Industry Interdependencies and Cross-Industry Return Predictability

David E. Rapach
Saint Louis University
rapachde@slu.edu

Jack K. Strauss
University of Denver
jack.strauss@du.edu

Jun Tu
Singapore Management University
tujun@smu.edu.sg

Guofu Zhou*
Washington University in St. Louis and CAFR
zhou@wustl.edu

June 14, 2015

*Corresponding author. Send correspondence to Guofu Zhou, Olin School of Business, Washington University in St. Louis, St. Louis, MO 63130; e-mail: zhou@wustl.edu; phone: 314-935-6384. We are grateful to Doron Avramov for very helpful comments. We thank Dmitriy Voznyuk for excellent research assistance.

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Abstract

We use the adaptive LASSO from the statistical learning literature to identify economically connected industries in a general framework that accommodates complex industry interdependencies. Our results show that lagged returns of interdependent industries are significant predictors of individual industry returns, consistent with gradual information diffusion across industries. Using network analysis, we find that industries with the most extensive predictive power are key central nodes in the production network of the U.S. economy. Further linking cross-industry return predictability to the real economy, lagged employment growth for the interdependent industries predicts individual industry employment growth. We also compute out-of-sample industry return forecasts based on the lagged returns of interdependent industries and show that cross-industry return predictability is economically valuable: an industry-rotation portfolio that goes long (short) industries with the highest (lowest) forecasted returns exhibits limited exposures to a variety of equity risk factors, delivers substantial alpha, and performs very well during business-cycle recessions, especially the recent Great Recession.

JEL classifications: C22, C58, G11, G12, G14

Key words: Complex industry interdependencies; Predictive regression; Adaptive LASSO; Central node; Industry-rotation portfolio; Business cycle; Multifactor model; Principal components; Partial least squares

1. Introduction

We investigate the predictability of industry returns based on a wide array of industry interdependencies. Our research extends the new perspective of Cohen and Frazzini (2008) and Menzly and Ozbas (2010), who find that economic links among certain individual firms and industries contribute significantly to cross-firm and cross-industry return predictability. They interpret their results as evidence of gradual information diffusion across economically connected firms, in line with the theoretical model of Hong, Torous, and Valkanov (2007). In contrast to Cohen and Frazzini (2008) and Menzly and Ozbas (2010), who explicitly identify economic links via customer-supplier relationships, our approach defines economic links more broadly: one industry is economically linked to another if its return can be predicted by the lagged return of the other. By this definition, the customer-supplier link is a special case of a more complex network of industry interdependencies. For example, due to technology spillovers, shocks in the information technology sector can affect returns in the manufacturing sector, even though the two sectors are not directly engaged in a customer-supplier relationship. Such complex industry interdependencies create greater scope for gradual information diffusion to generate cross-industry return predictability.

To accommodate a broad array of industry interdependencies, we specify a general predictive regression model for each industry that includes the lagged returns of all industries as predictors. Because we consider a large number of industries (30), conventional estimation of such a model with a plethora of correlated predictors suffers from serious statistical drawbacks, including overfitting, imprecise parameter estimates, and uninformative inferences. To circumvent these statistical problems, we employ Zou's (2006) adaptive version of Tibshirani's (1996) seminal least absolute shrinkage and selection operator (LASSO) from the statistical learning literature. The LASSO is designed to overcome the problems associated with estimating models with a multitude of regressors by continuously shrinking parameter estimates to zero and permitting shrinkage to exactly zero for some parameters; it thus performs both shrinkage and variable selection. The adaptive LASSO of Zou (2006) refines the original LASSO so that it satisfies the the so-called "oracle" properties.[1]

We use the adaptive LASSO to estimate the general predictive regression model for each industry. Based on monthly return data spanning 1960 to 2014 for 30 industry portfolios from Kenneth French's Data Library, the adaptive LASSO estimation results indicate that multiple lagged industry returns are significant return predictors for numerous individual industries. Indeed, the adaptive LASSO identifies four or more lagged industry returns as significant return predictors for 18 of the individual industries. In addition, lagged industry returns retain their significant predictive ability when we control for the popular predictor variables used by Ferson and Harvey (1991, 1999), Ferson and Korajczyk (1995), and Avramov (2005).

The relevant lagged industry returns identified by the adaptive LASSO appear economically sensible. For example, lagged financial sector returns are significant return predictors for 18 of the 30 industries, and the coefficient estimates are positive in all of these cases. This finding is highly plausible, as firms in many industries rely extensively on financial intermediaries for financing: when the financial sector experiences a positive return shock, financial firms have larger capital buffers and thus become more willing to provide credit on favorable terms to industries across the economy. Borrowers benefit directly from the better terms, while their customers benefit indirectly.

We also find that lagged returns for commodity- and material-producing industries located in earlier stages of the production chain are often significantly negatively related to returns for industries located in later stages of the production chain. This result is consistent with commodity price shocks raising product prices and returns for sectors located in earlier production stages, while squeezing profit margins and lowering returns for sectors located in later production stages. Overall, the adaptive LASSO approach highlights the important role played by complex industry interdependencies in generating industry return predictability.

Menzly and Ozbas (2010) point out that forming portfolios based on predefined customer-supplier links—as in Cohen and Frazzini (2008) and Menzly and Ozbas (2010)—has the practical effect of limiting the analysis to industries with positively correlated fundamentals. Hence, they

[1]Satisfying the oracle properties means that (asymptotically) the procedure selects the relevant variables and has the optimal estimation rate (Fan and Li, 2001).

recommend expanding their analysis to accommodate negatively correlated fundamentals and thus negative cross-industry return predictability. Our general predictive regression approach answers their call. Because our approach allows for complex industry interdependencies, it captures both positive and negative cross-industry return predictability, as evidenced by our empirical results. Our approach complements Cohen and Frazzini (2008) and Menzly and Ozbas (2010) by overcoming the potential weakness associated with limiting the analysis to positive cross-industry return predictability, which can understate the overall degree of industry return predictability.

What are the economic sources of cross-industry return predictability? Hong, Torous, and Valkanov (2007, HTV) incorporate insights from Merton (1987) and Hong and Stein (1999) to show theoretically how gradual information diffusion across industries generates cross-industry return predictability. In their model, investors who specialize in particular market segments have limited information-processing capabilities.[2] When a shock arises in a particular industry that raises expected cash flows for firms in the industry, investors specializing in the industry recognize the shock and immediately drive up equity prices in the industry. Due to industry interdependencies in the economy, a positive cash-flow shock in one industry also has implications for cash flows in other industries; but information-processing limitations prevent investors in other industries from immediately working out the full implications of the cash-flow shock for equity prices in other industries, thereby giving rise to cross-industry return predictability. However, HTV do not provide a method for identifying interdependent industries. In fact, their empirical results center on predicting the aggregate market return using lagged industry returns and not on predicting industry returns per se (as we do).

In line with HTV's theoretical model, the connected industries that we identify via the adaptive LASSO in terms of return predictability are also connected in terms of real economic activity. We provide evidence of economic links along two dimensions. First, applying network analysis to industry input-output tables for the U.S. economy (e.g., Acemoglu, Carvalho, Ozdaglar, and

[2] Hirshleifer, Lim, and Teoh (2002), Hirshleifer and Teoh (2003), and Peng and Xiong (2006) also develop theoretical asset pricing models that incorporate limited information-processing capabilities. See Kahneman (1973) on the limited cognitive resources paradigm in psychology and Sims (2003) on the implications of information-processing limitations for macroeconomic models.

Tahbaz-Salehi, 2012; Carvalho, 2014), we find that industries with the most extensive predictive power for individual future industry returns are among the key central nodes in the economy's production network. Second, for the vast majority of individual industries, we find that employment growth in the interdependent industries identified by the adaptive LASSO for a particular individual industry is a significant predictor of future employment growth in that particular industry. The links between interindustry return predictability and the real economy put our empirical evidence of cross-industry return predictability on firmer ground.

We also assess the economic importance of cross-industry return predictability by constructing a long-short industry-rotation portfolio. Specifically, we compute out-of-sample forecasts of monthly industry returns using the adaptive LASSO and sort the 30 industries according to their forecasted returns over the next month. We then construct a zero-investment portfolio that goes long (short) the top (bottom) decile of sorted industries. The long-short portfolio generates a significant average return of 9.22% per annum over the 1985:01 to 2014:12 out-of-sample period and performs especially well during business-cycle recessions, including the recent Great Recession. In addition, the long-short portfolio actually has negative exposure to the broad equity market factor (with a beta of -0.20) and insignificant exposures to a host of other equity risk factors, so that the portfolio delivers a very sizable annualized alpha of 11.32%.

Moskowitz and Grinblatt (1999) show that cross-sectional industry momentum largely accounts for the well-known cross-sectional momentum in individual firm returns (Jegadeesh and Titman, 1993). To make sure that our long-short portfolio is not unduly capturing cross-sectional industry momentum, we construct a cross-sectional industry momentum portfolio along the lines of Moskowitz and Grinblatt (1999): we first sort industries according to their cumulative returns over the previous twelve months and then construct a zero-investment portfolio that goes long (short) the top (bottom) decile of sorted industries. The cross-sectional industry momentum portfolio behaves very differently from our long-short industry-rotation portfolio constructed from individual industry return forecasts based on the adaptive LASSO. Specifically, unlike our industry-rotation portfolio based on the adaptive LASSO forecasts, the cross-sectional industry momentum portfolio is significantly related to a momentum factor (as expected), does not generate significant alpha, and does not perform well during recessions.

Finally, we examine the robustness of our results by considering two alternative approaches for estimating predictive regression models with a plethora of potential predictors. First, we assume that there are up to three latent factors underlying industry returns, and we use the standard principal component method to extract the factors from the 30 industry returns. Lags of the factors subsequently serve as regressors in predictive regression models for each of the 30 industry returns. Second, we employ the partial least squares (PLS) method pioneered by Wold (1975) and recently extended by Kelly and Pruitt (2013, 2015) to extract a "target-relevant" latent factor from the 30 industry returns that is maximally correlated with a given industry's return in the subsequent month. The lag of this factor then serves as the regressor in the predictive regression model for the given industry's return. Both the principal component and PLS approaches reinforce the relevance of lagged industry returns for predicting individual industry returns.

The rest of the paper is organized as follows. Section 2 discusses estimation of the general predictive regression model, reports the adaptive LASSO estimation results, and examines links to the real economy. Section 3 reports performance measures for our long-short industry-rotation portfolio constructed from out-of-sample industry return forecasts. Section 4 presents results for the principal component and PLS approaches. Section 5 contains concluding remarks.

2. General Predictive Regression Model

Our basic framework is the following general predictive regression specification:

$$r_{i,t+1} = a_i + \sum_{j=1}^{N} b_{i,j} r_{j,t} + \varepsilon_{i,t+1} \text{ for } t = 1, \ldots, T-1, \quad (1)$$

where $r_{i,t}$ is the month-t return on industry portfolio i in excess of the one-month Treasury bill return, N is the total number of industry portfolios, and $\varepsilon_{i,t+1}$ is a zero-mean disturbance term. Equation (1) allows for lagged returns for all industries across the economy to affect a given industry's excess return, thereby accommodating very general industry interdependencies. However, because we consider a large number of industries ($N = 30$), conventional estimation of (1) yields imprecise parameter estimates and uninformative inferences.

2.1. Adaptive LASSO

To improve estimation and inference for the general predictive regression (1), we employ the adaptive LASSO from the statistical learning literature. Tibshirani (1996) introduced the LASSO as a method for performing both shrinkage and variable selection in regression models with a large number of candidate explanatory variables. A drawback to the LASSO, however, is that it does not necessarily satisfy the oracle properties. Zou's (2006) adaptive LASSO includes parameter weights in the LASSO penalty term and satisfies the oracle properties for appropriate weights.

For (1), the adaptive LASSO estimates are defined as

$$\hat{\mathbf{b}}_i^* = \arg\min \left\| \tilde{r}_{i,t+1} - \sum_{j=1}^{N} b_{i,j} \tilde{r}_{j,t} \right\|^2 + \lambda_i \sum_{j=1}^{N} \hat{w}_{i,j} |b_{i,j}|, \tag{2}$$

where $\tilde{r}_{i,t}$ is the standardized return,[3] $\hat{\mathbf{b}}_i^* = (\hat{b}_{i,1}^*, \ldots, \hat{b}_{i,N}^*)'$ is the N-vector of adaptive LASSO estimates, λ_i is a nonnegative regularization parameter, and $\hat{w}_{i,j}$ is the weight corresponding to $|b_{i,j}|$ for $j = 1, \ldots, N$ in the penalty term. The first component on the right-hand-side of (2) is the familiar sum of squared residuals, while the second component is an ℓ_1 penalty that shrinks the parameter estimates to prevent overfitting. Unlike ridge regression, which relies on an ℓ_2 penalty, the ℓ_1 penalty in (2) allows for shrinkage to zero (for sufficiently large λ) and thus variable selection. We follow Zou (2006) and use the weighting function,

$$\hat{w}_{i,j} = |\hat{b}_{i,j}|^{-\gamma_i} \text{ for } \gamma_i > 0, \tag{3}$$

where $\hat{b}_{i,j}$ is the ordinary least squares (OLS) estimate of $b_{i,j}$ for $j = 1, \ldots, N$ in the general model

[3] That is, $\tilde{r}_{i,t} = (r_{i,t} - \hat{\mu}_i)/\hat{\sigma}_i$, where $\hat{\mu}_i$ and $\hat{\sigma}_i$ are the sample mean and standard deviation, respectively, of $r_{i,t}$.

(1) specified in terms of standardized returns. Intuitively, individual slope coefficients deemed important by OLS are penalized less severely in the regularization problem (2).

We estimate (1) using the adaptive LASSO and monthly excess return data for 30 value-weighted industry portfolios from Kenneth French's Data Library, where the industries are defined based on the Standard Industrial Classification (SIC) system.[4] Table 1 reports summary statistics for the industry portfolio excess returns for 1959:12 to 2014:12. Along with the fact that the industry portfolios are value weighted, starting the sample in 1959:12 mitigates illiquidity and thin-trading concerns.[5] SMOKE displays the highest average monthly excess return (0.96%) and annualized Sharpe ratio (0.55, along with FOOD), while STEEL has the lowest average return (0.29%) and Sharpe ratio (0.14).

Table 2 reports adaptive LASSO estimates of (1) for each industry. After accounting for the lagged predictors, the available estimation sample covers 1960:01 to 2014:12 (660 observations). We select λ_i and γ_i via five-fold cross-validation. Observe that we rescale the LASSO estimates of $b_{i,j}$ in Table 2 to correspond to the scales of the original returns.[6] We also compute a bootstrapped 90% confidence interval for each of the adaptive LASSO estimates.[7] To conserve space, we use asterisks to highlight significant coefficient estimates according to the bootstrapped confidence intervals.[8]

Overall, the adaptive LASSO estimates in Table 2 highlight the importance of lagged industry returns for predicting individual industry returns. The adaptive LASSO selects one to 16 lagged industry returns as return predictors for the 30 individual industries, and multiple lagged industry returns are significant return predictors according to the bootstrapped confidence intervals for nearly all of the individual industries. Four or more lagged industry returns are identified as

[4]The data are available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. We refer to the industries by their Data Library abbreviations (which are given in the notes to Table 1).

[5]We start the sample in 1959:12 to account for the lagged predictors when we estimate (1).

[6]Recall that the returns are standardized in (2); we thus multiply each of the coefficient estimates in (2) by $\hat{\sigma}_i$ to convert the scale of each coefficient back to that of the original return series.

[7]Chaterjee and Lahiri (2011) establish the validity of the bootstrap for the adaptive LASSO.

[8]Note that (1) includes an autoregressive term, so that we guard against spurious cross-industry return predictability due to industry return autocorrelation in conjunction with contemporaneously correlated returns. Boudoukh, Richardson, and Whitelaw (1994), Hameed (1997), and Chordia and Swaminathan (2000) warn of spurious return predictability when analyzing lead-lag relationships among portfolios sorted according to firm size and trading volume.

significant return predictors for 18 individual industries. Furthermore, there are a sizable number of both positive and negative coefficient estimates in Table 2, revealing complex industry interdependencies.

The adaptive LASSO coefficient estimates in Table 2 generally appear economically plausible. For example, lagged FIN returns are significant return predictors for 18 of the 30 individual industries, and all of these coefficient estimates are positive. This makes sense, as firms in many industries rely extensively on financial intermediaries for financing. A positive return shock in the financial industry increases financial firms' capital buffers, so that financial firms become more willing to make credit available to firms throughout the economy; in contrast, adverse shocks to the financial sector curtail intermediaries' capacity to lend, thereby driving up borrowing costs and driving down returns for many industries. Financial sector shocks have direct effects for firms that borrow from financial intermediaries as well as indirect effects for the customers of the borrowing firms, in line with complex industry interdependencies.

Another interesting pattern in Table 2 involves industries located in different stages of the production process. Lagged returns for commodity- and materials-producing industries located in earlier stages of the production chain (such as STEEL, COAL, and, especially, OIL) are often significantly negatively related to returns for industries located in later stages of the production chain (such as CLTHS, RTAIL, and MEALS). These relationships likely stem from supply shocks that raise product prices and returns for sectors located in earlier production stages but squeeze profit margins and lower returns for sectors located in later production stages.

Despite the fact that the adaptive LASSO shrinks the coefficients—many all the way to zero—the R^2 statistics in the last row of Table 2 show that the estimated models have substantial predictive power for monthly industry returns, with the R^2 statistics ranging from 1.32% (CHEMS) to 9.24% (TXTLS). Because monthly stock returns inherently contain a sizable unpredictable component, the degree of monthly stock return predictability will necessarily be limited; Campbell and Thompson (2008) suggest that a monthly R^2 statistic of 0.5% represents economic significance. Many of the R^2 statistics in Table 2 are well above this benchmark, while remaining at plausible levels.[9]

We stress that in a frictionless rational-expectations equilibrium, investors immediately and completely work out the full implications of cash-flow shocks for all industries; in this case, equity prices quickly adjust and compound all of the interindustry effects of cash-flow shocks, so that future industry returns are unaffected. The extensive evidence of individual industry return predictability based on lagged industry returns in Table 2 provides strong evidence that information frictions prevent monthly equity prices from completely adjusting across all industries to cash-flow shocks. Such frictions give rise to gradual information diffusion and cross-industry return predictability.

Of course, the industry return predictability that we detect in Table 2 could also reflect time variation in risk premiums. To shed light on this issue, we augment (1) with five lagged predictor variables similar to those used by Ferson and Harvey (1991, 1999), Ferson and Korajczyk (1995), and Avramov (2005): the market excess return, S&P 500 dividend yield, three-month Treasury bill yield, difference between the yields on a ten-year Treasury bond and a three-month Treasury bill (term spread), and the difference between the yields on BAA- and AAA-rated corporate bonds (default spread).[10] These variables represent a set of popular return predictors from the literature and are often viewed as capturing time-varying risk premiums. We again estimate the augmented model with the adaptive LASSO. When lagged economic variables are included in (1), many of the lagged industry returns that are significant in Table 2 continue to be identified as significant industry return predictors by the adaptive LASSO.[11] Popular measures of time-varying risk premiums thus do not readily account for the predictive power of lagged industry returns, lending further credence to the relevance of information frictions and gradual information diffusion.

[9] Of course, when we estimate the general predictive regression (1) using OLS, the R^2 statistics will necessarily be larger, as the OLS objective function maximizes the R^2 statistic. As we have emphasized, however, OLS estimation of (1) suffers from serious serious statistical drawbacks.

[10] The market excess return is from Kenneth French's Data Library and the other variables are from Global Financial Data.

[11] To conserve space, we do report the complete results, which are available upon request from the authors.

2.2. Cross-Industry Return Predictability and the Real Economy

We next investigate links between cross-industry return predictability and the real economy. We proceed along two dimensions. First, similarly to Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) and Carvalho (2014), we apply network analysis to U.S. industry input-output tables. Denote the matrix of input-output coefficients by $\mathbf{W}$, where a typical element $w_{i,j}$ gives the dollar amount of industry j output used to produce a dollar of industry i output for $i, j = 1, \dots, N$. Input-output tables capture important features of interindustry relationships in the production structure. From a network perspective, each of the N industries constitutes a vertice or node, each nonzero $w_{i,j}$ element is a directed edge representing the intersection of two nodes (in the form of an input-supplying relationship), and the set of nonzero $w_{i,j}$ elements is a collection of weights corresponding to each of the directed edges.

The weighted outdegree of a sector—the sum over all weights for which industry j appears as an input supplier in the network ($d_j = \sum_{i=1}^{N} w_{i,j}$)—provides a natural measure of a sector's importance in the production network. However, this measure only reflects direct network effects relating to immediate input-supplying relationships. Given our emphasis on complex industry interdependencies, we focus on eigenvector centrality (Katz, 1953; Bonacich, 1972), which is a more general measure of a node's importance in the network. In addition to direct input-supplying relationships, the centrality score incorporates indirect network effects that occur when an industry is an input supplier to another industry that itself is an important input supplier to other industries (and so on). For each sector, the centrality score equals the sum of a baseline centrality measure (identical across industries) and the centrality scores of the industries to which it directly supplies inputs. Following Carvalho (2014), we compute the vector of centrality scores as

$$\mathbf{c} = (0.5/N)(\mathbf{I}_N - 0.5\mathbf{W}')^{-1}\boldsymbol{\iota}_N, \tag{4}$$

where $\mathbf{c} = (c_1, \dots, c_N)'$ is the N-vector of centrality scores and $\boldsymbol{\iota}_N$ is an N-vector of ones.[12] In

[12]Industry j's centrality score is given by $c_j = 0.5\sum_{i=1}^{N} w_{i,j}c_i + (0.5/N)$. Taking the N industries together, $\mathbf{c} = 0.5\mathbf{W}'\mathbf{c} + (0.5/N)\boldsymbol{\iota}_N$; solving this expression for $\mathbf{c}$ yields (4).

addition to an industry's own weighted outdegree, its centrality score depends on the weighted outdegrees of all of its direct and indirect customers throughout the production network. Nodes with relatively high centrality scores are important (or central) nodes in the network.

To relate features of the network structure of U.S. production to the results in Table 2, we use annual U.S. input-output tables based on 35 industries for 1995 to 2011 from the Organization for Economic Cooperation and Development (OECD).[13] The OECD industry classifications do not exactly match those for the industry returns in Table 2. Nevertheless, there is enough of a correspondence between the classifications to shed light on the economic underpinnings for some of the important patterns in Table 2. Specifically, as we discussed in Section 2.1, lagged FIN returns as well as lagged returns for commodity- and materials-producing industries located earlier in the production chain (STEEL, COAL, and, OIL) are significant return predictors for numerous individual industries. To the extent that these industries are relatively important nodes in the production network, this helps to explain their pervasive predictive power in Table 2.

Figure 1 depicts annual centrality scores for four industries for 1995 to 2011 computed from the OECD input-output tables: Mining and Quarrying (Panel A); Coke, Refined Petroleum, and Nuclear Fuel (Panel B); Basic Metals and Fabricated Metal (Panel C); and Financial Intermediation (Panel D). The first three industries in Panels A through C of Figure 1 correspond reasonably closely to COAL, OIL, and STEEL, respectively, in Table 2, while the Financial Intermediation industry in Panel D corresponds very closely to FIN in Table 2. As benchmarks, Figure 1 also shows the median centrality score across all 35 OECD-defined industries as well as the 25th and 75th percentiles of the centrality scores across the 35 industries for each year. The figure indicates that sectors with extensive predictive ability in Table 2 are also among the most important nodes in the U.S. production network—especially FIN—as their centrality scores are typically well above the median and 75th percentiles. The widespread predictive ability of these industries' lagged returns in Table 2 thus appears linked to their importance as nodes in the U.S. production network.

Next, we explore parallels in the return dynamics uncovered by the adaptive LASSO estimates

[13]The tables are available at http://www.oecd.org/trade/input-outputtables.htm.

of (1) and dynamics in real economic activity. We examine this issue using industry employment data, which appears to be the only monthly measure of real activity for individual industries that is available for a reasonably long sample. In particular, the Bureau of Labor Statistics (BLS) reports monthly industry employment data for 1990 to 2014, where the industries are defined using the North American Industry Classification System (NAICS). We identify BLS employment series for 26 industries where the NAICS industry definitions match reasonably well with the SIC definitions used to define the industry portfolio returns (and where data beginning in 1990 are available).[14]

To formally explore dynamic links between the predictive power of lagged returns and real activity, we estimate the following model for employment growth for each industry:

$$y_{i,t+1} = \theta_{i,0} + \theta_{i,i} y_{i,t} + \sum_{j \in J_i^*} \theta_{i,j} y_{j,t} + u_{i,t+1}, \tag{5}$$

where $y_{i,t}$ is employment growth for industry i and J_i^* denotes the group of industries selected by the adaptive LASSO in Table 2 for industry i (apart from i, if applicable). In other words, we test whether employment growth for this group of industries jointly Granger causes employment growth for industry i. The idea is that if the predictive ability of lagged industry returns originates from industry interdependencies in the the real economy combined with information frictions (as in HTV's theoretical model), then we would expect the predictive relationships in industry returns to be reflected in parallel predictive relationships in real activity, which we measure using industry employment growth.

For each of the 26 industries for which data are available, Table 3 reports the F-statistic for testing the null hypothesis that $\theta_{i,j} = 0$ for all $j \in J_i^*$ in (5). We reject the null at conventional significance levels for 24 of the 26 individual industries, so that the dynamic relationships among industry returns are also present to a significant extent among industry employment growth. The results in Table 3 further link the extensive evidence of individual industry return predictability based on lagged industry returns in Table 2 to the real economy.

[14] BEER, SMOKE, CARRY, and OTHERS are the excluded industries. The industry employment data are available from the BLS webpage at http://www.bls.gov.

3. Long-Short Industry-Rotation Portfolio

This section reports out-of-sample evidence of cross-industry return predictability in the context of a monthly long-short industry-rotation portfolio, providing an economic valuation for the significant cross-industry return predictability reported in Section 2. We construct a long-short industry-rotation portfolio for 1985:01 to 2014:12 using out-of-sample industry excess return forecasts based on adaptive LASSO estimation of the general predictive regression (1).

We construct the long-short industry-rotation portfolio as follows. We first use data from the beginning of the sample through 1984:12 to estimate (1) for each industry via the adaptive LASSO and generate a set of 30 industry excess return forecasts for 1985:01. We sort the industries in ascending order according to the excess return forecasts and form equal-weighted decile portfolios; we then create a zero-investment portfolio that goes long (short) the top (bottom) decile portfolio. Next, we use data through 1985:01 to compute an updated set of industry excess return forecasts for 1985:02 based on adaptive LASSO estimation of (1), sort the industries according to the forecasts, form equal-weighted decile portfolios, and the zero-investment portfolio again goes long (short) the top (bottom) decile portfolio. Continuing in this fashion, we construct a monthly long-short industry-rotation portfolio guided by out-of-sample industry excess return forecasts for the 1985:01 to 2014:12 out-of-sample period (360 months).

Panel A of Figure 2 shows the log cumulative return for the long-short industry-rotation portfolio based on the adaptive LASSO forecasts. The long-short portfolio earns a sizable average return of 9.22% per annum, which is significant at the 1% level. Furthermore, the long-short portfolio provides quite consistent gains over time and has a maximum drawdown of only 25.79%. A striking feature of the portfolio is its relatively strong performance during business-cycle recessions, especially the recent Great Recession corresponding to the Global Financial Crisis.

For comparison purposes, Panels B and C of Figure 2 show the log cumulative returns for two benchmark long-short portfolios. The first is constructed in the same manner as the long-short portfolio in Panel A, except that we use industry excess return forecasts based on the prevailing mean. The prevailing mean forecast corresponds to the constant expected excess return model—

$r_{i,t+1} = a_i + \varepsilon_{i,t+1}$, that is, no return predictability—and is simply the mean industry excess return based on data from the beginning of the sample through the month of forecast formation. The long-short portfolio based on the prevailing mean forecasts in Panel B of Figure 2 generates an average return of -0.85% per annum (which is insignificant at conventional levels). Furthermore, there are protracted periods in Panel B during which the portfolio performs poorly (for example, from 1991 to 1995 and 1999 to 2004), and the maximum drawdown is a sizable 67.88%. Comparing Panels A and B of Figure 2, constructing long-short industry-rotation portfolios using the information in lagged industry returns generates superior performance relative to ignoring the information in lagged industry returns by assuming that industry returns are unpredictable.

The second benchmark long-short portfolio is simply the market excess return (or market factor, which is also from Kenneth French's Data Library). As indicated in Panel C of Figure 2, the market factor has an average return of 8.33% per annum, which is significant at the 1% level. However, in sharp contrast to our long-short industry-rotation portfolio based on the adaptive LASSO forecasts in Panel A, the market factor typically performs poorly during recessions—particularly the Great Recession—in Panel C and has a maximum drawdown (54.36%) that is nearly twice as large as that of the portfolio based on the adaptive LASSO forecasts.

To differentiate industry interdependencies from industry momentum, we also construct a cross-sectional industry momentum portfolio along the lines of Moskowitz and Grinblatt (1999), who show that cross-sectional industry momentum largely accounts for the well-known cross-sectional momentum in individual firm returns (Jegadeesh and Titman, 1993). Specifically, each month we sort the 30 industries in ascending order according to their cumulative excess returns over the previous twelve months and go long (short) the top (bottom) decile of sorted industries. By analyzing the performance of the cross-sectional industry momentum portfolio, we can gauge the extent to which our industry-rotation portfolio based on cross-industry return predictability in Panel A reflects the cross-sectional industry momentum effect identified by Moskowitz and Grinblatt (1999).

Panel D of Figure 2 shows the log cumulative return for the cross-sectional industry momentum portfolio. Like our long-short industry-rotation portfolios based on the adaptive LASSO forecasts, the average return for the cross-sectional industry momentum portfolio is sizable (9.86% per annum, which is significant at the 5% level). However, unlike our long-short portfolio based on the adaptive LASSO forecasts, the cross-sectional industry momentum portfolio often performs poorly during recessions—principally during the later stages of the Great Recession—and has a substantial maximum drawdown of 66.73%. The behavior of the cross-sectional industry momentum portfolio over the business cycle is similar to that reported by Chordia and Shivakumar (2002) for the Jegadeesh and Titman (1993) cross-sectional momentum portfolio based on individual firm returns. This similarity is perhaps not surprising, given the close relationship between cross-sectional industry momentum and cross-sectional momentum in individual firm returns documented by Moskowitz and Grinblatt (1999). The differences between Panels A and D of Figure 2 clearly indicate that our long-short industry-rotation portfolio based on the adaptive LASSO forecasts captures something quite different from cross-sectional industry momentum.

Next, we test whether exposures to equity risk factors can account for the behavior of our long-short industry-rotation portfolio based on the adaptive LASSO forecasts. We augment the Carhart (1997) four-factor model with the Pástor and Stambaugh (2003) liquidity factor and Asness, Frazinni, and Pedersen (2014) quality factor:

$$r_{p,t} = \alpha + \beta_{\mathrm{MKT}}\mathrm{MKT}_t + \beta_{\mathrm{SMB}}\mathrm{SMB}_t + \beta_{\mathrm{HML}}\mathrm{HML}_t + \beta_{\mathrm{UMD}}\mathrm{UMD}_t + \beta_{\mathrm{LIQ}}\mathrm{LIQ}_t + \beta_{\mathrm{QMJ}}\mathrm{QMJ}_t + e_{p,t}, \tag{6}$$

where $r_{p,t}$ is the long-short industry-rotation portfolio return, MKT_t is the market factor, SMB_t (HML_t) is the Fama and French (1993) "small-minus-big" size ("high-minus-low" value) factor, UMD_t is the "up-minus-down" momentum factor, LIQ_t is the liquidity factor, and QMJ_t is the "quality-minus-junk" factor.[15] The factors included in (6) cover a broad swath of potentially relevant risk factors for industry portfolios. Table 4 reports estimation results for (6).

[15] All of the factors are measured as returns on zero-investment long-short portfolios. Data for the size, value, and momentum factors are from Kenneth French's Data Library. Data for the liquidity factor are from Ľuboš Pastor's webpage at http://faculty.chicagobooth.edu/lubos.pastor/research/. Data for the quality-minus-junk factor are from AQR's Data Sets webpage at https://www.aqr.com/library/data-sets.

Our long-short industry-rotation portfolio based on the adaptive LASSO forecasts exhibits significant negative exposure to the market factor, with a market beta of -0.19, so that our portfolio provides a hedge against the broad equity market. The betas for the remaining factors are all statistically and economically insignificant. The set of six factors explains relatively little of the variation in portfolio returns, with an R^2 statistic of only 4.89%. Moreover, our long-short industry-rotation portfolio generates a statistically significant (at the 1% level) and economically sizable annualized alpha of 11.32%. The signals provided by past lagged industry returns as captured by the adaptive LASSO forecasts thus appear highly informative for generating risk-adjusted average returns.

Table 4 also reports estimation results for (6) when $r_{p,t}$ is, in turn, the long-short industry-rotation portfolio based on the prevailing mean forecasts and the cross-sectional industry momentum portfolio. The long-short industry-rotation portfolio based on the prevailing mean forecasts exhibits significant negative exposure to the value factor and significant positive exposures to the momentum, liquidity, and quality factors. The portfolio fails to generate significant alpha, so that a strategy of simply going long (short) industries with the historically highest (lowest) average returns does not produce meaningful risk-adjusted average returns.

In line with Moskowitz and Grinblatt (1999), the cross-sectional industry momentum portfolio displays a statistically significant and economically substantial exposure (1.14) to the momentum factor, while the annualized alpha for the cross-sectional industry momentum portfolio is insignificant. The differences in results in Table 4 between our long-short industry-rotation portfolio based on the adaptive LASSO forecasts and the cross-sectional industry momentum portfolio confirm that the former captures a phenomenon that is very different from cross-sectional industry momentum.

In sum, Table 4 reveals that the substantial average return for our long-short industry-rotation portfolio based on the adaptive LASSO forecasts in Panel A of Figure 2 cannot be explained by exposures to a wide variety of equity risk factors. Indeed, because the portfolio evinces negative exposure to the market factor and insignificant exposures to the other factors, its risk-adjusted average return in Table 4 (11.32%) is even higher than its unadjusted average return in Panel A of Figure 2 (9.22%). Along this line, because the long-short industry-rotation portfolio based on the adaptive LASSO forecasts performs very well during the recent Global Financial Crisis, it is difficult to view the portfolio's sizable average return as a "crisis" or "crash" risk premium.[16] The evidence in this section complements that in Section 2 and supports that notion that the predictive power of lagged industry returns for individual industry returns stems primarily from industry interdependencies combined with information frictions.

4. Alternative Approaches

In this section, we examine the robustness of the evidence for cross-industry return predictability. Specifically, we consider two alternative approaches for estimating predictive regressions with a multitude of potential predictors: principal components and PLS.

4.1. Principal Components

The principal component approach assumes that a small number of latent factors underly industry returns:

$$\tilde{r}_{j,t} = \sum_{k=1}^{K} \psi_{j,k} f_{k,t} + e_{j,t} \quad \text{for} \quad j = 1,\ldots,N;\ t = 1,\ldots,T; \tag{7}$$

where $\tilde{r}_{j,t}$ is the standardized excess return for industry j, $\mathbf{f}_t = (f_{1,t},\ldots,f_{K,t})'$ is a K-vector of latent factors ($K \ll N$) that are common across industries, $\boldsymbol{\psi}_j = (\psi_{j,1},\ldots,\psi_{j,K})'$ is a K-vector of factor loadings for industry j, and $e_{j,t}$ is a zero-mean disturbance term. A strict factor structure assumes that the disturbance term in (7) is serially uncorrelated as well as uncorrelated across industries, while an approximate factor structure permits a limited degree of correlation along these dimensions (Chamberlain and Rothschild, 1983); in either case, principal components provide consistent estimates of $\mathbf{f}_t$ and $\boldsymbol{\psi}_j$ (Bai, 2003). In our context, the estimated factors capture key

[16] Furthermore, the results are qualitatively unchanged when we include additional risk factors in (6), such as the Moskowitz, Ooi, and Pedersen (2012) time-series momentum factor, Frazzini and Pedersen (2014) betting against beta factor, and Fama and French (2015) profitability and investment factors.

comovements in lagged industry returns resulting from a variety of shocks that affect multiple industries and provide a convenient means for succinctly incorporating the information in the entire set of industry returns.

Instead of including all of the individual lagged industry returns as regressors in a predictive regression, the lagged estimated factors serve as regressors in a streamlined specification:

$$r_{i,t+1} = a_i + \sum_{k=1}^{K} b_{i,k} \hat{f}_{k,t} + \varepsilon_{i,t+1}, \tag{8}$$

where $\hat{f}_{k,t}$ is the principal component estimate of $f_{k,t}$ for $k = 1,\ldots,K$ in (7). Equation (8) provides a parsimonious specification for incorporating information from all of the lagged industry returns, alleviating the problems associated with the many correlated regressors in (1).[17] Bai and Ng (2006) show that the use of estimated factors as regressors in (8) does not affect conventional asymptotic inferences, so that inferences based on OLS estimates and familiar standard errors are valid in large samples.

We select K using the Bai and Ng (2002) modified information criteria for determining the number of relevant factors. Considering a maximum value of three to ensure a reasonably parsimonious specification for (8), the modified information criteria unanimously select $K = 3$. To provide economic insight into the estimated factors, Figure 3 shows the estimated loadings for each industry on each of the factors.[18] The industries load fairly uniformly on the first factor, so that the first factor represents broad comovements in industry returns, presumably reflecting common shocks that are generally bullish or bearish for industry returns.

The loadings on the second and third factors in Figure 3 are much less uniform. STEEL, FABPR, MINES, COAL, and OIL (FOOD, BEER, SMOKE, HSHLD, HLTH, and RTAIL) display sizably positive (negative) loadings on the second factor; SMOKE, COAL, OIL, and UTIL (GAMES, CLTHS, TXTLS, AUTOS, BUSEQ, and RTAIL) exhibit substantially positive (negative)

[17] In different contexts, Ludvigson and Ng (2007) and Neely, Rapach, Tu, and Zhou (2014) predict broad stock market returns using a small set of factors extracted from a large number of economic variables.

[18] We standardize the estimated factors to have zero mean and unit variance. This is solely for interpretational convenience and has no effect on inferences in (8).

loadings on the third factor. The second and third factors thus appear to capture complex industry interdependencies that have bullish implications for some industries and bearish implications for others. Generally speaking, industries with positive (negative) loadings on the second and third factors are concentrated in the earlier (later) stages of production processes, so that the second factor plausibly represents various supply shocks that raise product prices and returns for sectors located in earlier production stages while squeezing profit margins and lowering return for sectors in later production stages. These production-chain patterns are reminiscent of those that we identified in Section 2.1.

Table 5 reports OLS estimates of $b_{i,1}$, $b_{i,2}$, and $b_{i,3}$ in (8) for each of the 30 industries. All of the $\hat{b}_{i,1}$ estimates in the second and seventh columns are positive, and over half are significant at conventional levels according to the t-statistics in brackets. GAMES, BOOKS, CLTHS, TXTLS, CNSTR, AUTOS, CARRY, WHLSL, and MEALS are among the industries that respond most strongly to the lagged first factor. The first factor represents common shocks that have relatively similar effects across industries in a given month. If investors readily recognize all of the interindustry effects associated with these shocks, equity prices should adjust in the same direction across industries within the month to fully impound the interindustry effects. However, the significant $\hat{b}_{i,1}$ estimates in Table 5 suggest that such common shocks continue to significantly affect returns in the same direction for a number of industries in the subsequent month, consistent with the gradual diffusion of information across industries.

The $\hat{b}_{i,2}$ estimates in the third and eighth columns of Table 5 are predominantly negative (STEEL, FABPR, COAL, and OIL are the exceptions), and ten of these estimates are significant at conventional levels. Industries with the most sizable negative responses to the lagged second factor include BEER, BOOKS, HSHLD, CLTHS, RTAIL, and MEALS. In general, shocks that raise (lower) returns in a given month for industries located in earlier (later) stages of production processes continue to negatively affect returns in the subsequent month for industries located in later stages of production processes. All but one of the $\hat{b}_{i,3}$ estimates in the fourth and ninth columns are negative (SMOKE is the exception), and 19 are significant. GAMES, BOOKS,

CLTHS, TXTLS, AUTOS, COAL, PAPER, WHLSL, and MEALS evince the most sizable negative responses to the lagged third factor. Recall from Panels B and C of Figure 3 that the second and third factors have asymmetric effects across industries. Again, if investors immediately realize the full implications of these industry interdependencies, equity prices should adjust completely within the month to reflect these implications; the significant $\hat{b}_{i,2}$ and $\hat{b}_{i,3}$ estimates provide further evidence against the complete adjustment of equity prices across industries within a given month, thereby supporting the relevance of gradual information diffusion.

The R^2 statistics in Table 5 appear economically sizable in light of the Campbell and Thompson (2008) benchmark of 0.5%. In fact, 13 of the R^2 statistics are greater than 2% (and those for GAMES, BOOKS, TXTLS, and MEALS are above 4%), so that the degree of return predictability appears quite strong in a number of industries based on the principal component approach. These results are similar to those in Table 2, where we find strong return predictability for numerous industries based on adaptive LASSO estimation of the general predictive regression (1).[19]

As in Section 3, we form a long-short industry-rotation portfolio using predictive regression forecasts of industry excess returns as inputs, where we now compute out-of-sample industry excess return forecasts based on (8) instead of adaptive LASSO estimation of (1).[20] Panel E of Figure 2 depicts the log cumulative return for the long-short industry-rotation portfolio based on industry excess return forecasts generated via the principal component approach. Similarly to the industry-rotation portfolio based on the adaptive LASSO forecasts in Panel A, the portfolio based on the principal component forecasts exhibits impressive performance in Panel E. The portfolio produces an average return of 10.57% per annum, which is significant at the 1% level, and provides gains on a reasonably consistent basis, with the only significant drawdown occurring near the mid 2000s.[21] Furthermore, like the portfolio based on the adaptive LASSO forecasts in Panel A,

[19]The results in Table 5 are very similar when we include the lagged first principal component extracted from the five economic variables from Section 2.1 as an additional regressor in (8), so that time-varying risk premiums do not readily explain the results in Table 5. The complete results are available from the authors upon request.

[20]To avoid a "look-ahead" bias in the excess return forecasts, we only use data available at the time of forecast formation when computing the principal components that appear as regressors in (8).

[21]However, the maximum drawdown for the portfolio based on the principal components forecasts is nearly twice as large as that for the portfolio based on the adaptive LASSO forecasts.

the portfolio based on the principal component forecasts in Panel E performs very well during recessions, most notably the Great Recession. Again like the long-short industry-rotation portfolio based on the adaptive LASSO forecasts, Table 4 shows that the industry-rotation portfolio based on the principal component forecasts exhibits limited exposures to equity risk factors and delivers a statistically and economically significant annualized alpha of 11.18%.

4.2. Partial Least Squares

As a final robustness check, we incorporate information from the entire set of lagged industry returns in a predictive regression framework using PLS. The principal component approach in Section 4.1 estimates latent factors with the objective of explaining the maximum amount of variability in the predictors themselves. As such, principal components do not directly account for the relationship between the latent factors and the target variable (i.e., the predictand) when estimating the factors. Kelly and Pruitt (2013, 2015) develop a three-pass regression filter (3PRF) implementation of PLS to estimate target-relevant latent factors.[22] In our context, for a given industry we compute a unique target-relevant factor from the entire set of industry returns that is linked to the given industry's return in the subsequent month.

To estimate a target-relevant factor for industry i, we first estimate the following time-series regression for each $j = 1, \dots, N$:

$$r_{j,t} = \phi^i_{0,j} + \phi^i_{1,j} r_{i,t+1} + e^i_{j,t} \quad \text{for} \quad t = 1, \dots, T-1. \tag{9}$$

We then estimate the following cross-sectional regression for each $t = 1, \dots, T$:

$$r_{j,t} = \phi^i_{0,t} + g_{i,t}\,\hat{\phi}^i_{1,j} + u_{j,t} \quad \text{for} \quad j = 1, \dots, N, \tag{10}$$

where $\hat{\phi}^i_{1,j}$ denotes the OLS estimate of $\phi^i_{1,j}$ in (9). For each t, the PLS estimate of the target-relevant factor is equivalent to the OLS estimate of $g_{i,t}$ in (10). Finally, the lagged target-relevant

[22] PLS is actually a special case of the 3PRF.

factor serves as the predictor in the following bivariate predictive regression:

$$r_{i,t+1} = a_i + b_i \hat{g}_{i,t} + \varepsilon_{i,t+1}, \tag{11}$$

where $\hat{g}_{i,t}$ is the PLS estimate of the target-relevant factor for industry i.

Table 6 reports OLS estimates of b_i in (11) for each industry.[23] All but one of the $\hat{b}_i$ estimates in the second, fifth, and eighth columns of Table 6 are significant at the 1% level, and the other is significant at the 5% level. In addition, all but one of the R^2 statistics in the third, sixth, and ninth columns are above 2% (and six are above 4%), so that the degree of industry return predictability is economically significant. Complementing the results in Tables 2 and 5, information in lagged industry returns—as reflected in the target relevant factors—appears statistically and economically significant for predicting industry returns.[24]

Section 2.1 accommodates complex industry interdependences via adaptive LASSO estimation of the general predictive regression (1), while the common latent factor approach in Section 4.1 allows for such interdependencies by considering three common latent factors. For the target-relevant factor approach, the $\phi^i_{1,j}$ coefficients in (9)—which can be viewed as target-relevant loadings of a sort—also permit rich industry interdependencies: the vector of estimated target-relevant loadings, $\hat{\boldsymbol{\phi}}^i_1 = (\hat{\phi}^i_{1,1}, \ldots, \hat{\phi}^i_{1,N})'$, is unique to industry i and readily accommodates positive and negative correlations between $r_{j,t}$ and $r_{i,t+1}$. Indeed, the $\phi^i_{1,j}$ estimates in (9) are negative for a number of the i-j pairs.[25] Most of the negative estimates occur when j (i) is an industry located relatively early (late) in the production chain. This accords with the pattern in Table 2 (Figure 3 and Table 5) based on the adaptive LASSO (principal component) approach.

[23] For convenience and without loss of generality, we again standardize the estimated target-relevant factors. The t-statistics in Table 6 are computed based on Theorem 5 from Kelly and Pruitt (2015).

[24] We also estimated additional target-relevant factors for each industry using the Kelly and Pruitt (2015) Automatic Proxy-Selection Algorithm. The additional estimated factors, however, produce only modest gains in predictive accuracy. Furthermore, we estimated a target-relevant factor for each industry from the set of five economic variables from Section 2.1 and included this factor as an additional regressor in (11). The $\hat{b}_i$ estimates remain very similar to those in Table 6 with the inclusion of the additional factor. The complete results are available from the authors upon request.

[25] To conserve space, we do not report the complete set of $\phi^i_{1,j}$ estimates, as there are $30^2 = 900$ $\phi^i_{1,j}$ estimates (for $i, j = 1, \ldots, 30$). The complete results are available upon request from the authors.

Finally, as in Sections 3 and 4.1, we construct a long-short industry-rotation portfolio using predictive regression forecasts of industry excess returns as inputs, where we now compute the forecasts using (11).[26] Panel F of Figure 2 shows the log cumulative return for the long-short industry-rotation portfolio based on the PLS forecasts. Like the portfolios based on the adaptive LASSO and principal component forecasts in Panels A and E, respectively, the portfolio based on the PLS forecasts in Panel F generates a significant average return (8.25% per annum) and performs well during recessions.[27] Furthermore, Table 4 shows that the industry-rotation portfolio based on the PLS forecasts evinces insignificant exposures to the equity risk factors and produces a statistically and economically significant annualized alpha of 9.92%.

In sum, the results for the principal component and PLS approaches provide additional evidence for the statistical and economic significance of cross-industry return predictability. The results also confirm the complex nature of industry interdependencies and point to the relevance of gradual information diffusion across industries.

5. Conclusion

We analyze the importance of industry interdependencies for cross-industry return predictability. Generalizing the customer-supplier links studied by Cohen and Frazzini (2008) and Menzly and Ozbas (2010), we treat one industry as economically linked to another industry if its return can be predicted by the lagged return of the other, thereby accommodating complex industry interdependencies. To implement our approach, we begin with a predictive regression model for each industry that includes lagged returns for all 30 of the industries we consider as regressors. Because conventional estimation of predictive regressions with such a plethora of correlated predictors is fraught with statistical problems, we estimate the general predictive regressions using

[26] Again, to avoid a look-ahead bias in the excess return forecasts, we only use data available at the time of forecast formation when computing the target-relevant factor that appears as a regressor in (11).

[27] However, the portfolio based on the PLS forecasts produces a maximum drawdown of 61.61%, which is larger than that of the portfolio based on the principal component forecasts and much larger than that of the portfolio based on the adaptive LASSO forecasts.

the adaptive LASSO, which reflects recent advances in statistical learning.

The adaptive LASSO estimates provide extensive evidence of individual industry return predictability based on lagged industry returns. In support of the relevance of complex industry interdependencies, we uncover both positive and negative dynamic relationships among industry returns. The overall degree of industry return predictability is economically significant, and the parameter estimates are economically sensible. Using network analysis, we find that industries with the most pervasive predictive power are among the key central nodes in the U.S. production network. We also find important similarities in interindustry return and employment dynamics, further linking our empirical evidence of cross-industry return predictability to the real economy. Two alternative approaches for testing return predictability with many predictors, principal components and PLS, provide further evidence of individual industry return predictability based on lagged industry returns and again highlight the relevance of complex industry interdependencies.

Using the adaptive LASSO approach, we compute out-of-sample industry return forecasts based on lagged industry returns to construct a zero-investment industry-rotation portfolio that goes long (short) industries with the highest (lowest) forecasted returns. The long-short industry-rotation portfolio earns a significant average return and performs well during business-cycle recessions, particularly the recent Great Recession. The long-short portfolio is also weakly correlated with a wide variety of equity risk factors and delivers an annualized alpha of over 11%. The information in lagged industry returns thus proves valuable for generating risk-adjusted returns.

In a frictionless rational-expectations equilibrium, investors readily realize the full implications of cash-flow shocks for all industries, so that equity prices promptly impound all of the complex interindustry effects of cash-flow shocks, and lagged industry returns do not affect individual industry returns. Our extensive evidence of individual industry return predictability based on lagged industry returns thus points to the existence of significant information frictions in the presence of complex industry interdependencies. Such information frictions imply the gradual diffusion of information across industries, a delay in the complete impounding of complex industry interdependencies in equity prices, and cross-industry return predictability.

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Table 1
Summary statistics, monthly industry portfolio excess returns, 1959:12–2014:12.

The table reports summary statistics for excess returns on 30 value-weighted industry portfolios from Kenneth French's Data Library. Excess returns are computed relative to the CRSP risk-free rate. The industry abbreviations are as follows: FOOD = Food Products; BEER = Beer and Liquor; SMOKE = Tobacco Products; GAMES = Recreation; BOOKS = Printing and Publishing; HSHLD = Consumer Goods; CLTHS = Apparel; HLTH = Healthcare, Medical Equipment, and Pharmaceutical Products; CHEMS = Chemicals; TXTLS = Textiles; CNSTR = Construction and Construction Materials; STEEL = Steel Works Etc.; FABPR = Fabricated Products and Machinery; ELCEQ = Electrical Equipment; AUTOS = Automobiles and Trucks; CARRY = Aircraft, Ships, and Railroad Equipment; MINES = Precious Metals, Non-Metallic, and Industrial Metal Mining; COAL = Coal; OIL = Petroleum and Natural Gas; UTIL = Utilities; TELCM = Communication; SERVS = Personal and Business Services; BUSEQ = Business Equipment; PAPER = Business Supplies and Shipping Containers; TRANS = Transportation; WHLSL = Wholesale; RTAIL = Retail; MEALS = Restaurants, Hotels, and Motels; FIN = Banking, Insurance, Real Estate, and Trading; OTHER = Everything Else.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Industry portfolio	Mean (%)	Standard deviation (%)	Minimum (%)	Maximum (%)	Annualized Sharpe ratio	Industry portfolio	Mean (%)	Standard deviation (%)	Minimum (%)	Maximum (%)	Annualized Sharpe ratio
FOOD	0.69	4.39	−18.15	19.89	0.55	CARRY	0.72	6.36	−31.10	23.39	0.39
BEER	0.71	5.15	−20.19	25.53	0.48	MINES	0.52	7.41	−34.59	35.14	0.24
SMOKE	0.96	6.10	−25.32	32.38	0.55	COAL	0.83	9.79	−38.09	45.55	0.29
GAMES	0.69	7.23	−33.40	34.50	0.33	OIL	0.67	5.32	−18.96	23.70	0.43
BOOKS	0.55	5.82	−26.56	33.13	0.33	UTIL	0.49	4.01	−12.94	18.26	0.42
HSHLD	0.57	4.81	−22.24	18.22	0.41	TELCM	0.52	4.64	−16.30	21.20	0.39
CLTHS	0.70	6.47	−31.50	31.79	0.38	SERVS	0.68	6.59	−28.67	23.38	0.36
HLTH	0.67	4.95	−21.06	29.01	0.47	BUSEQ	0.58	6.80	−32.16	24.72	0.29
CHEMS	0.52	5.50	−28.60	21.68	0.33	PAPER	0.52	5.09	−27.74	21.00	0.35
TXTLS	0.68	7.09	−33.11	59.03	0.33	TRANS	0.60	5.76	−28.50	18.50	0.36
CNSTR	0.51	6.02	−28.74	25.02	0.29	WHLSL	0.63	5.65	−29.24	17.53	0.39
STEEL	0.29	7.24	−33.10	30.30	0.14	RTAIL	0.67	5.42	−29.77	26.48	0.43
FABPR	0.56	6.13	−31.62	22.86	0.32	MEALS	0.70	6.19	−31.84	27.31	0.39
ELCEQ	0.72	6.25	−32.80	23.21	0.40	FIN	0.60	5.42	−22.53	20.59	0.38
AUTOS	0.47	6.73	−36.49	49.56	0.24	OTHER	0.38	5.87	−28.02	19.93	0.22

Table 2
Adaptive LASSO predictive regression results, monthly industry portfolio excess returns, 1960:01–2014:12.

The table reports adaptive LASSO estimates of $b_{i,j}$ and the R^2 statistic for the general predictive regression model,

$$r_{i,t+1} = a_i + \sum_{j=1}^{30} b_{i,j}\, r_{j,t} + \varepsilon_{i,t+1},$$

where $r_{i,t}$ is the excess return on industry portfolio i. – indicates that the lagged industry portfolio return was not selected by the adaptive LASSO. * indicates significance according to bootstrapped 90% confidence intervals.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	i									
j	FOOD	BEER	SMOKE	GAMES	BOOKS	HSHLD	CLTHS	HLTH	CHEMS	TXTLS
FOOD	–	0.10*	–	–	–	–	–	–	–	–
BEER	–	–	–	–	–	–	–	–	–	–
SMOKE	–	–	–	–	–	–	–	–	–	–
GAMES	–	–	–	–	–	–	–	–	–	–
BOOKS	–	–	–	0.17*	–	–	0.02	0.06*	–	–
HSHLD	–	–	–	–	–	–	−0.06*	–	–	−0.01*
CLTHS	–	0.02	–	–	–	0.09*	0.03	–	0.06*	0.04
HLTH	–	–	–	–	–	–	–	–	–	–
CHEMS	–	–	–	–	–	–	0.13*	–	–	–
TXTLS	–	–	–	–	–	–	–	–	–	–
CNSTR	–	–	–	–	–	–	0.05	–	–	–
STEEL	–	–	–	–	–	−0.02*	−0.08*	–	–	–
FABPR	0.03*	–	–	–	–	–	–	–	–	0.10*
ELCEQ	–	–	–	–	–	–	−0.19*	–	–	−0.10*
AUTOS	–	–	–	–	–	–	–	–	–	0.08
CARRY	–	–	0.11*	–	–	–	0.02	–	–	–
MINES	–	–	–	–	–	–	–	−0.03*	–	–
COAL	−0.04*	−0.03*	–	–	–	−0.04*	−0.06*	−0.02*	–	−0.06*
OIL	−0.04*	–	−0.07*	−0.03*	−0.10*	–	−0.11*	−0.04	−0.05	−0.13*
UTIL	0.10*	–	0.18*	–	–	–	0.12*	0.08*	–	–
TELCM	–	–	–	–	–	–	−0.08*	–	–	–
SERVS	–	–	−0.10*	–	0.08*	–	0.13*	–	–	–
BUSEQ	–	–	–	–	–	–	0.10*	–	–	–
PAPER	–	–	–	–	–	–	–	–	–	–
TRANS	–	–	–	–	–	–	–	–	–	–
WHLSL	–	–	–	–	–	–	–	–	–	–
RTAIL	0.01	–	–	–	–	–	0.07	–	–	0.09*
MEALS	–	–	–	–	–	–	–	–	–	–
FIN	–	–	–	0.09*	0.14*	0.04*	0.07	–	–	0.22*
OTHER	–	–	–	–	–	–	–	–	–	–
R^2	2.56%	2.16%	4.17%	4.81%	5.30%	3.50%	8.18%	2.44%	1.32%	9.24%

Table 2 (continued)

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	i									
j	CNSTR	STEEL	FABPR	ELCEQ	AUTOS	CARRY	MINES	COAL	OIL	UTIL
FOOD	–	–	–	–	–	–	−0.08	–	–	0.02
BEER	–	–	–	–	–	–	–	−0.16*	–	−0.07*
SMOKE	–	–	–	–	–	–	0.02	−0.01	–	–
GAMES	–	–	–	–	–	–	−0.13*	–	–	–
BOOKS	–	–	–	–	–	–	–	0.12*	–	–
HSHLD	–	–	–	–	−0.15*	–	–	–	−0.07*	−0.04
CLTHS	–	–	–	–	–	–	–	–	–	–
HLTH	–	–	–	–	–	–	–	–	−0.01*	−0.02
CHEMS	–	–	–	–	–	–	–	–	–	–
TXTLS	–	–	–	–	–	–	–	–	–	–
CNSTR	–	–	–	–	–	–	–	–	–	−0.13*
STEEL	–	–	–	–	–	–	−0.09*	–	–	–
FABPR	–	–	–	–	–	0.07*	0.16*	–	–	0.07*
ELCEQ	–	–	–	–	–	–	–	–	–	–
AUTOS	–	–	–	–	–	–	0.09*	–	–	–
CARRY	–	–	–	–	–	–	0.09	–	0.07*	0.06*
MINES	–	–	–	–	–	–	–	–	–	−0.03
COAL	−0.03*	–	–	–	–	−0.03*	−0.04	0.01	–	–
OIL	−0.07*	–	–	−0.07*	−0.08*	−0.02*	–	−0.07*	–	−0.05*
UTIL	0.04	–	–	–	–	–	0.10	–	–	0.06*
TELCM	–	–	–	–	–	–	−0.11*	–	–	0.06*
SERVS	–	–	–	–	–	–	0.09	0.01	–	–
BUSEQ	–	–	–	–	0.05*	–	0.02	–	–	–
PAPER	–	–	–	–	–	–	–	0.07	–	–
TRANS	–	–	–	–	–	0.06*	–	–	–	–
WHLSL	–	–	–	–	–	–	−0.11	–	–	−0.10*
RTAIL	–	–	–	–	0.16*	–	–	–	–	–
MEALS	–	–	–	–	–	–	0.10	–	–	–
FIN	0.20*	0.11*	0.10*	0.11*	0.14*	0.06	–	–	–	0.10*
OTHER	–	–	–	–	–	–	–	–	–	0.07*
R^2	4.48%	1.42%	1.52%	1.72%	5.32%	3.12%	4.31%	2.11%	1.46%	6.96%

Table 2 (continued)

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	i									
j	TELCM	SERVS	BUSEQ	PAPER	TRANS	WHLSL	RTAIL	MEALS	FIN	OTHER
FOOD	–	–	–	–	–	−0.07*	–	–	–	–
BEER	−0.01*	–	–	–	−0.05	–	–	–	−0.05	–
SMOKE	–	−0.02	−0.07*	–	–	−0.02	–	–	–	−0.04
GAMES	–	–	–	–	−0.05*	–	–	–	−0.05	–
BOOKS	0.01	0.02	0.09*	–	0.09*	0.14*	–	0.08	0.07	–
HSHLD	–	–	–	–	−0.04	–	–	–	−0.03	–
CLTHS	–	–	–	0.02*	–	–	–	0.11*	0.05	0.05*
HLTH	–	–	–	–	–	–	–	–	–	–
CHEMS	–	–	–	–	–	–	0.03	–	–	–
TXTLS	–	–	–	–	–	–	–	–	–	–
CNSTR	–	–	–	–	–	–	–	–	–	–
STEEL	–	−0.04	−0.01*	–	−0.10*	–	−0.11*	−0.08*	−0.09*	–
FABPR	–	–	–	–	0.15*	–	–	–	0.10*	–
ELCEQ	–	–	–	−0.03*	−0.09*	–	−0.08*	–	–	–
AUTOS	–	–	–	–	–	–	–	–	–	–
CARRY	–	–	–	–	–	0.03	–	–	–	–
MINES	–	–	–	–	–	–	–	–	–	–
COAL	–	–	–	−0.02	–	−0.02	–	−0.05*	−0.02	–
OIL	−0.08*	−0.06*	−0.01	−0.07*	−0.14*	−0.13*	−0.08*	−0.11*	−0.12*	−0.04*
UTIL	0.06*	–	0.09*	–	0.09*	0.15*	0.04	0.04	0.11*	–
TELCM	–	–	–	–	–	−0.05*	–	–	–	–
SERVS	–	–	–	0.01	0.06*	0.04	0.05	0.07*	0.06	0.01
BUSEQ	–	–	–	–	–	–	0.07*	0.04	0.01	–
PAPER	–	–	–	–	–	–	–	–	–	–
TRANS	–	–	–	–	–	–	–	–	–	–
WHLSL	–	–	–	–	−0.03	–	–	–	−0.12*	–
RTAIL	0.04*	–	–	–	–	–	0.08*	–	–	–
MEALS	−0.09*	–	–	–	–	–	–	0.02	−0.02	–
FIN	0.11*	0.16*	0.02	0.13*	0.16*	0.09*	0.08*	0.03	0.13*	0.13*
OTHER	–	–	–	–	0.04	–	0.02	–	0.09*	–
R^2	3.28%	2.25%	2.59%	3.36%	5.74%	6.75%	5.49%	7.69%	6.52%	3.70%

Table 3
Granger causality test results, monthly industry employment growth, 1990:03–2014:12.

The table reports Granger causality test results based on the multivariate regression model,

$$y_{i,t+1} = \theta_{i,0} + \theta_{i,i}\, y_{i,t} + \textstyle\sum_{j \in J_i^*} \theta_{i,j}\, y_{j,t} + u_{i,t+1},$$

where $y_{i,t}$ is employment growth for industry i and J_i^* denotes the group of industries selected by the adaptive LASSO in Table 2 for industry i (apart from i, if applicable). Employment growth data are from the Bureau of Labor Statistics. The second and fifth columns give the industries contained in J_i^*. The third and sixth columns report a heteroskedasticity-consistent F-statistic for testing the null hypothesis that $\theta_{i,j} = 0$ for all $j \in J_i^*$; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

(1)	(2)	(3)	(4)	(5)	(6)
i	J_i^*	F-stat.	i	J_i^*	F-stat.
FOOD	FABPR, COAL, OIL, UTIL	0.40	CARRY	–	–
BEER	–	– –	MINES	GAMES, STEEL, FABPR, AUTOS, TELCM	7.11^{***} –
SMOKE	–	–	COAL	BOOKS, OIL	6.83^{***}
GAMES	BOOKS, OIL, FIN	3.15^{**}	OIL	HSHLD, HLTH	2.79^{*}
BOOKS	OIL, SERVS, FIN	21.03^{***}	UTIL	CNSTR, FABPR, OIL, TELCM, FIN, WHLSL, FIN	3.06^{***}
HSHLD	CLTHS, STEEL, COAL, FIN	9.56^{***}	TELCM	OIL, UTIL, RTAIL, MEALS, FIN	3.55^{***}
CLTHS	HSHLD, CHEMS, STEEL, ELCEQ, COAL, OIL, UTIL, TELCM, SERVS, BUSEQ	3.93^{***}	SERVS	OIL, FIN	4.15^{**}
HLTH	BOOKS, MINES, COAL, UTIL	2.05^{*}	BUSEQ	BOOKS, STEEL, UTIL	2.69^{**}
CHEMS	CLTHS	5.26^{**}	PAPER	CLTHS, ELCEQ, OIL, FIN	11.71^{***}
TXTLS	HSHLD, FABPR, ELCEQ, COAL, OIL, RTAIL, FIN	7.44^{***}	TRANS	GAMES, BOOKS, STEEL, FABPR, ELCEQ, OIL, UTIL, SERVS, FIN	4.62^{***}
CNSTR	COAL, OIL, FIN	15.06^{***}	WHLSL	FOOD, BOOKS, OIL, UTIL, TELCM, FIN	4.26^{***}
STEEL	FIN	8.21^{***}	RTAIL	STEEL, ELCEQ, OIL, BUSEQ, FIN	6.34^{***}
FABPR	FIN	2.00	MEALS	CLTHS, STEEL, COAL, OIL, SERVS	3.81^{***}
ELCEQ	OIL, FIN	2.52^{*}	FIN	STEEL, FABPR, OIL, UTIL, WHLSL	2.71^{**}
AUTOS	HSHLD, OIL, BUSEQ, RTAIL, FIN	5.61^{***}	OTHER	–	–

Table 4
Multifactor model estimation results, 1985:01–2014:12.

The table reports multifactor model estimation results for long-short industry-rotation portfolios. At the end of each month, we sort 30 industry portfolios according to their forecasted excess returns for the subsequent month. The industry excess returns forecasts are based on predictive regression models estimated via the adaptive LASSO, principal components, or PLS, as well as prevailing mean forecasts. We then form equal-weighted decile portfolios based on the sorts and each long-short industry-rotation portfolio is a zero-investment portfolio that goes long (short) the top (bottom) decile portfolio. We also sort the 30 industry portfolios according to the cumulative return over the previous twelve months; the cross-sectional industry momentum portfolio is a zero-investment portfolio that goes long (short) the top (bottom) decile portfolio. The multifactor model is given by

$$r_{p,t} = \alpha + \beta_{\text{MKT}}\text{MKT}_t + \beta_{\text{SMB}}\text{SMB}_t + \beta_{\text{HML}}\text{HML}_t + \beta_{\text{UMD}}\text{UMD}_t + \beta_{\text{LIQ}}\text{LIQ}_t + \beta_{\text{QML}}\text{QML}_t + e_{p,t},$$

where $r_{p,t}$ is the return for one of the long-short portfolios, MKT_t is the market factor, SMB_t (HML_t) is the Fama and French (1993) "small-minus-big" size ("high-minus-low" value) factor, UMD_t is the "up-minus-down" momentum factor, LIQ_t is the Pástor and Stambaugh (2003) liquidity factor, and QML_t is the Asness, Frazzini, and Pedersen (2014) quality-minus-junk factor. Brackets report heteroskedasticity-robust t-statistics; *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Portfolio	Ann. alpha	MKT	SMB	HML	UMD	LIQ	QML	R^2
Adaptive LASSO forecasts	11.32%	−0.19	0.03	0.08	−0.10	−0.06	0.05	4.89%
	[3.02]***	[−2.16]**	[0.23]	[0.62]	[−0.50]	[−0.80]	[0.32]	
Prevailing mean forecasts	−4.16%	−0.06	−0.10	−0.19	0.30	0.17	0.28	19.42%
	[−1.20]	[−0.94]	[−0.95]	[−1.83]*	[4.05]***	[2.31]**	[1.77]*	
Cross-sectional industry momentum	2.97%	−0.05	−0.04	0.11	1.14	0.06	−0.21	55.23%
	[0.90]	[−0.68]	[−0.31]	[0.86]	[17.61]***	[0.79]	[−1.27]	
Principal component forecasts	11.18%	−0.09	−0.06	−0.04	−0.06	−0.07	0.22	3.76%
	[2.98]***	[−1.04]	[−0.45]	[−0.34]	[0.43]	[−0.72]	[1.46]	
PLS forecasts	9.92%	−0.14	−0.13	−0.11	−0.05	−0.08	0.13	3.37%
	[2.24]**	[−1.25]	[−0.76]	[−0.70]	[−0.30]	[−0.76]	[0.68]	

Table 5
Principal component predictive regression results, monthly industry portfolio excess returns, 1960:01–2014:12.

The table reports ordinary least squares estimates of $b_{i,k}$ ($k = 1,2,3$) and the R^2 statistic for the predictive regression model,

$$r_{i,t+1} = a_i + \sum_{k=1}^{3} b_{i,k} \hat{f}_{k,t} + \varepsilon_{i,t+1},$$

where $r_{i,t}$ is the excess return on industry portfolio i and $\hat{f}_{1,t}$, $\hat{f}_{2,t}$, and $\hat{f}_{3,t}$ are the first three principal components extracted from all 30 industry portfolio excess returns. The principal components are standardized to have zero mean and unit variance. Brackets report heteroskedasticity-robust t-statistics; *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively. 0.00 indicates less than 0.005 in absolute value.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
i	$\hat{b}_{i,1}$	$\hat{b}_{i,2}$	$\hat{b}_{i,3}$	R^2	i	$\hat{b}_{i,1}$	$\hat{b}_{i,2}$	$\hat{b}_{i,3}$	R^2
FOOD	0.22	−0.49	−0.28	1.91%	CARRY	0.82	−0.07	−0.62	2.62%
	[1.06]	[−2.32]**	[−1.67]**			[3.14]***	[−0.27]	[−2.45]**	
BEER	0.32	−0.60	−0.21	1.92%	MINES	0.52	−0.06	−0.18	0.57%
	[1.48]	[−2.63]**	[−1.00]			[1.41]	[−0.18]	[−0.59]	
SMOKE	0.27	−0.46	0.14	0.81%	COAL	0.24	0.54	−0.91	1.24%
	[1.00]	[−1.81]*	[0.54]			[0.52]	[1.04]	[−1.78]*	
GAMES	1.23	−0.19	−0.75	4.06%	OIL	0.10	0.38	−0.41	1.15%
	[3.82]***	[−0.56]	[−2.61]***			[0.49]	[1.55]	[−1.88]*	
BOOKS	0.96	−0.53	−0.68	4.93%	UTIL	0.00	−0.12	−0.18	0.29%
	[3.68]***	[−1.97]**	[−3.05]**			[−0.03]	[−0.68]	[−1.16]	
HSHLD	0.40	−0.59	−0.36	2.72%	TELCM	0.07	−0.23	−0.27	0.61%
	[1.78]*	[−2.66]***	[−1.74]*			[0.34]	[−1.10]	[−1.30]	
CLTHS	0.87	−0.54	−0.71	3.72%	SERVS	0.41	−0.45	−0.34	1.13%
	[3.00]***	[−1.77]*	[−2.44]**			[1.43]	[−1.53]	[−1.16]	
HLTH	0.13	−0.53	−0.26	1.48%	BUSEQ	0.44	−0.39	−0.12	0.78%
	[0.50]	[−2.41]**	[−1.32]			[1.48]	[−1.20]	[−0.32]	
CHEMS	0.23	−0.22	−0.50	1.17%	PAPER	0.31	−0.53	−0.54	2.58%
	[0.88]	[−0.78]	[−2.23]**			[1.36]	[−2.15]**	[−2.63]***	
TXTLS	1.25	−0.42	−0.99	5.44%	TRANS	0.48	−0.29	−0.37	1.34%
	[3.32]***	[−1.27]	[−3.06]***			[1.93]*	[−1.17]	[−1.66]*	
CNSTR	0.72	−0.46	−0.52	2.74%	WHLSL	0.87	−0.17	−0.57	3.47%
	[2.70]***	[−1.56]	[−2.11]**			[3.53]***	[−0.69]	[−2.64]***	
STEEL	0.54	0.03	−0.26	0.69%	RTAIL	0.42	−0.76	−0.40	3.11%
	[1.79]*	[0.07]	[−0.76]			[1.82]*	[−3.03]***	[−1.78]	
FABPR	0.58	0.07	−0.37	1.28%	MEALS	0.86	−0.74	−0.94	5.67%
	[2.11]**	[0.22]	[−1.40]			[3.26]***	[−2.89]***	[−4.09]***	
ELCEQ	0.35	−0.31	−0.46	1.11%	FIN	0.48	−0.38	−0.45	1.98%
	[1.28]	[−1.02]	[−1.67]*			[1.82]*	[−1.49]	[−2.01]**	
AUTOS	0.85	−0.25	−0.72	2.90%	OTHER	0.75	−0.15	−0.51	2.49%
	[2.83]***	[−0.71]	[−2.35]**			[2.86]***	[−0.59]	[−2.30]**	

Table 6
PLS predictive regression results, monthly industry portfolio excess returns, 1960:01–2014:12.

The table reports ordinary least squares estimates of b_i and the R^2 statistic for the predictive regression model,

$$r_{i,t+1} = a_i + b_i \hat{g}_{i,t} + \varepsilon_{i,t+1},$$

where $r_{i,t}$ is the excess return on industry portfolio i and $\hat{g}_{i,t}$ is the target-relevant factor extracted from all 30 industry portfolio excess returns. The target-relevant factor is estimated using the Kelly and Pruitt (2015) three-pass regression filter. The target-relevant factor is standardized to have zero mean and unit variance. Brackets report heteroskedasticity-robust t-statistics; *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively. Parentheses below the R^2 statistics report adjusted R^2 statistics.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
i	$\hat{b}_i$	R^2	i	$\hat{b}_i$	R^2	i	$\hat{b}_i$	R^2
FOOD	0.74	2.83%	CNSTR	1.15	3.62%	TELCM	0.75	2.59%
	[3.89]***			[4.20]***			[3.59]***	
BEER	0.78	2.26%	STEEL	0.96	1.76%	SERVS	0.93	2.00%
	[3.37]***			[2.96]***			[3.28]***	
SMOKE	1.11	3.31%	FABPR	0.95	2.39%	BUSEQ	1.19	3.05%
	[3.96]***			[3.80]***			[3.80]***	
GAMES	1.47	4.15%	ELCEQ	0.91	2.11%	PAPER	0.94	3.43%
	[4.89]***			[3.38]***			[3.83]***	
BOOKS	1.26	4.68%	AUTOS	1.34	3.99%	TRANS	0.95	2.72%
	[5.17]***			[3.97]***			[4.07]***	
HSHLD	0.87	3.27%	CARRY	1.17	3.39%	WHLSL	1.17	4.29%
	[3.79]***			[4.63]***			[5.63]***	
CLTHS	1.38	4.53%	MINES	1.10	2.21%	RTAIL	1.03	3.58%
	[4.78]***			[3.76]***			[4.29]***	
HLTH	0.78	2.46%	COAL	1.50	2.35%	MEALS	1.54	6.15%
	[3.81]***			[2.53]**			[5.94]***	
CHEMS	0.84	2.31%	OIL	0.87	2.69%	FIN	0.99	3.34%
	[3.41]***			[4.12]***			[4.12]***	
TXTLS	1.76	6.12%	UTIL	0.77	3.68%	OTHER	1.07	3.35%
	[4.71]***			[4.23]***			[4.55]***	

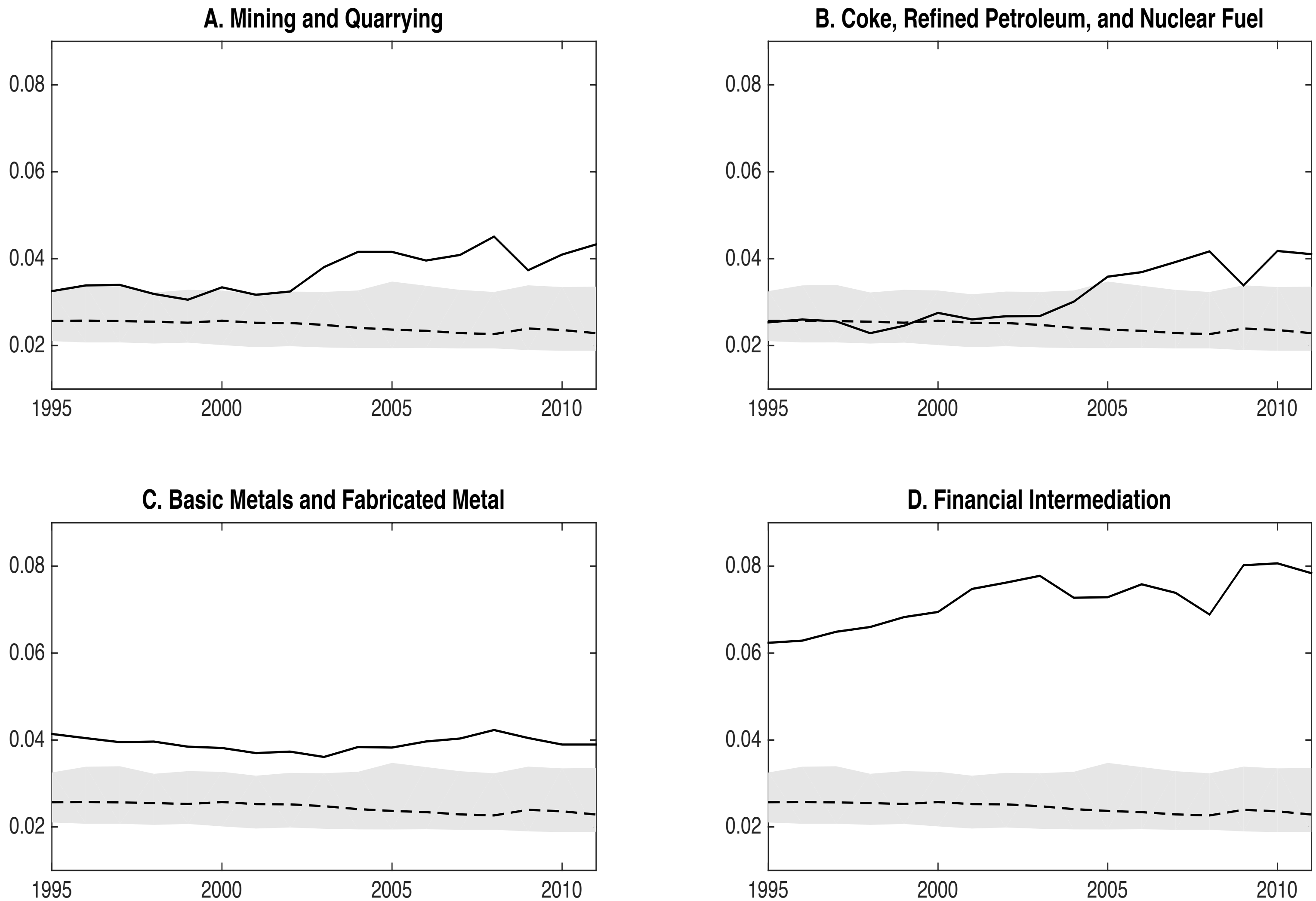

Figure 1. Eigenvector centrality scores, 1995–2011. The solid line in each panel shows annual centrality scores for the industry in the panel heading. The dashed line shows annual medians of the centrality scores across all 35 industries. The bands delineate the 25th and 75th percentiles of the centrality scores across all 35 industries. The centrality scores are based on U.S. industry input-output tables from the OECD.

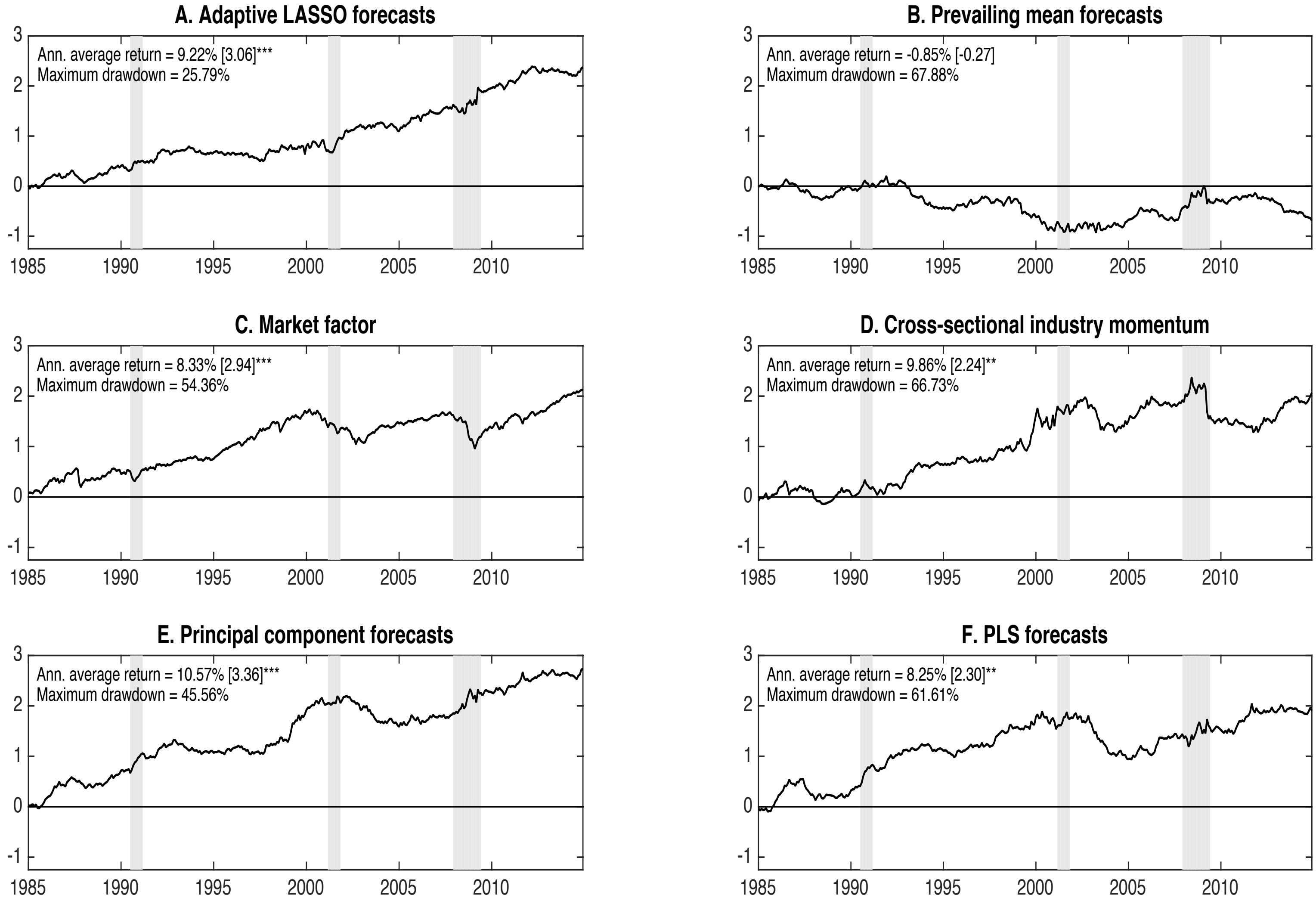

Figure 2. Log cumulative returns for long-short portfolios, 1985:01–2014:12. Panels A, B, E, and F show the log cumulative returns for long-short industry-portfolios that go long (short) the three industries with the highest (lowest) forecasted excess returns using the forecasts given in the panel headings. Panel C shows the log cumulative market excess return (market factor). The cross-sectional industry momentum portfolio in Panel D goes long (short) the three industries with the highest (lowest) cumulative excess returns over the previous twelve months. Vertical bars delineate recessions. Each panel also reports the annualized average return and maximum drawdown for the portfolio. Brackets report heteroskedasticity-robust t-statistics; *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

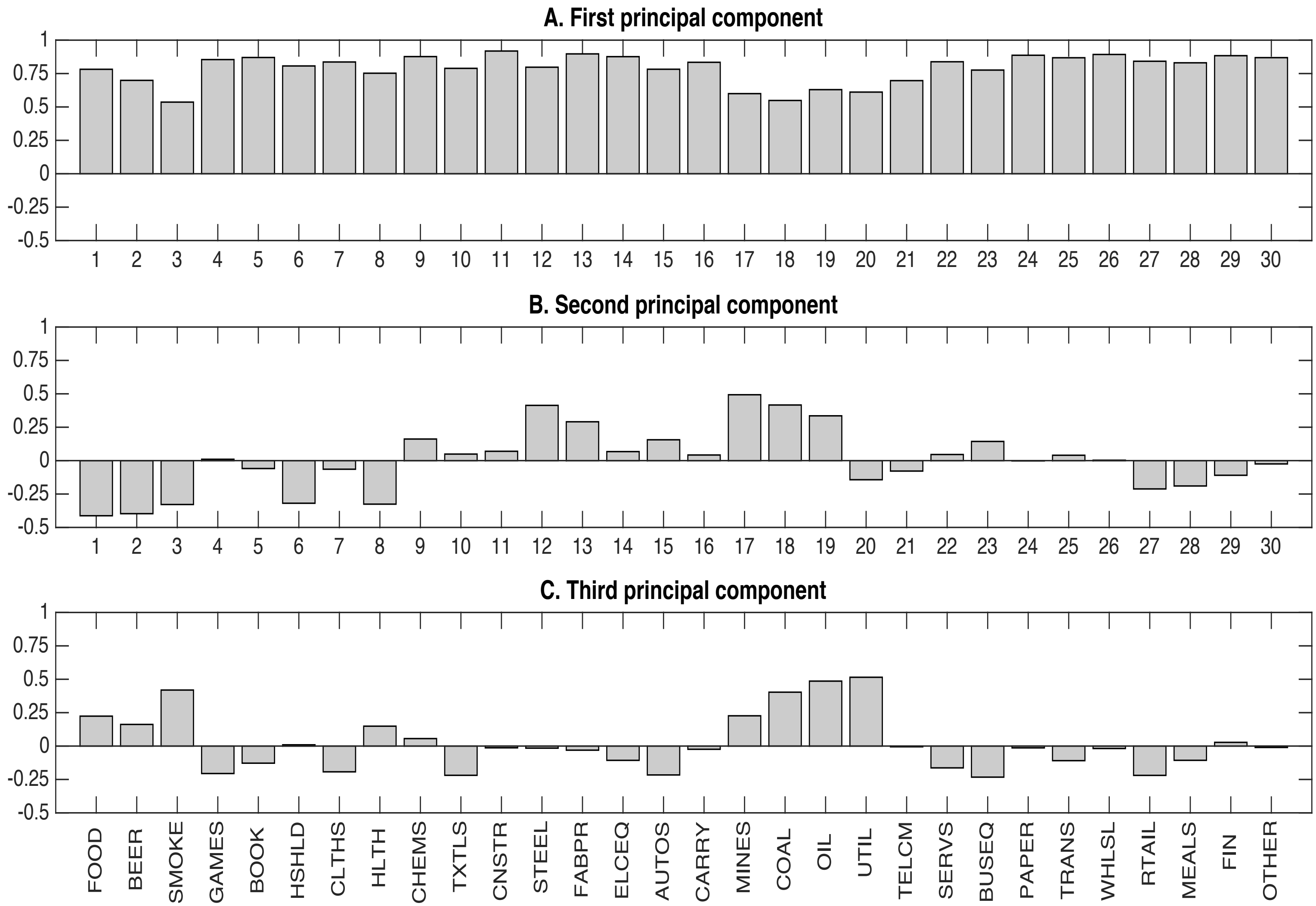

Figure 3. Loadings on first three principal components extracted from industry portfolio excess returns. The panels show individual industry portfolio excess return loadings on the first three principal components extracted from all 30 industry portfolio excess returns.