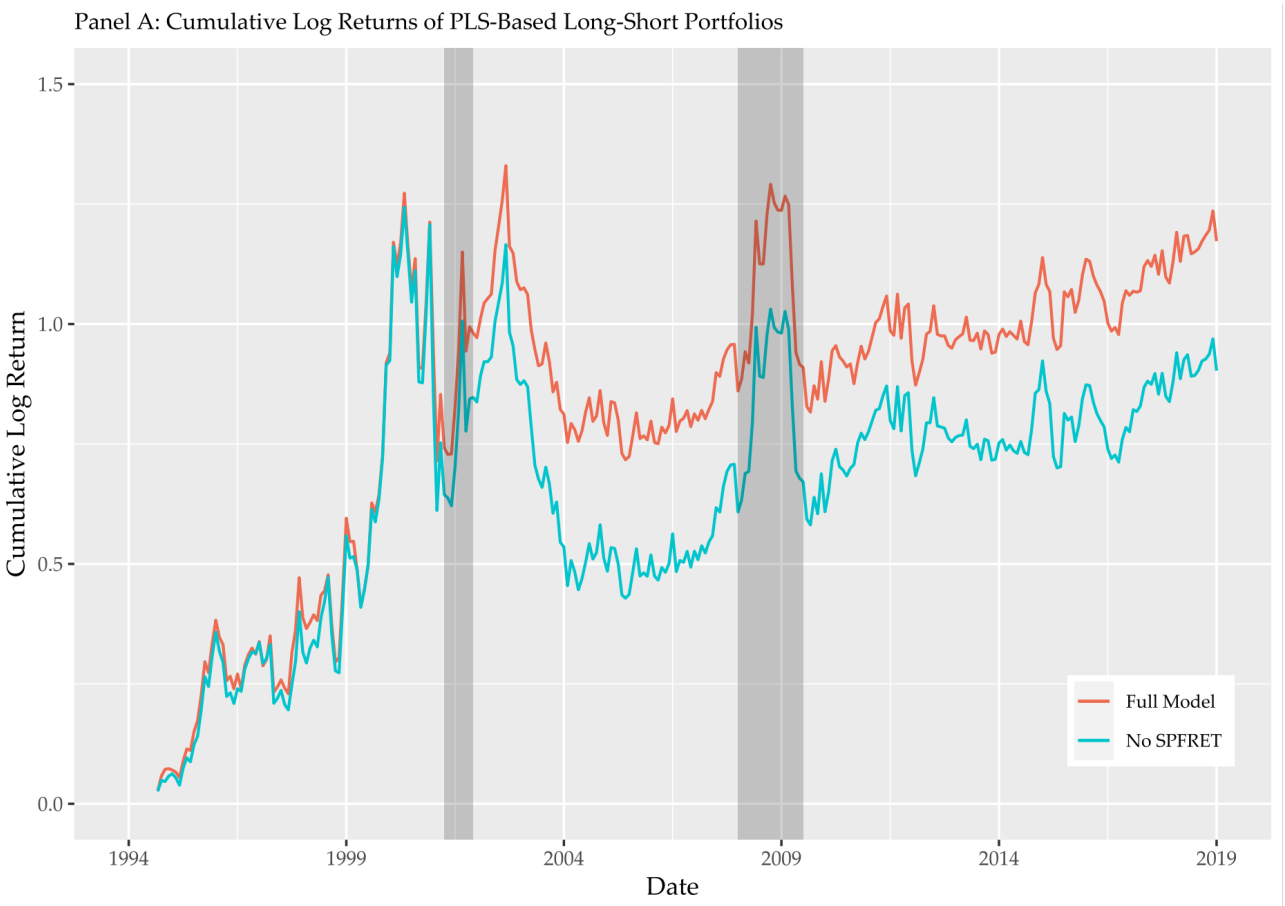


Figure 5: PLS-Based Long-Short Portfolio Analysis

The figure shows the cumulative returns of portfolios that are sorted based on the out-of-sample PLS predictor with and without *SPFRET* from August 1994 through December 2019. Panel A depicts the cumulative log return of the long-short (i.e., decile-10 minus decile-1) portfolios, while Panel B shows the cumulative log returns for long and short legs separately. Portfolios are value-weighted. Shaded areas indicate the NBER recession periods.



Panel B: Cumulative Log Returns of PLS-Based Long and Short Portfolios

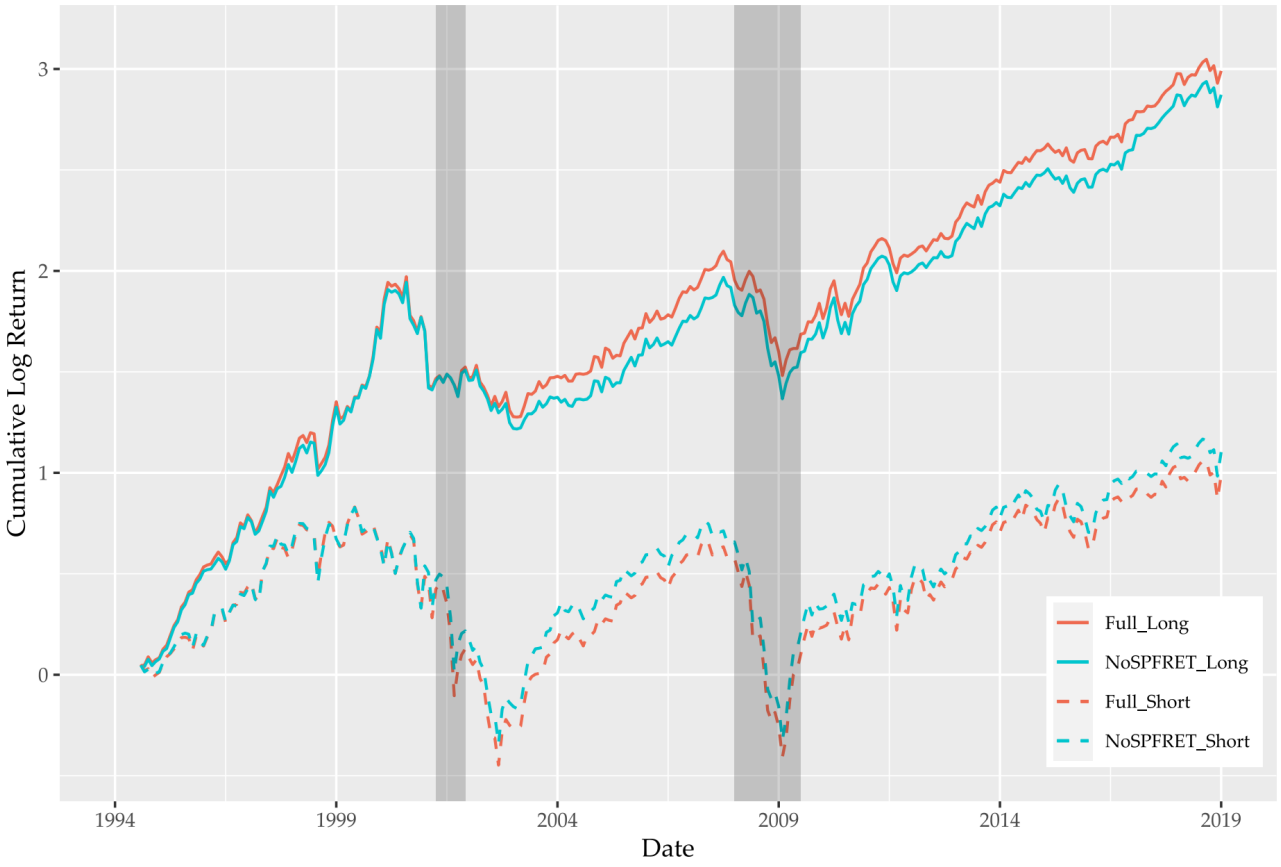


Table 1: Summary Statistics and Correlations

The table reports the summary statistics (Panel A) and time-series averages of cross-sectional correlations (Panel B) for the main variables used in the paper. RET_{t+1} is the monthly stock return following the portfolio formation month. *SPFRET* is the SCI-weighted average return of a firm's industry peers (excluding those from the same state). $SPFRET_{\perp}$ is *SPFRET* orthogonalized with respect to the equal-weighted industry returns. *SPFMOM* is the cumulative *SPFRET* over months $t-11$ through $t-1$. *INDRET* is the equal-weighted average return of stocks for a given industry. *INDMOM* is the cumulative *INDRET* over months t-11 through t-1. *GEORET* is the equal-weighted average return of peer firms that are in the same economic area as a stock (excluding those in the same industry). *GEOMOM* is the cumulative *GEORET* over months t-11 through t-1. *CFRET* is the average return of peer stocks that share at least one analyst with the focal stock over previous 12 months, weighted by the number of shared analysts between stocks. *CFMOM* is the cumulative *CFRET* over months t - 11 through t - 1. *CRET* is the equal-weighted average stock return of a firm's main customers. *TECHRET* is the weighted average stock return of technology-linked peer firms, where the weights are the technological closeness between the peer firm and the focal firm, determined by the similarities between patent distributions across different technology categories. *CONGRET* is the pseudo-conglomerate return, defined as the sales-weighted return of (value-weighted) single-segment firm portfolios, formed for each segment that a conglomerate firm operates in. *J2JRET* represents the contribution from the return predictability based on job-to-job movement across states. *TNICRET* is the text-based industry return of Hoberg and Phillips (2018). All returns are reported in percentages.

Panel A: Summary statistics

	N	Mean	Std. Dev.	Min.	25%	75%	Max.
RET_{t+1}	2618	1.096	10.973	-53.717	-4.746	6.176	104.679
SPFRET	2525	1.722	3.837	-14.521	-0.643	3.837	28.001
SPFMOM	2525	19.878	18.671	-32.533	7.887	29.027	164.051
INDRET	2543	1.187	3.215	-8.614	-0.884	3.145	13.377
INDMOM	2543	15.027	15.711	-24.081	4.651	24.479	71.097
GEORET	1612	1.243	1.929	-4.266	0.136	2.270	7.572
GEOMOM	1507	15.059	8.616	-7.843	10.062	19.375	44.855
J2JRET	2360	1.709	2.814	-11.133	0.344	2.951	20.447
J2JMOM	2212	20.882	13.303	-25.329	13.818	26.230	109.765
CONGRET	731	1.255	3.942	-12.948	-1.055	3.459	18.951
CONGMOM	660	14.662	15.743	-30.309	5.112	22.953	90.290
CRET	882	1.221	6.995	-26.711	-2.616	4.757	45.661
CMOM	809	13.878	26.306	-55.013	-1.227	25.900	223.881
TNICRET	2885	1.767	6.163	-33.748	-1.310	4.534	74.585
TNICMOM	2570	22.217	27.174	-60.958	6.172	34.897	330.843
TECHRET	805	1.631	2.401	-9.251	0.339	2.811	17.265
TECHMOM	752	19.788	10.993	-17.764	13.223	25.181	93.483
CFRET	2682	1.481	3.995	-18.192	-0.820	3.647	30.652
CFMOM	2682	17.893	18.928	-39.959	6.766	26.523	228.511

Panel B: Correlation matrix

	RET_{t+1}	SPFRET	SPFMOM	$SPFRET_{\perp}$	INDRET	INDMOM	GEORET	GEOMOM	J2JRET	J2JMOM	CONGRET	CONGMOM	CRET	CMOM	TNICRET	TNICMOM	TECHRET	TECHMOM	CFRET
SPFRET	0.038																		
SPFMOM	0.018	0.087																	
$SPFRET_{\perp}$	0.013	0.707	0.018																
INDRET	0.043	0.638	0.106	-0.033															
INDMOM	0.021	0.069	0.685	-0.036	0.134														
GEORET	0.011	0.019	0.007	0.011	0.016	0.009													
GEOMOM	0.007	0.006	0.024	0.002	0.006	0.027	0.091												
J2JRET	0.031	0.492	0.053	0.235	0.439	0.049	0.025	0.003											
J2JMOM	0.012	0.058	0.489	0.010	0.071	0.468	0.011	0.033	0.092										
CONGRET	0.025	0.352	0.024	0.114	0.363	0.022	0.034	0.009	0.267	0.015									
CONGMOM	0.016	0.047	0.361	-0.009	0.071	0.394	0.013	0.059	0.035	0.283	0.055								
CRET	0.020	0.130	0.007	0.041	0.141	0.006	0.061	0.004	0.079	0.003	0.134	0.008							
CMOM	0.017	0.030	0.147	0.000	0.037	0.158	0.017	0.068	0.010	0.081	0.009	0.151	0.016						
TNICRET	0.025	0.293	0.039	0.073	0.313	0.032	0.079	0.012	0.240	0.034	0.207	0.024	0.149	0.022					
TNICMOM	0.016	0.054	0.364	0.009	0.062	0.375	0.018	0.104	0.044	0.307	0.026	0.267	0.007	0.186	0.051				
TECHRET	0.024	0.223	0.040	0.075	0.249	0.031	0.062	0.000	0.064	0.016	0.173	0.035	0.121	0.022	0.234	0.036			
TECHMOM	0.023	0.047	0.284	0.011	0.057	0.297	0.007	0.067	0.006	0.069	0.019	0.211	0.015	0.140	0.034	0.304	0.079		
CFRET	0.046	0.470	0.036	0.146	0.490	0.025	0.093	0.013	0.370	0.026	0.399	0.030	0.205	0.019	0.365	0.039	0.349	0.037	
CFMOM	0.023	0.067	0.484	0.006	0.085	0.491	0.023	0.104	0.050	0.370	0.027	0.397	0.011	0.210	0.050	0.429	0.048	0.376	0.063

Table 2: Social Ties and Industry Momentum

We investigate whether social ties contribute to industry momentum effects by regressing a firm's returns (R_t) on the SCI-sorted industry momentum using Fama-MacBeth regressions. Every month and for a given firm, we sort the firm's Fama-French 48-industry peers (except the focal firm itself) into tercile portfolios (low, mid, and high) based on the SCI between the headquarters counties of the firm and its peer firms. We then define the SCI-sorted industry momentum, $INDRET_{LOW_SCI}$, $INDRET_{MID_SCI}$, and $INDRET_{HIGH_SCI}$, as the monthly returns of the corresponding portfolios. Columns 1 and 2 use the equal-weighted $INDRET$s, and columns 3 and 4 use value-weighted $INDRET$s. Columns 1 and 3 present the contemporaneous regressions, and columns 2 and 4 present the one-month ahead predictive regressions. Missing values of portfolio returns are imputed with the monthly medians. We cross-sectionally standardize all independent variables by mapping them into the $(0, 1]$ interval through scaling the monthly ranks by the number of observations (Gu et al., 2020; Kelly et al., 2019). We report t-statistics with standard errors based on Newey and West (1994) adjustments in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Equal weighted		Value weighted	
	RET_t	RET_{t+1}	RET_t	RET_{t+1}
	(1)	(2)	(3)	(4)
$INDRET_{HIGH_SCI}$	4.238***	0.882***	3.206***	0.626***
	(11.324)	(7.714)	(17.424)	(6.526)
$INDRET_{MED_SCI}$	2.906***	0.753***	2.822***	0.714***
	(16.156)	(7.603)	(12.382)	(8.010)
$INDRET_{LOW_SCI}$	2.301***	0.460***	2.246***	0.498***
	(24.160)	(5.460)	(19.342)	(5.594)
# Periods	678	677	678	677
# Stocks	2,608	2,618	2,608	2,618
R^2	0.042	0.016	0.032	0.013

Table 3: Return Predictability of Social Peer Firm Returns: Portfolio Analysis

The table reports the results of the univariate and bivariate portfolio sorts based on *SPFRET*, the SCI-weighted average return of a firm's industry peers (excluding those from the same state). In Panel A, for each month, we sort all common stocks into deciles based on *SPFRET*and calculate both the equal-weighted and value-weighted one-month-ahead returns for the decile portfolios, as well as the return of the portfolio that long the decile-10 portfolio and short the decile-1 portfolio. We present the raw returns and the FF5 alphas for the equal- and value-weighted portfolios respectively. Panel B and Panel C report the results of bivariate portfolio sorts based on industry momentum (*INDRET*) and *SPFRET*. We first sort stocks into quintiles based on *INDRET* and then, within each *INDRET* quintile, we further sort stocks into quintiles based on *SPFRET*. We then report the one-month-ahead FF5 alphas for the 25 equal-weighted (Panel B) and value-weighted (Panel C) portfolios and the portfolios that long in stocks in the *SPFRET* quintile 5 and short in the *SPFRET* quintile 1 stocks. Final rows in both panels report the average alphas for the *SPFRET* quintiles. All returns are in percentages. The corresponding *t*-statistics based on Newey and West (1994) standard errors are reported in parentheses below the alphas. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Univariate Sort

	(1 Low)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10 High)	(10-1)
Raw Return EW	0.277	0.534**	0.799***	0.970***	1.091***	1.219***	1.277***	1.438***	1.630***	1.766***	1.489***
	(1.146)	(2.473)	(3.967)	(4.436)	(4.933)	(5.838)	(5.898)	(6.832)	(7.131)	(7.233)	(8.569)
FF5 Alpha EW	−0.846***	−0.525***	−0.234**	−0.122	−0.036	0.083	0.142**	0.358***	0.610***	0.723***	1.568***
	(−7.043)	(−4.233)	(−2.050)	(−1.403)	(−0.596)	(1.481)	(2.304)	(5.169)	(6.341)	(6.135)	(7.058)
Raw Return VW	0.443**	0.655***	0.935***	0.834***	1.103***	1.032***	1.058***	1.168***	1.098***	1.208***	0.765***
	(2.122)	(3.360)	(5.049)	(4.410)	(5.771)	(5.533)	(5.650)	(7.160)	(5.275)	(6.188)	(4.781)
FF5 Alpha VW	−0.554***	−0.251**	0.007	−0.065	0.146	0.007	0.057	0.199***	0.255**	0.286***	0.840***
	(−5.516)	(−2.546)	(0.067)	(−0.711)	(1.415)	(0.082)	(0.705)	(2.706)	(1.985)	(3.177)	(5.216)

Panel B: Bivariate Sort with Equal-Weighted Portfolios

	SPFRET					
	(1 Low)	(2)	(3)	(4)	(5 High)	(5-1)
1 (Low INDRET)	-1.113^{***}	-0.874^{***}	-0.674^{***}	-0.564^{***}	-0.537^{***}	0.576^{***}
	(-7.309)	(-6.326)	(-4.512)	(-4.099)	(-3.773)	(4.184)
2	-0.572^{***}	-0.203^{*}	-0.087	0.015	0.088	0.660^{***}
	(-4.813)	(-1.695)	(-0.659)	(0.127)	(0.908)	(5.043)
3	-0.250^{***}	0.008	0.051	0.078	0.218^{**}	0.468^{***}
	(-2.684)	(0.089)	(0.636)	(0.886)	(2.345)	(4.517)
4	-0.010	0.152^{*}	0.234^{**}	0.379^{***}	0.472^{***}	0.482^{***}
	(-0.126)	(1.681)	(2.446)	(4.482)	(4.249)	(3.318)
5 (High INDRET)	0.373^{***}	0.631^{***}	0.816^{***}	0.767^{***}	1.002^{***}	0.630^{***}
	(3.446)	(4.791)	(6.358)	(5.520)	(6.219)	(4.599)
Average	-0.314^{***}	-0.057	0.068	0.135^{***}	0.249^{***}	0.563^{***}
	(-5.334)	(-1.329)	(1.542)	(3.282)	(5.278)	(7.384)

Panel C: Bivariate Sort with Value-Weighted Portfolios

	SPFRET					
	(1 Low)	(2)	(3)	(4)	(5 High)	(5-1)
1 (Low INDRET)	-0.725^{***}	-0.526^{***}	-0.230	-0.197	-0.240	0.485^{***}
	(-5.289)	(-3.609)	(-1.472)	(-1.507)	(-1.457)	(2.794)
2	-0.618^{***}	-0.102	0.160	0.187	0.146	0.764^{***}
	(-5.214)	(-0.795)	(1.239)	(1.438)	(1.218)	(4.875)
3	-0.057	0.007	-0.127	0.083	0.111	0.168
	(-0.529)	(0.059)	(-1.178)	(0.703)	(0.938)	(1.212)
4	0.004	0.046	0.069	0.245^{**}	0.186^{*}	0.182
	(0.042)	(0.378)	(0.608)	(2.350)	(1.648)	(1.108)
5 (High INDRET)	0.108	0.266^{*}	0.349^{***}	0.358^{**}	0.440^{***}	0.332^{**}
	(0.875)	(1.952)	(2.703)	(2.492)	(3.487)	(2.082)
Average	-0.258^{***}	-0.062	0.044	0.135^{***}	0.129^{**}	0.386^{***}
	(-4.931)	(-1.196)	(0.902)	(2.773)	(2.185)	(4.844)

Table 4: Spanning Regressions

The table presents the results of spanning regressions where the long-short (LS) portfolio return of *SPFRET* is regressed against LS portfolio returns obtained using other variables that capture economic linkages between firms. *SPFRET* is the SCI-weighted average return of a firm's industry peers (excluding those from the same state). The other variables that are used to form LS portfolios include industry momentum (*INDRET*), geographic momentum (*GEORET*), customer return (*CRET*), the technology-linked firm return (*TECHRET*), the pseudo-conglomerate return (*CONGRET*), the text-based industry return (*TNICRET*), the technology-linked firm return (*TECHRET*), and the job flow–based peer returns (*J2JRET*). We control for Fama-French five-factor model but do not report those coefficients for brevity. The results are based on a common sample for which all explanatory variables are available and all returns are reported in percentages. Newey-West heteroskedasticity and autocorrelation-corrected *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Alpha	0.915***	0.765***	0.749***	0.597***	0.574***	0.539***	0.513***	0.509***
	(3.004)	(3.996)	(3.972)	(3.478)	(3.107)	(3.132)	(3.104)	(3.095)
INDRET		0.766***	0.758***	0.583***	0.538***	0.523***	0.462***	0.433***
		(11.313)	(11.636)	(11.073)	(9.879)	(8.876)	(8.576)	(9.158)
GEORET			0.024	0.001	−0.018	−0.018	−0.057	−0.077*
			(0.441)	(0.031)	(−0.417)	(−0.420)	(−1.229)	(−1.890)
J2JRET				0.323***	0.272***	0.275***	0.273***	0.277***
				(8.972)	(6.791)	(7.155)	(6.500)	(6.916)
CONGRET					0.130***	0.115***	0.091**	0.076*
					(4.248)	(3.319)	(2.458)	(1.876)
CRET						0.057	0.046	0.036
						(1.328)	(1.054)	(0.729)
TNICRET							0.130***	0.106***
							(3.276)	(2.796)
TECHRET								0.088
								(1.297)
FF5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	276	276	276	276	276	276	276	276
R^2	0.006	0.691	0.691	0.739	0.755	0.757	0.763	0.767

Table 5: Predicting Returns: Fama-MacBeth Regressions

The table reports the results of Fama-MacBeth regressions where stock returns are regressed on lagged social peer firm returns. *SPFRET* is the SCI-weighted average return of a firm's industry peers (excluding those from the same state). *INDRET* is the short-term industry momentum. *GEORET* is the geographic momentum, *CFRET* is the analyst-connected firm return, *CRET* is the customer return, *TECHRET* is the technology-linked firm return. *CONGRET* is the pseudo-conglomerate return. *TNICRET* is the text-based industry return. *TECHRET* is the technology-linked firm return. *J2JRET* is the industry peer returns weighted by the average job flow between focal and peer firms (see Section 3.2). We also include the following control variables: *RET*, *SIZE*, *BMKT*, *BM*, *MOM*, *IVOL*, *ILLIQ*, *MAX*, *SKEW*, and *COSKEW*. Section 2.1 provides detailed descriptions. All returns are reported in percentages. Missing values of independent variables are imputed with the monthly medians. We cross-sectionally standardize all independent variables by mapping them into the $(0, 1]$ interval through scaling the monthly ranks by the number of observations (Gu et al. (2020)). t-statistics are computed with Newey and West (1994) standard errors and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	RET_{t+1}								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SPFRET	1.400***	0.787***	0.781***	0.679***	0.656***	0.644***	0.617***	0.708***	0.493***
	(9.914)	(7.669)	(7.652)	(7.075)	(5.515)	(5.470)	(4.468)	(4.539)	(3.321)
INDRET		1.040***	1.043***	0.990***	0.856***	0.847***	0.721***	0.878***	0.693***
		(9.057)	(9.035)	(8.828)	(6.214)	(6.179)	(4.258)	(4.723)	(3.723)
GEORET			0.205***	0.203***	0.220***	0.214***	0.205***	0.201***	0.165**
			(3.959)	(3.953)	(3.772)	(3.779)	(2.895)	(2.613)	(2.159)
J2JRET				0.297***	0.318***	0.320***	0.233***	0.318***	0.219**
				(4.640)	(4.435)	(4.421)	(2.674)	(3.276)	(2.293)
CONGRET					0.146**	0.139**	0.016	0.055	−0.035
					(2.496)	(2.384)	(0.239)	(0.690)	(−0.457)
CRET						0.364***	0.329***	0.384***	0.319***
						(4.441)	(4.209)	(4.209)	(3.583)
TNICRET							0.593***	0.791***	0.569***
							(4.368)	(5.422)	(4.627)
TECHRET								0.166	0.043
								(1.510)	(0.375)
CFRET									1.301***
									(8.185)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# Periods	672	672	672	672	509	509	365	276	276
# Stocks	2,634	2,634	2,634	2,634	3,193	3,193	3,633	3,867	3,867
R^2	0.071	0.074	0.075	0.076	0.065	0.066	0.063	0.067	0.069

Table 6: Information Environment and Return Predictability

The table reports Fama-MacBeth regression analysis of how stock characteristics affect the return predictability of social peer firm returns. We consider three stock characteristics: size, institutional ownership and analyst coverage. *SPFRET* is the SCI-weighted average return of a firm's industry peers (excluding those from the same state). *HIGH* is an indicator variable, which equals one if the focal stock's characteristic is above the corresponding cross-sectional median (or the NYSE sample median for the variable size), and zero otherwise. We include but do not report the following control variables for brevity: *INDRET*, *GEORET*, *CRET*, *CFRET*), *TNICRET*, *TECHRET*, *CONGRET*, *J2JRET*, *RET*, *SIZE*, *BMKT*, *BM*, *MOM*, *IVOL*, *ILLIQ*, *MAX*, *SKEW*, and *COSKEW* (see Section 2.1 for detailed descriptions). All returns are reported in percentages. Missing values of independent variables are imputed with the monthly medians. We cross-sectionally standardize all independent variables by mapping them into the $(0, 1]$ interval through scaling the monthly ranks by the number of observations (Gu et al. (2020)). We report *t*-statistics based on Newey-West adjusted standard errors in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	RET_{t+1}		
	Size	Inst. Own.	Analyst Cov.
	(1)	(2)	(3)
SPFRET	0.647^{***}	0.761^{***}	0.722^{***}
	(4.097)	(4.636)	(4.670)
SPFRET×HIGH	-1.253^{***}	-0.931^{***}	-0.904^{***}
	(-5.625)	(-4.067)	(-5.362)
	Yes	Yes	Yes
# Periods	276	276	276
# Stocks	2,238	2,220	2,238
R^2	0.087	0.087	0.086

Table 7: Firm Location Relative to Industry Clusters and Return Predictability

The table reports Fama-MacBeth regression analysis of how a firm's location relative to the locations of industry clusters affects the return predictability of *SPFRET*. *SPFRET* is the SCI-weighted average return of a firm's industry peers (excluding those from the same state). For a given Fama-French 48 industry and month, we measure the total industry market capitalization at the county level and define the top 20% (columns 1 and 2) or top 10% (columns 3 and 4) of counties as the industry cluster. The indicator variable *OUTCLS* is equal to one if the focal firm is headquartered outside of its corresponding industry cluster, and zero otherwise. The dependent variable in columns 1 and 3 is the contemporaneous focal stock return, and the dependent variable in columns 2 and 4 is the next month's return. We include but not report the following control variables: *INDRET*, *GEORET*, *CRET*, *CFRET*), *TNICRET*, *TECHRET*, *CONGRET*, *J2JRET*, *RET*, *SIZE*, *BMKT*, *BM*, *MOM*, *IVOL*, *ILLIQ*, *MAX*, *SKEW*, and *COSKEW* (see Section 2.1 for detailed descriptions). All returns are in percentages. Missing values of independent variables are imputed with the monthly medians. We cross-sectionally standardize all independent variables by mapping them into the $(0, 1]$ interval through scaling the monthly ranks by the number of observations (Gu et al. (2020)). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Top 20%		Top 10%	
	RET_t	RET_{t+1}	RET_t	RET_{t+1}
	(1)	(2)	(3)	(4)
SPFRET	4.327***	0.256	4.566***	0.310
	(4.870)	(1.569)	(5.029)	(1.639)
SPFRET× OUTCLS	−0.441**	0.405***	−0.432**	0.264
	(−2.571)	(2.974)	(−2.526)	(1.506)
Controls	Yes	Yes	Yes	Yes
# Periods	276	276	276	276
# Stocks	3,693	3,694	3,644	3,645
R^2	0.268	0.072	0.269	0.072

Table 8: Return Predictability in the Long Run

The table reports the long-run performance of calendar-time portfolios sorted by social peer firms' returns. *SPFRET* is the SCI-weighted average return of a firm's industry peers (excluding those from the same state). *SPFMOM* is the cumulative *SPFRET* over months $t-11$ through $t-1$. We report the equal-weighted portfolio return for deciles 1 and 10, and the 10-1 return differences for the following months relative to month t: 1–3, 4–6, 7–12, and 13–24. Panels A (C) and B (D) report, time-series averages of raw returns and FF5 alphas for equal-weighted (value-weighted) portfolios, respectively. t-statistics based on Newey-West standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Raw Returns (Equal-Weighted)

	SPFRET			SPFMOM		
	(1)	(10)	(10-1)	(1)	(10)	(10-1)
Month 1	0.277	1.767***	1.490***	0.722***	1.404***	0.682***
	(1.145)	(7.231)	(8.576)	(3.200)	(5.375)	(3.738)
Months 2–3	0.877***	1.143***	0.266**	0.776***	1.295***	0.518***
	(3.783)	(4.708)	(1.992)	(3.416)	(4.857)	(2.858)
Months 4–6	0.901***	1.149***	0.247**	0.803***	1.197***	0.394**
	(4.191)	(4.856)	(2.131)	(3.498)	(4.534)	(2.188)
Months 7–12	0.904***	1.185***	0.280***	0.984***	1.059***	0.075
	(4.107)	(5.344)	(3.206)	(4.334)	(4.369)	(0.484)
Months 13–24	1.119***	1.099***	−0.020	1.107***	1.009***	−0.098
	(5.340)	(4.875)	(−0.349)	(5.076)	(4.054)	(−0.627)

Panel B: FF5 Alphas (Equal-Weighted)

	SPFRET			SPFMOM		
	(1)	(10)	(10-1)	(1)	(10)	(10-1)
Month 1	−0.846***	0.722***	1.568***	−0.340**	0.354***	0.694***
	(−7.043)	(6.123)	(7.052)	(−2.322)	(3.048)	(2.907)
Months 2–3	−0.170	0.066	0.236	−0.315**	0.297***	0.611***
	(−1.367)	(0.725)	(1.238)	(−2.317)	(2.766)	(2.866)
Months 4–6	−0.174	0.089	0.262*	−0.331***	0.220**	0.550***
	(−1.525)	(1.250)	(1.674)	(−2.645)	(2.054)	(2.760)
Months 7–12	−0.150	0.128**	0.279***	−0.202**	0.098	0.300*
	(−1.476)	(2.268)	(2.597)	(−2.091)	(0.877)	(1.921)
Months 13–24	−0.029	0.082	0.110	−0.078	0.039	0.117
	(−0.497)	(0.976)	(1.636)	(−0.972)	(0.319)	(0.743)

Panel C: Raw Returns (Value-Weighted)

	SPFRET			SPFMOM		
	(1)	(10)	(10-1)	(1)	(10)	(10-1)
Month 1	0.442**	1.206***	0.764***	0.840***	1.165***	0.325**
	(2.121)	(6.191)	(4.783)	(4.029)	(5.808)	(1.986)
Months 2–3	0.937***	0.977***	0.040	0.810***	1.131***	0.321**
	(4.963)	(5.311)	(0.343)	(3.970)	(5.693)	(1.991)
Months 4–6	0.851***	0.959***	0.108	0.818***	1.029***	0.211
	(4.886)	(5.355)	(0.925)	(4.022)	(5.142)	(1.260)
Months 7–12	0.820***	1.003***	0.183**	0.880***	0.818***	−0.062
	(4.585)	(5.483)	(2.015)	(4.388)	(3.987)	(−0.379)
Months 13–24	0.994***	0.886***	−0.108	1.048***	0.798***	−0.250*
	(5.753)	(4.943)	(−1.482)	(5.886)	(3.973)	(−1.843)

Panel D: FF5 Alphas (Value-Weighted)

	SPFRET			SPFMOM		
	(1)	(10)	(10-1)	(1)	(10)	(10-1)
Month 1	−0.554***	0.287***	0.840***	−0.098	0.201*	0.299
	(−5.526)	(3.162)	(5.203)	(−0.671)	(1.778)	(1.353)
Months 2–3	0.057	−0.012	−0.069	−0.163	0.243**	0.405**
	(0.486)	(−0.116)	(−0.351)	(−1.244)	(2.484)	(2.069)
Months 4–6	−0.052	−0.007	0.045	−0.230**	0.151	0.382**
	(−0.558)	(−0.091)	(0.299)	(−2.289)	(1.589)	(2.272)
Months 7–12	−0.140**	0.072	0.213**	−0.216***	0.009	0.225*
	(−1.967)	(1.355)	(2.161)	(−2.702)	(0.120)	(1.810)
Months 13–24	−0.024	0.052	0.076	−0.038	0.014	0.052
	(−0.664)	(0.924)	(1.280)	(−0.577)	(0.156)	(0.426)

Table 9: Predicting Future Earnings Surprises, Analyst Forecast Errors, and Announcement Returns

The table presents the panel regression results of using social peer firm returns to predict a firm's future earnings surprises (Panel A), analyst forecast errors (Panel B), and cumulative abnormal returns around earnings announcements (Panel C) . The dependent variable in Panel A is the focal firm's standardized unexpected earnings (SUE) for the next four quarters. In Panel B, the dependent variable is the analyst forecast errors (FE) for the next four quarters. The dependent variable in Panel C is the three-day abnormal returns around the future four earnings announcements. *SPFRET* is the SCI-weighted average return of a firm's industry peers (excluding those from the same state). *SPFMOM* is the cumulative *SPFRET* over months $t-11$ through $t-1$. We include the following control variables: short- and long-term industry momentum (*INDRET* and *INDMOM*), geographic lead-lag effects (*GEORET* and *GEOMOM*), common analyst coverage effect (*CFRET* and *CFMOM*), customer return (*CRET* and *CMOM*), text-based return (*TNICRET* and *TNICMOM*), technology-linked firm return (*TECHRET* and *TECHMOM*), pseudo-conglomerate return (*CONGRET*), and *CONGMOM*), and job-to-job flow–based return (*J2JRET* and *J2JMOM*). We also include the following variables: *RET*, *SIZE*, *BMKT*, *BM*, *MOM*, *IVOL*, *ILLIQ*, *MAX*, *SKEW*, *COSKEW*, and month fixed effects (see Section 2.1 for detailed descriptions). All returns are reported in percentages. Missing values of independent variables are imputed with the monthly medians. We cross-sectionally standardize all independent variables by mapping them into the $(0,1]$ interval through scaling the monthly ranks by the number of observations (Gu et al. (2020)). *t*-statistics are computed with standard errors clustered by month, and stock and are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Standardized Unexpected Earnings

	Q1 (1)	Q2 (2)	Q3 (3)	Q4 (4)
SPFMOM	0.055**	0.050**	0.058**	0.052**
	(2.469)	(2.120)	(2.341)	(2.027)
SPFRET	−0.012	−0.006	0.002	−0.001
	(−0.875)	(−0.411)	(0.127)	(−0.055)
INDMOM	0.017	−0.002	−0.032	−0.066**
	(0.656)	(−0.065)	(−1.106)	(−2.255)
INDRET	0.042**	0.056***	0.054**	0.047**
	(2.332)	(2.995)	(2.550)	(2.419)
GEOMOM	0.002	−0.001	−0.005	−0.012
	(0.161)	(−0.089)	(−0.398)	(−0.969)
GEORET	−0.003	0.003	0.003	0.008
	(−0.399)	(0.352)	(0.372)	(0.995)
J2JMOM	−0.039**	−0.057***	−0.069***	−0.059***
	(−2.127)	(−2.986)	(−3.539)	(−3.027)
J2JRET	−0.008	−0.002	−0.007	0.001
	(−0.596)	(−0.149)	(−0.501)	(0.064)
CONGMOM	0.057***	0.059***	0.044***	0.011
	(3.459)	(3.446)	(2.694)	(0.645)
CONGRET	0.005	0.010	0.012	0.018
	(0.484)	(0.868)	(1.005)	(1.597)
CMOM	0.091***	0.097***	0.079***	0.041***
	(6.829)	(6.912)	(5.322)	(2.702)
CRET	−0.002	0.017**	0.025***	0.030***
	(−0.275)	(2.233)	(2.985)	(3.644)
TNICMOM	0.042***	0.044***	0.045***	0.039**
	(2.634)	(2.780)	(2.819)	(2.406)
TNICRET	0.005	0.020	0.032**	0.030**
	(0.390)	(1.545)	(2.485)	(2.364)
TECHMOM	−0.013	−0.005	−0.008	−0.005
	(−0.906)	(−0.314)	(−0.506)	(−0.300)
TECHRET	−0.019**	−0.009	−0.002	0.007
	(−2.265)	(−1.000)	(−0.174)	(0.798)
CFMOM	0.107***	0.115***	0.083***	0.049**
	(5.514)	(5.826)	(4.217)	(2.538)
CFRET	0.011	0.021	0.055***	0.048***
	(0.833)	(1.645)	(4.167)	(3.646)
Controls	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	867,248	872,254	877,527	882,953
R^2	0.101	0.077	0.059	0.048

Panel B: Analyst Forecast Errors

	Q1 (1)	Q2 (2)	Q3 (3)	Q4 (4)
SPFMOM	0.059**	0.065**	0.087***	0.066**
	(2.196)	(2.119)	(2.807)	(2.097)
SPFRET	0.011	0.007	0.026	0.019
	(0.674)	(0.406)	(1.248)	(0.779)
INDMOM	−0.029	−0.060*	−0.081**	−0.078**
	(−1.046)	(−1.884)	(−2.367)	(−2.248)
INDRET	−0.013	−0.017	−0.019	−0.024
	(−0.692)	(−0.783)	(−0.691)	(−0.770)
GEOMOM	−0.017	−0.023	−0.019	−0.028
	(−1.204)	(−1.394)	(−1.033)	(−1.377)
GEORET	−0.007	−0.005	−0.007	−0.004
	(−0.803)	(−0.418)	(−0.504)	(−0.348)
J2JMOM	0.026	0.066***	0.056**	0.066***
	(1.317)	(2.924)	(2.390)	(2.635)
J2JRET	−0.005	−0.011	0.016	0.009
	(−0.342)	(−0.596)	(0.838)	(0.434)
CONGMOM	0.049**	0.039*	0.014	0.002
	(2.529)	(1.646)	(0.541)	(0.065)
CONGRET	−0.002	0.018	0.014	0.011
	(−0.166)	(1.309)	(1.028)	(0.676)
CMOM	0.031*	−0.002	−0.028	−0.026
	(1.889)	(−0.104)	(−1.420)	(−1.201)
CRET	0.013	0.002	−0.005	−0.008
	(1.082)	(0.196)	(−0.451)	(−0.637)
TNICMOM	0.056***	0.067***	0.092***	0.101***
	(3.320)	(3.362)	(3.881)	(3.844)
TNICRET	0.004	0.016	0.021	0.043**
	(0.336)	(1.035)	(1.202)	(2.311)
TECHMOM	−0.051***	−0.052***	−0.055***	−0.048***
	(−3.453)	(−3.221)	(−3.059)	(−2.744)
TECHRET	−0.013	−0.022**	−0.027**	−0.009
	(−1.314)	(−2.248)	(−2.258)	(−0.722)
CFMOM	0.002	0.010	0.024	0.013
	(0.092)	(0.471)	(1.003)	(0.540)
CFRET	0.019	0.022	0.027	0.040**
	(1.195)	(1.137)	(1.319)	(2.051)
Controls	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	585,856	526,669	479,673	443,702
R^2	0.027	0.025	0.024	0.024

Panel C: Earnings Announcement Returns

	Q1 (1)	Q2 (2)	Q3 (3)	Q4 (4)
SPFMOM	0.252***	0.273***	0.198**	0.211**
	(3.116)	(3.157)	(2.420)	(2.525)
SPFRET	0.153***	0.048	0.048	0.045
	(2.995)	(0.920)	(0.835)	(0.762)
INDMOM	−0.180**	−0.226**	−0.372***	−0.282***
	(−2.000)	(−2.505)	(−4.176)	(−3.140)
INDRET	−0.022	−0.085	0.014	−0.041
	(−0.345)	(−1.383)	(0.226)	(−0.664)
GEOMOM	0.045	0.114**	0.099*	0.068
	(0.854)	(2.103)	(1.732)	(1.188)
GEORET	0.114***	0.008	0.076**	0.078**
	(3.166)	(0.203)	(1.964)	(1.963)
J2JMOM	−0.118**	−0.054	0.037	−0.055
	(−2.036)	(−0.897)	(0.601)	(−0.886)
J2JRET	0.011	−0.00003	−0.061	−0.100**
	(0.242)	(−0.001)	(−1.419)	(−2.182)
CONGMOM	0.049	−0.032	0.021	−0.036
	(0.820)	(−0.534)	(0.336)	(−0.565)
CONGRET	0.024	0.0005	0.025	0.006
	(0.609)	(0.012)	(0.645)	(0.154)
CMOM	0.211***	0.204***	0.128*	0.099
	(3.135)	(2.964)	(1.834)	(1.406)
CRET	0.034	−0.016	0.053	−0.003
	(0.788)	(−0.356)	(1.203)	(−0.060)
TNICMOM	0.096*	0.076	0.034	0.018
	(1.676)	(1.336)	(0.552)	(0.295)
TNICRET	−0.003	0.038	−0.002	0.048
	(−0.065)	(0.915)	(−0.053)	(0.978)
TECHMOM	−0.027	−0.020	0.008	−0.061
	(−0.437)	(−0.309)	(0.126)	(−0.916)
TECHRET	0.017	−0.099**	0.055	−0.022
	(0.405)	(−2.188)	(1.191)	(−0.484)
CFMOM	−0.236***	−0.138*	0.048	0.089
	(−3.199)	(−1.954)	(0.709)	(1.256)
CFRET	0.048	−0.084*	−0.104**	0.035
	(0.903)	(−1.669)	(−2.151)	(0.707)
Controls	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	981,702	966,859	952,343	937,526
R^2	0.002	0.002	0.002	0.002

Appendix

- Table A1: Variable Descriptions
- Table A2: Return Predictability of Peer Firms' Returns: Robustness Checks
- Table A3: Return Predictability of In-State Peer Firms and Non-Peer Firms
- Table A4: Long-Run Predictability, Earnings Surprises, Analyst Forecast Errors, and Earnings Returns (Orthogonalized SPFRET and SPFMOM)

Table A1: Variable Descriptions

Variable	Definition
Social Connectedness Index (SCI)	Number of Facebook friends links between firms' headquarters counties, scaled by the product of populations of the two counties
Social Peer Firm Return (SPFRET)	SCI-weighted returns based on all firms in the focal firm's industry, excluding same-state firms. $SPFRET_{ALL}$ is the SCI-weighted returns based on all the firms in the focal firm's industry except for the focal firm itself. SPFRET_{DIST} is an alternative social peer firm return measure for which social ties are measured with the inverse distance between firms headquarters locations. $SPFRET_{\perp}$ is *SPFRET* orthogonalized against industry momentum and/or other control variables, depending on the context.
Social Peer Firm Momentum (*SPFMOM*)	The compounded *SPFRET* from months $t-11$ to $t-1$.
Non-social peer Firm Return (*NSPFRET*)	The SCI-weighted average return of stocks that share neither the Fama-French 48-industry nor the state of the focal stock
Industry Return (INDRET)	The equal-weighted average return of stocks with the same Fama-French 48 industry classification as the focal stock, *INDMOM* is obtained by compounding *INDRET* from month $t-11$ to $t-1$.
Geographic Return (GEORET)	The equal-weighted average return of all stocks from the same economic area (EA) as the focal stock but from a different FF48 industry. *GEOMOM* is obtained by compounding *GEORET* from month $t-11$ to $t-1$.
Analyst Momentum (CFRET)	The weighted average return of stocks that share at least one analyst with the focal stock over the previous 12 months, where weights are the number of shared analysts between stocks. *CFMOM* is obtained by compounding *CFRET* from month $t-11$ to $t-1$.
Customer Return (CRET)	The equal-weighted average stock return of the main customers of the focal firm, where a six-month gap is required between the fiscal year-end of the supplier and stock returns. *CMOM* is obtained by compounding *CRET* from month $t-11$ to $t-1$.
Technology-Linked Firm Return (TECHRET)	The weighted average stock return of technology-linked peer firms, where the weights are the technological closeness between the peer firm and the focal firm, determined by the similarities between patent distributions across different technology categories. *TECHMOM* is obtained by compounding *TECHRET* from month $t-11$ to $t-1$.
Pseudo-Conglomerate Return (CONGRET)	The sales-weighted return of value-weighted, single-segment firm portfolios, formed for each segment that a conglomerate firm operates in. *CONGMOM* is obtained by compounding *CONGRET* from month $t-11$ to $t-1$.
Text-Based Industry Momentum (TNICRET)	Equal-weighted stock return of peer firms identified through 10-K product text. *TNICMOM* is obtained by compounding *TNICRET* from month $t-11$ to $t-1$.
Job-Flow-Based Return (J2JRET)	Weighted average stock return of same-industry peer firms, where the weights are the job-to-job flows. *J2JMOM* is obtained by compounding *J2JRET* from month $t-11$ to $t-1$.
Monthly Return (RET)	The monthly stock return. Following Shumway (1997), we adjust stock returns for delisting to avoid survivorship bias.
Firm Size (SIZE)	The logarithm of the market capitalization (in million dollars) as measured at the end of the previous June.
Market Beta (BMKT)	The CAPM beta computed using a 60-month window with a minimum window of 24 months.
Book-to-market (BM)	Computed as the book value of stockholders' equity, plus deferred taxes and investment tax credit (if available), minus the book value of the preferred stock for the last fiscal year, scaled by the market value of equity at the end of December of $T-1$. Depending on availability, the redemption, liquidation, or par value (in that order) is used to estimate the book value of the preferred stock.

Variable	Definition
Momentum (MOM)	Obtained by compounding RET from month $t-11$ to $t-1$.
Idiosyncratic Volatility (IVOL)	Computed as the standard deviation of the daily residuals obtained by regressing the daily excess stock returns on the daily market excess return, small-minus-big (SMB) and high-minus-low (HML) factors over the previous month.
Illiquidity (ILLIQ)	Amihud's illiquidity (Amihud, 2002), defined as the average daily ratio of the absolute stock return to the dollar trading volume within the previous month.
Maximum Return (MAX)	The maximum daily stock return realized over the previous month.
Skewness (SKEW)	The sample skewness of the daily stock returns from the previous month.
Coskewness (COSKEW)	The stock's monthly coskewness constructed following Harvey and Siddique (2000).
Cumulative Abnormal Return (CAR)	Market-adjusted returns cumulated over a three-day window around earnings announcements.
Standardized Unexpected Earnings (SUE)	Calculated as the difference between a stock's quarterly earnings minus the same-quarter value from the previous year, divided by its standard deviation over the past eight quarters.
Analyst Forecast Errors (FE)	Calculated as the difference between the announced earnings and analysts' consensus forecast, scaled by the stock price five trading days before the earnings announcement date.

Table A2: Return Predictability of Peer Firms' Returns: Robustness Checks

The table presents robustness checks for Table 5, column 9 with alternative specifications. Section 2.1 provides detailed variable descriptions. Column 1 is the same as Table 5, column 9. In column 2, we use a panel regression with month fixed effects and standard errors double-clustered by month and by stock. Column 3 replaces the equal-weighted industry return with its value-weighted version. Column 4 considers an alternative social peer firm return measure, $SPFRET_{DIST}$, in which we use the the geographical proximity of firms' headquarters locations as a proxy for social ties. Column 5 replaces county-based *SPFRET* with its ZIP code-based version. In column 6, we replace the Fama-French 48 classification with the text-based industry classification while calculating *SPFRET*. In column 7, we use an alternative standardization method and transform all the explanatory variables by subtracting its sample mean and dividing by its standard deviation. Note that the coefficient in this column is not directly comparable to those in the other columns due to the scale differences. In column 8, we use an orthogonalized *SPFRET*, defined as a regression residual of *SPFRET* on all the other independent variables. In column 9, *SPFRET* is calculated using only the peer firms that are headquartered in states where the focal firm does not have an economic presence. All returns are reported in percentages. Missing values of independent variables are imputed with the monthly medians. In all columns except column 2, standard errors are adjusted based on Newey and West (1994). *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	RET_{t+1}								
	(1)	$(2)_{Panel}$	$(3)_{VW}$	$(4)_{DIST}$	$(5_{ZIP}$	$(6)_{TNIC}$	$(7)_{SD}$	$(8)_{\perp}$	$(9)_{No\ Overlap}$
SPFRET	0.493***	0.748***	0.899***	0.500***	0.401***	0.742***	0.109**	0.265***	0.317***
	(3.320)	(3.860)	(5.112)	(2.977)	(3.578)	(6.143)	(2.516)	(2.811)	(3.047)
INDRET	0.693***	0.666**	0.082	0.689***	0.753***	0.887***	0.221***	0.894***	0.792***
	(3.723)	(2.348)	(0.531)	(3.586)	(5.329)	(5.213)	(3.616)	(4.855)	(4.404)
GEORET	0.165**	0.206*	0.150*	0.167**	0.161**	0.166**	0.066***	0.128	0.164**
	(2.159)	(1.702)	(1.954)	(2.212)	(2.117)	(2.191)	(2.701)	(1.521)	(2.145)
J2JRET	0.219**	0.196	0.236**	0.209**	0.257***	0.267***	0.095***	0.327***	0.287***
	(2.294)	(1.334)	(2.488)	(2.140)	(2.743)	(2.821)	(3.839)	(3.261)	(3.015)
CONGRET	−0.035	−0.105	−0.021	−0.032	−0.029	−0.030	−0.016	−0.047	−0.022
	(−0.457)	(−0.939)	(−0.286)	(−0.423)	(−0.360)	(−0.392)	(−0.899)	(−0.577)	(−0.294)
CRET	0.319***	0.308***	0.333***	0.317***	0.320***	0.315***	0.068***	0.303***	0.322***
	(3.583)	(2.770)	(3.790)	(3.552)	(3.590)	(3.538)	(3.659)	(3.340)	(3.605)
TNICRET	0.569***	0.739***	0.599***	0.574***	0.582***	0.144	0.147***	0.597***	0.584***
	(4.627)	(3.531)	(4.884)	(4.645)	(4.636)	(1.501)	(4.233)	(4.559)	(4.700)
TECHRET	0.043	0.115	0.065	0.040	0.050	0.045	−0.006	0.032	0.055
	(0.375)	(0.746)	(0.605)	(0.351)	(0.436)	(0.431)	(−0.204)	(0.262)	(0.490)
CFRET	1.301***	1.544***	1.335***	1.307***	1.322***	1.268***	0.415***	1.335***	1.334***
	(8.185)	(7.999)	(8.119)	(8.229)	(8.296)	(8.090)	(7.367)	(7.697)	(8.269)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# Periods	276	276	276	276	276	276	276	253	276
# Stocks	3,867	3,867	3,867	3,867	3,867	3,867	3,867	3,966	3,867
Month FE	–	Yes	–	–	–	–	–	–	–
Observations	–	1,067,332	–	–	–	–	–	–	–
R^2	0.069	0.126	0.069	0.069	0.069	0.069	0.072	0.070	0.069

Table A3: Return Predictability of In-State Peer Firms and Non-Peer Firms

The table presents robustness checks for Table 5, column 9 with two additional controls. $SPFRET_{STATE}$ is the SCI-weighted return of same-state peer firms and *NPFRET* is the SCI-weighted return of firms from other industries (excluding same-state firms). Section 2.1 provides detailed descriptions of the other variables. All returns are reported in percentages. Missing values of independent variables are imputed with the monthly medians. We cross-sectionally standardize all independent variables by mapping them into the $(0, 1]$ interval through scaling the monthly ranks by the number of observations (Gu et al. (2020)). We report *t*-statistics with standard errors based on Newey and West (1994) adjustments in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	RET_{t+1}	
	(1)	(2)
SPFRET	0.467***	0.478***
	(3.218)	(3.413)
SPFRET_STATE	0.331***	
	(4.515)	
NPFRET		−0.139
		(−1.634)
INDRET	0.627***	0.648***
	(3.343)	(3.760)
GEORET	0.159**	0.163**
	(2.113)	(2.314)
J2JRET	0.210**	0.221**
	(2.247)	(2.376)
CONGRET	−0.038	−0.032
	(−0.504)	(−0.423)
CRET	0.314***	0.320***
	(3.548)	(3.611)
TNICRET	0.558***	0.567***
	(4.585)	(4.638)
TECHRET	0.035	0.047
	(0.303)	(0.422)
CFRET	1.273***	1.297***
	(8.188)	(8.195)
Controls	Yes	Yes
# Periods	276	276
# Stocks	3,867	3,867
R^2	0.070	0.070

Table A4: Long-Run Predictability, Earnings Surprises, Analyst Forecast Error, and Earnings Returns (Orthogonalized SPFRET and SPFMOM)

The table presents robustness checks of Tables 8 and 9 with $SPFRET_{\perp}$ and $SPFMOM_{\perp}$, which are the version of *SPFRET* and *SPFMOM* orthogonalized to the other predictive variables, respectively. Panel A replicates Table 8, Panel B replicates Table 9 (Panels A and B), and Panel C replicates Table 9 (Panel C). See Tables 8 and 9 for detailed descriptions. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Calender-Time Portfolio Sort on $SPFRET_{\perp}$ and $SPFMOM_{\perp}$ (FF5 alphas)

	$SPFRET_{\perp}$			$SPFMOM_{\perp}$		
	(1)	(10)	(10-1)	(1)	(10)	(10-1)
Months 1–3	-0.204^{***}	0.124^{**}	0.329^{***}	-0.172^{**}	0.215^{***}	0.387^{***}
	(-3.229)	(2.357)	(4.177)	(-2.484)	(2.959)	(3.056)
Months 4–6	-0.104^{**}	0.031	0.136^{**}	-0.095	0.122	0.216
	(-2.080)	(0.714)	(2.437)	(-0.872)	(1.628)	(1.488)
Months 7–12	-0.139^{**}	0.010	0.149^{***}	-0.134	0.016	0.150
	(-2.207)	(0.226)	(2.966)	(-1.513)	(0.263)	(1.529)
Months 13–24	-0.128^{**}	0.004	0.131^{***}	-0.090	0.021	0.110
	(-2.140)	(0.083)	(3.631)	(-1.223)	(0.359)	(1.409)

Panel B: Cumulative Earnings Surprises and Analyst Forecast Error

	SUE				Analyst Forecast Error			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$SPFMOM_{\perp}$	0.037**	0.028*	0.032*	0.025	0.036*	0.043**	0.055**	0.042*
	(2.439)	(1.756)	(1.850)	(1.453)	(1.946)	(1.975)	(2.484)	(1.956)
$SPFRET_{\perp}$	−0.015	−0.009	−0.006	0.002	0.010	0.015	0.019	0.020
	(−1.587)	(−0.848)	(−0.571)	(0.200)	(0.917)	(1.238)	(1.268)	(1.084)
INDMOM	0.054**	0.034	0.013	−0.023	−0.003	−0.032	−0.037	−0.043
	(2.368)	(1.441)	(0.519)	(−0.945)	(−0.135)	(−1.291)	(−1.327)	(−1.520)
INDRET	0.041**	0.055***	0.055***	0.049***	−0.014	−0.017	−0.007	−0.020
	(2.496)	(3.252)	(2.906)	(2.721)	(−0.886)	(−0.865)	(−0.289)	(−0.735)
GEOMOM	0.0003	−0.0003	−0.002	−0.009	−0.015	−0.020	−0.017	−0.027
	(0.027)	(−0.025)	(−0.164)	(−0.689)	(−1.013)	(−1.178)	(−0.882)	(−1.276)
GEORET	−0.005	0.001	0.001	0.009	−0.009	−0.005	−0.007	−0.011
	(−0.627)	(0.158)	(0.114)	(1.106)	(−0.946)	(−0.416)	(−0.524)	(−0.815)
J2JMOM	−0.020	−0.038*	−0.049**	−0.039*	0.039*	0.087***	0.078***	0.084***
	(−1.061)	(−1.899)	(−2.330)	(−1.840)	(1.831)	(3.462)	(2.907)	(2.997)
J2JRET	−0.011	−0.004	−0.004	0.003	0.003	−0.010	0.027	0.016
	(−0.760)	(−0.287)	(−0.282)	(0.157)	(0.181)	(−0.560)	(1.362)	(0.771)
CONGMOM	0.043**	0.048***	0.039**	0.006	0.059***	0.053**	0.028	0.013
	(2.571)	(2.722)	(2.275)	(0.351)	(2.824)	(2.112)	(1.048)	(0.456)
CONGRET	0.004	0.006	0.010	0.018	−0.005	0.018	0.022	0.014
	(0.317)	(0.485)	(0.783)	(1.518)	(−0.409)	(1.192)	(1.503)	(0.807)
CMOM	0.097***	0.106***	0.088***	0.053***	0.037**	0.004	−0.024	−0.016
	(7.007)	(7.352)	(5.714)	(3.403)	(2.193)	(0.236)	(−1.176)	(−0.706)
CRET	−0.003	0.017**	0.027***	0.032***	0.010	0.001	−0.001	−0.013
	(−0.426)	(2.201)	(3.193)	(3.827)	(0.795)	(0.105)	(−0.111)	(−0.934)
TNICMOM	0.046***	0.050***	0.052***	0.046***	0.056***	0.072***	0.101***	0.114***
	(2.771)	(3.080)	(3.215)	(2.722)	(3.149)	(3.398)	(4.040)	(4.098)
TNICRET	0.004	0.019	0.030**	0.027**	0.005	0.016	0.024	0.044**
	(0.291)	(1.410)	(2.242)	(2.054)	(0.409)	(1.007)	(1.240)	(2.208)
TECHMOM	−0.023	−0.012	−0.014	−0.008	−0.040***	−0.048***	−0.053***	−0.041**
	(−1.517)	(−0.783)	(−0.841)	(−0.492)	(−2.748)	(−2.900)	(−2.899)	(−2.279)
TECHRET	−0.023***	−0.014	−0.006	0.002	−0.013	−0.022**	−0.028**	−0.011
	(−2.742)	(−1.581)	(−0.554)	(0.235)	(−1.361)	(−2.171)	(−2.326)	(−0.817)
CFMOM	0.087***	0.094***	0.062***	0.030	0.004	0.016	0.036	0.022
	(4.466)	(4.705)	(3.146)	(1.566)	(0.200)	(0.651)	(1.385)	(0.860)
CFRET	0.008	0.020	0.052***	0.043***	0.023	0.032	0.030	0.044**
	(0.625)	(1.512)	(3.670)	(3.115)	(1.382)	(1.586)	(1.374)	(2.064)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	812,690	817,056	821,603	826,164	549,509	492,687	447,513	413,251
R^2	0.100	0.077	0.059	0.049	0.026	0.025	0.024	0.025

Panel C: Cumulative Abnormal Returns Around Earnings Announcements

	CAR1	CAR2	CAR3	CAR4
	(1)	(2)	(3)	(4)
$SPFMOM_{\perp}$	0.154***	0.194***	0.140**	0.145**
	(2.719)	(3.291)	(2.563)	(2.555)
$SPFRET_{\perp}$	0.104***	0.039	0.052	0.027
	(2.699)	(1.029)	(1.212)	(0.644)
INDMOM	−0.028	−0.045	−0.244***	−0.148*
	(−0.365)	(−0.587)	(−3.040)	(−1.872)
INDRET	0.066	−0.053	0.040	−0.009
	(1.083)	(−0.920)	(0.696)	(−0.165)
GEOMOM	0.037	0.105*	0.086	0.063
	(0.672)	(1.849)	(1.435)	(1.062)
GEORET	0.106***	0.012	0.084**	0.072*
	(2.872)	(0.278)	(2.084)	(1.716)
J2JMOM	−0.077	−0.001	0.087	−0.005
	(−1.282)	(−0.012)	(1.381)	(−0.072)
J2JRET	0.040	0.011	−0.063	−0.104**
	(0.842)	(0.220)	(−1.377)	(−2.243)
CONGMOM	0.048	−0.042	0.014	−0.026
	(0.768)	(−0.659)	(0.212)	(−0.378)
CONGRET	0.017	0.001	0.020	−0.003
	(0.396)	(0.032)	(0.481)	(−0.069)
CMOM	0.227***	0.219***	0.153**	0.109
	(3.248)	(3.060)	(2.088)	(1.484)
CRET	0.032	−0.003	0.056	0.014
	(0.703)	(−0.062)	(1.224)	(0.312)
TNICMOM	0.114*	0.087	0.063	0.020
	(1.906)	(1.458)	(0.971)	(0.312)
TNICRET	0.012	0.035	−0.002	0.058
	(0.258)	(0.822)	(−0.035)	(1.127)
TECHMOM	−0.005	0.034	0.035	−0.027
	(−0.082)	(0.508)	(0.492)	(−0.390)
TECHRET	0.032	−0.098**	0.074	−0.018
	(0.736)	(−2.084)	(1.525)	(−0.377)
CFMOM	−0.245***	−0.152**	0.031	0.105
	(−3.211)	(−2.093)	(0.433)	(1.389)
CFRET	0.048	−0.067	−0.103**	0.020
	(0.865)	(−1.267)	(−2.037)	(0.378)
Controls	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	921,282	906,370	891,737	876,953
R^2	0.002	0.002	0.002	0.002