UCLA MFE — Applied Finance Project

Categorization Bias in the Stock Market

Group 21

Kartik Agarwal, Ching Fung “Joe” Chan, Kamilla Igibayeva, and Charles Rambo

Advisor: Professor Levon Goukasian

GIC Representatives: Dr. Fanesca Young and Eric Huang

December 2020

1 Introduction

The goal of our applied finance project is to study mispricing effects due to coarse industry classification. As a means of measuring the mispricing of assets, we use an alternative similarity metric to obtain firms' fundamental peers. The investment strategy was inspired by the paper “Categorization Bias in the Stock Market” by Krüger *et al.*.[1]

The strategy takes a long or short position in the stock of firm j based on the discrepancy between the returns of firm j's official industry $r_j^{(o)}$ and the returns of firm j's fundamental peers $r_j^{(f)}$. The premise behind the strategy is as follows:

- for each firm j, the divergence between firm j's industry returns $r_j^{(o)}$ and its fundamental peer returns $r_j^{(f)}$ implies mispricing of firm j's stock, and
- the fundamental returns $r_j^{(f)}$ gives a better estimate of how firm j's stock returns ought to behave than the returns of its industry $r_j^{(o)}$.

Building on this premise, we consider cumulative values across time of the difference

$$r_j^{(o)} - r_j^{(f)}. \tag{1}$$

If the cumulative value is negative, then the stock is a candidate for a long position because we expect the price of firm j's stock to increase as its average returns converge to those of its fundamental peers. Similarly, if the cumulative value is positive, firm j's stock may be too expensive and it would be a candidate for a short position. To provide contrast with the primary signal based on $r_j^{(o)} - r_j^{(f)}$, we considered alternative signals based on official returns $r_j^{(o)}$ and fundamental returns $r_j^{(f)}$.

The fundamental peers of firm j are determined using data generated by Hoberg and Phillips, which we obtained from their website.[1] The similarity score is based on the cosine similarity between the product descriptions in firms' 10-K filings.[2, 3] Within our analysis, we removed observations with a similarity score

[1] `http://hobergphillips.tuck.dartmouth.edu/`

less than or equal to 0.10. When we considered very low scores, the results were not like those described in "Categorization Bias in the Stock Market".[1]

To illustrate the concept of fundamental peers, consider the example of Morgan Stanley in December 2018. The firm is contained within the industry Capital Markets. Some of its fundamental peers, like Goldman Sachs, are in the same industry. However, some were in different industries; its peers included firms in the industry Consumer Finance, like Ally, and firms in the industry Insurance, like American International Group (AIG). Ally or AIG may provide a more informative picture of Morgan Stanley's business operations than alternative firms within the industry Capital Markets, and could be used as part of a signal to help predict future returns of Morgan Stanley's stock. In total, using our construction when we only consider similarity scores above 0.10, Morgan Stanley's fundamental peers contained 33 members of which 64 percent were from industries other than Capital Markets.

Initially, we faced computational issues conducting our analysis because our personal computers did not contain sufficient memory for some calculations. In particular, since the similarity score data contains pairs of two firms, a merge with a large return dataset would produce a data frame orders of magnitude larger than the initial returns data. However, we switched from our personal computers to a Government of Singapore Investment Corporation (GIC) server in August. This allowed us to complete our analysis without any further computational difficulties.

Switching to a private server did have some costs. It removed the possibility of using the Center for Research in Security Prices (CRSP) and Compustat data because GIC does not possess these datasets. Instead, we used GIC's MSCI Large- and Mid-Capitalization U.S. Return data. Besides the smaller allotment of firms within this universe, we no longer have SIC2 codes. In its place, we used Global Industry Classification Standard (GICS) but it is substantially finer than SIC2 as can be seen in Tables 7 and 18. However, this new dataset is of more utility to GIC since a replication within their universe provides more information regarding implementation viability.

The primary signal of our analysis based on $r_j^{(o)} - r_j^{(f)}$ does not appear to produce statistically significant abnormal returns even within the time-frame analyzed by Krüger *et al.*, as Tables 11 and 12 show. Table 7 demonstrates that market capitalization for firms was much larger than in the analysis of Krüger *et al.*, and Table 14 shows that this may be the critical difference because the strategy worked well when only the smallest third of firms within our universe were considered. An alternative explanation is that the much finer GICS industry classification scheme may have had more long-term explanatory power over firm-level returns than SIC2.

2 Literature Review

Our primary source for this project is "Categorization Bias in the Stock Market" by Krüger *et al.*.[1] As mentioned previously, our analysis was inspired by this paper. We replicated Tables I, III, and VII of the appendix, though we only report Table I in Section 5.

The fundamentals-based classification, which both Krüger *et al.* and we are using, was developed by Hoberg and Phillips. Their similarity metric is described in the papers "Text-Based Network Industries and Endogenous Product Differentiation" and "Product Market Synergies and Competition in Mergers and Acquisitions: A Text-Based Analysis".[2, 3]

We constructed investment strategies based on a cumulative return signal much like a momentum strategy. The construction was heavily influenced by the Daniel and Moskowitz momentum described in the paper "Momentum crashes".[4] Kent Daniel's website also helped us construct the momentum factors.[2] However, though our strategies consider individual stocks, the investment signals are industry returns, fundamental returns, or the difference between the two. Furthermore, we used the signals to sort firms into quintiles instead of deciles, and portfolios were equal-weighted instead of value-weighted. We did this to emulate the style of portfolio construction described in "Categorization Bias in the Stock Market".[1] We experimented with value-weighted and inverse value-weighted return signals as alternatives and return statistics for these strategies are in Tables 15, 16, 26, and 27.

Industry momentum strategies similar to ours were examined in the 1999 paper "Do Industries Explain Momentum?" by Moskowitz and Grinblatt. They find that industry momentum is more robust than firm-level momentum and that industry momentum is most powerful at the six- to twelve-month range.[5] This is somewhat consistent with our results; we considered three-, six-, and twelve-month industry momentum and our results were most powerful at the three- and six-month level. However, we found that industry momentum is far less robust in our back-test which began in January of 2010.

The paper "Categorical Thinking in Portfolio Choice" by Gupta-Mukherjee shows that categorical thinking—like associating firms with their official industry—is common practice in financial markets. It solidifies the thesis that mispricing due to categorization bias exists in equity markets and that it can be exploited.[6]

A goal of our project is to determine the risk profile of our constructed portfolios. This includes an analysis of factor loadings in a linear least-squares regression of our strategies' returns on excess market returns, small- over large-capitalization firm returns, value over growth firm returns, and momentum returns. For this aspect of our analysis, we used the work of Fama and French to guide us. In particular, the papers "Size, value, and momentum in international stock returns"[7] and "Common Risk Factors in the Returns on Stocks and Bonds"[8] were of utility as well as information from the Kenneth French data library.[3]

[2] http://www.kentdaniel.net/data/momentum/mom_data.pdf
[3] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

3 Data Description

Hoberg and Phillips Text-Based Network Industry Classifications Data.[4]

Table 1: Hoberg and Phillips Data

Columns	Remarks
Year	Year of similarity score. Years range from 1996 to 2017. Increased by 1 within our analysis to avoid forward looking bias.
gvkey1	The Global Company Key (GVKEY) is a unique six-digit company identifier, though not unique to firms.
gvkey2	The two GVKEYs collectively identify pairs of companies.
score	The similarity score is discussed in Subsection 4.3.

Monthly MSCI Large- and Mid-Capitalization Return Data.

Below we list the columns utilized within our analysis. We note that the industry and sector columns were merged from GICS data before it was shared with us.

Table 2: MSCI Monthly Data

Columns	Remarks
DATE	-
DW_INSTRUMENT_ID	Unique firm identifier.
TOTAL_SHARES	Measured in thousands.
MAIN_KEY	Identical to GVKEY. It uniquely identifies companies but not firms.
INDUSTRY	Identifies the industry in which a firm belongs. We used this instead of Compustat's SIC2 within our analysis.
SECTOR	A broader firm categorization scheme than industry. Eleven sectors total.
RETURN	Monthly firm returns including dividends as a percent.
PRICE_UNADJUSTED	The unadjusted price of firms' shares.
TOT_EQUITY	Total book value of firms' equity.

Weekly and Monthly Return Datasets.

These datasets are from a larger universe of weekly or monthly return data than the MSCI universe. They contain firms in the MSCI universe as well as firms that will enter the universe sometime within the year. However, these datasets only contain the columns shown below.

[4] `http://hobergphillips.tuck.dartmouth.edu/`

Table 3: Weekly/Monthly Alternative Return Datasets

Columns	Remarks
DATE	-
DW_INSTRUMENT_ID	Unique firm identifier.
RETURN	Weekly or monthly firm returns including dividends as a percent.

The monthly version was used to calculate fundamental returns at the monthly frequency, and the weekly version was used for both firm-level returns and fundamental returns. We used this more complete dataset for the weekly and monthly fundamental peer-groups because it improved the predictive power of the fundamental return signal, compared to an otherwise identical signal using the previously mentioned MSCI dataset.

For weekly firm-level returns, we needed PRICE_UNADJUSTED and TOT_EQUITY to exclude firms whose share price was below $5.00 and whose book equity is less than or equal to zero, respectively. The MAIN_KEY variable is required to merge the weekly data with the Hoberg and Phillips data. To calculate industry returns, the column INDUSTRY was needed. We merged the weekly data with the needed columns from the monthly MSCI universe. This merge was done by shifting monthly date one week less than a month forward in time and then merging on month and year. This means no firm-level returns considered were absent from the MSCI universe for more than a month.

Tables 15, 16, 26, and 27 considered value- and inverse value-weighted fundamental return signals. Since our alternative return dataset only had the columns listed in Table 3, we had to make some assumptions regarding the market capitalizations of firms not contained within the smaller MSCI universe. Our GIC contacts informed us that these firms tend to have smaller market capitalizations than the average firm within the MSCI Large- and Mid-Capitalization universe. As a result, we filled missing values with the 25th percentile of market capitalizations for firms within the MSCI Large- and Mid-Capitalization at the corresponding date.

Fama French Three-Factor Data.[5]

The Fama and French data are calculated using the CRSP universe, and not the MSCI Large- and Mid-Capitalization universe which we used for our firm-level returns. The CRSP universe is larger and contains more small-capitalization firms, which may result in the Fama-French factors overstating returns relative to what they would be if only firms within the MSCI universe were considered.

[5] `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

Table 4: Weekly/Monthly Fama French Three-Factor Data

Columns	Remarks
DATE	-
Mkt-RF	Excess returns of stocks over the risk-free rate.[8]
SMB	Long small market capitalization stocks and short large market capitalization stocks.[8]
HML	Long high book-to-market ratio firms and short low book-to-market ratio firms.[8]
RF	Based on the returns of a one-month treasury bill.

All return columns are written as a percent.

Fama French Momentum Factor.[6]

Once again, we note that these data are calculated from the CRSP universe and not the MSCI Large- and Mid-Capitalization universe. The Ken French data library does not include weekly momentum. We constructed it using cumulative daily momentum.

Table 5: Daily/Monthly Fama French Three-Factor Data

Columns	Remarks
DATE	-
MOM	Places firms into terciles based on their previous performance. Construction attempts to remove covariance with SMB factor. Long the third tercile and short the first.[7] Written as a decimal.

4 Methodology

4.1 Subsetting the Data

The strategies we considered are intended to be implementable. This requires subsetting of firm-level returns within the MSCI universe. To minimize trading costs, we removed firms whose stock price was less than $5. We also omitted firms with negative or zero book-equity because such firms are theoretically bankrupt.

The signals for the investment strategies must not be too heavily driven by the idiosyncratic features of the particular firms whose returns are used for the signals. Within Krüger *et al.*, this concern was addressed by only considering firms with at least five members in the corresponding industry and fundamental peer-group.[1] As Figure 1 shows, this restriction dramatically reduces the number of firms considered for the strategy. As a result, when we calculated industry momentum, we omitted industries with fewer than three firms. Similarly, when we used fundamental peer-group returns, we omitted groups with fewer than three members. When both industry and fundamental peer-group returns were needed, we removed firms that had fewer than three members in either of the classification schemes.

[6] `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

Tables 7 and 18 show summary statistics of our data after subsetting. Table 7 is a replication of Table I of the appendix of Krüger *et al.*, and it allows us to contrast our subsetted data with theirs. The results are broadly consistent. However, the average fundamental peer-group size is about 45 percent lower due to our smaller dataset and our more lenient group size restrictions. Furthermore, as mentioned the Section 1 and Table 2, the average number of firms within each industry was about 52 percent smaller than the average number of firms within each of Compustat's SIC2 as reported by Krüger *et al.*. The average firm market capitalization within our data is larger as well.[1]

We considered firm-level returns at a weekly frequency within our analysis. However, we do not report the results in Section 5, except within Tables 7 and 18. We did this at the request of our GIC contacts. They consider weekly strategies to be "too fast" for their purposes.

4.2 Signal Formation and Cumulative Returns

To determine whether investment in firm j is appropriate, we considered cumulative values of $r_j^{(f)}$, $r_j^{(o)}$, and $r_j^{(o)} - r_j^{(f)}$ as our signals. The calculations are analogous to those of a momentum signal. In fact, the signal construction was heavily inspired by the Daniel and Moskowitz momentum construction.[4]

Let us introduce some notation. Define

$$R_{j,t}^{(o)}(m,n) = \prod_{k=m+1}^{m+n} \left(1 + r_{j,t-k}^{(o)}\right) - 1, \quad R_{j,t}^{(f)}(m,n) = \prod_{k=m+1}^{m+n} \left(1 + r_{j,t-k}^{(f)}\right) - 1 \tag{2}$$

and

$$R_{j,t}^{(o-f)}(m,n) = \prod_{k=m+1}^{m+n} \left(1 + r_{j,t-k}^{(o)} - r_{j,t-k}^{(f)}\right) - 1. \tag{3}$$

That is, we consider $R_j^{(o)}(m,n)$ and $R_j^{(f)}(m,n)$ to be the cumulative returns from $t-m-n$ to $t-m-1$, inclusive. The value $R_j^{(o-f)}(m,n)$ was defined as in Equation 3 to be analogous to the others. When a return is missing it is assumed to be 0. These definitions give us the identities

$$R_{j,t}^{(o)}(0,1) = r_{j,t-1}^{(o)}, \quad R_{j,t}^{(f)}(0,1) = r_{j,t-1}^{(f)}, \quad \text{and} \quad R_{j,t}^{(o-f)}(0,1) = r_{j,t-1}^{(o)} - r_{j,t-1}^{(f)} \tag{4}$$

as long as the returns at $t-1$ exist.

Our analysis used $R_{j,t}^{(o)}(m,n)$, $R_{j,t}^{(f)}(m,n)$, and $R_{j,t}^{(o-f)}(m,n)$ as our investment signals. In particular, each firm j was placed into quintiles based on one of the three cumulative return values. Then equally weighted portfolios were formed using Q1 and Q5. In the cases of $R_j^{(o)}(m,n)$ and $R_j^{(f)}(m,n)$, we expected Q5 to have the highest returns and Q1 to have the lowest. Because we were supposing that the fundamental returns were a better predictor of future firm-level returns than industry, when we used $R_{j,t}^{(o-f)}(m,n)$ as the signal, we expected Q1 to have the highest returns and Q5 to have the lowest.

Analogous to momentum calculations, we introduced the first input m of our functions to account for short-term reversals. However, unlike the findings of Jegadeesh and Titman for individual stocks,[9] we did not see any evidence of the phenomenon. In fact, our results were strongest when $m = 0$, *i.e.* results based on investment at time t were best when signals were formed using information up to time $t - 1$. Hence, in Section 5, we only show results when $m = 0$.

In the complete final analysis of our strategy, we considered $m = 0$, and $n = 1, 3, 6$, and 12 months. We saw that the signal tended to be strongest for $n = 3$ or 6. However, for brevity, we only report signals of length $n = 1$ and 6 in our report.

These results are consistent with Moskowitz and Grinblatt. They find no short-term reversal for industry momentum, and—as mentioned previously—they find industry momentum is strongest for signals which use six to twelve months of return data.[5]

4.3 Fundamental Returns

The similarity score data which we used to calculate firms' fundamental peer-groups were constructed by Hoberg and Phillips. We obtained them from the Hoberg-Phillips Data Library.[7] The similarity scores were calculated using firms' product descriptions within their 10-K filings on the Electronic Data Gathering, Analysis, and Retrieval system (EDGAR) database on the Security and Exchange Commission (SEC) website. However, not all words within the product descriptions were used. Only nouns and proper nouns were included, and within this subset of words, only the rarest 25% were used to calculate similarity.

Each firm-year pair (j, y) has a corresponding word vector $P_{j,y}$. The vector has length equal to the total number of words within the entire dataset of accepted words in firms' 10-K filings. If a word is used in the product description of firm j in year y, a 1 is placed in the corresponding entry of $P_{j,y}$, and 0 is placed there otherwise. Normalize $P_{j,y}$ to obtain

$$V_{j,y} = \frac{1}{\sqrt{P_{j,y} \cdot P_{j,y}}} P_{j,y}. \tag{5}$$

The cosine similarity between firm i and j in year y is the inner product

$$V_{i,y} \cdot V_{j,y}. \tag{6}$$

Notice that the cosine similarity is between 0 and 1. The closer the similarity score is to 1, the more similar we consider firms i and j to be to each other.[2, 3]

Each year this procedure would generate a total of n^2 scores. Since n is large and the data are available for many years, such a data frame of similarity scores would be intractable for most purposes. Hoberg and Phillips resolved this issue by removing firms whose similarity scores were sufficiently low, subtracting the

[7] http://hobergphillips.tuck.dartmouth.edu/

lower bound from the remaining scores, and normalizing. This gives a similarity score $s_y(i,j)$ which is still between 0 and 1, but many firm-pairs no longer have scores.[1, 2, 3] Figure 2 suggests that this lower bound may have been reduced in 2004. Unfortunately, very little information about this lower bound is provided by Hoberg and Phillips.

Within our analysis, we created a further lower bound for our data. We removed observations from the similarity data frame when $s_y(i,j) \leq 0.10$. This score is substantially above the average similarity score of firm-pairs.

The fundamental peer-group return $r_j^{(f)}$ of firm j were calculated using to the returns of all firms whose similarity score with firm j was greater than 0.10. This construction is non-transitive because for firms i, j, and k, the assumption $s_y(i,j) > 0.10$ and $s_y(j,k) > 0.10$ does not imply $s_y(i,k) > 0.10$, *i.e.* if firm i is in the same peer-group as j and j is in the same peer-group as k we cannot conclude i is in the same peer-group as k. Our fundamental peer-group construction was not reflexive either because we did not consider firm j to be a member of its own fundamental peer-group. We did not consider subsidiaries of firm j to be members of firm j's fundamental peer-group either nor *vice versa*.

Our analysis contained some examination of transitive subsetting of the fundamental peer-groups. This was done using hierarchal clustering. We used the Hoberg and Phillips data to construct a distance metric. If $s_y(i,j)$ represents the Hoberg and Phillips similarity score between firms i and j, then the distance metric in year y was defined to be

$$d_y(i,j) = \begin{cases} 0, & i = j \\ 1 - s_y(i,j) & i \neq j \text{ and } s_y(i,j) \text{ is defined,} \\ 1.5, & i \neq j \text{ and } s_y(i,j) \text{ is undefined.} \end{cases} \tag{7}$$

This real-valued bivariate function satisfies the non-negativity, symmetry, and triangle inequality properties of a distance metric for our data. Using complete linkage, the distance between clusters is defined to be the maximum distance between the members of the two clusters. That is, for clusters $I = \{i_1, i_2, \ldots, i_m\}$ and $J = \{j_1, j_2, \ldots, j_n\}$, the distance between I and J is defined to be

$$d_y(I,J) = \max_{i \in I, j \in J} d_y(i,j). \tag{8}$$

The algorithm merges the clusters whose distance apart is minimum each iteration. Clusters are merged each iteration as long as the distance between the clusters is less than 0.9. That is, we merge clusters $I = \{i_1, i_2, \ldots, i_m\}$ and $J = \{j_1, j_2, \ldots, j_n\}$ only when

$$d(I,J) = \max_{i \in I, j \in J} d_y(i,j) < 0.90 \tag{9}$$

or equivalently when

$$\min_{i \in I, j \in J} s_y(i,j) > 0.10. \tag{10}$$

This means that all pairs of elements in each cluster have a similarity score above 0.10 and that these clusters induce a transitive fundamental peer-group. We used the hierarchical clustering algorithm within Python's Scikit-Learn package. We experimented with average linkage clustering as well, but it gave a weaker result and required a more conceptually muddled interpretation. Our clustering method used equal weighting.

Our primary analysis used equal weighting within the fundamental groups but we considered other weighting systems as well. We considered value-weighted, inverse value-weighted, and score weighted fundamental peer-groups. The alternative systems tended to produce comparable or weaker results than equal weighting. Tables 15, 16, 26, and 27 show results for value-weighted and inverse value-weighted fundamental peer-groups. We only performed a limited amount of analysis on score weighting because the results were poor.

5 Results

Section 5 is broken down into three parts: Subsections 5.1, 5.2, and 5.3. Results reported in these respective subsections span the entire time range of our analysis (1/1997–12/2018), the time range analyzed in Krüger *et al.* (1/1997–12/2009), and the time range after Krüger *et al.* (1/2010–12/2018). The time partition is strict in the sense that even signals are contained within the specified range.

Unless otherwise stated, assume data are subsetted as described in Subsection 4.1 and suppose all firm-pairs contained within the Hoberg and Phillips fundamental peer-group have a similarity scores more than 0.10. We winsorized return data cross-sectionally so that no observation is more than three standard deviations from the mean return of time t. The number of decimal digits reported in the tables is not an indication of accuracy.

Our set of results was simply too large to report everything. For example, in addition to the equally weighted signal results reported, we redid most of our calculations using value-weighted fundamental peer-group returns. However, the only value-weighted fundamental signal results reported are in Tables 15 and 26. The results reported in Section 5 were chosen because we found them to be the most meaningful and concise.

5.1 Complete Range

We define coverage to be the fraction of firms within any quintile of the investment strategy. Figure 1 considers coverage based on the signal of $R_{j,t}^{(o-f)}(0,1) = r_{j,t-1}^{(o)} - r_{j,t-1}^{(f)}$. The labelings have the following meanings:

1. Kruger: Remove firms with fewer than five members in industry or fundamental peer-group. Remove firms with negative book-equity or a stock price below \$5.

2. Kruger Ex Book Equity: The same subsetting as (1) except remove the book-equity restriction.

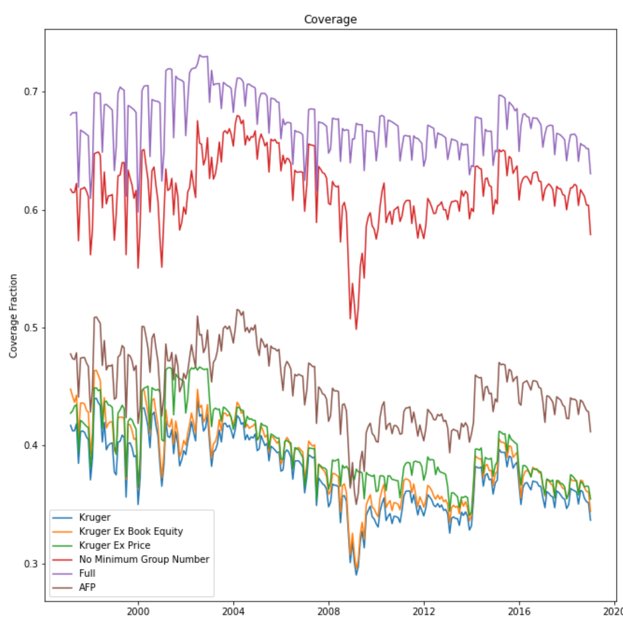
3. Kruger Ex Price: The same subsetting as (1) except remove the price restriction.

4. No Minimum Group Number: The same subsetting as (1) except remove restrictions regarding the minimum number of firms in industry or fundamental peer-group.

5. Full: Consider all firms with valid signal and return data.

6. AFP: Remove firms with fewer than three members in industry or fundamental peer-group. Remove firms with negative book-equity or a stock price below \$5.

Figure 1: *Strategy utilized is investment at time t based on signal $r_{j,t-1}^{(o)} - r_{j,t-1}^{(f)}$. Coverage denotes the fraction of firms contained within any quintile.*



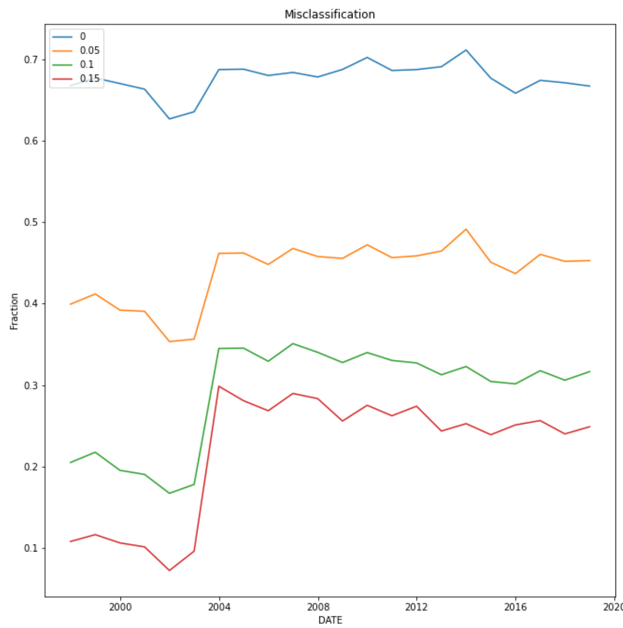
As discussed in Subsection 4.3, we omitted similarities scores $s_y(i,j) \leq 0.10$. We monitored the size of fundamental peer-groups when we chose our lower similarity score bound. Another consideration when we chose our lower bound was signal quality. If low scores were utilized, the fundamental return signal tended to be less predictive of firm-level returns.

Figure 2 helps create a more nuanced picture of how the upper rejection bound affects the firms selected within the fundamental peer-group. We define the misclassification ratio of firm j to be

$$\frac{\#(\text{firms in the fundamental peer-group of } j \text{ but not in the same industry as } j)}{\#(\text{firms in fundamental peer-group of } \ j)}. \tag{11}$$

The figure averages the misclassification ratio across all firms at time t. To reduce the data size, we only considered observations in December.

Figure 2: *Average misclassification ratio for all firms in December.*



As the upper rejection bound is decreased, a larger fraction of firms' fundamental peer-groups come from a different industry. After 2003, the misclassification ratio is relatively stable. At an upper bound of 0.15, the ratio is stable at about 25 percent, while with an upper rejection bound of 0.00 the ratio is stable at about 65 percent. This result suggests that the most similar firms tend to be from the same industry. Figure 2 also shows that some change in the similarity score must have occured in 2004; it appears that the lower bound of the raw similarity data before standardization was decreased.

Table 6 shows the misclassification ratio by sector which is firm-level misclassification averaged across firms and time. We see that every sector contains a substantial amount of misclassification, ranging from 12 percent for Real Estate to 49 percent for both Communication Services and Utilities. The misclassification ratio broken down by sector sheds some light on what types of firms are included within the fundamental peer-group. Table 6 also shows volatility of firm-level misclassification within the sectors.

Table 6: Industry misclassification ratio by sector

Sector	Communication Services	Consumer Discretionary	Consumer Staples
Mean	49%	26%	33%
SD	8%	6%	12%
Sector	Energy	Financials	Health Care
Mean	15%	28%	34%
SD	3%	10%	4%
Sector	Industrials	Information Technology	Materials
Mean	33%	34%	37%
SD	5%	6%	14%
Sector	Real Estate	Utilities	-
Mean	12%	49%	-
SD	1%	12%	-

The industry misclassification ratio by sector averaged across firms and time. The standard deviation is calculated across firms and time. The misclassification is measured in December of each year from 1997 to 2018, inclusive.

5.2 Krüger Time Range

Table 7 shows that our dataset produced aggregated results similar to Krüger *et al.*, though our universe was MSCI instead of CRSP. Our fundamental peer-group and industry sizes of 46 and 108, respectively, are less than the corresponding results in Krüger *et al.* whose respective sizes were 83 and 224. The smaller number of firms within our universe most likely played some role in our smaller group sizes. Our choice to eliminate observations with fewer than three members within the same industry or fundamental peer-group, instead of five, reduced our averages as well. Our finer industry classification may be a better scheme for our analysis than the SIC2 classification in Krüger *et al.*, because it provides a metric more comparable to the fundamental peer-group.[1]

Table 7: Table I Replication

Summary Statistics						*January 1997–December 2009*
	Panel A: Annual Variables					
	Mean	SD	P25	Median	P75	N
Firms per industry	108	73	61	94	133	212563
Firms per fundament group	46	67	6	16	49	212563
$\ln(BE/ME)$	-0.885	0.825	-1.306	-0.773	-0.356	18084
	Panel B: Monthly Variables					
	Mean	SD	P25	Median	P75	N
$r_{j,t}$	0.013	0.150	-0.058	0.008	0.075	212563
$r_{j,t}^{(o)}$	0.009	0.086	-0.029	0.011	0.051	212563
$r_{j,t}^{(f)}$	0.013	0.111	-0.036	0.013	0.059	212563
$r_{j,t}^{(o)} - r_{j,t}^{(f)}$	-0.004	0.063	-0.022	-0.001	0.018	212563
$R_{j,t}(1,11)$	0.130	0.594	-0.173	0.057	0.304	174462
$\ln(ME)$	13.964	1.491	12.883	13.753	14.849	209170
	Panel C: Weekly Variables					
	Mean	SD	P25	Median	P75	N
$r_{j,t}$	0.002	0.072	-0.030	0.000	0.031	935475
$r_{j,t}^{(o)}$	0.002	0.041	-0.016	0.003	0.020	935475
$r_{j,t}^{(f)}$	0.002	0.051	-0.019	0.003	0.024	935475
$r_{j,t}^{(o)} - r_{j,t}^{(f)}$	-0.001	0.028	-0.009	0.000	0.008	935475

Annual variables are calculated using monthly data. Book-to-market ratios use June data. Returns are not annualized.

Table 7 also reports statistics regarding the natural log of market capitalization. The mean result is 13.964, which is quite a bit larger than the 12.535 reported by Krüger *et al.*. The standard deviation between firms in our universe is also about 30 percent less than the corresponding result in Krüger *et al.*. Larger average firm market captilization may explain the discrepancy between our findings and those of Krüger *et al.*.

Tables 8, 9, and 10 show return statistics for our three investment strategies. We report results for signals of length one- and six-months. Signals of length three- and six-months tended to produce the best results, though three month signals were less stable.

Contrary to the findings of Jegadeesh and Titman,[9] we did not see evidence of a short-term reversal. Signals tended to be stronger when they ended a month before investment. As a result, we focus on results in which we invest at time t based on signals which are completely formed no earlier than time $t-1$, *i.e.* using the notation in Subsection 4.2 only data with signals having $m = 0$ are shown.

We mimicked the style of Krüger *et al.* when we constructed our portfolios. Return statistics are based on equal-weighted portfolios, and the long- and short-legs of our strategies are based on quintile sorts. The first quintile Q1 corresponds to the smallest values of the signal, while Q5 corresponds to the largest.

For returns based on industry or fundamental signals (Tables 8 and 9. respectively), we expect large values of the signal to be good signs for future firm-level returns. As a result, we long the Q5 portfolio for these strategies and short the Q1 portfolio.

In Table 10, we consider signals based on the cumulative divergence between industry and fundamental returns. Since we expected fundamental returns to be a better metric than industry, we long the first quintile Q1 and short the fifth quintile Q5.

Table 8: Returns from Signal $R^{(o)}_{j,t}$

Industry Return Statistics *January 1997–December 2009*

Panel A: One-Month Signal

	Mean	SD	P25	Median	P75	Sharpe Ratio	N
Q1	0.000	0.083	-0.036	0.006	0.047	-0.037	155
Q5	0.013	0.079	-0.026	0.014	0.050	0.128	155
Q5-Q1	0.013	0.081	-0.019	0.009	0.045	0.131	155

Panel B: Six-Month Signal

	Mean	SD	P25	Median	P75	Sharpe Ratio	N
Q1	0.002	0.088	-0.042	0.012	0.046	-0.005	150
Q5	0.013	0.073	-0.027	0.011	0.051	0.144	150
Q5-Q1	0.011	0.084	-0.028	0.013	0.046	0.100	150

Panels A and B correspond to respective signal $R^{(o)}_{j,t}(0,1)$ and $R^{(o)}_{j,t}(0,6)$. Our notation is explained in Subsection 4.2. Data are not annualized.

Table 9: Returns from Signal $R_{j,t}^{(f)}$

Fundamental Return Statistics *January 1997–December 2009*

Panel A: One-Month Signal

	Mean	SD	P25	Median	P75	Sharpe Ratio	N
Q1	0.002	0.084	-0.036	0.011	0.050	-0.012	155
Q5	0.014	0.077	-0.030	0.013	0.055	0.143	155
Q5-Q1	0.012	0.073	-0.022	0.007	0.042	0.129	155

Panel B: Six-Month Signal

	Mean	SD	P25	Median	P75	Sharpe Ratio	N
Q1	0.003	0.087	-0.037	0.007	0.050	0.002	150
Q5	0.012	0.079	-0.024	0.011	0.056	0.125	150
Q5-Q1	0.010	0.077	-0.021	0.012	0.041	0.091	150

Panels A and B correspond to respective signal $R_{j,t}^{(f)}(0,1)$ and $R_{j,t}^{(f)}(0,6)$. Our notation is explained in Subsection 4.2. Data are not annualized.

Table 10: Returns from Signal $R_{j,t}^{(o-f)}$

Industry minus Fundamental Return Statistics *January 1997–December 2009*

Panel A: One-Month Signal

	Mean	SD	P25	Median	P75	Sharpe Ratio	N
Q1	0.008	0.075	-0.041	0.017	0.055	0.076	155
Q5	0.007	0.072	-0.038	0.011	0.054	0.063	155
Q1-Q5	0.001	0.022	-0.006	0.001	0.009	-0.068	155

Panel B: Six-Month Signal

	Mean	SD	P25	Median	P75	Sharpe Ratio	N
Q1	0.008	0.080	-0.042	0.013	0.054	0.071	150
Q5	0.007	0.069	-0.035	0.015	0.050	0.071	150
Q1-Q5	0.001	0.031	-0.009	-0.001	0.008	-0.060	150

Panels A and B correspond to respective signal $R_{j,t}^{(f)}(0,1)$ and $R_{j,t}^{(f)}(0,6)$. Our notation is explained in Subsection 4.2. Data are not annualized.

Tables 11 and 12 show the factor loadings for one- and six-month signals, respectively. We tend to see positive alpha for long-short strategies based on $R_{j,t}^{(o)}$ and $R_{j,t}^{(f)}$, though the results are not always statistically significant. The alphas for long-short strategies based on the signal $R_{j,t}^{(o-f)}$ tend to be near zero. This strategy consistently produces statistically significant loadings on smb and mom, and the loading on hml is negative and statistically significant for the six-month signal.

Table 11: Monthly Factor Loadings: One-Month Signals

Factor Loadings					*January 1997–December 2009*		
	alpha	mrkt - rf	smb	hml	mom	R^2	N
Signal $R^{(o)}_{j,t}(0,1)$							
Q1	-0.005	1.206	0.652	0.159	-0.195	0.750	155
	(-1.491)	(15.490)	(7.014)	(1.546)	(-3.282)		
Q5	0.008	1.040	0.837	0.192	-0.123	0.705	155
	(2.135)	(12.890)	(8.683)	(1.793)	(-2.004)		
Q5-Q1	0.013	-0.166	0.185	0.032	0.071	0.022	155
	(1.917)	(-1.102)	(1.028)	(0.162)	(0.623)		
Signal $R^{(f)}_{j,t}(0,1)$							
Q1	-0.003	1.209	0.722	0.084	-0.225	0.803	155
	(-0.917)	(17.419)	(8.708)	(0.918)	(-4.256)		
Q5	0.009	0.994	0.882	0.081	-0.135	0.751	155
	(2.802)	(13.772)	(10.234)	(0.853)	(-0.678)		
Q5-Q1	0.012	-0.215	0.160	-0.003	0.090	0.039	155
	(1.991)	(-1.610)	(1.005)	(-0.016)	(0.889)		
Signal $R^{(o-f)}_{j,t}(0,1)$							
Q1	0.003	1.131	0.885	0.006	-0.110	0.954	155
	(2.552)	(37.610)	(24.650)	(0.153)	(-4.797)		
Q5	0.003	1.098	0.716	0.002	-0.217	0.964	155
	(2.874)	(42.869)	(23.414)	(0.052)	(-11.096)		
Q1-Q5	0.000	0.033	0.169	0.004	0.107	0.203	155
	(0.084)	(0.880)	(3.824)	(0.088)	(3.791)		

Factors obtained from the Ken French Data Library, and are derived from CRSP. Returns are written in decimal form and are not annualized.

Table 12: Monthly Factor Loadings: Six-Month Signals

Factor Loadings					*January 1997–December 2009*		
	alpha	mrkt - rf	smb	hml	mom	R^2	N
Signal $R^{(o)}_{j,t}(0,6)$							
Q1	0.001	0.001	0.520	-0.129	-0.129	0.854	150
	(0.561)	(18.252)	(7.354)	(-1.655)	(-14.070)		
Q5	0.005	1.134	0.910	0.910	0.381	0.862	150
	(2.296)	(21.974)	(14.768)	(4.942)	(9.742)		
Q5-Q1	0.004	0.053	0.390	0.465	1.013	0.612	150
	(0.861)	(0.538)	(3.299)	(3.565)	(13.489)		
Signal $R^{(f)}_{j,t}(0,6)$							
Q1	0.002	1.106	0.518	-0.158	-0.581	0.879	150
	(0.768)	(19.319)	(7.574)	(-2.097)	(-13.390)		
Q5	0.004	1.206	1.019	0.318	0.308	0.874	150
	(2.922)	(0.768)	(10.992)	(0.933)	7.542		
Q5-Q1	0.002	0.100	0.501	0.477	0.890	0.581	150
	(0.594)	(1.053)	(4.425)	(3.815)	(12.371)		
Signal $R^{(o-f)}_{j,t}(0,6)$							
Q1	0.003	1.170	0.983	-0.037	-0.091	0.956	150
	(2.367)	(37.053)	(26.079)	(-0.898)	(-3.812)		
Q5	0.004	1.077	0.594	0.135	-0.254	0.952	150
	(3.240)	(37.666)	(17.404)	(3.588)	(-11.721)		
Q1-Q5	-0.001	0.093	0.389	-0.173	0.163	0.561	150
	(-0.453)	(2.344)	(8.230)	(-3.309)	(5.428)		

Factors obtained from the Ken French Data Library, and are derived from CRSP. Returns are written in decimal form and are not annualized.

We explored signal quality in our analysis. The bars in Figures 3 and 4 show the equivalent annual return which would produce the corresponding cumulative return over the same time range. For the industry and fundamental strategies, strictly increasing bars are preferred, while strictly decreasing bars are best for industry minus fundamental.

Figure 3: *Annual returns of each quintile. January 1997–December 2009*

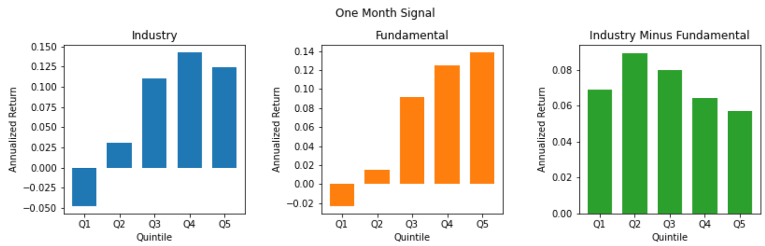


Figure 4: *Annual returns of each quintile. January 1997–December 2009*

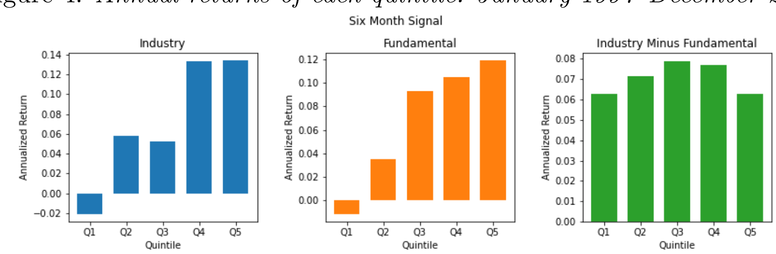


Table 24 analyzes the same phenomena as Figures 3 and 4 from a different perspective. The Spearman correlation is defined as

$$1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)}, \tag{12}$$

where n is the number of observations and d_i is the difference in rank between the signal $R_{j,t}^{(\cdot)}$ and the return $r_{j,t}$. The negative correlation between $R_{j,t}^{(o-f)}$ and $r_{j,t}$ is the desired direction since the strategy longs Q1 and shorts Q5.

Table 13: Spearman Correlation between Signal and Returns.

Correlations *January 1997–December 2009*

$\boldsymbol{n}$	$\boldsymbol{R_{j,t}^{(o)}(0,n)}$	$\boldsymbol{R_{j,t}^{(o)}(1,n)}$	$\boldsymbol{R_{j,t}^{(f)}(0,n)}$	$\boldsymbol{R_{j,t}^{(f)}(1,n)}$	$\boldsymbol{R_{j,t}^{(o-f)}(0,n)}$	$\boldsymbol{R_{j,t}^{(o-f)}(1,n)}$
1	0.147	-0.051	0.120	-0.035	-0.015	-0.001
6	0.026	0.001	0.032	0.011	-0.007	-0.003

Table 24 shows that signals formed using returns up to time $t-2$ tend have much lower Spearman correlations than those formed using returns up time time $t-1$. This provides evidence that there is no short-term reversal effect for any of the strategies within our analysis.

Table 14 explores the effect of market capitalization on the efficacy of the strategies. We refer to firm j as small at time t when its market capitalization is in the lowest third of firms within the MSCI universe at time t. Firm j is large when it is in the top third of firms. The table shows results from a one-month signal.

When we restrict our investment universe to only the smallest third of firms, our results are very strong. Assuming independence of returns, the annualized Sharpe ratios for the industry, fundamental, and industry minus fundamental signals are 0.755, 0.696, and 0.644. These conclusions many account for the discrepancy between our results and those of Krüger *et al.*.

Table 14: Capitalization Analysis

Return Statistics *January 1997–December 2009*

	Mean	SD	P25	Median	P75	Sharpe Ratio	N
Predict Small j by $r^{(o)}_{j,t-1}$							
Q1	0.021	0.079	-0.023	0.016	0.060	0.229	154
Q5	0.034	0.097	-0.031	0.027	0.097	0.325	154
Q5-Q1	0.013	0.049	-0.019	0.012	0.040	0.218	154
Predict Small j by $r^{(f)}_{j,t-1}$							
Q1	0.018	0.096	-0.034	0.013	0.069	0.159	154
Q5	0.039	0.097	-0.014	0.026	0.077	0.371	154
Q5-Q1	0.021	0.090	-0.019	0.018	0.050	0.201	154
Predict Small j by $r^{(o)}_{j,t-1} - r^{(f)}_{j,t-1}$							
Q1	0.038	0.095	-0.015	0.025	0.076	0.367	154
Q5	0.019	0.097	-0.032	0.014	0.074	0.164	154
Q1-Q5	0.019	0.088	-0.024	0.016	0.055	0.186	154
Predict Large j by $r^{(o)}_{j,t-1}$							
Q1	0.002	0.067	-0.038	0.010	0.047	-0.005	154
Q5	0.012	0.071	-0.031	0.015	0.058	0.125	154
Q5-Q1	0.009	0.037	-0.014	0.006	0.028	0.178	154
Predict Large j by $r^{(f)}_{j,t-1}$							
Q1	0.002	0.083	-0.033	0.012	0.049	-0.005	154
Q5	0.012	0.074	-0.028	0.012	0.052	0.124	154
Q5-Q1	0.010	0.086	-0.028	0.010	0.052	0.081	154
Predict Large j by $r^{(o)}_{j,t-1} - r^{(f)}_{j,t-1}$							
Q1	0.012	0.074	-0.028	0.012	0.051	0.123	154
Q5	0.002	0.083	-0.032	0.010	0.048	-0.002	154
Q1-Q5	0.009	0.085	-0.029	0.011	0.040	0.078	154

Use one-month signals to predict returns for the smallest and largest third of firms in the MSCI universe. Small and large refer to the smallest and largest third of firms by market capitalization. Data are not annualized.

Tables 15 and 16 explore alternative weighting schemes. Results for value-weighting were slightly worse than equal-weighting, while inverse value-weighting tended to be comparable.

As discussed in Section 3, the fundamental signal used a more complete data set than the MSCI universe. This larger dataset contained only the date, return, and DW Instrument ID. We were able to extract market capitalization from the corresponding MSCI data in many cases. However, this information was not complete. Since firms within this larger dataset but not in MSCI tend to have smaller market capitalization than the average firm within the MSCI universe, missing values of market capitalization were replaced with the 25th percentile of market capitalization for that date.

Table 15: Value-Weighted Signals

Return Statistics *January 1997–December 2009*

	Mean	SD	P25	Median	P75	Sharpe Ratio	N
Signal $R^{(o)}_{j,t}(0,1)$							
Q1	0.003	0.071	-0.026	0.012	0.044	0.005	154
Q5	0.005	0.061	-0.03	0.008	0.038	0.04	154
Q5-Q1	0.002	0.064	-0.022	0.001	0.032	-0.008	154
Signal $R^{(f)}_{j,t}(0,1)$							
Q1	0.006	0.067	-0.026	0.012	0.045	0.043	154
Q5	0.006	0.061	-0.027	0.008	0.044	0.059	154
Q5-Q1	0.001	0.061	-0.023	-0.002	0.024	-0.032	154
Signal $R^{(o-f)}_{j,t}(0,1)$							
Q1	0.006	0.058	-0.028	0.012	0.045	0.057	154
Q5	0.007	0.057	-0.02	0.014	0.044	0.073	154
Q1-Q5	-0.001	0.020	-0.012	-0.001	0.009	-0.172	154
Signal $R^{(o)}_{j,t}(0,6)$							
Q1	0.003	0.074	-0.033	0.010	0.040	0.007	150
Q5	0.009	0.061	-0.022	0.01	0.048	0.101	150
Q5-Q1	0.006	0.072	-0.027	0.008	0.040	0.042	150
Signal $R^{(f)}_{j,t}(0,6)$							
Q1	0.004	0.07	-0.034	0.012	0.042	0.022	149
Q5	0.009	0.059	-0.024	0.006	0.041	0.102	149
Q5-Q1	0.004	0.064	-0.023	0.008	0.033	0.030	149
Signal $R^{(o-f)}_{j,t}(0,6)$							
Q1	0.004	0.06	-0.031	0.015	0.042	0.027	149
Q5	0.006	0.056	-0.02 0	0.015	0.040	0.064	149
Q1-Q5	-0.002	0.023	-0.015	-0.004	0.007	-0.197	149

Missing market capitalization data for fundamental return calculations are filled with the 25th percentile of market capitalization for the corresponding date. Data are not annualized.

Table 16: Inverse Value-Weighted Signals

Return Statistics *January 1997–December 2009*

	Mean	SD	P25	Median	P75	Sharpe Ratio	N
Signal $R^{(o)}_{j,t}(0,1)$							
Q1	0.001	0.094	-0.045	0.008	0.052	-0.017	154
Q5	0.019	0.084	-0.022	0.016	0.056	0.199	154
Q5-Q1	0.018	0.080	-0.012	0.014	0.051	0.198	154
Signal $R^{(f)}_{j,t}(0,1)$							
Q1	0.002	0.095	-0.042	0.006	0.056	-0.004	154
Q5	0.015	0.083	-0.03 0	0.010	0.059	0.153	154
Q5-Q1	0.013	0.064	-0.017	0.007	0.042	0.163	154
Signal $R^{(o-f)}_{j,t}(0,1)$							
Q1	0.009	0.087	-0.042	0.009	0.059	0.078	154
Q5	0.009	0.084	-0.04	0.007	0.060	0.077	154
Q1-Q5	0.000	0.019	-0.011	0.000	0.010	-0.121	154
Signal $R^{(o)}_{j,t}(0,6)$							
Q1	0.003	0.102	-0.044	0.002	0.050	0.007	150
Q5	0.013	0.076	-0.024	0.011	0.051	0.138	150
Q5-Q1	0.010	0.084	-0.025	0.014	0.049	0.085	150
Signal $R^{(f)}_{j,t}(0,6)$							
Q1	0.004	0.100	-0.045	0.003	0.057	0.017	149
Q5	0.013	0.085	-0.033	0.010	0.061	0.125	149
Q5-Q1	0.009	0.073	-0.02 0	0.010	0.040	0.086	149
Signal $R^{(o-f)}_{j,t}(0,6)$							
Q1	0.010	0.094	-0.042	0.006	0.060	0.082	149
Q5	0.008	0.08	-0.036	0.011	0.055	0.071	149
Q1-Q5	0.002	0.028	-0.009	0.001	0.009	-0.019	149

Missing market capitalization data for fundamental return calculations are filled with the 25th percentile of market capitalization for the corresponding date. Data are not annualized.

The last result we report for Subsection 5.2 is return statistics for a subset of the transitive component of the fundamental peer groups. Using this subset of the fundamental peer-group as the signal tends to produce negative returns. This shows that the non-transitive component of the signal $R^{(o-f)}_{j,t}$ substantially improves results.

Table 17: Transitive Subsetting

Return Statistics							*January 1997–December 2009*
	Mean	SD	P25	Median	P75	Sharpe Ratio	N
Signal $\boldsymbol{R_{j,t}^{(f)}(0,1)}$							
Q1	0.011	0.061	-0.026	0.015	0.053	0.143	155
Q5	0.013	0.061	-0.022	0.012	0.055	0.163	155
Q5-Q1	0.001	0.024	-0.012	0.001	0.013	-0.061	155
Signal $\boldsymbol{R_{j,t}^{(o-f)}(0,1)}$							
Q1	0.008	0.073	-0.030	0.013	0.051	0.075	155
Q5	0.013	0.065	-0.025	0.016	0.049	0.159	155
Q1-Q5	-0.005	0.054	-0.030	-0.002	0.021	-0.139	155
Signal $\boldsymbol{R_{j,t}^{(f)}(0,6)}$							
Q1	0.010	0.060	-0.026	0.010	0.047	0.127	150
Q5	0.011	0.060	-0.024	0.013	0.048	0.138	150
Q5-Q1	0.001	0.026	-0.011	0.000	0.013	-0.073	150
Signal $\boldsymbol{R_{j,t}^{(o-f)}(0,6)}$							
Q1	0.009	0.071	-0.027	0.009	0.049	0.091	150
Q5	0.013	0.065	-0.027	0.010	0.050	0.153	150
Q1-Q5	-0.004	0.055	-0.029	-0.005	0.020	-0.112	150

Transitive subsetting is done using complete linkage clustering. See Subsection 4.3 for more details. Data are not annualized.

5.3 Post-Krüger Time Range

In this subsection, we explore how our strategies perform after the publication of Krüger *et al.*. In particular, the results below use data within the time-frame January 2010 to December 2018. We see substantial weakening for the signals $R_{j,t}^{(o)}$ and $R_{j,t}^{(f)}$. The signal $R_{j,t}^{(o-f)}$ appears to be less effective as well. For example, Table 24 shows that the Spearman correlation between the signal and returns is almost exactly zero. We provide more limited commenting within this subsection because the methodology is identical to Subsection 5.2.

Table 18: Table I Replication

Summary Statistics *January 2010–December 2018*

Panel A: Annual Variables

	Mean	SD	P25	Median	P75	N
Firms per industry	81	46	42	76	112	116936
Firms per fundamental group	42	54	6	14	53	116936
$\ln(BE/ME)$	-0.776	0.898	-1.241	-0.612	-0.170	9899

Panel B: Monthly Variables

	Mean	SD	P25	Median	P75	N
$r_{j,t}$	0.011	0.098	-0.042	0.010	0.061	116936
$r_{j,t}^{(o)}$	0.009	0.058	-0.023	0.013	0.045	116936
$r_{j,t}^{(f)}$	0.011	0.070	-0.028	0.013	0.051	116936
$r_{j,t}^{(o)} - r_{j,t}^{(f)}$	-0.002	0.037	-0.017	-0.001	0.014	116936
$R_{j,t}(1,11)$	0.140	0.337	-0.051	0.111	0.289	80039
$\ln(ME)$	14.672	1.470	13.562	14.461	15.545	115353

Panel C: Weekly Variables

	Mean	SD	P25	Median	P75	N
$r_{j,t}$	0.002	0.047	-0.021	0.002	0.026	526786
$r_{j,t}^{(o)}$	0.002	0.030	-0.013	0.004	0.020	526786
$r_{j,t}^{(f)}$	0.003	0.035	-0.016	0.003	0.022	526786
$r_{j,t}^{(o)} - r_{j,t}^{(f)}$	0.000	0.018	-0.007	0.000	0.007	526786

Annual variables are calculated using monthly data. Book-to-market ratios use June data. Returns are not annualized.

Table 19: Return Statistics from $R_{j,t}^{(o)}$

Industry Signal *January 2010–December 2018*

Panel A: One-Month Signal

	Mean	SD	P25	Median	P75	Sharpe Ratio	N
Q1	0.009	0.056	-0.025	0.010	0.044	0.148	107
Q5	0.008	0.046	-0.015	0.012	0.035	0.161	107
Q5-Q1	-0.001	0.032	-0.020	0.000	0.018	-0.037	107

Panel B: Six-Month Signal

	Mean	SD	P25	Median	P75	Sharpe Ratio	N
Q1	0.007	0.056	-0.028	0.006	0.041	0.125	102
Q5	0.010	0.042	-0.012	0.014	0.038	0.242	102
Q5-Q1	0.003	0.035	-0.015	0.002	0.024	0.078	102

Panels A and B correspond to respective signal $R_{j,t}^{(o)}(0,1)$ and $R_{j,t}^{(o)}(0,6)$. Our notation is explained in Subsection 4.2. Data are not annualized.

Table 20: Return Statistics from $R_{j,t}^{(f)}$

Fundamental Signal *January 2010–December 2018*

				Panel A: One-Month Signal			
	Mean	SD	P25	Median	P75	Sharpe Ratio	N
Q1	0.008	0.053	-0.027	0.011	0.042	0.149	107
Q5	0.008	0.048	-0.016	0.013	0.038	0.162	107
Q5-Q1	0.000	0.031	-0.017	0.000	0.019	-0.014	107
				Panel B: Six-Month Signal			
	Mean	SD	P25	Median	P75	Sharpe Ratio	N
Q1	0.007	0.053	-0.027	0.009	0.041	0.134	102
Q5	0.009	0.046	-0.016	0.016	0.037	0.191	102
Q5-Q1	0.002	0.032	-0.015	0.004	0.018	0.041	102

Panels A and B correspond to respective signal $R_{j,t}^{(o)}(0,1)$ and $R_{j,t}^{(o)}(0,6)$. Our notation is explained in Subsection 4.2. Data are not annualized.

Table 21: Return Statistics from $R_{j,t}^{(o-f)}$

Industry minus Fundamental Signal *January 2010–December 2018*

				Panel A: One-Month Signal			
	Mean	SD	P25	Median	P75	Sharpe Ratio	N
Q1	0.009	0.049	-0.016	0.012	0.043	0.174	107
Q5	0.008	0.047	-0.018	0.011	0.043	0.174	107
Q1-Q5	0.000	0.014	-0.005	0.000	0.006	0.011	107
				Panel B: Six-Month Signal			
	Mean	SD	P25	Median	P75	Sharpe Ratio	N
Q1	0.009	0.050	-0.017	0.011	0.040	0.172	102
Q5	0.008	0.045	-0.017	0.011	0.036	0.182	102
Q1-Q5	0.000	0.017	-0.007	0.000	0.008	0.012	102

Panels A and B correspond to respective signal $R_{j,t}^{(o-f)}(0,1)$ and $R_{j,t}^{(o-f)}(0,6)$. Our notation is explained in Subsection 4.2. Data are not annualized.

Table 22: Monthly Factor Loadings: One-Month Signals

Factor Loadings						*January 2010–December 2018*	
	alpha	mrkt - rf	smb	hml	mom	R^2	N
Signal $R^{(o)}_{j,t}(0,1)$							
Q1	-0.002	1.166	0.694	0.213	-0.156	0.908	107
	(-1.385)	(23.798)	(8.867)	(2.599)	(-2.525)		
Q5	-0.001	0.905	0.729	0.141	0.023	0.869	107
	(-0.617)	(18.343)	(9.373)	(2.126)	(-0.356)		
Q5-Q1	0.001	-0.286	0.024	-0.042	0.134	0.139	107
	(0.448)	(-3.352)	(0.178)	(-0.297)	(1.249)		
Signal $R^{(f)}_{j,t}(0,1)$							
Q1	-0.002	1.123	0.649	0.171	-0.155	0.906	107
	(-1.406)	(23.646)	(8.551)	(2.150)	(-2.586)		
Q5	-0.001	0.921	0.749	0.087	-0.103	0.864	107
	(-0.470)	(17.978)	(9.140)	(1.016)	(-1.600)		
Q5-Q1	0.002	-0.202	0.099	-0.084	0.051	0.064	107
	(0.494)	(-2.335)	(0.719)	(-0.579)	(0.472)		
Signal $R^{(o-f)}_{j,t}(0,1)$							
Q1	-0.001	1.040	0.731	-0.023	-0.164	0.957	107
	(-1.120)	(35.109)	(15.447)	(-0.468)	(-4.409)		
Q5	-0.001	1.009	0.648	0.136	-0.093	0.972	107
	(-1.629)	(44.118)	(17.717)	(3.572)	(-3.242)		
Q1-Q5	0.000	0.031	0.084	-0.160	-0.071	0.084	107
	(0.104)	(0.803)	(1.346)	(-2.450)	(-1.449)		

Factors obtained from the Ken French Data Library, and are derived from CRSP. Returns are written in decimal form and are not annualized.

Table 23: Monthly Factor Loadings: Six-Month Signals

Direct Hoberg and Phillips Data						*January 2010–December 2018*	
	alpha	mrkt - rf	smb	hml	mom	R^2	N
Signal $R^{(o)}_{j,t}(0,6)$							
Q1	-0.003	1.140	0.701	0.193	-0.463	0.923	102
	(-1.598)	(23.441)	(9.395)	(2.314)	(-7.468)		
Q5	0.000	0.894	0.612	0.167	0.252	0.880	102
	(0.213)	(19.905)	(8.885)	(2.169)	(4.401)		
Q5-Q1	0.003	-0.246	-0.089	-0.026	0.716	0.489	102
	(1.110)	(-3.127)	(-0.735)	(-0.192)	(7.134)		
Signal $R^{(f)}_{j,t}(0,6)$							
Q1	-0.003	1.128	0.608	0.173	-0.371	0.920	102
	(-1.776)	(24.043)	(8.443)	(2.150)	(-6.189)		
Q5	-0.002	0.938	0.753	0.014	0.203	0.876	102
	(-0.900)	(18.825)	(9.848)	(0.163)	(3.183)		
Q5-Q1	0.001	-0.189	0.146	-0.159	0.573	0.406	102
	(0.501)	(-2.466)	(1.234)	(-1.207)	(5.843)		
Signal $R^{(o-f)}_{j,t}(0,6)$							
Q1	-0.002	1.086	0.781	-0.152	-0.098	0.954	102
	(-2.075)	(32.612)	(15.290)	(-2.665)	(-2.307)		
Q5	-0.002	1.025	0.534	0.132	-0.136	0.971	102
	(-2.056)	(43.245)	(14.684)	(3.264)	(-4.507)		
Q1-Q5	-0.001	0.061	0.247	-0.284	0.038	0.303	102
	(-0.468)	(1.396)	(3.707)	(-3.825)	(0.692)		

Factors obtained from the Ken French Data Library, and are derived from CRSP. Returns are written in decimal form and are not annualized.

Figure 5: *Annual returns of each quintile. January 2010–December 2018*

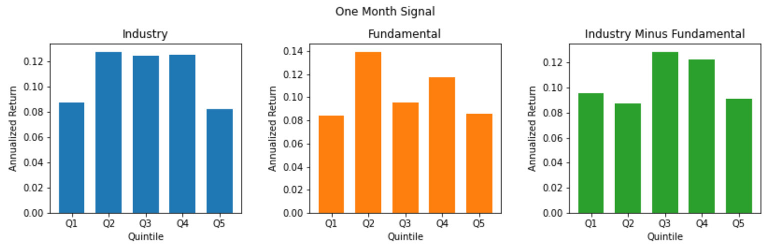


Figure 6: *Annual returns of each quintile. January 2010–December 2018*

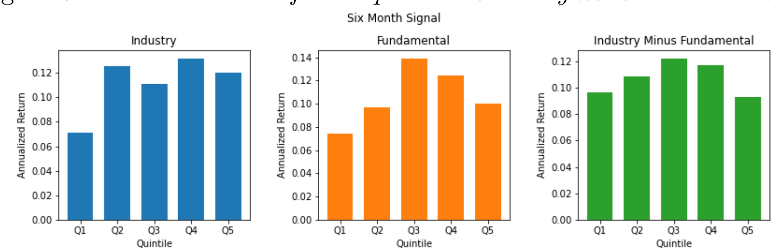


Table 24: *Spearman Correlation Between Signal and Returns*

Correlations *January 2010–December 2018*

n	$R^{(o)}_{j,t}(0,n)$	$R^{(o)}_{j,t}(1,n)$	$R^{(f)}_{j,t}(0,n)$	$R^{(f)}_{j,t}(1,n)$	$R^{(o-f)}_{j,t}(0,n)$	$R^{(o-f)}_{j,t}(1,n)$
1	-0.088	0.037	-0.082	0.019	-0.004	0.000
6	-0.053	-0.036	-0.055	-0.039	-0.001	0.005

Table 25: Capitalization Analysis

Return Statistics						*January 2010–December 2018*	
	Mean	SD	P25	Median	P75	Sharpe Ratio	N
Predict Small j by $r^{(o)}_{j,t-1}$							
Q1	0.011	0.061	-0.024	0.013	0.055	0.176	106
Q5	0.021	0.057	-0.014	0.025	0.058	0.362	106
Q5-Q1	0.010	0.034	-0.008	0.007	0.026	0.288	106
Predict Small j by $r^{(f)}_{j,t-1}$							
Q1	0.017	0.063	-0.024	0.017	0.056	0.263	106
Q5	0.017	0.062	-0.019	0.015	0.061	0.273	106
Q5-Q1	0.000	0.043	-0.020	0.003	0.026	-0.002	106
Predict Small j by $r^{(o)}_{j,t-1} - r^{(f)}_{j,t-1}$							
Q1	0.016	0.062	-0.014	0.015	0.062	0.258	106
Q5	0.018	0.064	-0.024	0.017	0.057	0.280	106
Q1-Q5	-0.002	0.044	-0.025	0.001	0.027	-0.054	106
Predict Large j by $r^{(o)}_{j,t-1}$							
Q1	0.003	0.053	-0.022	0.009	0.035	0.052	106
Q5	0.015	0.041	-0.011	0.019	0.042	0.358	106
Q5-Q1	0.012	0.035	-0.014	0.011	0.037	0.340	106
Predict Large j by $r^{(f)}_{j,t-1}$							
Q1	0.007	0.049	-0.018	0.011	0.037	0.147	106
Q5	0.010	0.039	-0.012	0.013	0.035	0.260	106
Q5-Q1	0.003	0.034	-0.017	0.006	0.021	0.081	106
Predict Large j by $r^{(o)}_{j,t-1} - r^{(f)}_{j,t-1}$							
Q1	0.010	0.039	-0.012	0.012	0.033	0.246	106
Q5	0.008	0.049	-0.018	0.011	0.037	0.165	106
Q1-Q5	0.002	0.034	-0.020	0.004	0.019	0.042	106

Use one-month signals to predict returns for the smallest and largest third of firms in the MSCI universe. Small and large refer to the smallest and largest third of firms by market capitalization. Data are not annualized.

Table 26: Value-Weighted Signals

Return Statistics						*January 2010–December 2018*	
	Mean	SD	P25	Median	P75	Sharpe Ratio	N
Signal $R^{(o)}_{j,t}(0,1)$							
Q1	0.012	0.047	-0.009	0.012	0.039	0.238	106
Q5	0.009	0.038	-0.015	0.011	0.031	0.222	106
Q5-Q1	-0.003	0.030	-0.019	-0.001	0.013	-0.106	106
Signal $R^{(f)}_{j,t}(0,1)$							
Q1	0.010	0.042	-0.012	0.014	0.032	0.228	107
Q5	0.010	0.038	-0.013	0.012	0.031	0.247	107
Q5-Q1	0.000	0.023	-0.010	0.000	0.011	-0.012	107
Signal $R^{(o-f)}_{j,t}(0,1)$							
Q1	0.011	0.040	-0.009	0.016	0.035	0.265	107
Q5	0.009	0.039	-0.010	0.011	0.034	0.227	107
Q1-Q5	0.002	0.011	-0.005	0.001	0.007	0.145	107
Signal $R^{(o)}_{j,t}(0,6)$							
Q1	0.010	0.047	-0.014	0.011	0.039	0.212	102
Q5	0.011	0.036	-0.016	0.012	0.036	0.288	102
Q5-Q1	0.001	0.034	-0.017	0.000	0.022	0.007	102
Signal $R^{(f)}_{j,t}(0,6)$							
Q1	0.011	0.042	-0.012	0.014	0.035	0.250	102
Q5	0.011	0.035	-0.013	0.014	0.034	0.304	102
Q5-Q1	0.000	0.024	-0.012	0.000	0.014	-0.011	102
Signal $R^{(o-f)}_{j,t}(0,6)$							
Q1	0.011	0.038	-0.006	0.012	0.033	0.282	102
Q5	0.011	0.038	-0.010	0.012	0.037	0.290	102
Q1-Q5	0.001	0.009	-0.006	-0.001	0.005	-0.064	102

Missing market capitalization data for fundamental return calculations are filled with the 25th percentile of market capitalization for the corresponding date. Data are not annualized.

Table 27: Inverse Value-Weighted

Return Statistics						*January 2010–December 2018*	
	Mean	SD	P25	Median	P75	Sharpe Ratio	N
Signal $R^{(o)}_{j,t}(0,1)$							
Q1	0.005	0.064	-0.027	0.008	0.044	0.073	106
Q5	0.005	0.053	-0.027	0.013	0.033	0.097	106
Q5-Q1	0.000	0.036	-0.020	0.013	0.021	0.005	106
Signal $R^{(f)}_{j,t}(0,1)$							
Q1	0.005	0.062	-0.031	0.007	0.044	0.083	107
Q5	0.005	0.055	-0.026	0.008	0.044	0.081	107
Q5-Q1	-0.001	0.034	-0.019	0.001	0.017	-0.028	107
Signal $R^{(o-f)}_{j,t}(0,1)$							
Q1	0.005	0.057	-0.025	0.005	0.044	0.088	107
Q5	0.006	0.053	-0.033	0.007	0.042	0.113	107
Q1-Q5	-0.001	0.016	-0.010	-0.001	0.009	-0.079	107
Signal $R^{(o)}_{j,t}(0,6)$							
Q1	0.001	0.066	-0.040	0.005	0.046	0.017	102
Q5	0.010	0.048	-0.016	0.012	0.045	0.200	102
Q5-Q1	0.008	0.038	-0.009	0.006	0.026	0.217	102
Signal $R^{(f)}_{j,t}(0,6)$							
Q1	0.003	0.062	-0.036	0.002	0.043	0.049	102
Q5	0.006	0.050	-0.024	0.007	0.041	0.123	102
Q5-Q1	0.003	0.034	-0.015	0.003	0.018	0.082	102
Signal $R^{(o-f)}_{j,t}(0,6)$							
Q1	0.004	0.057	-0.030	0.006	0.042	0.064	102
Q5	0.007	0.052	-0.030	0.009	0.040	0.125	102
Q1-Q5	-0.003	0.017	-0.014	-0.002	0.007	-0.187	102

Missing market capitalization data for fundamental return calculations are filled with the 25th percentile of market capitalization for the corresponding date. Data are not annualized.

Table 28: Clusters

Return Statistics						*January 2010–December 2018*
	Mean	SD	P25	Median	P75	Sharpe Ratio	N

Signal $R^{(f)}_{j,t}(0,1)$	Mean	SD	P25	Median	P75	Sharpe Ratio	N
Q1	0.012	0.048	-0.013	0.013	0.044	0.235	107
Q5	0.012	0.048	-0.012	0.015	0.042	0.245	107
Q5-Q1	0.001	0.012	-0.005	0.002	0.008	0.041	107
Signal $R^{(o-f)}_{j,t}(0,1)$							
Q1	0.013	0.053	-0.015	0.017	0.045	0.232	107
Q5	0.010	0.048	-0.013	0.013	0.042	0.197	107
Q1-Q5	0.003	0.026	-0.011	0.004	0.013	0.096	107
Signal $R^{(f)}_{j,t}(0,6)$							
Q1	0.013	0.047	-0.018	0.014	0.042	0.269	102
Q5	0.012	0.046	-0.011	0.018	0.035	0.264	102
Q5-Q1	-0.001	0.016	-0.012	0.000	0.011	-0.062	102
Signal $R^{(o-f)}_{j,t}(0,6)$							
Q1	0.012	0.053	-0.016	0.016	0.038	0.216	102
Q5	0.011	0.043	-0.015	0.014	0.040	0.255	102
Q1-Q5	0.000	0.025	-0.018	-0.001	0.013	0.004	102

Transitive subsetting is done using complete linkage clustering. See Subsection 4.3 for more details. Data are not annualized.

6 Conclusion

The signal $R_{j,t}^{(o-f)}$ does not appear to be particularly effective within the MSCI Large- and Mid-Capitalization universe. As Table 7 shows, market capitalization for firms within the universe tended to be much larger than corresponding firms within the CRSP universe analyzed by Krüger *et al.*. This may have been the critical difference between the two sets of results. As Table 14 shows, mean returns and Sharpe ratios were strong when limited to the smallest third of firms within the MSCI Large- and Mid-Capitalization universe. However, Table 25 suggests that even this effect diminished after 2009. Another explanation may be that the GICS industry classification scheme had much more long-term explanatory power over firm returns than the SIC2 classification system. Table 7 showed that this system produced far finer groups than SIC2. Furthermore, return statistic for the signal $R_{j,t}^{(o)}$ were robust; Tables 22 and 23 show positive—though statistically insignificant—abnormal returns for industry momentum even after 2009.

An Analysis of firms within portfolios formed using the signal $R_{j,t}^{(o-f)}$ showed that the strategy invested heavily in information technology during the early 2000s. This may partially explain the poor return statistics because the "dot-com bubble" and "bust" occurred within the time-frame of Krüger *et al.*. We explored sector neutralization of our signal using the entire time-range and this improved results. However, these conclusions may be spurious because there was no out-of-sample analysis and variations in the strategy were solely based on improvement in return statistics and no underlying theory.

Within the main-text of Krüger *et al.*, a further refinement of the strategy is suggested. In particular, for each firm j, they introduce a co-movement metric

$$\rho_j = \left| \frac{r_j - r_j^{(o)}}{\sigma_{24}(r_j - r_j^{(o)})} \right| \tag{13}$$

where $\sigma_{24}\left(r_j - r_j^{(o)}\right)$ is the rolling 24-month standard deviation of the difference. They suggest only consideration of firm j for the quintile sort at time t if ρ_j is in the smallest third of firm co-movement values at the corresponding time. This subsetting was not used within the tables of the appendix which we replicated and is not relevant to our analysis directly because it would reduce coverage to unacceptably low levels.[1] However, this subsetting may improve return statistics and therefore may be applicable to some future analysis.

Though our primary signal $R_{j,t}^{(o-f)}$ did not appear effective, the signal $R_{j,t}^{(f)}$ produced strong results, particularly before 2009. Signals which utilize fundamental returns could potentially be fruitful. For example, Professor Peleg suggests consideration of a signal based on cumulative values of

$$r_j^{(f)} - r_j. \tag{14}$$

This still utilizes some of the mispricing theory because it suggests divergence between fundamental peer-group returns and firm-specific returns may be the result of mispricing of firm j's stock. There may also be synergy with the well-documented short-term contrarian investment strategy.

We, Group 21, have concrete plans to continue our analysis with GIC for another month. A presentation of our findings will be given in late January of 2021. Alternative investment universes will also be considered. Some further variations of the strategy may be considered as well. We will see precisely when the strategy fails, and attempt to reconcile all of our discrepancies.

References

[1] Krüger, Philipp *et al.* "Categorization Bias in the Stock Market." *Das Centre for Financial Research an der Universität Köln.* 2012.

[2] Hoberg, Gerard and Gordon Phillips. "Text-Based Network Industries and Endogenous Product Differentiation," *Journal of Political Economy*, vol. 124, no. 5. 2016.

[3] Hoberg, Gerard and Gordon Phillips. "Product Market Synergies and Competition in Mergers and Acquisitions: A Text-Based Analysis," *The Review of Financial Studies*, vol. 23, no. 10. 2010.

[4] Daniel, Kent and Tobias J. Moskowitz. "Momentum crashes." *Journal of Financial Economics.* 2016.

[5] Moskowitz, Tobias J. and Mark Grinblatt. "Do Industries Explain Momentum?" *Journal of Finance*, vol 54, August 1999

[6] Gupta-Mukherjee, Swasti. "Categorical Thinking in Portfolio Choice." *European Financial Management Association.* 2013.

[7] Fama, Eugene and Kenneth French. "Size, value, and momentum in international stock returns." *Journal of Financial Economics*, vol. 105, Issue 3, September 2012, pp. 457-472

[8] Fama, Eugene and Kenneth French. "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics*, September 1992

[9] Jegadeesh, Narasimhan and Sheridan Titman. "Short horizon return reversals and the bid-ask spread." *Journal of Financial Intermediation*, vol. 4, April 1995.