Stocks through a Looking Glass:
Can Style Segment-Adjusted Mutual Fund Stock Holdings Predict Stock Returns?†

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ABSTRACT

Using stock characteristics to classify fund holdings into style segments, and peer group holdings as benchmarks to define active fund holdings, we introduce a new measure, stock investment quality, to infer information about future stock returns from the active fund holdings by skilled managers. Stocks ranked high on investment quality generate significantly higher excess market returns that persist through the ensuing year. The positive investment quality–future return relationship is robust to fund quality proxied by GVA or management fees. Future returns are highest on stock holdings of skillful and patient fund managers who exploit long term market mispricing.

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The preponderance of literature on active fund management focuses on the attribution of fund performance to stock selection and timing. Surprisingly, only a few studies examine the information about future stock returns contained in the heterogeneity of active mutual fund holdings (Wermers, Yao, and Zhao, 2012; Jiang and Sun, 2014; and Jiang, Verbeek, and Wang, 2020). Moreover, in these studies, the emphasis on differential information as the principal factor in portfolio holding outcomes obscures the equally important role of skill. Conditional on information, only skilled fund managers will invest similarly. Portfolio holding outcomes will depend not only on whether or not the fund manager is informed, but also on whether or not the informed fund manager is skilled. Last but not least, in these studies, portfolio holdings scaled by fund size can mask skill in smaller funds.

All things considered, only the stockholdings of a select group of fund managers who are skilled and privately informed at a given point in time should contain information about future stock returns.

> "It is far better to weight the opinions of more capable decision makers more heavily than those of less capable decision makers. … (B)est decisions are made by an idea meritocracy with believability-weighted decision making." Ray Dalio, 2019[1]

In this study, we introduce a new measure of stock investment quality (IQ) – the cross-product of active fund holdings and fund quality summed across funds scaled by the variance in the deviation of active fund holdings across funds. Our measure to predict future stock returns captures the latent stock value reflected in active fund holdings of privately informed and skilled fund managers who invest similarly (Cohen, Coval, and Pastor, 2005). To estimate active fund holdings, we use stock characteristics (Daniel, Grinblatt, Titman, and Wermers, 1997) to classify a fund's stock holdings into style segments and to define style segment-based peer group holdings as benchmarks.

Our measure makes an important contribution to the statistical extraction of private information about future stock returns contained in actively managed mutual fund holdings. Fund holdings expressed as portfolio value-weights embed the entwined effects of fund size with investment style and fund performance. The scalability of stock investments is constrained by fund size (Elton, Gruber, and Blake, 2012; and Berk and Green, 2004). Whereas a small fund can easily invest all its money in its best ideas, a lack of liquidity can force a large fund to invest in its not-so-good ideas, or take larger ownership positions in stocks than is optimal for risk diversification (Chen, Hong, Huang, and Kubrick, 2004). Diseconomies of fund size can conceal managerial skill (Zhu, 2018). The empirical relation between fund size and performance is an outcome of investment style and liquidity (Yan,

[1]Co-Chairman, Bridgewater Associates. See https://www.linkedin.com/pulse/work-principle-5-believability-weight-your-decision-making-ray-dalio.

2008).

Our stock quality measure is based on two key components – active fund holdings and fund quality. First, we classify stocks held by fund managers into style segments using a stock characteristics-based DGTW (1997) approach to sort stocks along size, value/growth, and momentum dimensions. Rather than portfolio value weights, we define fund holdings as the dollar value allocated to a stock in a style segment as a fraction of the fund's total dollar investment in this style segment. Style segment-adjusted fund holdings alleviate differences in fund size that can influence the stock selection decisions of fund managers.

Second, we use peer group holdings in style segments as benchmarks. A peer group is defined as all funds who invest in stocks in a style segment. Stock peer group holding is the aggregate dollar value allocated to a stock in a style segment expressed as a fraction of the aggregate dollar investment in the style segment. Fund managers who invest in the same style segment constitute a natural peer group whose members conceivably share the same information and adopt similar unobserved investment strategies (Hunter, Kandel, Kandel, and Wermers, 2014).

In a style segment, we define active fund holdings as the deviations of fund holdings from peer group holdings.[2] When skilled fund managers faced with the same information act similarly, we expect active fund holdings driven by the private information-based trading of skilled fund managers to be positively correlated with skill, and active fund holdings from sentiment-based trading of unskilled fund managers to be uncorrelated with skill.[3] Moreover, we expect the co-movements in active holdings among skilled fund managers to reflect the commonality in private information, and co-movements in active holdings of unskilled fund managers to reflect herding. Only the co-movements in active holdings from trading on private information by skilled fund managers will endure.

Controlling for stock characteristics, the deviations in active fund holdings impound differences in private information across fund managers, and the variance in deviations of active fund holdings, the cross-sectional divergence in private information between skilled and unskilled fund managers.[4] We show stock IQ is persistent and forecasts positive future stock returns over a 12-month horizon when active fund holdings are positively correlated with fund quality.

[2]Active fund holdings should not be confused with 'active share' which is defined as deviations in portfolio value-based fund holdings from return-based performance benchmark holdings.

[3]Let $h_{i,j}$ and $h_{i,j*}$ denote the holdings of stock i by funds j and j^*; α_j and α_{j*}, the fund performance of funds j and j^* which proxy for managerial skill. $Cov(h_{i,j}, \alpha_j)$ and $Cov(h_{i,j*}, \alpha_{j*})$ will embed $Cov(h_{i,j}, h_{i,j*})$ when funds j and j^* have skilled managers, and as a result, α_j and α_{j*} are correlated. Moreover, $Cov(h_{i,j}, h_{i,j*})$ is accentuated when $h_{i,j}$ and $h_{i,j*}$ are also functions of skill; i.e. skilled managers of funds j and j^* act similarly on the same information.

[4]In Jiang and Sun (2014) and Jiang, Verbeek, and Wang (2020), deviations in fund portfolio weights allocated to stocks from self-selected benchmarks are used to proxy for differences in information of fund managers.

Our stock characteristics-based peer group holdings avoid the drawbacks of portfolio value-weighted holdings on return-based performance benchmarks. For a vast majority of funds, portfolio value-weighted holdings on select benchmarks may not capture the perceived investment opportunities of fund managers and their true exposures to size and value/growth dimensions (Cremers, Fulkerson, and Riley, 2019). Mismatches appear strategically motivated to influence investor flows (Elton, Gruber, and Blake 2003; Sensoy, 2008) or managerial compensation (Del Guercio and Tkac, 2002). A focus on active share (Cremers and Petajisto, 2009) and tracking error (Cremers and Pareek, 2016) induces a moral hazard incentive for fund managers to inject noise into holdings (Brown and Davies, 2017). Accounting for differences in benchmark returns, fund return outperformance from active share is a result of underperforming benchmarks (Frazzini, Friedman, and Pomorski, 2016).

Third, we proxy fund quality by a fund's long-term gross value added (GVA) rather than by its net or raw alphas. Fund GVA accounts for diminishing returns to scale and constrained supply of skilled fund managers (Berk and Binsbergen 2015; and Zhu, 2018). Analogous to Wermers et al. (2012), our stock IQ measure assigns more credence to the active fund holdings of high quality funds.

Successful performing funds will employ more skilled managers and skillful fund managers will choose to join competitive fund families where performance incentives are high (Evans, Prado, and Zambrana, 2020). The distribution of gross value-added will predominantly mirror the distribution of managerial skill (Berk and Binsbergen, 2015) as the size of the active mutual industry changes and in conjunction with the entry of skilled and exit of unskilled funds (Pastor, Stambaugh, and Taylor, 2015). In a competitive securities market, the incentive for fund managers to incur costs to become informed is contingent on their ability to trade profitably on private information (Grossman and Stiglitz, 1980). When investors can identify talent, more skilled managers earn higher economic rents, manage larger funds, and asset prices are more information efficient (Gârleanu and Pedersen, 2018). Longer term, fund managers will not outperform passive benchmarks net of expenses when there is a competitive market for investors, managerial skills exhibit decreasing returns to scale, and investors can at low cost, learn about managerial skill from past returns (Berk and Green, 2004).

Lastly, we transform stock IQ into relative percentile ranks to meaningfully describe differences, in a consistent manner, across stocks and time-varying economic conditions across periods. A stock's relative percentile rank is an odds ratio, estimated as the cumulative fraction of all stocks with lower IQ divided by the cumulative fraction of all stocks with higher IQ. Relative percentile rank in IQ is independent of units used in measuring fund quality.

Our main findings are as follows. We show our stock IQ measure strongly persists up to lead four quarters. Using horserace regressions, we find the forecast return power of stock IQ is not subsumed by alternative empirically documented stock-return prediction measures which include herding by unskilled fund managers (Lakonishok, Shleifer, and Vishny, 1992; Jones, Lee, and Weis, 1999; Brown, Wei, and Wermers, 2014), adjusted 'dumb' money inflows (Frazzini and Lamont, 2007) from investor-sentiment driven trading, as well as delta fund ownership and delta breadth that may suggest short-sale constraints (Chen, Hong, and Stein, 2002). Controlling for competing stock return predictors, stock IQ significantly predicts positive stock returns over lead four quarters.

We find a strong positive relationship between stock IQ and future stock returns. A value-weighted portfolio of stocks in the highest IQ quintile outperforms a value-weighted portfolio of stocks in the lowest IQ quintile by an average quarterly excess market return of 1.533%. The buy-and-hold return outperformance of high over low IQ stocks persists up to a year.

Stock IQ signals the information advantage of skillful fund managers. Small cap stocks benefit the most from IQ, over and beyond large cap stocks. The average quarterly excess market return in lead one quarter on value-weighted high-low IQ quintile portfolios of small cap stocks is 1.825%. In comparison, the forecast quarterly excess market return on portfolios of midcap stocks is 1.596%, and 1.646% on portfolios of large cap stocks. Forecast returns are robust to alternative adjustments for risk and strongly persist through the year. Results do not change using DGTW returns and 4-factor alphas.

Regression results confirm that forecast stock returns increase with stock IQ, and the information advantage of skilled fund managers decays slowly. Accounting for delta breadth, delta active mutual fund ownership, and dispersion in holdings as well as other controls, two-way style and quarter fixed effect regressions substantiate a significant positive investment quality–forecast return relationship. A value-weighted portfolio of stocks in the 95th IQ percentile outperforms a similar portfolio of IQ stocks in the 5th percentile by a quarterly excess market return of 2.019%. Forecast returns from IQ decline each quarter but strongly persist through four quarters. In the fourth quarter, forecasted average quarterly excess market return is 75% of first quarter excess market return. Results using DGTW return and 4-factor alpha are analogous. As expected, our results are both statistically and economically unchanged when we proxy fund quality by management fees or by industry concentration (Kacperczyk, Sialm, and Zheng, 2005).

Large cap stocks benefit less from IQ than small cap stocks, which should not be surprising since large cap stocks attract more attention, are more closely scrutinized, and more transparent. On long-short value-weight portfolios of small cap stocks in the 95th and 5th percentiles of IQ, average forecast quarterly excess market return in lead one quarter is 2.330%. In contrast, forecast quarterly excess market return is 1.939% on portfolios of midcap stocks, and 1.654% on portfolios of large cap stocks. The same pattern is true for DGTW return and 4-factor alpha.

To assess the importance of conviction quality, we examine the forecast power of private information embedded in fund turnover. We define fund turnover as the sum product of four-quarter change in active holdings and fund quality signals. The more patient are fund managers, the lower is their turnover on underlying stocks and the higher their conviction quality. Future returns are highest on stock holdings of skillful fund managers who patiently exploit long term market mispricing. Patience is not, however, a substitute for skill. Accounting for the patience and conviction of fund managers through holdings turnover does not diminish forecast quarterly returns from IQ. On stocks where the trading activity of fund managers is high, however, forecast quarterly returns fall significantly.

Lastly, we examine the private information of skilled fund managers impounded in stock IQ that is made public in earnings announcements. Stock IQ strongly predicts cumulative abnormal return in the three-day windows around earnings announcements and in the post-earnings periods between quarterly earnings announcements. The post-earnings announcement drift in cumulative abnormal returns is consistent with a gradual diffusion of private fundamental information in stock prices.

In a closely related study to ours, Wermers, Yao, and Zhao (2012) use the identity that forecasted fund return is a sum product of value-based portfolio holdings and expected stock returns, to derive a "generalized inverse alpha" (GIA) measure of stock quality that efficiently extracts the private information of skilled fund managers about future stock returns from their value-weighted portfolio holdings.[5] Both their GIA and our stock IQ measure strongly predict future stock returns over one-year horizons. Sorting stocks into deciles by GIA, their Table 2 shows a high-low decile portfolio spreads generate a characteristic-adjusted return and 4-factor alpha of 1.14% and 1.15% respectively in the lead quarter; 2.60% and 3.44% respectively in the lead four quarters. Comparably, sorting stocks into quintiles by our stock IQ measure, we show in our Table 6, a high-low quintile generates a

[5]See equation 3. From an inverse linear projection of an $(N \times J)$ matrix of fund-portfolio value-based holdings onto a $(J \times 1)$ vector of fund characteristics-based return alphas, stock quality is an $(N \times 1)$ vector of implied consensus stock alphas computed as the matrix product of an inverse $(N \times N)$ covariance matrix of fund-portfolio value-based holdings and an $(N \times 1)$ vector of the cross-product of fund-portfolio value-based holdings and fund characteristics-based return alphas.

[5]The covariance matrix of fund-portfolio value-based holdings captures the cross-sectional variance in the dispersion of private information between skilled and unskilled fund managers.

characteristic-adjusted return and 4-factor alpha of 1.723% and 1.537% respectively in the lead quarter; 1.516% and 1.078% respectively in the average lead four quarters.

There are, however, important differences between GIA and our stock IQ measure. First and foremost, the inverse projection of fund portfolio holdings on fund alphas does not distinguish the within from between group variation in the portfolio holdings of skilled and unskilled fund managers. Our stock IQ recognizes the variance in the dispersion of information across skilled and unskilled fund managers, but only skilled fund managers will make informed portfolio investment decisions that are positively correlated. The sum product of active holdings and fund GVA proxy for differences in information and managerial skill.

Second, the GIA approach is novel but impractical without strong restrictions when the number of stocks held by mutual funds far exceeds the number of funds, $N \gg M$[6]. The issue of invertibility in the covariance matrix of GIA restricts the number of permissible non-zero eigenvalues K to be a sufficient order of magnitude of N such that $K < M$.[7] GIA can only be estimated for a small subset of stocks, *K*, especially in early sample years when number of funds M is small. Our stock IQ is not subject to such an estimation constraint.

Third, using portfolio holdings scaled by fund size can mask the skill of managers in small funds. We use DGTW stock characteristics-based benchmarks to define peer groups, and estimate active holdings as deviations of fund from peer group holdings scaled by their respective investments in style segments rather than by fund size. Lastly, fund alpha is an imperfect measure of fund performance when markets for assets under management are competitive (Berk and Green, 2004). Following Berk and Binsbergen (2015) and Zhu (2018), we use gross value-added (GVA) rather than fund alpha to proxy for fund performance. GVA takes diminishing returns to scale and constrained supply of skilled fund managers into account.

Other related studies (Jiang and Sun, 2014; and Jiang, Verbeek, and Wang, 2020) attribute the predictive content of value-weighted portfolio holdings to differential information. The dispersion in active share (Cremers et al., 2009) is used to infer the dispersion in fund managers' beliefs.[8] Active

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[6] N denotes the number of stocks in sample, and M denotes the number of funds.

[7] Wermers et al. (2012, p. 3496) set $K = M/2$ and treat the remaining $(N - K)$ eigenvalues as zero.

[8] Extracting future stock return information from active share (as) is predicated on the assumption that benchmark portfolios are zero-alpha. From Cremers and Petajisto (2009, p. 3335), $as = 0.5 \cdot \sum_i |w_{ip} - w_{ib}|$, where w_{ip} and w_{ib} denote the period t stockholdings of the fund and benchmark. Noting that $0 = \sum_i (w_{ip} - w_{ib})$, it can be shown $as = \sum_i max(w_{ip} - w_{ib}, 0) = \sum_i max(w_{ip}, w_{ib}) - \sum_i w_{ib}$ represents a call option. Excess portfolio return $r_{p,t+1} = \sum_i |w_{ip} - w_{ib}| \cdot r_{i,t+1}$, where $r_{i,t+1}$ denote period $t+1$ stock returns. Further, $r_{i,t+1} = \alpha_{i,t+1} + \sum_k \beta_{ik} r_{k,t+1} + \varepsilon_{i,t+1}$ where $\mathbf{r_k}$ denotes the vector of asset pricing factors. Predicted portfolio excess return $E(r_{p,t+1}|\mathbf{r_k}) = 2 \cdot \sum_i \{max(w_{ip}, w_{ib}) \cdot \alpha_{i,t+1}\}$ when $\sum_i w_{ib} \cdot \alpha_{i,t+1} = 0$, i.e., the benchmark portfolio is zero-alpha. $E(r_{p,t+1}|\mathbf{r_k})$ will correlate positively with active share, $|w_{ip} - w_{ib}|$ when funds overweight high alpha stocks and underweight low alpha stocks.

share will be high when fund managers who receive positive information signals can act freely to increase holdings, and low, when fund managers who receive negative information signals are subject to short-sale constraints.

But index-based benchmark portfolios may not represent the perceived investment opportunities of fund managers when funds differ widely in assets under management, nor adequately account for significant differences in stock characteristics across funds. More importantly, the large cross-sectional variation in fund performance suggests that not all actively managed fund managers are skilled (French, 2008; Pastor, Stambaugh and Taylor, 2015), and only skilled fund managers have an incentive to acquire and trade on costly information (Gârleanu and Pedersen, 2018). Further, skill is not prevalent among active mutual fund managers and exhibits diminishing marginal returns to fund size (Berk and Binsbergen 2015; Zhu, 2018). The ability of skilled fund managers to exploit other profitable opportunities, and importantly, that conditional on the same information, skilled fund managers will make better decisions than unskilled fund managers are critical. Skill is not limited to information advantage.

Jiang et al. (2014) show a value-weighted high-low quintile portfolio spreads, sorted on quarterly changes in average standard deviation of active shares across funds, generate an average monthly DGTW return of 0.55% and 4-factor alpha of 0.49% in lead three months.[9] In multivariate regressions, predicted stock returns on quarterly changes in average dispersion persist through four quarters but rapidly deteriorates to about 14% of first quarter return in the fourth quarter.[10] In Jiang et al. (2020), the equal-weighted average of deviations of fund from benchmark holdings describes the consensus in beliefs of fund managers. A high-low quintile portfolio of stocks sorted by consensus belief generates an average monthly DGTW return of 0.38% and 4-factor alpha of 0.31% in lead three months.[11] Differential returns on high-low quintile consensus portfolios do not reverse as price pressure from abnormal demand (Gompers and Metrick, 2001) or herding behavior (Sias, 2004) suggests, but quickly converge to zero after the first quarter.[12]

Our high-low quintile portfolio of stocks sorted on stock IQ generates an average monthly DGTW return of 0.574% and 4-factor alpha of 0.512% in lead three months similar to Jiang et al. (2014; and 2020), but returns strongly persist through the ensuing year. DGTW return and 4-factor

[9]See Jiang et al. (2014) Table 3 Panel D. High-low spread on average monthly DGTW return of 0.545=0.5*(0.27+0.30) -0.5*(-0.24-0.28) and 4-factor alpha of 0.485=0.5*(0.21+0.34)-0.5*(-0.21-0.23).
[10]See Jiang and Sun (2014) Table 6 Panel B.
[11]See Jiang et al. (2020) Table 2. High-low spread on average monthly DGTW return of 0.38%=0.5*(0.35+0.32)-0.5*(0.02-0.11) and 4-factor alpha of 0.305%=0.5*(0.33+0.24)-0.5*(0.00-0.04).
[12]See Jiang et al. (2020) Figure 1.

alpha in the fourth quarter are 88.0% and 70.1% of first quarter stock returns.

II. Active Performance Measures

Using fund holdings, Daniel et al. (1997) show that stock characteristics-based benchmarks are better at capturing the investment styles of mutual funds and provide better ex-ante forecasts of future fund returns. Decomposing fund returns, Wermers (2000) finds that funds who outperform their benchmarks own stocks that have characteristics associated with higher average returns than the return on broad market indices.

Stock characteristics-based style segments encapsulate potential investment style drift and limit tracking errors associated with a mismatch of a fund's stock holdings with its chosen benchmark. In contrast to an industry benchmark, a fund's stock characteristics-based benchmark defined by its actual stock holdings can gradually change over time. The value-weighted average return on all stocks that constitute a characteristic-based style segment can also serve as a benchmark return against which the returns on stocks in a style segment can be compared.

A. Active Fund Holdings by Style Segment

At the end of July each year, we sequentially sort all common stocks into 125 ($5\times5\times5$) portfolios by size, industry-adjusted book-to-market ratio, and momentum. Size quintiles use breakpoints based on NYSE stocks. Industry-adjusted book-to-market and momentum quintiles use breakpoints based on all stocks in each size quintile. From CRSP, size is the product of adjusted price and number of adjusted shares outstanding at June end for each firm. From S&P Compustat, book-to-market is the ratio of the book value of equity and market capitalization at the end of the fiscal year closest but prior to June each year (Daniel and Titman, 2006). To industry-adjust book-to-market, we follow Wermers (2003). The difference in the natural logs of a firm's book-to-market and average book-to-market of the industry to which the firm belongs is normed by the standard deviation of the natural log differences across firms in the industry.[13] Momentum is computed as the prior 12-month return by May end to avoid bid-ask bounce and monthly return reversals (Jegadeesh, 1990).

Using cutoffs from annual sorts, we assign the stock holdings of each fund in the subsequent four quarters into one of $k = 125$ style segments that collectively describe the fund's investment style. In each quarter, we denote stock i in style segment k by $i(k)$, fund by j, and the set of stocks in style segment k owned by fund j by $i(k) \epsilon I(k,j)$. Funds who own the same stock in a style segment

[13]Specifically, industry-adjusted book-to-market is computed as $[ln(BTM^i_{i,t}) - ln(BTM^j_t)]/\sigma[ln(BTM^i_{i,t}) - ln(BTM^j_t)]$ where $BTM^i_{i,t}$ is the book-to-market ratio of stock i that belongs to industry j at June end of year t and BTM^j_t is the aggregate book value of stocks i in industry j divided by aggregate market value of stocks i in industry j at June end of year t.

constitute a natural peer group. Peer group holdings capture the commonality in information and similarity in unobserved investment strategies across fund managers.

We define fund holding, $h_{i(k),j}$, as the dollar investment in stock i in style segment k by fund j as a percentage of the total dollar investment in all stocks owned by fund j in style segment k.

$$h_{i(k),j} = \left(shrown_{i(k),j} \cdot prc_{i(k)}\right) / \sum_{i(k)\epsilon I(j,k)} \left(shrown_{i(k),j} \cdot prc_{i(k)}\right) \tag{1}$$

Peer group holding, $\bar{h}_{i(k)}$, is the percentage of total investment allocated to stock i across all funds who own stocks in style segment k.

$$\bar{h}_{i(k)} = \sum_{j\epsilon J(k)} \left(shrown_{i(k),j} \cdot prc_{i(k)}\right) / \sum_{j\epsilon J(k)} \sum_{i(k)\epsilon I(j,k)} \left(shrown_{i(k),j} \cdot prc_{i(k)}\right) \tag{2}$$

where $J(k)$ are the set of funds who own stocks in style segment k. In (1) and (2), $prc_{i(k)}$ and $shrown_{i(k),j}$ denote the price and shares of stock i in style segment k owned by fund j respectively. Active fund holding, w_{ij}, is the deviation of fund from peer group holding of stock i in style segment k.

$$w_{ij} = h_{i(k),j} - \bar{h}_{i(k)} \tag{3}$$

In (3), for every fund $j\epsilon J(k)$, the sum of active holdings across stocks i in style segment k, $\sum_{i(k)\epsilon I(j,k)} w_{ij} = \sum_{i(k)\epsilon I(j,k)} \left(h_{i(k),j} - \bar{h}_{i(k)}\right) = 0$.

B. Stock Investment Quality

When fund managers are unskilled or predominantly trade on sentiment, we expect active holdings to be uncorrelated with skill. The dispersion in active fund holdings from sentiment-based herding by unskilled fund managers which drive prices away from fundamental value predict lower future stock returns.[14] When skilled fund managers have private information and faced with the same information act similarly, we expect active fund holdings to be positively correlated with skill and co-movements in active fund holdings to reflect differences in private information about future stock return between skilled and unskilled fund managers. We can identify stock IQ through linear projections of fund quality on active fund holdings of stocks across all style segments where GVA or management fees are used to proxy fund quality.

$$\tilde{\boldsymbol{\alpha}}_{ij} = a_i + \mathbf{w}_{ij} b_i + \tilde{\boldsymbol{\varepsilon}}_{ij} \tag{4}$$

for every stock i in style segment k, and $j\epsilon J(i,k)$ denote the set of funds who own stocks in style segment k. In (4), $\tilde{\boldsymbol{\alpha}}_{ij}$ and $\mathbf{w}_{ij}$ are vectors of fund quality and active holdings of funds on stock i.

[14]Interpreting dispersion in analysts' forecasts as a proxy for differences in opinion, Diether, Malloy and Scherbina (2002) find that future returns are lower on stocks that exhibit higher dispersion in analysts' earnings forecasts. They find the dispersion effect to be most pronounced on stocks that performed poorly in the past year.

Assuming errors are uncorrelated across stocks, the estimators of beta coefficients $\hat{b}_i$, are the covariances in active fund holdings on stock i with fund quality across funds $j \epsilon J(i,k)$ scaled by the variance in the dispersion of active fund holdings on stock i across funds $j \epsilon J(i,k)$.

$$\hat{b}_i = \frac{\sum_{j \epsilon J(i,k)} (w_{ij} . \alpha_j)}{\sum_{j \epsilon J(i,k)} w_{ij}^2} \tag{5}$$

where $\hat{a}_i = J(i,k)^{-1} \{ \sum_{j \epsilon J_i} \alpha_{ij} - \sum_{j \epsilon J_i} w_{ij} \hat{b}_i \}$. We use $\hat{b}_i$ as our measure of stock IQ.

Hypothesis 1a: Stock IQ will strongly persist when active holding is motivated by trades of privately informed skilled fund managers. Active holdings will be firmly and positively correlated with skill when stock IQ is high.

Hypothesis 1b: Further, stock IQ will predict high future stock returns when the stock is widely held in common by skilled and privately informed fund managers.

Denoting $\widehat{w}_{ij}$ as the active fund holding of stock i in style segment k by fund j standardized by the variance of the deviation in fund from peer group holding,

$$\widehat{w}_{ij} = w_{ij} / \sum_{j \epsilon J(i,k)} w_{ij}^2 \tag{6}$$

$\hat{b}_i$ simplifies to $\sum_{j \epsilon J(i,k)} (\widehat{w}_{ij} . \alpha_j)$. The cross-product of the standardized active fund holdings and fund performance imbeds the correlation of active holdings associated with informational asymmetry and latent managerial skill associated with fund quality, taking the variance in the active fund holdings associated with the distribution of information across fund managers into account.

To describe differences in fund manager skill that is consistent both across stocks and across quarters, we rank stocks by IQ $= \sum_{j \epsilon J(i,k)} (\widehat{w}_{ij} . \alpha_j)$. The percentile rank of stock i, p_i^s, is the fraction of all stocks where fund manager skill is less than or equal to the fund manager skill on stock i, and $(1 - p_i^s)$, the fraction of all stocks where fund manager skill is greater than that on stock i. We use an odds ratio, the relative percentile rank of stock i, $\theta_i^s = p_i^s / (1 - p_i^s)$, to proxy for the IQ of stocks.

C. Holdings Turnover and Conviction Quality

We also examine whether the selection skill of high performing fund managers is related to how frequently funds change their active stock holdings. Cremers et al. (2016) find that active share alone is not sufficient for fund managers to outperform. Only the most active and patiently managed funds outperform.[15] The conviction of fund manager beliefs on future stock returns is reflected in patience.

In current literature, fund turnover is proxied either by duration of holdings, reported fund

[15]See p. 295 in Cremers et al. (2016). In Pastor, Stambaugh, and Taylor (2017), fund turnover refers to frequent trading of stockholdings by funds rather than to the holding period of fund stockholdings or changes in active share in Cremers and Pareek (2016).

turnover ratio, or holding turnover. We consider each possible choice in turn. First, duration of stock ownership, which is the number of quarters a stock is held by a fund from ownership inception to the current quarter weighted by the percentage of shares outstanding each quarter (Cremers et al., 2016; and Lan, Moneta, and Wermers, 2019), has significant drawbacks. Fund age will bias holding horizons. On the same stock, inception dates will be earlier for mature funds compared to newly established funds. Second, changes in duration are capped and highly predictable. Holding horizon can at most increase by a quarter at a time and changes in stock ownership are slow to change from quarter to quarter. Third, reported fund turnover ratio cannot describe quarterly changes in individual holdings. In the spirit of Gaspar, Massa, and Matos (2005), we use style segment-adjusted holding turnover to proxy fund manager conviction and patience.

We characterize a fund manager's holding turnover on stock i by Δw_{ij}, changes in the active holdings of fund j in stock i from four-quarter prior. If stock i is not held by fund j four quarters prior, $w_{ij}(q-4)$ takes value of zero.

$$\Delta w_{ij} = w_{ij}(q) - w_{ij}(q-4) \tag{8}$$

Active fund holding turnover, $\Delta \widehat{w}_{ij}$, is fund holding turnover normed by the dispersion across funds from peer group holding turnover.

$$\Delta \widehat{w}_{ij} = \Delta w_{ij} / \sum_{j \epsilon J(i,k)} \Delta w_{ij}^2 \tag{9}$$

where $j \epsilon J(i,k)$ denotes the set of funds who trade stock i in style segment k. We identify the latent patience of fund managers on a stock, $\hat{\pi}_i$, by the cross-product of active fund holding turnover $\Delta \widehat{w}_{ij}$ and fund quality $\hat{\alpha}_{j,t}$ summed across funds.

$$\hat{\pi}_i = \sum_{j \epsilon J(i,k)} \Delta \widehat{w}_{ij} \cdot \hat{\alpha}_j \tag{10}$$

Stocks exhibit marked impatience when a stock is actively traded by fund managers and skilled fund managers trade actively.[16] Again, to meaningfully describe differences in the latent patience of fund managers that is consistent both across stocks and across quarters, we rank stocks by patience $\hat{\pi}_i$. The percentile rank of stock i, p_i^{π}, is the fraction of all stocks in which fund managers trade less actively than fund managers who own stock i, and $(1 - p_i^{\pi})$, the fraction of all stocks in which fund managers trade more actively than fund managers who own stock i. The relative percentile rank of stock i is an odds ratio, $\theta_i^{\pi} = p_i^{\pi}/(1 - p_i^{\pi})$. We use relative percentile rank, θ_i^{π}, to proxy the trading activity and conviction quality of fund managers on a stock.

[16]Note that $E(\Delta \widetilde{w}_{ij} \cdot \tilde{\alpha}_{j,t}) = E(\Delta \widetilde{w}_{ij}) E(\tilde{\alpha}_{j,t}) + Cov(\Delta \widetilde{w}_{ij}, \tilde{\alpha}_{j,t})$.

Hypothesis 2: High relative percentile ranks on active fund turnover indicate impatience and lack of conviction. Future returns will be lower on stocks with high trading activity and low conviction quality.

D. Fund Quality

High performing fund managers are more likely to hold high quality stocks (Cohen et al., 2005). As in Berk et al. (2015), we instrument the latent quality of fund management by GVA, the product of gross (pre-expense return) alpha and TNA under management. We use the monthly seasonally-adjusted CPI index (1982-1984=100) constructed by the U.S. Bureau of Labor Statistics (BLS) to adjust TNA under management for inflation.

For each fund, we estimate Fama and French (1993) and Carhart (1997) 4-factor model gross alphas from rolling twelve-month time series regressions of monthly gross excess returns on monthly excess market return $(r_{mt} - r_{ft})$, size (SMB_t), book-to-market (HML_t), and momentum (UMD_t) factors.

$$r_{jt} - r_{ft} = \alpha_i + \beta_i \cdot (r_{mt} - r_{ft}) + s_i \cdot SMB_t + h_i \cdot HML_t + u_i \cdot UMD_t + \varepsilon_{it} \quad (11)$$

Monthly gross (pre-expense) fund return, r_{jt}, is the net monthly fund return plus one-twelfth of the fund's annual expense ratio. From CRSP, the risk-free rate, r_{ft}, is the one-month Treasury bill yield at the beginning of month t. $(r_{mt} - r_{ft})$, SMB_t, HML_t, and UMD_t are the monthly market excess return, size, book-to-market, and momentum factors obtained from Ken French's website.

Monthly gross value-added, $\widehat{GVA}_{j,t}$, is the product of current month 4-factor alpha and prior month end TNA, as in Berk et al. (2015). To mitigate the volatile effects of transitory factors on long-term performance, gross value-added is time-averaged across current and prior months when the fund is in the sample, $T^{-1} \sum_{t=1}^{T} \hat{\alpha}_{j,t}$. Quarterly gross value-added is monthly gross value-added summed across months in the quarter.

When investors can detect skill, their allocation decisions determine fund size and managerial compensation. Net alpha is endogenously determined in equilibrium by competition among investors, and gross alpha, by the fees charged by funds. When managerial skill is in short supply and exhibit diminishing returns to scale, net alpha is driven to zero and managerial compensation is equal to gross value-added, the fund's gross excess return multiplied by total net assets under management. Gross alpha differentiates managers only when fees are such that all funds are the same size.

III. Data

A. Mutual Fund Sample

We select our sample of U.S. actively managed domestic equity mutual funds from the CRSP

Survivor-Bias-Free Mutual Fund Database. Because mutual funds can have multiple share classes with the same underlying stock holdings, we use the database variable CRSP_CL_GRP to consolidate different share classes into a single fund as in Cao and Wermers (2018). Average total net assets (TNA) under management is TNA summed across underlying share classes each quarter, and monthly return is a TNA-weighted sum of underlying share class returns. As in Doshi, Elkamhi, and Simutin (2015), we use the database variable CRSP_OBJ_CD to identify domestic equity mutual funds and exclude sector funds, foreign funds, fixed income funds as well as mixed style funds. We use index identifier and fund names to exclude ETFs and ETNs, as well as index mutual funds. Akin to Kacpercyzk et al. (2008), we also exclude funds who, on average over our sample period, own fewer than 10 stocks or manage less than $5 million in TNA.

We obtain quarterly mutual fund holdings from the Thomson Reuter Mutual Fund Holdings database. We link actively managed domestic equity mutual funds in our sample with stock holdings data through MFLINKS. We exclude funds we could not match. For funds with missing reports in four or less quarters, we linearly interpolate their holdings using the latest holdings available before and after the missing reporting period.

To compute stock level variables, we link the merged fund stock holdings to the CRSP stock database to obtain daily and monthly returns, price, volume, shares outstanding and other variables. We focus on common stocks with share code 10 or 11 that trade on NYSE, NASDAQ, or AMEX. We adjust stock trading volumes in NASDAQ broker-dealer markets reported in CRSP by one-half following French (2008). We also link stock holdings to the S&P Compustat database to obtain book-to-market ratios. To moderate the influence of outliers on our results, we only keep stocks held by at least five mutual funds in the quarter and eliminate stocks with share prices below $5.

Data availability constraints on CRSP_CL_GRP and WFICN in MFLINKS restrict our sample period to start in 2000 and end in 2017. A set of 2,224 unique mutual funds who collectively own 7,447 unique stocks meet our screening criteria. Over our sample period, the number of mutual funds rose from 897 to 1,331, and number of stocks owned fell from 3,422 to 2,927.

B. Characteristics of Style Segments

The characteristics of fund-stock ownership across the 125 style segments over our 72-quarter (2000-2017) sample period are summarized in Table I. Column 1 denotes size quintiles from small to large, and Column 2, book-to-market quintiles from low to high. Top row denotes momentum quintiles from low to high.

< Insert Table I here. >

Table I Panel A reports the median number of CRSP stocks in our sample that fall into each style segment, and in parentheses, the median stock ownership across funds in a style segment. Stock ownership is the number of stocks a fund owns expressed as a percentage of all stocks in a style segment. The median number and median stock ownership increases across momentum quintiles but only in the smallest size quintile. Two trends are apparent from the $Size\_BTM$ column, which reports median number and median stock ownership averaged across momentum quintiles on stocks sorted into size and book-to-market quintiles. The median number of stocks decreases across size quintiles, ranging from 46 to 56 in the smallest size quintile to 13 in the largest size quintile. At the same time, stock ownership increases across size quintiles, ranging from 3.4% to 3.8% in the smallest size quintile to 17.8% in the largest size quintile.

Table I Panel B reports the median number of funds who own stocks in the style segment, and in parentheses, the median fund ownership across stocks in a style segment. For each stock in a style segment, fund ownership is the number of funds who own the stock expressed as a percentage of the total number of funds in the style segment. With a few exceptions, the median number of funds increase across momentum quintiles. Median fund ownership also increases across momentum quintiles except in the smallest size quintile. In the smallest size quintile, fund ownership averaged across book-to-market quintiles is 8.3% on high momentum stocks compared to 9.5% on low momentum stocks.

Two trends are evident from the $Size\_BTM$ column, which reports median number of funds and median fund ownership averaged across momentum quintiles on stocks sorted by size and book-to-market quintiles. The median number of funds and median fund ownership do not vary notably across book-to-market quintiles. The median number of funds and median fund ownership, however, increase across size quintiles. In number, ranging from 172 to 232 in the smallest size quintile, and in the largest size quintile, from 574 to 692. In ownership, ranging from 8.3% to 9.1% in the smallest size quintile, and in the largest size quintile, from 19.8% to 21.0%.

It is apparent the small number of stocks in the largest size quintile attract the largest number of funds, and fund ownership is also highest. Stocks in the largest size quintile have the deepest breadth and ownership. Breadth and ownership is higher as firm market capitalization grows bigger.

< Insert Figure 1. >

Figure 1 graphs the distributions of stock and fund ownerships averaged across momentum quintiles on stocks sorted first by size (x_1), and secondly, by book-to-market (x_2) quintiles reported in the average columns in Table 1. The coordinate vectors $(x_1 x_2) = (k_1 k_2)$ on the $Size\_BTM$ axis denote the $k_1 = 1, \dots, 5$ size quintiles and $k_2 = 1, \dots, 5$ book-to-market quintiles. Symbols ○ and ◊ denote the variables of interest whose values are plotted along the left and right scales on the vertical axis.

A risk diversification motive is discernable. From Figure 1 Panel A, as market capitalization increases, the median number of stocks funds own declines from a high of 56 to a low of 13, and median stock ownership rises from a low of 3.4% to a high of 17.8%. Additionally, from Figure 1 Panel B, as market capitalization increases, the percentage of funds who own a stock, increases from a low of 8.3% to a high of 21%. The effect of book-to-market on stock and fund ownership is generally weak. Funds are more likely to own large cap stocks, and fund ownership is more concentrated in large cap stocks. Overall, stock and fund ownerships are higher on large cap stocks.

In summary, Table I shows that the average number of stocks that funds own as a percentage of all stocks in a style segment (stock ownership) and the average number of funds who own a stock as a percentage of the total number of funds in the stock's style segment (fund ownership) are lowest in the smallest size quintile and highest in the largest size quintile.

We also examine average fund quality across style segments. Results are reported in Appendix Tables II and III, and Appendix Figures I and II. Our findings substantiate Berk and Binsbergen (2015). In competitive markets for investible funds by investors who can detect managerial skill, net alpha is endogenously determined by fees. Gross value-added is a better proxy of fund quality. With diminishing returns to scale, gross alphas initially increase but eventually decrease with TNA. GVA will be a strictly concave function of TNA under management (see Zhu, 2018: Figure 2). In the remainder of the paper, we use GVA to instrument fund quality. We examine management fees as an alternative proxy for fund quality. A more detailed discussion can be found at the end of the paper.

C. Summary Statistics

Table II reports summary statistics on variables used in our analysis. To mitigate the effect of outliers, all variables are winsorized at the top and bottom 1%. Variables are defined in the table II heading and summarized as well in Appendix Table I.

< Insert Table II here. >

As an alternative proxy for fund quality we use management fees (Berk et al., 2015), which is estimated each month as the product of fund TNA at the end of the prior month and 1/12 of the annual management fee ratio as a percentage of fund TNA reported by CRSP, and time-averaged from the start of the sample period. Monthly management fees are summed over three months in a quarter to compute quarterly management fees. Both GVA and management fees are measured in dollars. Higher performing funds can extract higher management fees from investors. In a competitive market where investors are able to identify higher quality funds, fund return premia will be driven to zero. Management fees will equal GVA. Note that because we proxy selection and conviction qualities by relative percentile ranks, the selection quality and conviction measures have identical distributions across the whole sample as shown in Table II. The identical distributions make coefficients in subsequent regressions comparable and easy to interpret.

To fairly judge the contribution of IQ to forecast future stock returns, we take other documented empirical predictors into account. As in Chen, Hong, and Stein (2002), we use delta breadth and delta mutual fund ownership to proxy for differences in opinion and short-sale constraints. Low breadth and low institutional ownership signal short-sale constraints are tightly binding, and prices are high relative to fundamentals. Increases in delta breadth and institutional ownership should forecast higher returns. Following Jiang and Sun (2014), we compute breadth as $ln(1+N)$ where N denotes the number of funds who own the stock, and mutual fund ownership as the fraction of total shares outstanding owned by actively managed mutual funds. Quarterly changes in breadth and active mutual fund ownership are computed as the change in breadth and ownership from the prior quarter. The mean (median) breadth of 3.606 (3.689) suggests an average (median) of 36 (39) active mutual funds own a stock in our sample. Our mean (median) breadth is higher than 25 (11) reported in Jiang et al. (2014) because of the significant growth in the number and size of funds in our more recent sample period 2000 to 2017 in contrast to their sample period 1984 to 2008.

Jiang et al. (2014) and Jiang et al. (2020) find that disagreement and consensus in opinion among fund managers predict future stock returns. Akin to the dispersion in analysts' opinions in Diether, Malloy, and Scherbina (2002), we compute a dispersion index of active holding as the standard deviation of active holding divided by absolute value of mean in active holding, which has a sample mean (median) of 0.137 (0.139).

IV. Active Management and Future Stock Returns

A. Persistence in Stock Investment Quality

If stock IQ imbeds the co-movements in active fund holdings from trading on private information by skilled fund managers rather than from sentiment-based trading by unskilled fund managers, we should expect stock IQ to exhibit persistence over time. We use two methods to examine the persistency of IQ, and show that it is strongly persistent.

First, we sort all stocks into deciles by their IQ at the end of each quarter, and compute the average

IQ across all stocks by decile in lead two, four, eight, and twelve quarters. Spreads in average IQ between the top and bottom deciles and their t-statistics are reported in Table IV Panel A. Decile spreads decrease but are persistently significant over the next twelve quarters.

< Insert Table III here. >

Second, we examine the persistency of stock IQ through a transition table of quarterly stock IQ. At the end of the prior and current quarters, we sort stocks into quintiles by IQ and compute the fraction of stocks that move from quintile i in quarter $t-1$ to quintile j in quarter t. The transition matrix reported in Panel B, which has a dominant diagonal, converges. The likelihood that stocks in the bottom quintile remain in the bottom quintile is 75.74%, and the likelihood that stocks in the top quintile remain in the top quintile is 71.86%. Stock IQ is strongly persistent.

Table III Panel C reports summary statistics on active fund holdings, GVA, market capitalization, book-to-market, and Pearson rank correlations between fund active holdings and GVAs at the 5^{th} through 95^{th} percentiles. Negative fund active holdings and negative correlations between fund active holdings and GVAs indicate that skillful fund managers underinvest relative to their peer group on stocks at the lowest quintile of IQ. Fund active holdings and the correlations between fund active holdings and GVAs become increasingly more positive on stocks ranked higher on IQ. These corroborating results show that high IQ of stocks are in the hands of more skillful and better informed managers. The focus of stock selection at upper percentile ranks of IQ appears to be on growth rather than value stocks, and in middle percentile ranks of IQ, on small rather than large cap stocks.

B. Comparison with Alternative Fund Holdings-Based Stock Return Predictors

As in Wermers, Yao, and Zhao (2012), we use Fama-Macbeth (1973) regressions, corrected for correlated errors using a Newey-West estimator with one quarter lag, to examine the forecast return power of stock IQ in a horserace against four widely-cited empirically documented stock return predictors: herding by unskilled fund managers, adjusted 'dumb' money flow of investor-sentiment driven trading, as well as delta breadth and delta ownership in mutual fund holdings that reflect short-sale constraints. We compute herding in fund holdings following Lakonishok, Shleifer, and Vishny (1992, eq. 1) using an adjustment factor in Jones, Lee, and Weis (1999). Delta breadth and delta mutual fund ownerships are estimated following Chen, Hong, and Stein (2002). Adjusted money flow is computed following Frazzini and Lamont (2008, eq. 8) with one-month horizon and summed across three months in a quarter.

< Insert Table IV here. >

Regression results are reported in Table IV. Controlling for competing stock return predictors, the forecast power of stock IQ remains significant. The forecast return persistence of stock IQ substantiates trading by skilled fund managers on private information. The coefficients on stock IQ are significantly positive over lead four quarters. The significantly positive coefficients on delta breadth confirms Chen, Hong, and Stein (2002), and the relatively weak feedback effects on stock returns from mutual fund managers' buy and sell herding measures is consistent with Lakonishok, Shleifer, and Vishny (1992).

C. Portfolio Buy-and-Hold Returns: One-way Sorts

At the end of each quarter, we assign stocks into IQ sorted quintile portfolios using the stock's relative percentile rank, θ_i. We compute value-weight monthly and average quarterly buy-and-hold returns on each IQ quintile portfolio in the lead month and quarters following quarter-end portfolio formation and link quintile portfolio returns to form a time-series. Monthly and average quarterly quintile portfolio returns averaged across our sample period on the one-way sorts of stocks by IQ are reported in Table V.

< Insert Table V here. >

As evident in Table V, future stock returns rise with higher IQ. A value-weight portfolio of high IQ stocks outperforms a value-weight portfolio of low IQ stocks. In the subsequent quarter, portfolio returns are consistently negative in the bottom quintile, and positive in the top two quintiles of IQ. The forecast average quarterly excess market return is 1.533%, DGTW return is 1.723%, and 4-factor alpha is 1.537%. Because active fund holdings on IQ are based on style segments, positive spreads on high-low quintile portfolios of stocks by IQ cannot be attributed to size, book to market, or momentum stock characteristics. Forecast returns are robust to alternative adjustments for risk and strongly persist through a twelve-month period.

D. Portfolio Buy-and-Hold Returns: Two-way Sorts

Table VI reports average quarterly portfolio returns on two-way sorts of stocks, first into terciles by NYSE market capitalization, and second, into IQ quintile portfolios by a stock's relative percentile rank, θ_i. To prevent microcaps from driving portfolio outperformance, Hou, Xue, and Zhang (2020) stress the importance of using NYSE breakpoints for market capitalization and value-weighted portfolio returns (Fama and French, 1993). Portfolios sorted by NYSE breakpoints exhibit more consistency over time. At the end of each quarter, we report average value-weight buy-and-hold-returns on $3 \times 5 = 15$ portfolios following portfolio formation, in lead one to four quarters. The quintile portfolio returns are linked to form a time-series.

< Insert Table VI here. >

A long high-short low portfolio trading strategy generates statistically and economically significant excess quarterly returns across all market capitalizations on IQ. As apparent from Table VI, across all terciles of market capitalization, portfolio returns are consistently negative in the bottom quintile of IQ, and predominantly positive in the top two quintiles of IQ. Value-weight portfolios of high IQ stocks outperform low IQ stocks across all terciles of market capitalization. Forecast returns are higher on small cap stocks and lower on mid- and large-cap stocks for excess market return and DGTW return. On small cap stocks, average quarterly excess market return is 1.825%, DGTW return is 1.907%, and 4-factor alpha is 0.670%, in lead one quarter. In comparison, on large cap stocks, average quarterly excess market return, DGTW return, and 4-factor alpha are 1.646%, 1.607% and 1.241% in lead one quarter.

Large cap stocks benefit less from IQ than small cap stocks. Large cap stocks attract more attention, are more closely scrutinized, and more transparent. The information advantage of skillful managers is, as a result, more muted in large cap stocks. In subsequent multivariate regressions we confirm the finding that forecast returns are greater on small-cap stocks with higher IQ, and smaller on large-cap stocks.

V. Forecast Return Regressions

In this section, we estimate two-way style and quarter fixed effects regressions of lead quarter stock returns on IQ, controlling for delta breadth, delta active mutual fund ownership, dispersion in fund active holdings, natural logs of market cap and book-to-market, prior 12 month return, CRSP turnover, idiosyncratic volatility, and market beta. Errors are clustered by style and quarter. We add a squared IQ term to account for possible diminishing returns on IQ. Quarter returns in regression tables are expressed in percent. We winsorize all variables at the 1^{st} and 99^{th} percentiles. For ease of interpretation, all regressors are normalized by their standard deviations across the sample period, and control variables are demeaned. Investment style and time fixed effects are added to control for unobservable time-invariant style segments factors, as well as quarterly unobserved common factors. Results are reported in Table VII.

< Insert Table VII here. >

Forecast quarterly returns are significantly and economically greater on stocks ranked higher on IQ. In Table VII Panel A, estimated coefficients on IQ relate forecast quarterly returns to standardized units of IQ. Forecast quarterly return is the product of estimated coefficient and relative percentile rank scaled by the sample standard deviation of relative percentile ranks. We can compute relative percentile rank θ_i from percentile rank $p_i = \theta_i/(1+\theta_i)$. The forecast quarterly returns on a stock at percentile ranks p_i ranging from 0.05 to 0.95 are shown in Table VII Panel B.

A standard deviation increase in IQ will raise average forecast quarterly excess market return by 1.360%. In lead one quarter, average forecast quarterly excess market return at the mean IQ is 0.487% (=1.360*4.572/12.760), where 4.572 and 12.760 are the mean and standard deviation of IQ reported in Table III. To put this in perspective, a 5th to 95th percentile change in IQ increases average forecast quarterly excess market returns by 2.019% (=1.360*(19.0-0.053)/12.760), while a 90th to 95th percentile change, by 1.066% (=1.360*(19.0-9.0)/12.760). A percentile change in IQ has a greater impact on forecast returns at higher percentiles.

Results in Table VII Panel B corroborate Table V. A portfolio of stocks in the highest quintile by relative IQ percentile rank outperforms a portfolio of stocks in the lowest quintile rank by 1.533%, which is close to but slightly smaller than the 5th to 95th percentile spread. From Panel B of Table VII, in lead one quarter, the forecast excess market return spread on a long-short portfolio of stocks in the 95th and 5th percentile is 2.019%. The spreads on DGTW return and 4-factor alpha are 1.979% and 1.329%.

The magnitude of forecast quarterly returns from IQ decline each quarter but strongly persist through four quarters. In the fourth quarter, average quarterly excess market return, DGTW return, and 4-factor alpha are 25.15% (=(1.360-1.018)/1.360), 28.89%, and 14.41% lower compared to first quarter returns. The information advantage of fund managers from selection skill decay slowly.

We control for delta breadth and delta ownership (Chen et al., 2002). Estimated delta breadth coefficients, which are statistically significant at the 1% level in lead one and two quarters, are comparable to those in Table 6 Panel A of Chen et al. (2002). A standard deviation increase in delta breath forecasts a higher lead one quarter excess market return of 0.533%, DGTW return of 0.497%, and 4-factor alpha of 0.312%. On returns unadjusted for market return or risk, Chen et al. (2002) document a standard deviation increase in delta breadth forecasts a higher return of 0.546% (=1.187*0.46%) where 0.46% is the standard deviation of delta breadth reported in Table 1 of Chen et al. (2002). Note however that estimated coefficients on delta breadth lose statistical significance after the second quarter. Finding is consistent with McLean and Pontiff (2016), who show that as investors learn about and trade on empirically documented predictors, performance decays post-publication. As in Chen et al. (2002), we also find that controlling for delta breadth, delta ownership is insignificant.

Larger standard deviations in fund active holdings from peer group holding forecast lower future stock returns. Estimated coefficients on dispersion index in active holdings are negative but statistically insignificant in lead quarters. Finding of lower future stock returns is consistent with Diether et al. (2002) who show that higher dispersions in analysts' earnings forecasts indicate more uncertainty about fundamental value, and Miller (1997), that constraints on short-sales cause stock prices to be high relative to intrinsic value.

We use CRSP turnover to account for a possible performance-turnover relation (Brennan, Chordia and Subrahmanyam, 1998; and Pastor, Stambaugh, and Taylor, 2020). The estimated coefficients on CRSP turnover are negative and significant in lead two, three, and four quarters consistent with a negative effect of trading volume on stock returns documented in Brennan et al. (1998). CRSP turnover is also a proxy of stock liquidity, and the negative coefficients on CRSP turnover are consistent with that more liquid stocks require lower returns. In lead second quarter, a standard deviation increase in CRSP turnover predicts lower excess market return of 0.443%, DGTW return of 0.263%, and 4-factor alpha of 0.441%. Excess returns in lead three and four quarters from an increase in CRSP turnover are slightly more negative.

Negative coefficients on squared relative percentile IQ rank, ${\theta_i^s}^2$, indicate diminishing returns to investment quality. Marginal reductions in forecast quarterly return are shown in Table V Panel B at the 5th through 95th percentile ranks. On average, the impact is much smaller relative to the main effect of IQ on forecast returns.

Lastly, Table VII Panel C reports Fama-Macbeth (Fama and Macbeth, 1973) regressions over our sample period. Newey-West (1987) standard errors are estimated assuming a one-quarter lag in serially correlated errors. The coefficients on IQ closely resemble those in two-way style and quarter fixed effects regressions in Table VII Panel A. Overall, results are robust to alternative model estimation methods.

B. Alternative Proxy for Fund quality

Berk et al. (2004, 2015) argue that in a market where skill is in short supply, more skilled fund managers can choose the fees they charge investors. When investors can detect skill, net alpha is driven to zero in equilibrium by competition among investors. In equilibrium, fund gross alpha will equal fees charged.

We use management fees as an alternative proxy for fund quality. Each month, management fee is the product of a fund's TNA in the prior month end and one-twelfth of its annual (fiscal year) management fee, which is subsequently time-averaged from the start of the sample period to the current month. We sum up monthly management fees over three months in the quarter to obtain quarterly management fees. Each quarter, stock IQ based on management fees is estimated as the cross-product of active holding and management fees summed across funds. As previously, we rank stock IQ based on management fees and compute the odds ratio.

< Insert Table VIII here. >

Two-way fixed effects regression results reported in Table VIII mirror Table VII. Forecast quarterly returns using management fee based stock IQ strongly persist through four quarters. In lead one quarter, a standard deviation increase in management fee based stock IQ increases average forecasted quarterly excess market return, DGTW return, and 4-factor alpha on stocks by 1.328%, 1.364%, and 0.881%. Similar to Table VII Panel B, a long-short portfolio of stocks in the top 95th and bottom 5th percentile generates a quarterly excess market return of 1.972% (=1.328*(19.000-0.053)/12.760), where 12.760 is the standard deviation of IQ. Findings corroborate Berk et al. (2004, 2015) that fund managers can extract rent for skill through higher management fees. Slightly larger forecast quarterly returns in the third and fourth quarters on stocks ranked by IQ proxied by management fees suggest more skillful fund managers are able to charge more for their services, and as Zhu (2018) points out, is possible when investors can only discover managerial skill over time.

As a robustness test, we use industry concentration to proxy for fund quality. Kacperczyk et al. (2005) document significant diseconomies of scope. Skilled fund managers can exploit their information advantage and achieve superior performance by holding more concentrated industry portfolios. Each quarter, industry concentration is computed as the squared differences between industry weights of funds, $w_{j,\mathrm{I}}$, and aggregate industry weights, w_{I}, summed across ten broadly defined industries (Fama and French, 1997).

$$Industry\ concentration_{j,\mathrm{I}} = \sum_{\mathrm{I}=1}^{10}(w_{j,\mathrm{I}} - w_{\mathrm{I}})^2 \tag{12}$$

Aggregate industry weight is the dollar value invested in an industry as a percent of the total dollar value across all industries, aggregated over all sample funds. IQ is estimated in the same spirit as the sum product of fund quality and active holdings, with fund quality constructed by industry concentration time-averaged across current and prior quarters. Two-way stock and quarter fixed effects regression results, which are reported in Appendix Table III, closely resemble those in Table VII and Table VIII. Overall, the predictive return content of IQ is robust to management fee-based or industry concentration-based proxies of fund quality.

C. Market Capitalization and Investment Quality

Table IX examines the impact on forecast stock returns from IQ on stocks categorized by market capitalization. Using breakpoints on NYSE stocks, we sort stocks into terciles by market capitalization. The interaction between investment quality and market cap dummy is $\theta_i \cdot D_{i\kappa}$, where $D_{i,1} = 1$ if stock i is small cap and 0 otherwise, $D_{i,2} = 1$ if stock i is midcap and 0 otherwise, and $D_{i,3} = 1$ if stock i is large cap and 0 otherwise. Results of two-way stock and quarter fixed effects regressions of forecast stock returns on IQ among small cap, midcap, and large cap stocks are reported in Table IX.

< Insert Table IX here. >

As evident in Table IX Panel A, future stock returns are higher on stocks with better IQ regardless of market capitalization. Finding corroborates Table VI. IQ is, however, more important on small cap stocks. In lead one quarter, a standard deviation increase in IQ, increases average forecast quarterly excess market return on small cap stocks by 1.569%, compared to 1.306 % on midcap stocks, and 1.114 % on large cap stocks. Estimated forecast quarterly returns on the IQ of midcap and large cap stocks are on average 83.24% and 71.00% of those on small cap stocks. The same pattern is true for DGTW return and 4-factor alpha.

Further, forecast quarterly returns from IQ persist over four quarters, and small cap stocks benefit most from IQ over longer holding horizons. The quarterly returns with each additional quarter decline over small cap, midcap stocks, and large cap stocks, with the decay in large cap stocks much more attenuated. On small cap stocks, quarterly excess market return in the fourth quarter is lower than in the first quarter by 27.66% (=(1.569-1.135)/1.569), and on midcap stocks, lower by 30.25%. In comparison, quarterly excess market return in the fourth quarter is lowered by only 12.84% on large cap stocks. DGTW return and 4-factor exhibit the same pattern.

The forecast quarterly returns on small, mid, and large-cap stocks at percentile ranks p_i ranging from 5th to 95th are shown in Table IX Panel B. A portfolio of stocks ranked higher in IQ outperforms a portfolio of stocks ranked lower in IQ across all terciles of market capitalization. In lead one quarter, excess quarterly market return on a high-low IQ portfolio of small cap stocks is 2.330%, compared to 1.939% on midcap stocks, and 1.654 % on large cap stocks. Return spreads are similar on DGTW return and 4-factor alpha and strongly persist through the ensuing year.

D. Investment Quality and Conviction Quality

High fund active holdings turnover indicates less patience and low conviction quality. When patience and conviction of fund managers in a stock is important, we expect future returns to be lower on stocks with higher fund active holdings turnover. Results of style and quarter fixed effects regressions of forecast stock returns on IQ and trading activity are reported in Table X. All regressors are normalized by their standard deviations over the sample period and control variables are all demeaned.

< Insert Table X here. >

There are three panels in Table X. Panel A examines forecast quarterly returns from IQ and conviction quality, and Panel B, the interacted effect of IQ and conviction quality on forecast quarterly returns. Summary statistics on actively traded stocks in the 5th to 95th percentiles in conviction quality are reported in Panel C. For Panel B, Hi_IQ and Lo_IQ dummies denote stocks with above and below median IQ in the quarter. The interactions of Hi_IQ and Lo_IQ with conviction quality are used as regressors in Panel B model specifications.

Estimated coefficients on IQ in Table X Panel A are identical to coefficient estimates in Table VII Panel A. Accounting for the patience and conviction of fund managers does not diminish forecast quarterly returns from IQ. Combined with results in Panel B, on stocks where the trading activity of fund managers is high, however, forecast quarterly returns fall significantly. Further, forecast quarterly returns continue to decline each quarter. Compared to the first quarter, a standard deviation increase in trading activity will lead to a continuous fall in quarterly excess market return that returns in the fourth quarter are 53.92% (=0.227/0.421) of the first quarter, on above median IQ stocks. Results are similar for DGTW return and 4-factor alpha.

Active trading reduces forecast quarterly returns. The decline in forecast quarterly returns from trading activity shows the greatest profit from market mispricing occurs over longer holding periods. In Table X Panel B, forecast returns are higher when skillful fund managers are also patient investors. In lead one quarter, a standard deviation increase in conviction quality lowers average forecasted quarterly excess market return on a portfolio of above median IQ stocks by -0.421%. DGTW return and 4-factor alpha exhibit the same pattern, although the negative impact on 4-factor alpha is smaller in magnitude.

Patience is, however, not a substitute for skill. Forecast returns do not significantly increase when less skilled fund managers are also patient investors. Coefficients on the interactions of Lo_IQ and conviction quality are insignificant.

Lastly, Table X Panel C shows that for 80% of stocks, active turnover is negatively correlated with GVA. Correlation becomes more negative as active turnover increases from the 10th percentile to the 50th percentile, and turns positive between the 80th and 90th percentiles of active turnover. Trading activity is predominantly by less skilled fund managers, and highest in mid cap-value stocks where skilled fund managers contribute to trading activity.

Our results conform to the Cremers et al. (2009) thesis that turnover by unskilled fund managers does not add value. Only funds with high active share and low holdings turnover outperform their benchmarks. Forecast returns are the highest on high active fund holdings of stocks by skilled fund managers who are patient investors with long holding horizons. High turnover make unskilled fund managers look busy, and creates buy-sell pressure that drive stock prices away from fundamental values and forecast lower future returns (Miller, 1997).

E. Investment Quality and Conviction Quality of Stocks by Market Capitalization

Table XI examines the impact of conviction quality on future returns of stocks categorized by market capitalization. Similar to Table IX, we sort stocks into terciles by market capitalization using breakpoints on NYSE stocks. Conviction quality is the relative percentile rank on active turnover. We construct interaction terms $\theta_i^{\pi} \cdot D_{i\kappa}$, where $D_{i,1} = 1$ if stock i is small cap and 0 otherwise, $D_{i,2} = 1$ if stock i is midcap and 0 otherwise, and $D_{i,3} = 1$ if stock i is large cap and 0 otherwise. Style and quarter fixed effects regressions of forecast returns on the IQ and conviction quality of small cap, midcap, and large stocks are reported in Table XI.

< Insert Table XI here. >

As expected, results confirm prior Tables IX and X. Future stock returns are higher on stocks with better IQ regardless of market capitalization. Estimated coefficients on IQ by market capitalization closely resemble those in Table IX. The information advantage of skilled fund managers is greater on small cap stocks and more muted in large and mid-cap stocks. Large cap stocks benefit least from IQ in short run and mid cap stocks benefit least in long run. As in Table X, accounting for the patience and conviction of fund managers does not diminish forecast returns from IQ.

High active turnover and low patience adversely impact forecast returns on large cap stocks. In the first quarter, forecast quarterly returns on large cap stocks of fund managers who trade actively, are relatively lower by 0.720% on excess market return, 0.790% on DGTW return, and 0.745% on 4-factor alpha. Further, low conviction quality forecast lower returns that persist and increase in magnitude through the ensuing four quarters. Compared to the first quarter, average forecast quarterly excess market return, DGTW return, and 4-factor alpha on actively traded large cap stocks are relatively lower in the fourth quarter by 0.287%(=(-1.007%)-(-0.720%)), 0.034%, and 0.068%. Forecast returns are significantly lower in the fourth quarter, but insignificantly lower in the first quarter on midcap stock holdings for fund managers who trade frequently. For small cap stocks, forecast returns are significantly lower in most of the model specifications.

F. Investment and Conviction Quality by Fund Quality

Appendix Table II Panel C shows that fund quality falls approximately into terciles. Funds in the top tercile of fund quality have the highest (positive) GVA, and funds in the bottom tercile have the lowest (negative) GVA. If stock investment and conviction quality represent trading and turnover by skilled fund managers on private information, we should expect the forecast return power of investment and conviction quality to come mainly from funds in the top tercile of fund quality.

To test this thesis, we sort funds into terciles by GVA at the end of each quarter. We construct IQ as the sum products of active fund holdings and fund GVA across funds in each tercile. We compute fund active holdings turnover similarly by GVA tercile each quarter. Two-way fixed effects regressions of future stock returns for each GVA tercile are reported in Table XII.

< Insert Table XII here. >

Table XII confirms the forecast return power of investment and conviction quality come mainly from the top tercile of funds by GVA. In the top tercile of funds by GVA, IQ predicts significantly positive future stock excess market and DGTW returns as well as 4-factor alphas, which persist over four quarters. In the middle tercile, IQ predicts smaller and occasionally significantly positive future excess market and DGTW stock returns, and positive but insignificant 4-factor alpha. In the bottom tercile, IQ predicts insignificantly negative future excess market and DGTW stock returns, but significantly positive 4-factor alphas, which are smaller in magnitude than in the top GVA tercile. The results are not surprising. Funds are overfunded in the bottom tercile. As shown in Appendix Table II Panel C, net alphas do not correlate with GVA when funds are overfunded.

Coefficients on the conviction quality exhibit similar patterns. In the top tercile, low conviction quality-high $Turn$ predicts significantly negative future excess market and DGTW returns as well as 4-factor alphas. In the middle and bottom terciles, conviction quality predicts insignificant future stock returns excess market and DGTW returns as well as 4-factor alphas.

VI. Earnings Announcements

Lastly, we examine the private information of skilled fund managers, impounded in stock IQ, that is made public in earnings announcements. Earnings announcement dates are obtained from I/B/E/S database. We estimate CAR1 as the cumulative abnormal return over the three-day window [-1, 1] around the earnings announcement date, and CAR2 as the cumulative abnormal return over the window [3,60] from the 3rd day to the earlier of the day prior to the earnings announcement date in the subsequent quarter or 60th day post earnings announcement date. Abnormal daily returns are computed as daily returns in excess of returns on a 2×3 benchmark portfolio of stocks sorted by size (ME) and book-to-market equity (BE/ME) to which the stock belongs.[17] Two-way stock and quarter fixed effects regressions of CAR1 and CAR2 on stock IQ are reported in Table XIII. Errors are clustered by stock and quarter. Explanatory and control variables are normalized by their standard deviations over the sample period.

< Insert Table XIII here. >

The information content of earnings announcements in average CAR1 increases by 0.198% on a standard deviation rise in IQ. At the mean IQ, average forecast CAR1 in lead one quarter is 0.071% (=0.198*4.572/12.760), where 4.572 and 12.760 are the mean and standard deviation of IQ reported in Table III. To put this in perspective, forecast CAR1 is higher by 0.254% (=0.198*(19.0-0.053)/12.760) on a 5th to 95th percentile rise in IQ, and higher by 0.155% (=0.198*(19.0-9.0)/12.760) on a 90th to 95th percentile rise in IQ. Impact on forecast CAR1 is greater at higher percentiles of IQ.

< Insert Figure II here. >

CAR2 captures the private information in stock IQ made public in stock prices in the post-earnings periods following the three-day window around earnings announcements. The CAR for the top and bottom quintiles are graphed in Figure II. At the end of each quarter, we sort stocks into quintiles using stock IQ, and link each quintile over the sample period to form a time-series. We estimate the average CAR for each quintile in the lead one quarter post-earnings announcement period and compute the spread between the top and bottom quintiles.

The post-earnings announcement drift evident in CAR2 is consistent with a slow diffusion of fundamental information. When trading order imbalances create price pressure and signal informed trading when noise trading is low, informed traders will trade in such a way that their private information is incorporated into prices gradually (Kyle, 1985). The incidence of odd-lot trades in equity markets (O'Hara, Yao, and Ye, 2014) and order splitting (Bernhardt and Hughson, 2015) supports the slow diffusion of information.

Finally, Table XIII shows that post-earnings announcement CAR2 is greater on high IQ stocks as shown in Figure II. High IQ stocks embed more private information that is incorporated into prices around earnings announcement and post-earnings announcement periods. A standard deviation rise in IQ raises CAR2 in lead one quarter by 0.502%. IQ strongly predicts CAR2 up to lead four quarters.

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[17]At June end of each year t, stocks are sorted into 2×3 benchmark portfolios by size (ME) and book-to-market equity (BE/ME). Median ME on NYSE stocks and 30th and 70th percentiles of BE/ME on NYSE stocks, computed as book equity in the last fiscal year end in $t-1$ divided by ME in December of $t-1$, are used as breakpoints.

VII. Conclusion

We show stock IQ derived from publicly available information on fund holdings and fund quality can be used to make more profitable investment decisions. Using characteristics-based style segments, deviations in fund from peer group holdings by style segments weighted by fund quality signals a stock's IQ. Managers of high performing funds, who are more skilled and better informed, make similar decisions when they act on the same information. Stocks ranked high on IQ generate significant positive excess market and risk-adjusted returns that persist through the ensuing year. The positive return-IQ relationship is robust to whether fund quality is proxied by fund GVA, management fees or industry concentration. Moreover, we show private information impounded in stock IQ is made public in earnings announcements.

In contrast, active holdings turnover and low patience predict lower future stock returns which also persist through the ensuing year. Future returns on high IQ stocks are adversely affected when fund managers lack patience and conviction of beliefs.

The forecast return power of investment and conviction quality come mainly from funds in the top tercile of fund quality, where stock selection ability is more salient. Investors can benefit most from focusing on the holdings the top tercile performing active mutual funds.

Appendix: Tables and Figures

In this section, we confirm Berk and Binsbergen (2015) that fund gross value added (GVA) is a better measure of fund quality. In each style segment, Table II Panel A reports TNA in millions of dollars at quarter-end, and in parentheses, the average 4-factor gross alpha compounded over three months in the quarter. The $Size\_BTM$ column reports TNA, and in parentheses the 4-factor gross alpha, both averaged across momentum quintiles, on stocks sorted by size and book-to-market. Table II Panel B reports, for each style segment, the average quarterly gross value-added (GVA) in millions of dollars which is monthly GVA summed across three months in the quarter.

< Insert Appendix Table II here. >

Corroborating prior results on stock and fund ownerships, Figure 1 Panel A confirms that TNA increases across size quintiles. Figure 1 Panel B graphs 4-factor gross alpha and GVA against TNA. Gross alpha decreases with fund size. From the $Size\_BTM$ column in Table II Panel B, gross alpha declines from a high of 0.85% to a low of 0.57% as TNA grows from a low of \$482 million to a high of \$846 million. Further, GVA is concave in fund size. From the $Size\_BTM$ column Table II Panel B, GVA rises from an opening low of \$3.72 million on TNA of \$554 million to a peak high of \$4.85 million on TNA of \$770 million, then falling to a closing low of -\$0.53 million on TNA of \$846 million. GVA is also higher on low momentum stocks across all size and book-to-market quintiles. Lastly, GVA is higher on low book-to-market (growth) than high book-to-market (value) stocks across all size and momentum quintiles. The GVA gap of \$0.80 (=\$3.72-\$2.92) million is highest at the smallest size quintile and decreases to \$0.14 (=-\$0.39+\$0.53) million at the largest size quintile.

< Insert Appendix Figure 1 here. >

Using the quarterly distributions of gross alphas averaged across momentum quintiles on stocks sorted by size and book-to-market quintiles, we estimate a log-linear regression of gross alpha on the natural log of TNA controlling for quarter fixed effects. Results are reported in Column 1 in Table II Panel C. Our coefficient on $ln(TNA)$ of -0.0049, which is statistically significant at the 1% level, reflects a reduction in quarterly gross alpha of 49 bps on a 1% increase in TNA. In Table 12 of Zhu (2018), her estimated coefficient of -0.0020 indicates a 1% increase in TNA reduces monthly gross alpha by 20 bps.

We also estimate a quadratic log-linear regression with suppressed intercept of GVA on $ln(TNA)$ and its square, controlling for quarter fixed effects. Results are reported in Column 2 of Table II Panel C. The coefficients of 14.115 and -2.458, which are statistically significant at the 1% level, confirms a concave relationship between GVA and TNA. From the first-order condition, the predicted maximum GVA of $7.1 million is attained at TNA of $17.7 (=$exp(0.5 * 14.115/2.458)$ million.

< Insert Appendix Figure 2 here. >

Figure 2 graphs the frequency distribution of GVA and gross alpha against GVA. The predicted maximum GVA of $7.1 million is realized at an average gross alpha of 1.51% and TNA of $708 million. At average gross alpha of 0.05% and TNA of $682 million, realized GVA is $0.1 million. As shown in Table II Panel C, 31.2% of funds with negative gross alpha are overfunded, and 25.2% of funds with higher than predicted maximum GVA and significant positive gross alphas are underfunded. Compared to Table 7 in Zhu (2018), we have a lower percentage of overfunded funds and higher percentage of moderately funded funds. In contrast to Zhu (2018), our results are based on average fund holdings across style segments of stocks sorted by size, book-to-market, and momentum rather than average holdings across funds which do not take differences in investment strategies across funds into account.

In summary, in Appendix Table II Panel A, the average fund in the smallest size quintile has lower TNA under management but higher gross alpha. Average fund size rises, and gross alpha falls, with increasing size quintiles. In Appendix Table II Panel B and Figure 1, breadth and depth of ownership affects GVA, and managerial skill exhibits diminishing returns to scale. In Table Appendix II Panel C and Figure 2, GVA is negatively related to TNA for overfunded funds, and positively related, for underfunded funds. Moreover, gross alpha is negative for overfunded funds, and highly positive, for underfunded funds. TNA and gross alpha do not correlate with GVA when funds are over- or under-funded.

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Table I
Distributions of Stock and Fund Characteristics by Style Segments

Table reports median style segment characteristics. Cutoffs from annual Daniel, Grinblatt, Titman and Wermers (1997) sorts of stocks into quintiles by size, industry-adjusted book-to-market, and momentum are used to assign stocks into 125 style segments each quarter over our 72-quarter sample period 2000-2017. For each style segment we determine the number of stocks owned. In addition, for each fund in a style segment, we compute the number of stocks owned as a percentage of CRSP stocks in the style. Median number and percentages are reported in Panel A. Panel B reports the number of funds who own the stock., and for each stock in the style segment, the number of funds who own the stock as a percentage of the number of funds who own stocks in the style segment. Median number and percentages are reported in parentheses.

		PANEL A						**PANEL B**					
		Number of Stocks Held by Funds (Stock Ownership)						**Number of Funds (Fund Ownership)**					
SIZE	**BTM**	**MOMENTUM**						**MOMENTUM**					
		1	**2**	**3**	**4**	**5**	***Size_BTM***	**1**	**2**	**3**	**4**	**5**	***Size_BTM***
1	**1**	30 (4.6)	48 (3.6)	54 (3.6)	54 (3.5)	55 (3.6)	48 (3.8)	149 (9.3)	214 (7.8)	246 (8.1)	272 (8.1)	232 (8.1)	223 (8.3)
1	**2**	39 (3.7)	53 (3.4)	57 (3.3)	58 (3.2)	59 (3.4)	53 (3.4)	195 (8.5)	244 (8.2)	243 (8.6)	243 (8.1)	235 (7.9)	232 (8.3)
1	**3**	40 (3.9)	60 (3.3)	63 (3.2)	60 (3.1)	59 (3.3)	56 (3.4)	168 (9.3)	222 (9.0)	230 (8.8)	250 (9.0)	247 (8.8)	223 (9.0)
1	**4**	42 (4.0)	53 (3.5)	61 (3.4)	52 (3.3)	60 (3.7)	53 (3.5)	163 (9.4)	197 (9.0)	198 (9.4)	194 (9.0)	212 (8.7)	193 (9.1)
1	**5**	34 (4.8)	45 (3.5)	50 (3.3)	52 (3.3)	52 (3.6)	46 (3.7)	132 (11.0)	169 (8.5)	167 (8.0)	192 (7.9)	200 (8.2)	172 (8.7)
2	**1**	23 (6.5)	24 (7.0)	23 (8.3)	24 (8.2)	24 (8.2)	23 (7.5)	310 (12.0)	312 (11.9)	333 (12.8)	320 (12.8)	320 (13.4)	319 (12.5)
2	**2**	23 (7.3)	24 (7.6)	23 (7.9)	24 (8.0)	23 (8.5)	23 (7.7)	303 (12.2)	328 (12.5)	325 (12.8)	330 (12.8)	316 (13.7)	320 (12.8)
2	**3**	24 (7.1)	24 (7.6)	25 (7.6)	24 (7.9)	24 (7.9)	24 (7.5)	306 (13.0)	331 (13.1)	323 (13.4)	327 (14.2)	330 (13.6)	323 (13.5)
2	**4**	23 (6.9)	25 (7.9)	25 (7.8)	24 (7.7)	23 (8.6)	24 (7.6)	297 (13.4)	308 (14.9)	323 (14.7)	321 (14.5)	320 (15.5)	314 (14.6)
2	**5**	23 (6.1)	24 (6.7)	24 (7.3)	24 (7.2)	23 (7.7)	24 (6.8)	277 (13.9)	307 (13.5)	316 (14.4)	328 (14.3)	314 (15.1)	308 (14.2)
3	**1**	16 (7.4)	17 (9.0)	17 (9.8)	17 (10.4)	16 (11.7)	17 (9.2)	410 (13.1)	425 (13.4)	429 (14.1)	433 (15.1)	386 (16.7)	416 (14.5)
3	**2**	16 (7.2)	17 (9.9)	17 (9.8)	17 (10.6)	16 (11.3)	17 (9.4)	404 (13.2)	419 (14.1)	424 (14.3)	428 (15.0)	407 (16.0)	416 (14.5)
3	**3**	17 (7.2)	17 (8.7)	16 (9.8)	17 (9.3)	16 (11.2)	17 (8.7)	406 (12.9)	440 (13.5)	418 (14.7)	430 (14.6)	409 (15.8)	420 (14.3)
3	**4**	16 (7.6)	17 (7.8)	17 (9.3)	16 (9.8)	16 (11.0)	16 (8.6)	360 (14.1)	419 (13.7)	408 (14.9)	429 (15.4)	405 (16.0)	404 (14.8)
3	**5**	16 (6.8)	17 (8.4)	16 (8.2)	17 (8.9)	16 (9.1)	16 (8.1)	359 (14.5)	396 (14.9)	409 (15.0)	420 (15.1)	418 (15.3)	400 (15.0)
4	**1**	14 (7.5)	15 (7.1)	14 (7.5)	14 (10.0)	14 (11.4)	14 (8.0)	455 (14.5)	499 (14.1)	482 (14.8)	536 (15.5)	525 (16.5)	499 (15.1)
4	**2**	14 (8.0)	14 (8.0)	15 (7.7)	14 (9.8)	14 (11.0)	14 (8.4)	456 (14.8)	501 (14.6)	527 (13.9)	531 (15.4)	525 (16.9)	508 (15.1)
4	**3**	14 (7.2)	14 (7.1)	15 (7.8)	14 (8.5)	13 (11.0)	14 (7.7)	445 (14.6)	488 (14.6)	513 (14.7)	522 (15.3)	532 (16.5)	500 (15.1)
4	**4**	14 (7.7)	14 (7.9)	14 (9.1)	14 (9.1)	14 (10.5)	14 (8.4)	434 (15.7)	476 (14.6)	515 (15.5)	493 (15.2)	528 (16.1)	489 (15.4)
4	**5**	14 (7.7)	14 (8.1)	14 (8.7)	14 (8.4)	14 (10.8)	14 (8.3)	387 (16.9)	430 (15.8)	433 (16.1)	445 (16.2)	494 (17.4)	438 (16.5)
5	**1**	13 (17.2)	13 (16.4)	13 (19.0)	13 (18.5)	13 (17.6)	13 (17.8)	622 (19.2)	696 (19.5)	689 (22.4)	667 (21.6)	648 (22.2)	664 (21.0)
5	**2**	12 (16.9)	13 (18.0)	13 (17.8)	13 (17.9)	13 (17.3)	13 (17.6)	673 (19.6)	687 (20.8)	703 (20.3)	721 (21.1)	677 (21.2)	692 (20.6)
5	**3**	13 (16.5)	13 (16.0)	13 (18.1)	13 (16.5)	13 (17.0)	13 (16.8)	647 (19.1)	687 (19.3)	685 (19.9)	703 (20.0)	672 (20.9)	679 (19.8)
5	**4**	12 (16.5)	13 (16.7)	13 (16.3)	13 (16.8)	12 (16.4)	13 (16.6)	602 (19.9)	617 (19.9)	670 (19.9)	707 (20.2)	635 (21.5)	646 (20.3)
5	**5**	12 (16.0)	13 (17.2)	13 (16.2)	13 (16.8)	12 (16.4)	13 (16.6)	526 (20.2)	582 (20.5)	578 (20.7)	595 (20.7)	588 (21.7)	574 (20.7)

Table II
Summary Statistics

Table reports stock summary statistics on variables used in the paper. Excess market return is the monthly return in excess of the value-weighted CRSP return compounded over a quarter. DGTW return is the monthly return minus the average return on stocks in DGTW segment style k to which stock i belongs compounded over a quarter. 4-Factor adjusted alpha is the daily alpha estimated from time-series regressions of daily stock returns on Fama and French (1992) market, SMB, HML, and Carhart (1997) UMD factors each month compounded over a quarter. SUE is earnings per share minus median analyst forecast made earlier than the earnings announcement date but no more than 90 days in advance scaled by stock price at the end of quarter. Breadth is $ln(N+1)$, where N is the number of actively managed mutual funds with non-zero holdings of stock i in style segment k. Active MF ownership is the percentage of total shares outstanding of stock i owned by actively managed mutual funds j at the end of quarter q. Quarterly change in breadth and active MF ownership are computed as change in breadth and active MF ownership from the prior quarter. Dispersion index of active holding is the standard deviation of active holdings across all funds j with non-zero holdings in style segment k divided by the absolute value of the mean active holding. Market capitalization is the product of closing price and total shares outstanding of stock i at the end of the quarter q expressed in millions of dollars. Book-to-market is book equity to shareholders' equity following Daniel and Titman (2006). Prior year return in month t at quarter end is the cumulative monthly return over the prior 12 months starting from $t-2$ and ending in $t-13$. CRSP turnover is the total trading volume reported by CRSP summed across all 3 months in the quarter as a percentage of total shares outstanding where trading volume is adjusted following French (2008). Idiosyncratic volatility is the standard deviation of residuals from time series regressions of daily stock returns on Fama French (1992) market, SMB and HML factors each quarter. Market beta is the sum of the coefficients on contemporaneous and five lags of market excess returns estimated from time series regressions of daily stock excess returns on daily contemporaneous and five lags of market excess returns each quarter following Jiang and Sun (2014). As in Berk and Binsbergen (2015), we proxy fund performance by gross-value added (GVA). Monthly gross value-added is the product of current month 4-factor alpha and prior month end TNA. TNA is deflated by the monthly seasonally-adjusted CPI index (1982-1984=100) constructed by the U.S. Bureau of Labor Statistics (BLS). Quarterly gross value added is monthly gross value added summed across months in the quarter. Fund holding of stock i by fund j is the market value of stock i owned by fund j as a percentage of all stock holdings of fund j in style segment k. Portfolio formation is described in Table I. Peer group holding is the market value of stock i owned by all actively managed mutual funds j as a percentage of the market value of all stocks in style segment k owned by all actively managed mutual funds j. Active holding is the deviation of fund from peer group holding. Active holding turnover is the difference in active holding between current and four quarters prior. The cross-product of active holding and GVA summed across funds is used to identify selection skill. Investment quality $IQ \equiv \theta_i^s$ is the odds ratio of a stock's relative percentile rank, θ_i^s, on selection skill. In $\theta_i^s\_Mgmt\ Fee$, management fees proxy for GVA. The cross-product of active holding turnover and GVA summed across funds is used to identify active turnover – the patience and conviction of fund managers. Conviction quality $Turn \equiv \theta_i^\pi$ is the odds ratio of a stock's relative percentile rank, θ_i^π, on active turnover.

				Percentile				
	NOBS	Mean	Std Dev	10th	20th	50th	80th	90th
Excess Market Return (%)	191,274	0.70	10.81	-11.11	-6.30	0.32	7.37	12.64
DGTW Return (%)	191,274	-0.06	10.45	-11.65	-6.87	-0.29	6.44	11.48
4-Factor Alpha (%)	191,274	0.59	12.45	-12.43	-7.20	-0.06	7.50	13.89
Market Capitalization ($million)	191,274	5,118	21,384	69	149	672	3,390	9,050
Book-to-Market	191,274	0.745	0.797	0.187	0.287	0.575	1.018	1.380
Prior Year Return	191,274	0.138	0.442	-0.377	-0.155	0.137	0.423	0.634
CRSP Turnover	191,274	0.435	0.411	0.065	0.122	0.319	0.654	0.940
Idiosyncratic Volatility	191,274	0.023	0.015	0.009	0.012	0.019	0.031	0.042
Market Beta	191,274	1.177	1.172	-0.070	0.325	1.045	1.950	2.618
$\Delta Breadth$	191,274	0.008	0.173	-0.150	-0.086	0.000	0.102	0.167
$\Delta Active\ MF\ Ownership$	191,274	0.000	0.029	-0.016	-0.007	0.000	0.008	0.016
$Dispersion\ Index\ in\ Active\ Holdings$	191,274	0.137	0.084	0.011	0.057	0.139	0.210	0.245
$Breadth$	191,274	3.606	0.918	2.303	2.708	3.689	4.407	4.745
$Active\ MF\ Ownership$	191,274	0.108	0.120	0.017	0.032	0.080	0.158	0.208
$Investment\ Quality, \theta_i^s$	191,274	4.572	12.760	0.111	0.250	1.000	3.997	8.986
$IQ, \theta_i^s\_Mgmt\ Fee$	191,274	4.572	12.760	0.111	0.250	1.000	3.997	8.986
$IQ, \theta_i^s\_Industry\ Concentration$	191,274	4.572	12.760	0.111	0.250	1.000	3.997	8.986
$Conviction\ Quality\ \theta_i^\pi$	191,274	4.572	12.760	0.111	0.250	1.000	3.997	8.986
$Investment\ Quality, \theta_i^{s2}$	191,274	183.72	1,076.51	0.012	0.063	1.000	15.974	80.742
$IQ, \theta_i^{s2}\_Mgmt\ Fee$	191,274	183.72	1,076.51	0.012	0.063	1.000	15.974	80.742
$IQ, \theta_i^{s2}\_Industry\ Concentration$	191,274	183.72	1,076.51	0.012	0.063	1.000	15.974	80.742

Table III
Persistence in Stock Investment Quality

This table reports on the persistence of stock investment quality through lead four quarters. Stock investment quality is defined in Table III and in the Appendix. In Panel A, we sort stocks into deciles on investment quality at the end of each quarter. In each decile, we report the average stock investment quality in lead two, four, eight, and twelve quarters, as well as the spread in investment quality between the top and bottom deciles and associated t-statistics. In Panel B, we report a transition matrix. We sort stocks by investment quality into quintiles at the end of each quarter and compute the percentage of stocks that remain or change to another quintile in the subsequent quarter. Panel C presents summary statistics on investment quality in the selected percentiles between the 5th and the 95th percentiles. Superscripts a,b,c denote two-tailed tests of statistical significance at the 10%, 5%, and 1% levels.

Panel A	Investment Quality			
	Lead 2 Qtr	Lead 4 Qtr	Lead 8 Qtr	Lead 12 Qtr
Low	1.50	1.40	1.24	1.16
2	1.06	1.01	1.05	1.18
3	1.04	1.19	1.34	1.43
4	1.35	1.49	1.65	1.73
5	1.62	1.79	2.02	2.15
6	2.03	2.30	2.53	2.64
7	2.69	2.91	3.28	3.44
8	3.83	4.16	4.43	4.66
9	6.51	6.74	6.98	7.03
High	23.30	21.37	19.03	17.30
High-Low	**21.80**^{c}	**19.97**^{c}	**17.80**^{c}	**16.14**^{c}
t**-stat**	97.51	86.56	74.01	65.82

Panel B		Investment Quality Transition Matrix				
		Current Quarter End				
		1	**2**	**3**	**4**	**5**
Prior Quarter End	**1**	75.74%	13.88%	4.60%	2.74%	3.05%
	2	12.59%	55.39%	21.22%	7.13%	3.66%
	3	4.45%	20.24%	49.20%	20.79%	5.32%
	4	2.75%	7.15%	19.90%	54.03%	16.17%
	5	3.31%	3.81%	5.38%	15.63%	71.86%

Panel C	Investment Quality Percentile Rank p	Active Holdings (%)	GVA	$\rho\left(\begin{matrix}AH,\\GVA\end{matrix}\right)$	MCAP	Book-to-Market
	0.05	-0.002	4.55	-0.002	890	1.125
	0.10	-0.011	5.00	-0.017	2,754	0.992
	0.20	-0.033	5.92	-0.025	4,621	0.740
	0.50	0.007	5.59	-0.028	4,042	0.703
	0.80	0.015	5.90	0.011	6,442	0.649
	0.90	0.013	5.77	0.049	8,848	0.646
	0.95	0.005	5.76	0.092	9,493	0.652

Table IV

Alternative Empirical Stock Return Predictors: Herding, Delta Ownership, Delta Breadth and Flow Effect

This table compares stock investment quality with four other empirical measures used to forecast future stock returns. Table reports Fama-Macbeth (1973) regression results of lead quarter buy-and-hold stock returns on stock investment quality, herding (Brown, Wei, and Wermers, 2014), flow (Frazzini and Lamont, 2007), delta fund ownership and delta breadth (Chen, Hong, and Stein, 2002). In Fama-Macbeth regressions, serial correlation in error terms are corrected using a Newey-West estimator with one-quarter lag. p-values are reported in parentheses. Superscript $^{a, b, c}$ denote statistical significance at 10%, 5%, and 1% levels. Unreported estimated coefficients on control variables are reported in an Appendix.

	EXCESS MARKET RETURN				**DGTW RETURN**				**4-FACTOR ALPHA**			
	Lead 1 Qtr	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**	**Lead 1 Qtr**	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**	**Lead 1 Qtr**	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**
$IQ \equiv \theta_i^s$	1.171^{c}	1.037^{c}	0.920^{c}	0.819^{c}	1.187^{c}	1.042^{c}	0.935^{c}	0.826^{c}	1.040^{c}	0.903^{c}	0.807^{c}	0.711^{c}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Herding	-0.145^{b}	-0.050	0.002	0.011	-0.183^{c}	-0.085^{a}	-0.022	-0.013	-0.113	-0.045	-0.010	0.020
	(0.039)	(0.288)	(0.951)	(0.755)	(0.006)	(0.068)	(0.528)	(0.705)	(0.142)	(0.498)	(0.854)	(0.697)
Flow	0.150	0.159	0.192^{b}	0.201^{b}	0.142	0.152^{a}	0.195^{b}	0.205^{c}	0.146	0.154^{a}	0.143^{b}	0.151^{b}
	(0.200)	(0.101)	(0.036)	(0.023)	(0.170)	(0.084)	(0.014)	(0.010)	(0.144)	(0.058)	(0.043)	(0.034)
$\Delta Breadth$	0.383^{b}	0.217^{a}	0.060	-0.008	0.351^{b}	0.190	0.047	-0.015	0.300^{b}	0.178^{b}	0.014	-0.045
	(0.015)	(0.065)	(0.527)	(0.920)	(0.020)	(0.117)	(0.618)	(0.841)	(0.017)	(0.047)	(0.841)	(0.434)
$\Delta Active\ MF\ Ownership$	-0.145^{a}	-0.131^{b}	-0.054	-0.034	-0.155^{b}	-0.135^{b}	-0.083^{a}	-0.068	-0.173^{b}	-0.157^{c}	-0.051	-0.029
	(0.050)	(0.021)	(0.254)	(0.452)	(0.035)	(0.025)	(0.056)	(0.123)	(0.040)	(0.007)	(0.250)	(0.541)
$IQ^2 \equiv {\theta_i^s}^2$	-0.867^{c}	-0.802^{c}	-0.710^{c}	-0.658^{c}	-0.898^{c}	-0.826^{c}	-0.752^{c}	-0.690^{c}	-0.828^{c}	-0.725^{c}	-0.655^{c}	-0.585^{c}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Holding Dispersion Index	-0.010	-0.067^{a}	-0.049	-0.018	-0.041	-0.064^{a}	-0.046	-0.017	0.034	-0.050	-0.035	0.008
	(0.822)	(0.075)	(0.182)	(0.547)	(0.386)	(0.089)	(0.163)	(0.525)	(0.494)	(0.197)	(0.309)	(0.792)
NOBS	178,535	175,711	172,920	170,167	178,424	175,495	172,583	169,718	180,929	178250	175,505	172,798
R^2	0.066	0.071	0.076	0.078	0.032	0.037	0.040	0.043	0.031	0.040	0.046	0.053

Table V
Excess Returns on One-Way Sort by Stock Investment Quality

Table reports the average value-weighted buy-and-hold returns in the month and quarters following the formation of quintile portfolios on stocks sorted by investment quality. Monthly and average quarterly returns are expressed in percent. In each quarter, we estimate the percentage of total dollar holdings in a style segment allocated by a fund and its peers to the same stock. Active holding is the difference between fund and peer group holding of the same stock in a style segment. The cross-product of active holding and GVA summed across funds is used to identify selection skill. Investment quality $IQ \equiv \theta_i^s$ is the odds ratio of a stock's relative percentile rank, θ_i^s, on selection skill. Other variable definitions can be found in Table III. Superscripts [a,b,c] denote two-tailed tests of statistical significance at the 10%, 5%, and 1% levels.

	Lead 1 Mo	Lead 1 Qtr	Lead 2 Qtr	Lead 3 Qtr	Lead 4 Qtr
			EXCESS MARKET RETURN		
Low	-0.406	-0.774	-1.289	-1.392	-1.329
2	-0.199	-0.336	-0.753	-0.928	-0.982
3	0.026	-0.026	-0.449	-0.517	-0.564
4	0.123	0.548	0.033	-0.139	-0.277
High	0.269	0.759	0.403	0.277	0.102
High-Low	**0.675**[c]	**1.533**[c]	**1.692**[c]	**1.668**[c]	**1.431**[c]
***t*-stat**	2.75	3.05	5.74	6.10	5.73
			DGTW RETURN		
Low	-0.487	-1.013	-1.407	-1.498	-1.463
2	-0.274	-0.432	-0.696	-0.845	-0.877
3	-0.081	-0.199	-0.587	-0.602	-0.614
4	0.017	0.314	-0.138	-0.317	-0.430
High	0.137	0.710	0.361	0.196	0.053
High-Low	**0.624**[c]	**1.723**[c]	**1.768**[c]	**1.694**[c]	**1.516**[c]
***t*-stat**	2.83	4.38	6.82	6.97	6.69
			4-FACTOR ALPHA		
Low	-0.097	-0.561	-0.770	-0.781	-0.846
2	0.087	0.214	-0.128	-0.299	-0.360
3	0.379	0.309	-0.100	-0.158	-0.143
4	0.335	0.717	0.167	-0.053	-0.184
High	0.575	0.975	0.611	0.392	0.232
High-Low	**0.672**[b]	**1.537**[c]	**1.381**[c]	**1.173**[c]	**1.078**[c]
***t*-stat**	2.53	3.60	4.22	4.11	4.16

Table VI
Excess Returns on Double-Sorts by Market Capitalization and Stock Investment Quality

Table reports the average value-weighted buy-and-hold returns in the quarters following portfolio formation of stocks double-sorted first into terciles by market capitalization using NYSE stocks to establish breakpoints, and second, by investment quality. Average quarterly returns are expressed in percent. Portfolio formation is described in Table I. In each quarter, we estimate the percentage of total dollar holdings in a style segment allocated by a fund and its peers to the same stock. Active holding is the difference between fund and peer group holding of the same stock in a style segment. The cross-product of active holding and GVA summed across funds is used to identify selection skill. Investment quality $IQ \equiv \theta_i^s$ is the odds ratio of a stock's relative percentile rank, θ_i^s, on selection skill. Other variable definitions can be found in Table III. Superscripts a,b,c denote two-tailed tests of statistical significance at the 10%, 5%, and 1% levels.

		EXCESS MARKET RETURN			DGTW RETURN			4-FACTOR ALPHA		
		Market Capitalization			Market Capitalization			Market Capitalization		
		Small	Mid	Large	Small	Mid	Large	Small	Mid	Big
Lead 1 Quarter										
Stock Selection Quality	**Low**	0.225	-0.093	-0.637	-1.031	-1.057	-0.603	0.502	-0.305	-0.093
	2	0.079	0.595	-0.241	-1.192	-0.425	-0.310	-0.137	0.217	0.366
	3	1.323	1.089	0.191	0.171	0.150	0.210	1.001	0.567	0.601
	4	1.822	1.090	0.316	0.731	0.156	0.319	1.360	0.584	0.823
	High	2.050	1.503	1.009	0.876	0.515	1.004	1.171	0.788	1.148
	Hi-Lo	**1.825**[a]	**1.596**[c]	**1.646**[c]	**1.907**[c]	**1.572**[c]	**1.607**[c]	**0.670**[b]	**1.094**[c]	**1.241**[c]
	***t*-stat**	1.931	2.777	5.362	6.711	5.827	4.656	2.142	2.972	3.023
Lead 2 Quarter										
Stock Selection Quality	**Low**	-0.850	-0.722	-0.968	-1.928	-1.582	-0.769	-0.503	-0.880	-0.253
	2	-0.937	-0.116	-0.660	-1.995	-1.036	-0.615	-1.052	-0.459	-0.103
	3	0.027	0.273	-0.089	-0.990	-0.566	-0.137	-0.139	-0.034	0.328
	4	0.502	0.357	0.101	-0.463	-0.455	0.127	0.165	-0.060	0.512
	High	0.487	0.508	0.569	-0.514	-0.365	0.576	-0.120	-0.042	0.691
	Hi-Lo	**1.337**[c]	**1.230**[c]	**1.538**[c]	**1.414**[c]	**1.217**[c]	**1.345**[c]	**0.383**	**0.839**[c]	**0.944**[c]
	***t*-stat**	2.931	2.991	7.966	6.136	6.093	9.293	1.587	4.218	4.029
Lead 3 Quarter										
Stock Selection Quality	**Low**	-1.099	-0.892	-1.038	-2.142	-1.716	-0.810	-0.779	-1.094	-0.263
	2	-1.310	-0.360	-0.767	-2.303	-1.240	-0.685	-1.457	-0.655	-0.206
	3	-0.365	0.086	-0.207	-1.348	-0.755	-0.233	-0.606	-0.233	0.167
	4	0.035	0.093	-0.037	-0.875	-0.695	-0.021	-0.324	-0.250	0.309
	High	0.002	0.173	0.415	-0.972	-0.651	0.399	-0.594	-0.365	0.439
	Hi-Lo	**1.102**[c]	**1.064**[c]	**1.453**[c]	**1.170**[c]	**1.065**[c]	**1.209**[c]	**0.185**	**0.729**[c]	**0.702**[c]
	***t*-stat**	3.009	4.551	9.080	5.726	6.362	10.314	0.861	4.328	3.606
Lead 4 Quarter										
Stock Selection Quality	**Low**	-1.258	-1.010	-1.062	-2.206	-1.745	-0.822	-0.936	-1.172	-0.343
	2	-1.574	-0.446	-0.779	-2.428	-1.231	-0.678	-1.702	-0.713	-0.154
	3	-0.572	-0.029	-0.356	-1.463	-0.803	-0.385	-0.785	-0.331	0.026
	4	-0.180	-0.152	-0.162	-0.993	-0.865	-0.088	-0.510	-0.431	0.143
	High	-0.360	-0.076	0.325	-1.206	-0.801	0.301	-0.832	-0.578	0.363
	Hi-Lo	**0.898**[c]	**0.934**[c]	**1.386**[c]	**1.000**[c]	**0.944**[c]	**1.123**[c]	**0.104**	**0.594**[c]	**0.706**[c]
	***t*-stat**	2.819	4.813	9.510	5.381	6.406	10.739	0.526	4.092	4.041

Table VII
Forecast Returns: Investment Quality of Stocks

Table VI Panel A reports style and quarter fixed effects regressions of lead quarter buy-and-hold stock returns on selection quality and control variables, and in Panel C, Fama-Macbeth (1973) regressions. Panel B reports forecast returns at selected percentiles of selection quality between the 5th and the 95th percentiles.‡ indicates estimated coefficients from Panel A. Variable definitions can be found in Table III. The cross-product of active holding and GVA summed across funds is used to identify selection skill. Investment quality $IQ \equiv \theta_i^s$ is the odds ratio of a stock's relative percentile rank, θ_i^s, on selection skill. All variables are normalized by their standard deviations across the sample period. Control variables are demeaned. In two-way fixed effects regressions, errors are clustered by style and quarter. In Fama-Macbeth regressions, serial correlation in error terms are corrected using a Newey-West estimator with one-quarter lag. p-values are reported in parentheses. Superscript a, b, c denote statistical significance at 10%, 5%, and 1% levels.

Panel A	**EXCESS MARKET RETURN**				**DGTW RETURN**				**4-FACTOR ALPHA**			
	Lead 1 Qtr	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**	**Lead 1 Qtr**	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**	**Lead 1 Qtr**	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**
$IQ \equiv \theta_i^s$	1.360c	1.232c	1.140c	1.018c	1.333c	1.190c	1.083c	0.948c	0.895c	0.851c	0.844c	0.766c
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$IQ^2 \equiv \theta_i^{s\,2}$	-1.088c	-1.031c	-0.972c	-0.876c	-1.063c	-0.984c	-0.919c	-0.820c	-0.700c	-0.706c	-0.729c	-0.651c
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\Delta Breadth$	0.533c	0.248b	0.100	0.028	0.497c	0.241c	0.111	0.046	0.312c	0.231c	0.063	0.015
	(0.004)	(0.029)	(0.253)	(0.706)	(0.001)	(0.010)	(0.114)	(0.451)	(0.009)	(0.006)	(0.335)	(0.802)
$\Delta Active\ MF\ Ownership$	-0.062	-0.112a	-0.071	-0.044	-0.075	-0.099a	-0.071	-0.054	-0.044	-0.099a	-0.035	-0.016
	(0.372)	(0.060)	(0.231)	(0.366)	(0.264)	(0.055)	(0.174)	(0.222)	(0.512)	(0.053)	(0.496)	(0.711)
Holding Dispersion Index	-0.006	-0.058	-0.056	-0.028	-0.051	-0.072a	-0.062a	-0.033	-0.004	-0.072b	-0.052a	-0.011
	(0.906)	(0.116)	(0.102)	(0.320)	(0.296)	(0.057)	(0.064)	(0.231)	(0.933)	(0.034)	(0.091)	(0.663)
Ln(MCAP)	-0.832	-0.400	-0.294	-0.212	-1.006a	-0.464	-0.223	-0.063	-0.671	-0.440	-0.444	-0.399
	(0.129)	(0.327)	(0.366)	(0.438)	(0.051)	(0.191)	(0.418)	(0.770)	(0.322)	(0.431)	(0.323)	(0.323)
Ln(Book-to-Market)	0.674	0.824b	0.792c	0.791c	0.111	0.283	0.330a	0.370b	-0.024	0.231	0.357b	0.432c
	(0.176)	(0.015)	(0.002)	(0.001)	(0.739)	(0.201)	(0.058)	(0.014)	(0.915)	(0.177)	(0.021)	(0.002)
Prior Year Return	-0.590	-0.541	-0.511a	-0.500a	-0.313	-0.247	-0.241	-0.235	0.116	-0.012	-0.066	-0.114
	(0.219)	(0.166)	(0.098)	(0.059)	(0.309)	(0.233)	(0.153)	(0.101)	(0.474)	(0.918)	(0.510)	(0.214)
CRSP Turnover	-0.215	-0.443c	-0.442c	-0.466c	-0.082	-0.263b	-0.266b	-0.310c	-0.270	-0.441b	-0.495c	-0.544c
	(0.257)	(0.003)	(0.000)	(0.000)	(0.579)	(0.035)	(0.013)	(0.002)	(0.252)	(0.019)	(0.001)	(0.000)
Idiosyncratic Volatility	-0.430	-0.615	-0.620	-0.566a	-0.661a	-0.811c	-0.827c	-0.742c	-0.523	-0.861c	-0.966c	-0.943c
	(0.495)	(0.200)	(0.131)	(0.094)	(0.089)	(0.002)	(0.000)	(0.000)	(0.104)	(0.002)	(0.000)	(0.000)
Market Beta	-0.383	-0.325	-0.274a	-0.290a	-0.161	-0.146	-0.130	-0.146	-0.346c	-0.397c	-0.300c	-0.286c
	(0.264)	(0.162)	(0.096)	(0.061)	(0.443)	(0.344)	(0.214)	(0.138)	(0.003)	(0.000)	(0.001)	(0.000)
NOBS	201,235	197,921	194,636	191,422	201,110	197,676	194,276	190,944	204,070	200,913	197,688	194,504
R^2	0.042	0.051	0.052	0.055	0.007	0.013	0.020	0.026	0.008	0.017	0.023	0.029

Panel B			EXCESS MARKET RETURN				DGTW RETURN				4-FACTOR ALPHA			
			Lead 1 Qtr	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**	**Lead 1 Qtr**	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**	**Lead 1 Qtr**	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**
p	$\sigma(\theta)$	θ	1.360‡	1. 232‡	1.140‡	1.018‡	1.333‡	1.190‡	1.083‡	0.948‡	0.895‡	0.851‡	0.844‡	0.766‡
0.05		0.053	0.006	0.005	0.005	0.004	0.005	0.005	0.004	0.004	0.004	0.004	0.003	0.003
0.10		0.111	0.012	0.011	0.010	0.009	0.012	0.010	0.009	0.008	0.008	0.007	0.007	0.007
0.20		0.250	0.027	0.024	0.022	0.020	0.026	0.023	0.021	0.019	0.018	0.017	0.017	0.015
0.50		1.000	0.107	0.097	0.089	0.080	0.104	0.093	0.085	0.074	0.070	0.067	0.066	0.060
0.80		4.000	0.426	0.386	0.357	0.319	0.418	0.373	0.339	0.297	0.281	0.267	0.265	0.240
0.90		9.000	0.959	0.869	0.804	0.718	0.940	0.839	0.764	0.669	0.631	0.600	0.595	0.540
0.95		19.000	2.025	1.834	1.697	1.516	1.985	1.772	1.613	1.412	1.333	1.267	1.257	1.141
	12.760	**Hi-Lo**	2.019	1.829	1.693	1.512	1.979	1.767	1.608	1.408	1.329	1.264	1.253	1.137
p	$\sigma(\theta^2)$	θ^2	-1.088‡	-1.031‡	-0.972‡	-0.876‡	-1.063‡	-0.984‡	-0.919‡	-0.820‡	-0.700‡	-0.706‡	-0.729‡	-0.651‡
0.05		0.003	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
0.10		0.012	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
0.20		0.063	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
0.50		1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
0.80		16.000	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
0.90		81.000	-0.016	-0.015	-0.014	-0.013	-0.016	-0.015	-0.014	-0.012	-0.010	-0.010	-0.011	-0.010
0.95		361.00	-0.082	-0.078	-0.073	-0.066	-0.080	-0.074	-0.069	-0.062	-0.053	-0.053	-0.055	-0.049
	1,076.51	**Average**	-0.365	-0.346	-0.326	-0.294	-0.356	-0.330	-0.308	-0.275	-0.235	-0.237	-0.244	-0.218

Panel C	EXCESS MARKET RETURN				DGTW RETURN				4-FACTOR ALPHA			
	Lead 1 Qtr	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**	**Lead 1 Qtr**	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**	**Lead 1 Qtr**	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**
$IQ \equiv \theta_i^s$	1.198[c]	1.066[c]	0.977[c]	0.859[c]	1.225[c]	1.089[c]	0.990[c]	0.861[c]	0.992[c]	0.858[c]	0.825[c]	0.722[c]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$IO^2 \equiv {\theta_i^s}^2$	-0.909[c]	-0.881[c]	-0.829[c]	-0.738[c]	-0.965[c]	-0.915[c]	-0.858[c]	-0.759[c]	-0.776[c]	-0.719[c]	-0.725[c]	-0.623[c]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\Delta Breadth$	0.506[c]	0.282[c]	0.122	0.062	0.430[c]	0.209[a]	0.063	0.018	0.352[c]	0.223[b]	0.055	0.007
	(0.001)	(0.010)	(0.172)	(0.395)	(0.002)	(0.053)	(0.449)	(0.782)	(0.004)	(0.015)	(0.449)	(0.917)
$\Delta Active\ MF\ Ownership$	-0.148[b]	-0.154[c]	-0.085[a]	-0.076	-0.154[b]	-0.156[c]	-0.113[b]	-0.105[b]	-0.169[b]	-0.155[c]	-0.067	-0.047
	(0.049)	(0.005)	(0.073)	(0.103)	(0.039)	(0.005)	(0.010)	(0.019)	(0.038)	(0.005)	(0.127)	(0.304)
Holding Dispersion Index	-0.036	-0.081[b]	-0.070[a]	-0.039	-0.069	-0.083[a]	-0.068[a]	-0.038	-0.013	-0.072[a]	-0.054	-0.011
	(0.450)	(0.045)	(0.059)	(0.205)	(0.191)	(0.055)	(0.068)	(0.213)	(0.790)	(0.061)	(0.110)	(0.714)
Ln(MCAP)	-0.681[c]	-0.334[a]	-0.194	-0.079	-0.282[c]	0.136[a]	0.253[c]	0.331[c]	-0.618[c]	-0.339[a]	-0.210	-0.117
	(0.004)	(0.073)	(0.227)	(0.584)	(0.006)	(0.098)	(0.001)	(0.000)	(0.008)	(0.079)	(0.193)	(0.446)
Ln(Book-to-Market)	0.113	0.181	0.203	0.238	-0.123	-0.005	0.061	0.106	0.062	0.136	0.188	0.228[b]
	(0.617)	(0.363)	(0.245)	(0.114)	(0.289)	(0.967)	(0.525)	(0.198)	(0.644)	(0.289)	(0.132)	(0.045)
Prior Year Return	-0.102	-0.096	-0.112	-0.115	-0.098	-0.073	-0.075	-0.053	0.090	0.024	-0.014	-0.018
	(0.717)	(0.688)	(0.576)	(0.510)	(0.598)	(0.558)	(0.471)	(0.581)	(0.441)	(0.805)	(0.885)	(0.855)
CRSP Turnover	-0.147	-0.407[b]	-0.420[c]	-0.465[c]	-0.094	-0.320[b]	-0.327[c]	-0.372[c]	-0.177	-0.334[b]	-0.404[c]	-0.439[c]
	(0.483)	(0.016)	(0.002)	(0.000)	(0.586)	(0.017)	(0.003)	(0.000)	(0.284)	(0.023)	(0.001)	(0.000)
Idiosyncratic Volatility	-0.885[b]	-1.114[c]	-1.115[c]	-1.034[c]	-0.771[c]	-0.949[c]	-0.961[c]	-0.877[c]	-0.837[c]	-1.172[c]	-1.241[c]	-1.251[c]
	(0.014)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Market Beta	0.015	-0.031	-0.072	-0.141	0.060	0.029	-0.004	-0.056	-0.553[c]	-0.577[c]	-0.490[c]	-0.483[c]
	(0.953)	(0.873)	(0.627)	(0.299)	(0.766)	(0.853)	(0.973)	(0.605)	(0.001)	(0.000)	(0.000)	(0.000)
Constant	0.382	-0.640	-1.036[b]	-1.225[c]	-0.418	-1.406[c]	-1.693[c]	-1.807[c]	0.442[b]	-0.541[c]	-0.909[c]	-1.122[c]
	(0.504)	(0.196)	(0.014)	(0.001)	(0.204)	(0.000)	(0.000)	(0.000)	(0.019)	(0.009)	(0.000)	(0.000)
NOBS	201,235	197,921	194,636	191,422	201,110	197,676	194,276	190,944	204,070	200,913	197,688	194,504
R^2	0.067	0.073	0.077	0.080	0.031	0.036	0.038	0.041	0.029	0.038	0.045	0.052

Table VIII
Forecast Returns: Fund Performance using Management Fees

Table reports style and quarter fixed effects regressions of lead quarter buy-and-hold stock returns on investment quality and control variables. ‡indicates that management fees are used to proxy fund performance. The cross-product of active holding and management fees summed across funds is used to identify selection skill. Investment quality $IQ \equiv \theta_i^s$ is the odds ratio of a stock's relative percentile rank, θ_i^s, on selection skill. Average quarterly returns are expressed in percent. Variable definitions can be found in Table III. All variables are normalized by their standard deviations across the sample period. Control variables are demeaned. In two-way fixed effects regressions, errors are clustered by style and quarter. p-values are reported in parentheses. Superscript [a, b, c] denote statistical significance at 10%, 5%, and 1% levels.

	EXCESS MARKET RETURN				**DGTW RETURN**				**4-FACTOR ALPHA**			
	Lead 1 Qtr	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**	**Lead 1 Qtr**	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**	**Lead 1 Qtr**	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**
$IQ^{\ddagger} \equiv \theta_i^s$	1.328[c]	1.283[c]	1.145[c]	1.077[c]	1.364[c]	1.273[c]	1.110[c]	1.022[c]	0.881[c]	0.960[c]	0.912[c]	0.881[c]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$IO^2 \equiv \theta_i^{s\,2}$	-1.106[c]	-1.107[c]	-1.001[c]	-0.971[c]	-1.136[c]	-1.088[c]	-0.961[c]	-0.916[c]	-0.747[c]	-0.856[c]	-0.828[c]	-0.803[c]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\Delta Breadth$	0.529[c]	0.243[b]	0.096	0.024	0.492[c]	0.236[b]	0.107	0.042	0.309[c]	0.228[c]	0.060	0.011
	(0.005)	(0.032)	(0.273)	(0.748)	(0.001)	(0.011)	(0.128)	(0.492)	(0.009)	(0.006)	(0.357)	(0.845)
$\Delta Active\ MF\ Ownership$	-0.060	-0.110[a]	-0.069	-0.043	-0.073	-0.097[a]	-0.070	-0.053	-0.043	-0.098[a]	-0.034	-0.015
	(0.385)	(0.064)	(0.241)	(0.382)	(0.275)	(0.059)	(0.184)	(0.235)	(0.520)	(0.057)	(0.510)	(0.731)
Holding Dispersion Index	-0.002	-0.054	-0.053	-0.025	-0.047	-0.068[a]	-0.059[a]	-0.030	-0.000	-0.068[b]	-0.050	-0.009
	(0.970)	(0.141)	(0.120)	(0.375)	(0.341)	(0.073)	(0.079)	(0.278)	(0.993)	(0.045)	(0.110)	(0.736)
Ln(MCAP)	-0.814	-0.388	-0.282	-0.206	-0.988[a]	-0.454	-0.211	-0.057	-0.658	-0.437	-0.439	-0.400
	(0.138)	(0.343)	(0.388)	(0.450)	(0.055)	(0.202)	(0.443)	(0.789)	(0.330)	(0.434)	(0.328)	(0.323)
Ln(Book-to-Market)	0.670	0.825[b]	0.792[c]	0.791[c]	0.110	0.285	0.330[a]	0.371[b]	-0.032	0.230	0.358[b]	0.433[c]
	(0.179)	(0.015)	(0.002)	(0.001)	(0.741)	(0.198)	(0.058)	(0.014)	(0.889)	(0.182)	(0.021)	(0.002)
Prior Year Return	-0.592	-0.542	-0.513[a]	-0.501[a]	-0.315	-0.247	-0.243	-0.237[a]	0.116	-0.012	-0.067	-0.114
	(0.217)	(0.166)	(0.098)	(0.058)	(0.306)	(0.233)	(0.152)	(0.099)	(0.480)	(0.921)	(0.505)	(0.215)
CRSP Turnover	-0.225	-0.456[c]	-0.452[c]	-0.478[c]	-0.095	-0.278[b]	-0.276[b]	-0.321[c]	-0.278	-0.453[b]	-0.504[c]	-0.555[c]
	(0.233)	(0.003)	(0.000)	(0.000)	(0.522)	(0.026)	(0.010)	(0.002)	(0.240)	(0.016)	(0.000)	(0.000)
Idiosyncratic Volatility	-0.417	-0.608	-0.615	-0.563[a]	-0.650[a]	-0.804[c]	-0.823[c]	-0.740[c]	-0.513	-0.856[c]	-0.963[c]	-0.939[c]
	(0.509)	(0.206)	(0.135)	(0.096)	(0.095)	(0.003)	(0.000)	(0.000)	(0.113)	(0.002)	(0.000)	(0.000)
Market Beta	-0.386	-0.327	-0.275[a]	-0.292[a]	-0.164	-0.148	-0.131	-0.148	-0.350[c]	-0.400[c]	-0.301[c]	-0.288[c]
	(0.261)	(0.160)	(0.095)	(0.059)	(0.436)	(0.339)	(0.210)	(0.133)	(0.002)	(0.000)	(0.001)	(0.000)
NOBS	201,234	197,922	194,637	191,422	201,110	197,677	194,277	190,944	204,070	200,913	197,689	194,505
R^2	0.042	0.051	0.052	0.055	0.007	0.013	0.020	0.026	0.008	0.017	0.023	0.029

Table IX
Forecast Returns: Investment Quality of Stocks by Market Capitalization

Table Panel A reports two-way fixed effects regressions of lead quarter buy-and-hold stock returns on the investment quality of small cap, midcap and large cap stocks, as well as control variables. Panel B reports forecasted returns at selected percentiles of selection quality between the 5th and the 95th percentiles for each tercile of market capitalization.‡ indicates estimated coefficients from Panel A. Stocks are sorted into terciles by market capitalization using NYSE stocks to establish breakpoints. The cross-product of active holding and GVA summed across funds is used to identify selection skill. Investment quality $IQ \equiv \theta_i^s$ is the odds ratio of a stock's relative percentile rank, θ_i^s, on selection skill. Average quarterly returns are expressed in percent. Variable definitions can be found in Table III. All variables are normalized by their standard deviations across the sample period. Control variables are demeaned. Errors are clustered by style and quarter. p-values are reported in parentheses. Superscript [a, b, c] denote statistical significance at 10%, 5%, and 1% levels. Unreported estimated coefficients on control variables are reported in an Appendix.

	EXCESS MARKET RETURN				DGTW RETURN				4-FACTOR ALPHA			
Panel A	**Lead 1 Qtr**	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**	**Lead 1 Qtr**	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**	**Lead 1 Qtr**	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**
$IQ \times Small\ Cap$	1.569[c]	1.447[c]	1.304[c]	1.135[c]	1.557[c]	1.385[c]	1.227[c]	1.050[c]	1.020[c]	0.968[c]	0.960[c]	0.844[c]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$IQ \times Mid\ Cap$	1.306[c]	1.089[c]	1.007[c]	0.911[c]	1.304[c]	1.081[c]	0.972[c]	0.879[c]	0.890[c]	0.789[c]	0.784[c]	0.733[c]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$IQ \times Large\ Cap$	1.114[c]	1.076[c]	1.053[c]	0.971[c]	1.037[c]	1.028[c]	0.999[c]	0.881[c]	0.718[c]	0.749[c]	0.743[c]	0.690[c]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$IQ^2 \equiv \theta_i^{s\,2}$	-1.241[c]	-1.185[c]	-1.088[c]	-0.958[c]	-1.228[c]	-1.124[c]	-1.021[c]	-0.892[c]	-0.791[c]	-0.789[c]	-0.812[c]	-0.708[c]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\Delta Breadth$	0.533[c]	0.248[b]	0.100	0.028	0.497[c]	0.241[c]	0.111	0.046	0.312[c]	0.231[c]	0.063	0.015
	(0.005)	(0.029)	(0.252)	(0.704)	(0.001)	(0.010)	(0.113)	(0.449)	(0.009)	(0.006)	(0.334)	(0.800)
$\Delta Active\ MF\ Ownership$	-0.062	-0.112[a]	-0.071	-0.044	-0.075	-0.099[a]	-0.071	-0.054	-0.044	-0.099[a]	-0.035	-0.016
	(0.373)	(0.061)	(0.231)	(0.367)	(0.264)	(0.055)	(0.175)	(0.223)	(0.513)	(0.054)	(0.496)	(0.711)
Holding Dispersion Index	-0.006	-0.058	-0.056	-0.028	-0.051	-0.072[a]	-0.062[a]	-0.033	-0.004	-0.072[b]	-0.052[a]	-0.011
	(0.902)	(0.115)	(0.100)	(0.317)	(0.295)	(0.056)	(0.064)	(0.230)	(0.931)	(0.034)	(0.090)	(0.661)
NOBS	201,235	197,921	194,636	191,422	201,110	197,676	194,276	190,944	204,070	200,913	197,688	194,504
R^2	0.042	0.051	0.052	0.055	0.007	0.013	0.020	0.026	0.008	0.017	0.023	0.029
$Large/Small\ Cap$	71.00%	74.36%	80.75%	85.55%	66.60%	74.22%	81.42%	83.90%	70.39%	77.38%	77.40%	81.75%
$Mid\ Cap/Small\ Cap$	83.24%	75.26%	77.22%	80.26%	83.75%	78.05%	79.22%	83.71%	87.25%	81.51%	81.67%	86.85%

Panel B			EXCESS MARKET RETURN				DGTW RETURN				4-FACTOR ALPHA			
p	$\sigma(\theta)$	θ	Lead 1 Qtr	Lead 2 Qtr	Lead 3 Qtr	Lead 4 Qtr	Lead 1 Qtr	Lead 2 Qtr	Lead 3 Qtr	Lead 4 Qtr	Lead 1 Qtr	Lead 2 Qtr	Lead 3 Qtr	Lead 4 Qtr
Small Cap			1.569‡	1.447‡	1.304‡	1.135‡	1.557‡	1.385‡	1.227‡	1.050‡	1.020‡	0.968‡	0.960‡	0.844‡
0.05		0.053	0.006	0.006	0.005	0.005	0.006	0.006	0.005	0.004	0.004	0.004	0.004	0.003
0.10		0.111	0.014	0.013	0.011	0.010	0.014	0.012	0.011	0.009	0.009	0.008	0.008	0.007
0.20		0.250	0.031	0.028	0.026	0.022	0.031	0.027	0.024	0.021	0.020	0.019	0.019	0.017
0.50		1.000	0.123	0.113	0.102	0.089	0.122	0.109	0.096	0.082	0.080	0.076	0.075	0.066
0.80		4.000	0.492	0.454	0.409	0.356	0.488	0.434	0.385	0.329	0.320	0.303	0.301	0.265
0.90		9.000	1.107	1.021	0.920	0.801	1.098	0.977	0.865	0.741	0.719	0.683	0.677	0.595
0.95		19.000	2.336	2.155	1.942	1.690	2.318	2.062	1.827	1.563	1.519	1.441	1.429	1.257
	12.760	**Hi-Lo**	2.330	2.149	1.936	1.685	2.312	2.057	1.822	1.559	1.515	1.437	1.425	1.253
Mid Cap			1.306‡	1.089‡	1.007‡	0.911‡	1.304‡	1.081‡	0.972‡	0.879‡	0.890‡	0.789‡	0.784‡	0.733‡
0.05		0.053	0.005	0.004	0.004	0.004	0.005	0.004	0.004	0.004	0.004	0.003	0.003	0.003
0.10		0.111	0.011	0.009	0.009	0.008	0.011	0.009	0.008	0.008	0.008	0.007	0.007	0.006
0.20		0.250	0.026	0.021	0.020	0.018	0.026	0.021	0.019	0.017	0.017	0.015	0.015	0.014
0.50		1.000	0.102	0.085	0.079	0.071	0.102	0.085	0.076	0.069	0.070	0.062	0.061	0.057
0.80		4.000	0.409	0.341	0.316	0.286	0.409	0.339	0.305	0.276	0.279	0.247	0.246	0.230
0.90		9.000	0.921	0.768	0.710	0.643	0.920	0.762	0.686	0.620	0.628	0.556	0.553	0.517
0.95		19.000	1.945	1.622	1.499	1.356	1.942	1.610	1.447	1.309	1.325	1.175	1.167	1.091
	12.760	**Hi-Lo**	1.939	1.617	1.495	1.353	1.936	1.605	1.443	1.305	1.322	1.172	1.164	1.088
Large Cap			1.114‡	1.076‡	1.053‡	0.971‡	1.037‡	1.028‡	0.999‡	0.881‡	0.718‡	0.749‡	0.743‡	0.690‡
0.05		0.053	0.005	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.003	0.003	0.003	0.003
0.10		0.111	0.010	0.009	0.009	0.008	0.009	0.009	0.009	0.008	0.006	0.007	0.006	0.006
0.20		0.250	0.022	0.021	0.021	0.019	0.020	0.020	0.020	0.017	0.014	0.015	0.015	0.014
0.50		1.000	0.087	0.084	0.083	0.076	0.081	0.081	0.078	0.069	0.056	0.059	0.058	0.054
0.80		4.000	0.349	0.337	0.330	0.304	0.325	0.322	0.313	0.276	0.225	0.235	0.233	0.216
0.90		9.000	0.786	0.759	0.743	0.685	0.731	0.725	0.705	0.621	0.506	0.528	0.524	0.487
0.95		19.000	1.659	1.602	1.568	1.446	1.544	1.531	1.488	1.312	1.069	1.115	1.106	1.027
	12.760	**Hi-Lo**	1.654	1.598	1.564	1.442	1.540	1.526	1.483	1.308	1.066	1.112	1.103	1.025

Table X

Forecast Returns: Investment Quality and Conviction Quality of Stocks

Table reports two-way fixed effects regressions of lead quarter buy-and-hold stock returns on investment quality and conviction quality, as well as control variables. Panel A presents the average effect of investment quality and conviction quality. Panel B presents the interaction of investment quality and conviction quality. Panel C presents summary statistics on conviction quality in the selected percentiles between the 5th and the 95th percentiles. The cross-product of active holding and GVA summed across funds is used to identify selection skill. Investment quality $IQ \equiv \theta_i^s$ is the odds ratio of a stock's relative percentile rank, θ_i^s, on selection skill. The cross-product of active holding turnover and GVA summed across funds is used to identify active turnover – the patience and conviction of fund managers. Conviction quality $Turn \equiv \theta_i^\pi$ is the odds ratio of a stock's relative percentile rank, θ_i^π, on active turnover. Each quarter, Hi_IQ equals 1 when investment quality is above median and 0 otherwise, Lo_IQ equals 1 when investment quality is below median and 0 otherwise. Interaction terms of Hi_IQ with conviction quality and Lo_IQ with conviction quality are used as regressors in Panel B. Average quarterly returns are expressed in percent. Variable definitions can be found in Table III. All variables are normalized by their standard deviations across the sample period. Control variables are demeaned. Errors are clustered by style and quarter. p-values are reported in parentheses. Superscripts [a, b, c] denote statistical significance at 10%, 5%, and 1% levels. Unreported estimated coefficients on control variables are reported in an Appendix.

	EXCESS MARKET RETURN				DGTW RETURN				4-FACTOR ALPHA			
Panel A	**Lead 1 Qtr**	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**	**Lead 1 Qtr**	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**	**Lead 1 Qtr**	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**
$IQ \equiv \theta_i^s$	1.320[c]	1.202[c]	1.092[c]	0.983[c]	1.282[c]	1.128[c]	1.022[c]	0.900[c]	0.888[c]	0.841[c]	0.795[c]	0.731[c]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Turn \equiv \theta_i^\pi$	-1.007[c]	-0.939[c]	-0.861[c]	-0.797[c]	-0.970[c]	-0.875[c]	-0.809[c]	-0.735[c]	-0.684[c]	-0.669[c]	-0.647[c]	-0.603[c]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$IQ^2 \equiv \theta_i^{s\,2}$	-0.407[c]	-0.307[c]	-0.229[c]	-0.199[c]	-0.348[c]	-0.239[c]	-0.171[c]	-0.151[c]	-0.199[c]	-0.127[b]	-0.085	-0.067
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.026)	(0.116)	(0.171)
$\Delta Breadth$	0.361[b]	0.185[a]	0.047	-0.020	0.379[c]	0.199[b]	0.089	0.016	0.269[b]	0.217[b]	0.060	0.002
	(0.019)	(0.082)	(0.564)	(0.769)	(0.004)	(0.034)	(0.199)	(0.783)	(0.017)	(0.011)	(0.334)	(0.973)
$\Delta Active\ MF\ Ownership$	-0.039	-0.094	-0.047	-0.018	-0.061	-0.079	-0.051	-0.029	-0.041	-0.095[a]	-0.027	-0.003
	(0.540)	(0.112)	(0.413)	(0.706)	(0.367)	(0.106)	(0.295)	(0.513)	(0.557)	(0.083)	(0.609)	(0.939)
Holding Dispersion Index	0.024	-0.047	-0.039	-0.012	-0.021	-0.052	-0.042	-0.014	0.036	-0.054	-0.037	0.004
	(0.605)	(0.192)	(0.251)	(0.652)	(0.629)	(0.138)	(0.176)	(0.568)	(0.400)	(0.108)	(0.209)	(0.883)
NOBS	181,967	179,045	176,154	173,311	181,852	178,822	175,808	172,855	184,465	181,672	178,830	176,027
R^2	0.036	0.043	0.044	0.046	0.005	0.012	0.019	0.024	0.008	0.016	0.021	0.027
Relative to Lead 1 Qtr	1.000	0.911	0.827	0.745	1.000	0.880	0.797	0.702	1.000	0.947	0.895	0.823

Panel B	EXCESS MARKET RETURN				DGTW RETURN				4-FACTOR ALPHA			
	Lead 1 Qtr	Lead 2 Qtr	Lead 3 Qtr	Lead 4 Qtr	Lead 1 Qtr	Lead 2 Qtr	Lead 3 Qtr	Lead 4 Qtr	Lead 1 Qtr	Lead 2 Qtr	Lead 3 Qtr	Lead 4 Qtr
$Hi\_IQ \times Turn$	-0.421[c]	-0.321[c]	-0.256[c]	-0.227[c]	-0.359[c]	-0.243[c]	-0.187[c]	-0.169[c]	-0.183[c]	-0.117[a]	-0.086	-0.075
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.051)	(0.137)	(0.137)
$Lo\_IQ \times Turn$	-0.207	-0.115	0.021	0.046	-0.165	-0.109	0.015	0.032	-0.202	-0.097	-0.007	0.043
	(0.288)	(0.398)	(0.862)	(0.672)	(0.362)	(0.384)	(0.890)	(0.748)	(0.209)	(0.512)	(0.956)	(0.738)
$IQ^2 \equiv \theta_i^{s\,2}$	0.200[b]	0.160[b]	0.123[b]	0.086[a]	0.205[c]	0.168[c]	0.122[c]	0.082[a]	0.155[b]	0.120[a]	0.090	0.067
	(0.011)	(0.017)	(0.019)	(0.094)	(0.005)	(0.009)	(0.010)	(0.087)	(0.034)	(0.056)	(0.106)	(0.212)
$\Delta Breadth$	0.363[b]	0.186[a]	0.048	-0.019	0.381[c]	0.200[b]	0.089	0.017	0.271[b]	0.218[b]	0.060	0.002
	(0.019)	(0.081)	(0.561)	(0.774)	(0.004)	(0.033)	(0.196)	(0.777)	(0.017)	(0.010)	(0.330)	(0.966)
$\Delta Active\ MF\ Ownership$	-0.036	-0.091	-0.044	-0.016	-0.057	-0.076	-0.049	-0.027	-0.039	-0.093[a]	-0.025	-0.002
	(0.573)	(0.125)	(0.443)	(0.745)	(0.390)	(0.119)	(0.320)	(0.546)	(0.578)	(0.090)	(0.635)	(0.971)
Holding Dispersion Index	0.019	-0.051	-0.043	-0.016	-0.026	-0.055	-0.045	-0.017	0.034	-0.056[a]	-0.039	0.001
	(0.681)	(0.160)	(0.210)	(0.557)	(0.567)	(0.117)	(0.148)	(0.486)	(0.433)	(0.097)	(0.185)	(0.960)
NOBS	181,967	179,045	176,154	173,311	181,852	178,822	175,808	172,855	184,465	181,672	178,830	176,027
R^2	0.036	0.042	0.043	0.045	0.005	0.012	0.018	0.023	0.008	0.015	0.021	0.027

Panel C					
Active Turnover Percentile Rank p	**Change in Holdings (ΔAH)**	**GVA**	$\rho\left(\frac{\Delta AH,}{GVA}\right)$	**MCAP**	**Book-to-Market**
0.05	0.016	5.40	0.008	5,136	0.850
0.10	0.031	5.86	-0.002	4,900	0.731
0.20	0.036	5.91	-0.015	7,326	0.699
0.50	0.031	5.38	-0.021	3,811	0.703
0.80	0.034	5.91	-0.003	6,721	0.683
0.90	0.030	5.74	0.011	5,587	0.737
0.95	0.016	5.38	0.027	4,245	0.814

Table XI

Forecast Returns: Investment Quality and Conviction Quality of Stocks by Market Capitalization

Table reports two-way fixed effects regressions of lead quarter buy-and-hold stock returns on the investment quality and conviction quality of small cap, midcap and large cap stocks, as well as control variables. Average quarterly returns are expressed in percent. Stocks are sorted into terciles by market capitalization using NYSE stocks to establish breakpoint. The cross-product of active holding and GVA summed across funds is used to identify selection skill. Investment quality $IQ \equiv \theta_i^s$ is the odds ratio of a stock's relative percentile rank, θ_i^s, on selection skill. The cross-product of active holding turnover and GVA summed across funds is used to identify active turnover – the patience and conviction of fund managers. Conviction quality $Turn \equiv \theta_i^\pi$ is the odds ratio of a stock's relative percentile rank, θ_i^π, on active turnover. Variable definitions can be found in Table III. All variables are normalized by their standard deviations across the sample period. Control variables are demeaned. Errors are clustered by style and quarter. p-values are reported in parentheses. Superscript $^{a, b, c}$ denote statistical significance at 10%, 5%, and 1% levels. Unreported estimated coefficients on control variables are reported in an Appendix.

	EXCESS MARKET RETURN				**DGTW RETURN**				**4-FACTOR ALPHA**			
	Lead 1 Qtr	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**	**Lead 1 Qtr**	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**	**Lead 1 Qtr**	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**
$IQ \times Small\ Cap$	1.422^{c}	1.342^{c}	1.215^{c}	1.085^{c}	1.408^{c}	1.263^{c}	1.136^{c}	0.994^{c}	0.939^{c}	0.921^{c}	0.903^{c}	0.829^{c}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$IQ \times Midcap$	1.297^{c}	1.105^{c}	1.079^{c}	0.993^{c}	1.353^{c}	1.093^{c}	1.039^{c}	0.941^{c}	1.075^{c}	0.967^{c}	0.957^{c}	0.903^{c}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$IQ \times Large\ Cap$	1.283^{c}	1.289^{c}	1.213^{c}	1.100^{c}	1.178^{c}	1.141^{c}	1.090^{c}	0.963^{c}	0.833^{c}	0.875^{c}	0.813^{c}	0.755^{c}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IQ^2	-1.083^{c}	-1.043^{c}	-0.956^{c}	-0.876^{c}	-1.067^{c}	-0.975^{c}	-0.897^{c}	-0.809^{c}	-0.729^{c}	-0.735^{c}	-0.735^{c}	-0.686^{c}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Turn \times Small\ Cap$	-0.400^{c}	-0.292^{c}	-0.208^{c}	-0.179^{c}	-0.336^{c}	-0.226^{c}	-0.153^{c}	-0.134^{c}	-0.184^{c}	-0.107^{a}	-0.062	-0.043
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)	(0.064)	(0.258)	(0.378)
$Turn \times Midcap$	-0.475	-0.332	-0.637^{a}	-0.673^{b}	-0.615	-0.397	-0.592	-0.602^{a}	-0.738	-0.750^{a}	-0.953^{b}	-0.991^{c}
	(0.326)	(0.362)	(0.082)	(0.047)	(0.189)	(0.249)	(0.105)	(0.068)	(0.156)	(0.055)	(0.014)	(0.009)
$Turn \times Large\ Cap$	-0.720	-1.133^{c}	-1.146^{c}	-1.007^{c}	-0.790^{c}	-0.848^{b}	-0.912^{c}	-0.824^{c}	-0.745^{b}	-0.889^{c}	-0.882^{c}	-0.813^{c}
	(0.174)	(0.003)	(0.000)	(0.000)	(0.003)	(0.011)	(0.001)	(0.001)	(0.011)	(0.008)	(0.002)	(0.002)
$\Delta Breadth$	0.361^{b}	0.186^{a}	0.048	-0.019	0.379^{c}	0.199^{b}	0.089	0.017	0.269^{b}	0.217^{b}	0.060	0.002
	(0.020)	(0.082)	(0.560)	(0.774)	(0.004)	(0.034)	(0.196)	(0.778)	(0.017)	(0.011)	(0.332)	(0.968)
$\Delta Active\ MF\ Ownership$	-0.039	-0.094	-0.047	-0.019	-0.061	-0.080	-0.052	-0.029	-0.042	-0.096^{a}	-0.028	-0.004
	(0.537)	(0.109)	(0.405)	(0.695)	(0.363)	(0.104)	(0.289)	(0.503)	(0.550)	(0.080)	(0.596)	(0.923)
Holding Dispersion Index	0.024	-0.046	-0.038	-0.011	-0.021	-0.051	-0.041	-0.013	0.037	-0.053	-0.035	0.005
	(0.601)	(0.198)	(0.264)	(0.678)	(0.638)	(0.143)	(0.186)	(0.592)	(0.390)	(0.117)	(0.228)	(0.843)
NOBS	181,967	179,045	176,154	173,311	181,852	178,822	175,808	172,855	184,465	181,672	178,830	176,027
R^2	0.036	0.043	0.044	0.046	0.005	0.013	0.019	0.024	0.008	0.016	0.022	0.027

Table XII

Forecast Returns: Investment Quality and Conviction Quality predicted from funds in GVA terciles

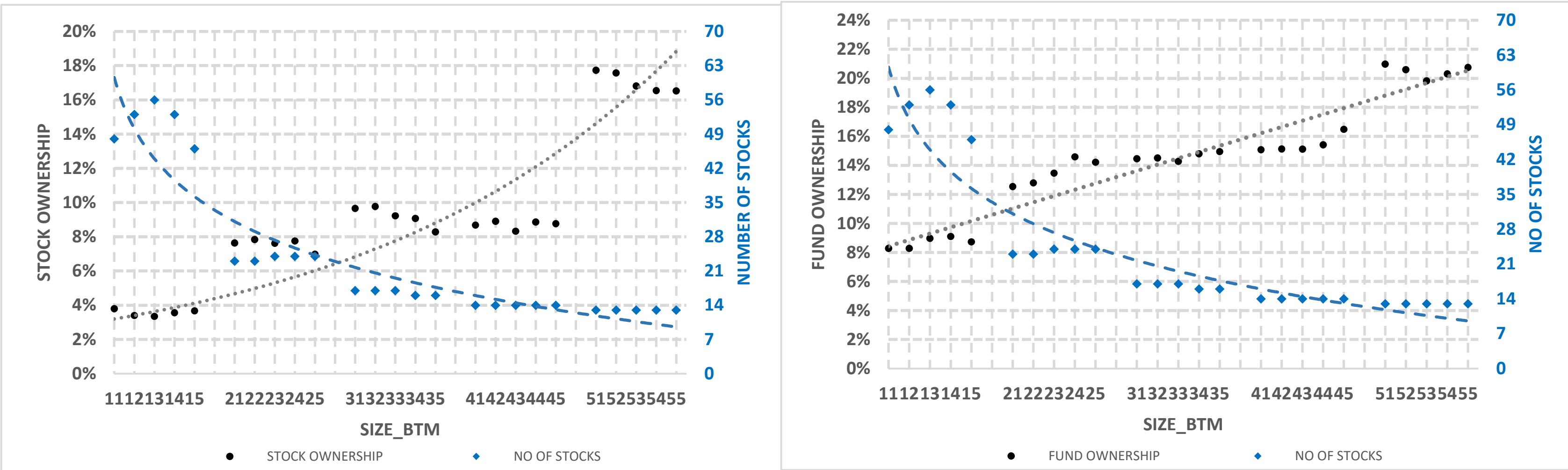
Table reports two-way fixed effects regressions of lead quarter buy-and-hold stock returns on the investment quality and conviction quality estimated from three fund GVA terciles, as well as control variables. At the end of each quarter, funds are sorted into terciles by their GVAs. The cross-products of active holding and GVA summed across funds in each tercile are used to identify selection skill. Investment quality $IQ \equiv \theta_i^s$ is the odds ratio of a stock's relative percentile rank, θ_i^s, on selection skill. The cross-products of active holding turnover and GVA summed across funds in each tercile are used to identify active turnover – the patience and conviction of fund managers. Conviction quality $Turn \equiv \theta_i^\pi$ is the odds ratio of a stock's relative percentile rank, θ_i^π, on active turnover. Variable definitions can be found in Table III. All variables are normalized by their standard deviations across the sample period. Control variables are demeaned. Errors are clustered by style and quarter. Average quarterly returns are expressed in percent. p-values are reported in parentheses. Superscript [a, b, c] denote statistical significance at 10%, 5%, and 1% levels. Unreported estimated coefficients on control variables are reported in an Appendix.

	EXCESS MARKET RETURN				**DGTW RETURN**				**4-FACTOR ALPHA**			
	Lead 1 Qtr	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**	**Lead 1 Qtr**	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**	**Lead 1 Qtr**	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**
IQ: top GVA tercile	0.356^{c}	0.334^{c}	0.298^{c}	0.245^{c}	0.376^{c}	0.336^{c}	0.290^{c}	0.238^{c}	0.243^{c}	0.241^{c}	0.220^{c}	0.197^{c}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.001)
IQ: middle GVA tercile	0.074	0.064	0.092^{b}	0.101^{c}	0.109^{a}	0.088^{a}	0.094^{b}	0.102^{c}	0.078	0.085	0.099^{b}	0.108^{b}
	(0.276)	(0.193)	(0.045)	(0.008)	(0.092)	(0.054)	(0.032)	(0.005)	(0.230)	(0.102)	(0.041)	(0.012)
IQ: bottom GVA tercile	-0.085	-0.091	-0.058	-0.014	-0.077	-0.023	-0.004	0.032	0.142^{a}	0.134^{a}	0.154^{b}	0.157^{c}
	(0.474)	(0.296)	(0.442)	(0.811)	(0.476)	(0.741)	(0.943)	(0.529)	(0.077)	(0.065)	(0.025)	(0.005)
$Turn$: top GVA tercile	-0.312^{c}	-0.298^{c}	-0.239^{c}	-0.217^{c}	-0.287^{c}	-0.285^{c}	-0.227^{c}	-0.215^{c}	-0.209^{c}	-0.207^{c}	-0.197^{b}	-0.184^{c}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.012)	(0.004)
$Turn$: middle GVA	-0.044	0.051	0.049	0.047	-0.015	0.088^{a}	0.085	0.088	-0.022	0.068	0.095	0.098
	(0.529)	(0.396)	(0.498)	(0.445)	(0.817)	(0.100)	(0.174)	(0.109)	(0.807)	(0.270)	(0.198)	(0.132)
$Turn$: bottom GVA	-0.185^{a}	-0.115	-0.098	-0.109	-0.132	-0.065	-0.033	-0.034	-0.030	0.050	0.058	0.042
	(0.094)	(0.190)	(0.189)	(0.124)	(0.122)	(0.306)	(0.558)	(0.544)	(0.663)	(0.423)	(0.301)	(0.419)
IQ^2: top GVA tercile	0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	0.000	-0.000	-0.000	-0.000
	(0.853)	(0.239)	(0.195)	(0.352)	(0.853)	(0.282)	(0.135)	(0.233)	(0.701)	(0.400)	(0.277)	(0.411)
IQ^2: middle GVA tercile	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	0.000	-0.000	0.000	0.000	-0.000	-0.000
	(0.532)	(0.453)	(0.392)	(0.193)	(0.559)	(0.772)	(0.953)	(0.701)	(0.847)	(0.947)	(0.473)	(0.282)
IQ^2: bottom GVA tercile	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.166)	(0.153)	(0.516)	(0.269)	(0.236)	(0.221)	(0.753)	(0.501)	(0.410)	(0.167)	(0.185)	(0.116)
NOBS	181,785	178,871	175,989	173,153	181,671	178,649	175,644	172,697	184,268	181,490	178,656	175,862
R^2	0.036	0.042	0.043	0.045	0.005	0.012	0.018	0.023	0.008	0.016	0.021	0.027

Table XIII
Cumulative Abnormal Returns around Earnings Announcements

Table reports two-way fixed effects regressions of cumulative abnormal returns (CAR1) in the three-day window [-1, 1] around earnings announcement dates each quarter, and cumulative abnormal returns (CAR2) beginning from the third day post-earnings announcement date to the earlier of the day prior to the earnings announcement date in the subsequent quarter or the 60th day post earnings announcement date. Earnings data and earnings announcement dates are from the IBES database. At June end of each year t, stocks are sorted into 2×3 benchmark portfolios by size (ME) and book-to-market equity (BE/ME). Median ME on NYSE stocks and 30th and 70th percentiles of BE/ME on NYSE stocks, computed as book equity in the last fiscal year end in $t-1$ divided by ME in December of $t-1$, are used as breakpoints. Abnormal returns are computed as daily returns in excess of the benchmark portfolio to which the stock belongs. Daily portfolio returns are value-weighted daily abnormal returns across stocks in the portfolio. p-values are reported in parentheses. Superscript [a, b, c] denote statistical significance at 10%, 5%, and 1% levels.

	CAR1 [-1, 1]	**CAR2 [3, 60]**			
	Lead 1 Qtr	**Lead 1 Qtr**	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**
$IQ \equiv \theta_i^s$	0.198[c]	0.502[c]	0.555[c]	0.475[b]	0.313
	(0.002)	(0.003)	(0.002)	(0.014)	(0.104)
$IQ^2 \equiv \theta_i^{s\,2}$	-0.211[c]	-0.375[b]	-0.520[c]	-0.426[b]	-0.256
	(0.002)	(0.018)	(0.001)	(0.025)	(0.197)
$\Delta Breadth$	0.148[c]	0.030	-0.096	-0.134[a]	0.050
	(0.000)	(0.818)	(0.277)	(0.080)	(0.542)
$\Delta Active\ MF\ Ownership$	-0.035	0.005	-0.058	-0.080	-0.175[b]
	(0.408)	(0.966)	(0.520)	(0.286)	(0.032)
Holding Dispersion Index	0.004	-0.089[b]	-0.004	-0.049	-0.014
	(0.813)	(0.020)	(0.934)	(0.274)	(0.755)
Ln(MCAP)	0.079	0.318	-0.215	-0.142	-0.376[a]
	(0.307)	(0.216)	(0.371)	(0.570)	(0.094)
Ln(Book-to-Market)	0.052	-0.124	-0.128	-0.125	-0.198
	(0.223)	(0.487)	(0.468)	(0.476)	(0.219)
Prior Year Return	-0.032	-0.370[a]	-0.143	-0.038	0.056
	(0.449)	(0.067)	(0.418)	(0.801)	(0.675)
CRSP Turnover	-0.181[c]	-0.168	-0.128	-0.182	-0.122
	(0.000)	(0.365)	(0.456)	(0.311)	(0.441)
Idiosyncratic Volatility	0.094	1.035[c]	0.724[c]	0.606[c]	0.613[c]
	(0.208)	(0.000)	(0.004)	(0.006)	(0.000)
Market Beta	-0.020	0.009	0.129	0.109	0.043
	(0.505)	(0.950)	(0.410)	(0.479)	(0.760)
NOBS	136,775	136,777	132,710	128,824	124,965
R^2	0.002	0.012	0.011	0.011	0.011



PANEL A

PANEL B

Figure 1: Characteristics of Fund Ownership of Stocks by Style Segments

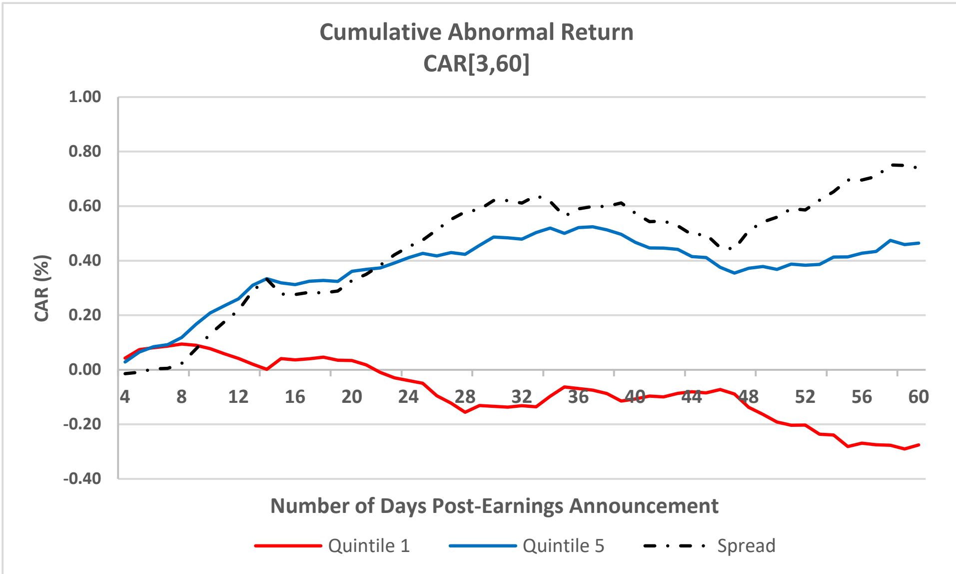


Figure 2: Cumulative Abnormal Returns on Stocks sorted into Quintiles by Stock IQ

APPENDIX

Table I: Variable Definitions

Style Segments: Cutoffs from annual DGTW (Daniel et al. 1997) sorts in July each year of stocks into quintiles by size, industry-adjusted book-to-market, and momentum are used to assign every CRSP stock i into $k = 125$ style segments each quarter over our 72-quarter sample period 2000-2017.

Active Holding: Fund holding of stock i owned by fund j, $h_{i(k),j}$, is the market value of stock i owned by fund j as a percentage of all stock holdings of fund j in segment style k minus the peer group weight of stock i in segment style k.

$$h_{i(k),j} = \left(shrown_{i(k),j} \cdot prc_{i(k)}\right) / \sum_{i(k)\epsilon I(j,k)} \left(shrown_{i(k),j} \cdot prc_{i(k)}\right)$$

where $prc_{i(k)}$ and $shrown_{i(k),j}$ denote the price and shares of stock i in style segment k owned by fund j. Peer group holding, $\bar{h}_{i(k)}$, is the total market value of stock i owned by all actively managed mutual funds j as a percentage of the total market value of all stocks in segment style k owned by all actively managed mutual funds j.

$$\bar{h}_{i(k)} = \sum_{j\epsilon J(k)} \left(shrown_{i(k),j} \cdot prc_{i(k)}\right) / \sum_{j\epsilon J(k)} \sum_{i(k)\epsilon I(j,k)} \left(shrown_{i(k),j} \cdot prc_{i(k)}\right)$$

where $j\epsilon J(k)$ are the set of funds that own stocks in style segment k. Active holding, w_{ij}, is the deviation of fund from peer group holding of stock i in style segment k.

$$w_{i,j} = h_{i(k),j} - \bar{h}_{i(k)}$$

Active Holdings Turnover: Active turnover of stock i owned by fund j is the difference in active holding between the current and prior 4 quarters.

Investment Quality: For stock *i*, the sum product of active holdings and fund quality over all funds in the style segment which stock *I* belongs to. We use the odds ratio of the sum product as investment quality in the regressions.

Conviction Quality: For stock *i*, the sum product of active holdings turnover and fund quality over all funds in the style segment which stock *I* belongs to. We use the odds ratio of the sum product as conviction quality in the regressions.

Gross Alpha: Estimated from rolling 12-month time series regressions of monthly fund gross return on Fama and French (1992) market return, SMB and HML factors and Carhart(1997) momentum factor, and as in Berk and Binsbergen (2015), averaged across the current and prior months over our sample period. Monthly gross fund return is the sum of fund monthly net return and 1/12 of fund expense ratio.

TNA: Monthly total net assets under management averaged across the current and prior months over our sample period.

Gross Value-Added: Product of fund monthly gross alpha and TNA averaged across the current and prior months over our sample period. Monthly GVA is then multiplied by 3 to get quarterly fund GVA.

Management fees: Monthly fund management fee is estimated as sum of product of share class TNA at month end and monthly management fee ratio over all share classes for each fund, and then averaged across the current and prior months over our sample period. Monthly fund management fee multiplied by 3 is quarterly management fees.

Industry Concentration: In each quarter, industry concentration is computed as the squared differences between industry weights of funds, $w_{j,\mathrm{I}}$, and aggregate industry weights, w_{I}, summed across 10 broadly defined Fama and French (1997) industries.

$$Industry\ concentration_{j,\mathrm{I}} = \sum_{\mathrm{I}=1}^{10} (w_{j,\mathrm{I}} - w_{\mathrm{I}})^2$$

Dispersion Index of Active Holding: Standard deviation of active holdings across all funds j with non-zero holdings in segment style k divided by the mean active holding.

Breadth: $Ln(N)$, where N is the number of actively managed mutual funds with non-zero holdings of stock i in segment style k. Delta breadth is computed as the change in breadth from the prior quarter.

Active Mutual Fund Ownership: The percentage of total shares outstanding of stock i owned by actively managed mutual funds j at the end of quarter q. Quarterly change in active mutual fund ownership is computed as the change in active mutual fund ownership from the prior quarter.

Market Capitalization: Market equity capitalization is the product of closing price and total shares outstanding of stock

i at the end of the quarter q expressed in millions of dollars. We use natural log of market capitalization in regressions.

Book-to-Market: Book equity to shareholders' equity in Daniel and Titman (2006). We use nature log of book to market ratio in regressions.

Prior year return: In month t at quarter end is the cumulative monthly return over the prior 12 months starting from $t-2$ and ending in $t-13$.

CRSP Turnover: Total trading volume reported by CRSP summed across all 3 months in the quarter as a percentage of total shares outstanding where trading volume is adjusted following French (2008).

Idiosyncratic Volatility: Standard deviation of residuals from time series regressions of daily stock returns on Fama French (1992) market, SMB and HML factors over the quarter.

Market Beta: Sum of the coefficients on contemporaneous and five lags of market excess returns estimated from time series regressions of daily stock excess returns on daily contemporaneous and five lags of market excess returns each quarter following Jiang and Sun (2014).

Standardized Earnings Surprise (SUE): For each stock in the quarter, we compute the SUE as actual earnings per share minus median analyst forecasts made earlier than earnings announcement date but no more than 90 days in advance expressed as a percent of stock price at the end of quarter. If there are multiple forecasts from the same analyst, we use the latest one in the restricted forecasting period.

Excess Market Return: Monthly return in excess of the value-weighted CRSP return and compounded over months in a quarter to estimate quarterly return.

DGTW Return: Monthly return minus the average return on stocks in DGTW segment style k to which stock i belongs and compounded over months in a quarter to estimate quarterly return.

4-Factor Alpha: Daily alpha estimated from time-series regressions of daily stock returns on Fama and French (1992) market, SMB and HML factors and Carhart (1997) UMD factor each month and compounded over days in a quarter to estimate quarterly return.

Cumulative Abnormal Return (CAR): CARs are computed from daily returns in excess of returns on a benchmark portfolio to which the stock belongs, over a three-day window around the earnings announcement dates [-1, 1]. Earnings announcement dates are obtained from I/B/E/S database. To construct benchmark daily returns, we follow French's website, and sort stocks into 2×3 benchmark portfolios by size (ME) and book-to-market equity (BE/ME) at June end of each year t. Median ME on NYSE stocks and the 30th and 70th percentiles of BE/ME on NYSE stocks, computed as book equity in the last fiscal year end in $t-1$ divided by ME in December of $t-1$, are used as breakpoints.

Table II
Fund Size and Performance by Style Segments

Table reports fund size and performance by style segments. Portfolio formation is described in Table I. For each style segment, Panel A reports the average inflation adjusted total net assets under management (TNA) expressed in millions of dollars and in parentheses average 4-factor adjusted quarterly compounded gross alpha in percent. Panel B reports average gross value-added expressed in millions of dollars. Panel C reports regressions of gross alpha against ln TNA, regressions of gross value added against ln TNA and squared ln TNA, the characteristics of excessively underfunded, excessively over-funded and moderately funded funds. Gross alpha is estimated from rolling 12-month time series regressions of monthly fund gross return on Fama and French (1992) market, SMB, HML, and Carhart(1997) UMD factors, and as in Berk and Binsbergen (2015), averaged across current and prior months. Monthly gross fund return is the sum of fund monthly net return and one-twelfth of fund annual expense ratio. TNA is monthly total net assets under management averaged across current and prior months, adjusted by inflation. Gross value-added is the product of fund monthly gross alpha and TNA averaged across current and prior months.

		PANEL A						PANEL B					
		Total Net Assets Under Management (4-Factor Quarterly Return Alpha)						Gross Value-Added					
SIZE	BTM	MOMENTUM						MOMENTUM					
		1	2	3	4	5	*Size_BTM*	1	2	3	4	5	*Size_BTM*
1	1	594 (0.65)	543 (0.74)	532 (0.70)	520 (0.80)	581 (0.76)	554 (0.73)	4.05	4.09	4.08	3.05	3.33	3.72
1	2	598 (0.77)	538 (0.74)	501 (0.78)	483 (0.81)	487 (0.71)	521 (0.76)	3.05	3.22	2.52	3.10	2.86	2.95
1	3	628 (0.71)	535 (0.68)	470 (0.84)	482 (0.73)	457 (0.77)	514 (0.75)	3.97	4.02	3.17	2.34	2.62	3.23
1	4	573 (0.81)	460 (0.80)	457 (0.66)	468 (0.91)	453 (0.71)	482 (0.78)	3.98	2.73	2.41	3.52	2.39	3.01
1	5	544 (0.91)	520 (0.79)	497 (0.88)	469 (0.83)	468 (0.84)	500 (0.85)	2.91	2.64	3.20	3.07	2.78	2.92
2	1	596 (0.72)	561 (0.66)	548 (0.72)	575 (0.65)	617 (0.65)	580 (0.68)	4.10	3.34	3.64	3.71	3.89	3.74
2	2	595 (0.63)	585 (0.77)	534 (0.68)	574 (0.70)	590 (0.62)	575 (0.68)	3.69	3.98	3.10	3.54	3.10	3.48
2	3	574 (0.73)	542 (0.68)	509 (0.73)	552 (0.70)	544 (0.66)	544 (0.70)	3.42	3.95	3.36	3.14	2.98	3.37
2	4	563 (0.78)	511 (0.73)	530 (0.73)	489 (0.67)	507 (0.72)	520 (0.73)	3.62	3.09	3.60	3.11	3.30	3.34
2	5	567 (0.65)	576 (0.69)	541 (0.67)	541 (0.67)	508 (0.62)	546 (0.66)	3.67	4.07	3.51	2.73	3.15	3.42
3	1	629 (0.71)	626 (0.75)	587 (0.75)	614 (0.75)	643 (0.66)	620 (0.72)	3.92	3.65	3.93	3.93	4.02	3.89
3	2	641 (0.64)	611 (0.71)	573 (0.67)	572 (0.64)	615 (0.64)	602 (0.66)	4.21	0.56	2.57	3.35	1.20	2.38
3	3	629 (0.69)	580 (0.74)	566 (0.70)	575 (0.65)	612 (0.64)	592 (0.68)	4.53	3.31	3.25	3.32	0.72	3.03
3	4	631 (0.67)	595 (0.71)	583 (0.66)	577 (0.75)	585 (0.66)	594 (0.69)	3.63	0.17	3.45	3.66	0.39	2.26
3	5	637 (0.71)	631 (0.72)	630 (0.68)	583 (0.70)	646 (0.63)	625 (0.69)	3.80	3.50	3.83	1.66	3.78	3.32
4	1	837 (0.68)	802 (0.74)	780 (0.71)	723 (0.66)	710 (0.62)	770 (0.68)	5.82	5.43	4.36	4.77	3.87	4.85
4	2	849 (0.76)	764 (0.70)	766 (0.72)	749 (0.66)	726 (0.60)	771 (0.69)	1.22	-1.58	4.80	1.59	4.08	2.02
4	3	831 (0.68)	823 (0.69)	753 (0.70)	698 (0.67)	713 (0.70)	763 (0.69)	2.11	5.16	0.67	4.39	0.58	2.58
4	4	829 (0.70)	773 (0.64)	751 (0.68)	748 (0.73)	722 (0.66)	765 (0.68)	3.71	4.67	1.64	4.32	4.47	3.76
4	5	848 (0.70)	792 (0.68)	758 (0.76)	782 (0.69)	746 (0.65)	785 (0.70)	5.18	4.53	4.87	4.81	4.21	4.72
5	1	843 (0.60)	813 (0.62)	804 (0.61)	817 (0.60)	809 (0.58)	817 (0.60)	-0.37	-0.20	-0.50	-0.68	-0.21	-0.39
5	2	817 (0.58)	812 (0.57)	797 (0.57)	797 (0.56)	803 (0.57)	805 (0.57)	-0.26	-0.57	-0.48	-0.13	-0.49	-0.39
5	3	827 (0.58)	807 (0.60)	800 (0.56)	800 (0.6)	820 (0.59)	811 (0.58)	-0.19	-0.15	-0.57	-0.07	-0.59	-0.31
5	4	843 (0.62)	827 (0.61)	800 (0.60)	808 (0.54)	820 (0.57)	820 (0.59)	-0.09	0.47	-0.36	-0.15	-0.88	-0.20
5	5	869 (0.59)	850 (0.59)	857 (0.55)	832 (0.58)	824 (0.57)	846 (0.58)	0.75	-0.94	-0.86	0.48	-2.08	-0.53

PANEL C

	Gross Alpha	Gross Value Added	Zhu (2018)
$ln(TNA)$	-0.0049[c]	14.1149[c]	-0.002[c]
	(0.000)	(0.000)	(0.000)
$[ln(TNA)]^2$	-	-2.4575[c]	-
		(0.000)	
Constant	0.0391[c]	-	0.003
	(0.000)		
NOBS	1,800	1,800	
Adjusted R^2	0.907	0.623	
Quarter Fixed Effects	Y	Y	

			Gross Value Added ($mil)			Gross Alpha (bps)			TNA		
	Zhu (2018)	Percentile	Average (σ)	Min	Max	Average (σ)	Min	Max	Average (σ)	Min	Max
Overfunded	58.8	31.20	-45.0	-90.0	0.0	-0.0045	-0.0070	-0.0021	685.5	417.5	953.6
			(63.6)			(0.0035)			(379.1)		
Moderately Funded	25.9	43.60	3.6	0.0	7.1	0.0040	-0.0040	0.0120	619.7	531.5	707.9
			(5.0)			(0.0113)			(233.1)		
Underfunded	17.5	25.20	28.6	7.1	50.2	0.0260	0.0089	0.0430	1,218.0	861.1	1,574.9
			(30.4)			(0.0241)			(504.7)		

Table III

Forecast Returns: Fund Performance using Industry Concentration

Table reports style and quarter fixed effects regressions of lead quarter buy-and-hold stock returns on investment quality and control variables. ‡ indicates that industry concentration are used to proxy fund performance. The cross-product of active holding and industry concentration summed across funds is used to identify selection skill. Investment quality $IQ \equiv \theta_i^s$ is the odds ratio of a stock's relative percentile rank, θ_i^s, on selection skill. Average quarterly returns are expressed in percent. Variable definitions can be found in Table III. All variables are normalized by their standard deviations across the sample period. Control variables are demeaned. In two-way fixed effects regressions, errors are clustered by style and quarter. p-values are reported in parentheses. Superscript $^{a,\,b,\,c}$ denote statistical significance at 10%, 5%, and 1% levels.

	EXCESS MARKET RETURN				**DGTW RETURN**				**4-FACTOR ALPHA**			
	Lead 1 Qtr	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**	**Lead 1 Qtr**	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**	**Lead 1 Qtr**	**Lead 2 Qtr**	**Lead 3 Qtr**	**Lead 4 Qtr**
$IQ^{\ddagger} \equiv \theta_i^s$	1.255^{c}	1.295^{c}	1.131^{c}	1.097^{c}	1.337^{c}	1.307^{c}	1.146^{c}	1.100^{c}	0.881^{c}	1.036^{c}	0.949^{c}	0.879^{c}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$IO^2 \equiv \theta_i^{s\,2}$	-1.087^{c}	-1.161^{c}	-0.933^{c}	-0.904^{c}	-1.176^{c}	-1.188^{c}	-0.977^{c}	-0.920^{c}	-0.737^{c}	-0.913^{c}	-0.765^{c}	-0.700^{c}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\Delta Breadth$	0.345^{b}	0.166	0.032	-0.033	0.363^{c}	0.182^{a}	0.076	0.005	0.261^{b}	0.204^{b}	0.050	-0.006
	(0.024)	(0.115)	(0.694)	(0.627)	(0.005)	(0.051)	(0.275)	(0.940)	(0.021)	(0.015)	(0.419)	(0.911)
$\Delta Active\ MF\ Ownership$	-0.037	-0.081	-0.034	-0.008	-0.058	-0.067	-0.041	-0.020	-0.045	-0.086	-0.019	0.003
	(0.543)	(0.161)	(0.544)	(0.873)	(0.357)	(0.154)	(0.394)	(0.642)	(0.498)	(0.108)	(0.709)	(0.953)
Holding Dispersion Index	0.037	-0.035	-0.031	-0.005	-0.008	-0.040	-0.034	-0.007	0.045	-0.047	-0.032	0.007
	(0.426)	(0.343)	(0.367)	(0.860)	(0.865)	(0.265)	(0.275)	(0.773)	(0.298)	(0.175)	(0.279)	(0.770)
Ln(MCAP)	-0.736	-0.464	-0.263	-0.166	-0.804	-0.375	-0.135	0.034	-0.619	-0.468	-0.471	-0.414
	(0.193)	(0.252)	(0.420)	(0.537)	(0.120)	(0.293)	(0.626)	(0.874)	(0.356)	(0.380)	(0.261)	(0.262)
Ln(Book-to-Market)	0.350	0.465	0.562^{b}	0.551^{c}	0.010	0.187	0.275	0.289^{b}	-0.001	0.209	0.332^{b}	0.375^{c}
	(0.419)	(0.129)	(0.019)	(0.007)	(0.973)	(0.381)	(0.104)	(0.041)	(0.996)	(0.220)	(0.028)	(0.004)
Prior Year Return	-0.108	-0.120	-0.191	-0.204	-0.094	-0.055	-0.094	-0.088	0.100	0.047	0.003	-0.010
	(0.775)	(0.680)	(0.436)	(0.312)	(0.751)	(0.772)	(0.549)	(0.503)	(0.490)	(0.680)	(0.974)	(0.909)
CRSP Turnover	-0.306	-0.538^{c}	-0.527^{c}	-0.535^{c}	-0.120	-0.292^{b}	-0.300^{c}	-0.337^{c}	-0.305	-0.525^{c}	-0.571^{c}	-0.627^{c}
	(0.106)	(0.000)	(0.000)	(0.000)	(0.434)	(0.027)	(0.007)	(0.001)	(0.200)	(0.006)	(0.000)	(0.000)
Idiosyncratic Volatility	-0.071	-0.178	-0.270	-0.272	-0.489	-0.622^{b}	-0.661^{c}	-0.599^{c}	-0.449	-0.704^{b}	-0.797^{c}	-0.771^{c}
	(0.905)	(0.692)	(0.494)	(0.389)	(0.189)	(0.020)	(0.004)	(0.002)	(0.158)	(0.011)	(0.001)	(0.000)
Market Beta	-0.175	-0.190	-0.154	-0.172	-0.067	-0.107	-0.085	-0.096	-0.341^{c}	-0.396^{c}	-0.296^{c}	-0.270^{c}
	(0.560)	(0.378)	(0.329)	(0.221)	(0.719)	(0.477)	(0.429)	(0.322)	(0.004)	(0.000)	(0.001)	(0.001)
NOBS	182,023	179,098	176,206	173,359	181,908	178,875	175,860	172,903	184,524	181,728	178,883	176,080
R^2	0.036	0.042	0.044	0.046	0.005	0.012	0.019	0.024	0.008	0.016	0.022	0.028

Table IV: Regression Results on Control Variables

Table IV (contd.)												
Ln(MCAP)	-0.578[c]	-0.275	-0.128	-0.031	-0.264[c]	0.096	0.218[b]	0.292[c]	-0.503[b]	-0.259	-0.137	-0.067
	(0.006)	(0.120)	(0.409)	(0.826)	(0.009)	(0.253)	(0.011)	(0.001)	(0.028)	(0.180)	(0.408)	(0.677)
Ln(Book-to-Market)	0.036	0.078	0.125	0.150	-0.125	-0.035	0.030	0.060	0.068	0.115	0.160	0.177
	(0.877)	(0.725)	(0.544)	(0.404)	(0.313)	(0.782)	(0.798)	(0.553)	(0.606)	(0.408)	(0.267)	(0.186)
Prior Year Return	0.038	0.048	0.019	0.026	-0.030	0.007	0.008	0.038	0.092	0.072	0.053	0.080
	(0.890)	(0.831)	(0.923)	(0.880)	(0.852)	(0.946)	(0.925)	(0.631)	(0.377)	(0.413)	(0.573)	(0.419)
CRSP Turnover	-0.162	-0.340[b]	-0.390[c]	-0.430[c]	-0.175	-0.327[b]	-0.348[c]	-0.380[c]	-0.250	-0.422[c]	-0.472[c]	-0.506[c]
	(0.410)	(0.042)	(0.008)	(0.001)	(0.260)	(0.014)	(0.003)	(0.000)	(0.104)	(0.002)	(0.000)	(0.000)
Idiosyncratic Volatility	-0.725[b]	-0.989[c]	-1.020[c]	-0.955[c]	-0.635[c]	-0.844[c]	-0.868[c]	-0.799[c]	-0.734[c]	-1.055[c]	-1.132[c]	-1.161[c]
	(0.041)	(0.001)	(0.000)	(0.000)	(0.007)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)
Market Beta	0.097	0.033	-0.011	-0.080	0.119	0.067	0.038	-0.014	-0.499[c]	-0.551[c]	-0.463[c]	-0.449[c]
	(0.625)	(0.846)	(0.937)	(0.567)	(0.475)	(0.638)	(0.746)	(0.905)	(0.005)	(0.000)	(0.000)	(0.000)
Constant	0.192	-0.695	-1.055[b]	-1.218[c]	-0.256	-1.155[c]	-1.443[c]	-1.560[c]	0.488[c]	-0.448[b]	-0.788[c]	-0.993[c]
	(0.699)	(0.133)	(0.010)	(0.001)	(0.438)	(0.000)	(0.000)	(0.000)	(0.001)	(0.010)	(0.000)	(0.000)

Table IX (contd.)												
Market Capitalization	-0.827	-0.395	-0.290	-0.209	-1.001[a]	-0.459	-0.219	-0.061	-0.668	-0.437	-0.442	-0.398
	(0.131)	(0.333)	(0.372)	(0.444)	(0.052)	(0.195)	(0.425)	(0.778)	(0.324)	(0.435)	(0.326)	(0.325)
Book-to-Market	0.674	0.824[b]	0.792[c]	0.791[c]	0.110	0.283	0.329[a]	0.370[b]	-0.024	0.231	0.357[b]	0.432[c]
	(0.176)	(0.015)	(0.002)	(0.001)	(0.739)	(0.201)	(0.059)	(0.014)	(0.914)	(0.178)	(0.021)	(0.002)
Prior Year Return	-0.585	-0.536	-0.507	-0.497[a]	-0.307	-0.242	-0.238	-0.233	0.119	-0.009	-0.063	-0.112
	(0.221)	(0.169)	(0.100)	(0.060)	(0.316)	(0.241)	(0.158)	(0.104)	(0.464)	(0.938)	(0.528)	(0.222)
CRSP Turnover	-0.215	-0.442[c]	-0.441[c]	-0.465[c]	-0.083	-0.263[b]	-0.265[b]	-0.309[c]	-0.271	-0.441[b]	-0.494[c]	-0.544[c]
	(0.257)	(0.004)	(0.000)	(0.000)	(0.576)	(0.036)	(0.014)	(0.002)	(0.251)	(0.019)	(0.001)	(0.000)
Idiosyncratic Volatility	-0.432	-0.617	-0.621	-0.567[a]	-0.663[a]	-0.812[c]	-0.828[c]	-0.743[c]	-0.524	-0.862[c]	-0.968[c]	-0.944[c]
	(0.493)	(0.198)	(0.130)	(0.093)	(0.088)	(0.002)	(0.000)	(0.000)	(0.104)	(0.002)	(0.000)	(0.000)
Market Beta	-0.386	-0.328	-0.275[a]	-0.291[a]	-0.164	-0.148	-0.131	-0.147	-0.348[c]	-0.398[c]	-0.301[c]	-0.287[c]
	(0.260)	(0.159)	(0.094)	(0.059)	(0.433)	(0.336)	(0.207)	(0.134)	(0.003)	(0.000)	(0.001)	(0.000)

Table X Panel A (contd.)												
Market Capitalization	-1.244[b]	-0.878[b]	-0.632[a]	-0.506[a]	-1.268[b]	-0.728[b]	-0.447	-0.263	-0.916	-0.705	-0.698[a]	-0.619[a]
	(0.033)	(0.036)	(0.059)	(0.066)	(0.013)	(0.042)	(0.110)	(0.229)	(0.169)	(0.181)	(0.087)	(0.081)
Book-to-Market	0.372	0.480	0.574[b]	0.559[c]	0.028	0.197	0.284[a]	0.293[b]	0.012	0.215	0.337[b]	0.378[c]
	(0.390)	(0.119)	(0.017)	(0.007)	(0.924)	(0.356)	(0.096)	(0.040)	(0.955)	(0.206)	(0.026)	(0.004)

Prior Year Return	-0.081	-0.096	-0.167	-0.181	-0.068	-0.034	-0.074	-0.067	0.116	0.062	0.020	0.006
	(0.831)	(0.740)	(0.492)	(0.369)	(0.819)	(0.859)	(0.639)	(0.612)	(0.422)	(0.582)	(0.840)	(0.946)
CRSP Turnover	-0.347[a]	-0.567[c]	-0.552[c]	-0.555[c]	-0.151	-0.313[b]	-0.318[c]	-0.351[c]	-0.328	-0.536[c]	-0.582[c]	-0.637[c]
	(0.068)	(0.000)	(0.000)	(0.000)	(0.317)	(0.016)	(0.004)	(0.001)	(0.169)	(0.005)	(0.000)	(0.000)
Idiosyncratic Volatility	-0.092	-0.200	-0.292	-0.289	-0.518	-0.648[b]	-0.685[c]	-0.618[c]	-0.463	-0.725[c]	-0.816[c]	-0.788[c]
	(0.877)	(0.658)	(0.464)	(0.362)	(0.164)	(0.016)	(0.003)	(0.001)	(0.147)	(0.009)	(0.001)	(0.000)
Market Beta	-0.187	-0.199	-0.160	-0.177	-0.075	-0.113	-0.087	-0.099	-0.343[c]	-0.396[c]	-0.295[c]	-0.270[c]
	(0.528)	(0.351)	(0.308)	(0.205)	(0.683)	(0.449)	(0.415)	(0.307)	(0.004)	(0.000)	(0.001)	(0.000)

Table X Panel B (contd.)

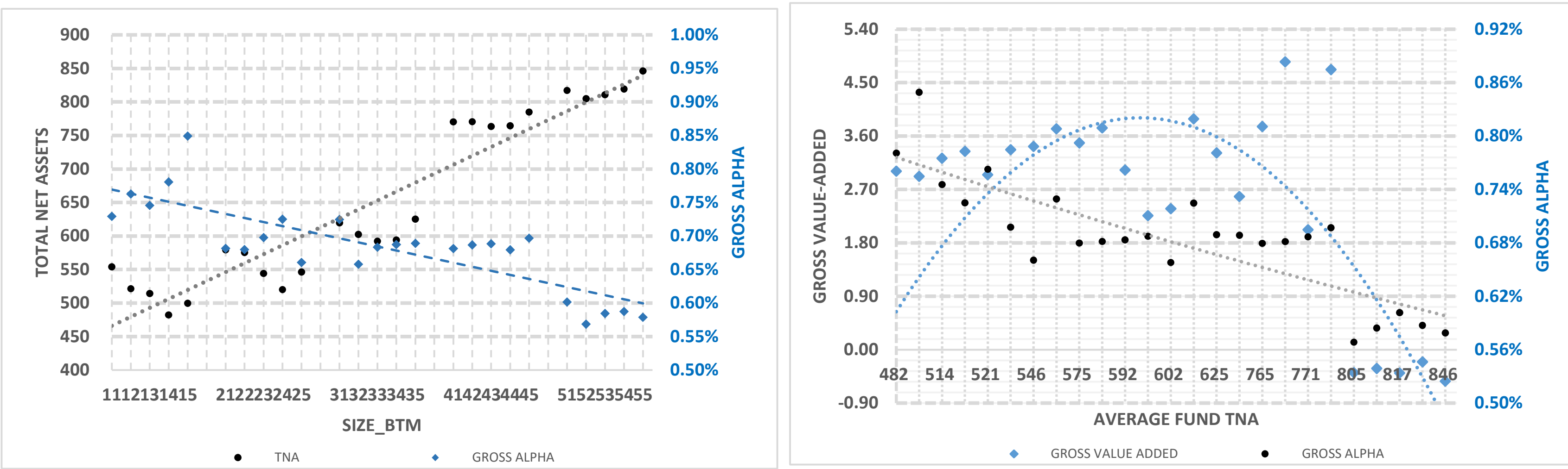
Market Capitalization	-1.160[b]	-0.802[a]	-0.570[a]	-0.451	-1.186[b]	-0.653[a]	-0.384	-0.210	-0.849	-0.644	-0.644	-0.573
	(0.045)	(0.055)	(0.088)	(0.101)	(0.020)	(0.069)	(0.171)	(0.342)	(0.202)	(0.223)	(0.116)	(0.110)
Book-to-Market	0.338	0.450	0.547[b]	0.535[c]	-0.005	0.169	0.259	0.272[a]	-0.011	0.193	0.316[b]	0.360[c]
	(0.435)	(0.143)	(0.023)	(0.009)	(0.987)	(0.431)	(0.130)	(0.057)	(0.958)	(0.256)	(0.035)	(0.005)
Prior Year Return	-0.083	-0.098	-0.169	-0.182	-0.070	-0.036	-0.075	-0.068	0.113	0.060	0.018	0.005
	(0.826)	(0.734)	(0.490)	(0.367)	(0.812)	(0.850)	(0.633)	(0.608)	(0.433)	(0.595)	(0.853)	(0.957)
CRSP Turnover	-0.305	-0.528[c]	-0.518[c]	-0.524[c]	-0.111	-0.277[b]	-0.286[b]	-0.323[c]	-0.300	-0.508[c]	-0.556[c]	-0.613[c]
	(0.107)	(0.000)	(0.000)	(0.000)	(0.465)	(0.035)	(0.010)	(0.002)	(0.208)	(0.007)	(0.000)	(0.000)
Idiosyncratic Volatility	-0.080	-0.188	-0.280	-0.278	-0.507	-0.638[b]	-0.675[c]	-0.608[c]	-0.457	-0.718[c]	-0.809[c]	-0.781[c]
	(0.893)	(0.678)	(0.482)	(0.382)	(0.175)	(0.018)	(0.004)	(0.001)	(0.152)	(0.010)	(0.001)	(0.000)
Market Beta	-0.182	-0.196	-0.157	-0.175	-0.071	-0.109	-0.084	-0.096	-0.339[c]	-0.393[c]	-0.292[c]	-0.268[c]
	(0.540)	(0.361)	(0.317)	(0.212)	(0.702)	(0.466)	(0.431)	(0.320)	(0.004)	(0.000)	(0.001)	(0.001)

Table XI (contd.)

Market Capitalization	-1.232[b]	-0.853[b]	-0.602[a]	-0.478[a]	-1.251[b]	-0.707[b]	-0.421	-0.239	-0.896	-0.678	-0.667	-0.589[a]
	(0.034)	(0.042)	(0.073)	(0.083)	(0.014)	(0.049)	(0.133)	(0.276)	(0.181)	(0.201)	(0.104)	(0.099)
Book-to-Market	0.372	0.480	0.574[b]	0.558[c]	0.028	0.197	0.283[a]	0.293[b]	0.012	0.215	0.336[b]	0.378[c]
	(0.390)	(0.119)	(0.017)	(0.007)	(0.924)	(0.357)	(0.097)	(0.041)	(0.955)	(0.207)	(0.026)	(0.004)
Prior Year Return	-0.079	-0.095	-0.166	-0.180	-0.066	-0.032	-0.073	-0.066	0.116	0.063	0.021	0.007
	(0.834)	(0.744)	(0.495)	(0.370)	(0.823)	(0.866)	(0.645)	(0.616)	(0.422)	(0.579)	(0.831)	(0.937)
CRSP Turnover	-0.348[a]	-0.568[c]	-0.554[c]	-0.557[c]	-0.154	-0.315[b]	-0.321[c]	-0.354[c]	-0.332	-0.540[c]	-0.587[c]	-0.641[c]
	(0.068)	(0.000)	(0.000)	(0.000)	(0.310)	(0.016)	(0.004)	(0.001)	(0.165)	(0.004)	(0.000)	(0.000)
Idiosyncratic Volatility	-0.092	-0.199	-0.290	-0.287	-0.518	-0.648[b]	-0.684[c]	-0.617[c]	-0.462	-0.723[c]	-0.814[c]	-0.786[c]
	(0.877)	(0.659)	(0.466)	(0.365)	(0.164)	(0.016)	(0.003)	(0.001)	(0.148)	(0.009)	(0.001)	(0.000)
Market Beta	-0.188	-0.200	-0.160	-0.178	-0.076	-0.114	-0.088	-0.099	-0.344[c]	-0.396[c]	-0.295[c]	-0.271[c]
	(0.526)	(0.348)	(0.305)	(0.203)	(0.677)	(0.444)	(0.410)	(0.303)	(0.004)	(0.000)	(0.001)	(0.000)

Table XII (contd.)

$\Delta Breadth$	0.368[b]	0.187[a]	0.049	-0.018	0.384[c]	0.200[b]	0.089	0.017	0.276[b]	0.220[c]	0.061	0.003
	(0.017)	(0.078)	(0.547)	(0.792)	(0.004)	(0.033)	(0.196)	(0.775)	(0.015)	(0.009)	(0.321)	(0.954)
$\Delta Active\ MF\ Ownership$	-0.035	-0.089	-0.043	-0.014	-0.057	-0.075	-0.048	-0.026	-0.041	-0.095[a]	-0.027	-0.003
	(0.580)	(0.129)	(0.450)	(0.767)	(0.397)	(0.126)	(0.323)	(0.560)	(0.562)	(0.083)	(0.612)	(0.948)
Holding Dispersion Index	0.008	-0.061[a]	-0.050	-0.021	-0.036	-0.061[a]	-0.048	-0.018	0.038	-0.052	-0.033	0.008
	(0.872)	(0.095)	(0.140)	(0.440)	(0.409)	(0.082)	(0.123)	(0.465)	(0.395)	(0.129)	(0.270)	(0.760)
Market Capitalization	-1.290[b]	-0.897[a]	-0.610	-0.455	-1.267[b]	-0.661[a]	-0.348	-0.138	-0.757	-0.508	-0.470	-0.395
	(0.044)	(0.058)	(0.104)	(0.133)	(0.022)	(0.087)	(0.245)	(0.556)	(0.264)	(0.342)	(0.245)	(0.244)
Book-to-Market	0.354	0.466	0.561[b]	0.544[c]	0.011	0.184	0.271	0.280[b]	-0.000	0.203	0.324[b]	0.366[c]
	(0.413)	(0.128)	(0.020)	(0.008)	(0.969)	(0.389)	(0.112)	(0.049)	(0.998)	(0.233)	(0.031)	(0.005)
Prior Year Return	-0.072	-0.093	-0.167	-0.182	-0.063	-0.037	-0.079	-0.075	0.104	0.046	0.000	-0.012
	(0.848)	(0.745)	(0.489)	(0.360)	(0.831)	(0.843)	(0.611)	(0.566)	(0.464)	(0.677)	(0.997)	(0.891)
CRSP Turnover	-0.331[a]	-0.550[c]	-0.532[c]	-0.535[c]	-0.133	-0.292[b]	-0.294[c]	-0.327[c]	-0.299	-0.501[c]	-0.546[c]	-0.602[c]
	(0.078)	(0.000)	(0.000)	(0.000)	(0.367)	(0.023)	(0.007)	(0.001)	(0.213)	(0.009)	(0.000)	(0.000)
Idiosyncratic Volatility	-0.078	-0.185	-0.284	-0.282	-0.508	-0.637[b]	-0.680[c]	-0.614[c]	-0.461	-0.731[c]	-0.817[c]	-0.792[c]
	(0.896)	(0.683)	(0.477)	(0.374)	(0.178)	(0.019)	(0.004)	(0.001)	(0.148)	(0.009)	(0.001)	(0.000)
Market Beta	-0.188	-0.199	-0.159	-0.176	-0.073	-0.108	-0.082	-0.092	-0.330[c]	-0.381[c]	-0.280[c]	-0.259[c]
	(0.525)	(0.350)	(0.308)	(0.208)	(0.688)	(0.464)	(0.440)	(0.337)	(0.006)	(0.000)	(0.001)	(0.001)



PANEL A

PANEL B

Figure I: Fund Size and Performance by Style Segment

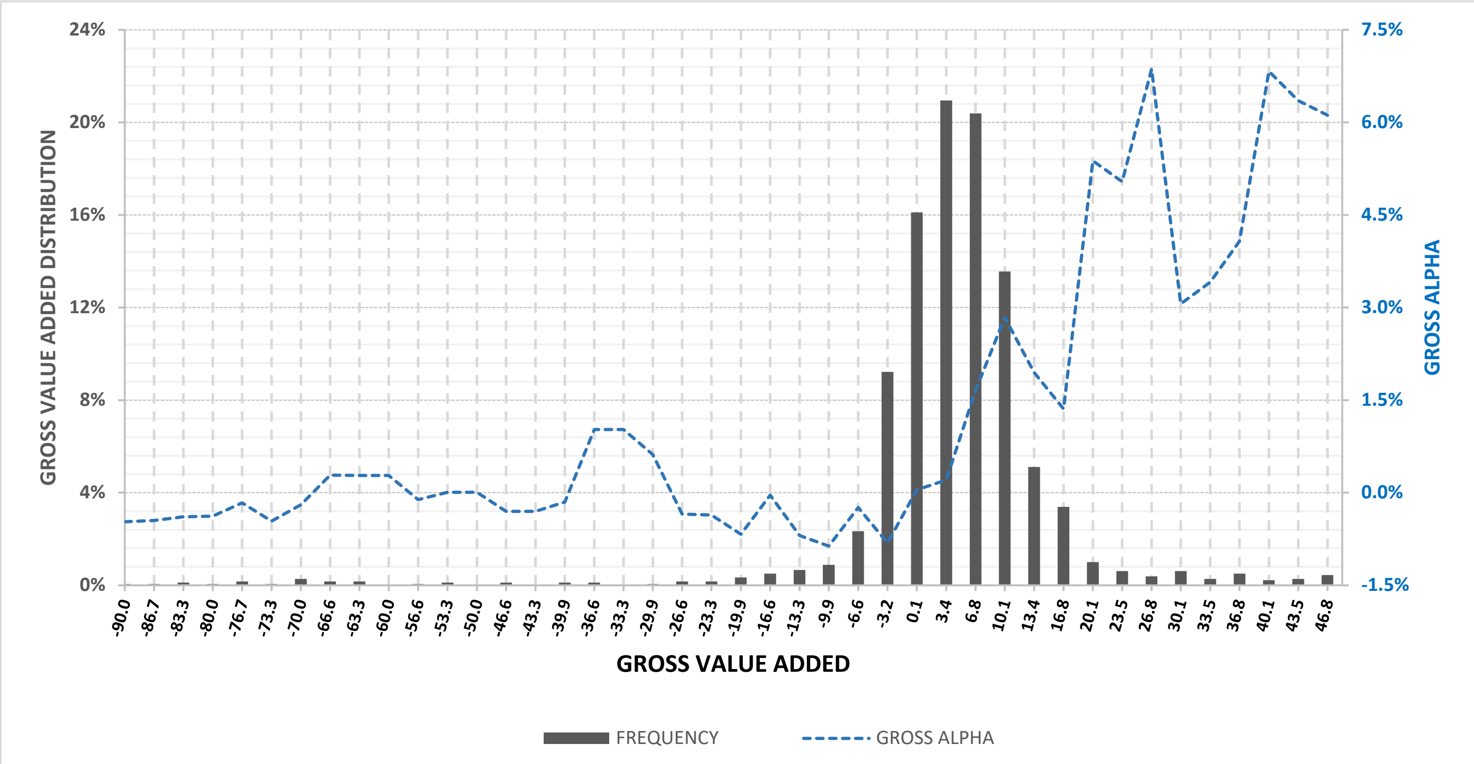


Figure II: Distribution of Gross Value-Added and Total Net Assets by Gross Alpha