JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS Vol. 56, No. 8, Dec. 2021, pp. 2634–2658
© THE AUTHOR(S), 2020. PUBLISHED BY CAMBRIDGE UNIVERSITY PRESS ON BEHALF OF THE MICHAEL G. FOSTER SCHOOL OF BUSINESS, UNIVERSITY OF WASHINGTON
doi:10.1017/S0022109020000885

https://doi.org/10.1017/S0022109020000885 Published online by Cambridge University Press

Where Does the Predictability from Sorting on Returns of Economically Linked Firms Come From?

Aaron Burt
University of Oklahoma Price College of Business
aaronburt@ou.edu

Christopher Hrdlicka
University of Washington Foster School of Business
hrdlicka@uw.edu (corresponding author)

Abstract

Cross-firm predictability among economically linked firms can arise when both firms exhibit their own momentum and their returns are contemporaneously correlated. We show that cross-firm predictability can last up to 10 years, which is hard to reconcile with an interpretation of slow information diffusion. However, it is consistent with the economically linked firms' commonality in momentum. The contribution of each source can be found by decomposing leaders' returns into the predictable (momentum) and news components. Sorting on each, we find that both sources contribute almost equally to 1-month predictability, whereas commonality in momentum is solely responsible for longer-horizon cross-firm predictability.

I. Introduction

The speed of information diffusion is central to the understanding of financial markets and their efficiency. Dozens of articles have interpreted cross-firm return predictability among economically linked firms as a measure of delayed information diffusion.[1] The intuition is that if investors are inattentive, then a shock appearing in a firm's return will diffuse with a delay into the returns of firms to which it is economically linked. Such delayed diffusion can be observed by sorting lagging firms into portfolios based on their economically linked leader firms' returns. The long–short alphas from these sorts can reveal both the economic importance of the delay and its length. The literature has found such alphas at the

We are grateful to Brad Barber, Hank Bessembinder, Philip Bond, Jennifer Conrad (the editor), Tarun Chordia, John Cochrane, Ran Duchin, Thomas Gilbert, Amit Goyal, Mark Grinblatt, Jarrad Harford, Cam Harvey, Raymond Kan, Jonathan Karpoff, Roni Kisin, Ralph Koijen, Juhani Linnainmaa, Charles Martineau, Ľuboš Pástor, Cesare Robotti, Sergei Sarkissian, Andy Siegel, Stephan Siegel, and Mark Westerfield and seminar participants at the University of Calgary, the University of Notre Dame, the University of Washington, the 2015 Western Finance Association (WFA) Meetings, the 2016 Northern Finance Association (NFA) meetings, and the 2015 Conference on Advances in the Analysis of Hedge Fund Strategies for helpful comments and suggestions. Any errors are our own.

[1]See Appendix A for a full list of these articles.

1-month horizon of 1.5% per month, some of which persist up to 1 year. The interpretation has been that markets are very inefficient.

We argue that such alphas may not always reflect delays in information diffusion. For intuition purposes, consider the persistent seasonalities documented by Heston and Sadka (2008), Bessembinder and Zhang (2014), and Keloharju, Linnainamaa, and Nyberg (2016). We show that sorting laggard firms into portfolios based on their linked leading firms' average returns in the predicted month over the last 10 years produces long–short portfolios with statistically significant 3-factor alphas as large as 76 basis points (bps) per month. As opposed to showing slow information diffusion, we argue that this 10-year cross-firm predictability is more likely due to common seasonal variation in the expected returns (rational or behavioral) among these economically linked firms.

Although the literature has not previously documented the 10-year alphas, it does provide evidence of delays ranging from 1 month to an entire year. At these long but more moderate horizons, both slow information diffusion and commonality in momentum plausibly contribute to cross-firm predictability. To empirically disentangle the two sources, we decompose each leader's return into its predictable nonidiosyncratic component and unpredictable idiosyncratic "news" component. The predictable component is a firm's estimated alpha plus its estimated betas times the contemporaneous factor realizations. The predictability of this component of the leader's return makes it not news by definition. Therefore, the remaining component of returns is, by definition, news. Sorting laggards on this news component allows us to track the diffusion of information, with the resulting long–short alphas providing a measure of the economic importance of the delay.

We show the empirical magnitude of these two components of cross-firm predictability by analyzing three sets of economically linked firms: i) customers predicting suppliers (Cohen and Frazzini (2008)), ii) stand-alone pure players predicting conglomerates (Cohen and Lou (2012)), and iii) strategic-alliance–linked firms predicting another firm in the alliance (Cao, Chordia, and Lin (2016)). We choose these settings both because of their influence on the literature and because they represent varied types and strengths of economic links.

Sorting on returns in these settings, we find long–short alphas similar to those documented in the original articles. Sorting on the news component, however, produces 3-factor long–short alphas of 60% of the original setting's results at a 1-month horizon. Over the 2- to 12-month horizon, the news component contributes no statistically significant predictability. The lower alpha is the true contribution of slow information diffusion, suggesting information diffusion completes after 1 month. Thus, the persistent long-horizon alphas documented in previous articles are unlikely to be driven by slow information diffusion. Instead, they appear to be driven by the commonality in the own-firm momentum of economically linked firms.

A concern is that the lower alpha is a result of noise induced through the estimation of the decomposition. Were the leaders' returns unpredictable, this decomposition would simply induce noise in the sorts. Thus, the predictability in the leaders' returns is the key identifying assumption. To address this alternative hypothesis, we verify that the predictable component of the leaders is itself able to predict the laggards' returns. Not surprisingly, at the 1-month horizon, sorting on the predictable components generates long–short alphas that are 40% of

https://doi.org/10.1017/S0022109020000885 Published online by Cambridge University Press

https://doi.org/10.1017/S0022109020000885 Published online by Cambridge University Press

those found by sorting on returns. At the 2- to 12-month horizons, sorting on the predictable component generates alphas that closely match those from sorting on returns. Of course, even when the leaders' returns are predictable, noise is still induced through the estimation of the model parameters. To address this, we derive a closed-form correction for the noise induced in estimating the news component and apply this correction throughout the article.[2]

A second concern is that the decomposition crucially depends on parameter estimates for the leaders in the presorting window: $t-12$ to $t-1$. We choose this window to align with the previously documented horizon of own-firm momentum.[3] Because the window overlaps with the 1-year predictability horizon claimed by prior articles, one might worry that our results are due to the leaders' alphas estimated using this window containing not only the true alpha but also the average of the old news (i.e., idiosyncratic shocks) in that window. We provide three pieces of evidence that refute this second alternative hypothesis.

First, we further decompose the predictable component of the leaders' return into the alpha component that contains this old news and the beta exposures times factor realizations (modeled risk). We find that the betas-times-factors component of leaders' returns predicts the laggards' returns. The betas-times-factors component is not plausibly related to news. Therefore, the ability of this component to predict the laggards shows both that i) the long–short alphas from sorting on the predictable component of the leaders' returns is not driven solely by old news, and ii) the cross-firm predictability observed from sorting on returns is not entirely due to slow information diffusion.

Second, we test whether leaders' estimated idiosyncratic returns at long horizons predict the laggards' returns. Because the ability of the information in the leaders' returns to predict laggards should decrease with horizon, the average predictability of the old news will always be smaller than the predictability from the news in the current period, regardless of the prediction horizon. Thus, in each period, if any delay remains, the estimated idiosyncratic shock should generate positive net predictability (the predictability of current information minus the predictability of the average of the old news). Even if the predictability from this remaining old news is small, the cumulative net predictability over many months (e.g., 2–12) should be apparent. However, we find no such predictability.

Third, we test whether the old news can predict the laggards. For this test, we create proxies for the old news by using an even earlier estimation window ($t-24$ to $t-13$) to measure the asset pricing parameters. Using these earlier parameter estimates, we calculate idiosyncratic shocks during the main estimation window ($t-12$ to $t-1$). We use these idiosyncratic shocks to sort the laggard firms in the prediction window ($t+1$ to $t+12$). In these sorts, we find no evidence of predictability. This evidence shows that although in theory, old news could explain some of our results, in practice, it does not because old news does not predict the laggards.

[2]The correction only applies to the news component. Thus, our results on the predictable component are an underestimate of its true contribution. The econometrics underlying the decomposition, including the correction, are included in the Supplementary Material.

[3]Although a short estimation window would induce more noise, the closed-form correction we describe previously addresses this issue.

https://doi.org/10.1017/S0022109020000885 Published online by Cambridge University Press

For an additional robustness check that does not rely on the decomposition of the leaders' returns, we use predictability regressions. The coefficient of the leaders' returns in the regression predicting the returns of economically linked laggards has also been used by the literature as a measure of slow price discovery. (See Kamstra (2017) for a detailed discussion of these regressions.) This coefficient suffers from an issue similar to that of the long–short alphas from sorts. It is not solely driven by slow price discovery: The coefficient is an average of the predictability from slow price discovery and the predictability from the commonality in own-firm momentum. In these regressions, we use the leaders' contemporaneous returns as a different proxy for this commonality in momentum. This proxy does not rely on the decomposition of returns or the estimation of an asset pricing model.

If slow price discovery is present, the coefficient on the leaders' returns should remain relatively stable after including the contemporaneous returns in the regression. However, if the coefficient on the leaders' returns is driven primarily by the commonality in own-firm momentum, such inclusion will reduce the coefficient. We find, at a 1-month lag, that including the contemporaneous return has little effect, suggesting delayed information diffusion at the 1-month horizon. At a 2-month lag, the contemporaneous return drives out the coefficient on the lagged returns, suggesting that information diffusion has been completed. The results of these regressions are consistent with our findings from the sorts.

We also use our decomposition in the regression framework to see how much the predictable and news components contribute to the cross-firm predictability. At a 1-month lag, we find that the (standardized) coefficient on the predictable component ranges from being approximately the same to almost 40% larger than the coefficient on the news component. At longer horizons, the coefficient on the predictable component is more stable, whereas that on the news component disappears. These findings are consistent with those from the sorts.

Our article contributes to a large literature that focuses on improving economic measures.[4] Our analysis also has parallels in regression-based tests of information diffusion, where laggards' returns are regressed on leaders' returns to measure slow price discovery.[5] The closest article to ours is that by Kamstra (2017), which provides a detailed discussion of a similar concern in predictability regressions. Whereas our article focuses on the sort methodology, both articles seek to improve the measures of predictability. Though our results are both consistent, Kamstra (2017) proposes including additional controls, whereas we advocate for using the leaders' idiosyncratic returns in the regressions.

[4]See, for example, Lo and MacKinlay (1990), Conrad and Kaul (1993), (1998), Barber and Lyon (1996, 1997), Conrad, Gultekin, and Kaul (1997), Lyon, Barber, and Tsai (1999), Berk (2000), Pástor and Stambaugh (2002a), (2002b), Bessembinder (2003), Ferson, Sarkissian, and Simin (2003) (2008), Asparouhova, Bessembinder, and Kalcheva (2010), (2013), Lewellen, Nagel, and Shanken (2010), Kan and Robotti (2011), Bessembinder and Zhang (2013), Kan, Robotti, and Shanken (2013), Gospodinov, Kan, and Robotti (2014a), (2014b), (2017), (2019), Ferson and Chen (2015), Pástor, Stambaugh, and Taylor (2015), and Harvey, Liu, and Zhu (2016).

[5]See, for example, Boudoukh, Richardson, and Whitelaw (1994), Hou (2007), Shahrur, Becker, and Rosenfeld (2010), Cen, Chan, Dasgupta, and Gao (2013), Rapach, Strauss, and Zhou (2013), Aobdia, Caskey, and Ozel (2014), Wu and Birge (2014), Leung, Agarwal, Konana, and Kumar (2016), and Madsen (2016).

https://doi.org/10.1017/S0022109020000885 Published online by Cambridge University Press

Although we show that the predictable (nonidiosyncratic) component does not measure slow information diffusion as is traditionally understood, an open question remains as to the source of the commonality in momentum among economically linked firms. Perhaps leaders and laggards respond with a delay to leaders in the same way, or perhaps our asset pricing models do not account for risks common to economically linked firms. Regardless, this commonality in momentum and expected returns leaves a new puzzle that any explanation of momentum (rational or behavioral) must account for.

II. Common Predictability in Leaders and Laggards

A. Common Seasonalities Produce Long-Horizon Cross-Firm Predictability

We first provide intuition for how cross-firm predictability can arise without slow information diffusion by showing a case of this predictability that is hard to rectify with slow information diffusion. For this example, we exploit the fact that firms exhibit seasonality in their expected returns that persists over very long horizons (Heston and Sadka (2008), Bessembinder and Zhang (2014), and Keloharju et al. (2016)). To see this persistent seasonality, for each leader firm at time t, which is month m in year y, we measure the average return in the same month m for years $y-10$ to $y-1$. Using these averages, each month we sort the leader firms themselves into quantile portfolios at time t: month m in year y. We refer to this as the *own-firm sort.* We also use the leader's 10-year same-month average return to sort the laggard firms into quantile portfolios at time t: month m in year y. We refer to this second sort as the *cross-firm sort.* For both the leader and laggard portfolios, we compute the equal-weighted (value-weighted) average return for each portfolio of leader firms. We then form a long–short portfolio from the highest and lowest quantile.[6] We regress the long–short portfolio returns on the Fama and French (1993) 3 factors to produce a monthly alpha for each setting.[7]

Table 1 shows these 3-factor alphas for the three sets of economically linked firms. The predicted leaders' alphas from the own-firm sort are shown in the first row of each panel. They are all economically and statistically significant, ranging from 68 to 108 bps per month. The positive alphas show the leaders' ability to predict their own returns over long horizons and are consistent with the prior literature's finding that stocks tend to have similar returns in the same calendar month every year.

The predicted laggards' alphas of the cross-firm sort are shown in the second row of each panel. They are also economically significant, ranging from 26 to 76 bps per month. These alphas are typically smaller than those arising from the own-firm sorts and exhibit variation in the statistical significance across the three sets of economically linked firms and different portfolio weightings.

[6] We use the same number of quantiles as in the original articles with a given set of economic links.

[7] We focus on the 3-factor alphas because this is the benchmark used in the prior literature, and we wish to document how this commonality in own-firm predictability contributes to the literature's prior results and conclusions. For example, the long-horizon graphs of Cohen and Frazzini (2008) and Cohen and Lou (2012) show cumulative 3-factor alphas. We obtain similar results throughout the article for untabulated 5-factor alphas, although the 5-factor alphas consistently reveal less delay in information diffusion.

TABLE 1

Portfolio Alphas Obtained from Sorting on Average Same-Month Returns for Past 10 Years

Table 1 shows the long–short portfolio alphas obtained from sorting leaders and laggards on the leaders' average return in the same month over the previous 10 years. At each date t, we compute the leaders' average return in the same month for years $y-10$ to $y-1$. At each date t in year y, we rank leaders by the preceding 10-year same-month return. We use these rankings to assign the corresponding leaders (laggards) into quantile portfolios. We compute the equal-weighted (value-weighted) returns for each portfolio. The table shows the long–short alphas from these sorts. Alpha is the intercept on a regression of the monthly returns for the long–short portfolio using the Fama and French (1993) 3-factor model. Alpha is reported in percentage per month. Panel A uses customers (leaders) to assign suppliers (laggards) to quintile portfolios. Panel B uses stand-alone firms (leaders) to assign conglomerates (laggards) to decile portfolios. Panel C uses alliance-linked firms (leaders) to assign another firm in the alliance (laggards) to quintile portfolios. Joint significance is shown in Table B-1 in Appendix B. t-statistics are in parentheses.

	Equal Weighted	Value Weighted
Panel A. Customer–Suppliers		
Leader	1.083	0.715
	(3.90)	(1.89)
Laggard	0.261	0.763
	(1.14)	(2.04)
Panel B. Stand-Alone-Conglomerates		
Leader	0.725	0.768
	(3.72)	(2.97)
Laggard	0.377	0.276
	(1.84)	(0.88)
Panel C. Alliance-Linked Firms		
Leader	0.680	
	(2.84)	*Not applicable*
Laggard	0.269	*in original article*
	(1.21)	

We test for the joint significance by forming a portfolio based on the average of all five time series. In doing so, we average across the months in which all five portfolios are populated. The predicted leaders' alpha of the joint portfolio is 101 bps and, as expected, is highly significant, with a t-statistic of 4.08. The predicted laggards' alpha of the joint portfolio is 42 bps and also significant, with a t-statistic of 2.68. (See Table B1 in Appendix B.) In addition, consistent with the common predictability driving this cross-firm predictability, we find (in untabulated results) that the cross-firm predictability disappears when the own-firm predictability disappears (e.g., shifting the prediction 1 month forward or backward, such as having January predict December or February rather than January).

This common pattern across all three sets of economic links indicates cross-firm predictability in the same months up to 10 years between leaders and laggards. Given the extreme time horizon, the cross-firm predictability represented by these alphas is unlikely to be generated by slow information diffusion between the leaders and laggards, as is traditionally understood. We next show that the cross-firm predictability at horizons previously documented is due to more than slow information diffusion.

B. Commonality Exists in Own-Firm Momentum

Although commonality in seasonalities drives very long-horizon cross-firm predictability, commonality in own-firm momentum contributes to the cross-firm

https://doi.org/10.1017/S0022109020000885 Published online by Cambridge University Press

predictability at the 1- to 12-month horizon documented in the previous literature.[8] This own-firm momentum combined with the economically linked firms' contemporaneously correlated returns means that the momentum has a common component across economically linked firms. This commonality in momentum (i.e., the predictable component of returns) produces cross-firm predictability because either firm's returns can predict the common momentum of the other. This source of cross-firm predictability means that sorting laggards based on leaders' prior returns generates alpha even when there is no delayed information diffusion across the firms.

This commonality in momentum (predictable-return component) can be seen by sorting leader firms in the same way that we sort laggard firms: using leaders' own returns h months prior. Performing this sort, we obtain two long–short portfolios: one composed of leaders and one of laggards. The first long–short portfolio (equal or value weighted) is formed by assigning leaders at $t+h-1$ to quantile portfolios based on the leader's own t return, where $h=1$ to $h=12$ months. Predicted returns are at $t+h$. The second long–short portfolio is constructed similarly but instead assigns *laggards* at $t+h-1$ into quantile portfolios based on the leader's t return. We refer to this portfolio as the *cross-firm predictability portfolio*. For each of the long–short portfolios at horizon h, we regress the portfolio's excess return on the Fama and French (1993) 3-factor model to obtain a monthly alpha.

Table 2 gives the alpha for the 1-month predictability and the alpha for the total predictability from months 2 to 12 for both the leaders' and laggards' portfolios. We separate the predictability in month 1 from that in months 2–12 for two reasons. First, as we will show in later sections, we find evidence for slow information diffusion at the 1-month horizon but not at longer horizons. Second, the short-term reversal effect (e.g., Jegadeesh (1990), Lehmann (1990)) complicates the interpretation of the commonality at the 1-month horizon by giving negative predictability for the leader portfolios. At the 1-month horizon, the long–short leader portfolio alphas are strongly negative and typically statistically significant, ranging from -3 to -228 bps. By comparison, the cross-firm predictability portfolios generate large positive and highly statistically significant alphas at the 1-month horizon, ranging between 93 and 161 bps. These 1-month laggard portfolio alphas are the main results documented in the original articles.

The leader own-momentum portfolios over the 2- to 12-month horizon generate highly significant cumulative alphas ranging from 456 to 820 bps over the course of 11 months.[9] For the laggard (cross-firm predictability) portfolios, we find, consistent with the prior literature, that the 2- to 12-month cumulative alphas are also economically large and statistically significant. They range from 256 to 352 bps. As expected, the laggards' alphas represent only a fraction of

[8]We focus on the phenomenon of momentum, which is broader than the momentum factor because that factor does not completely capture all positive autocorrelation among stocks.

[9]The predictability of the leaders' returns over 12 months using a previous single-month return is closely related to the documented own-firm momentum effect where the sorting is instead based on the leaders' average returns over the previous 12 months. See Bali, Engle, and Murray (2016) for a comprehensive review of the momentum effect.

https://doi.org/10.1017/S0022109020000885 Published online by Cambridge University Press

TABLE 2

Alphas of Leaders Predicting Leaders and Laggards

Table 2 shows the long–short portfolio alphas for leaders and laggards from sorting on leaders' returns. At each date $t+h-1$ (returns at $t+h$), we assign a leader (laggard) to a quantile portfolio based on the corresponding leader's return at t. For each portfolio, we form the equal-weighted value-weighted) return at $t+h$. We calculate the Fama and French (1993) 3-factor model monthly long–short alpha for each horizon h. Alpha is reported in percentage per month. Alphas are for the 1-month horizon after the sort and for the cumulative period of months 2 through 12 after the sort. Panel A uses customers (leaders) to assign suppliers (laggards) into quintile portfolios. Panel B uses stand-alone firms (leaders) to assign conglomerates (laggards) into decile portfolios. Panel C uses alliance-linked firms (leaders) to assign another firm in the alliance (laggards) into quintile portfolios. t-statistics are in parentheses.

	Equal Weighted	Value Weighted
Panel A. Customer–Suppliers		
Leader $t+1$	−0.500 (−2.25)	−0.032 (−0.13)
Laggard $t+1$	1.186 (4.84)	1.606 (4.02)
Leader $t+2:t+12$	5.159 (7.63)	4.903 (6.12)
Laggard $t+2:t+12$	2.717 (3.42)	3.520 (2.71)
Panel B. Stand-Alone–Conglomerates		
Leader $t+1$	−2.279 (−6.76)	−0.278 (−0.76)
Laggard $t+1$	1.189 (5.77)	1.205 (3.99)
Leader $t+2:t+12$	4.876 (5.72)	8.195 (8.17)
Laggard $t+2:t+12$	3.119 (4.23)	2.561 (2.57)
Panel C. Alliance-Linked Firms		
Leader $t+1$	−0.750 (−3.26)	
Laggard $t+1$	0.926 (4.17)	*Not applicable in original article*
Leader $t+2:t+12$	4.558 (6.51)	
Laggard $t+2:t+12$	3.193 (4.56)	

the 2- to 12-month cumulative alphas generated in the leader-predicting-leader own-momentum portfolios.

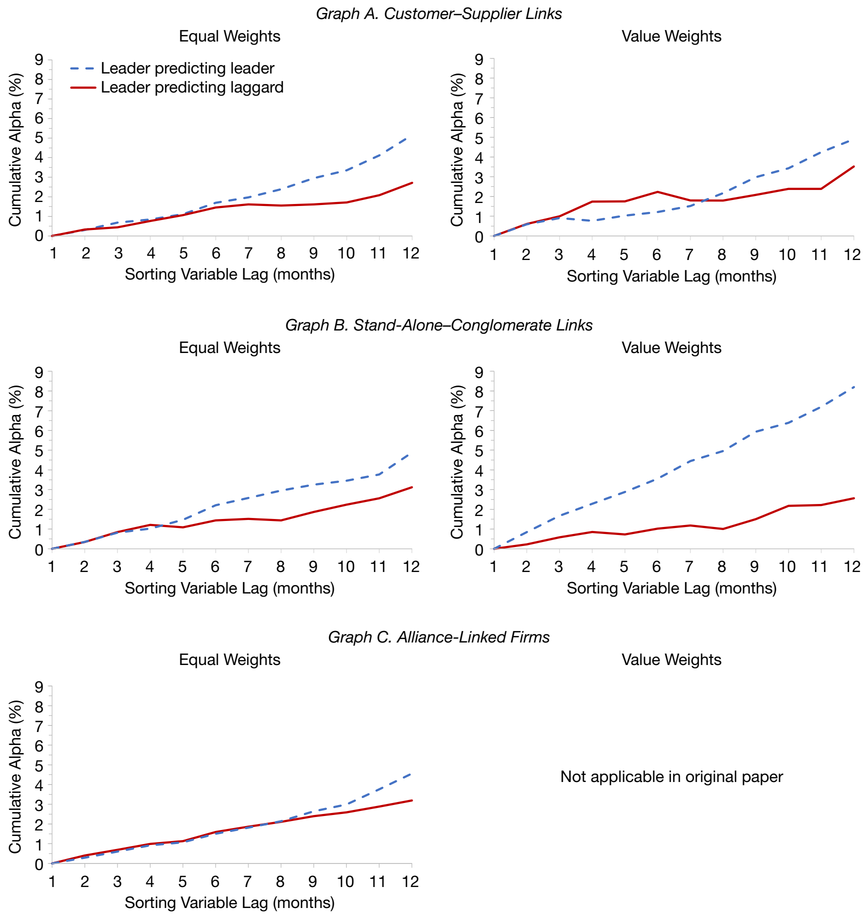
Figure 1 shows the cumulative alphas from months 2 through 12 for both the leader own-momentum portfolio (dashed line) and the laggard cross-firm predictability portfolio (solid line). These lines show that the similar, albeit smaller, trend in the predictability of laggards occurs relatively evenly over the 2- to 12-month window. Taken as a whole, the similarity in trend and magnitude suggests that the alphas reflecting cross-firm predictability may simply be a mechanical result arising from the commonality in the leaders' own-firm momentum combined with their contemporaneous comovement. Thus, positive alphas generated from lead–lag sorts of economically linked firms may not necessarily be due to cross-firm information diffusing directly from leaders to laggards. In the following sections, we show how to separate the cross-firm predictability into that driven by cross-firm information flow and that due to commonality in own-firm momentum.

https://doi.org/10.1017/S0022109020000885 Published online by Cambridge University Press

FIGURE 1

Cumulative Alphas Sorting Laggards and Leaders on Leaders' Returns

Figure 1 compares the cumulative alphas from sorting laggards on leaders' returns to the cumulative alphas of sorting leaders on leaders' returns. At each date $t+h-1$ (returns at $t+h$), we assign laggards (leaders) into quantile portfolios based on the leader's return at t. At each horizon h we calculate the Fama and French (1993) 3-factor model monthly alpha for the long–short portfolio. The cumulative alpha is the sum of alphas for each of the periods 2 through horizon h. The 1-month horizon is omitted because both the common trend and slow information play a role at that horizon. Alpha is in percentage per month. Graph A uses customers (leaders) to assign suppliers (laggards) into quintile portfolios. Graph B uses stand-alone firms (leaders) to assign conglomerates (laggards) into decile portfolios. Graph C uses alliance-linked firms (leaders) to assign another firm in the alliance (laggards) into quintile portfolios.



III. Sort on News to Measure Information Diffusion

Cross-firm predictability arises from commonality in momentum and direct cross-firm information diffusion. The latter is the ability of the nonpredictable component of leaders' returns to predict the future returns of laggards. Given that it is nonpredictable, this component of leaders' return is, by definition, news. Hence, tracking its ability to predict laggards' returns makes this predictability a measure of slow information diffusion.

https://doi.org/10.1017/S0022109020000885 Published online by Cambridge University Press

https://doi.org/10.1017/S0022109020000885 Published online by Cambridge University Press

Forming this measure of slow information diffusion requires decomposing the leaders' returns into these predictable and unpredictable (idiosyncratic) components.[10] Crucially, the identification between these two components comes from the ability to use an asset pricing model and the leader's prior returns to predict its return at t given the time t factor realizations. Thus, the decomposition is determined by the asset pricing model used to measure delays in information diffusion and, to a lesser extent, the estimation procedure for the model parameters. The better the asset pricing model used for the decomposition, the better one is able to isolate the news.

We compute these components as follows: The alpha and betas for each leader firm at each time t come from a regression of that firm's monthly returns from $t-12$ to $t-1$ on the Fama and French (1993) 3-factor model augmented with momentum (Carhart (1997)) and liquidity (Pástor and Stambaugh (2003)).[11] We focus on the 12-month estimation window because it is well documented that firms have an own-momentum trend over this horizon. These parameter estimates combined with the factor realizations at t are used to decompose the leader's time t return into a nonidiosyncratic component ($\widehat{\alpha}_{t-1}+\widehat{\vec{\beta}}'_{t-1}\vec{f}_t$) and the complementary idiosyncratic component, which is simply the excess return minus the nonidiosyncratic component. We further decompose the nonidiosyncratic component into the alpha ($\widehat{\alpha}_{t-1}$) and the modeled risk component (estimated betas multiplied by the factor realizations at t, or $\widehat{\vec{\beta}}'_{t-1}\vec{f}_t$).

Roughly speaking, the estimated idiosyncratic component thus extracted contains three pieces: i) the true idiosyncratic shock, ii) the innovations in the model parameters between the estimation window and date t, and iii) the negative average of the idiosyncratic returns over the estimation window (i.e., "old news"). These first two components capture the unpredictable news in the leader. The last component, the average realized idiosyncratic returns over the estimation window, potentially acts as a contaminate and could bias the measure of slow information diffusion downward. In practice (as we show in more detail in Section IV), because this average of the idiosyncratic returns over the model estimation window is old news, it has no predictive power. This old news thus only introduces measurement noise, for which we derive a closed-form correction in the Supplementary Material. We implement that correction throughout the article to remove the downward effect of this noise.

In the following sections, we report and analyze the predictability of the laggards arising from sorting on the different components of the leaders' returns. We focus first on the short-horizon predictability (1-month horizon) and then show how this contrasts with the predictability at the longer 2- to 12-month horizons.

A. One-Month Predictability Is Split Across the Two Components

The first row in each panel of Table 3 shows the 1-month cross-firm predictability and the decomposition of this predictability into various sources.

[10]The Supplementary Material shows the econometrics of this decomposition in detail.

[11]We obtain similar results when using the Fama–French 3-factor model to form the predictable component.

TABLE 3

Laggard Portfolio Alphas from Sorting on Leader Return Components

Table 3 compares the long–short portfolio alphas obtained from sorting on returns, predictable returns (alpha plus betas times factors), each component of the predictable returns, and idiosyncratic returns (residuals). The first specification uses the leader firm's time t return to assign an economically linked laggard firm into quantile portfolios at $t+h-1$ (returns at $t+h$). The second specification uses a leader firm's time t predictable nonidiosyncratic component, which is the alpha plus the betas-times-factor realizations, to assign linked laggard firms into quantile portfolios. The third and fourth specifications use the alpha and betas-times-factor realizations (respectively) to sort the laggard firms. The fifth specification uses a leader firm's idiosyncratic return to sort laggard firms. For each leader, we estimate the alphas and factor loadings of the 5-factor model (Fama and French (1993), Carhart (1997), and Pástor and Stambaugh (2003)) by using the previous 12 monthly returns ($t-12$ to $t-1$). We use these parameter estimates with the realized factor returns to compute expected returns as the predictable nonidiosyncratic component (using factor realizations). The idiosyncratic return is the realized return minus the predictable nonidiosyncratic return. We report the alphas of the long–short portfolio of laggards at the 1-month prediction horizon and the cumulative alpha for the prediction horizon of 2 through 12 months. These alphas are the intercept of a regression of the long–short portfolio's monthly returns on the Fama and French (1993) 3-factor model. Alphas and standard errors obtained from sorting on idiosyncratic returns are corrected to eliminate attenuation arising from estimating the leader firm's idiosyncratic return. The nonidiosyncratic (predictable) component sorts have no such correction and, therefore, are understated. Alpha is reported in percentage per month. Panel A uses customers (leaders) to assign suppliers (laggards) into quintile portfolios. Panel B uses stand-alone firms (leaders) to assign conglomerates (laggards) into decile portfolios. Panel C uses alliance-linked firms (leaders) to assign another firm in the alliance (laggards) into quintile portfolios. t-statistics are in parentheses.

	Equal Weighted					Value Weighted				
Sort on Leaders' →	Return	Alpha + $\vec{\beta}'\vec{f}_{t-1}$	Alpha	$\vec{\beta}'\vec{f}_{t-1}$	Idiosyncratic Return	Return	Alpha + $\vec{\beta}'\vec{f}_{t-1}$	Alpha	$\vec{\beta}'\vec{f}_{t-1}$	Idiosyncratic Return
	1	2	3	4	5	6	7	8	9	10
Panel A. Customer–Suppliers										
Laggard $t+1$	1.186	0.468	0.668	0.214	0.719	1.606	0.370	1.115	0.124	1.181
	(4.84)	(2.05)	(3.87)	(0.91)	(2.46)	(4.02)	(1.05)	(3.28)	(0.34)	(2.37)
Laggard $t+2:t+12$	2.717	3.150	4.173	1.057	0.125	3.520	3.038	1.894	1.603	−0.182
	(3.42)	(3.94)	(6.03)	(1.33)	(0.13)	(2.71)	(2.42)	(1.58)	(1.27)	(−0.11)
Panel B. Stand-Alone–Conglomerates										
Laggard $t+1$	1.189	0.617	0.326	0.597	0.753	1.205	0.775	0.348	0.794	0.501
	(5.77)	(2.99)	(1.41)	(2.75)	(2.87)	(3.99)	(2.80)	(1.19)	(2.56)	(1.34)
Laggard $t+2:t+12$	3.119	2.190	3.449	1.560	0.458	2.561	0.939	3.607	−0.171	0.831
	(4.23)	(3.14)	(5.14)	(2.27)	(0.50)	(2.57)	(0.99)	(4.00)	(0.00)	(0.63)
Panel C. Alliance-Linked Firms										
Laggard $t+1$	0.926	0.329	0.402	0.185	0.571					
	(4.17)	(1.61)	(2.02)	(0.92)	(2.46)					
Laggard $t+2:t+12$	3.193	1.501	0.516	1.191	1.208					
	(4.56)	(2.29)	(0.87)	(1.88)	(1.55)			*Not applicable in original article*		

https://doi.org/10.1017/S0022109020000885 Published online by Cambridge University Press

Predictability is measured as the long–short 3-factor alphas of the laggards when portfolios are formed by sorting on different components of the leaders' prior-month returns. Columns 1 and 6 show the results of sorting on returns, the sorts in the original articles. Columns 2 and 7 show the predictability from sorting on the predictable nonidiosyncratic component ($\widehat{\alpha}_{t-1}+\widehat{\vec{\beta}}'_{t-1}\vec{f}_t$) of the leaders' returns. Across the three sets of economically linked firms, the long–short portfolio alpha from the predictable component of leaders' returns is between 23% and 64% (averaging 43%) of that from sorting on returns, with most values being statistically significant.[12] This shows that the common predictability, or commonality in own-firm momentum, of the economically linked firms substantially contributes to the previously documented cross-firm predictability.

Columns 5 and 10 of Table 3 show the alphas from sorting on leaders' unpredictable idiosyncratic returns. These columns capture new information diffusing directly from leaders to laggards and, therefore, the slow information diffusion the prior literature intended to measure. These long–short alphas average only 60% of those of the total cross-firm predictability, revealing less delay in cross-firm information diffusion than previously documented.[13]

B. Long-Horizon Predictability Due to the Nonidiosyncratic Component

The second row in each panel of Table 3 shows the cumulative alphas of the laggards over the 2- to 12-month horizon. To compute these cumulative alphas, at each date $t+h-1$ (returns at $t+h$), the laggards are sorted into portfolios based on the respective component of the leaders' returns at time t. In months 2 to 12, sorting on leaders' returns generates positive and statistically significant long–short alphas for both the equal- and value-weighted portfolios of laggards in all three settings (columns 1 and 6). A similar magnitude and statistical significance is also observed when sorting directly on the leaders' predictable nonidiosyncratic components (columns 2 and 7). In contrast, the predictability from sorting on the leader's idiosyncratic component is neither economically nor statistically significant in all cases (columns 5 and 10).

Figure 2 plots these cumulative alphas by month. We observe only a slight (but statistically insignificant) increase in the cumulative alpha generated by sorting on the idiosyncratic component (dashed line).[14] At some horizons, the cumulative alphas from the idiosyncratic returns decrease, even becoming negative at times, meaning that the 1-month predictability is reversed. This reversal suggests (but

[12]The point estimates are the best estimate of how each part contributes to the whole, regardless of the statistical significance of each individual component (e.g., Cochrane (2007)).

[13]The alphas generated from sorting on the nonidiosyncratic component and the idiosyncratic component do not sum exactly to the alpha generated from sorting on returns because of estimation error and the way each component acts as "noise" on the other components of the sorts. In particular, the predictability of the nonidiosyncratic component is biased downward because a simple correction for the noise attenuation does not exist, unlike in the case of idiosyncratic sorts. See the Supplementary Material for details.

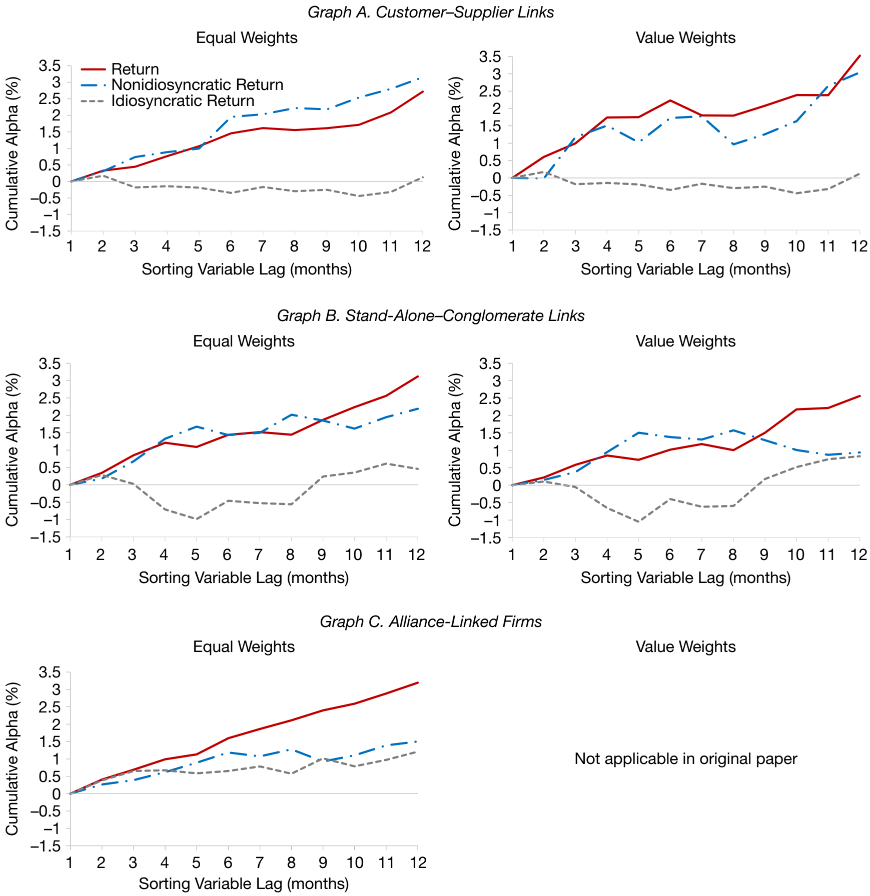
[14]Figure 2 of Cohen and Frazzini (2008) shows graphical evidence of long-horizon predictability, suggesting that supplier returns eventually "catch up" with customer returns following the initial return shock. The evidence is distorted by a scaling applied to the customer returns variable. We discuss the scaling in further detail in Appendix Section O.X of the Supplementary Material.

https://doi.org/10.1017/S0022109020000885 Published online by Cambridge University Press

FIGURE 2

Cumulative Alphas from Sorting on Returns, Nonidiosyncratic Components, and Idiosyncratic Components

Figure 2 shows the cumulative alphas for the long–short portfolios of laggards for different sets of economically linked firms. At each date $t+h-1$, we assign laggards to quantile portfolios based on their linked leaders' returns, nonidiosyncratic components, and idiosyncratic components at t. We calculate the equal-weighted (value-weighted) Fama and French (1993) 3-factor-model monthly alpha for the long–short portfolio at each horizon h. The cumulative alpha is the sum of alphas for each of the periods 2 through horizon h. Long–short alphas from sorting on idiosyncratic returns are corrected to eliminate attenuation from estimating the leaders' idiosyncratic returns. The nonidiosyncratic component sorts have no such correction and, therefore, are understated. Alpha is in percentage per month. Panel A uses customers (leaders) to assign suppliers (laggards) into quintile portfolios. Panel B uses stand-alone firms (leaders) to assign conglomerates (laggards) into decile portfolios. Panel C uses alliance-linked firms (leaders) to assign another firm in the alliance (laggards) into quintile portfolios.



inconclusively so) that the 1-month result of slow information diffusion may at times be spurious. In all cases, we observe that the cumulative alphas over the 2- to 12-month horizon from the return sorts are substantially larger than those from the idiosyncratic return sorts, the measure of information diffusion we advance.

The finding of Table 3 that, in almost all cases, the cross-firm predictability over the 2- to 12-month horizon is attributable to the predictable nonidiosyncratic component can be seen in Figure 2 where the cumulative alphas from the nonidiosyncratic return sort (dash-dot line) closely track those of the cumulative alphas

https://doi.org/10.1017/S0022109020000885 Published online by Cambridge University Press

https://doi.org/10.1017/S0022109020000885 Published online by Cambridge University Press

from the return sorts (solid line). The tracking pattern diverges prior to 12 months in only two cases: The case of alliance-linked firms diverges after approximately 6 months, and the value-weighted stand-alone–conglomerate links diverge after 9 months.

The results show that the previously documented long-horizon cross-firm predictability does not appear to be from slow information diffusion across firms. Instead, cross-firm information diffusion between economically linked firms appears to complete within 1 month, suggesting that the market is more efficient than previously documented.

IV. Results Not Driven by Removing Old News

We identify the predictable component by estimating the model parameters for the leaders using returns from $t-12$ to $t-1$, a window consistent with the known phenomenon of momentum. One can think of these idiosyncratic shocks during the estimation window as "old news." The predictable component is made up of alpha and betas times factor realizations. The alpha contains the true alpha plus the average old news (idiosyncratic shocks) over the estimation window.

Two concerns arise here. First, the old news contained in the predictable component could generate the long–short alpha obtained by sorting on the predictable component. Second, removing the old news from the idiosyncratic component could induce a negative bias in the alpha found when sorting on the idiosyncratic component. That is, sorting on the estimated idiosyncratic component is merely sorting on the true idiosyncratic news minus the average old news. We provide three tests that address these concerns.

A. Beta Predictability Contributes to Cross-Firm Predictability

To address the concern that the old news is the only driver of the alpha from sorting on the predictable component, we separate the predictable piece even further into the alpha and the betas-times-factors component of the leaders' returns. If the concern is correct, then sorting solely on the betas-times-factors component should not generate any predictability because it contains no old news.

Columns 4 and 9 of Table 3 show the predictability from sorting on the betas-times-factors component. For the stand-alone–conglomerate links, the majority of the predictability arising from sorting on the predictable nonidiosyncratic component comes from this component. Unlike the other two sets of links, in this setting, the predictability generated is statistically significant. For the customer–supplier links and alliance-linked firms, sorting on the betas-times-factors component produces one-third of the predictability of the total predictability attained by sorting on the leaders' predictable nonidiosyncratic return.

The contribution of the betas-times-factors component also matters at the longer 2- to 12-month horizon, although the importance (and, therefore, the statistical significance) of this component continues to vary across the type of economic link. Across the different sets of firms, this component captures between one-third and one-half of the predictability of the total predictable component (columns 2 and 7 of Table 3). The value-weighted case of the stand-alone–conglomerates is the only instance in which the betas-times-factors component does not contribute to the predictability.

Given that the betas-times-factors component, which is unrelated to old news, contributes to the cross-firm predictability, slow information diffusion is not the only source of cross-firm predictability previously documented.[15]

B. Idiosyncratic Return Sorts Have No Predictive Ability

To address the concern that the lower alpha obtained from sorting on the idiosyncratic component is a result of the negative bias discussed, we test whether the leaders' idiosyncratic returns at long horizons predict the laggards' returns. Because the ability of the information in leaders' returns to predict laggards should decrease with horizon, the average predictability of the old news will always be smaller than the predictability from the news in the current period, regardless of the prediction horizon. At any horizon with delayed diffusion, the estimated idiosyncratic shock should generate positive net predictability (the predictability of current information minus the predictability of the average of the old news). Even if the predictability from this remaining old news is small, we verify both theoretically and empirically that the cumulative net predictability over many months (e.g., 2–12) should be apparent.[16]

We do not find any predictability in the idiosyncratic component at horizons beyond 1 month (see Table 3 and Figure 2). The lack of cumulative predictability is consistent with the conclusion that the laggards' response to the unpredictable information in the leaders' returns is limited to 1 month. Because of the same intuition outlined previously, the sorts on estimated idiosyncratic returns also provide a diagnostic for whether the estimation window chosen has a sufficient gap to avoid this theoretical bias. The gap between the estimation window and the predictability window should encompass at least as many periods as the cumulative alphas suggest as having evidence of slow price discovery. In this case, because we observe no cumulative predictability beyond month 1, using a window ending at $t-1$ when testing for predictability at t is sufficient for avoiding this bias.

C. Sorts on Old News Show No Predictability

To further allay the concern that the estimation window from $t-12$ to $t-1$ overlaps with the predictability horizon, we construct a measure of the old news in this window to test its ability to predict the lagging firms. We proxy for leaders' old

[15]For completeness, we also show (columns 3 and 8) the predictability from the portion of the leaders' predictable return that is due to the estimated alphas. Note that the sum of the long–short alphas from each subcomponent of the predictable component can total more than the long–short alphas from sorting on their sum because each subcomponent can act like noise for the other component in the sort based on their total (e.g., columns 3 and 4 do not sum to column 2).

[16]Appendix Section O.VI.B in the Supplementary Material provides the detailed econometrics of this prediction. Simulations in Appendix Section O.VII of the Supplementary Material illustrate the intuition by showing that even a small persistence (e.g., 10% of the 1-month predictability remains in the 2- to 12-month window) in information delay beyond 1 month results in an upward slope in the cumulative alpha from the idiosyncratic return sorts.

https://doi.org/10.1017/S0022109020000885 Published online by Cambridge University Press

news (idiosyncratic shocks) during the estimation window ($t-12$ to $t-1$) with the estimated idiosyncratic shocks in that window as measured by an asset pricing model estimated in the preceding 12-month window ($t-24$ to $t-13$).

Using these old news shocks for the leaders at each date in the estimation window ($t-12$ to $t-1$), we sort the laggards into portfolios at each of the prediction dates ($t+1$ to $t+12$) and compute long–short alphas as before. This gives 144 long–short alphas (12 idiosyncratic-shock dates multiplied by 12 prediction horizons) for each set of economic links and portfolio weightings (i.e., value or equal weighted).

Consistent with our prior findings, we find no evidence that this old news is able to predict the laggards' returns. The handful of prediction horizons that are statistically significant is consistent with the number of significant values one would expect from multiple comparisons (31 out of 720, or approximately 4%). Consistent with these statistically significant increments being due to noise, they appear at random horizon lengths rather than being concentrated at the shortest prediction horizons where we expect information diffusion to be the most salient. For concision, we tabulate these alphas only in the Supplementary Material (Table O-2).

V. Contemporaneous Returns Drive Out Longer Lags in Regressions

One reason for cross-firm predictability is that leaders' returns predict the commonality in own-firm momentum (i.e., variation in expected or predictable returns for rational or behavioral reasons). To see how much this channel contributes to cross-firm predictability, we use leaders' contemporaneous returns as a proxy for the common momentum component in cross-sectional regressions. Specifically, we consider these two Fama–MacBeth cross-sectional regressions:[17]

(1) $$R_{t+h}^{\text{laggard}} = a + bR_t^{\text{leader}} + \text{controls} \quad \text{and}$$

(2) $$R_{t+h}^{\text{laggard}} = a + bR_t^{\text{leader}} + dR_{t+h}^{\text{leader}} + \text{controls},$$

where we control for the laggard's size, book-to-market ratio, previous month's return (reversal), momentum, profitability, asset growth, and leverage. The controls serve as a characteristic-based asset pricing model (e.g., Bessembinder and Zhang (2013)). For all specifications, we standardize all variables to have a mean of 0 and standard deviation of 1.

Under our proposed mechanism for cross-firm predictability, the coefficient on the lagged leader's return captures two effects: the true delay in information diffusion and the predictability from the commonality in momentum. The coefficient is thus a weighted average of these two effects. The weights are based on the cross-sectional variation in the leaders' idiosyncratic news component and the cross-sectional variation in the leaders' momentum returns. When no true information diffusion occurs, the coefficient on the lagged leaders' returns is due only to

[17]See Kamstra (2017) for a detailed discussion of predictability regressions.

https://doi.org/10.1017/S0022109020000885 Published online by Cambridge University Press

the commonality in momentum. Our hypothesis suggests that this coefficient should be reduced (become insignificant) with the inclusion of another proxy for the common momentum component. Because both the lagged and contemporaneous returns are noisy proxies, the prediction is that the predictability from the common momentum will be split across these two variables in relation to their noisiness.[18] The main test of interest is how the coefficient b changes across the two regressions.

We also use the decomposed leaders' lagged returns in the regression context to provide a different way of seeing the contribution of each component to the cross-firm predictability. We run

$$(3) \qquad R_{t+h}^{\text{laggard}} = a + bR_t^{\text{leader,news}} + cR_t^{\text{leader,pred}} + \text{controls},$$

where we control as before. The main test is to compare the size of the coefficients b and c.

Although there are not strong predictions for the effect of including the contemporaneous returns along with the leaders' decomposed return, we include that specification for completeness:

$$(4) \qquad R_{t+h}^{\text{laggard}} = a + bR_t^{\text{leader,news}} + cR_t^{\text{leader,pred}} + dR_{t+h}^{\text{leader}} + \text{controls},$$

where we control as before. How much each component of the leaders' lagged returns will be affected by including contemporaneous returns is determined by two things: i) the extent to which our decomposition is deliberately conservative, leaving some of the common momentum component in the news component, and ii) the relative noisiness of the predictable component and the contemporaneous returns as proxies for the common momentum component.

We run these regressions for up to 3 lags. Beyond 3 lags, we do not find any predictability in the original regression specification, equation (1).[19] We note that the cross-firm predictability in the regression setting is weaker than that shown from sorts. This is most likely due to the substantially different weighting imposed in regressions compared with sorts. The latter emphasizes the extreme observations, where predictability from all sources appears to be stronger.

Table 4 presents the results of the regressions. Columns 1–4 show the results for the predictability at a 1-month lag ($h = 1$). Columns 5–8 show the predictability at a 2-month lag. Columns 9–12 show the predictability at a 3-month lag. We discuss each horizon in turn.

A. One-Month-Horizon Predictability Remains

At a 1-month lag, across all three settings, column 1 of Table 4 shows that the coefficient of predictability (leader return t) is statistically and economically significant, ranging from 0.020 to 0.042. Column 2 shows that controlling for the

[18]The contemporaneous returns are correlated from both the commonality in expected returns and the commonality in new return shocks. This first component is what we wish to use the leaders' contemporaneous returns as a proxy for.

[19]The original articles, where applicable, only show the 1-month-lag results for the regression context.

https://doi.org/10.1017/S0022109020000885 Published online by Cambridge University Press

TABLE 4

Cross-Sectional Regressions

Table 4 shows Fama–MacBeth predictability regressions. Returns of laggard firms at $t+h$, for $h \in \{1,2,3\}$, are regressed on leader firm returns at t along with controls. Additional specifications include the contemporaneous leader return at $t+h$ as a proxy for the common momentum among the economically linked firms. The last two specifications replace the lagged leader returns with that return decomposed into its predictable component and the idiosyncratic news component. The full specification of the regressions can be found in Equations (1) to (4). The controls serve as a characteristic-based asset pricing model and include the laggard's size, book-to-market ratio, previous month's return (reversal), momentum, profitability, asset growth, and leverage. All variables are standardized to have mean 0 and standard deviation 1. t-statistics are in parentheses. Panel A uses customers as leaders and suppliers as laggards. Panel B uses standalone firms as leaders and conglomerates as laggards. Panel C uses alliance-linked firms as both leaders and laggards.

	Dep. Var: Laggard $t+1$				Dep. Var: Laggard $t+2$				Dep. Var: Laggard $t+3$			
Leaders'↓	1	2	3	4	5	6	7	8	9	10	11	12
Panel A. Customer-Suppliers												
Return t	0.022	0.023			0.012	0.007			0.003	0.004		
	(4.03)	(4.39)			(2.82)	(1.55)			(0.53)	(0.78)		
Alpha$+\vec{\beta}'\vec{f}_t$			0.040	0.038			0.021	0.012			0.020	0.018
			(3.90)	(3.98)			(2.36)	(1.21)			(1.94)	(1.78)
Idiosyncratic return t			0.029	0.029			0.017	0.009			0.003	0.003
			(3.83)	(4.02)			(2.65)	(1.60)			(0.45)	(0.46)
Contemp. return $(t+h)$		0.089		0.087		0.093		0.091		0.093		0.087
		(13.01)		(13.32)		(12.28)		(12.08)		(11.40)		(13.32)
Panel B. Stand-Alone-Conglomerates												
Return t	0.042	0.034			0.015	0.009			0.008	0.019		
	(5.66)	(5.32)			(2.77)	(1.40)			(1.23)	(1.14)		
Alpha$+\vec{\beta}'\vec{f}_t$			0.042	0.038			0.020	0.019			0.016	0.020
			(2.72)	(3.59)			(2.00)	(2.13)			(1.60)	(1.52)
Idiosyncratic return t			0.032	0.031			0.012	0.006			0.008	0.015
			(4.15)	(5.24)			(2.26)	(0.92)			(1.49)	(1.35)
Contemp. return $(t+h)$		0.143		0.133		0.145		0.138		0.138		0.134
		(19.39)		(12.91)		(22.70)		(16.48)		(10.83)		(9.94)
Panel C. Alliance-Linked Firms												
Return t	0.020	0.021			0.002	0.002			0.003	0.003		
	(4.81)	(4.85)			(0.66)	(0.45)			(0.98)	(0.97)		
Alpha$+\vec{\beta}'\vec{f}_t$			0.033	0.030			0.003	0.000			0.014	0.012
			(2.98)	(2.79)			(0.35)	(−0.02)			(1.42)	(1.27)
Idiosyncratic return t			0.030	0.031			0.005	0.004			0.006	0.006
			(4.99)	(5.23)			(0.91)	(0.66)			(1.05)	(1.16)
Contemp. return $(t+h)$		0.078		0.078		0.080		0.080		0.083		0.083
		(14.54)		(15.35)		(14.31)		(14.51)		(12.82)		(12.27)

https://doi.org/10.1017/S0022109020000885 Published online by Cambridge University Press

contemporaneous leader return does not substantively affect this predictability. This is consistent with our earlier cross-firm-sort results showing that cross-firm information diffusion indeed occurs at the 1-month horizon. When there is delayed information diffusion occurring, as we argue, at the 1-month horizon, we would expect the delayed information component to dominate the regression coefficient because the cross-sectional variation in idiosyncratic shocks is much larger than that in expected returns (i.e., dispersion in momentum).

The coefficient on the contemporaneous return ranges from 0.078 to 0.143 across the three settings. As expected, the coefficients are highly statistically significant and economically large. The effect of the contemporaneous return is approximately 4 times larger in magnitude than that of the leader's lagged return.

Columns 3 and 4 of Table 4 show the regressions in which the leader's 1-month lagged return has been split into its subcomponents. For both customer–supplier and stand-alone–conglomerate links, we find in column 3 that the predictable component contributes approximately one-third more to the cross-firm predictability observed than the idiosyncratic component contributes. For alliance-linked firms, both components appear to contribute an equal amount. In all cases, the coefficients on the predictable and idiosyncratic components are statistically and economically significant. This is also consistent with our previous findings in Section III.A that the 1-month cross-firm predictability observed is due to both cross-firm delayed information diffusion and the commonality in the firms' own momentum.

B. Two-Month-Horizon Predictability Subsumed

We now look at the effect of controlling for the leader's contemporaneous return at lags beyond 1 month. In all three settings, column 5 of Table 4 shows that the coefficient on the leader's lagged return at 2 lags is economically smaller and statistically weaker than the coefficient of the 1-month lagged return shown in column 1. For the alliance-linked firms, we find no predictability for lags of 2 months and beyond, even though we attain alpha when using sorts.

The lack of predictability in the regression framework, despite sorts generating long–short portfolio alphas, likely occurs for two reasons. First, the various controls in the regression capture most of the predictable variation in the laggard's returns. Thus, the (characteristic-based) asset pricing model used in the regression framework appears to be more effective than the Fama–French 3-factor model used in the sort method. The controls' ability to capture what the sorts attribute to predictability is consistent with our findings that commonality in expected returns drives this longer-horizon cross-firm predictability.

Second, the regression framework averages across all links, whereas the sort method uses only those links in the long and short quantiles. Thus, the links are weighted differently under the two methods. Our findings of alphas from the sorts but no significant coefficients in the regressions suggest that the cross-firm predictability is stronger in the extremes. Because the predictability for alliance-linked firms is nonexistent at 2- and 3-month lags, we ignore the alliance-linked firms for the rest of the discussion of these regressions.

https://doi.org/10.1017/S0022109020000885 Published online by Cambridge University Press

https://doi.org/10.1017/S0022109020000885 Published online by Cambridge University Press

Column 6 of Table 4 shows the predictability of the laggard's return at $t+2$ based on the leader's t return after controlling for the leader's contemporaneous return. For customer–supplier links, the coefficient decreases from 0.012 to 0.007 and becomes statistically insignificant. For stand-alone–conglomerate links, the coefficient decreases from 0.015 to 0.009 and also becomes statistically insignificant.

Columns 7 and 8 of Table 4 show the results of decomposing the leaders' lagged returns. For the customer–supplier links in Panel A, column 7 shows that the coefficient of 0.021 on the predictable component is economically large and statistically significant, with a t-statistic of 2.36. The coefficient on the idiosyncratic return is slightly smaller, at 0.017, but also statistically significant, with a t-statistic of 2.65. Column 8 shows that after controlling for the laggard's contemporaneous return, the coefficients on the predictable component and the idiosyncratic return both become statistically insignificant. That both the predictable and unpredictable components are driven out in this case suggests that our decomposition is particularly noisy in this setting, with the contemporaneous return serving as a better proxy for the common momentum component.[20]

For the stand-alone–conglomerate links in Panel B of Table 4, we see a similar pattern, except that the predictable component of the leader's return remains important after including the leader's contemporaneous return. After controlling for the leader's contemporaneous return in column 6, the coefficient on the leader's t return is reduced from 0.015 (in column 5) to 0.009 and becomes statistically insignificant. Column 7 shows that both components of the leader's lagged return exhibit coefficients that are both statistically and economically significant at 0.020 and 0.012, respectively. The predictable component is nearly twice as important as the unpredictable component. However, after controlling for the leader's contemporaneous return in column 8, the coefficient on the idiosyncratic return drops by half and becomes statistically insignificant. The coefficient on the predictable component remains at nearly the same magnitude at 0.019 and is statistically significant.

In summary, the leader's contemporaneous return subsumes the predictability of the leader's lagged return at the 2-month horizon. This is consistent with our prior findings of no delay in information diffusion beyond 1 month.

C. Three-Month-Horizon Has No Predictability

We include the same regressions for the 3-month lags. We find that the predictability in the original specification has disappeared by 3 months. The reason for the difference in regression results and portfolio sorts across all three economic links is the same as that described for the alliance-linked firms at 2 months. Although no predictability in the original specification is present in column 9 of Table 4, we continue to see some, albeit weaker, evidence of the predictable component of the leaders' returns predicting the laggards' returns ($\text{alpha}+\vec{\beta}'\vec{f}_t$) in column 11. The similarity of the coefficients on the predictable component at lags of 2 and 3 (columns 7 and 11) is consistent with our finding in the sort context that

[20]In the sort setting, we correct for this noise in the news sorts.

the commonality in momentum among economically linked firms drives the cross-firm predictability beyond 1 month.

Taken together across all horizons, the regression-framework results are consistent with the findings from the sorting framework. At the 1-month horizon, the cross-firm predictability is driven by both the commonality in leaders' and laggards' own momentum and cross-firm information diffusion. Beginning with the 2-month horizon, we find that the cross-firm predictability observed is either nonexistent (alliance-linked firms) or attributable to the commonality in own-firm momentum.

VI. Conclusion

Many articles have used cross-firm predictability among economically linked firms to measure slow information diffusion. These articles have found large alphas that persist as long as a year in long–short portfolios formed by sorting lagging firms into portfolios based on the returns of the economically linked leading firms. Interpreting these alphas as a measure of the economic importance of slow information diffusion, these articles suggest pervasive, long-lasting market inefficiencies.

We show that slow information diffusion is not the only source of this cross-firm predictability. Cross-firm predictability can also arise from the own-firm momentum of economically linked firms combined with the contemporaneous correlation in their returns, creating a commonality in momentum. We exemplify this alternative mechanism by showing, in the context of seasonalities, that cross-firm predictability can last as long as 10 years. Such predictability is hard to reconcile with slow information diffusion.

We decompose the leading firms' returns into a component that is predictable and a component that is news. Sorting on the news component provides a measure of slow information diffusion, whereas sorting on the predictable component gives a measure of the predictability from the commonality in the own-firm momentum of the economically linked firms. At the 1-month horizon, each source of predictability contributes roughly equally to the previously documented long–short alphas. Thus, slow information diffusion appears to occur at the 1-month horizon. At the 2- to 12-month horizon, sorting on the news component produces no statistically significant long–short alpha, suggesting that information diffusion completes within 1 month.

Our findings suggest a market much more efficient, setting aside momentum, than that previously documented. The importance of commonality in own-firm momentum among economically linked firms in producing cross-firm predictability bears the caveat that we cannot distinguish the source of the commonality in momentum. On the one hand, lagging firms may simply be responding to old (predictable) information about leaders in the same way the leaders themselves respond to old information. Such a common "delayed" reaction is distinct from slow *direct* cross-firm information diffusion as traditionally understood. On the other hand, the commonality in own-firm momentum may be due to other unmodeled factors common to firms sharing economic links and, therefore, economic risk exposures. We leave the source of this common momentum among economically linked firms as a new puzzle to solve about momentum.

https://doi.org/10.1017/S0022109020000885 Published online by Cambridge University Press

https://doi.org/10.1017/S0022109020000885 Published online by Cambridge University Press

Appendix A. Articles Using Lead–Lag Sorts with Economically Linked Firms

The following is a selection of recent papers using the lead–lag sort method among firms with economic links: Menzly and Ozbas (2004), Cohen and Frazzini (2008), Chen, Chen, and Li (2009), Easton, Gao, and Gao (2010), Menzly and Ozbas (2010), Rizova (2010), Kulak and Schmidt (2011), Cohen and Lou (2012), Hou, Scherbina, Tang, and Wilhelm (2012), Nguyen (2012), Noh (2014), Albuquerque, Ramadorai, and Watugala (2015), Scherbina and Schlusche (2015), Huang (2015), Cao et al. (2016), Liu (2016), Parsons, Sabbatucci, and Titman (2016), Scherbina and Schlusche (2016), Chen, Khan, Kogan, and Serafeim (2021), Kumar and Moon (2016), Agarwal, Leung, Konana, and Kumar (2017), Ali (2017), Cen, Hertzel, and Schiller (2017), Chava, Hsu, and Zeng (2019), Gao, Moulton, and Ng (2017), Hoberg and Phillips (2018), Lee, Sun, Wang, and Zhang (2019), Li, Tang, and Yan (2016), Müller (2019), Pantzalis and Wang (2017), Petzev (2017), Phua (2017), Qiu, Xu, and Zeng (2017a), Qiu, Wang, and Zhou (2017b), Shen (2018), Zhang and Gonzalez (2018), and Bian, Sarkissian, Tu, and Zhang (2019).

Appendix B. Joint Portfolio Alphas from 10-year Sorts

TABLE B1

Joint Portfolio Alphas from Sorting on Average Same-Month Returns for the Past 10 Years

Table B-1 shows the long-short portfolio alphas obtained from sorting leaders and laggards on the leaders' average return in the same month over the previous 10 years. At each date t, we compute the leader's average return in the same month for years $y-10$ to $y-1$. At each date t in year y, we rank leaders by the preceding 10-year same-month return. We use these rankings to assign the corresponding leaders (laggards) into quantile portfolios. We compute the equal- (value-) weighted returns for each portfolio. The table shows the estimates of the long-short alphas from these sorts. Alpha is the intercept on a regression of the monthly returns for the long-short portfolio using the Fama and French (1993) 3-factor model. Alpha is reported in percentage per month. This table shows the joint significance of the various portfolios reported in Table 1. The column "All" is the alpha from the portfolio formed by taking the equal-weighted average of all five long-short portfolio returns. The column "Value-Weighted" shows the alpha of the portfolio that takes the equal-weighted average of both value-weighted portfolios. The column "Equal-Weighted" shows the alpha of the portfolio that takes the equal-weighted average of the three equal-weighted portfolios. t-statistics are in parentheses.

	All	Value-Weighted	Equal-Weighted
Leader	1.010	0.907	1.079
	(4.08)	(2.78)	(4.91)
Laggard	0.416	0.370	0.320
	(2.68)	(1.86)	(2.28)

Supplementary Material

To view supplementary material for this article, please visit http://dx.doi.org/10.1017/S0022109020000885.

References

Agarwal, A.; A. C. M. Leung; P. Konana; and A. Kumar. "Cosearch Attention and Stock Return Predictability in Supply Chains." *Information Systems Research*, 28 (2017), 265–288.

Albuquerque, R.; T. Ramadorai; and S. W. Watugala. "Trade Credit and Cross-Country Predictable Firm Returns." *Journal of Financial Economics*, 115 (2015), 592–613.

Ali, U., and D. Hirshleifer. "Shared Analyst Coverage: Unifying Momentum Spillover Effects." *Journal of Financial Economics*, 136 (2020), 649–675.
Aobdia, D.; J. Caskey; and N. B. Ozel. "Inter-Industry Network Structure and the Cross-Predictability of Earnings and Stock Returns." *Review of Accounting Studies*, 19 (2014), 1191–1224.
Asparouhova, E.; H. Bessembinder; and I. Kalcheva. "Liquidity Biases in Asset Pricing Tests." *Journal of Financial Economics*, 96 (2010), 215–237.
Asparouhova, E.; H. Bessembinder; and I. Kalcheva. "Noisy Prices and Inference Regarding Returns." *Journal of Finance*, 68 (2013), 665–714.
Bali, T. G.; R. F. Engle; and S. Murray. *Empirical Asset Pricing: The Cross Section of Stock Returns*, New York, NY: John Wiley & Sons (2016).
Barber, B. M., and J. D. Lyon. "Detecting Abnormal Operating Performance: The Empirical Power and Specification of Test Statistics." *Journal of Financial Economics*, 41 (1996), 359–399.
Barber, B. M., and J. D. Lyon. "Detecting Long-Run Abnormal Stock Returns: The Empirical Power and Specification of Test Statistics." *Journal of Financial Economics*, 43 (1997), 341–372.
Berk, J. B. "Sorting Out Sorts." *Journal of Finance*, 55 (2000), 407–427.
Bessembinder, H. "Issues in Assessing Trade Execution Costs." *Journal of Financial Markets*, 6 (2003), 233–257.
Bessembinder, H., and F. Zhang. "Firm Characteristics and Long-Run Stock Returns after Corporate Events." *Journal of Financial Economics*, 109 (2013), 83–102.
Bessembinder, H., and F. Zhang. "Predictable Corporate Distributions and Stock Returns." *Review of Financial Studies*, 28 (2014), 1199–1241.
Bian, X.; S. Sarkissian; J. Tu; and R. Zhang. "Return Cross-Predictability in Firms with Similar Employee Satisfaction." Working Paper, available at http://dx.doi.org/10.2139/ssrn.3469633 (2019).
Boudoukh, J.; M. P. Richardson; and R. Whitelaw. "A Tale of Three Schools: Insights on Autocorrelations of Short-Horizon Stock Returns." *Review of Financial Studies*, 7 (1994), 539–573.
Cao, J.; T. Chordia; and C. Lin. "Alliances and Return Predictability." *Journal of Financial and Quantitative Analysis*, 51 (2016), 1689–1717.
Carhart, M. M. "On Persistence in Mutual Fund Performance." *Journal of Finance*, 52 (1997), 57–82.
Cen, L.; K. Chan; S. Dasgupta; and N. Gao. "When the Tail Wags the Dog: Industry Leaders, Limited Attention, and Spurious Cross-Industry Information Diffusion." *Management Science*, 59 (2013), 2566–2585.
Cen, L.; M. G. Hertzel; and C. M. Schiller. "Speed Matters: Limited Attention and Supply-Chain Information Diffusion." Working Paper, available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2925460 (2017).
Chava, S.; A. Hsu; and L. Zeng. "Does History Repeat Itself? Business Cycle and Industry Returns." *Journal of Monetary Economics*, 116 (2019), 201–218.
Chen, H.; S. Chen; and F. Li. "Firm-Level Return Comovement." Working Paper, University of British Columbia (2009).
Chen, W.; M. Khan; L. Kogan; and G. Serafeim. "Cross-Firm Return Predictability and Accounting Quality." *Journal of Business Finance & Accounting*, 48 (2021), 70–101.
Cochrane, J. H. "The Dog That Did Not Bark: A Defense of Return Predictability." *Review of Financial Studies*, 21 (2007), 1533–1575.
Cohen, L., and A. Frazzini. "Economic Links and Predictable Returns." *Journal of Finance*, 63 (2008), 1977–2011.
Cohen, L., and D. Lou. "Complicated Firms." *Journal of Financial Economics*, 104 (2012), 383–400.
Conrad, J.; M. N. Gultekin; and G. Kaul. "Profitability of Short-Term Contrarian Strategies: Implications for Market Efficiency." *Journal of Business and Economic Statistics*, 15 (1997), 379–386.
Conrad, J., and G. Kaul. "Long-Term Market Overreaction or Biases in Computed Returns?" *Journal of Finance*, 48 (1993), 39–63.
Conrad, J., and G. Kaul. "An Anatomy of Trading Strategies." *Review of Financial Studies*, 11 (1998), 489–519.
Easton, P.; G. Gao; and P. Gao. "Pre-Earnings Announcement Drift." Working Paper, University of Notre Dame (2010).
Fama, E. F., and K. R. French. "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics*, 33 (1993), 3–56.
Ferson, W., and Y. Chen. "How Many Good and Bad Funds Are There, Really?" In *Handbook of Financial Economics, Mathematics, Statistics, and Machine Learning*, Vol. IV, C. F. Lee and J. C. Lee, eds. Singapore: World Scientific (2020), 3753–3827.
Ferson, W.; S. Sarkissian; and T. Simin. "Is Stock Return Predictability Spurious?" *Journal of Investment Management*, 1 (2003), 1–10.

https://doi.org/10.1017/S0022109022000885 Published online by Cambridge University Press

Ferson, W. E.; S. Sarkissian; and T. Simin. "Asset Pricing Models with Conditional Betas and Alphas: The Effects of Data Snooping and Spurious Regression." *Journal of Financial and Quantitative Analysis*, 43 (2008), 331–353.
Gao, G. P.; P. C. Moulton; and D. T. Ng. "Institutional Ownership and Return Predictability across Economically Unrelated Stocks." *Journal of Financial Intermediation*, 31 (2017), 45–63.
Gospodinov, N.; R. Kan; and C. Robotti. "Misspecification-Robust Inference in Linear Asset-Pricing Models with Irrelevant Risk Factors." *Review of Financial Studies*, 27 (2014a), 2139–2170.
Gospodinov, N.; R. Kan; and C. Robotti. "Spurious Inference in Unidentified Asset-Pricing Models." Working Paper 2014-12, Federal Reserve Bank of Atlanta (2014b).
Gospodinov, N.; R. Kan; and C. Robotti. "Spurious Inference in Reduced-Rank Asset-Pricing Models." *Econometrica*, 85 (2017), 1613–1628.
Gospodinov, N.; R. Kan; and C. Robotti. "Too Good to Be True? Fallacies in Evaluating Risk Factor Models." *Journal of Financial Economics*, 132 (2019), 451–471.
Harvey, C. R.; Y. Liu; and H. Zhu. "… and the Cross-Section of Expected Returns." *Review of Financial Studies*, 26 (2016), 5–68.
Heston, S. L., and R. Sadka. "Seasonality in the Cross-Section of Stock Returns." *Journal of Financial Economics*, 87 (2008), 418–445.
Hoberg, G., and G. M. Phillips. "Text-Based Industry Momentum." *Journal of Financial and Quantitative Analysis*, 53 (2018), 2355–2388.
Hou, K. "Industry Information Diffusion and the Lead-Lag Effect in Stock Returns." *Review of Financial Studies*, 20 (2007), 1113–1138.
Hou, K.; A. Scherbina; Y. Tang; and S. Wilhelm. "Information Leaders." Working Paper, Ohio State University, University of California at Davis, Fordham University, and the University of Basel (2012).
Huang, X. "Thinking Outside the Borders: Investors' Underreaction to Foreign Operations Information." *Review of Financial Studies*, 28 (2015), 3109–3152.
Jegadeesh, N. "Evidence of Predictable Behavior of Security Returns." *Journal of Finance*, 45 (1990), 881–898.
Kamstra, M. J. "Momentum, Reversals, and Other Puzzles in Fama–MacBeth Cross-Sectional Regressions." Working Paper, available at http://dx.doi.org/10.2139/ssrn.2947340 (2017).
Kan, R., and C. Robotti. "On the Estimation of Asset Pricing Models Using Univariate Betas." *Economics Letters*, 110 (2011), 117–121.
Kan, R.; C. Robotti; and J. Shanken. "Pricing Model Performance and the Two-Pass Cross-Sectional Regression Methodology." *Journal of Finance*, 68 (2013), 2617–2649.
Keloharju, M.; J. T. Linnainamaa; and P. Nyberg. "Return Seasonalities." *Journal of Finance*, 71 (2016), 1557–1590.
Kulak, J. P., and C. Schmidt. "Vertical Integration and Predictable Returns." Working Paper, École Polytechnique Féderalé de Lausanne (EPFL) and the University of Lausanne (2011).
Kumar, A., and A. Moon. "Geographical Accessibility and Portfolio Choice." Working Paper, University of Miami (2016).
Lee, C.; S. T. Sun; R. Wang; and R. Zhang. "Technological Links and Predictable Returns." *Journal of Financial Economics*, 132 (2019), 76–96.
Lehmann, B. N. "Fads, Martingales, and Market Efficiency." *Quarterly Journal of Economics*, 105 (1990), 1–28.
Leung, A. C. M.; A. Agarwal; P. Konana; and A. Kumar. "Network Analysis of Search Dynamics: The Case of Stock Habitats." *Management Science*, 63 (2016), 2667–2687.
Lewellen, J.; S. Nagel; and J. Shanken. "A Skeptical Appraisal of Asset Pricing Tests." *Journal of Financial Economics*, 96 (2010), 175–194.
Li, J.; Y. Tang; and A. Yan. "Corporate Equity Ownership and Expected Stock Returns." Working Paper 2766799, Gabelli School of Business, Fordham University (2016).
Liu, B. "Circle of Competence and the Gradual Diffusion of Information in Prices." Working Paper, available at http://dx.doi.org/10.2139/ssrn.2356752 (2016).
Lo, A. W., and A. C. MacKinlay. "Data-Snooping Biases in Tests of Financial Asset Pricing Models." *Review of Financial Studies*, 3 (1990), 431–467.
Lyon, J. D.; B. M. Barber; and C.-L. Tsai. "Improved Methods for Tests of Long-Run Abnormal Stock Returns." *Journal of Finance*, 54 (1999), 165–201.
Madsen, J. "Anticipated Earnings Announcements and the Customer-Supplier Anomaly." *Journal of Accounting Research*, 55 (2016), 709–741.
Menzly, L., and O. Ozbas. "Cross-Industry Momentum." Working Paper, University of Southern California (2004).
Menzly, L., and O. Ozbas. "Market Segmentation and Cross-Predictability of Returns." *Journal of Finance*, 65 (2010), 1555–1580.

https://doi.org/10.1017/S0022109020000885 Published online by Cambridge University Press

https://doi.org/10.1017/S0022109020000885 Published online by Cambridge University Press

Müller, S. "Economic Links and Cross-Predictability of Stock Returns: Evidence from Characteristic-Based 'Styles'." *Review of Finance*, 23 (2019), 363–395.

Nguyen, Q. H. "Geographic Momentum." Working Paper, available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1921537 (2012).

Noh, J. "Industry Networks and the Speed of Information Flow." Working Paper, available at http://dx.doi.org/10.2139/ssrn.2531450 (2014).

Pantzalis, C., and B. Wang. "Shareholder Coordination, Information Diffusion and Stock Returns." *Financial Review*, 52 (2017), 563–595.

Parsons, C. A.; R. Sabbatucci; and S. Titman. "Geographic Momentum." Working Paper, Centre for Economic Policy Research (2016).

Pástor, L̆., and R. F. Stambaugh. "Investing in Equity Mutual Funds." *Journal of Financial Economics*, 63 (2002a), 351–380.

Pástor, L̆., and R. F. Stambaugh. "Mutual Fund Performance and Seemingly Unrelated Assets." *Journal of Financial Economics*, 63 (2002b), 315–349.

Pástor, L̆., and R. F. Stambaugh. "Liquidity Risk and Expected Stock Returns." *Journal of Political Economy*, 111 (2003), 642–685.

Pástor, L̆.; R. F. Stambaugh; and L. A. Taylor. "Scale and Skill in Active Management." *Journal of Financial Economics*, 116 (2015), 23–45.

Petzev, I. "Information Diffusion in Analyst Portfolios." Working Paper, available at http://dx.doi.org/10.2139/ssrn.2872902 (2017).

Phua, J. K. "Commonality in Analyst Coverage and Information Diffusion." Working Paper, available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3002915 (2017).

Qiu, B.; F. Xu; and C. Zeng. "Contagious Stock Price Crashes." Working Paper, available at http://dx.doi.org/10.2139/ssrn.3069993 (2017a).

Qiu, J.; J. Wang; and Y. Zhou. "Technology and Return Predictability." Working Paper, available at http://dx.doi.org/10.2139/ssrn.3056433 (2017b).

Rapach, D. E.; J. K. Strauss; and G. Zhou. "International Stock Return Predictability: What Is the Role of the United States?" *Journal of Finance*, 68 (2013), 1633–1662.

Rizova, S. "Predictable Trade Flows and Returns of Trade-Linked Countries." Working Paper, American Finance Association (2010).

Scherbina, A., and B. Schlusche. "Cross-Firm Information Flows and the Predictability of Stock Returns." Working Paper, available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2263033 (2015).

Scherbina, A., and B. Schlusche. "Economic Linkages Inferred from News Stories and the Predictability of Stock Returns." Working Paper, American Enterprise Institute (2016).

Shahrur, H.; Y. L. Becker; and D. Rosenfeld. "Return Predictability along the Supply Chain: The International Evidence." *Financial Analysts Journal*, 66 (2010), 60–77.

Shen, S. "Political Ties and Predictable Returns." Working Paper, available at http://dx.doi.org/10.2139/ssrn.3292672 (2018).

Wu, J., and J. R. Birge. "Supply Chain Network Structure and Firm Returns." Working Paper, available at http://dx.doi.org/10.2139/ssrn.2385217 (2014).

Zhang, R., and A. Gonzalez. "Ownership Links and Return Predictability." Working Paper, American Finance Association (2018).