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Investor Demand for Industry Factor Price Exposure

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Abstract

Market frictions make markets incomplete. Firms' equity securities can help to complete markets by offering investors opportunities to invest in assets that are otherwise unavailable or costly to acquire. However, stocks offer a substitute for the underlying assets only if the firm maintains exposure to the assets. In incomplete markets, investors should display preferences for stocks with high industry exposure, especially when the costs of direct investment in the industry assets are high. We provide evidence that investors display preferences for stocks with high industry exposure based on a robust positive relation between investor interest (turnover, and the number of institutions and mutual funds) and industry exposure. The association is unrelated to levels of diversification. The attraction to industry exposure is greatest in industries in which returns differ significantly from those of the aggregate market portfolio, where the benefits from investing in industry exposed stocks as substitutes for the underlying assets are the greatest. Preferences for industry exposure are most pronounced for transient investors investing based on public information, and sector funds seeking industry exposure.

1. Introduction

Market frictions make markets incomplete in the sense that investors cannot construct a complete set of gambles on states of nature with existing assets. Storage costs, for example, make direct investment in commodities, such as oil, infeasible for most investors. Wealth constraints can inhibit investment in large, indivisible assets such as real estate, while statutory investment restrictions, as well as less formal investment standards, can limit an investor's access to assets. Stocks can help to complete markets by providing investors with exposure to underlying assets that are otherwise unavailable or costly to acquire. However, stocks substitute for underlying assets only if the firm maintains exposure to those assets.

Recognizing that "pure-play" stocks are a second-best substitute for underlying assets in investor portfolios leads to the prediction that investors will display preferences for stocks with industry factor price exposure (hereafter, industry exposure). In this paper, we characterize investor attraction to industry exposure using a large sample of firms in the 30 Fama-French industries during the period from 1983 to 2006.

Our analysis of several proxies for investor interest suggests that investors, on average, show a significant preference for pure-play stocks. Industry exposure, measured using the industry beta from an extended (two-factor) market model, is positively associated with three proxies for investor interest: share turnover, the number of institutional investors, and the number of mutual funds that hold the firm's stock. Across all three proxies, the positive association between industry exposure and investor interest comes from both an attraction to high exposure stocks and an aversion to low exposure stocks. Moreover, there is no evidence that investor preferences for exposure are driven by a preference for concentrated firms relative to diversified firms.

Having documented a robust positive association between industry exposure and investor interest, we investigate whether *asset-specific* and *investor-specific* market frictions explain investor preferences for industry exposure. We hypothesize that equities are more likely to act as a substitute for underlying assets in industries in which the cash flows differ significantly from those of the aggregate market portfolio because the benefits of asset substitution are greatest. To identify such industries, we create a market-based proxy for industry specificity that measures the degree to which the returns of firms in an industry differ from those of the aggregate market portfolio. Consistent with our hypothesis, investor preferences for stocks with high industry exposure are greatest in industries with high industry specificity. *Ceteris paribus*, high-exposure stocks in high-specificity industries have 44% higher turnover than low-exposure stocks. By contrast, the difference in turnover falls to 20% in medium- and low- specificity industries.

We report three cross-sectional patterns in the association between industry exposure and investor interest that are a function of investor-specific characteristics. First, we document that differences in fiduciary standards across institutional investors are associated with different preferences for exposure. All classes of institutional investors, regardless of fiduciary standards, have an attraction to high exposure stocks and an aversion to low exposure stocks. These preferences, however, are least pronounced for banks, which is consistent with the view that banks expect that courts may view high industry exposure stocks as imprudent investments (Del Guercio, 1996).

Second, we document that institutions' investment styles, which are correlated with differences in information acquisition costs, are associated with their preferences for industry exposure. Dedicated owners, who invest in a small number of stocks about which they acquire private information, do not display a preference for high exposure stocks. In contrast, quasi-indexers and transient investors, who hold a large number of stocks and do not rely on private information, display strong preferences for high exposure stocks. These results are consistent with the view that industry exposure is negatively correlated with information acquisition costs.

Finally, we document that mutual fund investment objectives are associated with different preferences for exposure. Mutual funds bond themselves to their individual investors by committing to an investment policy in the prospectus. The bonding is optimal given information asymmetry frictions between the fund and its investors. Sector funds that commit to a policy of investing in the assets of a particular industry will attract individual investors who seek exposure to the cash flows of the underlying assets in that industry. We hypothesize that sector funds will display preferences for industry exposure to reflect the demands of their individual investors. Consistent with our hypothesis, we find robust evidence that sector funds exhibit preferences for high exposure stocks.

Overall, our analyses provide evidence that market frictions are associated with investor demand for industry exposure. These analyses are the first steps in addressing a broader question: How do market frictions affect firms' optimal hedging decisions? Contrary to the traditional view that market frictions create incentives for firms to reduce risk (i.e., to hedge), our results suggest that market frictions may create incentives for some firms to *not* hedge. Firms that choose to remain a pure play on their underlying assets fill a market niche. The broader market interest means greater liquidity, and hence a lower cost of capital given evidence that liquidity is a priced risk factor (e.g., Chordia, Subrahmanyam, and Anshuman, 2001, Chan, 2002, Pastor and Stambaugh, 2003, Acharya and Pedersen, 2005).[1] Firms will trade-off this cost-of-capital benefit that comes from *not* hedging against the expected benefits of hedging. The result

[1] The idea that retaining exposure generates broader market interest is akin to thinking about the exposed firms as having greater "visibility" in the sense of Merton (1987).

can be that a firm forgoes the risk management benefits of hedging for the sake of the market liquidity benefits associated with exposure. The idea that *not* hedging is the optimal decision for some firms could help reconcile the controversy over whether hedging is a value-enhancing activity.[2]

However, the question of whether the liquidity benefits associated with being a pure-play firm are incorporated into a firm's hedging decision is secondary, in the sense that it can only be addressed if we understand the nature of investor demand for exposure. Our goal in this paper is to characterize investor preferences for industry exposure; future research can then appropriately test whether catering to investor demand affects firms' optimal hedging decisions.

The paper is organized as follows. Section 2 develops our hypotheses. Section 3 describes the sample and methodology. Section 4 presents the results for the unconditional analysis of the association between industry exposure and investor interest. Section 5 examines cross-sectional differences in preferences for exposure as a function of asset-specific and investor-specific market frictions. Section 6 concludes.

2. Hypothesis development

2.1 Market frictions and investor demand for industry exposure

A complete market is one in which investors can construct a complete set of gambles on future states of nature with existing assets. In the context of an investor's optimal portfolio allocation decision, the existing assets can include physical commodities, equity securities, and other financial assets. When markets are not complete due to market frictions, entrepreneurs have incentives to create new assets that overcome these frictions. Securitized loans and real estate investment trusts (REITs) are classic examples of assets created to make access to an

[2] See, for example, Allayannis and Weston (2001), and Jin and Jorion (2006).

underlying asset, mortgage loans or real estate, feasible investments for a greater number of investors. Despite such incentives, markets remain incomplete. As noted by Stiglitz (1972), various market frictions prevent the creation of new assets that would complete markets.[3]

We propose that stocks that retain exposure to the assets underlying the firm's operations help to complete markets. The stock becomes a substitute for the underlying assets in that it has commensurate payoffs in corresponding states of the world. A firm that uses financial or operational hedges will alter the payoff structure of the firm's assets such that the firm's stock will not be a substitute for the cash flows of the underlying assets.

Firms only benefit from providing a substitute, however, if direct investment in the underlying asset is prohibitively costly or infeasible. Costly investment may be attributed to characteristics of the asset, such that investment is costly across all classes of investors, or to characteristics of particular investors. An example of an *asset-specific* market friction is asset indivisibility, which makes investment in assets such as real estate and utilities either impractical or infeasible in the presence of wealth constraints. Storage costs are another asset-specific characteristic that can make investing in physical commodities prohibitively costly for many investors.

An example of an *investor-specific* market friction is the litigation environment in the United States, in which courts hold different classes of investors to different fiduciary standards with respect to their investment decisions (Del Guercio, 1996). A second example is information frictions in equity markets between managers and investors. The associated adverse selection concerns create investor-specific differences in incentives for, and costs of, gathering information, which affects the cost/benefit trade-off of using stocks as a substitute for direct investment in the underlying assets. A third example is information asymmetry between

[3] See, for example, Radner (1968) and Hahn (1971).

institutional investors and the individual investors who invest with them. As a result of the associated moral hazard concerns, investor-specific contracts emerge such as self-imposed constraints on investment allocations that are the norm in the mutual fund industry.

2.2 Diversification

An alternative hypothesis that predicts a positive association between investor interest and industry exposure is that investors are attracted to concentrated (non-diversified) firms, and concentrated firms have greater industry exposure. For this alternative hypothesis to explain the results investors must have preferences for concentrated firms and concentrated firms must have higher industry exposure than diversified firms.

The first necessary condition – that investors have preferences for concentrated firms – seems plausible given the extensive evidence of a diversification discount.[4] The second necessary condition – that concentrated firms have higher industry exposure than diversified firms – also seems plausible given evidence in Lamont (1997) that more concentrated firms have greater cash flow risk associated with the underlying assets. However, the correlation between diversification and industry exposure is ultimately an empirical question because firms that have more concentrated business segments also may use financial instruments or real hedges to alter cash flow risks (Géczy, Minton, and Schrand, 2007). In Section 4.3 we examine diversification as an alternative explanation to our hypothesis that market frictions create incentives for investor attraction to industry exposure.

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[4] One explanation for the diversification discount is value destruction related to greater agency conflicts in diversified firms (Jensen, 1986; Shleifer and Vishny, 1989; Jensen and Murphy, 1990; Stulz, 1990; Rajan, Servaes, and Zingales, 2000). A second explanation is greater information transparency in non-diversified firms (Bushman, Chen, Engel, and Smith, 2004; Berger and Hann, 2003; Bens and Monahan, 2004).

2.3 Related literature

The prediction that certain investors are "attracted to" industry exposure, or that there is increased "investor interest" in industry exposure, sounds similar to predictions from models that assume behavioral biases on the part of investors. If one assumes that such biases exist, it would be natural to predict that firms may cater to investor preferences for industry exposure through their exposure decisions. Our hypothesis differs from catering theory stories in that we do not assume that investor preferences for industry exposure result from behavioral biases. Rather, investors have economic incentives to invest in exposed firms because direct investment in the underlying assets is infeasible or prohibitively costly. This investment is a second-best portfolio decision, but it is not a suboptimal decision.

The literature on tracking stocks provides a useful point of reference. When a firm issues a tracking stock, the parent firm and the tracking business segment file separate financial statements with the Securities and Exchange Commission (SEC). Firms experience a positive stock price reaction at the announcement of the creation of tracking stock (e.g., Billett and Mauer, 2000; Boone, Haushalter, and Mikkelson, 2003; Chemmanur and Paeglis, 2000; D'Souza and Jacob, 2000; Elder and Westra, 1999; and Zuta, 2000). The positive stock price reactions are attributed to an expected reduction in information asymmetries or to reduced agency costs.[5] The benefits from issuing a tracking stock are similar to the hypothesized benefits of remaining exposed to industry risks.

3. Methodology

[5] With respect to the information benefits, the issuance of tracking stock is associated with an increase in analyst following (D'Souza and Jacob (2000), Chemmanur and Paeglis (2000) Zuta, 2000; Gilson, Healy, Noe, and Palepu (2001), but there is mixed or weak evidence on whether analyst forecast accuracy is higher and spreads are lower (e.g., Billett and Vijh, 2004; Gilson, Healy, Noe, and Palepu, 2001; Elder, Jain and Kim, 2005).

The general format of the analysis is to estimate the following reduced form model of ownership interest on control variables and measures of industry exposure:

$$OWNERSHIP_{iy} = \alpha + \lambda INDEXP_{iy} + \sum_k \delta_k CONTROL_{kiy} + \varepsilon_{iy} \qquad (1)$$

where *OWNERSHIP* represents various proxies for firm-year ownership intensity; *INDEXP* is firm-year industry exposure; and *CONTROL* is a matrix of firm-year control variables. Section 3.1 describes our proxies for ownership interest. Section 3.2 describes our measures of industry exposure, and Section 3.3 describes the control variables.

3.1 Ownership interest

We use three measures of ownership interest (*OWNERSHIP*). The first proxy is share turnover, which captures aggregate investor interest across both individuals and institutions (Barber and Odean, 2008; Hou, Peng, and Xiong, 2006; and Loh, 2008). *TURNOVER* is the natural logarithm of average monthly turnover (volume divided by shares outstanding), computed for each firm *i* for each year *y*.

The second proxy for ownership interest is the natural log of 1 + the number of institutions that hold stock *i* at the end of year *y (LNUMGR)*. Data on annual institutional ownership are from the Thomson Financial 13-F database. The Thomson database is based on the universe of 13-F filings without any selection or removal of firms. Holdings under $20,000 and holdings by an institution with less than $100 million in equity are not required to be reported on a 13-F filing. Since all of our firms are publicly traded, we assume that the firm has zero institutional investors if it is not included in the reported holdings of any institutions on the Thomson Financial database.

The final proxy for ownership interest is the natural log of 1 + the number of mutual funds that hold stock *i* at the end of year *y (LNUMFUNDS)*. We consider mutual fund investment to be a proxy for individual investor interest since mutual funds are created to meet the demands of individual investors. Data on annual fund ownership are from the Thomson Financial Mutual Fund database. Mutual funds (i.e., investment companies) are a class of investors in the Thomson Financial database of 13-F filers, but data on mutual fund holdings in the mutual fund database are different from the data for the Investment Companies in the 13-F database.[6] We eliminate from the mutual fund database funds that have an investment objective code (IOC) equal to 1, 5 or 6, which represent International funds, Municipal Bond funds, and Bond and Preferred Stock funds, respectively. We also eliminate funds that have less than three annual observations in which the market value of assets at the beginning of the year is less than $1 million.

3.2 Industry factor price exposure

We use the industry definitions provided on Kenneth French's website to construct 30 industry portfolios. The 30th industry includes firms that do not fall into industries 1 to 29; we discard the small number of firms assigned to the 30th industry.

For each firm (*i*), we calculate industry exposure at the end of each year (*y*) by estimating an extended market model using the past 60 months of return data:

$$r_{i,t} = \beta_{\mathrm{i}}^{\mathrm{mkt}} r_{mkt,t} + \beta_{\mathrm{i}}^{ind} r_{ind,t} + \varepsilon_{i,t} \tag{2}$$

[6] The Thomson Investment Company category includes institutions that are not regulated investment companies (i.e., not mutual funds) but that derive a significant portion of their business from the mutual fund business (determined by Thomson). In addition, holdings data on the Thomson Mutual Fund database is compiled primarily from the funds' required semi-annual reports to shareholders (N-30D filings) rather than 13-F filings.

where r_{mkt} denotes the monthly return on the CRSP equally weighted market index, and r_{ind} denotes the monthly return on the appropriate equally weighted industry portfolio.[7] For a firm-year observation to be included in the sample we require at least 24 monthly return observations to estimate the extended market model.

The estimated coefficient β_i^{ind} is a continuous measure of firm *i*'s industry exposure (*INDEXP*). We also create indicator variables for high and low exposure (*BETAHIGH* and *BETALOW*, respectively). *BETAHIGH* = 1 (*BETALOW* = 1) if $INDEXP_{iy}$ is above (below) the 70th (30th) percentile exposure for its industry group for year *y*. The ranking is done before requiring that the sample firms have non-missing Compustat data.

Table 1 reports descriptive statistics for the exposure measures. There is considerable variation in the magnitude of industry exposure across the 29 industries, with the average exposure ranging from 0.51, for the Coal industry, to in excess of 1.00 for the Retail and Business equipment industries. Columns 3 and 4 report estimates of the average stock market βs across each industry. *MKTBETA2* is the estimate of β_i^{mkt} from the extended (two-factor) market model specified in equation (2). *MKTBETA* is the estimate of firm *i*'s stock market β using the standard market model. Not surprisingly, the introduction of industry returns in the extended market model results in lower estimates of stock market βs.

(Insert Table 1 here.)

We adopt an out of sample portfolio approach to assess our exposure measure as a proxy for future exposure. At the start of year y + 1, we form an equally weighted portfolio that buys

[7] We use equally weighted returns to ensure that the returns from a small number of large companies do not drive our measure of industry returns.

stocks classified as high exposure (*BETAHIGH* = 1) as of year-end *y* and shorts low exposure stocks (*BETALOW* = 1). The portfolio is rebalanced annually. We regress the returns from the portfolio strategy on the excess returns from the market portfolio and the relevant industry portfolio:

$$r_{high\exp} - r_{low\exp} = \alpha + \delta_m \left(r_{mkt} - r_f\right) + \delta_{ind} \left(r_{ind} - r_f\right) + \varepsilon. \tag{3}$$

If the *BETAHIGH* and *BETALOW* classifications capture meaningful differences in exposure, we expect to observe $\delta_{ind} > 0$. The final column of Table 1 reports that, for all industries other than Food and Books, there is robust evidence that $\delta_{ind} > 0$, which indicates that our proxy for industry exposure based on historical data predicts future exposures effectively.

In addition, the exposure proxies are fairly stable from year to year. Of firms that are classified as high beta (medium beta) {low beta} in year t-1, approximately 76.4% (68.5%) {74.9%} are in the same category in year t. Of firms that are classified as high beta (medium beta) {low beta} in year t - 2, approximately 65.1% (58.6%) {63.6%} are in the same category in year t.

3.3 Control variables

We draw the control variables (*CONTROL*) from four papers that examine the determinants of institutional ownership: Del Guercio, 1996, Falkenstein, 1996, Gompers and Metrick, 2001, and Hong and Kacperczyk, 2007. Broadly speaking, these papers include various specifications of proxies for the following constructs: firm size, growth, share price, systematic risk, dividend yield, returns, return volatility, and firm age. Appendix A provides a detailed description of our proxies for these constructs.

Table 2 reports the control variables separately for the high exposure (*BETAHIGH*), low exposure (*BETALOW*), and remaining medium exposure (*BETAMED*) firms. There is a robust monotonic relation between industry exposure, turnover, and stock market βs estimated using a standard market model (*MKTBETA*). High exposure firms also tend to have lower dividend yields and higher debt-to-equity ratios than low exposure firms. Market-to-book ratios, which prior literature has used as a proxy for growth opportunities, do not vary significantly across the beta classifications. Overall, Table 2 shows that there are substantial differences in firm characteristics across low, medium, and high exposure firms. We control for these differences in the subsequent empirical analysis of investor interest in industry exposure.

(Insert Table 2 here.)

4. Investor interest and industry factor price exposure

4.1 Analysis of turnover

Table 3 reports the results of regressions that measure the association between industry exposure and the natural logarithm of share turnover (*TURNOVER*). We estimate equation (1) annually and report the average of the coefficient estimates. Significance levels are based on Z-statistics associated with annual t-statistics that control for cross-sectional and serial correlations. Standard errors are clustered by industry in the annual regressions. We also report the average number of annual observations and the average adjusted R^2s.

The results for the control variables are generally consistent with prior research and show that greater investor interest is positively associated with firm size, market-to-book ratios, return volatility, stock market βs, past returns, inclusion in the S&P 500 index, and listing on NASDAQ, and negatively associated with the inverse of price, dividend yields, debt-to-equity ratios, and firm age.

(Insert Table 3 here.)

As reported in Column 1, the coefficient on the continuous industry exposure proxy (*INDEXP*) is positive and significant, which is consistent with the prediction that higher industry exposure is associated with higher investor interest. Table 1 provides evidence that the continuous measure of industry exposure, *INDEXP*, varies systematically across industries. In regressions not reported, we use a standardized measure of *INDEXP* to control for the possibility that investors are attracted to particular industries rather than exposure *per se*. The results are similar. Investors display robust preferences for industry exposure.

In Column 2 we use the indicator variables defined in the previous section, *BETAHIGH* and *BETALOW*, to measure industry exposure. These variables control for industry effects, as firms are classified as high, medium, or low exposure firms relative to other firms in the same industry each year. The results indicate that the positive association between *INDEXP* and share turnover comes from both an attraction to high exposure stocks and an aversion to low exposure stocks. *Ceteris paribus*, the turnover in firms with high industry exposure is 16% higher than that of firms with medium levels of exposure, while the turnover of low exposure firms is 8% lower. The annual difference in turnover between the high and low industry exposure firms is significant in all 24 sample years.[8]

[8] Eliminating financial institutions, which represent approximately 20% of the sample observations, suggests even stronger preferences for exposure within the remaining industries. The average annual sample size drops to 2,015. The coefficient estimate on *INDEXP* increases to 0.08, and the coefficient estimates on *BETALOW* and *BETAHIGH* are -0.12 and 0.17, respectively.

We conduct two subsample analyses to mitigate concerns that the turnover results are driven by measurement error in the industry exposure proxy related to non-synchronicity in monthly stock returns. Industry exposure estimates for infrequently traded (i.e., low turnover) stocks may be underestimated. A downward bias would induce a positive relation between exposures and turnover. Including the stock market β as a control variable in the regression should mitigate this concern since any downward bias due to non-synchronicity should also be reflected in the stock market β. Moreover, if measurement error drives our results, we would expect to observe a negative relation between low industry exposure firms and turnover, but we would not necessarily expect to observe a positive relation between high industry exposure firms and turnover.

Columns 3 and 4 report estimates from equation (1) for a sample that excludes the smallest quartile of firms in each year. Columns 5 and 6 report estimates for a sample that excludes observations with a stock price at the start of the year below $5. The results using either the continuous specification for industry exposure (*INDEXP*) or the indicator variables are similar to those reported in Columns 1 and 2 for the full sample, both in terms of statistical and economic significance.

4.2 Analysis of institutional ownership

This section discusses results for the estimation of equation (1) using the number of institutional owners (*LNUMGR)* as a proxy for institutional ownership interest and the number of mutual fund owners (*LNUMFUNDS*) as a proxy for mutual fund interest.[9] Table 4 presents the results. As in Table 3, the results for the control variables are consistent with prior research.

[9] The lagged value of the natural logarithm of turnover is added to the set of control variables. Standard diagnostic tests do not indicate upwardly biased coefficient estimates or variances due to collinearity among the regressors.

Institutional and mutual fund ownership are positively associated with firm size, the inverse of price, share turnover, past returns (for mutual funds), firm age, and inclusion in the S&P 500 index (for institutions), and negatively associated with market-to-book ratios, dividend yields, debt-to-equity ratios, return volatility, and listing on the NASDAQ exchange.

(Insert Table 4 here.)

There is a positive association between industry exposure and investor interest. Columns 1 and 2 of Table 4 report that the number of institutions (*LNUMGR*) that hold a firm's stock is significantly and positively related to industry exposure, as measured by the continuous variable *INDEXP*.[10] Similar to the turnover results in Table 3, the positive relation is driven by both an attraction to stocks with high industry exposure and an aversion to stocks with low industry exposure, relative to stocks with medium levels of industry exposure. The difference between the coefficient estimates on the high and low industry exposure indicator variables is statistically significant in all years. In terms of economic magnitude, a change in a firm's industry exposure from the 30th percentile to the 70th percentile is, *ceteris paribus*, associated with a 13% increase in the number of institutions holding the stock.

Column 3 of Table 4 reports that the number of mutual funds (*LNUMFUNDS*) that hold a firm's stock also is significantly positively related to the continuous measure of industry exposure, *INDEXP*. The results using indictor variables for industry exposure (Column 4) indicate a significant aversion to low exposure stocks. The Z-statistic measuring the significance of the average coefficient estimate on *BETAHIGH* is 1.79, just below conventional significance

[10] Results for the standardized measure of *INDEXP* are similar.

levels. Overall, the relation between industry exposure and mutual fund investors is weaker than the relation for institutional investors as a whole.[11]

4.3 Diversification

In this section, we explore the possibility that diversification explains the positive association between industry exposure and investor interest because diversification is negatively correlated with both variables. We use three proxies for business and geographic diversification, all of which are specified such that a higher value implies greater diversification.[12] The first proxy is the number of business (geographic) segments in which a firm operates (*NUMSEG*). The second proxy is an indicator variable equal to one if the firm is a multi-segment firm (regardless of the number of segments) and equal to zero if the firm is a single-segment firm (*MULTISEG*). The third proxy is one minus the firm's revenue-based concentration ratio (*DIVERSE*), which is computed following Comment and Jarrell (1995). The minimum value of *DIVERSE* is zero for a single segment firm and it approaches one as diversity increases (concentration decreases).

(Insert Table 5 here.)

Table 5 reports the average levels of the diversification proxies for high and low exposure firms within each industry. In Panel A, there is some evidence that business diversification is negatively correlated with our measure of industry exposure. High industry exposure firms have lower diversity as measured by the three proxies in 19 to 24 of the 29 industries, but these

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[11] The results in Table 4 are somewhat sensitive to the elimination of financial institutions from the sample. The coefficient estimates on *INDEXP* are slightly reduced in magnitude, but remain significant at a 1% significance level. The aversion to the low industry exposure stocks is virtually identical, but the attraction to high industry exposure stocks declines. For the *LNUMGR* analysis, the coefficient estimate is 0.017 and it is not significant at conventional levels. For the *LNUMFUNDS* analysis, the coefficient estimate is 0.016 and it remains insignificant.

[12] See discussions of the merits of proxies for diversification in Bushman, Chen, Engel, and Smith (2004) and Denis, Denis, and Sarin (1997).

differences in the measures of diversity are significant for only 14 of the industries. For at least four industries we observe significantly higher levels of diversification among high industry exposure firms. Panel B reports the results for geographic diversification. Similar to Panel A, there is evidence that diversification and exposure are negatively correlated. High exposure firms have fewer geographic segments and higher geographic concentration in 20 of the 29 industries, but the differences are only significant for nine industries. Thus, *ex ante*, while there is some evidence of that diversification and exposure are negatively correlated, it does not appear that diversification is likely to be an important omitted variable.

To examine whether diversification generates the result that investors are attracted to industry exposure, we adopt an approach similar in spirit to Daniel and Titman (1997). We sort firms into portfolios based on measures of line-of-business diversification and examine whether investors display preferences for industry exposure within each portfolio.[13] If investors are attracted to industry exposure because it is negatively correlated with diversification, we would expect to observe no evidence that investors are attracted to industry exposure within portfolios of firms with similar levels of diversification.

Table 6 presents the results from estimating equation (1) for each of our proxies for ownership intensity (*TURNOVER*, *LNUMGR*, and *LNUMFUNDS*) within each of the portfolios of firms with similar diversification levels. Panel A sorts the firms into two portfolios: single segment firms (*MULTISEG* = 0) and multi-segment firms (*MULTISEG* = 1). Panel B sorts the firms into three portfolios based on the rank of the continuous measure *DIVERSE*: the bottom quartile, the middle two quartiles, and the upper quartile. Firms are ranked within industry by year. We only report the results for the model specification that includes the indicator variables *BETAHIGH* and *BETALOW* to measure industry exposure. Results using the continuous

[13] Similar results are obtained sorting by measures of geographic diversification.

variable (*INDEXP*) yield similar inferences. All models include the same set of control variables as in the previous analyses. The results for the control variables are not reported to conserve space, but are consistent with those reported in Tables 3 and 4.

(Insert Table 6 here.)

For all three proxies for ownership intensity (*TURNOVER*, *LNUMGR*, and *LNUMFUNDS*), the coefficients on *BETAHIGH* and *BETALOW* within all the diversification-sorted portfolios indicate that investors display robust preferences for stocks with high industry exposure and an aversion to stocks with low industry exposure. The magnitudes and significance levels of the coefficient estimates are similar to those presented in Tables 3 and 4 and are robust across the diversification-sorted portfolios. Interestingly, when *TURNOVER* is the proxy for ownership intensity, among the most diverse firms there is some evidence that investors display increased preferences for exposure and are less averse to low exposure stocks. This *greater* preference for industry exposure within diverse firms is inconsistent with diversification being an omitted correlated variable.

We further analyze the results over two sub-periods: 1983 to 1997 and 1998 to 2006. Effective in 1998, Statement of Financial Accounting Standards (SFAS) No. 131, *Disclosures about Segments of an Enterprise and Related Information* (FASB 1997), changed how firms define segments and resulted in an increase in the number of segments reported by firms (e.g., Berger and Hann, 2003).[14] The changes potentially decrease the ability of our diversification proxies to capture the negative correlation between diversification and industry exposure relative

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[14] In our sample, the average number of business segments increases from 1.62 prior to the introduction of SFAS No. 131 to 2.05 afterwards, and the average measure of diversification (*DIVERSE*) increases from 0.14 to 0.21.

to the pre-SFAS 131 period, when segments were primarily defined at the industry level.[15] The results in both the pre and post-SFAS 131 periods are similar to those reported in Table 6. There is, however, some evidence that institutional investors are not attracted to high exposure stocks in the pre-SFAS 131 period, although they do display a robust aversion to low industry exposure stocks within all the diversification-sorted portfolios.

We also re-estimate all regressions excluding financial institutions. This analysis is particularly important because not only are financial institutions a significant percentage of the sample (almost 20%), but also the summary statistics reported in Table 5 suggest that the high exposure financial institutions are actually more diversified than the low exposure financial institutions. This is not consistent with the results for the majority of industries in which high exposure firms are less diversified than low exposure firms. Thus, including financial institutions in the sample may obscure the possibility that diversification is an omitted correlated variable for the majority of industries. The results using the sample that excludes financial institutions are qualitatively similar to those presented in Table 6.

Overall, our analysis suggests that diversification does not explain investor attraction to industry exposure.

5. Cross-sectional analysis of exposure preferences

[15] For periods prior to 1998, SFAS No. 14, *Financial Reporting for Segments of a Business Enterprise* (FASB 1976) mandated the reporting requirements for segment-level financial information. The segments roughly corresponded to the firm's distinct product market industries. Under SFAS No. 131, firms define their segments based on the internal management structure of the firm, which may or may not be by industry-level product line. For example, a firm that has one industry-level segment, such as oil, would have reported only one segment in the pre-1998 period. However, if this firm manages its operations as two separate business units, such as oil-retail and oil-wholesale, the firm reports two segments rather than one under SFAS No. 131.

The results thus far provide robust evidence that, on average, investors exhibit preferences for industry exposure. In Sections 5.1 and 5.2, we investigate the nature of asset-specific and investor-specific market frictions that might explain these preferences.

5.1 Asset-specific market frictions

We predict that the benefits of investing in a high exposure stock as a substitute for direct investment in the underlying asset are greatest when the cash flows and risks of the asset differ significantly from those of the aggregate market. We refer to this asset characteristic as "specificity," which we measure at the industry level.

To measure industry specificity for industry *j* in year *y*, we estimate a standard market model and an extended market model for each firm *i* within industry *j* using monthly return data over the period January of year *y* – 4 to December of year *y*. The extended market model includes the equally-weighted market returns and the appropriate equally-weighted industry returns. For each firm *i* in year y, we compute the difference between the adjusted R^2 values of the two models. We use the average difference in adjusted R^2 values within an industry as our measure of industry specificity.[16] The result is 24 annual observations for the 29 Fama-French industry groups, which is 696 industry-year observations of industry specificity (*SPECIFICITY*).

Our measure of industry specificity has two important features. First, it is measured using market data, which is available monthly. While the covariances of industry cash flows with aggregate market cash flows might be a more conceptually appropriate construct for industry specificity, financial statement data necessary to estimate the covariances between industry and market cash flows are available only annually. These estimates based on 24 annual

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[16] An alternative metric to the difference in adjusted R^2 is the F statistic associated with the test of whether industry returns improve model specification. The correlation between these two variables is 0.98.

observations are likely to be poor measures. Second, our measure applies equally well across industries. Measures based on an *ex ante* identifiable market frictions, such as asset indivisibility or storage costs, would, by necessity, be industry-specific.

(Insert Figure 1 here.)

Figure 1 presents boxplots of the average industry specificity metric over our sample period from 1983 to 2006 for each of the 29 Fama-French industries. The greater is the average difference in adjusted R^2s, the greater is the industry specificity. Five industries stand out as having substantially higher specificity measures: Utilities, Mining, Tobacco, Crude Oil and Natural Gas, and Coal. These five industries are considered high-specificity industries in the empirical analysis. For these high-specificity industries, the adjusted R^2 in the extended (two factor) model increases by 17% in absolute terms, on average, over the adjusted R^2 in the standard market model. The industries with the lowest average specificity are: Wholesale, Electrical Equipment, Services, Games, and Consumer Goods. These five industries are considered low-specificity industries in the empirical analysis. For the low-specificity industries, the adjusted R^2 increases by just 1.3% in absolute terms following the addition of industry returns to the market model.

Our classification of industries as high, medium, or low specificity is static over the sample period, but the boxplots in Figure 1 illustrate variation in specificity during the sample period for many industries. Much of the variation in *SPECIFITY* within each industry, however, is due to an increasing trend in *SPECIFICITY* from 1983 through 2006 across all industries. The relative ranking of the industries, however, generally remains stable throughout the sample period. The only exception is the specificity measure for the Coal industry. We classify the Coal industry as a high-specificity industry in all years, but it has the most significant time-series variation, which is not surprising given the small number of firms in the industry (Table 1). All of the results are robust to exclusion of the Coal industry observations from the regressions.

We adopt two approaches to test the prediction that investor preferences for industry exposure are greatest for industries in which expected returns and cash flows differ significantly from those of the aggregate market portfolio. First we estimate equation (1) with three additional regressors: *SPECIFICITY* and the interaction of *SPECIFICTY* with the indicator variables, *BETALOW* and *BETAHIGH*. If industry specificity increases investor attraction to industry exposure, we expect a positive coefficient on the interaction between *BETAHIGH* and *SPECIFICITY* and a negative coefficient on the interaction between *BETALOW* and *SPECIFICITY*. Second, we separately estimate equation (1) within three portfolios formed based on industry specificity (low, medium, and high specificity). We expect to observe stronger investor preferences for industry exposure within the high specificity portfolio. The results of both analyses are reported in Table 7.

(Insert Table 7 here.)

Consistent with our conjecture, the results in Panel A show that the coefficient on the interaction term between *BETAHIGH* and *SPECIFICITY* is positive and significantly different from zero for all three measures of investor interest. In addition, the coefficient on the interaction term between *BETALOW* and *SPECIFICITY* is negative and significantly different from zero when turnover and the number of institutional investors are used as proxies for investor interest.

Panel B reports results for high-, medium-, and low-specificity industries, respectively. In Column 1, share turnover is used as a proxy for investor interest. Within high-specificity industries, there is robust evidence that investors are attracted to high industry exposure stocks and display an aversion to low industry exposure stocks. In terms of economic magnitude, a change in a firm's industry exposure from the 30^{th} percentile to the 70^{th} percentile is associated with a 44% increase in turnover, *ceteris paribus*. In medium- and low-specificity industries, investors also display an attraction to high industry exposure and an aversion to low industry exposure. However, the coefficients are attenuated relative to the high-specificity industries. For example, within medium-specificity industries, a change in a firm's industry exposure from the 30^{th} percentile to the 70^{th} percentile is associated with a 22% increase in turnover, *ceteris paribus*, which is half that in the high-specificity industries. This value falls to less than 20% in low-specificity industries. The difference between the coefficients on *BETAHIGH* and *BETALOW* for the high-specificity industries is greater than the difference for the medium (low) specificity industries in 23 (21) of the 24 annual regressions (not reported).

The results using the number of institutional owners and mutual funds as proxies for investor interest follow a similar pattern. The differences between the coefficients on *BETAHIGH* and *BETALOW* increase with industry specificity. In the institutional ownership regressions, the difference between the coefficients on *BETAHIGH* and *BETALOW* for the high-specificity industries is greater than the difference for the medium (low) specificity industries in 17 (21) of the 24 annual regressions (not reported). In the mutual fund ownership regressions, the difference between the coefficients on *BETAHIGH* and *BETALOW* for the high-specificity industries is greater than the difference for the medium (low) specificity industries in 16 (18) of the 24 annual regressions.[17]

[17] The results in Table 7 are robust to the exclusion of financial institutions from the sample. In Panel A, using the interaction variables for *SPECIFICITY*, there is a greater aversion to low-exposure stocks in the *TURNOVER* regressions. This is consistent with the effects of excluding financial institutions on the results in Table 3. The results in Panel B are similar. Again, consistent with the effects of excluding financial institutions on the results in Tables 3 and 4, the aversion to low exposure stocks is stronger in the *TURNOVER* regressions and the attraction to high exposure stocks is weaker in the *LNUMGR* and *LNUMFUNDS* regressions.

Overall, the results reported in Table 7 indicate that investors have stronger preferences for high industry exposure stocks and a greater aversion to low industry exposure stocks in industries in which returns differ substantially from those of the aggregate market.

5.2 Investor-specific market frictions

In this section, we examine the impact of *investor-specific* market frictions on investor preferences for industry exposure. We consider three partitions of the sample based on investor characteristics. We first partition the institutional investors (13-F filers) based on fiduciary standards. Consistent with the classification system in the Thomson Financial database and numerous studies of institutional ownership, we classify institutions into five types: (1) bank trust, (2) insurance company, (3) investment company, (4) investment advisor, and (5) other. The "other" category includes pension and endowment funds.[18] We aggregate the investment companies and investment advisors into one institution type because the predictions are the same for both classes of institutions.[19]

We predict that banks will exhibit lower preferences for exposure than insurance companies, pension funds, endowments, and investment companies/advisors because banks are the only institution governed by the common-law "prudent-man" rule. As Del Guercio (1996) notes, when the courts consider whether an investment is prudent or not, they tend to focus on the characteristics of assets in isolation, rather than considering the role of the asset in the bank's overall portfolio. If banks expect that courts will view stocks with high industry exposure as

[18] We thank Brian Bushee for providing us with his institution classifications during the sample period. There is a coding error in the Thomson Financial 13-F database. Thomson reports that partway through 1998, and in subsequent years, many banks (Type 1) and independent investment advisors (Type 4) are misclassified as other institutions (Type 5). Bushee's database provides a consistent classification of the institutions on the Thomson Financial database.

[19] In addition, in the Thomson Financial 13-F database, the distinction between the two types is (necessarily) somewhat *ad hoc*. The Investment Company category (Type 3) includes investment advisors for which a "significant" portion of their advisory services are to the mutual fund business (as determined by Thomson).

imprudent investments, then banks will exhibit lower preferences for industry exposure than other institutions.

Table 8 Panel A presents the results. We report the results only for the model specification that includes the indicator variables *BETAHIGH* and *BETALOW* to measure industry exposure. Results using the continuous variable (*INDEXP*) yield similar inferences. All models include the same set of control variables as in the previous analyses; results for the control variables are consistent with those reported in Tables 3 and 4 and are not tabulated.

Regardless of fiduciary standards, all types of institutions display a significant attraction to high exposure stocks and a significant aversion to low exposure stocks. Consistent with our predictions, these preferences are slightly less pronounced for banks. *Ceteris paribus*, a high industry exposure firm will have 11% more banks holding its stock relative to a low industry exposure firm. In contrast, for investment advisors and pensions/endowments the difference is about 13%.[20] In terms of statistical significance however, the difference between the preferences displayed by banks and other institutional investors is only significant in six of the 24 sample years.

(Insert Table 8 here.)

We next partition the institutional investors (13-F filers) based on investment style, which we propose affects the institution's degree of information acquisition and monitoring. We classify institutions following Bushee (1998) who decomposes institutions into three types: dedicated owners, quasi-indexers, and transient investors.[21] Dedicated owners have large, long-

[20] When financial institutions are excluded from the sample firms, the results are similar except that the investment advisors exhibit only a significant aversion to low exposure stocks and not a significant attraction to high exposure stocks.

[21] Brian Bushee also generously provided us with his classifications of investors based on monitoring incentives. The Bushee (1998) annual institution classifications are based on k-means clustering of standardized factor scores, which are created on an institution-year basis using the weighted average of firm-specific characteristics of an

term holdings, concentrated in a small number of firms, and are more likely to gather private information about a firm and directly monitor its managers. Quasi-indexers tend not to rely heavily on private information and adopt a passive monitoring style. Transient investors hold small stakes in many firms and trade frequently on publicly available information, but they do not generally acquire private information.

We predict that different investment styles will influence the extent to which investors are attracted to exposure because investment style is associated with information acquisition. Both quasi-indexers and transient investors rely mostly on public information. Neither investor type wants to incur high information acquisition costs. Thus, both types will seek to avoid firms in which potential information asymmetries are large. In the context of explaining portfolio under-diversification, Van Nieuwerburgh and Veldkamp (2006) suggest that information acquisition costs are lower for correlated assets, because investors who acquire information about the underlying asset are able to use it to invest in multiple firms that hold the same assets, and that these costs are traded-off against diversification benefits in optimal investment decisions. Under the assumption that industry exposure is negatively correlated with information acquisition costs, we predict that transient investors will display the greatest preferences for industry exposure, followed by quasi-indexers and dedicated investors.

The results in Table 8 Panel B are consistent with these predictions. Dedicated owners do not exhibit a preference for high industry exposure stocks, while quasi-indexers and transient investors do. Indeed, the preferences for exposure displayed by quasi-indexers and transient investors are significantly greater than the preferences displayed by dedicated owners in the majority of sample years. *Ceteris paribus*, a firm with high industry exposure has 13% (14%)

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institution's portfolio holdings. Approximately 4% of institution-year observations are dedicated owners, 60% are quasi-indexers, and 36% are transient investors.

more quasi-indexer (transient) investors than a low exposure firm, but only 5% more dedicated owners.[22]

The averaging of the annual coefficient estimates across the 1983 to 2006 sample period obscures a time trend in the significance of the *BETAHIGH* coefficient estimate for transient and quasi-indexers investors. The coefficients are not statistically different from zero in the 1980's and early 1990's, but they are consistently significantly positive in the last ten years of the sample period. While the time trend does not affect our statistical analysis, it does suggest that preferences for industry exposure have increased for transient and quasi-index investors in the last decade.

The increased preference for industry exposure among transient and quasi-index investors coincides with the introduction and rapid growth of Exchange Traded Funds (ETFs). In 1993 the first ETF was traded on the American Stock Exchange (AMEX). The number of funds grew from one in 1993 to 359 by the end of 2006, and the assets invested in ETFs grew from approximately \$1 billion to \$422 billion.[23] ETFs are designed to track returns in particular sectors or markets, providing investors with access to sector or market exposure at a lower cost than more traditional mutual funds. A cost effective way to for ETFs to track returns in a particular sector, such as utilities, is to invest in the stocks of firms that have high industry exposure. ETFs typically hold a large number of stocks, so they are likely to be classified as either transient or quasi-index investors. The rapid growth in ETFs may, at least in part, explain the increased preferences for industry exposure among transient and quasi-index investors over the last decade.

[22] When financial institutions are excluded from the sample, the results are similar except that the quasi-indexers no longer exhibit a significant attraction to high exposure stocks.
[23] The source of the annual statistics is the Investment Company Institute (ICI) Fact Book, 2008.

Finally, we partition the mutual funds by investment style. We classify mutual funds that primarily hold equities into three groups: balanced funds, market timers, and sector funds. The balanced fund category consists of funds that do not concentrate their assets in one of the 29 Fama-French industry groups. The market-timers concentrate their investments in a single industry each period, but the industry changes over time. The sector funds have a consistently high concentration in the same industry across time. Appendix B provides a detailed discussion of our methodology to classify funds. Under the assumptions that individual investors invest in sector funds to obtain exposure to the underlying cash flows of a particular segment, and that sector funds attempt to meet this demand, we predict that sector funds will display a greater preference for high exposure stocks.

Table 8 Panel C presents the results. We find that sector funds display a robust positive preference for high industry exposure stocks that is significantly different from zero at a 1% significance level. A stock with high industry exposure experiences 5% (9%) higher levels of sector fund ownership relative to a stock with medium (low) industry exposure. There is some evidence that mutual funds that invest the majority of their funds in one industry, but switch industries over time (market timers), display a preference for high industry exposure stocks, but the evidence is weaker in both statistical terms and in economic magnitude relative to the sector funds. Balanced funds also display preferences for high industry exposure stocks and an aversion to low industry exposure stocks. The economic magnitude of these preferences is similar to that for sector funds. This result is not surprising *per se* because there is some overlap between the funds that we classify as "balanced" and the funds that are classified as "transient investors" using Bushee's (1998) approach. The final column reports results for "Other" funds, which are generally non-equity funds that invest a large percentage of their assets in non-reportable items such as cash or OTC products (see Appendix A). These funds show *no* significant attraction to high exposure stocks or aversion to low exposure stocks, which is as it should be. This finding suggests that our results for the other classified funds (balanced, market timing, and sector) are not simply a mechanical outcome of the variable specification.

6. Conclusion

Stiglitz (1972) notes there are strong theoretical and empirical grounds on which to object to the assumption that stock markets are complete. We propose that a firm's stock can help to complete the market if the firm maintains exposure to the assets underlying its operations. The stock provides investors with exposure to payoffs in states of nature that are otherwise unavailable or costly to acquire. Under this proposal, investors will demand "pure-play" stocks as a substitute for costly or infeasible direct investment.

Consistent with our hypothesis, we find that share turnover is positively associated with industry exposure, which suggests that investors, in general, are attracted to the stocks of firms that maintain exposure to the underlying assets of the industry. Institutions and mutual funds also exhibit robust preferences for industry exposure. Among institutions, banks show the least significant attraction to exposure, consistent with greater fiduciary standards associated with their portfolio holdings. Among mutual funds, sector funds exhibit the most significant preferences for exposure, consistent with a bonding commitment to the fund's investors to produce returns commensurate with a sector.

Across all classes of investors, the positive association between industry exposure and investor interest comes from both an attraction to high industry exposure stocks and an aversion to low industry exposure stocks. Moreover, investor attraction to exposure is greatest in industries with a high degree of asset specificity, where the benefits from investing in stocks as substitutes for direct investment in the underlying assets are the greatest.

These findings challenge the conventional view that risk management is a value-maximizing strategy in the presence of market frictions. By contrast, our results suggest that market frictions may create incentives for firms to *not hedge* and remain exposed to industry risks in order to increase their stock liquidity.

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Appendix A: Summary of control variables

Summary of control variables used throughout the analysis. We draw the control variable constructs for the determinants of institutional ownership from four sources: Del Guercio (1996), Falkenstein (1996), Gompers and Metrick (2001), and Hong and Kacperczyk (2007).

Construct	Name	Description
Firm size	LOGSIZE_MVE	Natural log of the market value of equity (in $ thousands) at year end.
	TOTAL ASSETS	Total assets (in $ millions) at year end.
Market-to-book ratio	LOGMB	Natural log of market value of equity divided by common book equity at year end.
Share price	INVPRICE	Inverse of stock price at year end.
	PRICE DUM	Indicator variable = 1 if the firm's share price < $5 at the start of the calendar year, and = 0 otherwise.
Systematic risk	MKTBETA2	Market beta from estimation of the two-factor extended market model in equation (1).
	MKTBETA	Market beta from estimation of a single factor market model.
Dividends	DIVYLD	Annual dividend yield.
	DIVPAYER	Indicator variable = 1 if the firm declares dividends during the year, and = 0 otherwise.
Leverage	DE RATIO	Total long-term debt (including current portion) divided by total common equity at year end. Values greater than the 99th percentile in the industry are winsorized.
Turnover	TURNOVER	Natural log of average monthly turnover during the year.
Returns	AVGRET	Average monthly return during the year.
Idiosyncratic return volatility	RETVOL	Standard deviation of daily firm returns during the year.
Firm age	FIRMAGE	Natural log of the number of months from the CRSP start date to year end.
In the S&P 500	S&P500	Indicator variable = 1 if the firm is in the S&P 500 index as of year end, and = 0 otherwise.
Trades on NASDAQ exchange	NASDAQ	Indicator variable = 1 if the firm is traded on the NASDAQ exchange as of year end according to CRSP and = 0 if it is traded on the NYSE/AMEX.

Appendix B. Fund classification

We begin with the full set of funds on the Thomson Financial Mutual Fund database. Funds that have an investment objective code of 1, 5, and 6 are eliminated. These categories represent International funds, Municipal Bond funds, and Bond and Preferred Stock funds, respectively. Funds with less than three annual observations for which the market value of assets at the beginning of the year is less than $1 million also are eliminated.

A fund is classified as "other" if a significant portion of its total assets are not reportable securities (i.e., with cusips). Specifically, we classify as a fund as "other" if the market value of reportable assets scaled by the market value of total fund assets is, on average over the sample years, greater than the median in the sample *and* if the minimum value of this ratio in any year is greater than the median minimum value for the sample. These funds are generally non-equity funds that invest a large percentage of their assets in non-reportable items such as cash or OTC products.

The remaining funds are classified into three categories: Balanced funds, Market-timers, and Sector funds. The classification is based on the fund's industry concentration index (*ICI*), computed following Kacperczyk, Sialm, and Zheng (2005). The industry concentration index for fund *f* in year *y* is:

$$ICI_{f,y} = \sum_{j=1}^{30} (w_{f,j,y} - \overline{w}_{j,y})^2$$

where $w_{f,j,y}$ is the dollar value of fund *f*'s holdings in industry *j* equity securities scaled by the dollar value of fund *f*'s total equity holdings at the end of year *y*, and $\overline{w}_{j,y}$ is the market capitalization of industry *j* scaled by the sum of the market capitalizations of all 30 Fama-French industries.[24] The average *ICI* for fund *f* is $\overline{ICI} = \sum_{y=1}^{n} ICI_y$, where n is the number of annual observations. We require three annual observations to compute the average *ICI*.

A fund is classified as a balanced fund if its average *ICI* is less than the third quartile of average *ICI*s. The third quartile of *ICI* is 1.81. A low *ICI* indicates that the fund does not concentrate its holdings in any particular industry. A fund is classified as a sector fund if its average *ICI* is greater than the third quartile of average *ICI*s and if 90% of its time-series observations are in a single industry (of the 30 industries). The 90% cutoff was determined based on the average holding percentage for a set of funds known to be sector funds in the gold and oil and gas industry.

A fund is classified as a market-timer if its average *ICI* is greater than the third quartile of average *ICI*s but if less than 90% of its time-series observations are in a single industry. This combination of restrictions implies that the market-timers concentrate their holdings in particular industries each year but the industries change from year to year.

[24] Industry market capitalizations are from Kenneth French's website.

Figure 1: Industry Specificity

To measure industry specificity for industry *j* in year *y*, we estimate a standard market model and an extended market model for each firm *i* within industry *j* using monthly return data over the period January of year *y* – 4 to December of year *y*. The extended market model includes the appropriate equally-weighted industry returns and the equally-weighted market returns. For each firm *i* in year y, we compute the difference between the adjusted R^2 values of the two models. We use the average difference in adjusted R^2 values within an industry as our measure of industry specificity. The box plot below summarizes the industry specificity across our sample period of 1983 – 2006.

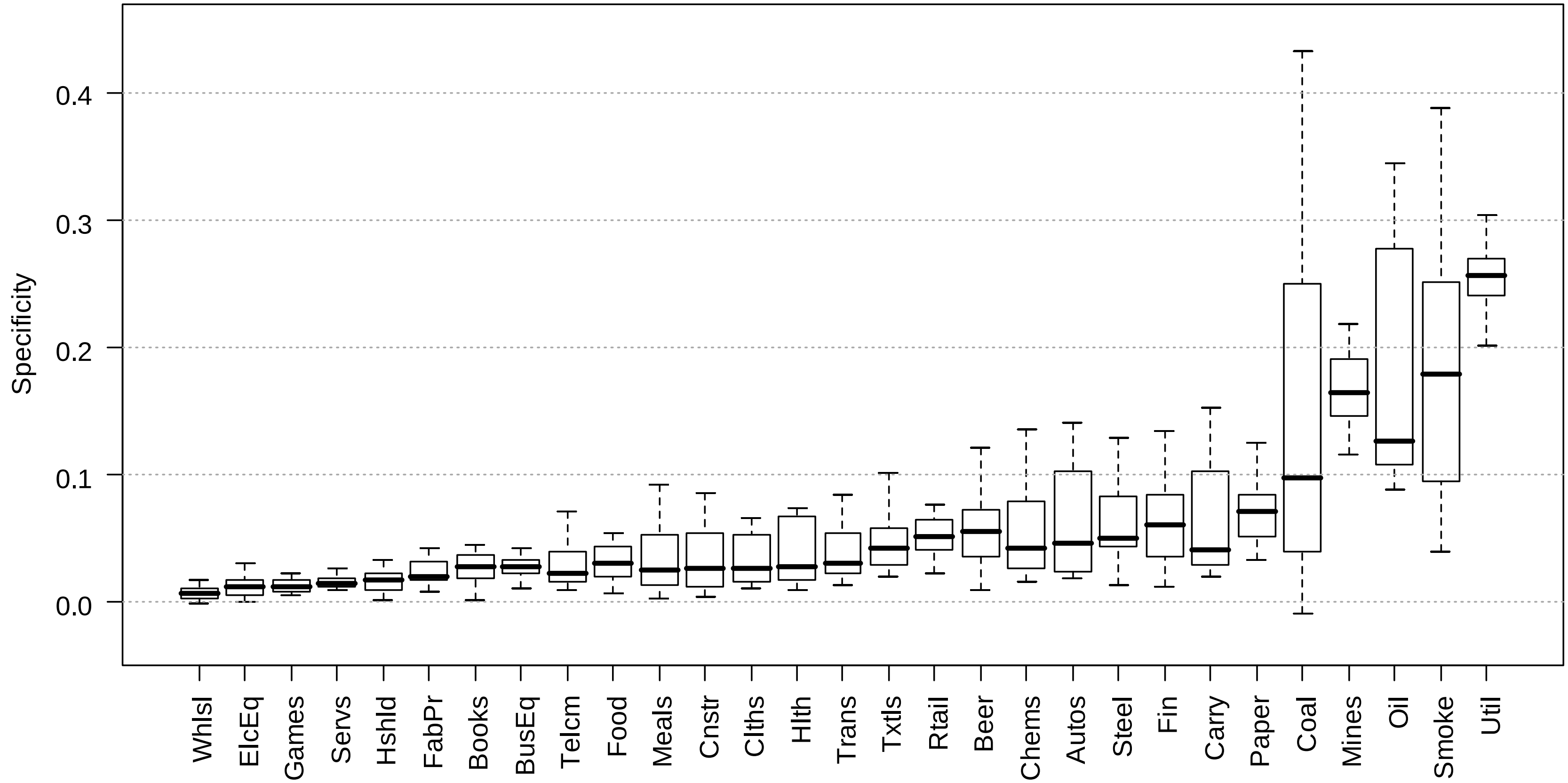

Table 1. Summary of exposure measures by industry

Summary of exposure measures by industry. *INDEXP* is the mean of the firm-specific estimates of the monthly industry factor betas. *MKTBETA2* is the mean of the firm-specific estimates of stock market betas from the two-factor market model. *MKTBETA* is the mean of the firm-specific estimates of stock market betas from a simple market model. δ_{ind} is the estimated industry factor exposure on a portfolio that buys high industry exposure firms and shorts low industry exposure firms, where exposure is measured using historical data. (*){**}[***] indicate statistical significance at the (10%) {5%} [1%] level.

	Industry	N	INDEXP	MKTBETA2	MKTBETA	δ_{ind}
18	Coal	105	0.5051	0.3570	0.7041	0.1478*
21	Telecommunications	1,743	0.5378	0.3679	1.0634	0.1175**
2	Beer	264	0.5540	0.2606	0.5730	0.5398***
4	Games	2,049	0.5623	0.4628	1.0966	0.3936***
26	Wholesale	3,564	0.5648	0.4066	0.9949	0.1870*
3	Smoke	102	0.6081	0.1596	0.4901	0.3732***
14	Electrical Equipment	1,304	0.6361	0.3794	1.0878	0.2120*
6	Household	1,812	0.6917	0.2537	0.9183	0.1851**
5	Books	1,204	0.7056	0.1650	0.7697	-0.0804
10	Textiles	648	0.7375	0.2881	0.9556	0.2124**
1	Food	1,938	0.7677	0.1646	0.6966	0.1287
25	Transportation	2,189	0.7694	0.1434	0.8545	0.6189***
22	Services	8,523	0.7907	0.2317	1.3449	0.7209***
15	Autos	1,247	0.7963	0.1939	0.9662	0.4708***
28	Meals	1,473	0.7983	0.1665	0.8920	0.1421**
11	Construction	3,203	0.8001	0.1842	0.9901	0.4825***
12	Steel	1,396	0.8084	0.1446	1.0131	0.3523***
16	Carry	626	0.8314	0.1056	0.8551	0.4064***
9	Chemicals	1,556	0.8672	0.1044	0.8176	0.3294***
13	FabPr	3,817	0.8807	0.1593	1.0838	0.5408***
7	Clothes	1,307	0.8810	0.1272	0.9786	0.3090***
17	Mines	1,153	0.8916	0.0693	0.8034	0.5389***
29	Financial	18,254	0.9027	0.0416	0.5946	0.5770***
24	Paper	1,821	0.9507	0.0491	0.8132	0.6032***
8	Health	7,578	0.9557	-0.0076	1.3119	0.7174***
19	Oil	3,454	0.9582	0.0231	0.7874	0.5498***
20	Utilities	3,666	0.9778	-0.0002	0.2661	0.6856***
27	Retail	4,492	1.0135	-0.0127	1.0304	0.4196***
23	Business Equipment	11,287	1.0317	-0.0634	1.5013	0.5985***

Table 2. Descriptive characteristics of sample firms

Means of industry factor price exposure (*INDEXP)*, log monthly turnover (*TURNOVER)*, and control variables across low exposure (*BETALOW*), medium exposure (*BETAMED*), and high exposure (*BETAHIGH*) firm-year observations. A firm is considered high exposure (low exposure) if its industry factor price exposure is greater (less) than the 70th (30th) percentile exposure, respectively. The percentiles are recalculated for each industry for each calendar year. The table presents the mean for the sample across the years 1983 - 2006. (*){**}[***] indicate statistical significance at the (10%) {5%} [1%] level. Significance levels are based on a Z-statistic associated with the annual t-statistics that controls for cross-sectional and serial correlations.[25]

	BETALOW (n = 27,847)	BETAMED (n = 36,084)	BETAHIGH (n = 27,844)	HIGH vs MED	HIGH vs. LOW	MED vs. LOW
INDEXP	-0.2931	0.7959	2.1168	***	***	***
TURNOVER	-3.1522	-2.9824	-2.6254	***	***	***
LOGSIZE_MVE	4.8536	5.4472	5.1717	***	***	***
INVPRICE	0.2859	0.1967	0.3171	***	*	***
LOGMB	0.5922	0.5890	0.6013			
DIVYLD	0.0235	0.0198	0.0141	***	***	
DIVPAYER	0.4758	0.5367	0.3817	***	***	***
DE RATIO	1.2623	1.1713	1.4832	***	***	***
RETVOL	0.0325	0.0298	0.0377	***	***	***
MKTBETA	0.8687	0.8857	1.2168	***	***	
MKTBETA2	1.2480	0.1031	-1.0380	***	***	***
AVGRET	0.0134	0.0132	0.0189	**	*	
FIRMAGE	4.8338	4.9548	4.7490	***	***	***
S&P500	0.0773	0.1258	0.0943	***		***
NASDAQ	0.5378	0.5043	0.5931	***	*	*

[25] $Z = \frac{\bar{t}\sqrt{(N-1)}}{\sigma(t)}$ where t_j is the *t*-statistic for year *j, N* is the number of years, and $\bar{t}$ and $\sigma(t)$ are the mean and standard deviation, respectively, of the *N* realizations of t_j. *Z* has a *t* distribution with $N-1$ degrees of freedom.

Table 3. Determinants of turnover

Models of industry factor price exposure as a determinant of the natural logarithm of average monthly turnover (*TURNOVER*). Factor price exposure is measured by the continuous variable *INDEXP* and by indicator variables that equal 1 if a firm's industry factor price exposure is greater (less) than the 70th (30th) percentile exposure (*BETAHIGH* and *BETALOW*). The percentiles are recalculated for each industry for each calendar year. Control variables measured at or for the year ended *t-1* include: the natural logarithm of the market value of equity, the inverse price ratio, the natural logarithm of the market-to-book ratio, dividend yield, debt equity ratio, idiosyncratic return volatility, and average monthly firm returns. Control variables measured at or for the year ended *t* include: stock market betas, firm age, and indicator variables for S&P 500 stocks and NASDAQ listed stocks. The models are estimated annually from 1983 through 2006. The coefficient estimates, adjusted R^2s, and number of observations (N) are the averages of the annual estimates. The models are estimated for three samples: (1) the full sample, (2) firms that have a market equity value greater than the 25th percentile in each year , and (3) firms with a share price greater than $5 at the start of each calendar year. (*){**}[***] indicate statistical significance at the (10%) {5%} [1%] level. Significance levels are based on a Z-statistic associated with the annual t-statistics that controls for cross-sectional and serial correlations (see Table 2). Parenthetical amounts represent the number of annual test statistics that are significant at the 10% level in the 24 annual regressions.

	Full Sample		Size > 25th Percentile		Stock Price > $5	
Intercept	-4.7132***	-4.6644***	-4.6961***	-4.6386***	-5.0910***	-5.0222***
LOGSIZE_MVE	0.1852***	0.1826***	0.1358***	0.1351***	0.1817***	0.1802***
INVPRICE	-0.0916***	-0.0921***	-0.3876***	-0.3847***	-0.1179	-0.1174
LOGMB	0.0447***	0.0492***	0.0214	0.0245	0.0375**	0.0409***
DIVYLD	-0.6240**	-0.5576**	-0.6125	-0.5152	-0.1243	-0.0483
DE RATIO	-0.0105***	-0.0116***	-0.0047*	-0.0056*	-0.0040	-0.0050
RETVOL	7.6166***	7.3977***	15.0818***	14.9381***	17.1404***	16.9660***
MKTBETA	0.5384***	0.5352***	0.5422***	0.5440***	0.6072***	0.6066***
AVGRET	1.6319***	1.6102***	1.8268***	1.8119***	1.9400***	1.9193***
FIRMAGE	-0.0378*	-0.0373*	-0.0072	-0.0083	-0.0147	-0.0159
S&P500	0.1295***	0.1303***	0.2013***	0.2002***	0.1220***	0.1208***
NASDAQ	0.2392***	0.2370***	0.2179***	0.2172***	0.1885***	0.1872***
INDEXP	0.0632***		0.0820***		0.0840***	
BETALOW		-0.0782***		-0.0873***		-0.0881***
BETAHIGH		0.1644***		0.1622***		0.1651***
Difference		0.2426		0.2495		0.2532
# of annual diffs sig		(24/24)		(24/24)		(24/24)
Average annual N	2,427	2,427	1,916	1,916	1,993	1,993
Average annual Adj R^2	31.19%	31.57%	30.07%	30.31%	35.29%	35.53%

Table 4. Determinants of ownership intensity by institutions and mutual funds

Models of industry factor price exposure as a determinant of institutional ownership intensity and fund ownership intensity. The proxies for ownership intensity are the (log of 1 + the) number of institutions (*LNUMGR*) or mutual funds (*LNUMFUNDS*) that hold the firm's stock. Factor price exposure is measured by the continuous variable *INDEXP* and by indicator variables that equal 1 if a firm's industry factor price exposure is greater (less) than the 70th (30th) percentile exposure (*BETAHIGH* and *BETALOW*). The percentiles are recalculated for each industry for each calendar year. Control variables measured at or for the year ended *t-1* include: the natural logarithm of the market value of equity, the inverse price ratio, the natural logarithm of the market-to-book ratio, dividend yield, debt equity ratio, the natural logarithm of average monthly turnover, idiosyncratic return volatility, and average monthly firm returns. Control variables measured at or for the year ended *t* include: stock market betas, firm age, and indicator variables for S&P 500 stocks and NASDAQ listed stocks. The models are estimated annually from 1983 through 2006. The coefficient estimates, adjusted R^2s, and number of observations (N) presented are the averages of the annual estimates. (*){**}[***] indicate statistical significance at the (10%) {5%} [1%] level. Significance levels are based on a Z-statistic associated with the annual t-statistics that controls for cross-sectional and serial correlations (see Table 2). Parenthetical amounts represent the number of annual test statistics that are significant at the 10% level in the 24 annual regressions.

	LNUMGR		*LNUMFUNDS*	
Intercept	1.2143***	1.2669***	1.7925***	1.8184***
LOGSIZE_MVE	0.4713***	0.4705***	0.2769***	0.2770***
INVPRICE	0.1110***	0.1102***	0.1173***	0.1165***
LOGMB	-0.0314**	-0.0305**	-0.0317**	-0.0301**
DIVYLD	-0.6390***	-0.5721**	-1.5721***	-1.5089***
DE RATIO	-0.0078***	-0.0074***	-0.0075**	-0.0074**
TURNOVER	0.2443***	0.2423***	0.2231***	0.2211***
RETVOL	-5.5739***	-5.5231***	-8.7531***	-8.6728***
MKTBETA	-0.0039	0.0013	0.0480*	0.0508*
AVGRET	0.0339	0.0462	1.0665***	1.0662***
FIRMAGE	0.1505***	0.1499***	0.0609***	0.0609***
S&P500	0.3356***	0.3339***	0.0403	0.0381
NASDAQ	-0.1486***	-0.1487***	-0.1370***	-0.1375***
INDEXP	0.0449***		0.0329***	
BETALOW		-0.1008***		-0.0682***
BETAHIGH		0.0337***		0.0366
Difference		0.1346		0.1047
# of annual diffs that are significant		(24/24)		(13/24)
Average annual N	2,427	2,427	2,792	2,792
Average annual adjusted R^2	82.96%	83.00%	45.38%	45.40%

Table 5. Univariate comparisons of proxies for diversification

Mean values of firm-level proxies for diversification for firms in the high exposure (*BETAHIGH*) and low exposure (*BETALOW*) samples. The proxies for diversification include: the number of segments in which the firm operates (*NUMSEG*); an indicator variable = 1 if the firm operates in multiple segments and = 0 otherwise (*MULTISEG*); and 1 – a firm's revenue-based concentration ratio (*DIVERSE*). All three variables are specified such that a higher value implies greater diversification. Panel A reports the results for line-of-business diversification. Panel B reports the results for geographic diversification. A firm is considered high exposure (low exposure) if its industry factor price exposure is greater (less) than the 70th (30th) percentile exposure, respectively. The percentiles are recalculated for each industry for each calendar year. (*){**}[***] indicate statistical significance of a test of the difference in the means between the *BETALOW* and *BETAHIGH* samples at the (10%) {5%} [1%] level. Significance levels are based on a Z-statistic associated with the annual t-statistics that controls for cross-sectional and serial correlations (see Table 2).

Panel A: Line-of-business diversification

		NUMSEG		MULTISEG		DIVERSE	
		BETALOW	BETAHIGH	BETALOW	BETAHIGH	BETALOW	BETAHIGH
1	Food	1.9102	1.7085**	0.4170	0.3305**	0.1815	0.1563
2	Beer	2.1758	1.7935	0.4725	0.4022	0.2494	0.1604
3	Smoke	3.2326	3.3488	0.7674	0.8372	0.3476	0.3458
4	Games	1.7295	1.5371	0.3929	0.3000*	0.1573	0.1194
5	Books	1.9946	2.2243	0.4946	0.5351	0.2408	0.2582
6	Household	1.8091	1.5592**	0.4055	0.3188	0.2009	0.1326**
7	Clothes	1.5062	1.4638	0.2968	0.2693	0.1172	0.1065
8	Health	1.5914	1.1861***	0.3281	0.1310***	0.1396	0.0493***
9	Chemicals	1.9538	2.8211***	0.4538	0.6884***	0.2072	0.3824***
10	Textiles	1.6293	1.6293	0.3561	0.3268	0.1517	0.1367
11	Construction	2.3478	2.0062**	0.6398	0.5353***	0.2952	0.1972***
12	Steel	2.2529	2.2617	0.6159	0.5678	0.3012	0.2674
13	FabPr	2.0070	1.7680*	0.5166	0.4260*	0.2501	0.2059*
14	Electrical Equipment	2.1475	1.8061	0.5800	0.4811	0.2694	0.2204
15	Autos	1.9555	2.0263	0.4686	0.5538	0.2270	0.2008
16	Carry	2.9192	2.1878*	0.8131	0.5584*	0.4387	0.2897*
17	Mines	2.5199	1.5458***	0.6192	0.1937***	0.3133	0.0961***
18	Coal	2.0270	2.0930	0.5946	0.5814	0.2021	0.1525
19	Oil	2.5082	1.6599***	0.5558	0.3324***	0.2435	0.1388***
20	Utilities	2.2663	2.4570	0.5743	0.6525**	0.2125	0.2600***
21	Telecommunications	2.1753	1.8916	0.5010	0.3954	0.2178	0.1630**
22	Services	1.8089	1.5274***	0.3998	0.2831***	0.1718	0.1193***
23	Business Equipment	1.6416	1.3319***	0.3369	0.2066***	0.1563	0.0836***
24	Paper	1.9084	2.6158***	0.4740	0.7271***	0.2236	0.3819***
25	Transportation	1.8879	1.5472***	0.4076	0.2609***	0.1696	0.0936***
26	Wholesale	1.9431	1.6429***	0.5159	0.3553***	0.1952	0.1303***
27	Retail	1.4685	1.3465**	0.2777	0.2019**	0.1031	0.0745***
28	Meals	1.6814	1.4128***	0.3474	0.2119***	0.1469	0.0810***
29	Financial	1.7679	2.3603***	0.3187	0.4924***	0.1349	0.2215***
BETALOW > BETAHIGH		(19/29)		(22/29)		(24/29)	
Difference significant and BETALOW > BETAHIGH		(14/29)		(14/29)		(14/29)	

Panel B: Geographic diversification

		NUMSEG		MULTISEG		DIVERSE	
		BETAHIGH	BETALOW	BETAHIGH	BETALOW	BETAHIGH	BETALOW
1	Food	1.5784	1.7186	0.2793	0.3292	0.1160	0.1330
2	Beer	2.4578	1.4756***	0.6506	0.2439***	0.2940	0.1040*
3	Smoke	2.5814	1.6667**	0.6047	0.3333**	0.3570	0.1710
4	Games	1.6644	1.4837*	0.3476	0.2504**	0.1430	0.0870***
5	Books	1.6124	1.6667	0.3118	0.3571	0.1080	0.1030
6	Household	1.8731	1.6506	0.5224	0.4170	0.1940	0.1410*
7	Clothes	1.6104	1.5580	0.3134	0.2992	0.0920	0.0780
8	Health	1.8912	1.4400***	0.4265	0.2556***	0.1850	0.0850***
9	Chemicals	2.6630	2.8323	0.6808	0.8026**	0.3250	0.3880*
10	Textiles	1.5260	1.4293	0.2760	0.2626	0.1100	0.0800
11	Construction	1.8729	1.4038***	0.4359	0.2313***	0.1570	0.0750***
12	Steel	2.2333	2.0821	0.4786	0.4734	0.1740	0.1640
13	FabPr	2.2567	2.5331***	0.5916	0.6681**	0.2420	0.2900***
14	Electrical Equipment	2.2923	2.0296	0.6026	0.5430	0.2190	0.2110
15	Autos	2.0471	2.2304	0.5817	0.5664	0.2070	0.2040
16	Carry	2.2460	1.6898***	0.4973	0.3316***	0.1640	0.1250*
17	Mines	2.0669	1.5634***	0.4648	0.3060***	0.1820	0.1180***
18	Coal	1.2703	1.2558	0.2432	0.1395	0.0530	0.0170
19	Oil	1.9969	1.8539	0.4238	0.3861	0.1840	0.1690
20	Utilities	1.1768	1.1720	0.0941	0.1069	0.0220	0.0180*
21	Telecommunications	1.4508	1.3846	0.2213	0.2058	0.0670	0.0740
22	Services	1.9257	2.1135	0.4494	0.5306**	0.1720	0.2220**
23	Business Equipment	2.0842	2.3905**	0.5309	0.5745	0.2210	0.2710**
24	Paper	1.8271	2.1175*	0.4963	0.5317	0.1710	0.1810
25	Transportation	1.6232	1.3917***	0.3134	0.2426	0.1300	0.0950**
26	Wholesale	1.5937	1.4408**	0.3132	0.2570**	0.1130	0.0930
27	Retail	1.1656	1.1284	0.1133	0.1051	0.0310	0.0240
28	Meals	1.3412	1.0841***	0.1469	0.0608**	0.0720	0.0170**
29	Financial	1.2096	1.2858	0.1201	0.1740	0.0380	0.0510
BETALOW > BETAHIGH		(20/29)		(20/29)		(21/29)	
Difference significant and BETALOW > BETAHIGH		(10/29)		(9/29)		(10/29)	

Table 6. Determinants of ownership intensity for diversification-sorted portfolios

Average annual coefficient estimates for proxies for industry factor price exposure from models of the determinants of ownership intensity as a function of diversification. Panel A reports results for single segment vs. multi-segment firms. Panel B reports results for firms in the lower quartile, middle two quartiles, and upper quartile of the variable *DIVERSE*. Firms are ranked within industry by year. *DIVERSE* is 1 - a revenue-based concentration ratio such that higher values represent greater diversification. The proxies for ownership intensity are the (log of 1 + the) number of institutions or mutual funds of a given type that hold the firm's stock. Factor price exposure is measured by indicator variables that equal 1 if a firm's industry factor price exposure is greater (less) than the 70^{th} (30^{th}) percentile exposure (*BETAHIGH* and *BETALOW*). The percentiles are recalculated for each industry for each calendar year. Coefficient estimates for the control variables, which are included in all models, are untabulated. Control variables measured at or for the year ended *t-1* are: the natural logarithm of the market value of equity, the inverse price ratio, the natural logarithm of the market-to-book ratio, dividend yield, debt equity ratio, the natural logarithm of average monthly turnover (except in the *TURNOVER* regression), idiosyncratic return volatility, and average monthly firm returns. Control variables measured at or for the year ended *t* are: stock market betas, firm age, and indicator variables for S&P 500 stocks and NASDAQ listed stocks. The models are estimated annually from 1983 through 2006. The coefficient estimates, adjusted R^2s, and number of observations (N) presented are the averages of the annual estimates. (*){**}[***] indicate statistical significance at the (10%) {5%} [1%] level. Significance levels are based on a Z-statistic associated with the annual t-statistics that controls for cross-sectional and serial correlations (see Table 2). Parenthetical amounts represent the number of annual test statistics that are significant at the 10% level in the 24 annual regressions.

Panel A: Single Segment firms vs. multi-segment firms			
MULTISEG = 0	*TURNOVER*	*LNUMGR*	*LNUMFUNDS*
Intercept	-4.6076***	0.0210	0.7650*
BETALOW	-0.1023***	-0.1155***	-0.0851***
BETAHIGH	0.1639***	0.0466***	0.0474**
Difference	0.2662	0.1621	0.1325
# of annual differences that are significant	(22/24)	(22/24)	(13/24)
MULTISEG = 1			
Intercept	-4.5376***	0.4637***	1.0643*
BETALOW	-0.0975***	-0.1209***	-0.0838***
BETAHIGH	0.1617***	0.0487***	0.0308
Difference	0.2592	0.1696	0.1146
# of annual differences that are significant	(23/24)	(23/24)	(10/24)

Panel B: By quartiles of DIVERSE			
Bottom quartile DIVERSE			
Intercept	-4.6098***	0.0108	0.7640*
BETALOW	-0.1025***	-0.1149***	-0.0858***
BETAHIGH	0.1647***	0.0471***	0.0514**
Difference	0.2672	0.1620	0.1372
# of annual differences that are significant	(22/24)	(22/24)	(13/24)
Middle quartiles DIVERSE			
Intercept	-4.7393***	0.5405***	1.0955**
BETALOW	-0.1188***	-0.1166***	-0.0734***
BETAHIGH	0.1494***	0.0472***	0.0158
Difference	0.2682	0.1638	0.0892
# of annual differences that are significant	(19/24)	(13/24)	(5/24)
Upper quartile DIVERSE			
Intercept	-4.3676***	0.4563***	1.0401
BETALOW	-0.0541***	-0.1155***	-0.0749***
BETAHIGH	0.1826***	0.0476***	0.0482
Difference	0.2367	0.1631	0.1231
# of annual differences that are significant	(19/24)	(18/24)	(4/24)

Table 7. Industry specificity and investor attraction to exposure

Average annual coefficient estimates on proxies for industry factor price exposure from models of the determinants of ownership intensity. Proxies for ownership intensity include the natural logarithm of average monthly turnover (*TURNOVER*), institutional ownership intensity (*LNUMGR*), and fund ownership intensity (*LNUMFUNDS*). Industry factor price exposure is measured by indicator variables that equal 1 if a firm's industry factor price exposure is greater (less) than the 70th (30th) percentile exposure (*BETAHIGH* and *BETALOW*). Panel A reports results for models that include a continuous measure of industry specificity (*SPECIFICITY*) and interaction terms of *SPECIFICITY* with *BETAHIGH* and *BETALOW*. Panel B reports coefficient estimates on *BETAHIGH* and *BETALOW* for firms that operate in high-specificity, medium-specificity, and low-specificity industries. Coefficient estimates for the control variables, which are included in all models, are untabulated. Control variables measured at or for the year ended *t-1* are: the natural logarithm of the market value of equity, the inverse price ratio, the natural logarithm of the market-to-book ratio, dividend yield, debt equity ratio, the natural logarithm of average monthly turnover (except in the *TURNOVER* regression), idiosyncratic return volatility, and average monthly firm returns. Control variables measured at or for the year ended *t* are: stock market betas, firm age, and indicator variables for S&P 500 stocks and NASDAQ listed stocks. The models are estimated annually from 1983 through 2006. The coefficient estimates presented are the averages of the annual estimates. (*){**}[***] indicate statistical significance at the (10%) {5%} [1%] level. Significance levels are based on a Z-statistic associated with the annual t-statistics that controls for cross-sectional and serial correlations (see Table 2). Standard errors are clustered by industry within each annual regression.

Panel A: Interaction variables for *SPECIFICITY*			
	TURNOVER	*LNUMGR*	*LNUMFUNDS*
Intercept	-4.6435***	1.2910***	1.8293
SPECIFICITY	0.0781	0.3582***	-0.0379
BETALOW	-0.0764***	-0.0883***	-0.0690***
BETALOW*SPECIFICITY	-0.8863***	-0.3884*	0.2905
BETAHIGH	0.1088***	-0.0233**	0.0112
BETAHIGH*SPECIFICITY	0.3571***	0.1621**	0.1993**
Average annual N	2,427	2,427	2,792
Average annual adjusted R^2	31.70%	83.09%	45.42%
Panel B: By quartiles of *SPECIFICITY*			
High Specificity Industries			
Intercept	-4.5722***	1.5459***	1.8563***
BETALOW	-0.2546***	-0.1654***	-0.1115***
BETAHIGH	0.1879***	0.0787***	0.0452
Difference	0.4425	0.2441	0.1567
Average annual N	255	253	321
Average annual adjusted R^2	26.93%	82.97%	46.70%
Medium Specificity Industries			
Intercept	-4.6165***	1.2634***	1.7776***
BETALOW	-0.0669***	-0.1004***	-0.0722***
BETAHIGH	0.1496***	0.0394**	0.0364*
Difference	0.2165	0.1398	0.1086
Average annual N	1,601	1,543	1865
Average annual adjusted R^2	33.38%	83.80%	45.92%
Low Specificity Industries			
Intercept	-4.6932***	1.3597***	1.9423***
BETALOW	-0.0359	-0.0626***	-0.0182***
BETAHIGH	0.1619**	-0.0074	0.0272
Difference	0.1978	0.0552	0.0454
Average annual N	572	551	605
Average annual adjusted R^2	30.93%	82.09%	46.02%

Table 8. Attraction to exposure by institution and fund type

Average annual coefficient estimates for industry factor price exposure proxies from multivariate models of the determinants of ownership intensity by institutions and funds classified by type. Institutions are classified based on fiduciary standards (Panel A) and investment style (Panel B). Funds are classified based on investment style (Panel C). The proxies for ownership intensity are the (log of 1 + the) number of institutions or mutual funds of a given type that hold the firm's stock. Factor price exposure is measured by indicator variables that equal 1 if a firm's industry factor price exposure is greater (less) than the 70th (30th) percentile exposure (*BETAHIGH* and *BETALOW*). The percentiles are recalculated for each industry for each calendar year. Coefficient estimates for the control variables, which are included in all models, are untabulated. Control variables measured at or for the year ended *t-1* are: the natural logarithm of the market value of equity, the inverse price ratio, the natural logarithm of the market-to-book ratio, dividend yield, debt equity ratio, the natural logarithm of average monthly turnover (except in the *TURNOVER* regression), idiosyncratic return volatility, and average monthly firm returns. Control variables measured at or for the year ended *t* are: stock market betas, firm age, and indicator variables for S&P 500 stocks and NASDAQ listed stocks. The models are estimated annually from 1983 through 2006. The coefficient estimates, adjusted R^2s, and number of observations (N) presented are the averages of the annual estimates. (*){**}[***] indicate statistical significance at the (10%) {5%} [1%] level. Significance levels are based on a Z-statistic associated with the annual t-statistics that controls for cross-sectional and serial correlations (see Table 2). Parenthetical amounts represent the number of annual test statistics that are significant at the 10% level in the 24 annual regressions.

Panel A: 13-F filers by fiduciary standards	*Banks*	*Insurance Companies*	*Investment Advisors*	*Pensions/ Endowments*
BETALOW	-0.0831***	-0.0699***	-0.0888***	-0.0818***
BETAHIGH	0.0310***	0.0469***	0.0291**	0.0526***
Difference	0.1141	0.1168	0.1179	0.1344
# of annual differences that are significant	(23/24)	(21/24)	(23/24)	(21/24)
Test vs. Banks		(5/24)	(6/24)	(6/24)
Test vs. Insurance Companies			(7/24)	(7/24)
Test vs. Investment Advisors				(8/24)

Panel B: 13-F filers by investment style	*Dedicated Owners*	*Quasi-indexers*	*Transient Investors*
BETALOW	-0.0497***	-0.0965***	-0.0868***
BETAHIGH	0.0019	0.0329**	0.0546***
Difference	0.0516	0.1294	0.1414
# of annual differences that are significant	(17/24)	(23/24)	(24/24)
Test vs. Dedicated Owners		(16/24)	(18/24)
Test vs. Quasi-indexers			(4/24)

Panel C: Funds by investment style	*Balanced*	*Market timers*	*Sector*	*Others*
BETALOW	-0.0586***	-0.0384***	-0.0384***	-0.0197
BETAHIGH	0.0462*	0.0193	0.0542***	0.0163
Difference	0.1048	0.0577	0.0926	0.0360
# of annual differences that are significant	(10/24)	(8/24)	(18/24)	(6/24)
Test vs. Balanced funds		(6/24)	(7/24)	(9/24)
Test vs. Market timing funds			(8/24)	(6/24)
Test vs. Sector funds				(9/24)