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Implied cost of capital and mutual fund performance

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Implied cost of capital and mutual fund performance

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Implied Cost of Capital and Mutual Fund Performance

Mario Hendriock[♋]

November 18, 2020

Abstract

This study provides evidence for a positive association between mutual fund holdings' implied cost of capital (ICC) and future performance. Consistent with large transaction costs of ICC-based investments impeding their exploitation and employing a ICC-based strategy reflecting skill, family-level trading efficiency and manager-level SAT score positively correlate with fund-level ICC. A negative association between ICC and mid-year risk shifting corroborates the notion of fund managers decisively choosing and relying on high-ICC strategies. Institutional investors able to identify funds with high ICC direct their investments accordingly, whereas flows of retail funds are unaffected, consistent with limited investor attention and financial literacy.

JEL classification: G11, G14, G17, G23, G31, M41.
Keywords: implied cost of capital, mutual funds, portfolio choice, financial forecasting.

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For a long time, finance researchers have been trying to discern, whether mutual fund managers, as a large and important class of institutional investors, have skill when it comes to picking stocks. This quest by scholars has been at the heart of understanding important concepts in finance, such as the efficient market hypothesis or how information advantages are developed and exploited by market participants. However, research on the ability of active mutual fund managers to beat their benchmark, i. e., generate positive active returns after costs commonly referred to as "alpha",[1] unanimously provides evidence for the scarcity of this skill. Fama and French (2010) conclude that "true alpha [...] is negative for most if not all active funds". Yet, the U.S. mutual fund industry has seen enormous growth, having decupled over the past 25 year alone, with 21.3 trillion U.S. dollar under management by the end of 2019 [Investment Company Institute (2020)]. This mismatch between the track record of the mutual fund industry's performance and its growth gave rise to the "mutual fund puzzle" put forth by Gruber (1996).

In this paper, I try to add a piece to this puzzle and examine the ability of funds' holdings' implied cost of capital (ICC) to ex-ante identify funds with positive alpha and thereby inform the capital allocation process of financial decision makers. Hereof, research documents that it is mainly guided by past performance[2] - yet, on average, funds outperforming in one period do not repeat their achievement in the next. Persistence documented in early studies was later explained by recently successful managers holding stocks with high past performance - i.e., momentum; further, persistence seems to be entirely absent in recent times.[3] Thus, research turned towards analyzing whether fund characteristics help discern future "winners" from "losers", documenting associations of performance with, e.g., fund age, flows, and expenses.[4]

[1] A different topic is active managers' ability to extract money from the market and generate positive value for their firms, confer Berk and van Binsbergen (2015), Berk, van Binsbergen, and Liu (2017), and van Binsbergen, Kim, and Kim (2019).

[2] Confer, e.g., Ippolito (1992), Sirri and Tufano (1998), Guercio and Tkac (2008), Barber, Huang, and Odean (2016), and Berk and van Binsbergen (2016).

[3] Carhart (1997) attributes persistence as documented in Grinblatt and Titman (1992) and Hendricks, Patel, and Zeckhauser (1993) to momentum; Choi and Zhao (2020) do not find evidence for persistence between 1994 and 2018.

[4] Confer Howell (2001) and Ferson and Schadt (1996) and Rakowski and Wang (2009), as well as Carhart (1997) and Russell (2010), respectively. For a review of studies on the association between characteristics

While these findings are important to further our understanding of the nature of skill in the mutual fund industry, we still lack an understanding of what strategies managers in their day-to-day business (should) employ and how fund investors can turn mere correlations into implementable investment strategies with real profits.

This study aims to document the extent to which ICC of a fund can serve as a building block for such kind of a strategy. The main insight of this paper is that current ICC appear to map into future fund performance in a way that lets investors profit from the small fraction of mutual fund managers which indeed seems to have skill picking stocks. That is, ICC seem to be one information advantage successfully exploited by skilled managers.

The focus on ICC is motivated by literature on their return-predictive capabilities. Conceptually, ICC of a firm equate its current market value of equity to present value of expected future cash flows. Pástor, Sinha, and Swaminathan (2008) show theoretically how ICC are particularly apt as a proxy for time-varying expected returns; based on theoretically justifiable valuation models, ICC take into consideration future growth opportunities and, as a function of current market values, are inherently forward looking. Empirically, ICCs indeed have been documented to positively predict future returns and other measures for "performance".[5] When it comes to exploiting this association between current ICC and future performance, however, Esterer and Schröder (2014) underline the detrimental effect of transaction costs necessary, stating profit potentials "revealed by the ICC [were] not large enough to allow for substantial trading opportunities using diversified equity portfolios."

Regarding transaction costs and implementation opportunities, active mutual funds arguably are in a preferential position; as part of potentially large institutions specialized on financial transactions, respective costs are comparably low [Frazzini, Israel, and Moskowitz (2018)]. Further, whereas ICC-based investment rules analyzed in literature either simply

both at the manager as well as fund level and fund performance, confer Jones and Wermers (2011).

[5]Confer, e.g., Claus and Thomas (2001), Botosan and Plumlee (2005), Easton (2007), Pástor, Sinha, and Swaminathan (2008), Botosan, Plumlee, and Wen (2011), Hou, van Dijk, and Zhang (2012), Li, Ng, and Swaminathan (2013), Li and Mohanram (2014), Esterer and Schröder (2014), Schröder (2018), and Bielstein and Hanauer (2019). The literature on ICC in general as well as its applications in research is extensive; Richardson, Tuna, and Wysocki (2010) provide a review.

value-, though mostly equal-weight stocks, mutual fund managers can - both to the detriment as well as advantage - exert their discretion in portfolio selection. An issue yet unexplored is whether investors, by means of funds' reported holdings and respective ICCs, can turn paper gains of ICC-based strategies into actual profits.

This study provides empirical evidence that they can. On the onset, it conducts a portfolio-based analysis to study the relation between fund-level ICC and future performance. Each quarter, a fund-level ICC is calculated as the value-weighted average of the ICCs of the stocks in the fund's portfolio, which in turn are computed as the mean over eight commonly used metrics. Proxies for expected earnings used to calculate ICCs obtain from analysts respectively the three most widely used cross-sectional earnings prediction models [Hou, van Dijk, and Zhang (2012) and Li and Mohanram (2014)]. Consecutively, funds are sorted into equally-weighted portfolios, based on ICC-quintiles. Over a horizon of 25 years, a $1 investment into bottom portfolios led to a seven-fold increase from 1992 to 2016. In comparison, $1 invested in top portfolios would have grown to $15.

Considering adjustments for factor tilts respectively investment styles, funds in bottom quintile portfolios show average one and six factor alphas of around -30 to -20 basis points per month, whereas top portfolios deliver alphas between zero and ten basis points, resulting in a significant spread. In terms of loadings according to the six factor model in Fama and French (2018), high-ICC managers appear to place bets on small and value firms as well as gross profitability and against stock momentum, consistent with both ICCs being used as part of an investment strategy based on fundamental analysis and a "mechanical" effect owing to ICCs' computational properties.

Although quintile-based analyses are parsimonious and such widely used in literature, they cannot serve as basis for a viable outperforming investment strategy. While reported individual fund returns are net of transaction costs, portfolio turnover, which amounts to approximately 30% in the top quintile, necessitates additional payments of front-end loads for entering new positions and back-end loads to sell off funds leaving the portfolio. Additionally,

only the spread-portfolio's performance is significant, which is infeasible, as mutual funds cannot be shorted. Further, given the small fraction of funds being able to generate positive alpha in the first place, quintiles are hardly fine enough. Also after excluding load-funds, yielding a time series of returns purely net of costs, and stratification based on ICC-deciles the positive difference in performance between top and bottom portfolio remains. Additionally, top decile portfolios exhibit positive one and six factor alphas of roughly 25 basis points per month, resolving the necessity to short funds.

The portfolio analysis provides evidence for positive factor alphas, corroborating the notion that returns from an ICC-based strategy do not simply reflect investment styles respectively originate from factor tilts. However, it does not allow to control for other fund characteristics potentially associated with future performance. Hence, I relate current ICC to future fund performance in panel regressions. Results provide evidence of a close to one-to-one correspondence between changes in ICC and future performance, independent of what earnings estimates enter the calculation of ICCs. Also holding fund-manger-matches fixed to control for unobserved time-invariant heterogeneity at the fund-manager-level, ICCs continue to be positively correlated with future performance, corroborating the notion that a high-ICC strategy in itself is associated with high fund performance; this association is not explained by high-ICC funds being systematically concentrated in particular styles at certain times either. With regard to persistence of this association, ICCs are strongly correlated with performance up to two years in the future.

After documenting this baseline result, this study seeks to delve deeper into trading mechanisms associated with an ICC strategy. Relating trading decisions with ex-post realized fund performance, it tries to shed light on whether fund managers' active decisions altering their funds' ICC correlate with contemporaneous performance. It documents that the larger the fraction of a manager's buys (sells) was in firms with increasing (decreasing) ICC, the higher was contemporaneous fund performance. A complete "correct" trading decision on average translated into roughly 2.5 percentage points higher quarterly fund performance,

reinforcing that ICC-based strategies seem to pay off.

Next, this study turns towards possible determinants of managers employing such kind of strategies. A main motivation for combining return predictability via ICCs and identification of skilled managers is based on evidence for, on the one hand, transaction costs preventing effective utilization of ICCs for portfolio selection and, on the other hand, managers' alleged access to a more efficient trading apparatus [Frazzini, Israel, and Moskowitz (2018)]. Along these lines, cross-sectional heterogeneity among funds potentially correlates with their likelihood of adopting high-ICC strategies. Whereas trading costs are not reported, Cici, Dahm, and Kempf (2018) construct a proxy for the efficiency of a mutual fund family's trading desk, expected to be negatively correlated with transaction costs. Consistent with funds facing lower transaction costs being more likely to employ a high-ICC strategy, funds with higher trading desk efficiency exhibit higher ICCs, corroborating the notion that favorable transaction costs are part of the explanation for why mutual funds are able to gather rents of a strategy based on ICC. With regard to manager characteristics, in accordance to successfully implementing strategies based on ICCs representing a form of skill, managers who received their bachelor's degree from universities with high average matriculate SAT scores, meant to proxy for innate abilities, display above average ICCs.

To learn more about possible implications of ICC-based strategies, this study examines, whether they change incentives faced by managers. If they consider ICCs for portfolio allocation and are aware of the potential performance consequences, ICCs in particular add to the repertoire of how managers can react to being ranked unfavorable relative to their peers and such might influence risk-taking. Brown, Harlow, and Starks (1996) are the first to document how fund managers with poor interim performance increase risk in the second half of the year to catch up with interim winners. A high ICC, however, provides another means to close the gap towards their peers. Consistent with managers relying on this strategy paying off, this study provides evidence that mid-year losers with high ICCs increase risk less relative to their peers with low ICCs.

Finally, this study closes with an analysis of whether investors respond towards funds' ICCs. Given the positive association between current ICC and future performance, investors might direct their money accordingly. A fund's ICC, however, is not reported in its prospectus; instead, an investor would need to collect both market and fundamental information to compute ICCs by herself. Given evidence for limited resources, attention, and financial literacy of less sophisticated retail investors,[6] they might be insensitive to a fund's ICC. In contrast, institutional investors with both the means and knowledge to determine its value and uncovering its positive association with future fund performance potentially respond to it. In this vein, this study documents that retail share classes do not receive additional money based on ICCs, whereas institutional investors appear to reward funds with high ICC with higher flows, consistent with awareness of and confidence in ICCs' association with future fund performance.

This study contributes to the literature on delegated asset management, specifically with regard to the question of whether there exists skill in the active mutual fund industry and if so, how it can be identified. Previous studies evolved in an effort to increase the power of tests, shifting the focus of analysis from fund returns to more specialized tests intended to separate skill from luck. Accepting that a subset of mutual fund managers appears to have skill, research has turned to understanding which characteristics of mutual funds and their managers are associated with better performance.[7] This study provides evidence that funds implementing a theoretically motivated strategy backed by research based on ICCs generate outperformance and are identifiable ex-ante.

[6]For studies suggesting retail respectively individual investors being less sophisticated than institutional, confer, e.g., Hand (1990), Lee, Shleifer, and Thaler (1991), Walther (1997), Balsam, Bartov, and Marquardt (2002), Bonner, Walther, and Young (2003), Asthana, Balsam, and Sankaraguruswamy (2004), Franco, Lu, and Vasvari (2007), Mikhail, Walther, and Willis (2007), Hirshleifer, Myers, Myers, and Teoh (2008), and Kaniel, Liu, Saar, and Titman (2012).

[7]Respective studies start from Jensen (1968), who, using a market model, denies the existence of skill, and continue over, e.g., Lehmann and Modest (1987), Ippolito (1989), Grinblatt and Titman (1989, 1992, 1993), Malkiel (1995), Gruber (1996), Carhart (1997), Daniel, Grinblatt, Titman, and Wermers (1997), Wermers (1999), Chen, Jegadeesh, and Wermers (2000), Wermers (2000), Kothari and Warner (2001), Pinnuck (2003), Barras, Scaillet, and Wermers (2010), Fama and French (2010), and Wermers (2020), who all, to varying degree, document some sort of skill.

Further, this study adds to the literature on managerial incentives in the mutual fund industry. In particular, compensation schemes based on assets under management and asymmetric performance-based boni [Elton, Gruber, and Blake (2003) and Ma, Tang, and Gómez (2019)], paired with a convex performance-flow relation [e.g., Sirri and Tufano (1998) and Ferreira, Keswani, Miguel, and Ramos (2012)], according to which investors punish bad performance less by disinvestment than they reward good performance by inflows, give rise to an option-like pay-off, incentivizing managers to engage into "tournament" behavior [Nalebuff and Stiglitz (1983) and Rosen (1986)]. Brown, Harlow, and Starks (1996) document evidence for tournaments in the fund industry per se, whereas Kempf and Ruenzi (2008) find evidence for tournaments within fund families. Kempf, Ruenzi, and Thiele (2009) show how career concerns due to higher unemployment risk during recessions alleviate tournament behavior, as the option-like pay-off is distorted because of managers facing more severe consequences of bad performance. This paper provides evidence that another determinant of how managers respond towards trailing their peers is which investment strategies they follow and how much they (can) rely on them by documenting that managers with high ICC temper their tournament behavior.

This paper also contributes to the literature on determinants of investors' capital allocation. Previous research documents strong evidence for mutual fund investors catering to past performance [Ippolito (1992), Sirri and Tufano (1998), Guercio and Tkac (2008), Barber, Huang, and Odean (2016), and Berk and van Binsbergen (2016)], despite its limited use forecasting future performance. This study documents that sophisticated investors able to identify funds with high ICC steer their investments accordingly, whereas there appears to be no such behavior for an investor class less well equipped.

Finally, this study adds to the literature on ICCs and their association with future realized returns (see above). Whereas there is mixed evidence at the individual stock- respectively strong evidence for return predictability at the stock-portfolio-level, in either regard, ICC-based strategies appear to fail being monetizable owing to underlying costs. This paper

provides evidence for mutual fund managers being able to seize the potential of an ICC-based strategy, in particular due to their access to efficient trading opportunities.

The results of this study potentially have both theoretical and practical implications. Theoretically, the opportunity to ex-ante identify investments going to generate positive performance unexplained by pertinent factor models opens questions with regard to market efficiency and the correct specification of performance measurement. The two most obvious implications were that markets lack a form of semi-strong efficiency or performance attribution is ill-specified, i.e., ICCs capture a risk factor not accounted for. Retail investors' insensitivity towards a fund's ICC, as they potentially lack the necessary capabilities to detect it, would speak towards the former, such that performance can persist. Hence, as a potential practical implication, disseminating information about a fund's ICC, e.g., via incorporation into ratings investors are shown to respond to,[8] could help increasing awareness and such drive flows, with the potential to eliminate performance opportunities, i.e., increase efficiency of markets. Yet still, the concept of ICC might be hard to communicate or "sell" to an investor group with low involvement and financial training. For asset managers, this study's findings might serve as positive evidence for the viability of ICC-based investments.

The remainder of the paper is organized as follows. Section I describes the sample and how earnings estimates and ICCs of firms and ultimately funds are calculated. Section II presents the main result, portfolio- and regression-based evidence for the ability of ICC to forecast fund performance. In Section III, I explore possible determinants of funds employing a high-ICC strategy, analyzing the impact of trading efficiency at the family- and innate ability at the manager-level. Section IV considers whether the positive association between ICC and fund performance triggers responses by market participants, analyzing managers' incentives to engage into tournament-like behavior and how investors react to ICCs. Finally, Section V concludes.

[8] In particular, Evans and Sun (2018) provide evidence for modifications of how "Morningstar Stars" are calculated implicitly changing the asset pricing respectively style attribution model investors cater to. Hartzmark and Sussman (2019) show how investors respond to newly introduced sustainability ratings. The general effect of Morningstar ratings on flows is studied by Guercio and Tkac (2008).

I. Data

A. Sources

The data in this study are collected from several sources. Fund and family names, monthly net returns, total nets assets under management, investment styles, and further fund specific information such as expense and turnover ratios, as well as loads for years 1992 to 2016 are obtained from the Center for Research on Security Prices Survivorship Bias Free Mutual Fund (CRSP MF) Database. For mutual funds with different share classes, all observations are aggregated at the fund-level. In case of quantitative information, aggregation is performed based on the asset value of share classes; qualitative information on investment style and family is the same across all share classes. A fund's age is determined by the initial offering date of its oldest share class. I limit the universe to include only actively managed, diversified, domestic U.S. equity funds, thereby excluding index, international, balanced, bond, money market, and sector funds.

To obtain information on managerial fund employment records, I use Morningstar Direct [confer, e.g., Berk, van Binsbergen, and Liu (2017) and Patel and Sarkissian (2017)], which is merged with the CRSP MF database by CUSIPs and dates. In case of missing CUSIPs, I use a fund share class's TICKER and date combination. If TICKER is also missing, funds are manually matched by name.

Portfolio holdings data come from the Thomson Financial Mutual Fund Holdings database, which are merged with CRSP mutual fund data using the MFLINKS database and with the CRSP stock data using stock CUSIPS. Portfolio holdings for each fund are either of semi-annual or quarterly frequency.[9] Data on firm fundamentals come from COMPUSTAT. I obtain consensus analyst forecasts for earnings and earnings' growth rates from I/B/E/S.

[9]Confer SEC rule RIN 3235-AG64, effective date May 10, 2004.

B. *ICCs and Expected Earnings Proxies*

The central metric used in this study derives from firms' ICC. Based on a certain corporate valuation model, they represent the rate of return implied by current price and forecasts of future pay-offs, which in turn are determined by earnings and their growth.[10] Such, most generally, ICC solve

$$P_{i,t} = \sum_{\tau=0}^{T} \frac{\mathbb{E}_t(X_{i,t+\tau})}{(1 + r_{i,t+\tau})^{\tau}}, \tag{1}$$

where $P_{i,t}$ denotes market value of equity of firm i at time t, $\mathbb{E}_t(X_{i,t+\tau}) =: \mathbb{E}(X_{i,t+\tau}|\Psi_t)$ the expected value, conditional on the information set available at time t, Ψ_t, of "pay-off", reified within the respective model framework, of firm i τ periods ahead, and $r_{i,t+\tau}$ are the cost of equity, i.e., just ICC, of firm i for the τth period ahead. T represents the end point of business activities. More specifically, according to the going-concern principle, T is assumed to converge to infinity and the term structure of equity rates to be flat, such that $r_{i,t+\tau} = r_{i,t} \; \forall \; \tau$. Hence, for one firm, $r_{i,t}$ is still allowed to vary over time, but for one point in time, is constant.

Over the last 25 years, literature developed numerous models to obtain ICCs, which can be grouped into dividend discount models (DDMs), residual income models (RIMs), and abnormal earnings growth models (AEGMs). Under the assumptions inherent to all of them,[11] however, they are mere algebraic reformulations of each other, which lend themselves to expose certain economic concepts.

In a first step, following literature [e.g., Hou, van Dijk, and Zhang (2012), Li and Mohanram (2014), Hess, Meuter, and Kaul (2019), and Hess and Lorsbach (2019)], a firm's ICC obtains as the average over commonly used ICCs.[12] In particular, I employ the two

[10] This is analogous to internal rates of return calculated from the market price of a bond and coupon payments, commonly referred to as "yield to maturity".

[11] Heinrichs et al. (2013), employing the principle of financial statement articulation, extend the standard models to establish empirical equivalence under non-ideal conditions.

[12] Theoretically, forecasts combination is motivated by a diversification motive with regard to specification respectively model error. Empirically, "simple", "robust" estimation schemes tend to work well [Timmermann, Granger, and Elliott (2006)].

DDMs employed by Pástor, Sinha, and Swaminathan (2008), Lee, Ng, and Swaminathan (2009), and Li, Ng, and Swaminathan (2013) respectively Gordon and Gordon (1997). The two RIMs used in this study are the three-phase model by Gebhardt, Lee, and Swaminathan (2001) respectively two-phase model in Claus and Thomas (2001). Finally, the four AEGMs I employ are the model introduced by Ohlson and Juettner-Nauroth (2005) as well as the modified price earnings growth (MPEG) model [Easton (2004)], the price earnings growth (PEG) model, and ICCs based on the forwarded price earnings ratio (PE). Appendix C provides details on how each of these eight models is specified and their empirical implementation.

In a second step, firm-level ICCs are aggregated at the fund-quarter-level computing a value-weighted average of the respective ICCs corresponding to the stocks in a fund's portfolio,

$$ICC_{f,t} = \sum_{n=1}^{N_{f,t}} w_{f,i,t} \cdot ICC_{i,t}, \tag{2}$$

where $ICC_{f,t}$ denotes the ICC associated with fund f at time t, $N_{f,t}$ the number of stocks the fth fund holds at time t, and $w_{f,i,t}$ the weight of fund f in stock i at time t. $ICC_{i,t}$ denotes the ICC of stock i at time t.

While market value of equity is observable to the econometrician, the numerator in equation (1), expected pay-off, is not. Historically, literature used analysts' forecasts as a proxy for market expectations of future earnings to derive expected pay-offs, one venue also followed in this paper. However, these forecasts come with certain restrictions. There is evidence for systematic biases, resulting from, e.g., career concerns to curry favor with target firms' executives to secure future investment banking business respectively not be excluded from certain meetings [e.g., McNichols and O'Brien (1997), Lin and McNichols (1998), Dechow, Hutton, and Sloan (2000), Westphal and Clement (2008), Mohanram and Gode (2013), and Larocque (2013)]. Further, coverage by analysts is limited, especially for earlier years and smaller firms.

As a response, research developed cross-sectional or "mechanical" earnings forecasts [e.g., Fama and French (2000), Gerakos and Gramacy (2012), Hou, van Dijk, and Zhang (2012),

and Li and Mohanram (2014)], which are also used in this study. Literature documents that related earnings surprises exhibit higher earnings response coefficients than surprises with regard to analysts' forecasts. This suggests that they better reflect market expectations and such better align the left-hand-side of equation (1) with the numerator on its right-hand-side.

To obtain cross-sectional earnings forecasts, in pooled OLS-regressions,[13] a constant and current accounting data are related to earnings τ periods ahead. This results into coefficient estimates for each regressor, which subsequently are multiplied with current accounting data and summed to obtain an estimate for earnings in $t + \tau$. Following literature, I use rolling regressions with a window of ten years and assume a reporting lag of minimum three and maximum fourteen months. As fund holdings are reported every quarter, four separate regression specifications are run each year in March, June, September, and December.

[Please insert Figure 1 here]

Figure 1 shall illustrate the estimation procedure in June of year t. For example, to obtain an earnings estimate for June $t + 1$, first, using the past ten years of data, a pooled OLS-regression of earnings one year ahead on current accounting information is performed (i.e., earnings in $t, ..., t-9$ are regressed on accounting information in $t-1, ..., t-10$, avoiding look-ahead bias). Second, for each firm in t, resulting coefficients are multiplied with its accounting data in t to obtain an earnings forecast. That way, firms for which earnings estimates in t can be computed do not have to have entered the previous regression; coefficients are the same for all firms and applied to all with relevant accounting data in t, which reduces survivorship requirements and distinguishes the cross-sectional from a time series approach, where regressions are run for each firm separately.[14] Appendix D provides an overview of the three models used in this paper: The earnings persistence (EP) model, as the most reduced model, and residual income (RI, to distinguish from ICC-models) model by Li and Mohanram

[13] Recent research examines the usefulness of quantile regressions, in particular median regressions, confer Konstantinidi and Pope (2016) and Easton, Kapons, Kelly, and Neuhierl (2020).

[14] Empirical evidence is in favor of analyst over time series forecast, confer Ball and Brown (1968), Brown, Richardson, and Schwager (1987), O'Brien (1988), Lobo (1992), and Bradshaw, Drake, Myers, and Myers (2012).

(2014) as well as the pioneer, most comprehensive model by Hou, van Dijk, and Zhang (2012) (HvDZ).

C. Descriptive Statistics

[Please insert Table I here]

Table I reports summary statistics for the 3,699 funds analyzed in this study. The sample period spans from 1992 to 2016. Panel A provides information about the distribution of fund characteristics. It reports 25th, 50th, and 75th percentiles, alongside the mean and standard deviation, for the main covariates used in regression analyses as well as fund-level ICC. The average fund is 13 years old, oversees approximately 1 billion U.S. dollars, has an expense ratio of 1.3 percent per year, and turns over its portfolio slightly less than once on an annual basis. Flows, net of the impact of returns, amount to 2.22% per quarter, on average. Over half of funds are managed by a team. Fund-level ICCs are distinguishable between analyst-based ICCs on the one hand and ICCs with mechanical earnings forecasts as inputs on the other; whereas the latter, with means of roughly 6.5%, closely resemble each other, ICCs based on analysts are approximately 50% larger. This is consistent with the positive analyst forecast bias documented in literature [e.g., Lim (2001), Hou, van Dijk, and Zhang (2012), Mohanram and Gode (2013), and Larocque (2013)], as, ceteris paribus, higher expected pay-offs in equation (1) imply higher ICC. Cross-sectional variation seems to be considerable, as the interquartile range amounts to ⅓ of the median.

Panel B informs about cross-sectional correlations between different ICC measures; below the diagonal, it reports Pearson correlation coefficients and Spearman rank correlation coefficients above.[15] Again, a stratification into analyst- and model-based ICCs is recognizable; whereas correlations with analyst-based ICCs amount to roughly 0.60, correlations between model-based ICCs are never below 0.79. ICCs based on RI and HvDZ show the highest correlation (0.93 respectively 0.95), consistent with the high similarity between the underlying

[15] All correlation coefficients are statistically significant at the 1%-level.

models' inputs.

Finally, Panel C reports autocorrelation coefficients for lags up to eight quarters, i.e., two years. Although it is lowest for EP-based ICCs, persistence in general appears to be high, with coefficients of around 0.85 for one lag and still above 0.60 for eight lags in case of the two more complex earnings models and below 0.50 for analyst- and EP-based ICCs. These findings may be relevant for persistence of possible performance-predicting capabilities of ICCs and, related, turnover in portfolio-based analyses I turn to in the next section.

II. ICC and Fund Performance

This section is concerned with the main research object of this paper, the association between current ICC and future fund performance. It starts with a portfolio-based analysis in Section II.A. Thereafter, in Section II.B, it transitions to a regression-based approach in an aim to control for possible confounding covariates. Within this framework, Section II.C studies trading mechanisms related to ICCs.

A. Portfolio Approach

The portfolio analysis is specified in following manner. Each quarter, funds are sorted into quintile portfolios, based on their current holdings' implied ICC. Funds with the lowest ICC enter portfolio 1 (bottom portfolio), whereas funds with the highest ICC are allocated to portfolio 5 (top portfolio). Within portfolios, funds are equally weighted. The five portfolios are held for three months, until the next holdings' report date, when the sorting procedure is repeated. The first sort is based on holdings in December 1991, the last on holdings in September 2016. This results into a return series over 300 months (25 years à 12 months) and 98 rebalances.

[Please insert Figure 2 here]

To get a first impression of ICCs' discriminating capabilities in terms of future fund performance, Figure 2 plots cumulative returns of the bottom (magenta) and top (blue) portfolio

for each of the four earnings specifications. Values are all in the same ball park; whereas bottom portfolios never show more than a seven-fold increase, top portfolios reach values twice as large. None of these strategies, however, seems to be charmed against recessions. Losses during the 2008/2009-crisis are particularly high. Considering that ICCs are based on market prices, which during "extraordinary" periods potentially are less informative,[16] this finding seems to be less of a surprise.

Although Figure 2 provides evidence for ICCs being able to discern funds with high returns from funds with low returns, differences could be attributable to differences in risk (or factor respectively style exposure), leaving ICCs useless to discriminate skillful managers. Hence, in addition to returns ($Return$), besides style-adjusted returns ($SReturn$), which obtain by subtracting from a fund's return in one month the mean return of all funds in the same investment category in the same month, I calculate two performance measures based on linear factor models: Jensen-Alpha ($Alpha1$), the intercept from a regression of fund-portfolio excess returns over the risk-fee rate on a proxy for the market factor, and $Alpha6$, the Fama and French (2015) 5-factor alpha, augmented with the momentum factor [Barillas and Shanken (2018) and Fama and French (2018)], calculated analogously to $Alpha1$.[17] While $Alpha1$ has been documented as the performance measure a large fraction of investors and hence fund customers, whose investment and divestment decisions determine fund managers' career outcomes, care for most [Barber, Huang, and Odean (2016) and Berk and van Binsbergen (2016)], $Alpha6$ is meant to capture additional risk or investment styles mutual fund managers follow and more "sophisticated", like institutional, investors may "correct" for. Finally, I adjust returns as in Daniel, Grinblatt, Titman, and Wermers (1997) ($DGTW$), where a stock's characteristic-adjusted return in a given month is computed by subtracting from its

[16]Literature argues mainly based on insights from behavioral finance. For a review, confer Hirshleifer (2015). E.g., crises are seen as periods with strong negative emotions alleviating existing biases as well as particularly bad news, to which investors appear to systematically falsely react to [e.g., Chopra, Lakonishok, and Ritter (1992) and Hong, Lim, and Stein (2000)]. Veronesi (1999) provides a dynamic, rational expectations equilibrium model where prices underreact to good news in bad times. In all cases, the gap between prices and fundamental values widens.

[17]Returns for factor mimicking portfolios and a proxy for the risk-free rate are obtained from `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

return the return of its benchmark portfolio, which is a value-weighted portfolio of all stocks in the same size, book-to-market, and one-year past return quintile. These adjusted returns are then value-weighted at the fund-portfolio-level. To asses statistical significance for *Return*, *SReturn*, and *DGTW*, their time series are regressed on a constant; corresponding t-values are based on Newey and West (1987)-adjusted standard errors accounting for a lag length of twelve months.

[Please insert Table II here]

Table II, Panel A, reports performance measures for each of the five quintile portfolios separately as well as the hypothetical top-minus-bottom-portfolio short in the bottom and long in the top portfolio. Consistent with previous research on ICC at the stock-level, spreads are highest and always statistically significant at the 1%-level for ICCs based on mechanical earnings forecasts. Alphas and returns are approximately of same magnitude (30 to 40 basis points per month), indicating that spread returns do not simply originate from factor exposure. Values for *DGTW*, which are based on a fund's holdings, are, with on average 15 basis points, the lowest. An adjustment of returns for which investment category the funds belong to reduces the spread by 10 basis points, leaving it still statistically significant, though.

[Please insert Figure 3 here]

The spread, however, does not inform about general discriminating power of ICCs. Even absent a steady increase in performance from bottom to top portfolios, it could potentially be significant. Hence, Panel A also reports performance of the respective quintile portfolios. For illustration, Figure 3 plots the five performance measures for all quintile portfolios based on ICCs derived from earnings forecasts according to the model by HvDZ. It shows that for all measures, performance increases from bottom to top portfolio. Style or factor adjusted measures are all (statistically significant) below zero in the lower part and increase to values of around 10 basis points for style-adjusted returns, *Alpha*1, and *DGTW*, respectively -2

basis points for $Alpha6$. This could be interpreted as evidence that ICCs do not simply show extreme results at the tails but no (or even perverse) discriminating power in-between.

To shed light on which factor tilts are associated with which ICC strategy, Panel B tabulates the whole set of coefficients in regressions underlying $Alpha6$, β_{MKT}, β_{SMB}, β_{HML}, β_{RMW}, β_{CMA}, and β_{UMD}, i.e., loadings corresponding to the market, small-minus-big (size), high-minus-low (value), robust-minus-weak (profitability), conservative-minus-aggressive (investment), and up-minus-down (momentum) factor-mimicking portfolio, respectively. In comparison to funds with low ICCs, high-ICC funds show larger exposure to firms which behave like small value-firms with high operating profitability; in addition, they show a negative exposure to the momentum portfolio. Value and profitability tilts are consistent with a fundamental investment approach, which screens firms with "cheap" valuations in relation to their profitability prospects. However, size and momentum exposures could also simply reflect how ICCs are calculated. If the market value of equity is relatively low, which tends to be the case for small firms or firms with recent losses in terms of stock returns, ceteris paribus, the larger the ICC needed to equate it to discounted expected pay-offs. Further, high current profitability, considering the regressors in earnings regression equations, tends to translate into comparably high future earnings, which, ceteris paribus, also increase a firm's ICC.

Cut-offs based on quintiles reveal a certain sorting pattern. However, only returns, but none of the top portfolios' risk- or style-adjusted performance measures, are statistically significant different from zero, necessary for a feasible investment approach. Additionally, considering portfolio turnover (not reported), on average 70% of the funds remain in the top portfolio from one period to the next (in line with autocorrelations reported in Table I, Panel B), such that investors potentially need to pay back-end and front-end loads concerning the remnant 30%. Further, provided evidence in previous research for managers able to beat their benchmark after costs being scarce, 20%-percentiles might simply be too coarse.

In an aim to address these issues, the sorting-exercise, now based on decile portfolios,

is repeated for no-load share classes. Panel C reports performance measures for bottom and top as well as corresponding spread portfolios. In general, spreads increase; further, investors could realize a return of 1% per month. More importantly, top portfolios now exhibit statistically significant risk respectively style adjusted performance measures. Alphas range between 19 basis points and 37 basis points, statistically significant at the 5%-level, on average. Hence, feasible investments into mutual funds with high ICC had led to entirely net-of-cost alphas for investors free from any assumptions on trading costs, not readily reconstructed for analyses at the stock-level.

B. Regression Analysis

Whereas portfolio sorts seem to provide first evidence for a positive association between current ICC and future fund performance, possibilities to control for confounding characteristics at the fund level are limited. Hence, for the rest of the paper, I turn towards panel regressions at the fund-quarter-level of the form

$$y_{f,t+1} = \beta \cdot ICC_{f,t} + \vec{\boldsymbol{\gamma}} \cdot \vec{\boldsymbol{c}}_{f,t} + \vec{\boldsymbol{\iota}} \cdot \vec{\boldsymbol{\varphi}} + \varepsilon_{f,t+1}, \tag{3}$$

where $y_{f,t+1}$ denotes one of the five performance measures of fund f in quarter $t+1$.[18] $ICC_{f,t}$ is a fund's quarterly[19] ICC at time time t, calculated as described in Section I.B. $\vec{\boldsymbol{\gamma}}$ is the vector of coefficients associated with fund-level covariates, which are described in Section I.C respectively Table I and stacked into vector $\vec{\boldsymbol{c}}_{f,t}$. Thereby, following literature, Age and TNA are log-transformed to reduce skewness. The specification of fixed effects is captured by $\vec{\boldsymbol{\varphi}}$, which denotes a vector of length h, where h equals the number of fixed effects included in the model. $\vec{\boldsymbol{\iota}}$ is the corresponding vector of ones and hence also of length h. $\varepsilon_{f,t+1}$ denotes

[18] In quarterly regressions, $Alpha1$ and $Alpha6$ are obtained as follows. First, for a given fund, monthly alphas are computed as the difference between actual returns and expected return, estimated using factor loadings computed from a regression of the preceding 36 monthly excess returns on a constant and proxies for the respective factor(s). Second, these monthly alphas are aggregated to the quarterly level using compounding.

[19] To obtain quarterly ICCs with matching maturities to ease interpretation, I subtract one from $\sqrt[4]{1 + ICC_{f,t}}$.

the error term, while $\cdot$ symbolizes the scalar product. The main variable of interest is β, the coefficient of a fund's ICC, where a positive coefficient were consistent with ICCs being able to positively predict future performance.

[Please insert Table III here]

Table III shows results for regression (3), estimated with three different specifications of fixed effects, separately for each of the four earnings specifications. Throughout, given a "large" N (3,699) relative to a "small" T (100), standard errors are clustered at the fund level [Petersen (2009)]. The first five columns report results of regressions with time and style fixed effects to account for common time variant factors and commonalities within one style. In the next five columns, time and style fixed effects are interacted to control for commonality within time-style-combinations. The addition of fund fixed effects in the last five columns is meant to capture the impact of time-invariant unobserved heterogeneity between funds; this constitutes the main specification for the rest of the paper. Results are in line with the observations from the portfolio-sort analysis and uniform across different specifications of fixed effects. In general, ICCs are statistically significantly associated with future fund performance at the 1%-level. With respect to economic interpretation of coefficients, an increase in quarterly ICC by one percentage point, on average, was associated with an increase in future quarterly fund performance by one percentage point, irrespective of the specific performance measure. This corroborates the notion that the positive correlation between current ICCs and future fund performance does not seem to be attributable to effects specific to one time, style, or fund respectively characteristics at the fund-level.

[Please insert Table IV here]

With respect to the latter, Table IV adds four additional variables shown to be associated with fund performance.[20] Besides active share ($ActShare$)[21] [Cremers and Petajisto (2009)

[20]Due to data limitations - the sample size drops by ⅘ - this specification is merely used as an additional analyses of whether the effect of ICCs is subsumed by different variables instead of being used as the main specification.

[21]Data on active share is obtained from `http://www.petajisto.net/data.html`.

and Cremers, Petajisto, and Zitzewitz (2013)], a measure for how much a fund deviates from its benchmark, it adds the industry concentration index (ICI) by Kacperczyk, Sialm, and Zheng (2005), a proxy for how concentrated a fund's holdings are within one industry relative to the market, and return gap ($RetGap$) [Kacperczyk, Sialm, and Zheng (2008)], aimed to quantify "unobserved actions" of mutual fund managers, calculated as the difference between actual gross fund returns and returns implied by the fund's latest portfolio disclosure. Finally, it adds the respective performance measure over the past quarter ($LaggedPerf$). In addition, I replace fund with fund-by-manager fixed effects. The intuition is that if high-ICC strategies were indeed able to translate into higher future fund performance, skilled managers might be more likely to choose them. Simultaneously, skilled managers, following an assortative matching rationale,[22] potentially are matched to specific funds with higher resources. Holding those matches constant, I aim to control for endogeneity at the time-invariant manager-skill- and manager-fund-match-level. Results indicate, that none of the considered aspects is able to explain the positive association of current ICCs with future fund performance, suggesting that a high-ICC strategy per se can help funds to achieve better performance.

Combining the positive association between future fund performance and current ICC on the one hand with its high autocorrelation and moderate turnover in portfolio sorts on the other suggests that correlation with performance might persist. That is, the association of ICCs with performance were not limited to next quarter's value, but to performance further afar. To test this hypothesis, I relate semi-annual, annual, and biennial future performance with current, correspondingly scaled ICC in regression (3). To avoid using overlapping observations and more closely resemble investment decisions of investors,[23] I consider ICCs as of December; semi-annual regressions allow to also use ICCs derived from holdings in June.

[Please insert Table V here]

[22] For studies on assignment models, confer Mayer (1960), Sattinger (1975, 1993), Rosen (1982), Gabaix and Landier (2008), and Terviö (2008).

[23] Several studies argue that investors primarily make their investment decisions based on calendar year returns, confer, e.g., Brown, Harlow, and Starks (1996), Sirri and Tufano (1998), and Chaudhuri, Ivković, and Trzcinka (2018).

Table V documents results of corresponding regressions. While ICCs largely remain statistically significant for all maturities, consistent with strong, yet decreasing autocorrelation in Table I, both economic significance, measured by the size of coefficients, and statistical significance decrease with increasing horizon. For example, the coefficients in regressions related to *Alpha*6 for HvDZ-based ICCs decrease from approximately 0.8, statistically significant at the 1%-level, to 0.2, statistically significant at the 10%-level. *Alpha*6 is also the measure with lowest signs of persistence; while significant in semi-annual and annual regressions, it is not significantly related to ICCs in biennial regressions for EP- and RI-based earnings forecasts. This is in line with factor loadings in Table II, which seem to explain part of the return accruing to ICC-based strategies.

Results are consistent with the notion that ICCs as a persistence characteristic lend themselves as a measure for the long-term fate of a fund. This potentially accommodates investors, considering that determination of a fund's ICC arguably is not a straightforward endeavor, in particular for retail investors (as discussed in Section IV.B). Further, whereas investors' positive flow response to high past fund performance is still erroneous on average, for the subset of funds with both high past performance and high ICC, investors are more likely to see their expectation of high future performance fulfilled. Hence, albeit spuriously, for these investors investment decisions could lead to a positive feed-back loop, potentially adding to the explanation for why investors cater to past returns.

C. Fund Trades

After documenting evidence for a positive association between current ICC and future fund performance, this study turns towards a closer examination of trading mechanisms related to ICC. Retrospectively, given the time series of past returns and holdings, one can discern by how much contemporary fund performance was influenced by fund managers' trades. To investigate how trading decisions based on ICC altered a fund's performance, I determine the fraction of a manager's buys and sells "in the same direction" traded firms' ICCs changed.

In particular, I compute the trade-weighted percentage of buys (sells) in firms whose ICC increased (decreased) over the same quarter, $\%SameDir\ Buys$ ($\%SameDir\ Sells$).

[Please insert Table VI here]

Table VI presents results for regression (3), augmented by the two trading variables. Statistically significant at the 1%-level, economically, the results imply that in case 100% of a fund's buys and sells have been in the same direction as the underlying firms' change in ICC, contemporary fund performance was higher by, respectively, approximately 2.5 percentage points. This corroborates the notion that explicitly tailoring a fund's strategy towards firms with higher ICC supports higher performance.

In summary, Section II provides evidence for a positive association between current ICC and future fund performance. This does not seem to be driven by time effects, differences in styles, or specific fund-manager-matches and appears to be distinct from associations with fund characteristics found in previous literature.

III. Determinants of ICC Strategies

Having documented possible performance implications of a strategy based on ICCs, this section seeks to uncover potential determinants of how likely managers are to employ such a strategy. For this, I examine cross-sectional heterogeneity to study correlations of ICCs with fund family and manager characteristics. Section III.A analyses the relation between trading efficiency as a measure for trading costs and ICCs, whereas Section III.B investigates correlations with fund managers' SAT scores as a proxy for skill.

A. Trading Efficiency and ICC

Evidence of this study points towards a fund-investment strategy based on ICC yielding actual profits, contrasting literature on ICC at the individual stock- and stock-portfolio-level, where transaction costs appear to predominate returns. One possible part of the

explanation for why mutual funds seem to be able to seize the performance potential inherent to a strategy based on ICC could be, that mutual funds, as institutional investors, face particularly favorable trading conditions. This in turn could imply that the height of trading costs mutual funds face were negatively correlated with the probability that they employ high-ICC strategies.

Yet, funds' trading costs are not directly observable. However, Cici, Dahm, and Kempf (2018) derive a proxy for the efficiency of their families' trading desk. The higher the trading desk's efficiency, the lower trading costs arguably are. Hence, I test for the correlation between contemporaneous ICC and trading desk efficiency.

I follow Cici, Dahm, and Kempf (2018) to estimate trading desk efficiency at the family-level. In particular, it obtains as the difference between the gross return of the family's SP500 index fund,[24] incorporating trading costs, and the return of the underlying index, inherently net of costs, within a week before and after index reconstitutions. This difference is averaged for each index fund across all non-overlapping index adjustment periods in a specific quarter to obtain the variable $TradingEffiency$. It reflects the family's decisions, e.g., in terms of when to trade, which trading venues and/or brokers to use to what extent, and how to place and split which types of orders.

I use Morningstar Direct to obtain data on which funds identify as SP500 index funds (benchmark "SP 500 TR USD"). Because funds outsourced to an external asset management company presumably do not profit from the family's trading desk, Cici, Dahm, and Kempf (2018) exclude them from the analysis. To determine outsourced funds, I retrieve semi-annual and annual NSAR-A and -B filings from the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system maintained by the SEC. Item #8. informs about a fund's advisors, the employers of the asset managers conducting the day-to-day-business. I manually match NSAR-information by fund share class name and date and construct a time series of which family is affiliated with which advisor.

[24] In cases of multiple SP500 index funds, Cici, Dahm, and Kempf (2018) choose the index fund with the longest track record.

[Please insert Table VII here]

Table VII presents results from a regression akin to model (3), where I correlate contemporaneous ICC as the dependent variable to trading efficiency, which is the same for all funds in the same family in quarter t. Statistically significant at the 5%-level, results indicate that funds in families with higher trading efficiency are more likely to employ a high-ICC strategy. This is consistent with the notion that a favorable transaction cost environment helps funds monetizing the previously documented potential of ICC-based investments to generate outperformance.[25]

B. Fund Manager Skill and ICC

The positive association between ICC and fund performance is consistent with successfully employing investment strategies based on firms' ICCs reflecting skill, which some managers are equipped with and which others lack. Hence, measures for a manager's skill might positively correlate with her funds' ICC.

As a proxy for managerial skill I follow literature [e.g., Greenwood and Nagel (2009) and Fang, Kempf, and Trapp (2014)] and use the average matriculates' SAT score of the institution where a manager obtained her bachelor's degree. To collect information on which universities managers obtained their degree from, I use the following data sources. Besides Morningstar Direct and Morningstar Principia CDs from 1996 to 2005, I search through fund filings with the SEC (e.g., forms 485APOS/485BPOS, 497, and accompanying statements of additional information), Marquis Who's Who, newspaper articles, LinkedIn, Bloomberg, the websites of fund companies, as well as university sources such as yearbooks, alumni, and donation pages. Average SAT scores of these institutions are obtained from the College Scorecard provided by the U.S. Department of Education.[26] To arrive at a value for SAT at the fund-level, SAT, I compute the mean over the SAT scores of all managers managing a

[25] Adding $TradingEfficency$ as a regressor to ICC in the analysis in Table IV does not alter results, reinforcing ICCs themselves being the actual driver behind performance.

[26] Confer `https://collegescorecard.ed.gov/`.

fund at a specific point in time, requiring non-missing values for all the fund's managers. In order to ease interpretation of coefficients, SAT scores are divided by 1,000.

[Please insert Table VIII here]

Table VIII documents results from a regression of contemporaneous fund-level ICC on *SAT*. Statistically significant at the 1%-level for each of the four ICC specifications, economically results imply that managers associated with the highest SAT scores, on average, had quarterly ICCs which were approximately 10 basis points larger than ICCs of managers from universities at the other end of the spectrum, which amounts to roughly 15% of the interquartile range of quarterly ICCs. This provides evidence for skillful managers being more likely to tailor their investments towards high ICCs, consistent with that one particular manifestation of innate ability in the mutual fund industry consists of applying a high-ICC strategy.

IV. Implications of ICCs' Correlation with Fund Performance

This final section examines, what responses the positive association between current ICCs and future fund performance might evoke, considering two of the central parties involved in mutual fund markets. Section IV.A analyses if incentives of managers themselves are altered, whereas Section IV.B turns towards an examination of whether investors into mutual funds are influenced in their investment decisions.

A. ICCs' Impact on Managerial Tournament Incentives

Given funds posses the means to capitalize on ICC strategies, they should try to seize them. This knowledge in turn potentially affects a manager's incentives. In particular, she may rely on high ICCs to pay off in the future. This might induce her to react differently from a manager who does not count on such a strategy.

Past research documents how a manager's incentives influence risk-taking. In particular, managers which lie behind their peers in the middle of the year tend to engage into "risk

shifting", i.e., to increase risk, in an aim to catch up. Incentives for this behavior are rooted in the pay-off structure managers in the mutual fund industry face, which resembles a "tournament", where winners obtain a price whilst losers come away empty handed. This is due to the industry's remuneration structure. Managers' compensation comprises claims on variable, asymmetric boni [Ma, Tang, and Gómez (2019)] "simply" expiring worthless, given a certain threshold is not met. Simultaneously, another part of managerial pay is based on assets under management [Hu, Hall, and Harvey (2000) and Elton, Gruber, and Blake (2003)]. In this regard, it are investors who incentivize managers via their asymmetric response to past performance; whereas high past performance is eminently rewarded with large inflows, funds with low past performance loose comparably low amounts of assets [e.g., Sirri and Tufano (1998) and Ferreira, Keswani, Miguel, and Ramos (2012)]. Taken together, managers' pay-off resembles that of an option - whose value, ceteris paribus, increases with increasing "risk".

Hence, managers have incentives to "shift" their risk to higher levels given they trail behind their peers in order to increase their chances to catch up. If a manager, however, in addition or instead relies on other parts of her investment strategy, e.g., high ICC, to pay off, her incentives to increase risk might be muted respectively shut off.

To test for whether managers with high ICC temper their risk shifting, which were lending support to the notion that managers are aware of the benefits of high-ICC strategies and indeed utilize them, I relate mid-year, i.e., end-of-June, ICCs with mid-year performance of managers. To capture how much fund managers intend to change their risk in the second half of the year relative to the first, I construct the risk adjustment ratio as in Kempf, Ruenzi, and Thiele (2009),

$$RAR_{f,t} = \frac{\sigma_{f,t}^{(2),int}}{\sigma_{f,t}^{(1)}}, \tag{4}$$

where $\sigma_{f,t}^{(1)}$ denotes realized portfolio risk of fund f in the first half of the year (January to June), calculated using actual portfolio holdings and volatility of corresponding daily

portfolio returns in the first half of the year; $\sigma_{f,t}^{(2),int}$ represents intended portfolio risk for the second part of the year (July to December), which is computed using actual portfolio holdings in the second half of the year and a forecast of volatility of corresponding returns, obtained as realized volatility of that portfolio had it been held in the first half of the year. The regression model to test for the impact of high-ICC strategies on tournament behavior is given by

$$RAR_{f,t} = \delta_1 \cdot Rank_{f,t} + \delta_2 \cdot HighICC_{f,t} + \delta_3 \cdot Rank_{f,t} \cdot HighICC_{f,t} + \vec{\boldsymbol{\gamma}} \cdot \vec{\boldsymbol{c}}_{f,t} + \vec{\boldsymbol{\iota}} \cdot \vec{\boldsymbol{\varphi}} + \epsilon_{f,t}, \quad (5)$$

where $\epsilon_{f,t}$ denotes the error term. $Rank_{f,t}$, based on fund performance over the first six months each year, is calculated for each investment category separately. It is normalized to be equally distributed between zero and one, with the best manager in its respective investment category being assigned rank one. As $Rank_{f,t}$ is interacted with a fund's ICC, I transform it into indicator variable $HighICC_{f,t}$, equal to one for all funds whose ICC is larger than the median ICC in the same investment category in June of the respective year and zero else. A negative δ_1 were consistent with the tournament literature, suggesting that the lower a manager's rank, the larger her risk shifting. The main variable of interest is δ_3; a positive value lent support to the notion that managers with the same low mid-year rank, albeit high ICC, increase risk less relative to managers with low ICC.

[Please insert Table IX here]

Table IX documents results from regression (5). The negative coefficient of $Rank$, statistically significant at the 1%-level, provides evidence for the existence of tournament-like behavior in the sample. In comparison, the coefficient of the interaction with $HighICC$ is statistically significant positive at the same level. Furthermore, associated coefficients, δ_1 and δ_3, are approximately on par in absolute values, with $|\delta_3|$ amounting to roughly 75% of $|\delta_1|$, on average, consistent with managers strongly tempering risk-shifting in case they have a high-ICC strategy at command. This might serve as evidence for managers being both

aware of the merits of such a strategy and indeed relying on it.

B. Investors' Response to Fund ICCs

Finally, this study aims to investigate investors' awareness of the association between ICCs and fund performance. For this purpose, it considers the relation between current ICC and future fund flows. Rational investors probably would react to the signal ICCs allegedly pose and direct investments into funds with high expected performance. This signal, however, comes at a cost, which presumably is not constant throughout a fund's investor base. In terms of data necessary to determine a fund's ICC, a fund only provides its holdings. Data at the stock-level, e.g., market and book values of equity, dividends, and earnings together with predictions thereof, which are either based on analysts or obtained via statistical models, have to be accessible for and gathered by investors themselves. Consecutively, ICCs need to be actually computed, necessitating the knowledge of the various models and respective resources required for calculation. Furthermore, the association between ICC and fund performance is not advertised either, such that investors have to uncover it themselves.

I hypothesize that a moderating factor for the subjective costs of the signal and hence investors' reaction can be derived from their classification into retail and institutional. While the "representative agent" for the former might be the average U.S.-household with presumably limited "resources" (confer the references in the introduction), institutional investors might have the means mentioned above at command. This suggests that retail investors would not react to current ICC, while institutional did.

[Please insert Table X here]

Table X tests for this hypothesis, employing a fund's future flow as the dependent variable in regression (3) and past fund return (*Past Return*) as an additional control variable.[27] The analysis is stratified by retail (Panel A) and institutional share classes (Panel B). While there is no association between current ICC and future flow in the retail stratum, it is positive and

[27]Inferences remain the same, when return is replaced by either of the other four performance measures.

significant at the 5%-level for EP-based ICCs and at the 1%-level for the remaining ICCs in the panel of institutional share classes. Concerning economic significance, a 1-percentage-point increase in ICCs is associated with a 1.5 percentage point increase in quarterly flows, on average. This is consistent with limited attention of retail investors respectively allegedly more sophisticated institutional investors' awareness of ICCs' positive association with future fund performance.

V. Conclusion

What kind of trading strategies do skillful mutual fund managers employ and how can investors identify them? Although research documents that portfolio selection based on firms' ICCs in general founders on necessary transaction costs, mutual fund managers seem to be able to bring to bearing corresponding return potentials.

Computing holdings' implied ICC of mutual funds, this study provides evidence for a viable correlation between a fund's current ICC and its future performance. This association is present both in portfolio sorts, which result into actual, risk- respectively style-adjusted performance after costs, and panel regressions, which allow to control for confounding factors at the time-, style-, and fund-level. Consistent with mutual funds being particularly well equipped to actually implement ICC-based investment decisions due to their preferential trading opportunities, funds with access to trading desks with a high degree of efficiency are more prone to employ a high-ICC strategy. Likewise, based on the average matriculates' SAT score of the institutions managers received their bachelor's degree from, managers with supposed higher innate ability employ such a strategy more often. In general, managers themselves appear to be both aware of and confident with respect to ICC-based investment strategies, as they are less likely to engage into risk-shifting should they lie behind their peers in the middle of the year but have a high-ICC strategy at their command. With regard to investors' awareness, however, only more sophisticated institutional investors seem to recognize and trade based on the positive association between current ICCs and future

performance as opposed to retail investors.

In summary, with regard to the questions raised in the introduction that are tackled by research - whether mutual fund managers have skill picking stocks and how information advantages are developed and exploited by market participants -, a fraction of funds seems to demonstrate skill by exploiting information and trading cost advantages with respect to an investment strategy based on ICC. Hence, part of the explanation for the "puzzling" prosperity of the mutual fund industry might be, that some funds with reliable proficiencies indeed exist.

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Appendix A: Tables

Table I: Descriptive Statistics

This table shows descriptive statistics for the quarterly sample of 3,699 mutual funds during 1992-2016. Panel A presents 25, 50, and 75 percentiles (p_{25}, p_{50}, and p_{75}, respectively), as well as the mean ($\bar{x}$) and standard deviation (Std) of fund characteristics. *Age* denotes fund age in years. TNA denotes fund size, measured as fund total net assets in $ million. *Exp. Ratio* is the fund expense ratio in % p.a. *Turn. Ratio* is the fund turnover ratio in % p.a. *Flow* is the percentage quarterly growth in funds' new money, net of the effect of returns. $I(Team)$ is an indicator variable equal to one if the fund is managed by a team and zero else. ICC, for every fund every quarter, obtains as a value-weighted ICC of the funds' portfolios' constituents, based on four different proxies for expected earnings, as described in Section I.B. Panel B reports average cross-sectional Pearson correlation coefficients below and Spearman rank correlation coefficients above the diagonal between fund-level ICCs. Panel C provides autocorrelation coefficients of fund-level ICCs up to a lag length of eight quarters.

Panel A: Fund Characteristics

	p_{25}	p_{50}	p_{75}	$\bar{x}$	Std
Control variables					
Age [years]	4.67	9.50	16.75	13.23	13.15
TNA [$ million]	45.60	181.10	708.90	1,042.48	3,523.40
Exp. Ratio [%]	0.98	1.21	1.50	1.30	1.35
Turn. Ratio [%]	34.00	63.00	108.00	87.07	117.60
Flow [%]	−3.85	−0.75	3.99	2.22	15.96
I(Team) [%]	0.00	100.00	100.00	59.93	49.00
Fund-level ICC					
Analyst [%]	8.24	9.01	9.93	9.15	1.52
EP (2014) [%]	5.09	6.00	7.09	6.28	2.25
RI (2014) [%]	5.06	6.13	7.34	6.33	1.89
HvDZ (2012) [%]	4.75	5.96	7.28	6.15	1.99

Panel B: Pearson and Spearman Correlations between Fund-level ICC

	Analyst	EP (2014)	RI (2014)	HvDZ (2012)
Analyst	1.00	0.65	0.63	0.56
EP (2014)	0.58	1.00	0.82	0.78
RI (2014)	0.59	0.79	1.00	0.95
HvDZ (2012)	0.53	0.74	0.93	1.00

Panel C: Autocorrelation of Fund-Level ICC

	1	2	3	4	5	6	7	8
Analyst	0.83	0.73	0.64	0.61	0.57	0.54	0.50	0.49
EP (2014)	0.85	0.73	0.66	0.61	0.55	0.50	0.47	0.44
RI (2014)	0.92	0.85	0.80	0.77	0.73	0.70	0.67	0.64
HvDZ (2012)	0.93	0.87	0.82	0.78	0.75	0.72	0.70	0.69

Table II: ICC and Mutual Fund Performance: Portfolio Sorts

This table presents results from portfolio sort analyses of funds' ICC and future fund performance. For every fund every quarter, a value-weighted ICC of the funds' portfolios' constituents, ICC, based on four different proxies for expected earnings, is constructed as described in Section I.B. Each quarter, funds are sorted according to their most recent ICC. Panel A presents average monthly returns ($Return$), style-adjusted returns ($SReturn$), Jensen Alpha ($Alpha1$), the Fama and French (2015) 5-factor alpha, augmented with the momentum factor ($Alpha6$), and characteristics adjusted returns ($DGTW$), described in Section II.A, of equally-weighted ICC quintile portfolios, stratified according to which earnings estimates entered the calculation of ICC. Besides quintile porfolio performance measures, the bottom row reports the top-minus-bottom-performance of the corresponding spread portfolio. Panel B presents factor loadings corresponding to regressions underlying $Alpha6$. Finally, Panel C reports the top and bottom portfolio performance as well as the spread portfolio performance for decile portfolios based on no-load fund share classes. Performance measures are reported in % per month. T-statistics [according to Newey and West (1987), considering 12 monthly lags, in case of $Return$, $SRetun$, and $DGTW$] are reported in parentheses. Throughout the table, ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Panel A: Performance of Quintile Portfolios.

	Analyst					EP (2014)				
ICC-rank	Return	SReturn	Alpha1	Alpha6	DGTW	Return	SReturn	Alpha1	Alpha6	DGTW
1	0.60^{**}	-0.12^{**}	-0.19^{***}	-0.22^{***}	-0.07	0.57^{**}	-0.13^{***}	-0.25^{***}	-0.31^{***}	-0.08
	(2.48)	(−2.36)	(−3.27)	(−3.76)	(−1.32)	(2.28)	(−3.34)	(−4.72)	(−5.63)	(−1.46)
2	0.72^{***}	-0.01	-0.08^{**}	-0.14^{***}	-0.02	0.68^{***}	-0.03	-0.12^{***}	-0.2^{***}	-0.00
	(3.12)	(−0.33)	(−2.02)	(−4.18)	(−0.51)	(2.91)	(−0.85)	(−2.83)	(−5.28)	(−0.04)
3	0.77^{***}	0.04	-0.03	-0.14^{***}	0.01	0.77^{***}	0.03	-0.03	-0.15^{***}	0.02
	(3.18)	(1.20)	(−0.6)	(−3.97)	(0.25)	(3.19)	(0.96)	(−0.55)	(−4.21)	(0.59)
4	0.85^{***}	0.06	0.03	-0.15^{***}	0.08	0.89^{***}	0.09	0.09	-0.10^{*}	0.03
	(3.41)	(0.93)	(0.40)	(−2.63)	(1.54)	(3.65)	(1.49)	(1.10)	(−1.83)	(0.63)
5	0.90^{***}	0.07	0.05	-0.14^{*}	0.05	0.93^{***}	0.07	0.10	−0.04	0.07
	(3.17)	(0.89)	(0.42)	(−1.91)	(0.83)	(3.37)	(0.93)	(0.84)	(−0.72)	(1.33)
5-1	0.29^{**}	0.19^{*}	0.25^{*}	0.08	0.12^{*}	0.36^{***}	0.20^{**}	0.35^{***}	0.26^{***}	0.15^{**}
	(2.18)	(1.86)	(1.81)	(0.83)	(1.80)	(2.95)	(2.11)	(2.81)	(3.94)	(2.32)

	RI (2014)					HvDZ (2012)				
ICC-rank	Return	SReturn	Alpha1	Alpha6	DGTW	Return	SReturn	Alpha1	Alpha6	DGTW
1	0.55^{**}	-0.15^{***}	-0.25^{***}	-0.29^{***}	-0.10^{*}	0.57^{**}	-0.15^{***}	-0.26^{***}	-0.30^{***}	-0.09^{*}
	(2.27)	(−3.93)	(−5.68)	(−6.27)	(−1.86)	(2.24)	(−4.30)	(−4.98)	(−5.66)	(−1.68)
2	0.68^{***}	−0.05	-0.12^{***}	-0.20^{***}	−0.01	0.69^{***}	−0.05	-0.12^{***}	-0.21^{***}	−0.00
	(2.91)	(−1.41)	(−2.87)	(−5.45)	(−0.35)	(2.92)	(−1.44)	(−2.69)	(−5.39)	(−0.08)
3	0.77^{***}	0.02	−0.04	-0.16^{***}	0.01	0.76^{***}	0.02	−0.05	-0.16^{***}	−0.00
	(3.12)	(0.46)	(−0.76)	(−4.51)	(0.13)	(3.06)	(0.62)	(−1.08)	(−4.52)	(−0.02)
4	0.88^{***}	0.09	0.06	-0.12^{**}	0.05	0.89^{***}	0.11^{*}	0.09	-0.10^{*}	0.05
	(3.49)	(1.48)	(0.70)	(−2.17)	(1.01)	(3.66)	(1.74)	(1.15)	(−1.93)	(0.94)
5	0.96^{***}	0.13	0.14	−0.01	0.10^{*}	0.95^{***}	0.11	0.13	−0.02	0.09
	(3.57)	(1.52)	(1.26)	(−0.18)	(1.67)	(3.56)	(1.41)	(1.22)	(−0.41)	(1.50)
5-1	0.40^{***}	0.28^{***}	0.39^{***}	0.28^{***}	0.2^{***}	0.38^{***}	0.27^{***}	0.39^{***}	0.28^{***}	0.18^{**}
	(3.4)	(2.70)	(3.28)	(3.68)	(2.80)	(3.51)	(2.71)	(3.54)	(3.90)	(2.48)

Table II: ICC and Mutual Fund Performance: Portfolio Sorts (Continued)

Panel B: Factor Loadings of Regressions underlying Alpha6.

Analyst

ICC-rank	Alpha6	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	β_{UMD}
1	-0.22^{***}	0.95^{***}	0.00	0.04	0.05^{**}	0.03	-0.04^{***}
	(-3.76)	(58.39)	(-0.13)	(1.46)	(1.97)	(0.83)	(-3.06)
2	-0.14^{***}	0.96^{***}	0.01	0.05^{***}	0.10^{***}	0.01	-0.02^{***}
	(-4.18)	(104.6)	(0.99)	(3.07)	(6.61)	(0.43)	(-3.34)
3	-0.14^{***}	0.97^{***}	0.11^{***}	0.10^{***}	0.13^{***}	0.03	-0.02^{***}
	(-3.97)	(100.44)	(9.25)	(6.43)	(7.71)	(1.31)	(-3.03)
4	-0.15^{***}	1.00^{***}	0.28^{***}	0.14^{***}	0.18^{***}	0.06^{*}	-0.04^{***}
	(-2.63)	(63.35)	(14.44)	(5.28)	(6.59)	(1.68)	(-3.63)
5	-0.14^{*}	0.99^{***}	0.56^{***}	0.19^{***}	0.20^{***}	0.04	-0.08^{***}
	(-1.91)	(49.42)	(21.9)	(5.59)	(5.94)	(0.76)	(-5.08)
5-1	0.08	0.04	0.56^{***}	0.15^{***}	0.15^{***}	0.00	-0.04^{*}
	(0.83)	(1.61)	(16.17)	(3.24)	(3.19)	(0.06)	(-1.91)

EP (2014)

ICC-rank	Alpha6	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	β_{UMD}
1	-0.31^{***}	1.01^{***}	0.01	0.02	0.08^{***}	0.01	0.01
	(-5.63)	(67.67)	(0.38)	(0.69)	(3.09)	(0.15)	(1.17)
2	-0.2^{***}	0.98^{***}	0.01	0.06^{***}	0.11^{***}	0.02	-0.02^{**}
	(-5.28)	(93.5)	(0.73)	(3.47)	(6.26)	(0.72)	(-2.35)
3	-0.15^{***}	0.98^{***}	0.10^{***}	0.10^{***}	0.14^{***}	0.04^{*}	-0.03^{***}
	(-4.21)	(102.69)	(8.31)	(6.42)	(8.76)	(1.87)	(-3.69)
4	-0.10^{*}	0.97^{***}	0.28^{***}	0.15^{***}	0.17^{***}	0.08^{**}	-0.05^{***}
	(-1.83)	(66.94)	(15.82)	(6.34)	(6.92)	(2.28)	(-5.05)
5	-0.04	0.95^{***}	0.57^{***}	0.18^{***}	0.16^{***}	0.03	-0.11^{***}
	(-0.72)	(60.01)	(28.43)	(6.75)	(5.89)	(0.94)	(-9.7)
5-1	0.26^{***}	-0.06^{***}	0.56^{***}	0.16^{***}	0.08^{**}	0.03	-0.13^{***}
	(3.94)	(-3.17)	(24.17)	(5.25)	(2.57)	(0.69)	(-9.3)

RI (2014)

ICC-rank	Alpha6	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	β_{UMD}
1	-0.29^{***}	0.97^{***}	0.01	0.01	0.07^{***}	-0.02	0.01
	(-6.27)	(77.08)	(0.56)	(0.43)	(3.06)	(-0.78)	(1.35)
2	-0.20^{***}	0.98^{***}	0.04^{***}	0.06^{***}	0.13^{***}	0.00	-0.02^{***}
	(-5.45)	(95.01)	(3.38)	(3.29)	(7.23)	(0.18)	(-2.69)
3	-0.16^{***}	0.99^{***}	0.14^{***}	0.12^{***}	0.13^{***}	0.04	-0.02^{***}
	(-4.51)	(98.8)	(11.37)	(7.39)	(7.63)	(1.52)	(-3.06)
4	-0.12^{**}	1.00^{***}	0.28^{***}	0.16^{***}	0.18^{***}	0.04	-0.05^{***}
	(-2.17)	(63.98)	(14.55)	(6.33)	(6.75)	(1.15)	(-4.43)
5	-0.01	0.94^{***}	0.48^{***}	0.17^{***}	0.16^{***}	0.10^{**}	-0.12^{***}
	(-0.18)	(53.65)	(21.79)	(5.71)	(5.41)	(2.49)	(-9.11)
5-1	0.28^{***}	-0.03	0.47^{***}	0.16^{***}	0.10^{***}	0.12^{***}	-0.13^{***}
	(3.68)	(-1.51)	(18.18)	(4.59)	(2.73)	(2.6)	(-8.56)

Table II: ICC and Mutual Fund Performance: Portfolio Sorts (Continued)

Panel B: Factor Loadings of Regressions underlying Alpha6 (Continued).

		HvDZ (2012)					
ICC-rank	Alpha6	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	β_{UMD}
1	-0.30^{***}	0.99^{***}	0.08^{***}	-0.01	0.08^{***}	-0.03	0.02
	(-5.66)	(68.43)	(4.53)	(-0.56)	(3.08)	(-0.88)	(1.43)
2	-0.21^{***}	0.98^{***}	0.07^{***}	0.06^{***}	0.13^{***}	0.00	-0.02^{**}
	(-5.39)	(92.29)	(5.17)	(3.49)	(7.2)	(0.18)	(-2.5)
3	-0.16^{***}	0.99^{***}	0.12^{***}	0.11^{***}	0.13^{***}	0.02	-0.04^{***}
	(-4.52)	(100.78)	(9.81)	(6.97)	(8.01)	(1.05)	(-5.08)
4	-0.10^{*}	0.98^{***}	0.26^{***}	0.15^{***}	0.18^{***}	0.08^{**}	-0.05^{***}
	(-1.93)	(68.62)	(14.35)	(6.37)	(7.31)	(2.33)	(-4.49)
5	-0.02	0.95^{***}	0.44^{***}	0.20^{***}	0.14^{***}	0.09^{**}	-0.11^{***}
	(-0.41)	(59.97)	(22.2)	(7.64)	(5.24)	(2.48)	(-9.26)
5-1	0.28^{***}	-0.04^{**}	0.36^{***}	0.21^{***}	0.07^{**}	0.12^{***}	-0.12^{***}
	(3.9)	(-2.21)	(14.74)	(6.66)	(1.97)	(2.69)	(-8.64)

Table II: ICC and Mutual Fund Performance: Portfolio Sorts (Continued)

Panel C: Performance of Decile Portfolios.

Analyst

ICC-rank	Return	SReturn	Alpha1	Alpha6	DGTW
1	0.61**	−0.16**	−0.23**	0.00	−0.34
	(2.08)	(−2.21)	(−2.09)	(0.01)	(−1.36)
10	1.07***	0.20**	0.24**	0.37***	0.17**
	(3.9)	(2.29)	(2.3)	(3.06)	(2.07)
10-1	0.47***	0.35***	0.47***	0.37**	0.50*
	(3.46)	(3.08)	(3.50)	(2.22)	(1.95)

EP (2014)

ICC-rank	Return	SReturn	Alpha1	Alpha6	DGTW
1	0.62**	−0.14**	−0.25***	−0.13	−0.13*
	(2.57)	(−2.50)	(−3.12)	(−0.93)	(−1.70)
10	1.06***	0.19**	0.26**	0.21**	0.17**
	(3.76)	(2.02)	(2.06)	(2.46)	(2.23)
10-1	0.43***	0.34***	0.51***	0.34**	0.28***
	(2.92)	(3.07)	(3.82)	(2.20)	(2.79)

RI (2014)

ICC-rank	Return	SReturn	Alpha1	Alpha6	DGTW
1	0.58	−0.14**	−0.29***	−0.10	−0.32
	(1.60)	(−2.19)	(−3.22)	(−0.72)	(−1.58)
10	1.01***	0.19**	0.27**	0.21**	0.37**
	(3.22)	(2.04)	(2.4)	(2.49)	(2.03)
10-1	0.42**	0.33***	0.56***	0.31**	0.68***
	(2.17)	(2.79)	(4.31)	(2.07)	(2.63)

HvDZ (2012)

ICC-rank	Return	SReturn	Alpha1	Alpha6	DGTW
1	0.64**	−0.18*	−0.23	−0.26*	−0.05
	(2.18)	(−1.76)	(−1.54)	(−1.68)	(−0.35)
10	1.05***	0.23**	0.32**	0.19*	0.23***
	(3.82)	(2.02)	(2.11)	(1.75)	(3.87)
10-1	0.41***	0.41***	0.55***	0.46**	0.28**
	(3.10)	(2.69)	(3.92)	(2.59)	(1.97)

Table III: ICC and Mutual Fund Performance: Panel Regressions

This table presents results from pooled OLS regressions that relate future, quarterly fund performance with most recent fund-level ICC. The analysis is performed at the fund-quarter-level. The five analyzed performance measures are return (*Return*), style-adjusted return (*SReturn*), calculated by subtracting from the raw return of a fund the mean raw return of funds with the same investment objective, Jensen-Alpha (*Alpha*1) and the Fama and French (2015) 5-factor alpha, augmented with the momentum factor (*Alpha*6), computed for a given fund each month as the difference between the actual return minus the expected return, estimated using factor loadings computed from a regression of the preceding 36 monthly excess returns returns on the one respectively six risk factor(s), as well as characteristic-adjusted returns (*DGTW*), estimated as in Daniel, Grinblatt, Titman, and Wermers (1997), where a stock's characteristic-adjusted return in a given month is computed by subtracting from its return the return of the benchmark portfolio to which that particular stock belongs. These adjusted returns are then value-weighted at the fund-portfolio-level. Monthly measures are aggregated to the quarterly level using compounding. The main independent variable is *ICC*; for every fund every quarter, a value-weighted ICC of the funds' portfolios' constituents, based on four different proxies for expected earnings, is constructed as described in Section I.B. Controls are described in Table I. Regressions are run with time and style [columns (1) to (5)], time-by-style [columns (6) to (10)], and time-by-style and fund fixed effects (FE) [columns (11) to (15)], respectively. The four panels correspond to the four earnings specifications used to obtain stock-level ICCs. T-statistics, based on standard errors clustered at the fund level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table III: ICC and Mutual Fund Performance: Panel Regressions (Continued)

Analyst

	(1) Return	(2) SReturn	(3) Alpha1	(4) Alpha6	(5) DGTW	(6) Return	(7) SReturn	(8) Alpha1	(9) Alpha6	(10) DGTW	(11) Return	(12) SReturn	(13) Alpha1	(14) Alpha6	(15) DGTW
ICC	2.0715***	1.5225***	1.4616	0.2157*	0.4956***	1.2985***	1.1014***	0.7188***	0.3709***	0.4933***	1.6527***	1.4006***	1.2999***	0.8570***	0.7004***
	(18.17)	(14.24)	(14.25)	(1.88)	(4.21)	(11.52)	(9.83)	(6.40)	(2.60)	(3.63)	(9.72)	(8.26)	(6.76)	(4.03)	(3.38)
Log(Age)	−0.0003	−0.0002	−0.0005**	−0.0005**	0.0001	−0.0008***	−0.0007***	−0.0007***	−0.0006***	−0.0001	0.0002	−0.0001	−0.0006	−0.0014*	0.0017***
	(−1.37)	(−0.99)	(−2.34)	(−2.35)	(0.57)	(−4.07)	(−3.28)	(−3.32)	(−2.84)	(−0.56)	(0.27)	(−0.16)	(−0.83)	(−1.90)	(3.22)
Log(TNA)	−0.0005***	−0.0006***	−0.0004***	−0.0002**	−0.0004***	−0.0003***	−0.0004***	−0.0001*	−0.0001*	−0.0003***	−0.0054***	−0.0053***	−0.0047***	−0.0032***	−0.0032***
	(−5.37)	(−6.29)	(−3.84)	(−2.17)	(−5.22)	(−3.38)	(−4.56)	(−1.87)	(−1.79)	(−4.14)	(−27.10)	(−26.73)	(−23.41)	(−18.89)	(−19.65)
Exp. Ratio	−0.3043***	−0.2869***	−0.2996***	−0.2579***	−0.0254	−0.2889***	−0.2758***	−0.2877***	−0.2562***	−0.0190	−0.2157***	−0.2070***	−0.2222***	−0.2691***	−0.0107
	(−14.44)	(−17.42)	(−12.19)	(−17.08)	(−0.68)	(−16.25)	(−19.18)	(−12.21)	(−16.43)	(−0.50)	(−7.13)	(−5.21)	(−11.57)	(−7.91)	(−0.25)
Turn. Ratio	−0.0007**	−0.0007**	−0.0008***	−0.0007***	−0.0008***	−0.0007***	−0.0006**	−0.0010***	−0.0007***	−0.0007***	0.0003	0.0003	−0.0005	−0.0003	−0.0004
	(−2.35)	(−2.30)	(−2.68)	(−2.98)	(−3.58)	(−2.68)	(−2.34)	(−3.65)	(−3.24)	(−3.23)	(0.75)	(0.78)	(−1.43)	(−1.01)	(−1.08)
Flow	−0.0000**	0.0000	−0.0000	−0.0000	−0.0000	−0.0000	0.0000	−0.0000	−0.0000	−0.0000	0.0000	0.0000**	−0.0000	−0.0000**	0.0000
	(−2.05)	(0.49)	(−1.48)	(−0.08)	(−1.52)	(−0.86)	(0.10)	(−1.02)	(−1.23)	(−0.35)	(0.16)	(2.09)	(−0.79)	(−2.17)	(0.18)
I(Team)	0.0002	0.0002	0.0000	−0.0004	−0.0002	0.0001	0.0001	−0.0001	−0.0004*	−0.0003	−0.0001	0.0002	−0.0003	−0.0003	−0.0006*
	(0.61)	(0.78)	(0.02)	(−1.57)	(−0.79)	(0.42)	(0.54)	(−0.26)	(−1.66)	(−1.36)	(−0.36)	(0.63)	(−0.86)	(−0.70)	(−1.77)
Time FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No	No	No
Style FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No	No	No
Time×Style FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	124,371	124,371	114,618	114,618	118,823	124,371	124,371	114,618	114,618	118,823	124,371	124,371	114,618	114,618	118,823
Adj. R^2	0.785	0.014	0.110	0.081	0.111	0.865	0.233	0.426	0.166	0.270	0.869	0.251	0.441	0.184	0.282

EP (2014)

	(1) Return	(2) SReturn	(3) Alpha1	(4) Alpha6	(5) DGTW	(6) Return	(7) SReturn	(8) Alpha1	(9) Alpha6	(10) DGTW	(11) Return	(12) SReturn	(13) Alpha1	(14) Alpha6	(15) DGTW
ICC	1.0728***	0.6747***	0.9108***	0.4925***	0.0888	0.6128***	0.5551***	0.5712***	0.6413***	0.2290	1.0707***	0.9715***	1.1198***	1.0451***	0.6935**
	(6.41)	(5.65)	(6.20)	(4.87)	(0.36)	(4.60)	(4.46)	(4.83)	(4.95)	(0.70)	(5.95)	(5.70)	(6.13)	(6.22)	(2.06)
Log(Age)	−0.0003	−0.0002	−0.0005**	−0.0005**	0.0001	−0.0008***	−0.0007***	−0.0007***	−0.0006***	−0.0001	0.0003	0.0000	−0.0005	−0.0014*	0.0017***
	(−1.18)	(−0.84)	(−2.32)	(−2.44)	(0.71)	(−4.07)	(−3.31)	(−3.49)	(−3.11)	(−0.45)	(0.52)	(0.04)	(−0.70)	(−1.88)	(3.32)
Log(TNA)	−0.0005***	−0.0006***	−0.0003***	−0.0001	−0.0004***	−0.0002***	−0.0003***	−0.0001	−0.0001	−0.0003***	−0.0053***	−0.0053***	−0.0047***	−0.0031***	−0.0032***
	(−4.95)	(−6.23)	(−3.22)	(−1.32)	(−4.71)	(−2.92)	(−4.18)	(−1.11)	(−0.76)	(−3.20)	(−26.64)	(−26.43)	(−22.79)	(−17.79)	(−17.25)
Exp. Ratio	−0.3120***	−0.2881***	−0.3009***	−0.2611***	−0.0313	−0.2908***	−0.2801***	−0.2852***	−0.2642***	−0.0305	−0.2261***	−0.2186***	−0.2246***	−0.2756***	−0.0206
	(−12.18)	(−18.11)	(−11.57)	(−20.34)	(−0.77)	(−14.90)	(−18.52)	(−13.34)	(−23.49)	(−0.67)	(−13.02)	(−9.20)	(−13.28)	(−11.59)	(−0.40)
Turn. Ratio	−0.0006*	−0.0006*	−0.0007**	−0.0007***	−0.0007***	−0.0006**	−0.0005**	−0.0009***	−0.0007***	−0.0006***	0.0002	0.0003	−0.0006*	−0.0004	−0.0004
	(−1.83)	(−1.89)	(−2.15)	(−2.86)	(−3.44)	(−2.39)	(−2.04)	(−3.33)	(−2.98)	(−3.07)	(0.55)	(0.59)	(−1.66)	(−1.23)	(−1.07)
Flow	−0.0000***	−0.0000	−0.0000***	−0.0000	−0.0000	−0.0000*	−0.0000	−0.0000**	−0.0000**	−0.0000	−0.0000	0.0000*	−0.0000	−0.0000**	−0.0000
	(−3.24)	(−1.11)	(−2.74)	(−0.75)	(−1.45)	(−1.77)	(−0.67)	(−2.10)	(−2.23)	(−0.58)	(−0.34)	(1.78)	(−1.35)	(−2.56)	(−0.03)
I(Team)	0.0000	0.0001	−0.0001	−0.0004	−0.0003	0.0000	0.0001	−0.0001	−0.0004	−0.0003	−0.0003	0.0001	−0.0004	−0.0003	−0.0006*
	(0.13)	(0.34)	(−0.32)	(−1.46)	(−1.10)	(0.07)	(0.26)	(−0.38)	(−1.57)	(−1.52)	(−0.70)	(0.33)	(−1.13)	(−0.87)	(−1.84)
Time FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No	No	No
Style FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No	No	No
Time×Style FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	124,429	124,429	114,663	114,663	118,868	124,429	124,429	114,663	114,663	118,868	124,429	124,429	114,663	114,663	118,868
Adj. R^2	0.784	0.010	0.109	0.082	0.109	0.865	0.231	0.425	0.168	0.265	0.868	0.249	0.440	0.185	0.278

Table III: ICC and Mutual Fund Performance: Panel Regressions (Continued)

RI (2014)

	(1) Return	(2) SReturn	(3) Alpha1	(4) Alpha6	(5) DGTW	(6) Return	(7) SReturn	(8) Alpha1	(9) Alpha6	(10) DGTW	(11) Return	(12) SReturn	(13) Alpha1	(14) Alpha6	(15) DGTW
ICC	1.8835***	1.3627***	1.6200***	0.5290***	0.4765***	1.2893***	1.2117***	0.8511***	0.6960***	0.6436***	1.7995***	1.6212***	1.3281***	1.1927***	0.9658***
	(19.86)	(14.64)	(19.31)	(5.46)	(4.69)	(14.32)	(12.97)	(9.90)	(6.15)	(5.27)	(13.12)	(10.83)	(9.59)	(6.44)	(5.27)
Log(Age)	−0.0001	−0.0001	−0.0004*	−0.0004**	0.0002	−0.0007***	−0.0006***	−0.0006***	−0.0005***	−0.0001	0.0002	−0.0001	−0.0005	−0.0014*	0.0017***
	(−0.47)	(−0.30)	(−1.76)	(−2.15)	(0.83)	(−3.70)	(−2.99)	(−3.23)	(−2.77)	(−0.40)	(0.39)	(−0.09)	(−0.73)	(−1.89)	(3.27)
Log(TNA)	−0.0006***	−0.0006***	−0.0004***	−0.0002**	−0.0004***	−0.0003***	−0.0004***	−0.0002*	−0.0001*	−0.0003***	−0.0053***	−0.0052***	−0.0047***	−0.0032***	−0.0032***
	(−6.06)	(−6.90)	(−4.24)	(−2.06)	(−5.23)	(−3.63)	(−4.84)	(−1.93)	(−1.78)	(−4.06)	(−26.71)	(−26.41)	(−22.97)	(−18.62)	(−18.66)
Exp. Ratio	−0.3025***	−0.2849***	−0.2939***	−0.2516***	−0.0343	−0.2876***	−0.2782***	−0.2779***	−0.2518***	−0.0308	−0.2240***	−0.2167***	−0.2189***	−0.2697***	−0.0180
	(−14.90)	(−20.29)	(−13.41)	(−14.49)	(−0.80)	(−16.02)	(−20.13)	(−16.12)	(−15.71)	(−0.68)	(−12.43)	(−8.90)	(−12.24)	(−9.67)	(−0.37)
Turn. Ratio	−0.0005	−0.0005*	−0.0006**	−0.0006***	−0.0007***	−0.0005**	−0.0004*	−0.0008***	−0.0006***	−0.0006***	0.0004	0.0004	−0.0004	−0.0003	−0.0004
	(−1.65)	(−1.73)	(−2.03)	(−2.74)	(−3.42)	(−2.12)	(−1.77)	(−3.22)	(−2.86)	(−2.90)	(1.08)	(1.05)	(−1.30)	(−0.86)	(−1.18)
Flow	−0.0000**	0.0000	−0.0000**	−0.0000	−0.0000*	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	0.0000	0.0000**	−0.0000	−0.0000**	0.0000
	(−2.45)	(0.09)	(−2.04)	(−0.15)	(−1.68)	(−1.16)	(−0.13)	(−1.21)	(−1.47)	(−0.46)	(0.27)	(2.17)	(−0.89)	(−2.11)	(0.25)
I(Team)	0.0001	0.0002	−0.0000	−0.0004	−0.0002	0.0001	0.0001	−0.0001	−0.0004	−0.0003	−0.0002	0.0002	−0.0004	−0.0003	−0.0006*
	(0.31)	(0.55)	(−0.11)	(−1.48)	(−0.81)	(0.28)	(0.47)	(−0.31)	(−1.62)	(−1.27)	(−0.48)	(0.52)	(−1.01)	(−0.77)	(−1.75)
Time FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No	No	No
Style FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No	No	No
Time×Style FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	124,399	124,399	114,635	114,635	118,848	124,399	124,399	114,635	114,635	118,848	124,399	124,399	114,635	114,635	118,848
Adj. R^2	0.785	0.014	0.113	0.082	0.110	0.865	0.234	0.426	0.167	0.268	0.869	0.251	0.441	0.185	0.280

HvDZ (2012)

	(1) Return	(2) SReturn	(3) Alpha1	(4) Alpha6	(5) DGTW	(6) Return	(7) SReturn	(8) Alpha1	(9) Alpha6	(10) DGTW	(11) Return	(12) SReturn	(13) Alpha1	(14) Alpha6	(15) DGTW
ICC	1.3982***	1.0384***	1.3457***	0.4581***	0.3893***	0.8791***	0.8380***	0.7186***	0.5783***	0.4673***	1.3443***	1.2327***	1.1755***	1.0208***	0.7308***
	(16.82)	(12.55)	(18.25)	(5.39)	(4.53)	(11.46)	(10.18)	(9.64)	(5.98)	(4.82)	(11.85)	(10.51)	(8.96)	(6.27)	(5.02)
Log(Age)	−0.0002	−0.0001	−0.0005**	−0.0004**	0.0001	−0.0008***	−0.0006***	−0.0006***	−0.0005***	−0.0001	0.0003	−0.0000	−0.0005	−0.0013*	0.0017***
	(−0.83)	(−0.57)	(−2.03)	(−2.26)	(0.72)	(−3.81)	(−3.08)	(−3.29)	(−2.81)	(−0.46)	(0.47)	(−0.02)	(−0.68)	(−1.83)	(3.32)
Log(TNA)	−0.0006***	−0.0006***	−0.0004***	−0.0001*	−0.0004***	−0.0003***	−0.0004***	−0.0001*	−0.0001	−0.0003***	−0.0054***	−0.0053***	−0.0047***	−0.0032***	−0.0032***
	(−5.76)	(−6.61)	(−3.80)	(−1.89)	(−5.10)	(−3.40)	(−4.60)	(−1.67)	(−1.55)	(−3.92)	(−27.13)	(−26.80)	(−23.25)	(−18.73)	(−19.20)
Exp. Ratio	−0.2969***	−0.2812***	−0.2913***	−0.2512***	−0.0337	−0.2835***	−0.2742***	−0.2773***	−0.2511***	−0.0294	−0.2152***	−0.2086***	−0.2126***	−0.2640***	−0.0143
	(−15.95)	(−20.63)	(−13.61)	(−14.35)	(−0.78)	(−17.46)	(−21.40)	(−16.04)	(−15.33)	(−0.65)	(−8.77)	(−6.57)	(−10.42)	(−7.87)	(−0.32)
Turn. Ratio	−0.0004	−0.0005	−0.0006*	−0.0006***	−0.0007***	−0.0006**	−0.0005*	−0.0009***	−0.0007***	−0.0006***	0.0003	0.0003	−0.0006*	−0.0004	−0.0004
	(−1.47)	(−1.60)	(−1.85)	(−2.78)	(−3.30)	(−2.14)	(−1.78)	(−3.25)	(−2.94)	(−2.84)	(0.72)	(0.74)	(−1.65)	(−1.23)	(−1.07)
Flow	−0.0000**	−0.0000	−0.0000**	−0.0000	−0.0000*	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	0.0000	0.0000**	−0.0000	−0.0000*	0.0000
	(−2.55)	(−0.38)	(−2.21)	(−0.30)	(−1.77)	(−1.29)	(−0.32)	(−1.54)	(−1.59)	(−0.54)	(0.77)	(2.53)	(−0.51)	(−1.83)	(0.45)
I(Team)	0.0000	0.0001	−0.0001	−0.0004	−0.0002	0.0000	0.0001	−0.0001	−0.0004*	−0.0003	−0.0002	0.0002	−0.0004	−0.0003	−0.0006*
	(0.12)	(0.39)	(−0.20)	(−1.53)	(−0.86)	(0.11)	(0.31)	(−0.34)	(−1.65)	(−1.35)	(−0.61)	(0.41)	(−1.07)	(−0.84)	(−1.84)
Time FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No	No	No
Style FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No	No	No
Time×Style FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	124,396	124,396	114,635	114,635	118,842	124,396	124,396	114,635	114,635	118,842	124,396	124,396	114,635	114,635	118,842
Adj. R^2	0.784	0.012	0.111	0.082	0.111	0.865	0.232	0.426	0.167	0.270	0.868	0.250	0.440	0.184	0.281

Table IV: ICC and Mutual Fund Performance: Subsumption Test

This table presents results from pooled OLS regressions akin to Table III, that relate future, quarterly fund performance with most recent fund-level ICC. The analysis is performed at the fund-quarter-level. The five analyzed performance measures are return ($Return$), style-adjusted return ($SReturn$), calculated by subtracting from the raw return of a fund the mean raw return of funds with the same investment objective, Jensen-Alpha ($Alpha1$) and the Fama and French (2015) 5-factor alpha, augmented with the momentum factor ($Alpha6$), computed for a given fund each month as the difference between the actual return minus the expected return, estimated using factor loadings computed from a regression of the preceding 36 monthly excess returns returns on the one respectively six risk factor(s), as well as characteristic-adjusted returns ($DGTW$), estimated as in Daniel, Grinblatt, Titman, and Wermers (1997), where a stock's characteristic-adjusted return in a given month is computed by subtracting from its return the return of the benchmark portfolio to which that particular stock belongs. These adjusted returns are then value-weighted at the fund-portfolio-level. Monthly measures are aggregated to the quarterly level using compounding. The main independent variable is ICC; for every fund every quarter, a value-weighted ICC of the funds' portfolios' constituents, based on four different proxies for expected earnings, is constructed as described in Section I.B. In relation to Table III, active share ($ActShare$) as per Cremers and Petajisto (2009) and Cremers, Petajisto, and Zitzewitz (2013), the industry concentration index (ICI) by Kacperczyk, Sialm, and Zheng (2005), the return gap ($RetGap$) in Kacperczyk, Sialm, and Zheng (2008), and the lagged, respective performance measure ($LaggedPerf$) are added as regressors. Controls are described in Table I. Regressions are run with time-by-style and fund-by-manager fixed effects (FE), for each of the four earnings specifications used to obtain stock-level ICCs separately. T-statistics, based on standard errors clustered at the fund level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	Analyst					EP (2014)				
	(1) Return	(2) SReturn	(3) Alpha1	(4) Alpha6	(5) DGTW	(1) Return	(2) SReturn	(3) Alpha1	(4) Alpha6	(5) DGTW
ICC	2.6604***	2.5550***	2.0001***	1.3484***	1.5171***	1.5251***	1.4000***	1.4995***	1.9167***	0.8574***
	(8.44)	(8.09)	(5.98)	(4.12)	(4.85)	(5.38)	(4.77)	(5.00)	(6.40)	(3.36)
ActShare	0.0177***	0.0162***	0.0191***	0.0116**	0.0109**	0.0236***	0.0220***	0.0226***	0.0112**	0.0142***
	(3.78)	(3.46)	(4.05)	(2.43)	(2.56)	(4.94)	(4.61)	(4.70)	(2.28)	(3.24)
ICI	−0.0166***	−0.0196***	−0.0103*	−0.0054	−0.0091	−0.0214***	−0.0240***	−0.0138**	−0.0076	−0.0118**
	(−3.02)	(−3.33)	(−1.76)	(−0.90)	(−1.60)	(−3.71)	(−3.94)	(−2.28)	(−1.24)	(−2.02)
RetGap	0.0098	−0.0035	−0.0091	−0.0226	0.0392*	0.0166	0.0032	−0.0048	−0.0234	0.0390*
	(0.44)	(−0.16)	(−0.43)	(−0.82)	(1.79)	(0.75)	(0.14)	(−0.23)	(−0.85)	(1.79)
LaggedPerf	0.1605***	0.1901***	0.1525***	−0.0147	0.0790***	0.1495***	0.1800***	0.1454***	−0.0142	0.0741***
	(13.45)	(17.05)	(11.84)	(−0.94)	(5.64)	(12.80)	(16.25)	(11.31)	(−0.92)	(5.36)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time×Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund×Manager FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,668	25,668	24,744	24,744	25,185	25,668	25,668	24,744	24,744	25,185
Adj. R^2	0.830	0.361	0.443	0.181	0.292	0.829	0.357	0.443	0.186	0.291

	RI (2014)					HvDZ (2012)				
	(1) Return	(2) SReturn	(3) Alpha1	(4) Alpha6	(5) DGTW	(1) Return	(2) SReturn	(3) Alpha1	(4) Alpha6	(5) DGTW
ICC	1.8381***	1.7737***	1.3603***	1.5988***	0.8105***	1.4636***	1.4422***	1.2160***	1.3543***	0.5570**
	(6.72)	(6.57)	(4.96)	(5.11)	(3.22)	(5.88)	(5.94)	(4.90)	(5.36)	(2.43)
ActShare	0.0229***	0.0211***	0.0231***	0.0123**	0.0145***	0.0265***	0.0245***	0.0255***	0.0153***	0.0163***
	(4.74)	(4.39)	(4.79)	(2.50)	(3.31)	(5.54)	(5.15)	(5.28)	(3.08)	(3.73)
ICI	−0.0231***	−0.0258***	−0.0149**	−0.0089	−0.0128**	−0.0235***	−0.0263***	−0.0154**	−0.0094	−0.0130**
	(−3.99)	(−4.21)	(−2.47)	(−1.43)	(−2.19)	(−4.09)	(−4.29)	(−2.54)	(−1.52)	(−2.20)
RetGap	0.0149	0.0012	−0.0048	−0.0236	0.0402*	0.0163	0.0025	−0.0040	−0.0223	0.0403*
	(0.68)	(0.06)	(−0.23)	(−0.86)	(1.84)	(0.75)	(0.11)	(−0.19)	(−0.81)	(1.85)
LaggedPerf	0.1540***	0.1845***	0.1477***	−0.0109	0.0752***	0.1541***	0.1847***	0.1478***	−0.0115	0.0742***
	(13.20)	(16.73)	(11.45)	(−0.70)	(5.33)	(13.21)	(16.86)	(11.66)	(−0.74)	(5.29)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time×Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund×Manager FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,661	25,661	24,738	24,738	25,179	25,661	25,661	24,738	24,738	25,179
Adj. R^2	0.830	0.358	0.441	0.183	0.290	0.830	0.357	0.441	0.182	0.290

Table V: ICC and Mutual Fund Performance: Persistence

This table presents results from pooled OLS regressions that relate future, quarterly fund-portfolio performance with most recent fund-level ICC. The analysis is performed at the fund-semi-annual-, fund-annual- and fund-biannual-level. The five analyzed performance measures are return (*Return*), style-adjusted return (*SReturn*), calculated by subtracting from the raw return of a fund the mean raw return of funds with the same investment objective, Jensen-Alpha (*Alpha*1) and the Fama and French (2015) 5-factor alpha, augmented with the momentum factor (*Alpha*6), computed for a given fund each month as the difference between the actual return minus the expected return, estimated using factor loadings computed from a regression of the preceding 36 monthly excess returns returns on the one respectively six risk factor(s), as well as characteristic-adjusted returns (*DGTW*), estimated as in Daniel, Grinblatt, Titman, and Wermers (1997), where a stock's characteristic-adjusted return in a given month is computed by subtracting from its return the return of the benchmark portfolio to which that particular stock belongs. These adjusted returns are then value-weighted at the fund-portfolio-level. Monthly measures are aggregated to the respective time-level using compounding. In particular, for each performance measure, the first columns correspond to semi-annual, the second columns to annual, and the third columns to biannual values of the respective performance measures. The main independent variable is *ICC*; for every fund every quarter, a value-weighted ICC of the funds' portfolios' constituents, based on four different proxies for expected earnings, is constructed as described in Section I.B. ICCs are scaled to match the respective time horizon. Controls are described in Table I. Regressions are run with time-by-style and fund fixed effects (FE), for each of the four earnings specifications used to obtain stock-level ICCs separately. T-statistics, based on standard errors clustered at the fund level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table V: ICC and Mutual Fund Performance: Persistence (Continued)

Analyst

	Return			SReturn			Alpha1			Alpha6			DGTW		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
ICC	1.4296***	1.3464***	1.4351***	1.2638***	1.0832***	1.2203***	1.4274***	0.8486***	1.1244***	0.9238***	0.3717***	0.5196***	0.7900***	0.7764***	0.7876***
	(5.80)	(5.51)	(7.96)	(5.49)	(5.26)	(8.47)	(10.63)	(4.92)	(8.02)	(5.90)	(2.86)	(3.82)	(6.46)	(6.24)	(6.37)
Log(Age)	−0.0005	0.0024	0.0052	−0.0010	0.0018	0.0099	−0.0085***	0.0001	−0.0015	−0.0077***	−0.0030	0.0009	0.0026**	0.0075***	0.0134**
	(−0.38)	(0.92)	(0.69)	(−0.83)	(0.75)	(1.50)	(−5.05)	(0.05)	(−0.22)	(−4.91)	(−1.04)	(0.14)	(2.33)	(3.53)	(2.20)
Log(TNA)	−0.0109***	−0.0230***	−0.0462***	−0.0105***	−0.0215***	−0.0431***	−0.0034***	−0.0185***	−0.0365***	−0.0023***	−0.0125***	−0.0277***	−0.0065***	−0.0135***	−0.0280***
	(−25.91)	(−23.84)	(−22.58)	(−25.99)	(−24.30)	(−23.68)	(−9.15)	(−22.37)	(−21.11)	(−6.66)	(−18.25)	(−16.62)	(−19.56)	(−19.68)	(−18.02)
Exp. Ratio	−0.4029***	−0.5965***	−0.8918***	−0.3959***	−0.5625***	−0.7957***	−0.3403***	−0.4704***	−0.7026***	−0.3494***	−0.6585***	−0.6834***	0.0699***	0.1109***	−1.5375***
	(−10.32)	(−8.13)	(−5.05)	(−10.69)	(−7.57)	(−4.14)	(−12.10)	(−6.37)	(−6.39)	(−9.66)	(−8.08)	(−5.59)	(2.89)	(3.55)	(−5.40)
Turn. Ratio	0.0016**	0.0022	0.0054**	0.0016*	0.0031	0.0049*	−0.0005	−0.0011	0.0003	−0.0007	−0.0008	−0.0012	−0.0015**	−0.0024*	−0.0062**
	(1.97)	(1.08)	(1.96)	(1.81)	(1.43)	(1.95)	(−0.85)	(−1.25)	(0.22)	(−1.23)	(−0.82)	(−0.72)	(−2.42)	(−1.82)	(−1.97)
Flow	0.0000***	−0.0000***	−0.0000	0.0000*	−0.0000***	0.0000	0.0000	−0.0000	−0.0000	0.0000***	−0.0000	0.0000	0.0000*	0.0000***	0.0000
	(3.06)	(−3.55)	(−0.23)	(1.81)	(−4.37)	(1.20)	(1.47)	(−1.10)	(−0.73)	(4.24)	(−0.40)	(0.47)	(1.92)	(3.13)	(0.12)
I(Team)	−0.0003	−0.0012	−0.0068*	0.0005	−0.0000	−0.0052	−0.0013*	−0.0023	−0.0050	−0.0013*	−0.0012	−0.0034	−0.0011*	−0.0016	−0.0019
	(−0.47)	(−0.75)	(−1.88)	(0.71)	(−0.01)	(−1.61)	(−1.70)	(−1.48)	(−1.38)	(−1.82)	(−0.78)	(−1.04)	(−1.73)	(−1.23)	(−0.61)
Time×Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	60,014	29,462	12,182	60,014	29,462	12,182	54,472	27,592	12,175	54,472	27,592	12,175	56,159	26,476	10,208
Adj. R^2	0.837	0.843	0.886	0.292	0.296	0.316	0.449	0.482	0.517	0.159	0.204	0.174	0.316	0.330	0.341

EP (2014)

	Return			SReturn			Alpha1			Alpha6			DGTW		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
ICC	0.9516***	0.9972***	0.7169***	0.9363***	0.9280***	0.7555***	0.9927***	0.5812***	0.1974	0.6691***	0.3605***	0.2174	0.6366***	0.7890***	0.4877***
	(7.88)	(5.82)	(4.22)	(7.87)	(6.30)	(5.81)	(7.62)	(3.94)	(1.58)	(4.97)	(2.80)	(1.62)	(5.99)	(6.12)	(5.05)
Log(Age)	−0.0001	0.0028	0.0053	−0.0007	0.0021	0.0097	−0.0081***	0.0002	−0.0006	−0.0075***	−0.0030	0.0009	0.0028**	0.0076***	0.0135**
	(−0.06)	(1.08)	(0.71)	(−0.56)	(0.86)	(1.48)	(−4.90)	(0.08)	(−0.09)	(−4.82)	(−1.07)	(0.15)	(2.45)	(3.53)	(2.23)
Log(TNA)	−0.0109***	−0.0227***	−0.0464***	−0.0104***	−0.0212***	−0.0429***	−0.0033***	−0.0184***	−0.0375***	−0.0022***	−0.0123***	−0.0278***	−0.0065***	−0.0132***	−0.0280***
	(−26.27)	(−23.85)	(−22.67)	(−26.19)	(−24.20)	(−23.55)	(−9.21)	(−22.74)	(−21.22)	(−6.82)	(−18.48)	(−16.85)	(−19.48)	(−19.40)	(−17.82)
Exp. Ratio	−0.4014***	−0.6349***	−0.8050***	−0.3768***	−0.5438***	−0.7602***	−0.3512***	−0.5136***	−0.6145***	−0.3807***	−0.6335***	−0.6343***	0.0063	0.1164***	−1.6381***
	(−15.15)	(−9.69)	(−5.94)	(−9.89)	(−9.75)	(−4.44)	(−17.46)	(−11.06)	(−6.69)	(−16.43)	(−9.72)	(−5.63)	(0.11)	(4.48)	(−6.09)
Turn. Ratio	0.0016**	0.0024	0.0045*	0.0016**	0.0032*	0.0043*	−0.0005	−0.0008	−0.0005	−0.0007	−0.0005	−0.0016	−0.0013**	−0.0023*	−0.0060*
	(2.41)	(1.35)	(1.80)	(2.16)	(1.67)	(1.89)	(−0.87)	(−0.95)	(−0.40)	(−1.22)	(−0.62)	(−0.97)	(−2.06)	(−1.74)	(−1.96)
Flow	0.0000***	−0.0000***	−0.0000	0.0000*	−0.0000***	0.0000	0.0000	−0.0000	−0.0000	0.0000***	−0.0000	0.0000	0.0000*	0.0000***	0.0000
	(3.06)	(−3.28)	(−0.26)	(1.76)	(−4.17)	(1.23)	(1.35)	(−1.10)	(−0.89)	(4.17)	(−0.43)	(0.45)	(1.88)	(3.53)	(0.19)
I(Team)	−0.0005	−0.0016	−0.0084**	0.0004	−0.0002	−0.0064*	−0.0015*	−0.0026	−0.0068*	−0.0014**	−0.0012	−0.0040	−0.0012*	−0.0017	−0.0026
	(−0.64)	(−0.92)	(−2.20)	(0.57)	(−0.14)	(−1.90)	(−1.88)	(−1.59)	(−1.77)	(−1.96)	(−0.80)	(−1.20)	(−1.83)	(−1.25)	(−0.81)
Time×Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	60,042	29,472	12,187	60,042	29,472	12,187	54,493	27,598	12,180	54,493	27,598	12,180	56,178	26,478	10,210
Adj. R^2	0.836	0.843	0.884	0.291	0.298	0.314	0.449	0.481	0.508	0.161	0.208	0.174	0.315	0.332	0.340

Table V: ICC and Mutual Fund Performance: Persistence (Continued)

RI (2014)

	Return			SReturn			Alpha1			Alpha6			DGTW		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
ICC	1.3488***	1.2200***	1.0160***	1.2238***	1.0612***	0.9090***	1.1786***	0.7885***	0.4322***	0.7873***	0.3909***	0.0973	0.7438***	0.6485***	0.4366***
	(11.02)	(7.25)	(5.65)	(10.23)	(7.45)	(6.43)	(10.69)	(5.95)	(3.22)	(6.14)	(3.66)	(0.81)	(6.96)	(4.97)	(4.25)
Log(Age)	−0.0003	0.0027	0.0049	−0.0009	0.0020	0.0096	−0.0084***	−0.0001	−0.0010	−0.0076***	−0.0031	0.0013	0.0027**	0.0076***	0.0135**
	(−0.21)	(1.02)	(0.67)	(−0.69)	(0.83)	(1.46)	(−5.01)	(−0.03)	(−0.15)	(−4.87)	(−1.08)	(0.20)	(2.35)	(3.55)	(2.21)
Log(TNA)	−0.0108***	−0.0229***	−0.0464***	−0.0105***	−0.0214***	−0.0432***	−0.0033***	−0.0184***	−0.0372***	−0.0023***	−0.0124***	−0.0282***	−0.0065***	−0.0135***	−0.0285***
	(−26.15)	(−23.84)	(−22.89)	(−25.96)	(−24.20)	(−23.73)	(−9.07)	(−22.43)	(−21.23)	(−6.69)	(−18.27)	(−16.91)	(−19.38)	(−19.70)	(−18.04)
Exp. Ratio	−0.3879***	−0.6377***	−0.8261***	−0.3621***	−0.5434***	−0.7721***	−0.3357***	−0.5190***	−0.6299***	−0.3702***	−0.6322***	−0.6277***	0.0215	0.1291***	−1.6543***
	(−12.57)	(−9.11)	(−5.49)	(−8.47)	(−10.35)	(−4.23)	(−16.20)	(−10.12)	(−6.42)	(−18.82)	(−9.96)	(−5.44)	(0.43)	(4.16)	(−5.72)
Turn. Ratio	0.0015**	0.0020	0.0045*	0.0015**	0.0029	0.0043*	−0.0005	−0.0012	−0.0004	−0.0007	−0.0009	−0.0016	−0.0014**	−0.0022*	−0.0062**
	(2.19)	(1.18)	(1.66)	(1.97)	(1.54)	(1.78)	(−1.00)	(−1.46)	(−0.33)	(−1.33)	(−0.97)	(−0.97)	(−2.24)	(−1.72)	(−1.98)
Flow	0.0000***	−0.0000***	−0.0000	0.0000*	−0.0000***	0.0000	0.0000	−0.0000	−0.0000	0.0000***	−0.0000	0.0000	0.0000*	0.0000***	0.0000
	(3.05)	(−3.04)	(−0.16)	(1.80)	(−3.86)	(1.25)	(1.40)	(−1.10)	(−0.80)	(4.20)	(−0.40)	(0.41)	(1.95)	(3.37)	(0.13)
I(Team)	−0.0004	−0.0014	−0.0079**	0.0005	−0.0001	−0.0061*	−0.0014*	−0.0025	−0.0064*	−0.0014*	−0.0012	−0.0041	−0.0012*	−0.0018	−0.0026
	(−0.47)	(−0.87)	(−2.11)	(0.71)	(−0.10)	(−1.83)	(−1.78)	(−1.54)	(−1.70)	(−1.87)	(−0.80)	(−1.25)	(−1.74)	(−1.33)	(−0.83)
Time×Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	60,027	29,465	12,181	60,027	29,465	12,181	54,480	27,592	12,174	54,480	27,592	12,174	56,168	26,473	10,208
Adj. R^2	0.837	0.843	0.884	0.293	0.298	0.313	0.449	0.483	0.509	0.161	0.208	0.172	0.317	0.329	0.337

HvDZ (2012)

	Return			SReturn			Alpha1			Alpha6			DGTW		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
ICC	1.0415***	1.1818***	1.1578***	0.9633***	1.0441***	0.9992***	1.1440***	0.7225***	0.5272***	0.7779***	0.2578*	0.1914*	0.5953***	0.6021***	0.4220***
	(5.51)	(5.77)	(7.41)	(5.00)	(5.99)	(7.87)	(10.87)	(4.13)	(4.52)	(6.07)	(1.79)	(1.72)	(5.54)	(5.70)	(4.28)
Log(Age)	−0.0002	0.0027	0.0058	−0.0008	0.0020	0.0104	−0.0083***	0.0000	−0.0007	−0.0076***	−0.0029	0.0013	0.0028**	0.0076***	0.0139**
	(−0.12)	(1.01)	(0.78)	(−0.61)	(0.80)	(1.58)	(−4.97)	(0.01)	(−0.10)	(−4.83)	(−1.03)	(0.19)	(2.45)	(3.57)	(2.27)
Log(TNA)	−0.0110***	−0.0229***	−0.0461***	−0.0106***	−0.0213***	−0.0430***	−0.0034***	−0.0184***	−0.0370***	−0.0023***	−0.0125***	−0.0280***	−0.0066***	−0.0135***	−0.0285***
	(−26.35)	(−24.18)	(−23.00)	(−26.00)	(−24.41)	(−23.89)	(−9.11)	(−22.68)	(−21.23)	(−6.68)	(−18.25)	(−16.87)	(−19.75)	(−19.98)	(−18.12)
Exp. Ratio	−0.3819***	−0.6305***	−0.8239***	−0.3568***	−0.5375***	−0.7683***	−0.3330***	−0.5119***	−0.6309***	−0.3686***	−0.6256***	−0.6318***	0.0207	0.1167***	−1.5969***
	(−10.48)	(−10.72)	(−5.75)	(−7.14)	(−8.98)	(−4.36)	(−15.73)	(−11.52)	(−6.56)	(−19.21)	(−9.01)	(−5.48)	(0.44)	(4.25)	(−5.48)
Turn. Ratio	0.0015**	0.0024	0.0042	0.0016**	0.0032*	0.0040*	−0.0006	−0.0009	−0.0005	−0.0008	−0.0006	−0.0016	−0.0013**	−0.0021*	−0.0060*
	(2.35)	(1.51)	(1.59)	(2.08)	(1.81)	(1.71)	(−1.01)	(−1.14)	(−0.42)	(−1.29)	(−0.73)	(−0.98)	(−2.05)	(−1.66)	(−1.92)
Flow	0.0000***	−0.0000***	0.0000	0.0000*	−0.0000***	0.0000	0.0000	−0.0000	−0.0000	0.0000***	−0.0000	0.0000	0.0000*	0.0000***	0.0000
	(3.10)	(−3.09)	(0.15)	(1.82)	(−3.93)	(1.47)	(1.47)	(−1.11)	(−0.64)	(4.27)	(−0.41)	(0.48)	(1.90)	(3.42)	(0.09)
I(Team)	−0.0004	−0.0014	−0.0077**	0.0005	−0.0001	−0.0059*	−0.0014*	−0.0024	−0.0063*	−0.0013*	−0.0012	−0.0040	−0.0012*	−0.0018	−0.0025
	(−0.55)	(−0.83)	(−2.03)	(0.64)	(−0.06)	(−1.78)	(−1.75)	(−1.52)	(−1.66)	(−1.85)	(−0.83)	(−1.21)	(−1.81)	(−1.34)	(−0.81)
Time×Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	60,027	29,464	12,181	60,027	29,464	12,181	54,481	27,593	12,174	54,481	27,593	12,174	56,168	26,473	10,208
Adj. R^2	0.836	0.843	0.885	0.290	0.299	0.317	0.449	0.482	0.510	0.161	0.207	0.173	0.315	0.329	0.337

Table VI: Directional Trades and Fund Performance

This table presents results from pooled OLS regressions that relate quarterly fund performance with the percentage of buys and sells into the direction of the change in stock-level ICCs over the corresponding quarter. The analysis is performed at the fund-quarter-level. The five analyzed performance measures are return (*Return*), style-adjusted return (*SReturn*), calculated by subtracting from the raw return of a fund the mean raw return of funds with the same investment objective, Jensen-Alpha (*Alpha*1) and the Fama and French (2015) 5-factor alpha, augmented with the momentum factor (*Alpha*6), computed for a given fund each month as the difference between the actual return minus the expected return, estimated using factor loadings computed from a regression of the preceding 36 monthly excess returns returns on the one respectively six risk factor(s), as well as characteristic-adjusted returns (*DGTW*), estimated as in Daniel, Grinblatt, Titman, and Wermers (1997), where a stock's characteristic-adjusted return in a given month is computed by subtracting from its return the return of the benchmark portfolio to which that particular stock belongs. These adjusted returns are then value-weighted at the fund-portfolio-level. Monthly measures are aggregated to the quarterly level using compounding. The main independent variables are *ICC*, *%SameDir Buys*, and *%SameDir Sells*. For every fund every quarter, a value-weighted ICC of the funds' portfolios' constituents, *ICC*, based on four different proxies for expected earnings, is constructed as described in Section I.B. *%SameDir Buys* (*%SameDir Sells*) denotes the trade-weighted fraction of total buys (sells) in stocks where the ICCs increased (decreased) from one quarter to the next. Controls are described in Table I. Regressions are run with time-by-style and fund fixed effects (FE), for each of the four earnings specifications used to obtain stock-level ICCs separately. T-statistics, based on standard errors clustered at the fund level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	Analyst					EP (2014)				
	(1) Return	(2) SReturn	(3) Alpha1	(4) Alpha6	(5) DGTW	(1) Return	(2) SReturn	(3) Alpha1	(4) Alpha6	(5) DGTW
ICC	1.2962***	1.1142***	0.9705***	0.6674***	0.3565***	1.4509***	1.2897***	1.4655***	1.2824***	0.5706***
	(8.49)	(7.64)	(6.73)	(4.42)	(2.63)	(10.49)	(9.92)	(9.16)	(8.35)	(4.22)
%SameDir Buys	0.0226***	0.0206***	0.0205***	0.0147***	0.0165***	0.0297***	0.0271***	0.0264***	0.0199***	0.0202***
	(20.10)	(18.68)	(19.34)	(15.36)	(16.22)	(25.76)	(23.84)	(24.40)	(20.78)	(19.11)
%SameDir Sells	0.0239***	0.0215***	0.0216***	0.0134***	0.0267***	0.0355***	0.0328***	0.0319***	0.0212***	0.0397***
	(23.80)	(21.28)	(23.79)	(15.57)	(27.55)	(32.65)	(30.50)	(31.85)	(22.63)	(37.97)
Log(Fund Age)	0.0005	0.0002	−0.0004	−0.0014	0.0020***	0.0007	0.0002	−0.0002	−0.0010	0.0021***
	(0.63)	(0.25)	(−0.45)	(−1.54)	(3.00)	(0.95)	(0.31)	(−0.19)	(−1.13)	(3.19)
Log(AUM)	−0.0057***	−0.0057***	−0.0050***	−0.0035***	−0.0032***	−0.0055***	−0.0054***	−0.0046***	−0.0031***	−0.0030***
	(−24.84)	(−25.30)	(−21.28)	(−16.59)	(−17.03)	(−24.73)	(−24.59)	(−21.20)	(−15.38)	(−16.21)
Exp. Ratio	−0.0877**	−0.0948**	−0.0690***	−0.1383***	0.0478***	−0.1498***	−0.1560***	−0.0970***	−0.1907***	0.0097
	(−2.42)	(−2.53)	(−3.66)	(−5.41)	(3.02)	(−3.71)	(−3.87)	(−2.85)	(−6.09)	(0.50)
Turn. Ratio	0.0001	−0.0004	−0.0003	0.0002	−0.0004	−0.0001	−0.0005	−0.0004	−0.0001	−0.0005
	(0.28)	(−0.91)	(−0.89)	(0.84)	(−1.33)	(−0.19)	(−1.35)	(−1.29)	(−0.17)	(−1.62)
Flow	0.0000	0.0000	−0.0000	−0.0000	0.0000	0.0000	0.0000	−0.0000	−0.0000	0.0000
	(0.06)	(1.48)	(−0.49)	(−1.35)	(0.38)	(0.37)	(1.39)	(−0.08)	(−0.95)	(0.55)
I(Team)	−0.0001	0.0003	−0.0002	−0.0006	−0.0005	−0.0001	0.0003	−0.0003	−0.0004	−0.0005
	(−0.29)	(0.79)	(−0.57)	(−1.36)	(−1.20)	(−0.33)	(0.61)	(−0.67)	(−0.87)	(−1.41)
Time×Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	105,453	105,453	97,964	97,964	102,881	104,200	104,200	96,708	96,708	101,644
Adj. R^2	0.851	0.257	0.425	0.190	0.293	0.852	0.277	0.446	0.200	0.316

Table VI: Directional Trades and Fund Performance (Continued)

	RI (2014)					HvDZ (2012)				
	(1) Return	(2) SReturn	(3) Alpha1	(4) Alpha6	(5) DGTW	(1) Return	(2) SReturn	(3) Alpha1	(4) Alpha6	(5) DGTW
ICC	1.7562***	1.5651***	1.1841***	0.9860***	0.6093***	1.2241***	1.1124***	1.0276***	0.8140***	0.3834***
	(13.57)	(12.09)	(10.41)	(8.67)	(5.15)	(10.48)	(9.24)	(9.11)	(7.17)	(3.58)
%SameDir Buys	0.0260***	0.0236***	0.0233***	0.0167***	0.0179***	0.0231***	0.0207***	0.0218***	0.0160***	0.0163***
	(23.53)	(21.86)	(22.15)	(17.89)	(17.95)	(20.49)	(18.66)	(20.72)	(16.82)	(16.29)
%SameDir Sells	0.0328***	0.0304***	0.0297***	0.0208***	0.0380***	0.0289***	0.0270***	0.0274***	0.0197***	0.0343***
	(31.02)	(29.06)	(30.42)	(23.15)	(37.27)	(28.56)	(26.84)	(29.06)	(22.60)	(35.28)
Log(Fund Age)	0.0006	0.0001	−0.0001	−0.0011	0.0020***	0.0007	0.0002	0.0001	−0.0007	0.0021***
	(0.79)	(0.14)	(−0.09)	(−1.17)	(3.11)	(0.95)	(0.30)	(0.09)	(−0.78)	(3.25)
Log(AUM)	−0.0054***	−0.0053***	−0.0046***	−0.0032***	−0.0029***	−0.0054***	−0.0054***	−0.0047***	−0.0032***	−0.0030***
	(−24.49)	(−24.74)	(−21.24)	(−15.83)	(−16.05)	(−25.17)	(−25.41)	(−21.14)	(−16.13)	(−16.49)
Exp. Ratio	−0.1409***	−0.1524***	−0.0937***	−0.1849***	0.0406**	−0.1261***	−0.1343***	−0.0853***	−0.1635***	0.0549**
	(−3.91)	(−3.88)	(−3.04)	(−5.50)	(2.38)	(−5.00)	(−5.12)	(−3.51)	(−8.99)	(2.08)
Turn. Ratio	−0.0002	−0.0007*	−0.0008**	−0.0003	−0.0007**	−0.0001	−0.0005	−0.0003	0.0001	−0.0003
	(−0.66)	(−1.84)	(−2.46)	(−1.16)	(−2.45)	(−0.29)	(−1.37)	(−1.10)	(0.18)	(−1.11)
Flow	0.0000	0.0000**	0.0000	−0.0000	0.0000	0.0000	0.0000	−0.0000	−0.0000	0.0000
	(0.78)	(1.98)	(0.29)	(−0.71)	(0.67)	(0.36)	(1.36)	(−0.08)	(−0.84)	(0.27)
I(Team)	−0.0002	0.0002	−0.0004	−0.0007	−0.0006	−0.0001	0.0003	−0.0004	−0.0006	−0.0005
	(−0.41)	(0.57)	(−1.04)	(−1.55)	(−1.59)	(−0.30)	(0.67)	(−0.94)	(−1.53)	(−1.41)
Time×Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	103,745	103,745	96,331	96,331	101,198	103,565	103,565	96,241	96,241	101,040
Adj. R^2	0.855	0.276	0.446	0.202	0.316	0.855	0.269	0.443	0.199	0.313

Table VII: Trading Efficiency and ICC

This table presents results from pooled OLS regressions which relate quarterly fund-level ICC with family-level trading efficiency. The analysis is performed at the fund-quarter-level. For every fund every quarter, a value-weighted ICC of the funds' portfolios' constituents, ICC, based on four different proxies for expected earnings, is constructed as described in Section I.B and serves as the dependent variable. The main independent variable is $TradingEfficiency$, a contemporaneous measure for trading-efficiency at the family-level, following Cici, Dahm, and Kempf (2018), described in Section III.A. Controls are described in Table I. Regressions are run with time-by-style and fund fixed effects (FE). T-statistics, based on standard errors clustered at the fund level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	(1) Analyst	(2) EP (2014)	(3) RI (2014)	(4) HvDZ (2012)
TradingEfficiency	0.1343**	0.1435**	0.2284***	0.2262***
	(2.26)	(2.33)	(4.10)	(3.97)
Log(Age)	0.0003**	0.0000	0.0001	0.0002
	(2.29)	(0.13)	(0.65)	(1.17)
Log(TNA)	−0.0002***	−0.0003***	−0.0003***	−0.0003***
	(−5.88)	(−4.68)	(−6.17)	(−6.09)
Exp. Ratio	−0.0081	0.0484**	−0.0023	0.0003
	(−0.48)	(2.30)	(−0.12)	(0.01)
Turn. Ratio	−0.0000	0.0000	0.0000	0.0000
	(−0.20)	(0.10)	(1.04)	(0.53)
Flow	0.0000	0.0000***	0.0000***	−0.0000
	(0.95)	(3.72)	(3.31)	(−0.95)
I(Team)	−0.0001	0.0001	−0.0000	−0.0001
	(−0.66)	(0.45)	(−0.12)	(−0.99)
Time×Style FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	20,432	20,458	20,443	20,436
Adj. R^2	0.705	0.674	0.824	0.836

Table VIII: Fund Manager SAT Score and ICC

This table presents results from pooled OLS regressions which relate quarterly fund-level ICC with fund managers' SAT score. The analysis is performed at the fund-quarter-level. For every fund every quarter, a value-weighted ICC of the funds' portfolios' constituents, ICC, based on four different proxies for expected earnings, is constructed as described in Section I.B and serves as the dependent variable. The main independent variable is SAT, a contemporaneous measure for the SAT score of a fund's managers, which obtains as the mean of a fund's corresponding managers' associated SAT score. Controls are described in Table I. Regressions are run with time-by-style and fund fixed effects (FE). T-statistics, based on standard errors clustered at the fund level, are reported in parentheses. Throughout this table, ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	(1) Analyst	(2) EP (2014)	(3) RI (2014)	(4) HvDZ (2012)
SAT	0.0007***	0.0009***	0.0008***	0.0010***
	(3.47)	(3.04)	(2.86)	(3.18)
Log(Age)	0.0001*	0.0001	0.0002*	0.0001
	(1.70)	(1.07)	(1.80)	(1.44)
Log(TNA)	−0.0002***	−0.0002***	−0.0002***	−0.0002***
	(−8.57)	(−8.80)	(−5.98)	(−6.12)
Exp. Ratio	−0.0115***	0.0428***	0.0280***	0.0087***
	(−3.93)	(11.83)	(8.90)	(4.47)
Turn. Ratio	0.0000	0.0000	0.0000**	0.0000
	(1.25)	(1.16)	(2.06)	(0.86)
Flow	−0.0000	0.0000	−0.0000	−0.0000
	(−0.73)	(0.32)	(−0.15)	(−0.92)
I(Team)	−0.0001***	−0.0001*	−0.0001***	−0.0002***
	(−2.61)	(−1.67)	(−2.74)	(−2.97)
Time×Style FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	83,843	83,870	83,863	83,856
Adj. R^2	0.805	0.825	0.877	0.872

Table IX: ICC and Tournament Behavior

This table presents results from pooled OLS regressions which relate mid-year risk-shifting to mid-year performance-ranks and fund-level ICC. The analysis is performed at the fund-year-level. The dependent variable is the risk-adjustment ratio, RAR, as defined in Section IV.A, equation (4). The main independent variables are $Rank$, $HighICC$, and their interaction. $Rank$ is calculated for each investment category and year separately. It is normalized to be equally distributed between zero and one, with the best fund manager in its respective investment category being assigned rank one. To obtain $HighICC$, first, for every fund every quarter, a value-weighted ICC of the funds' portfolios' constituents, ICC, based on four different proxies for expected earnings, is constructed as described in Section I.B. Second, this ICC is transformed into an indicator variable, $HighICC$, which takes the value of one, if the respective fund's ICC is larger than the median ICC in that year in the investment category the fund belongs to, and zero else. Controls are described in Table I. Regressions are run with time-by-style and fund fixed effects (FE). T-statistics, based on standard errors clustered at the fund level, are reported in parentheses. Throughout this table, ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	(1) Analyst	(2) EP (2014)	(3) RI (2014)	(4) HvDZ (2012)
Rank	−0.0171***	−0.0189***	−0.0178***	−0.0171***
	(−5.63)	(−6.55)	(−5.74)	(−5.45)
HighICC	−0.0069**	−0.0043	0.0040	0.0031
	(−2.43)	(−1.57)	(1.41)	(1.06)
Rank · HighICC	0.0117***	0.0158***	0.0135***	0.0125***
	(2.78)	(3.76)	(3.20)	(2.98)
Log(Age)	0.0047*	0.0046	0.0046*	0.0045
	(1.67)	(1.64)	(1.65)	(1.63)
Log(TNA)	−0.0011	−0.0010	−0.0009	−0.0009
	(−1.56)	(−1.41)	(−1.24)	(−1.27)
Exp. Ratio	−0.2092***	−0.2143***	−0.2129***	−0.2133***
	(−11.65)	(−11.76)	(−11.87)	(−11.83)
Turn. Ratio	−0.0002	−0.0002	−0.0002	−0.0002
	(−0.18)	(−0.16)	(−0.18)	(−0.14)
Flow	−0.0000***	−0.0000***	−0.0000***	−0.0000***
	(−6.34)	(−7.01)	(−5.32)	(−5.70)
I(Team)	−0.0008	−0.0008	−0.0008	−0.0007
	(−0.53)	(−0.54)	(−0.51)	(−0.48)
Time×Style FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	22,415	22,441	22,442	22,436
Adj. R^2	0.164	0.164	0.166	0.166

Table X: ICC and Mutual Fund Flows

This table presents results from pooled OLS regressions, that relate quarterly flows with fund-level ICC. The analysis is performed at the fund-share-class-quarter-level. The dependent variable is *Flow*, the percentage quarterly growth in fund's new money in %, net of the effect of returns. The analysis is split between retail share classes in Panel A and institutional share classes in Panel B. The main independent variable is *ICC*; for every fund every quarter, a value-weighted ICC of the funds' portfolios' constituents, based on four different proxies for expected earnings, is constructed as described in Section I.B. Controls are described in Table I. Regressions are run with time-by-style and fund fixed effects (FE). T-statistics, based on standard errors clustered at the fund level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	Panel A: Retail share classes				Panel B: Institutional share classes			
	(1) Analyst	(2) EP (2014)	(3) RI (2014)	(4) HvDZ (2012)	(1) Analyst	(2) EP (2014)	(3) RI (2014)	(4) HvDZ (2012)
ICC	−0.0543	0.0884	−0.0679	0.2443	1.5890***	1.1785**	1.5882***	2.4125***
	(−0.20)	(0.51)	(−0.28)	(0.87)	(2.69)	(2.00)	(3.07)	(4.20)
Log(Age)	−0.0301***	−0.0301***	−0.0300***	−0.0300***	−0.0315***	−0.0315***	−0.0316***	−0.0318***
	(−19.25)	(−19.27)	(−19.40)	(−19.39)	(−12.70)	(−12.70)	(−12.73)	(−12.81)
Log(TNA)	−0.0094***	−0.0094***	−0.0094***	−0.0094***	−0.0240***	−0.0239***	−0.0239***	−0.0239***
	(−15.08)	(−15.10)	(−15.18)	(−15.18)	(−24.03)	(−24.02)	(−24.01)	(−24.03)
Exp. Ratio	−0.1422**	−0.1404**	−0.1354**	−0.1351**	−6.0129***	−6.0082***	−5.9959***	−6.0227***
	(−2.03)	(−2.05)	(−2.03)	(−2.02)	(−10.85)	(−10.85)	(−10.83)	(−10.88)
Turn. Ratio	0.0033**	0.0032**	0.0030**	0.0030**	−0.0056**	−0.0054**	−0.0056**	−0.0056**
	(2.41)	(2.45)	(2.38)	(2.38)	(−2.10)	(−2.02)	(−2.07)	(−2.09)
Flow	0.1987***	0.1986***	0.2000***	0.2000***	0.1558***	0.1553***	0.1555***	0.1555***
	(12.84)	(12.84)	(13.17)	(13.17)	(21.86)	(21.84)	(21.87)	(21.88)
I(Team)	−0.0015	−0.0015	−0.0014	−0.0014	0.0009	0.0005	0.0006	0.0008
	(−0.78)	(−0.79)	(−0.74)	(−0.74)	(0.22)	(0.13)	(0.14)	(0.19)
Past Return	0.3320***	0.3337***	0.3326***	0.3333***	0.3392***	0.3399***	0.3405***	0.3435***
	(15.43)	(15.71)	(15.66)	(15.66)	(12.17)	(12.29)	(12.27)	(12.38)
Time×Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	274,757	275,068	274,973	274,882	109,094	109,134	109,155	109,149
Adj. R^2	0.181	0.181	0.181	0.181	0.130	0.130	0.130	0.130

Appendix B: Figures

Figure 1: Illustration of Cross-Sectional Earnings Estimation Procedure

This figure illustrates the procedure of how cross-sectional earnings estimates are obtained, by way of example for forecasts made in June. Each year t, depicted on the time-axis, under consideration of minimum three and maximum fourteen months reporting lag, denoted by the overbrace, a constant and firms' latest balance sheet information are collected in matrix $\mathbf{X_t}$, where each row corresponds to one firm-year. Based on ten years of accounting data, pooled cross-sectional OLS regressions are run of τ periods ahead realized earnings, $\tau \in \{1, \ldots, 5\}$, on balance sheet information, specified according to EP (2014), RI (2014), and HvDZ (2012), respectively. Underbraces depict the interval of data points entering the respective regressions. Resulting estimated coefficients are stacked into column vectors $\widehat{\vec{\boldsymbol{\beta}}}_\tau \ \forall \ \tau$. Post-multiplication with $\mathbf{X_t}$ results into forecasts, $\widehat{E}_{i,t+\tau}$, for each firm, stacked into column-vectors $\widehat{\vec{\mathbf{E}}}_{t+\tau}$.

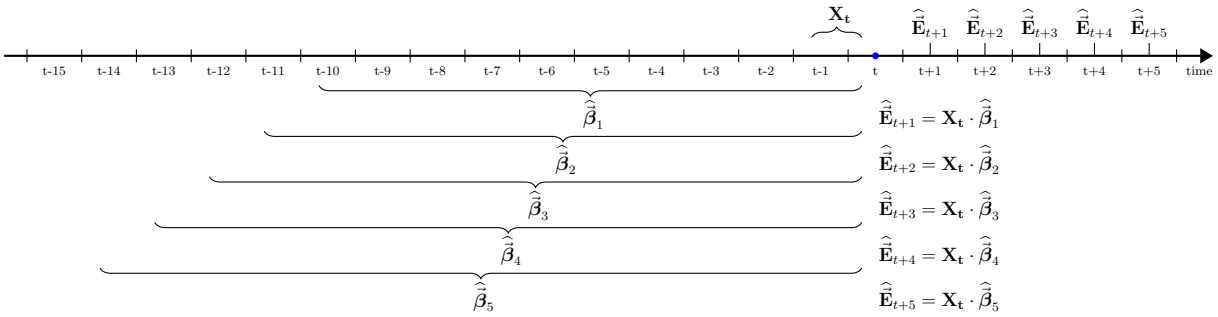


Figure 2: Cumulative Fund Returns of ICC-Percentile-Portfolios.

This figure plots cumulative returns of equally-weighted fund-portfolios corresponding to the bottom (magenta) and top (blue) quintiles of fund-level ICCs. These obtain as value-weighted ICCs of the funds' portfolios' constituents, based on four different proxies for expected earnings, constructed for every fund every quarter as described in Section I.B. Each quarter, funds are sorted based on their holdings' implied ICC and quintiles are determined. According to these quintiles, equally-weighted portfolios are built and held over the subsequent quarter.

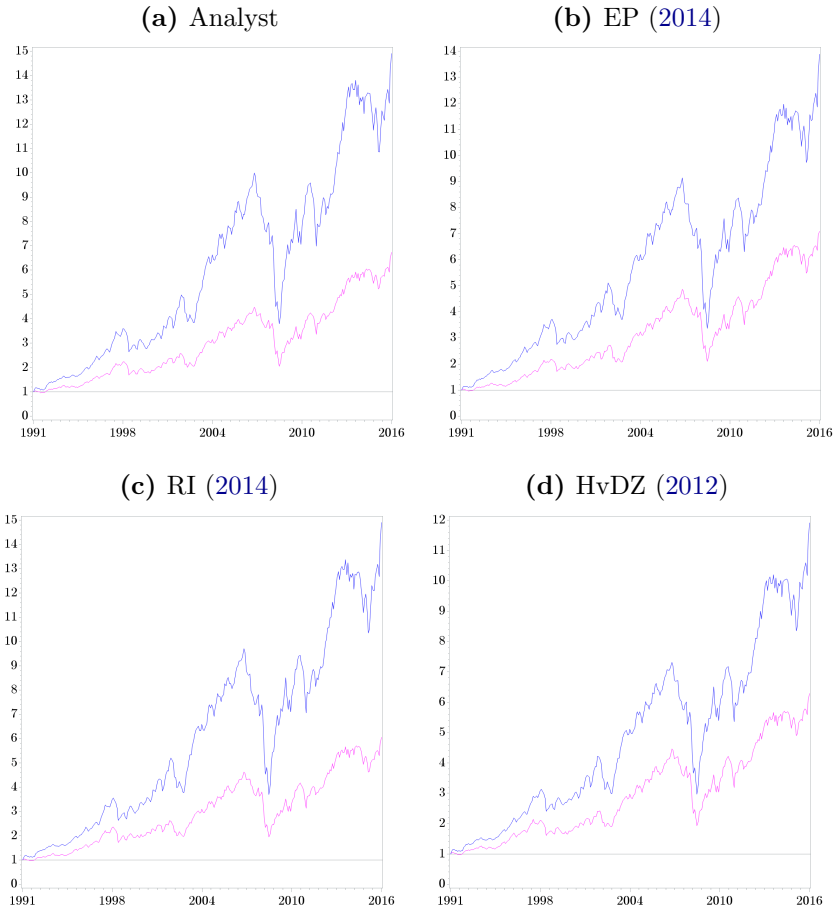
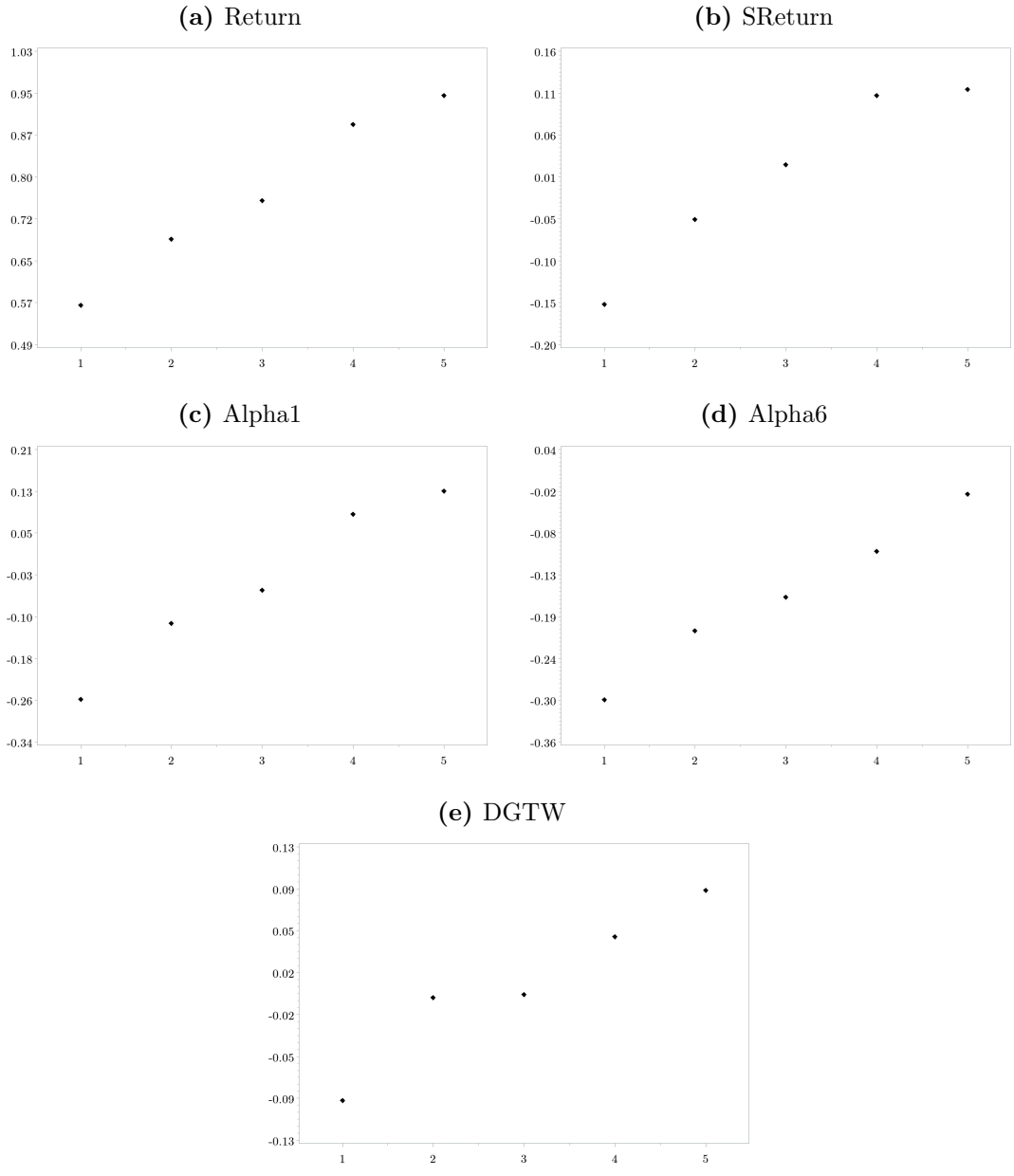


Figure 3: Average Monthly Performance of ICC-Percentile-Portfolios.

This figure plots, for all quintile portfolios indicated on the x-axis, average performance measures in % per month, denoted on the y-axis, corresponding to the analysis in Table II, Panel A, for ICCs derived from earnings forecasts according to HvDZ (2012). In particular, for every fund every quarter, a value-weighted ICC of the funds' portfolios' constituents, based on proxies for expected earnings following HvDZ (2012), is constructed as described in Section I.B. Each quarter, funds are sorted based on their holdings' implied ICC and quintiles are determined. According to these quintiles, equally-weighted portfolios are built and held over the subsequent quarter. Performance measures include average monthly returns (*Return*), style-adjusted returns (*SReturn*), Jensen Alpha (*Alpha*1), the Fama and French (2015) 5-factor alpha, augmented with the momentum factor (*Alpha*6), and characteristics adjusted returns (*DGTW*), described in Section II.A.



Appendix C: Implied Cost of Capital Models

This appendix provides a brief description of the models underlying the implied cost of capital used throughout the analysis. For each firm, an average of eight commonly used metrics, ICC_{LNS13}, ICC_{GG97}, ICC_{GLS01}, ICC_{CT01}, ICC_{OJ05}, ICC_{MPEG}, ICC_{PEG}, and ICC_{PE}, is calculated.

If not obtained differently by means explicit to one model, proxies for expected earnings of firm i one, two, three, four, and five years ahead, conditional on the information set at time t, Ψ_t, $\mathbb{E}(E_{i,t+\tau}|\Psi_t) := \mathbb{E}_t(E_{i,t+\tau}) \; \forall \; \tau \in \{1, ..., 5\}$, are obtained following Li, Ng, and Swaminathan (2013). The approach necessitates an estimate for long-term earnings growth, $\overline{g}_{i,t}$. For expected earnings proxies based on analysts, this value is potentially reported; if not and for mechanical earnings forecasts, it is computed as the ratio of the farthest consecutive non-negative earnings forecasts, $\widehat{E}_{i,t+\tau}$, minus one, i.e., $\overline{g}_{i,t} = \widehat{E}_{i,t+5}/\widehat{E}_{i,t+4} - 1 | \widehat{E}_{i,t+5} \wedge \widehat{E}_{i,t+4} > 0, \; \ldots, \; \widehat{E}_{i,t+2}/\widehat{E}_{i,t+1} - 1 | \widehat{E}_{i,t+2} \wedge \widehat{E}_{i,t+1} > 0$.

If the respective one-year-ahead earnings forecast is not smaller zero, $\mathbb{E}_t(E_{i,t+1})$ is set equal to this value. Else, if past earnings, $E_{i,t}$, are positive and the estimate for earnings two years ahead is larger zero, $\mathbb{E}_t(E_{i,t+1})$ obtains assuming geometric growth, i.e., $\mathbb{E}_t(E_{i,t+1}) = E_{i,t} \cdot \sqrt{\widehat{E}_{i,t+2}/E_{i,t}}$. Finally, given only two-year-ahead forecasts being non-negative, they are scaled down by long-term growth, such that $\mathbb{E}_t(E_{i,t+1}) = \widehat{E}_{i,t+2}/(1 + \overline{g}_{i,t})$.

A proxy for expected earnings in two years, $\mathbb{E}_t(E_{i,t+2})$, obtains in a similar manner. Provided a non-negative two-year-ahead earnings forecast, $\mathbb{E}_t(E_{i,t+2})$ is set equal to this value. Else, in cases of both positive past earnings and forecast of earnings one year ahead, the latter is assumed to grow by the rate implied through growth from past earnings to next year's forecast, i.e., $\mathbb{E}_t(E_{i,t+2}) = \widehat{E}_{i,t+1} \cdot (\widehat{E}_{i,t+1}/E_{i,t})$. Finally, if only the earnings forecast one year ahead is positive, it is assumed to grow by the long-term growth rate, such that $\mathbb{E}_t(E_{i,t+2}) = \widehat{E}_{i,t+1} \cdot (1 + \overline{g}_{i,t})$.

Proxies for expected earnings three, four, and five years ahead obtain as the respective forecasts in cases they are positive and alternatively by assuming growth of last period's

expected earnings proxy by the long-term growth rate.

A proxy for expected plowback rates of earnings, $\mathbb{E}_t(b_{i,t+1})$, if not stated otherwise, following literature, is obtained as one minus the ratio of most recent dividends, $D_{i,t}$, over earnings, $\mathbb{E}_t(b_{i,t+1}) = 1 - D_{i,t}/E_{i,t}$, if past year's earnings were larger zero. Else, a surrogate obtains using the ratio of past year's dividends over 6% of total assets, which proxies for normal earnings levels based on the long-run return on total assets in the U.S., $\mathbb{E}_t(b_{i,t+1}) = 1 - D_{i,t}/(0.06 \cdot AT_{i,t})$. $\mathbb{E}_t(b_{i,t+1})$ is winsorized to lie between zero and one.

The first two ICC-models belong to the realm of dividend discount models (DDMs). To begin with, ICCs according the model used by Pástor, Sinha, and Swaminathan (2008), Lee, Ng, and Swaminathan (2009), and Li, Ng, and Swaminathan (2013), ICC_{LNS13},

$$P_{i,t} = \sum_{\tau=1}^{15} \frac{\mathbb{E}_t[E_{i,t+\tau} \cdot (1 - b_{i,t+\tau})]}{(1 + r_{i,t})^{\tau}} + \frac{\mathbb{E}_t(E_{i,t+16})}{r_{i,t} \cdot (1 + r_{i,t})^{15}}, \tag{C.1}$$

where $P_{i,t}$ denotes the market value of equity of firm i at time t and $r_{i,t}$ the implied cost of equity, are calculated. The model is partitioned into three phases; in phase one, for the first two expected earnings, the authors consider the respective explicit model forecasts, which imply a certain growth rate, $g_{i,t+2} = \mathbb{E}_t(E_{i,t+2})/\mathbb{E}_t(E_{i,t+1}) - 1$.[28] Thereafter, in phase two, earnings are expected to grow at rate $g_{i,t+\tau}$. For all firms, this rate is assumed to exponentially converge towards a long-term growth rate, $\overline{g}_t$, dictated by the historical mean growth rate of nominal GDP.[29] This in turn governs the plowback rate in the terminal value phase, $\overline{b}_{i,t}$ (since sustainable growth in general obtains as the product of return on equity and plowback rate), such that $\overline{b}_{i,t} = \overline{g}_{GDP,t}/r_{i,t}$; the initial plowback rate is assumed to linearly converge to

[28] Li, Ng, and Swaminathan (2013) winsorize $g_{i,t+2}$ to lie between 2% and 100%.

[29] Data on GDP is obtained from the Bureau of Economic Analysis, `https://www.bea.gov/data/gdp/gross-domestic-product`.

this long-term value in phase three. Taken together, the respective quantities obtain by

$$\mathbb{E}_t(E_{i,t+\tau}) = \mathbb{E}_t[E_{i,t+\tau-1} \cdot (1 + g_{i,t+\tau})] \quad | \quad \tau \in \{3, ..., 16\}, \tag{C.2}$$

$$\mathbb{E}_t(g_{i,t+\tau}) = \mathbb{E}_t \left\{ g_{i,t+\tau-1} \cdot exp \left[log \left(\frac{\overline{g}_{GDP,t}}{g_{i,t+2}} \right) \right] \right\} \quad | \quad \tau \in \{3, ..., 16\}, \tag{C.3}$$

$$\mathbb{E}_t(b_{i,t+\tau}) = \mathbb{E}_t \left(b_{i,t+\tau-1} - \frac{b_{i,1} - \overline{b}_{i,t}}{T} \right) \quad | \quad \tau \in \{2, ..., 16\}. \tag{C.4}$$

The second DDM is the finite horizon growth model by Gordon and Gordon (1997). The name alludes to the fact that the authors consider the first five estimates for expected earnings explicitly, allowing for growth. Thereafter, earnings are assumed to be fully distributed (such that necessarily no growth is possible, leaving the growth phase being finite). Formally, assuming constant $\mathbb{E}_t(b_{i,t+\tau}) = \mathbb{E}_t(b_{i,t+1}) \; \forall \; \tau$, ICC_{GG97} solves

$$P_{i,t} = \sum_{\tau=1}^{4} \frac{\mathbb{E}_t[E_{i,t+\tau} \cdot (1 - b_{i,t+\tau})]}{(1 + r_{i,t})^\tau} + \frac{\mathbb{E}_t(E_{i,t+5})}{r_{i,t} \cdot (1 + r_{i,t})^4}. \tag{C.5}$$

Next, two models based on the residual income model (RIM) are considered.[30] All models rely on the clean surplus relation (CSR) to hold, according to which all profits and expenses are recognized in the income statement, such that future book value of equity, $B_{i,t+1}$, obtains as current book value plus retained earnings, $B_{i,t} + E_{i,t+1} \cdot b_{i,t+1}$. Residual income is defined as income above capital requirements of equity holders, i.e., just earnings superseding ICC in monetary units, $E_{i,t} - r_{i,t} \cdot B_{i,t-1}$, which can be rephrased, using $roe_{i,t} := E_{i,t}/B_{i,t-1}$, as $(roe_{i,t} - r_{i,t}) \cdot B_{i,t-1}$.

The first RIM is based on the three-phase model by Gebhardt, Lee, and Swaminathan (2001). For the first three periods, they use explicit earnings forecasts. During the second phase, lasting until the twelfth year, return on equity is assumed to linearly converge to historical median return on equity in industry j[31] firm i belongs to, $\overline{roe}_{j,t}$, calculated based

[30] Occasionally, the model is referred to as the Edwards-Bell-Ohlson valuation equation, confer Gebhardt, Lee, and Swaminathan (2001) and references therein, in particular Preinreich (1938), Edwards and Bell (1961), Peasnell (1982), and Ohlson (1995) for theoretical treatments, Feltham and Ohlson (1995, 1996) for implementations of this formula, and Lee (1999) for a survey of the literature on accounting-based valuation with focus on the RIM.

[31] Following Gebhardt, Lee, and Swaminathan (2001), I use the same 48 industry classification as in Fama

on a rolling window of ten years. Finally, for the terminal value phase, return on equity is assumed to stay constant at this rate. Hence, ICC_{GLS01} obtains as $r_{i,t}$ in following equation,

$$P_{i,t} = B_{i,t} + \sum_{\tau=1}^{11} \frac{\mathbb{E}_t[(roe_{i,t+\tau} - r_{i,t}) \cdot B_{i,t+\tau-1}]}{(1+r_{i,t})^{\tau}} + \frac{\mathbb{E}_t[(\overline{roe}_{j,t} - r_{i,t}) \cdot B_{i,t+11}]}{r_{i,t} \cdot (1+r_{i,t})^{11}}. \tag{C.6}$$

The two-phase model by Claus and Thomas (2001) takes an even more "aggressive" stand on the terminal value phase; the authors do not only assume residual income to stay constant, but to even grow at an estimate for the inflation rate, $g_{CT01,t}$, calculated as the maximum of the difference between the current yield of ten-year government bonds[32] and 3% and zero. Such, ICC_{CT01} equates

$$\begin{aligned} P_{i,t} = B_{i,t} + \sum_{\tau=1}^{5} \frac{\mathbb{E}_t[(roe_{i,t+\tau} - r_{i,t}) \cdot B_{i,t+\tau-1}]}{(1+r_{i,t})^{\tau}} \\ + \frac{\mathbb{E}_t[(roe_{i,t+5} - r_{i,t}) \cdot B_{i,t+11} \cdot (1+g_{CT01,t})]}{(r_{i,t} - g_{CT01,t}) \cdot (1+r_{i,t})^{5}}. \end{aligned} \tag{C.7}$$

The last four models can (but do not necessarily have to) be subsumed under the umbrella of abnormal earnings growth models (AEGMs).[33] Ohlson and Juettner-Nauroth (2005) model the dynamics of abnormal growth in earnings, i.e., growth in earnings above compounded retained earnings, $E_{i,t+1} - E_{i,t} - r_{i,t} \cdot (E_{i,t} - D_{i,t})$. In particular, they assume that short-term growth of abnormal growth in earnings asymptotically converges towards a long-term value, denoted as $(\gamma - 1)$, resulting into following valuation equation,

$$P_{i,t} = \frac{\mathbb{E}_t(E_{i,t+1})}{r_{i,t}} + \frac{\mathbb{E}_t[E_{i,t+2} - E_{i,t+1} - r_{i,t} \cdot (E_{i,t+1} - D_{i,t+1})]}{r_{i,t} \cdot [r_{i,t} - (\gamma - 1)]}, \tag{C.8}$$

such that ICC_{OJ05} obtains as

$$r_{i,t} = A_i + \sqrt{A_i^2 + \mathbb{E}_t\{(E_{i,t+1}/P_{i,t}) \cdot [g_{i,t+2} - (\gamma - 1)]\}}, \tag{C.9}$$

and French (1997).

[32] Data on the term structure of interest rate is obtained from Federal Reserve Bank of St. Louis, `https://www.federalreserve.gov/`.

[33] Confer Easton (2004) for a detailed discussion.

where

$$A_i = 0.5 \cdot [(\gamma - 1) + \mathbb{E}_t(D_{i,t+1}/P_{i,t})], \tag{C.10}$$

$$\mathbb{E}_t(g_{i,t+2}) = \mathbb{E}_t[(E_{i,t+2} - E_{i,t+1})/E_{i,t+1}]. \tag{C.11}$$

Ohlson and Juettner-Nauroth (2005) set $(\gamma - 1)$ equal to the maximum of the difference between the current yield of a ten-year government bond and 3% and zero, analogously to the empirical implementation of long-term growth of residual income by Claus and Thomas (2001).

As illustrated by Easton (2004), assuming zero long-term growth, i.e., $(\gamma - 1) = 0$, leads to the modified price earnings growth (MPEG) model,

$$P_{i,t} = \frac{\mathbb{E}_t(E_{i,t+2} - E_{i,t+1} + r_{i,t} \cdot D_{i,t+1})}{r_{i,t}^2}, \tag{C.12}$$

such that ICC_{MPEG} obtains as

$$r_{i,t} = \mathbb{E}_t(D_{i,t+1})/(2 \cdot P_{i,t}) + \sqrt{[\mathbb{E}_t(D_{i,t+1})/2 \cdot P_{i,t}]^2 + \mathbb{E}_t(E_{i,t+2} - E_{i,t+1})/P_{i,t}}. \tag{C.13}$$

Imposing further zero expected dividends in $t+1$ yields the familiar price earnings growth (PEG) model,

$$P_{i,t} = \frac{\mathbb{E}_t(E_{i,t+2} - E_{i,t+1})}{r_{i,t}^2}, \tag{C.14}$$

which ICC_{PEG} solves as

$$r_{i,t} = \sqrt{\mathbb{E}_t(E_{i,t+2} - E_{i,t+1})/P_{i,t}}. \tag{C.15}$$

Finally, assuming zero (abnormal) growth in earnings whatsoever results into

$$P_{i,t} = \frac{\mathbb{E}_t(E_{i,t+1})}{r_{i,t}}, \tag{C.16}$$

such that ICC_{PE} obtains solely from the inverse forwarded price earnings (PE) ratio,

$$r_{i,t} = \mathbb{E}_t(E_{i,t+1})/P_{i,t}. \tag{C.17}$$

Following literature, ICCs smaller zero are set missing; further, ICCs are winsorized at the 1st and 99th percentile.

Appendix D: Mechanical Earnings Forecast Models

This appendix provides a brief sketch of the regression equations underlying mechanical earnings forecasts used to compute ICC.

The first model is the earnings persistence (EP) model by Li and Mohanram (2014), specified as

$$E_{i,t+\tau} = \alpha_0 + \alpha_1 \cdot E_{i,t} + \alpha_2 \cdot NegE_{i,t} + \alpha_3 \cdot E_{i,t} \cdot NegE_{i,t} + \eta_{i,t+\tau}. \tag{D.1}$$

$E_{i,t}$ denotes earnings of firm i in period t. $NegE_{i,t}$ is an indicator variable equal to one, if earnings of firm i in period t are negative, and zero else.[34]

As a second model, I employ the residual income model (abbreviated RI to allow for distinction towards ICC-models, abbreviated RIM), which takes the following form,

$$E_{i,t+\tau} = \lambda_0 + \lambda_1 \cdot B_{i,t} + \lambda_2 \cdot E_{i,t} + \lambda_3 \cdot NegE_{i,t} + \lambda_4 \cdot E_{i,t} \cdot NegE_{i,t} + \lambda_5 \cdot TACC_{i,t} + \omega_{i,t+\tau}. \tag{D.2}$$

$B_{i,t}$ denotes book value of equity and $TACC_{i,t}$ total accruals following Richardson, Sloan, Soliman, and Tuna (2005), defined as the sum of the change in non-cash working capital, net non-current operating assets and net financial assets.[35]

The third, most comprehensive model was introduced by Hou, van Dijk, and Zhang (2012) (HvDZ),

$$E_{i,t+\tau} = \kappa_0 + \kappa_1 \cdot A_{i,t} + \kappa_2 \cdot D_{i,t} + \kappa_3 \cdot DD_{i,t} + \kappa_4 \cdot E_{i,t} + \kappa_5 \cdot NegE_{i,t} + \kappa_6 \cdot AC_{i,t} + \varrho_{i,t+\tau}. \tag{D.3}$$

The authors add dividend payments, $D_{i,t}$ and a related indicator variable, $DD_{i,t}$, equal to one, if firm i paid a dividend in t, and zero else.[36] Accruals, $AC_{i,t}$, are calculated using

[34] Hence, the EP model resembles an autoregressive model, allowing for differences in persistence depending on whether a firm accrued losses in the τ periods lagged fiscal year, based on economic reasoning and empirical evidence for losses being less persistent, confer, e.g., Elliott and Shaw (1988), Elgers and Lo (1994), and Fama and French (2000).

[35] The inclusion of accruals owes to evidence for lower persistence in the accrual part of earnings as opposed to the fraction related to cash flow, confer, e.g., Sloan (1996) and Fama and French (2006).

[36] Firms paying dividends have been documented to be more profitable and striving for persistence and smoothness in dividend payments, confer, e.g., Fama and French (2001). Further, Fama and French (2000) argue that dividends contain information about expected earnings because of firms targeting dividends to

the balance-sheet method prior to 1988, as the change in non-cash current assets less the change in current liabilities, excluding the change in short-term debt and the change in taxes payable, minus depreciation and amortization expenses, and using the cash flow statement method, as the difference between earnings and cash flows from operations, thereafter.

$\eta_{i,t+\tau}$, $\omega_{i,t+\tau}$, and $\varrho_{i,t+\tau}$ are the respective error terms. For each point in time t, explicit earnings forecasts for up to five periods ahead are calculated, i.e., $\tau \in \{1, ..., 5\}$. Following literature, level variables are winsorized at the 1st and 99th percentile.

the permanent component of earnings [Miller and Modigliani (1961)].

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