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Abstract

We use the adaptive LASSO from the statistical learning literature to identify economically connected industries in a general predictive regression framework. The framework permits complex industry interdependencies, including both direct and indirect sectoral links. Consistent with gradual information diffusion across economically connected industries, we find extensive evidence that lagged returns of interdependent industries are significant predictors of individual industry returns. Using network analysis, we detect a significant relation between an industry's importance in the U.S. production network and the pervasiveness of the predictive power of the industry's lagged return. 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 the recent Global Financial Crisis.

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

Key words: Complex industry interdependencies; Predictive regression; Adaptive LASSO; Network analysis; Industry-rotation portfolio; 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. Furthermore, industries can be indirectly linked along the production chain, so that important economic connections extend beyond the direct customer-supplier link. Overall, 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 21 of the individual industries. Furthermore, the Campbell and Thompson (2008) metric indicates that the degree of return predictability is economically significant for each industry. 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 (2004). In sum, our adaptive LASSO estimation results uncover extensive evidence of cross-industry return predictability.

The relevant lagged industry returns identified by the adaptive LASSO appear economically sensible. For example, lagged financial sector returns are significant return predictors for numerous industries, and the coefficient estimates are always positive. 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. Our results highlight the key role played by complex industry interdependencies in generating industry return predictability.

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

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 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 extends the studies of Cohen and Frazzini (2008) and Menzly and Ozbas (2010) beyond direct customer-supplier links to more fully explore cross-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 economically interdependent 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's empirical analysis centers on predicting the aggregate market return using lagged industry returns rather than predicting industry returns per se (as we do). Our approach allows us to identify the dynamic cross-industry return relations that are generated by industry interdependencies in conjunction with information-processing frictions.

In line with HTV's theoretical model, we find a significant relation between the pervasiveness

[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.

of the predictive power of an industry's lagged return and the industry's importance in the production network of the U.S. economy. Similarly to Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) and Carvalho (2014), we apply network analysis to U.S. industry input-output data. Using data from the Organization for Economic Cooperation and Development (OECD) for 36 industries, we compute each industry's centrality score, a measure of an industry's importance in the U.S. production network which takes into account both direct and indirect links across industries. We can reasonably match 20 of the 36 industries defined by the OECD to those in Kenneth French's Data Library. For this set of 20 industries, there is a significant relation between an industry's centrality score and the extent of its predictive ability according to the adaptive LASSO estimation results.

We also assess the economic value of cross-industry return predictability by constructing a long-short industry-rotation portfolio. Specifically, we compute simulated 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. In addition, the long-short portfolio has negative exposure to the broad equity market factor (with a beta of -0.19) and insignificant exposures to a host of other equity risk factors, so that the portfolio delivers a very sizable annualized alpha of 11.32%. Overall, it is difficult to provide a risk explanation for the high average return of the long-short industry-rotation portfolio, as we also find that the portfolio provides significantly higher returns during times when marginal utility is likely to be high, such as periods of reduced economic activity and high implied market volatility.

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 ensure that our long-short industry-rotation 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) and does not generate significant alpha.

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 a 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 relates cross-industry return predictability to the industry structure of the U.S. production network. 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:

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

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. Eq. (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.[3] However, because we consider a large number of industries ($N = 30$), conventional estimation of Eq. (1) entails in-sample overfitting and yields imprecise parameter estimates and uninformative inferences.

2.1. Adaptive LASSO

To improve estimation and inference and avoid overfitting for the general predictive regression Eq. (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 Eq. (1), the adaptive LASSO estimates are defined as

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

where $\tilde{r}_{j,t}$ is the standardized excess return for industry j,[4] $\hat{\mathbf{b}}_i^* = (\hat{b}_{i,1}^*, \ldots, \hat{b}_{i,N}^*)'$ is the N-vector

[3] Eq. (1) can be viewed as a representative equation for a first-order vector autoregression for the entire set of N industry portfolio excess returns.

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

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 Eq. (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 Eq. (2) allows for shrinkage to zero (for sufficiently large λ_i) 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 Eq. (1) specified in terms of the standardized explanatory variables. Intuitively, individual slope coefficients deemed important by OLS are penalized less severely in the regularization problem given by Eq. (2).

2.2. Estimation Results

We estimate Eq. (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.[5] 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.[6] 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 excess return (0.29%) and Sharpe ratio (0.14).

Table 2 reports adaptive LASSO estimates of Eq. (1) for each industry. After accounting for the

[5] 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). We implement adaptive LASSO estimation using the Glmnet MATLAB package (Qian, Hastie, Friedman, Tibshirani, and Simon, 2013). Glmnet fits the adaptive LASSO using the highly efficient coordinate descent algorithm described in Friedman, Hastie, and Tibshirani (2010).

[6] We start the sample in 1959:12 to account for the lagged predictors when estimating Eq. (1).

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.[7] We also compute a bootstrapped 90% confidence interval for each of the adaptive LASSO estimates.[8] To conserve space, bold entries indicate significant coefficient estimates according to the bootstrapped confidence intervals.[9]

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 significant return predictors for 21 individual industries. Furthermore, there are a sizable number of both positive and negative coefficient estimates in Table 2, revealing complex industry interdependencies.[10]

The adaptive LASSO coefficient estimates in Table 2 generally appear economically plausible. For example, lagged FIN returns are selected by the adaptive LASSO for 22 of the 30 individual industries, and 18 of coefficient estimates are significant. Furthermore, all of the coefficient estimates for lagged FIN returns 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

[7]Recall that the returns are standardized on the right-hand-side of Eq. (2); we thus divide each of the coefficient estimates in Eq. (2) by $\hat{\sigma}_i$ to convert the scale of each coefficient back to that of the original return series.

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

[9]Note that Eq. (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.

[10]Figure A1 shows that the adaptive LASSO often considerably shrinks the OLS estimates. Indeed, the substantial shrinkage produced by the adaptive LASSO mitigates the overfitting problem that plagues OLS estimation of models with a multitude of parameters to provide a more reliable picture of cross-industry return predictability.

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 OIL—are often negatively related to returns for industries located in later stages of the production chain—such as CLTHS, RTAIL, and MEALS. Lagged STEEL, COAL, and OIL returns are selected by the adaptive LASSO for nine, 14, and 24, respectively, of the individual industries in Table 2 (nine, ten, and 22, respectively, of the coefficient estimates are significant), and the estimated coefficients for these lagged industry returns are nearly all negative. These negative dynamic relations 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.

The R^2 statistics at the bottom of Table 2 range from 1.35% (CHEMS) to 9.20% (TXTLS).[11] Because monthly stock returns inherently contain a sizable unpredictable component, the degree of monthly stock return predictability will necessarily be limited. To assess the economic significance of the R^2 statistics in Table 2, we use the convenient metric suggested by Campbell and Thompson (2008):

$$\text{CT} = \left(\frac{R_i^2}{1-R_i^2}\right)\left(\frac{1+S_i^2}{S_i^2}\right), \tag{4}$$

where R_i^2 is the R^2 statistic for the predictive regression for $r_{i,t+1}$ and S_i is its unconditional Sharpe ratio. Eq. (4) measures the proportional increase in average excess return for a mean-variance investor who allocates between the industry i equity portfolio and risk-free bills when the investor utilizes return predictability relative to the case where the investor ignores return predictability.

The parentheses below the R^2 statistics in Table 2 report the CT metric for each industry based on its monthly Sharpe ratio in Table 1 (where we divide the annualized Sharpe ratio by $\sqrt{12}$ to

[11] Of course, when we estimate the general predictive regression Eq. (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 Eq. (1) suffers from overfitting.

compute the monthly Sharpe ratio) and its R^2 statistic in Table 2. According to the CT metrics in Table 2, return predictability increases the average excess return for a mean-variance investor by proportional factors ranging from 0.93 (OIL) to 11.68 (AUTOS), and the average proportional factor increase across the 30 industries is 4.72. The substantial proportional increases in average excess return clearly indicate that the R^2 statistics represent an economically significant degree of return predictability.[12]

2.3. Time-Varying Risk Premiums

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 Eq. (1) with four lagged predictor variables similar to those used by Ferson and Harvey (1991, 1999), Ferson and Korajczyk (1995), and Avramov (2004): the 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).[13] 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

[12] We use the Campbell and Thompson (2008) metric in Table 2 to analyze the economic significance of return predictability for each industry individually; in Section 3, we further analyze the economic value of cross-industry return predictability by constructing an industry-rotation portfolio that simultaneously invests across multiple industries.

[13] Data for these variables are from Global Financial Data.

model with the adaptive LASSO. When lagged economic variables are included in Eq. (1), the estimates of the coefficients on lagged industry returns typically remain very similar to those reported in Table 2.[14] 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 across industries.

2.4. Network Analysis

To further investigate the economic underpinnings of cross-industry return predictability, we explore links between the predictive regression results in Table 2 and the structure of the U.S. production network. To this end, and similarly to Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) and Carvalho (2014), we apply network analysis to U.S. industry input-output data.

Network analysis envisions production occurring at N distinct (or specialized) nodes. In our context, each node constitutes an individual industry. The flow of inputs among the industries can be represented by a matrix of input-output coefficients, $\mathbf{W}$, where a typical element $w_{i,j}$ gives the share of industry j in the total intermediate input use by industry i for $i, j = 1, \dots, N$.[15] The matrix of input-output coefficients characterizes key features of the interindustry relations in the production structure. From a network perspective, each nonzero $w_{i,j}$ element is a directed edge representing the intersection of two nodes (in the form of an input-supplying relation), while the set of nonzero $w_{i,j}$ elements is a collection of weights corresponding to each of the directed edges.

We are interested in measuring each industry's importance in the production network. Intuitively, shocks to industries that are relatively important in the production network likely have widespread implications for cash flows in other industries; in the presence of information frictions, we thus expect that lagged returns for these relatively important industries would tend to exhibit more pervasive predictive ability across industries.

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

[15] In the model of Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012), the $w_{i,j}$ coefficients correspond to parameters in a Cobb-Douglas production function with constant returns to scale for industry i: $x_i = z_i^{\alpha} l_i^{\alpha} \prod_{i=1}^{N} x_{i,j}^{(1-\alpha)w_{i,j}}$, where x_i is the output of i, z_i is a productivity shock to i, l_i is the amount of labor employed by i, and $x_{i,j}$ is the amount of industry j output used to produce output in i.

A natural measure of a sector's importance in the production network is the weighted outdegree of a sector—the sum over all weights for which industry j appears as an input supplier in the network ($d_j = \sum_{i=1}^{N} w_{i,j}$). However, this measure only reflects direct network effects relating to immediate input-supplying relations. 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 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), the vector of centrality scores can be expressed as

$$\mathbf{c} = (0.5/N)(\mathbf{I}_N - 0.5\mathbf{W}')^{-1}\boldsymbol{\iota}_N, \tag{5}$$

where $\mathbf{c} = (c_1, \ldots, c_N)'$ is the N-vector of centrality scores and $\boldsymbol{\iota}_N$ is an N-vector of ones.[16] In 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.

The OECD provides input-output data for the United States for 36 industries.[17] Based on data for the mid 2000s (the most recent data vintage available from the OECD),[18] we compute each industry's centrality score. Unfortunately, the OECD's industry definitions do not exactly match those for the industries in our predictive regression analysis in Section 2.2, which are based on the industry definitions in Kenneth French's Data Library. Nevertheless, we can reasonably match 20 of the French Data Library industries to industries defined by the OECD. The 20 industries from the French Data Library are as follows (with the corresponding OECD industry definitions

[16]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 Eq. (5).

[17]The data are available at https://stats.oecd.org.

[18]The results reported in this section are similar for earlier data vintages.

in parentheses): FOOD (Agriculture, Hunting, Forestry, and Fishing), BOOKS (Pulp, Paper, Paper Products, Printing, and Publishing), HLTH (Health and Social Work), CHEMS (Chemicals and Chemical Products), TXTLS (Textiles, Textile Products, Leather, and Footwear), CNSTR (Construction), STEEL (Basic Metals), FABPR (Fabricated Metal Products Except Machinery and Equipment), ELCEQ (Electrical Machinery and Apparatus N.E.C.), AUTOS (Motor Vehicles, Trailers, and Semi-Trailers), CARRY (Other Transport Equipment), COAL (Mining and Quarrying), OIL (Coke, Refined Petroleum Products, and Nuclear Fuel), UTIL (Electricity, Gas, and Water Supply), TELCM (Post and Telecommunications), SERVS (Other Community, Social, and Personal Services), BUSEQ (Office, Accounting, and Computing Machinery), TRANS (Transport and Storage), MEALS (Hotels and Restaurants), FIN (Financial Intermediation).

To investigate connections between the industry structure of the U.S. production network and cross-industry return predictability, Figure 1 presents a scatterplot relating each industry's centrality score to the number of times that the industry's lagged return is selected by the adaptive LASSO in Table 2. Figure 1 reveals a positive relation between an industry's importance in the U.S. production network, as measured by its centrality score, and the pervasiveness of the predictive power of the industry's lagged return. Indeed, the fitted cross-sectional regression delineated by the solid line indicates a statistically significant relation (t-statistic of 2.60) with sizable explanatory power (R^2 statistic of 27.30%). The industries highlighted in Section 2.2 in terms of their extensive predictive ability—FIN, STEEL, COAL, and OIL—are also among the most important nodes in the U.S. production network in Figure 1. In the presence of information frictions, the relation in Figure 1 is consistent with HTV's theoretical model.[19]

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, thereby shedding additional light on the economic

[19]The cross-sectional regression results in Figure 1 are very similar when we replace the number of times that an industry's lagged return in selected by the adaptive LASSO with the number of times that it is significant in Table 2.

value of cross-industry return predictability. 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 Eq. (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 Eq. (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 Eq. (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).[20]

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 notable 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 ($r_{i,t+1} = a_i + \varepsilon_{i,t+1}$, i.e., no return predictability); the forecast is simply the mean industry excess

[20]Starting the out-of-sample period in 1985:01 provides a reasonably long initial in-sample period for reliably estimating the parameters of the general predictive regression model used to generate the initial out-of-sample industry excess return forecasts.

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 (e.g., from 1991 to 1995 and 1999 to 2004), and the maximum drawdown is a very 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, 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 contrast to our long-short industry-rotation portfolio based on the adaptive LASSO forecasts in Panel A, the market factor in Panel C typically performs poorly during recessions—particularly the Great Recession—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 portfolio 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%.[21] 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 very 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:

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

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.[22] The factors included in Eq. (6) cover a broad range of potentially relevant risk factors for industry portfolios. Note that not all of the factors in Eq. (6) necessarily constitute risk factors per se. In particular, QMJ_t is perhaps best viewed as a "strategy" factor, as Asness, Frazinni, and Pedersen (2014) show that it is difficult to provide a risk-based explanation for the behavior of the quality factor.

Table 3 reports estimation results for Eq. (6). Our long-short industry-rotation portfolio based on the adaptive LASSO forecasts exhibits significant negative exposure to the market factor, with

[21]The sharp drawdown in the cross-sectional industry momentum portfolio in 2009 is consistent with the momentum "crashes" documented by Daniel and Moskowitz (2015).

[22]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 the AQR Data Sets webpage at https://www.aqr.com/library/data-sets.

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. The signals also produce an investment strategy that is unrelated to the quality-based strategy of Asness, Frazzini, and Pedersen (2014).

Table 3 also reports estimation results for Eq. (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 portfolio is insignificant. The differences in results in Table 3 between our long-short industry-rotation portfolio based on the adaptive LASSO forecasts and the cross-sectional industry momentum portfolio confirm that the former bears little relation to cross-sectional industry momentum.

Table 3 reveals that the substantial average return for our long-short industry-rotation portfolio based on the adaptive LASSO forecasts in Figure 2, Panel A cannot be explained by exposures to a 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 3 (11.32%) is even higher than its unadjusted average return in Figure 2, Panel A (9.22%).[23]

[23]The long-short industry-rotation portfolio based on the adaptive LASSO forecasts continues to generate sizable alpha when we include additional risk factors in Eq. (6), such as the Moskowitz, Ooi, and Pedersen (2012) time-series

In addition to the risk factors considered in Table 3, it is difficult to view the sizable average return of our long-short industry-rotation portfolio as a "crisis" or "crash" risk premium. As discussed in the context of Figure 2, the portfolio performs very well during the recent Global Financial Crisis, so that instead of suffering substantial losses during the recent crisis, it delivers sizable gains.

Table 4 provides additional evidence on the performance of our long-short industry-rotation portfolio during "extreme" periods when marginal utility is likely to be high. Specifically, we estimate bivariate regressions of the form:

$$r_{p,t} = c + d I_t + e_{p,t}, \tag{7}$$

where I_t is an indicator variable that takes a value of one during extreme months and zero otherwise. We define extreme months based, in turn, on the Federal Reserve Bank of Chicago national activity index, University of Michigan consumer sentiment index, and the VIX.[24] For the national activity index and consumer sentiment (VIX), we define extreme months as those with observations in the bottom (top) quintile of the sample observations. A negative estimate for d in Eq. (7) indicates that the long-short industry-rotation portfolio performs worse during extreme circumstances when marginal utility is high, consistent with the notion that the portfolio's high average return represents compensation for distress risk. However, the results in Table 4 point to the opposite situation: the average monthly return for the portfolio is substantially higher for extreme months defined using each of the three variables.

In sum, it is difficult to provide a risk-based explanation for the performance of our long-short industry-rotation portfolio based on the adaptive LASSO forecasts.[25] The results in this section complement those in Section 2 and support that idea that the predictive power of lagged industry

momentum, Asness, Moskowitz, and Pedersen (2013) global value and momentum, Frazzini and Pedersen (2014) betting against beta, and Fama and French (2015) profitability and investment factors.

[24]Data for these variables are via the Federal Reserve Bank of St. Louis from Federal Reserve Economic Data at https://research.stlouisfed.org/fred2/.

[25]The results in Frazzini, Israel, and Moskowitz (2015) indicate that, at least for a large institutional manager, transaction costs will have relatively little impact on the large average excess return and alpha generated by our long-short industry-rotation portfolio based on the AdLASSO forecasts.

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:

$$\tilde{r}_{j,t} = \sum_{k=1}^{K} \psi_{j,k} f_{k,t} + e_{j,t} \text{ for } j = 1,\ldots,N;\ t = 1,\ldots,T; \tag{8}$$

where $\mathbf{f}_t = (f_{1,t},\ldots,f_{K,t})'$ 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 Eq. (8) 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 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:

$$r_{i,t+1} = a_i + \sum_{k=1}^{K} b_{i,k} \hat{f}_{k,t} + \varepsilon_{i,t+1}, \tag{9}$$

where $\hat{f}_{k,t}$ is the principal component estimate of $f_{k,t}$ for $k = 1, \ldots, K$ in Eq. (8). Eq. (9) provides a parsimonious specification for incorporating information from all of the lagged industry returns, alleviating the problems associated with the many correlated regressors in Eq. (1).[26] Bai and Ng (2006) show that the use of estimated factors as regressors in Eq. (9) 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 Eq. (9), 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.[27] 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) 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 theese factors plausibly represent various supply shocks that raise product prices and returns for sectors located in earlier production stages while squeezing profit margins and lowering returns for sectors in later production stages. These production-chain patterns are reminiscent of those that we identified in Section 2.2.

[26]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.

[27]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 Eq. (9).

Table 5 reports OLS estimates of $b_{i,1}$, $b_{i,2}$, and $b_{i,3}$ in Eq. (9) 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 the fifth and tenth columns in Table 5 generally appear economically sizable in light of the Campbell and Thompson (2008) metrics reported in parentheses below the statistics. 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 Eq. (1).[28]

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 Eq. (9) instead of adaptive LASSO estimation of Eq. (1).[29] 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.[30] Furthermore, like the portfolio based on the adaptive LASSO forecasts in Panel A, the portfolio based on the principal component forecasts in Panel E performs well during recessions, most notably the Great Recession. Again like the long-short industry-rotation portfolio based on the adaptive LASSO forecasts, Table 3 shows that the 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%, while Table 4 shows that it does not experiences lower average returns during extreme conditions.

[28]The results in Table 5 are very similar when we include the lagged first principal component extracted from the economic variables from Section 2.3 as an additional regressor in Eq. (9), so that time-varying risk premiums do not readily explain the results in Table 5.

[29]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 Eq. (9).

[30]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.

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.[31] 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 $j = 1, \ldots, N$:

$$r_{j,t} = \phi^i_{0,j} + \phi^i_{1,j} r_{i,t+1} + e^i_{j,t} \text{ for } t = 1, \ldots, T-1. \tag{10}$$

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

$$r_{j,t} = \phi^i_{0,t} + g_{i,t} \hat{\phi}^i_{1,j} + u_{j,t} \text{ for } j = 1, \ldots, N, \tag{11}$$

where $\hat{\phi}^i_{1,j}$ denotes the OLS estimate of $\phi^i_{1,j}$ in Eq. (10). For each t, the PLS estimate of the target-relevant factor is equivalent to the OLS estimate of $g_{i,t}$ in Eq. (11). Finally, the lagged target-relevant factor serves as the predictor in the following bivariate predictive regression:

$$r_{i,t+1} = a_i + b_i \hat{g}_{i,t} + \varepsilon_{i,t+1}, \tag{12}$$

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

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

Table 6 reports OLS estimates of b_i in Eq. (12) for each industry.[32] 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, the R^2 statistics and corresponding Campbell and Thompson (2008) metrics in the third, sixth, and ninth columns point to an economically significant degree of industry return predictability. 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.[33]

Section 2 accommodates complex industry interdependences via adaptive LASSO estimation of the general predictive regression Eq. (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 Eq. (10)—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 Eq. (10) are negative for a number of the i-j pairs.[34] 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.

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 Eq. (12).[35] 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

[32] 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).

[33] 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 economic variables from Section 2.3 and included this factor as an additional regressor in Eq. (12). The $\hat{b}_i$ estimates remain very similar to those in Table 6 with the inclusion of the additional factor.

[34] 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 $i, j = 1, \ldots, 30$).

[35] 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 Eq. (12).

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.[36] Furthermore, Table 3 shows that the industry-rotation portfolio based on the PLS forecasts exhibits insignificant exposures to the equity risk factors and produces a statistically and economically significant annualized alpha of 9.92%, while Table 4 indicates that the portfolio does not produce lower average returns in extreme environments.

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

The adaptive LASSO estimation results 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

[36]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.

returns. The overall degree of industry return predictability is economically significant, and the parameter estimates are economically sensible. Using network analysis, we find a significant link between the pervasiveness of the predictive power of an industry's lagged return and the industry's importance in the U.S. production network. 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 simulated out-of-sample industry return forecasts based on lagged industry returns and 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 cyclical downturns, particularly the recent Great Recession. The long-short portfolio is also weakly correlated with a variety of equity risk factors and delivers an annualized alpha of over 11%. The information in lagged industry returns thus appears quite valuable for generating risk-adjusted returns. Although we cannot definitively rule out a risk-based explanation of the behavior of the long-short industry-rotation portfolio, such an explanation does not seem readily available.

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	4.38	−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. Bold indicates significance according to bootstrapped 90% confidence intervals. Parentheses report the Campbell and Thompson (2008) measure of the proportional increase in average excess return for a mean-variance investor who utilizes return predictability when allocating between the industry i equity portfolio and risk-free bills.

(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**	–	–	**−0.02**
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**	−0.02	**−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	2.62%	2.21%	4.16%	4.88%	5.32%	3.47%	8.21%	2.51%	1.35%	9.20%
	(1.10)	(1.22)	(1.79)	(5.76)	(6.32)	(2.57)	(7.69)	(1.42)	(1.53)	(11.17)

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	4.51%	1.41%	1.51%	1.73%	5.30%	3.18%	4.37%	2.13%	1.43%	7.08%
	(6.70)	(8.99)	(1.87)	(1.32)	(11.68)	(2.60)	(9.29)	(3.06)	(0.93)	(5.16)

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	3.34%	2.19%	2.62%	3.32%	5.79%	6.74%	5.51%	7.65%	6.56%	3.76%
	(2.83)	(2.15)	(3.75)	(3.39)	(5.78)	(5.80)	(3.84)	(6.54)	(5.89)	(9.54)

Table 3
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 return 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

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

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	Annualized alpha	MKT	SMB	HML	UMD	LIQ	QMJ	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 4
Long-short industry-rotation portfolio performance during extreme conditions, 1985:01–2014:12.

The table reports bivariate regression slope coefficient estimates 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 return forecasts are based on predictive regression models estimated via the adaptive LASSO, principal components, or PLS. 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. Each bivariate regression is given by

$$r_{p,t} = c + d I_t + e_{p,t},$$

where $r_{p,t}$ is the return for the long-short portfolio in the first column and I_t is the indicator variable in the column heading. "Bottom quintile national activity index" equals one (zero) if the Federal Reserve Bank of Chicago national activity index is less than or equal to (greater than) its 20th percentile value for the sample period. "Bottom quintile consumer sentiment" equals one (zero) if the University of Michigan consumer sentiment index is less than or equal to (greater than) its 20th percentile value for the sample period."Top quintile implied volatility" equals one (zero) if the VIX is greater than or equal to (less than) its 80th percentile value for the sample period; the sample period for VIX begins in 1990:01. Brackets report heteroskedasticity-robust t-statistics; *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

(1)	(2)	(3)	(4)
Portfolio	Bottom quintile national activity index	Bottom quintile consumer sentiment	Top quintile implied volatility
Adaptive LASSO forecasts	1.52%	1.09%	2.00%
	[1.75]*	[1.27]	[2.07]**
Principal component forecasts	1.00%	1.26%	1.14%
	[1.20]	[1.56]	[1.12]
PLS forecasts	0.58%	1.39%	0.68%
	[0.59]	[1.44]	[0.59]

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. Parentheses below the R^2 statistics report the Campbell and Thompson (2008) measure of the proportional increase in average excess return for a mean-variance investor who utilizes return predictability when allocating between the industry i equity portfolio and risk-free bills.

(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]**	(0.80)		[3.14]***	[−0.27]	[−2.45]**	(2.14)
BEER	0.32	−0.60	−0.21	1.92%	MINES	0.52	−0.06	−0.18	0.57%
	[1.48]	[−2.63]**	[−1.00]	(1.05)		[1.41]	[−0.18]	[−0.59]	(1.17)
SMOKE	0.27	−0.46	0.14	0.81%	COAL	0.24	0.54	−0.91	1.24%
	[1.00]	[−1.81]*	[0.54]	(0.34)		[0.52]	[1.04]	[−1.78]*	(1.77)
GAMES	1.23	−0.19	−0.75	4.06%	OIL	0.10	0.38	−0.41	1.15%
	[3.82]***	[−0.56]	[−2.61]***	(4.75)		[0.49]	[1.55]	[−1.88]*	(0.75)
BOOKS	0.96	−0.53	−0.68	4.93%	UTIL	0.00	−0.12	−0.18	0.29%
	[3.68]***	[−1.97]**	[−3.05]**	(5.83)		[−0.03]	[−0.68]	[−1.16]	(0.20)
HSHLD	0.40	−0.59	−0.36	2.72%	TELCM	0.07	−0.23	−0.27	0.61%
	[1.78]*	[−2.66]***	[−1.74]*	(2.00)		[0.34]	[−1.10]	[−1.30]	(0.50)
CLTHS	0.87	−0.54	−0.71	3.72%	SERVS	0.41	−0.45	−0.34	1.13%
	[3.00]***	[−1.77]*	[−2.44]**	(3.32)		[1.43]	[−1.53]	[−1.16]	(1.10)
HLTH	0.13	−0.53	−0.26	1.48%	BUSEQ	0.44	−0.39	−0.12	0.78%
	[0.50]	[−2.41]**	[−1.32]	(0.83)		[1.48]	[−1.20]	[−0.32]	(1.09)
CHEMS	0.23	−0.22	−0.50	1.17%	PAPER	0.31	−0.53	−0.54	2.58%
	[0.88]	[−0.78]	[−2.23]**	(1.33)		[1.36]	[−2.15]**	[−2.63]***	(2.61)
TXTLS	1.25	−0.42	−0.99	5.44%	TRANS	0.48	−0.29	−0.37	1.34%
	[3.32]***	[−1.27]	[−3.06]***	(6.34)		[1.93]*	[−1.17]	[−1.66]*	(1.28)
CNSTR	0.72	−0.46	−0.52	2.74%	WHLSL	0.87	−0.17	−0.57	3.47%
	[2.70]***	[−1.56]	[−2.11]**	(3.99)		[3.53]***	[−0.69]	[−2.64]***	(2.88)
STEEL	0.54	0.03	−0.26	0.69%	RTAIL	0.42	−0.76	−0.40	3.11%
	[1.79]*	[0.07]	[−0.76]	(4.37)		[1.82]*	[−3.03]***	[−1.78]	(2.12)
FABPR	0.58	0.07	−0.37	1.28%	MEALS	0.86	−0.74	−0.94	5.67%
	[2.11]**	[0.22]	[−1.40]	(1.58)		[3.26]***	[−2.89]***	[−4.09]***	(4.75)
ELCEQ	0.35	−0.31	−0.46	1.11%	FIN	0.48	−0.38	−0.45	1.98%
	[1.28]	[−1.02]	[−1.67]*	(0.85)		[1.82]*	[−1.49]	[−2.01]**	(1.69)
AUTOS	0.85	−0.25	−0.72	2.90%	OTHER	0.75	−0.15	−0.51	2.49%
	[2.83]***	[−0.71]	[−2.35]**	(6.23)		[2.86]***	[−0.59]	[−2.30]**	(6.25)

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 the Campbell and Thompson (2008) measure of the proportional increase in average excess return for a mean-variance investor who utilizes return predictability when allocating between the industry i equity portfolio and risk-free bills.

(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]***	(1.19)		[4.20]***	(5.32)		[3.59]***	(2.18)
BEER	0.78	2.26%	STEEL	0.96	1.76%	SERVS	0.93	2.00%
	[3.37]***	(1.24)		[2.96]***	(11.28)		[3.28]***	(1.96)
SMOKE	1.11	3.31%	FABPR	0.95	2.39%	BUSEQ	1.19	3.05%
	[3.96]***	(1.41)		[3.80]***	(2.98)		[3.80]***	(4.38)
GAMES	1.47	4.15%	ELCEQ	0.91	2.11%	PAPER	0.94	3.43%
	[4.89]***	(4.86)		[3.38]***	(1.63)		[3.83]***	(3.50)
BOOKS	1.26	4.68%	AUTOS	1.34	3.99%	TRANS	0.95	2.72%
	[5.17]***	(5.52)		[3.97]***	(8.67)		[4.07]***	(2.63)
HSHLD	0.87	3.27%	CARRY	1.17	3.39%	WHLSL	1.17	4.29%
	[3.79]***	(2.42)		[4.63]***	(2.79)		[5.63]***	(3.60)
CLTHS	1.38	4.53%	MINES	1.10	2.21%	RTAIL	1.03	3.58%
	[4.78]***	(4.08)		[3.76]***	(4.60)		[4.29]***	(2.45)
HLTH	0.78	2.46%	COAL	1.50	2.35%	MEALS	1.54	6.15%
	[3.81]***	(1.40)		[2.53]**	(3.39)		[5.94]***	(5.17)
CHEMS	0.84	2.31%	OIL	0.87	2.69%	FIN	0.99	3.34%
	[3.41]***	(2.65)		[4.12]***	(1.79)		[4.12]***	(2.90)
TXTLS	1.76	6.12%	UTIL	0.77	3.68%	OTHER	1.07	3.35%
	[4.71]***	(7.18)		[4.23]***	(2.59)		[4.55]***	(8.48)

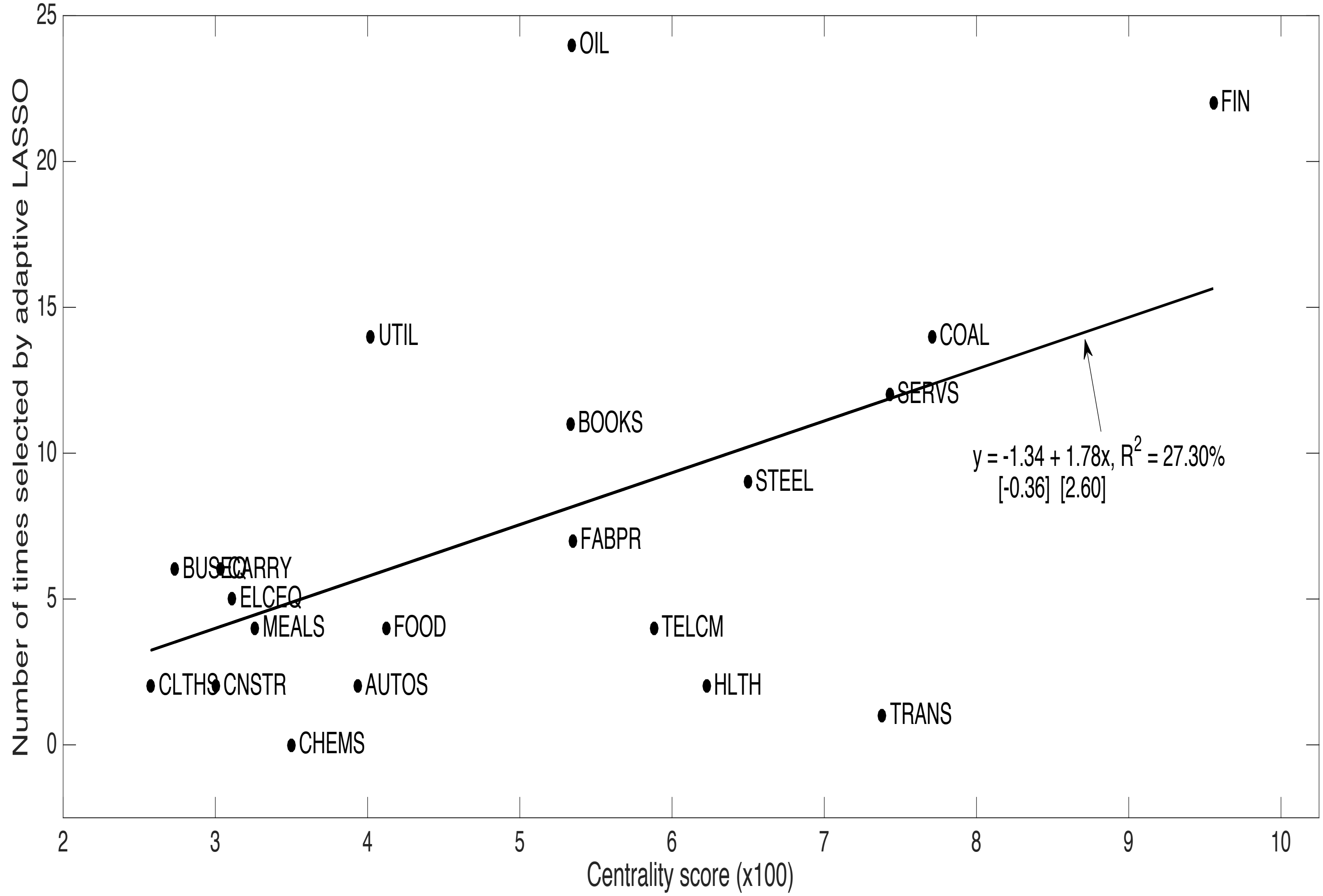

Figure 1. Centrality scores and selection by the adaptive LASSO. The scatterplot shows the relation between the eigenvector centrality score for an industry and the number of times that the industry's lagged return is selected by the adaptive LASSO in Table 2. The centrality scores are based on U.S. industry input-output data from the OECD. The scatterplot shows results for 20 industries. The solid line delineates the fitted regression line; *t*-statistics are reported in brackets.

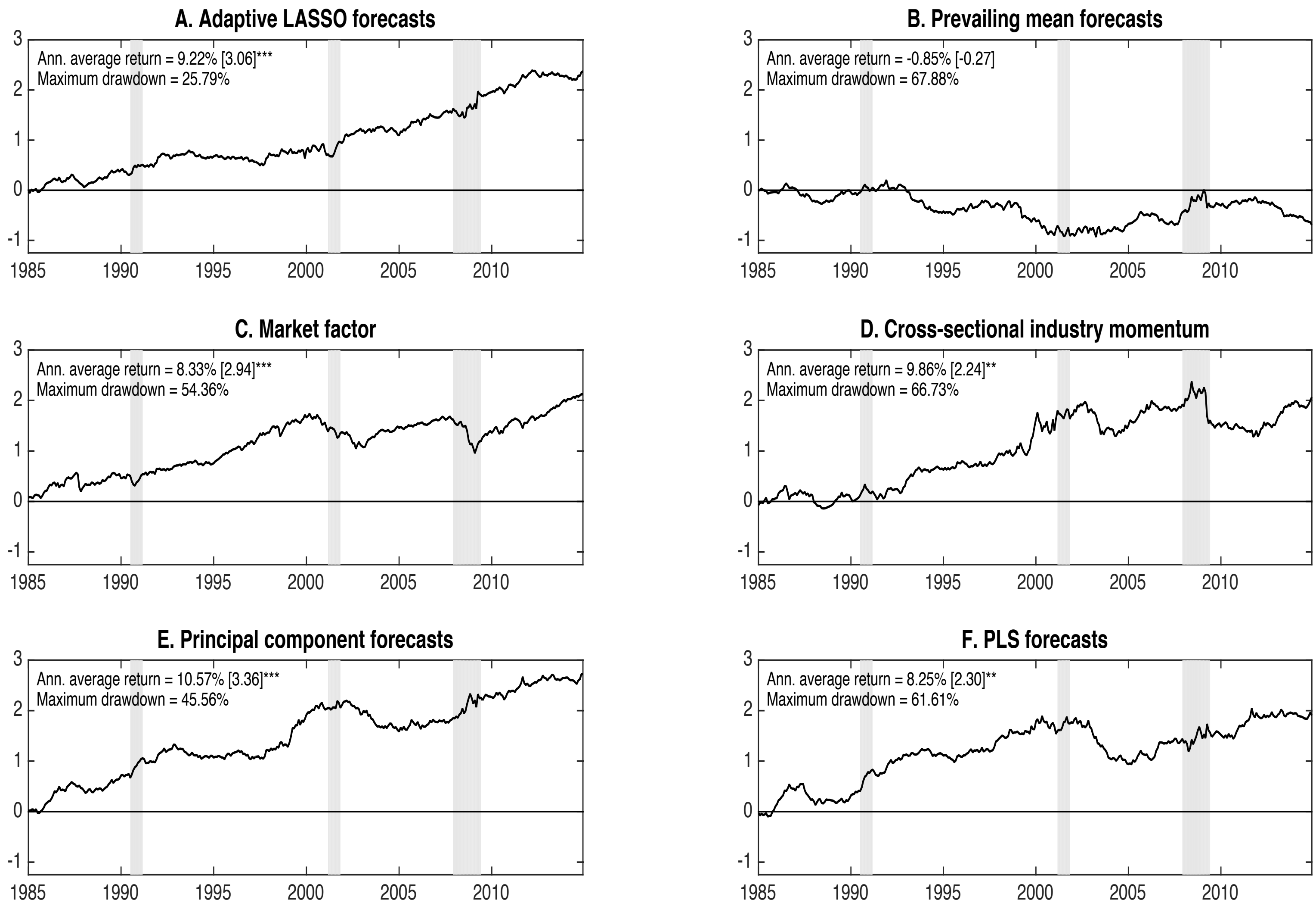

Figure 2. Log cumulative returns for long-short portfolios, 1985:01–2014:12. Panels A, B, E, and F show the log cumulative returns for long-short industry-portfolios that go long (short) the three industries with the highest (lowest) forecasted excess returns using the forecasts given in the panel headings. 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.

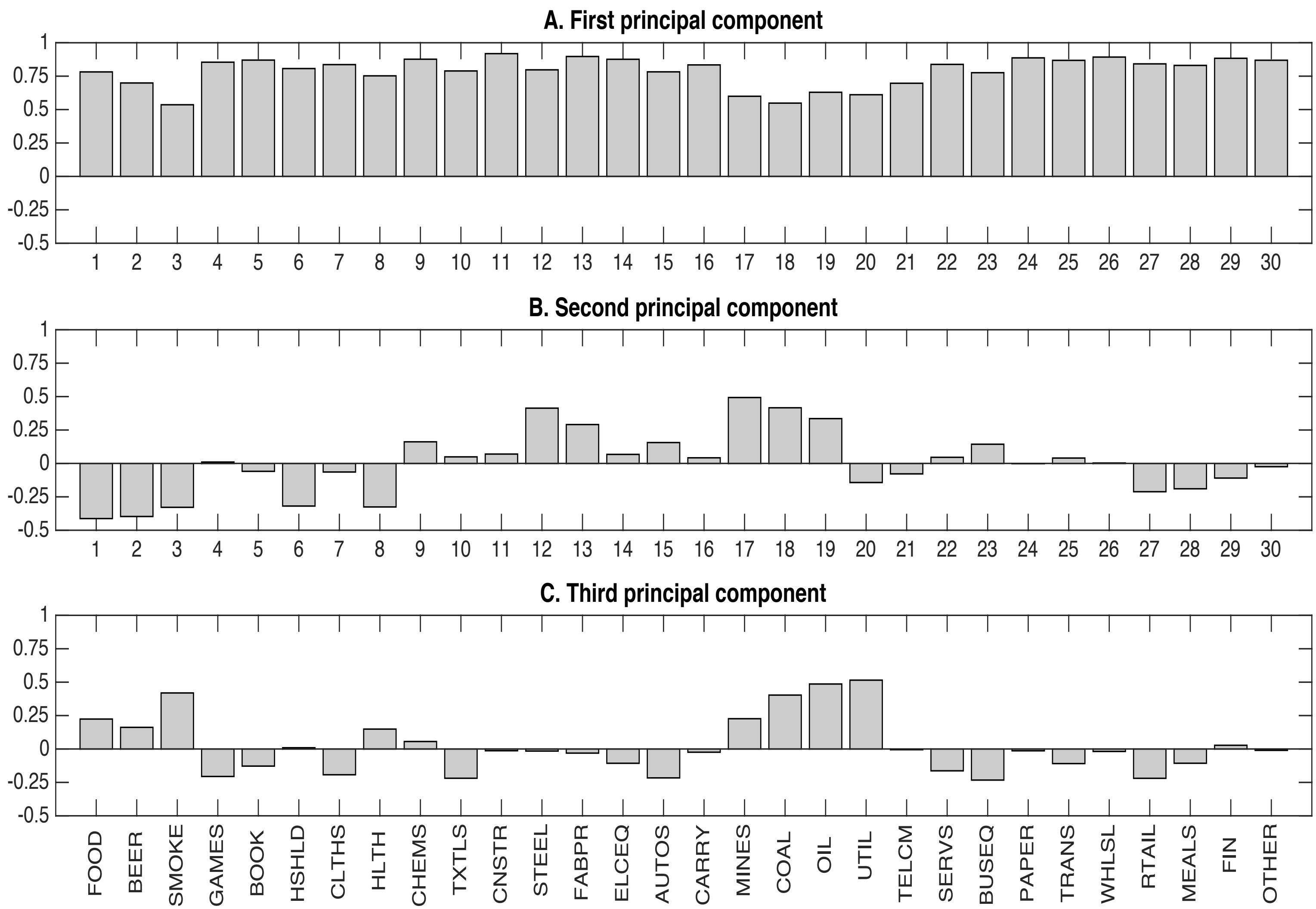

Figure 3. Loadings on first three principal components extracted from industry portfolio excess returns. The panels show individual industry portfolio excess return loadings on the first three principal components extracted from all 30 industry portfolio excess returns.

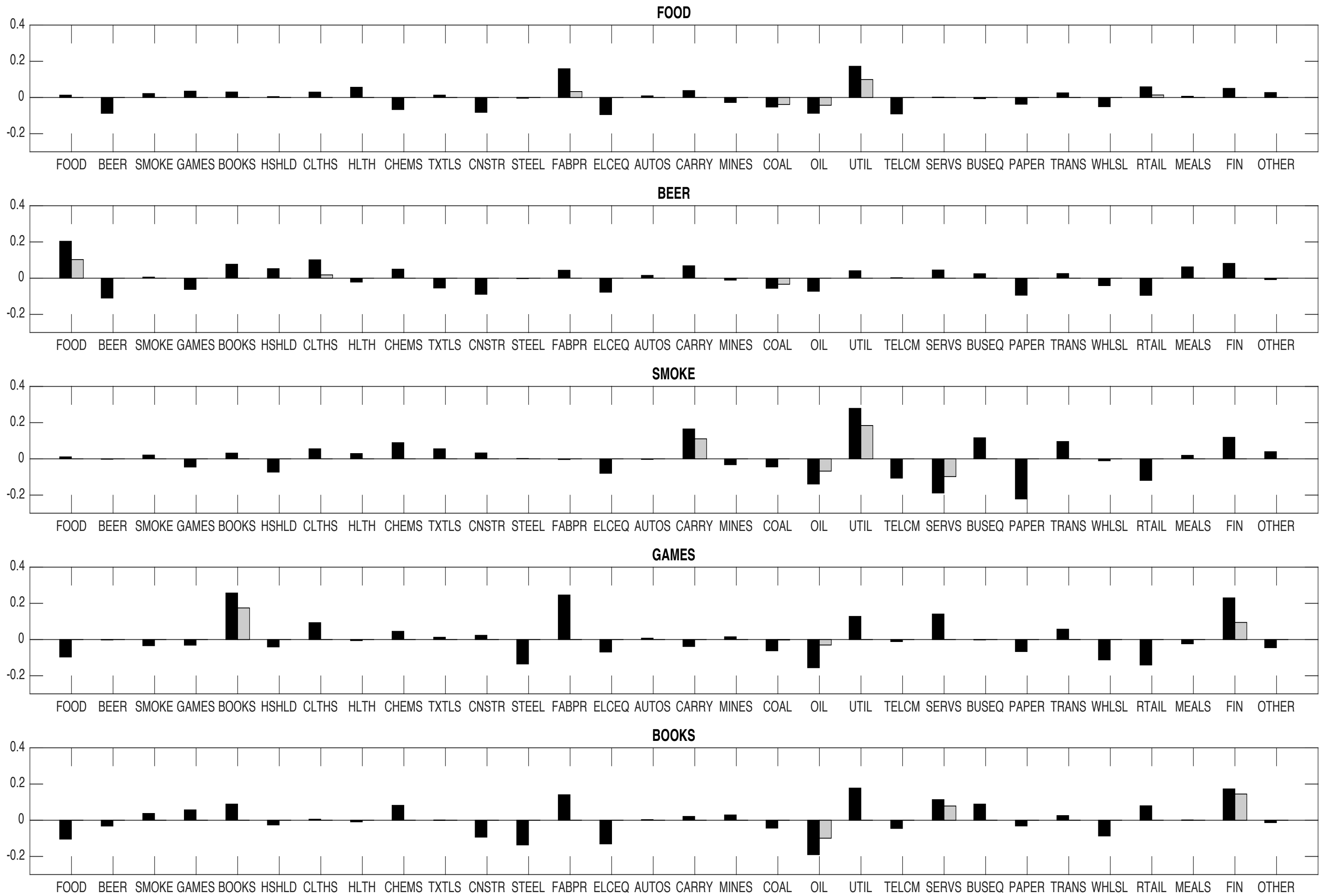

Figure A1. Shrinkage by adaptive LASSO estimates. The figure shows ordinary least squares and adaptive LASSO parameter estimates for the $b_{i,j}$ coefficients in the general predictive regression model Eq. (1), where $r_{i,t}$ is the industry excess return in the panel heading. The black (gray) bars depict the ordinary least squares (adaptive LASSO) estimates.

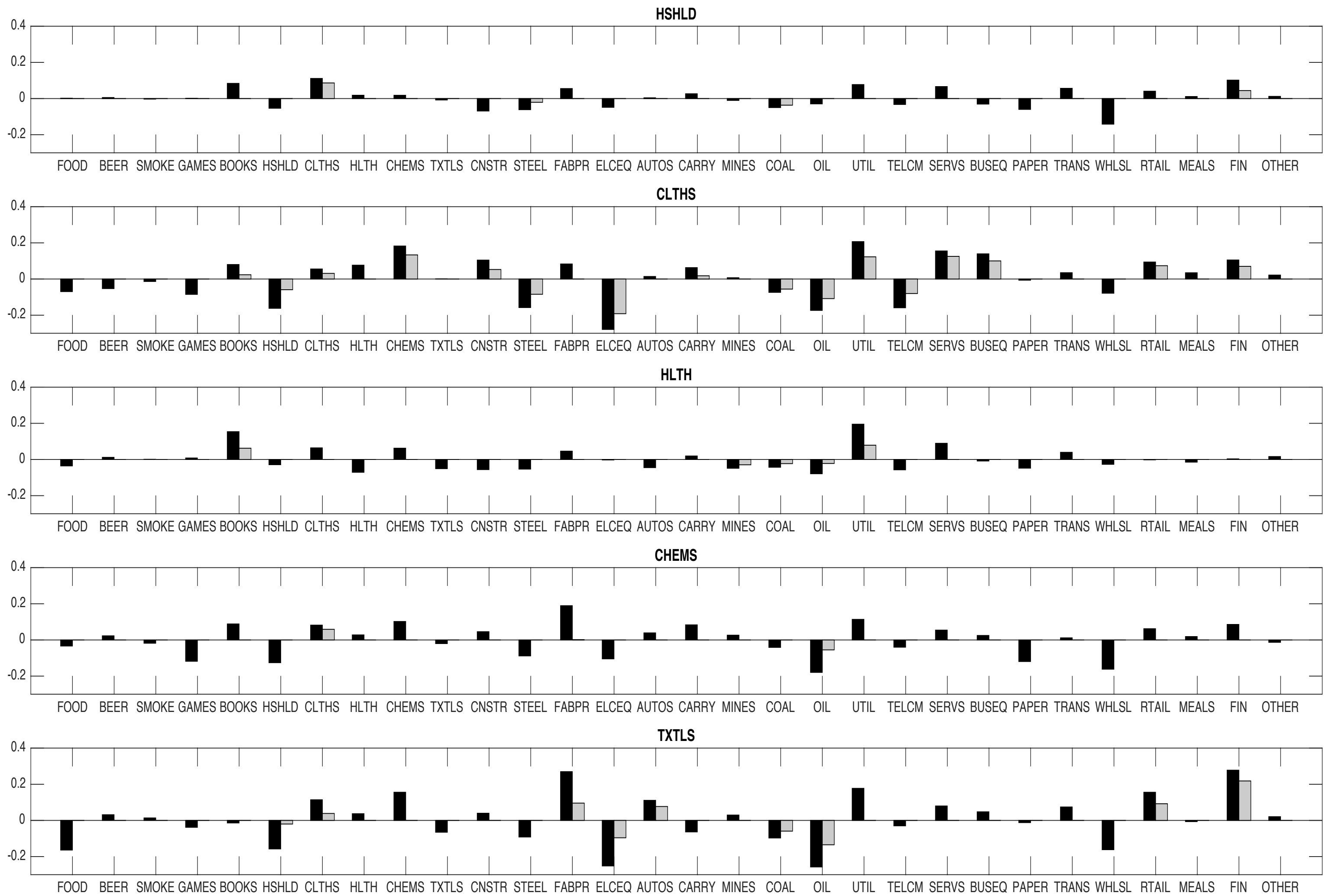

Figure A1 (continued).

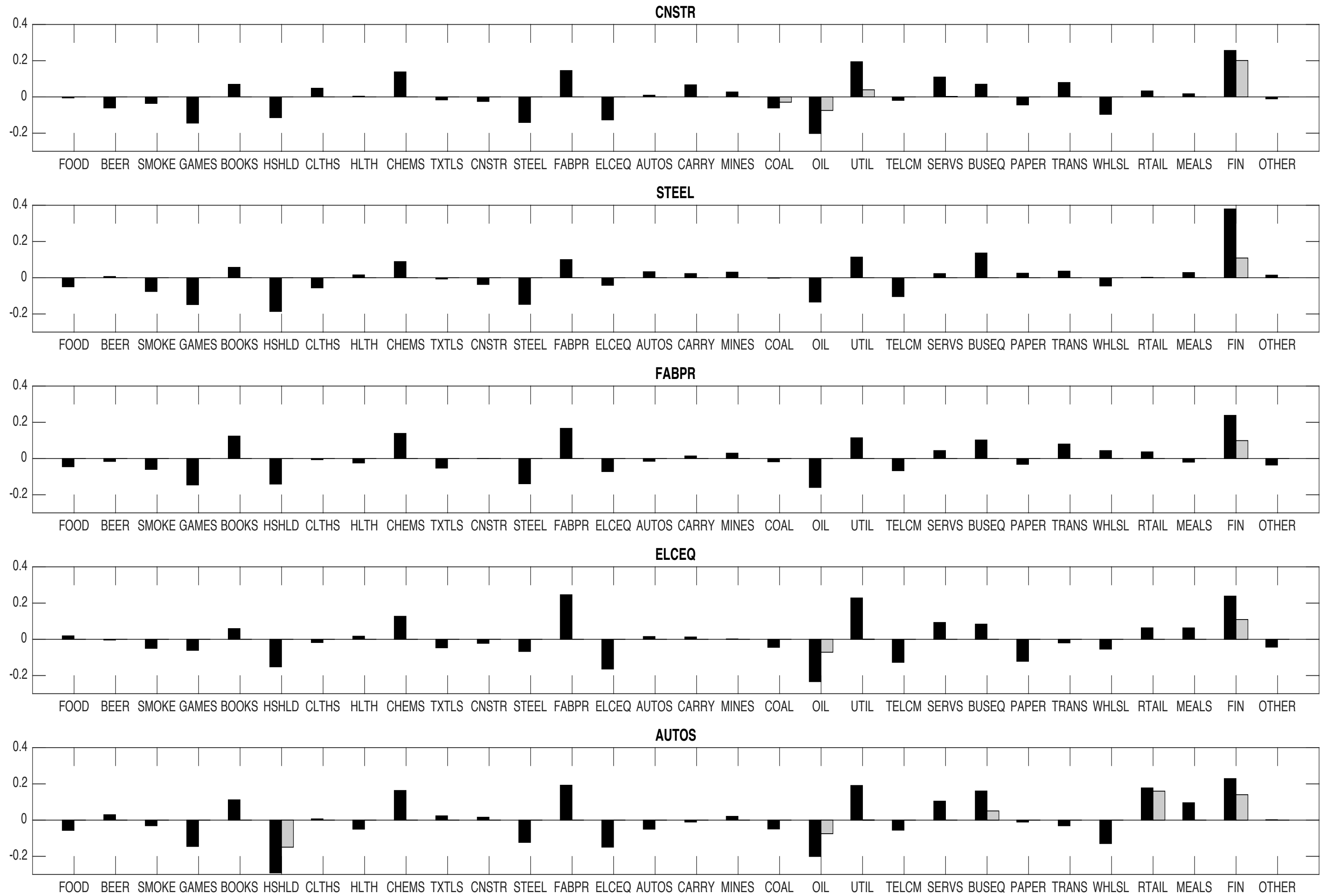

Figure A1 (continued).

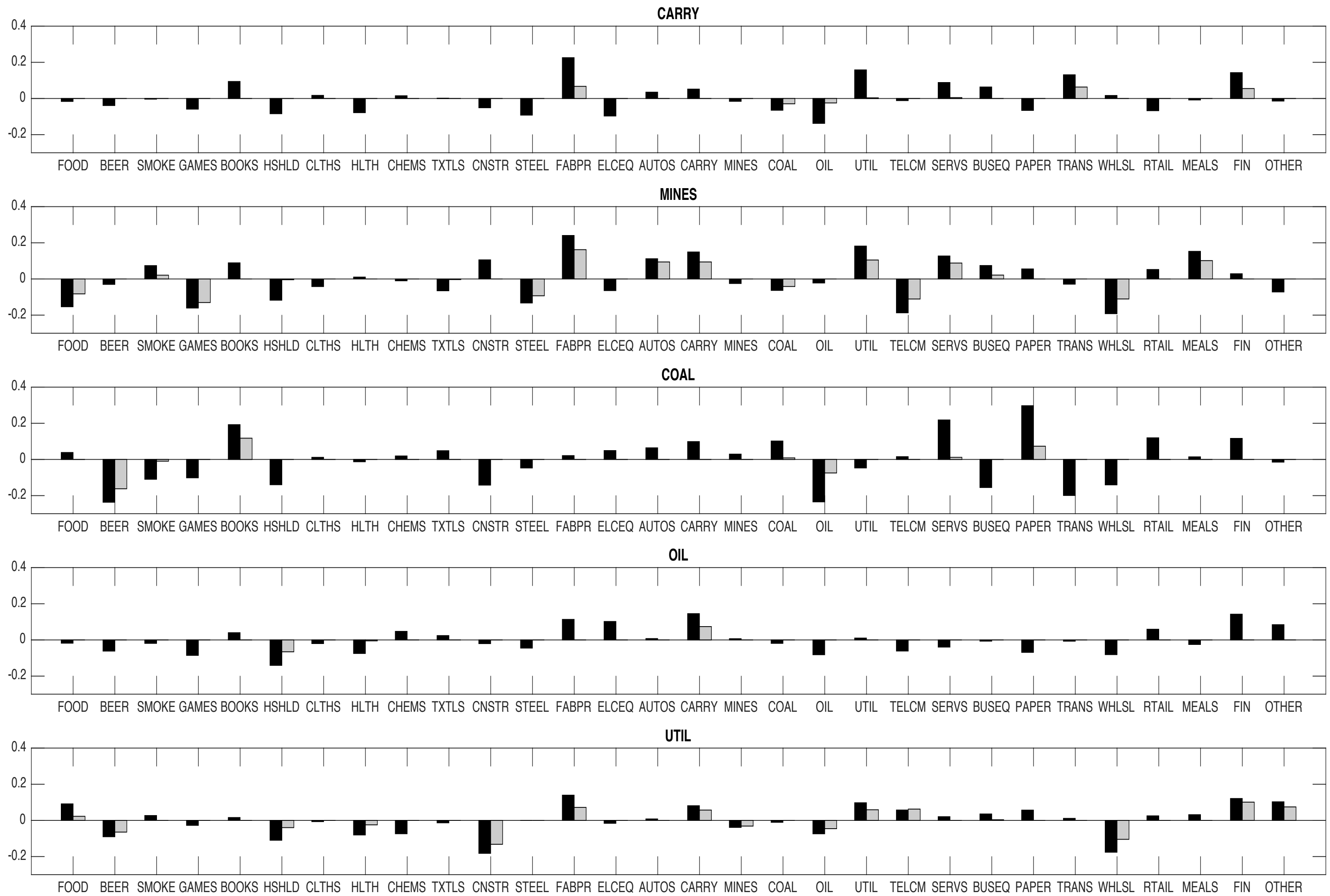

Figure A1 (continued).

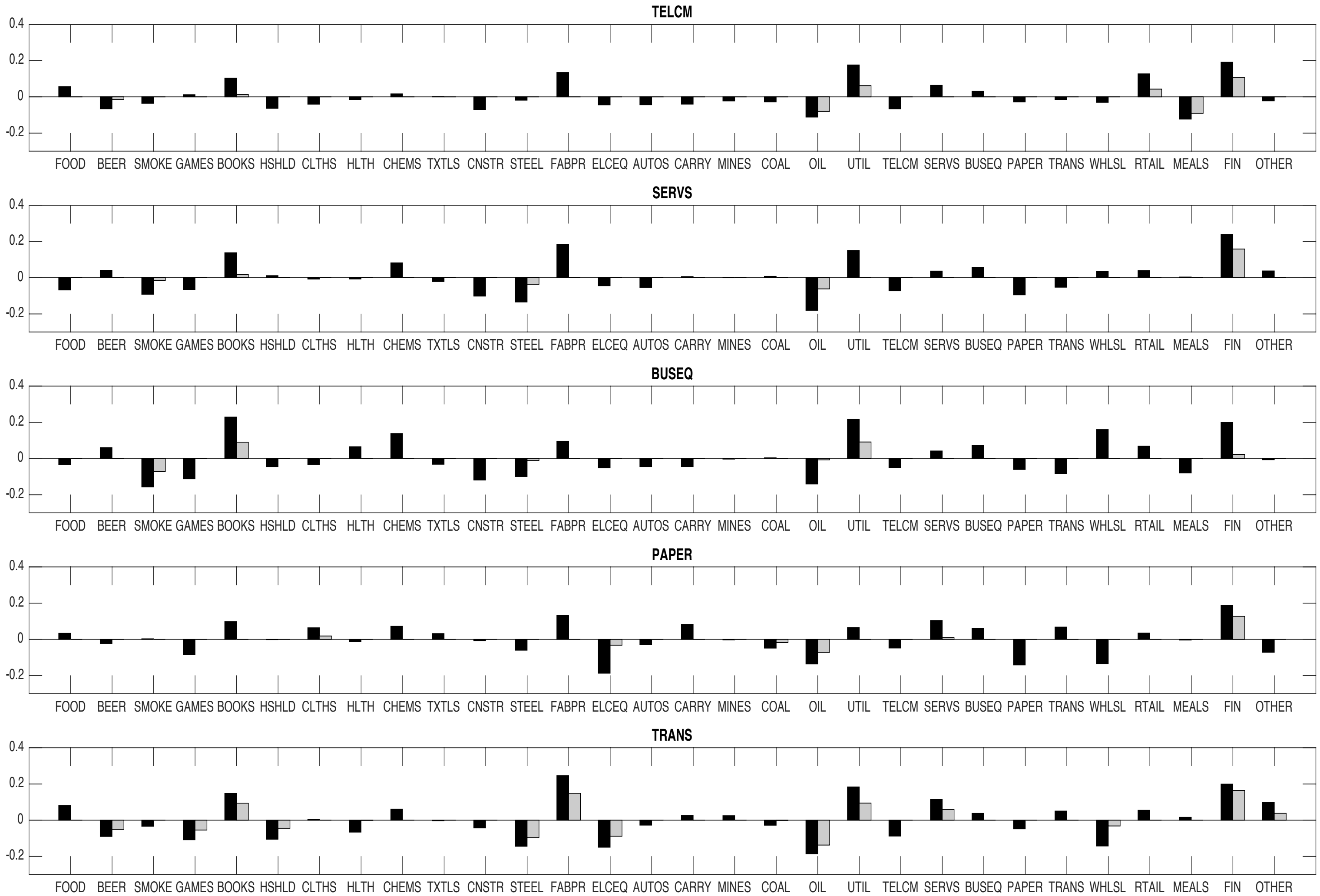

Figure A1 (continued).

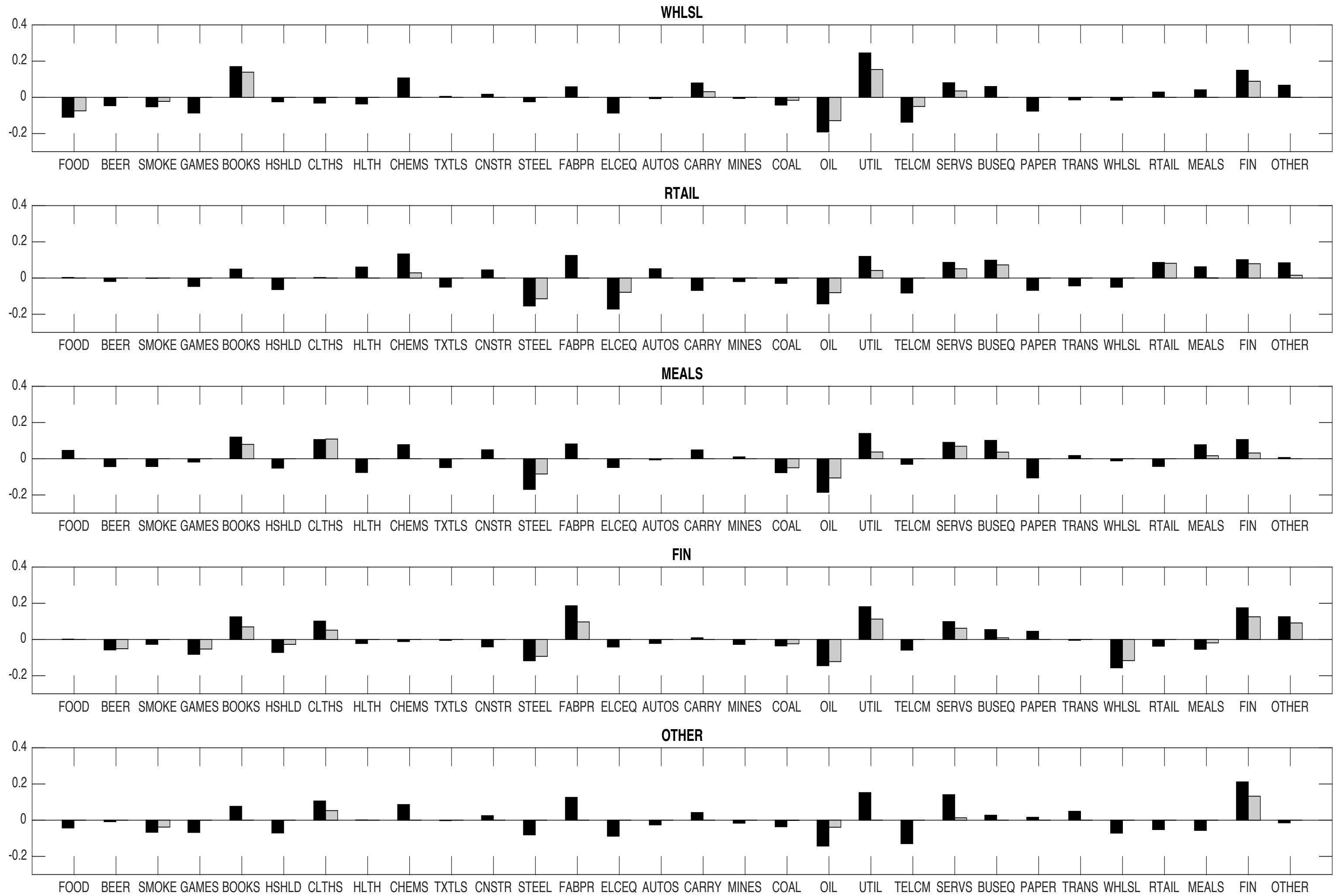

Figure A1 (continued).