



## **Investment Advising: Pay-to-Play, or Capture?**

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### **Abstract**

In “Theory of Economic Regulation,” Stigler introduces the ideas of demand for, and supply of regulation (Stigler, 1971). Similar to capture in regulation, consultants to institutional investors enhance the benefits of their own firms, create a loss in information ratio to their clients, and reveal capture in their classification schemes, which serve the interests of portfolio managers that demand intermediation. Portfolio managers are modeled as perceptron units with a tactical element and a strategic mandate. The classification schemes of portfolios, supplied by internet platforms of consulting firms, distort the ‘default’ tactical prominence over strategic mandates and reshuffle the reviewed portfolios away from contemporaneous, performance-based rankings. Due to capture, the excess-fee incentive becomes compatible only with inconsistent narratives that the consultants of the firm can deliver to a client. The bifurcation in accountability between client-facing consultants and platform-supporting researchers creates a technology-amplified vacuum perceived by money management firms, which then rush-in to establish advisory capture. In a manner that “defies rational explanation” consulting firms appear cognizant of, but shun the better way to serve their clients (Stigler, 1971:3). In addition to fees, institutional investors stoically bear the loss in risk-adjusted performance, as their responsibility-transfer enables advisory capture. Ultimate realization of the loss due to on-line classifications, combined with conflicting scenarios embedded in classification schemes, may result in systemic-level redemptions that should concern the U.S. and global regulatory authorities.

**JEL Classification:** G11, G18, G23

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### **1. Introduction**

Finance literature and regulatory scrutiny on investment advising are strongly concerned with the recommendations of portfolio strategies offered by consulting firms to their institutional clients. An issue that has occupied U.S. regulators is “pay-to-play.” It refers to advisers’ encouraging or receiving monetary contributions from a portfolio manager, in exchange for benefits in accessing advisers’ client-investors. Access increases the flow of investor assets into a portfolio managed by the investment firm.

The U.S regulators investigate the payments by various methods, indirectly imposed on money management firms, in exchange for access to the advisor firms' clients (Office of Compliance Inspections and Examinations, 2005). An appreciation of the systemic exposure created by investment consulting practices may require elevating the depiction of pay-to-play into "capture" by money management firms (Stigler, 1971). I explore the similarities of "regulatory capture" as proposed by Stigler to "advisory capture" by the investment management firms, of the consulting firms' research advisors who evaluate the investment firms' portfolios while serving investor-clients.

Consulting firms function as regulating gate-keepers for the flows of assets under management (AUM) in and out of portfolios. Recommendations are revealed through classification schemes maintained by research advisory teams and made available in the firms' on-line platforms. In place of the investor-public whose welfare they should safeguard, consulting firms may produce recommendations that serve interests of the evaluated portfolio managers. The incentive of excess fees is less compatible with producing a classification scheme, which accurately reflects the key characteristics of portfolios, in the same way that standard performance-based metrics would. Yet based on performance metrics, but not on actual portfolios included in a classification assigned, the schemes in platforms betray the ability of research advisors to differentiate between portfolios that belong to a homogeneous universe, and those that do not. The ultimate classifications of portfolios in a universe reveal distortion in the "default" relation between tactical elements and strategic mandates of portfolios, contribute to higher fees due to capture, necessitate client-narratives that are not driven by consultant assessments, and point to market externalities in the form of systemic loss in information ratio, for institutional investor-clients. On-line classification schemes make the relation between tactics and mandates less robust, across universes. As discussed in literature, institutional investors continue to rely on ineffective schemes.

These investors could be tolerating a symbiotic relation of consultants with investment managers. Consulting firms "supply" the classification schemes to institutional investors. The schemes imply investment recommendations aimed at institutional clients, in allocating funds of retiree accounts, endowments, foundations, etc.

On-line platforms house classification schemes and augment face-to-face interaction with clients. These proprietary, web-based database platforms contain information on many portfolios and often underpin the selection of managers, as well as support the monitoring of manager performance by institutional investor-clients. Platforms provide analyses on performance and holdings of portfolios classified in groups, referred to here as *k*-groups. The classification for each portfolio is performed by expert research advisory teams within a consulting firm. I refer to researchers in these units as 'advisors' as they inadvertently produce advice on allocation, through schemes that they maintain. I reserve the term 'consultants' for professionals at the consulting organization, who come in direct client-contact and monitor or alter the list of recommended investment portfolios. They rely on the schemes of research advisors, whose independence appears ambivalent, and whose full fiduciary responsibility is hitherto unspecified. Per the Investment Adviser's Act of 1940 "advisers" must evaluate portfolios in a "disinterested" manner that involves "reasonable care to avoid misleading clients" (Barbash and Massari, 2018:633). But the research advisors that support an on-line scheme reveal behaviors akin to capture by the investment firms that they evaluate. Any related losses are "material facts" with potentially severe systemic effects on the consulting firms' investor-clients and the markets overall. Benefits of advisory capture lead to advice tainted by financial interest, because of (i) potential employment of the research advisor at a firm whose investment portfolios the research advisor evaluates and (ii) generation of excess fees by the consulting firm that owns and operates the platform. Since fees are charged for on-line platform

access, an advisor is deemed a fiduciary (Ellis, 2005). But pay-to-play is imputed on investment firms, as compensation outside of fees officially charged to clients. Capture, on the other hand, is imputed on research advisors and supports additional compensation within fees, for access to the platform.

In this regard, advisory capture may be less easily detectable than pay-to-play. Still, fees generated are in excess of a flat rate. I state a formalized argument, that the goal of maximizing fees to platforms is served by the distortions due to advisory capture, of portfolio characteristics commonly referred to as tactical and strategic. Compared to a 'default' case where an institutional investor does not adhere to outside schemes on investment portfolios, the choice to rely on them switches the prominence of assets affected by nonlinear events, from high to low or vice-versa, depending on the universe and the time at which portfolio performance is observed. Switching takes place by plan sponsors' investing in portfolios classified as suitable for recommendation, by the consultants of the same firm.

Contrary to an antagonistic relationship between investment firms and the consultant, as implied by pay-to-play, investment firms may actually seek the market regulation supplied on a large scale by a consulting platform, in a manner that appears as symbiotic with research advisors that maintain schemes in the on-line platform.

The literature has documented the transfer of responsibility from institutional investors' officers, generally referred to as plan sponsors, to the consultants. Between responsibility-transfer from plan sponsor to consultant and the capture of research advisors by the investment manager, there is the ad-hoc evaluation of tactical and strategic elements. Ratings restrict the recommendations by consultants, who are thus conflicted between shouldering client-responsibility transferred upon them, and serving the fee incentive of a platform, blended-in by the classification scheme. Without convincing quality control on schemes, internal conflict is almost certain.

The contributions of this study are that: (i) advisory capture distorts the relation of tactical to strategic elements of portfolios in inconsistent but predictable ways, as the schemes maintained by research advisors reveal, (ii) the distortions created by advisory capture can be congruent with excess fee generation by the on-line platforms. Specifically, the arbitrary portrayal of tactical as inversely related to strategic affords a narrative that panders to clients in a responsibility transfer-friendly manner, (iii) the schemes distort the prominence of tactical elements in a way that reduces granularity of tactical ability in a universe, and necessitates a narrative that is less appealing to the client, with concomitant escalation of internal conflict, (iv) the schemes imply the existence of an unobserved method that is equal or superior to the 'default option' of performance-quartiles, and by far surpasses the observed schemes in serving clients. The losses in investor wealth, which the schemes create, appear to be a mystery at best. In a manner that "defies rational explanation" (Stigler, 1971:3), distortions in the relation of tactical to strategic result in loss of investor wealth.

## 2. Institutional Background and Literature Review

This study uses standard vocabulary of active management. For example, "[a]lpha is interpreted as a measure of skill" by the global investment community (Ang, 2014:307). In its most generic formulation *alpha* is the intercept, while *beta* is the slope of a linear regression of portfolio returns, against a portfolio benchmark. All performance metrics referred to in this study are used in the investment industry. For example, *active return* is defined as the return of a portfolio strategy, in excess of the benchmark. *Tracking error* is defined as the standard deviation of active returns. Information ratio (*IR*) is *alpha* divided by the *tracking* error. Thus,

information ratio (*IR*) measures portfolio returns beyond the returns of a benchmark, usually an index, compared to the volatility of those returns. The benchmark used is typically an index that represents the market or a particular sector or industry. The distinction in *IR* generated by strategic elements from that of a tactical allocation is of paramount importance to investors. “Strategic” is the mere translation of the investment policy into assigned benchmarks from broad asset classes, and the incurring of market beta-risk. “Tactical” allocations on the other hand, seek extra returns by taking advantage of deviations from this fundamental economic exposure (Anson, 2006).

Numerous studies have suggested that consultant recommendations fail to outperform. The implication is that, investors who elected to rely on recommendations could have used a method that resulted in selections of equal or better performance and/or at lower fees. For example, Chalmers et al., 2017, find that investors who go through an intermediary are younger, less educated, and less highly paid. The clients of brokers take on greater risk and pay higher fees. Investors that rely on these financial advisors would most likely accept the “default investment option,” had they not relied on advisors. In my study, the “default option” in recommended portfolios amounts to selecting ones near the top of a universe or peer group, based solely on estimated information ratio (*IR*) and the way it is split into strategic (*S*) and tactical (*T*) elements by the estimation model. On the other hand, advice constitutes relying on schemes available through on-line platforms and the manner that they imply a separation between *S* and *T*. I estimate information ratio (*IR*) by a regime-switching model that uses betas to a number of indices as independent variables. The linear part is identified as *S*. The hyperbolic tangent transfer function in the model portrays *T*.<sup>1</sup> Institutional investors who switch from estimated information ratio to following classification schemes, subject a pension plan, a retirement account, endowment or foundation, to distortions in the prominence of *T* versus *S* in generating *IR*. The fee incentive aligns with the capture-related distortion, resulting in a market-external loss of investor wealth.

In the absence of a platform, responsibility-transfer still incents institutional investors to switch from outperformance rankings to consultant recommendations. But the latter are not revealed to the evaluated investment firms, on a mass-scale. A platform augments, but at the same time restricts recommendations, through a rule connecting them with classifications, which the evaluated investment firms gain access to. Compared to the instances in literature where the researcher is also the client-facing consultant, the technologically superior platforms introduce bifurcation of duties between the client-facing consultant, and the scheme-supporting research advisor. On-line platforms of consulting firms that employ both client-facing consultants and research advisors are bound to introduce conflict, in the absence of a robust quality control framework. As scale grows, client-facing consultants have little time to meet with portfolio managers, whose portfolios these consultants recommend. On the other, research advisors have no contact with the client, who relies on their schemes but only has access to firm consultants.

If client-facing consultants retained exposure to portfolio managers, their recommendations made to clients could have instigated less distortion of portfolio tactical prominence. At worst, consultants would merely fill-in for the role of pandering to the opinions of investor-clients. On the other hand, it is possible that realization of responsibility-transfer could raise standards in portraying tactical skill, and reduce vulnerability to capture, if research advisors

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<sup>1</sup> Hertz, et al., 1991: 28. Tactical decisions of a portfolio manager are likened to this “simplest problem in statistical mechanics, that of a single spin in a fixed external magnetic field.” What makes this function amendable to analysis, compared to the logistic form, is that it centers on zero, similar to portfolio or asset returns.

came in direct contact with investor-clients. When platforms stand between consultants facing clients and research advisors interacting with portfolio managers, the resulting void of accountability is perceived by the astute investment manager, whose client-relations associates selectively rush in to capture the advisors.

Fees generated by the platform in excess of a flat rate raise the incentive to the consulting firm to leave things as are. The literature finds that fee incentives skew recommendations. Chalmers et al., 2012, show that face-to-face interaction of financial advisors with institutional investors entail conflicts of interest. The fee-generation incentive leads to investors' making riskier but underperforming choices, and paying higher fees. When access to recommendations is free of charge, these conflicts of interest vanish. Peculiarly, investor-clients continue to follow these ineffective recommendations. My results show that excess-fee generation appears compatible with capture of the research advisors. In addition to shouldering plan-sponsor responsibility transfer, client-facing consultants are tasked with sustaining fee-generation of the scheme, while relying on classifications in making their invest/don't-invest recommendations. What evades the consulting firms' realization is that these schemes often embed contradictory client-narratives. Beyond a binary indication, the methodology and quality of research behind rating schemes may not be clearly conveyed to institutional investors. This reality is congruent with findings in literature, in which knowledge-transfer between consultant and client is impossible. Most of what communication could achieve is the perturbation of an institutional investor-client into triggering some positive changes. Actual knowledge transfer is not possible when each system is "operatively closed" (Mohe and Seidl, 2011:16). The shell (client) and not the grain of perturbing sand (advisor), ultimately produces the pearl (investment). In the case of direct recommendations to institutional investors, the specter of sponsor responsibility transfer hinders improvement beyond operative closed-ness. Compounded by the platform-induced bifurcation between consultants and research advisors, the classification schemes widen the responsibility gap between plan sponsor and consultant, enough for advisory capture to fit through. In terms of underperformance, the partitions of a universe by rating schemes may be more costly to investors than the recommendations issued by consultants privately. Institutional investor reliance on rating platforms could have an effect that is worse than that of direct recommendations by client-consultants. Classification schemes are technologically superior to client-facing. They intensely reshuffle portfolios recommended and they benefit the investment manager who stands on the demand side for "responsibility-transfer licenses" issued to the plan sponsors. The research advisors supply such "issuance" in the form of schemes that regulate client asset flows across the rated investment firms. It is advisory capture and the fee incentive that inadvertently dictate such issuance. The distortion of portfolio tactical prominence, ensues.

The reasoning found in literature, concerning the need or efficacy of investment consultants, extends to on-line platforms of a sizable footprint. In principle, investment firms should not need a platform-scheme. Gennaioli et al., 2015, allude to the fact that investment management firms are flexible enough to respond to the biases of institutional investors, all by themselves. Money managers pander to investors who exhibit persistent biases. This pandering affects arbitrage, and poses risk of market destabilization. To receive higher fees, portfolio managers abandon arbitrage and turn into noise traders, if investors become trusting. Contrarianism pays in the long run, but becomes less attractive to profit-maximizing managers, these authors conclude. Similar results are found in Jegadeesh, et al., 2004, in the context of recommending individual stocks: analysts' excessive focus on glamour stocks contributes to noise trading. In this paper, I allude to the possibility that platform schemes can exacerbate the systemic risk of market destabilization. Investors graduate into responsibility-transferors sooner when the

platforms increase the distance between plan-sponsor and investment consultant. Noise-trading raises market volatility, as per Gennaioli et al., 2015. But the realization of portfolio element distortion by on-line ratings can lead to en-masse redemptions. Regime-switching tactical skill reflects an otherwise normally distributed market return into a portfolio profile with excess kurtosis. Platform schemes leave the investor in the dark by obfuscating the statistical relation of  $T$  to  $S$ , making consultants look like ‘noise-recommenders.’ The nonlinearity in retiree wealth raises systemic risk. In universes where strategic elements increase (decrease) with tactical, a client perceives that not enough (too much) tactical tail-risk is undertaken. Either case elevates the risk of systemic-level redemptions in a crisis. As is the case in regulatory capture, technology itself is not critiqued. The way in which consulting intermediaries implement technology, and specifically the lack of quality control, is.

Advisory capture resembles regulatory. A research advisor assigns a classification to a portfolio. Before posting it on-line, the classification is argued upon at a committee meeting, infrequently involving client-facing consultants. Consulting relations teams (CRT’s) of investment managers have access to the platform, come in direct contact with research advisors and informally inquire, “How’d the meeting go?” They also are in contact with the client-facing consultants, who can substantiate recommendation of a favored strategy, stemming from the research advisors’ rating. External influence is in the career-interest of the research advisor, who seeks future employment opportunities at the investment firms evaluated. Not every research advisor is captured, let alone in review of the same portfolios, or by the same evaluated investment firms. Thus, distortions among universes and over time are inconsistent. If contradictory to investment manager interests or client-facing consultant opinion, an adverse rating assigned can lead to departmental strife, inequitable disciplining, even discharge. To cushion career risk, the captured advisor portrays the prominence of tactical elements of a portfolio in a way that would not betray lack a clear view of investment firm capabilities, as conveyed by the CRT’s, or promoted by internal client-facing consultants. With research advisors prompted toward “pandering” to an investment manager, the corresponding CRT seizes the opportunity to contact the clients directly, and to point to that one consultant in the firm operating the platform, who ‘handled’ this investment manager’s portfolio strategy. The investment manager can also separate portfolios into those marketed directly to investor-clients, and inferior ones rated by platforms. That may exert further pressure on research advisor independence. But capture of any kind has always been of concern to the U.S. regulatory authorities. Weber, 2015, mentions capture in the context of the regulators’ hesitation to restrict the flow of capital from banks to the stockholders before the 2008 financial crisis, from 2005 to 2007. In advisory capture, it is the research advisor, who “curries” favors (Weber, 2015, p. 45). By analogy, classification schemes that safeguard investor interests should act as an impediment to en-masse redemption of funds entrusted to money managers by such shareholder/institutional investor. Lack of quality control in schemes contributes to the fallacy of composition, where one investor runs for the proverbial theatre exit, while every other investor does. A cushioning effect by ratings is hard to envision. These classification schemes encourage an indiscriminate selection of portfolios with an understated or overgeneralized nonlinear/tactical element. The statistical prominence of tactical propensity turns from robust, to hazy. This practice amounts to less-granular assessment of tactician ability by the research advisor. That can only hurt clients. Research advisors maintain a façade of independence in review, while the CRT’s cash their chips of capture by inviting advisor visits to their website where employment opportunities are posted. Important interaction also takes place at a level above that of the lower-ranking research advisors.

Current literature on investment consulting does not cast a shadow on the motivation of the consulting firms as an intermediary between investors and portfolio managers.

Responsibility-transfer appears as a main role fulfilled by investment consultants. I expand this reasoning by illustrating the excess compensation in the form of fees, made possible when the consultants' recommendations depend on rating schemes on-line. This study entails a platform, where rating schemes are maintained. The consultants meet with clients, but have little participation in the process that supports a classification grouping of portfolios they recommend. The whole edifice requires scrutiny. In general, consultants are not necessary to attract assets, if performance is there, per Jenkinson et al., 2016. Better-performing investment managers attract plan sponsor assets without face-to-face recommendations, as the literature refers to. To the extent that rating schemes dictate recommendations, on-line platforms may be similarly unneeded. Jones and Martinez, 2014, find asset flows based on recommendations to be distinct from performance expectations, but consistent with agency issues and with plan-sponsor shielding of their own responsibility. Therefore plan sponsors' following consultant recommendations is attributed to responsibility-transfer. I add that responsibility transfer supplies the fertile ground for capture of the research advisor, who is found in a position of issuing licenses in demand by investment firms; only on a large scale, facilitated by the technological advantage of on-line platforms.

Like the original regulatory capture in Stigler, 1971, who proposed a "second view" of the political process, advisory capture "defies rational explanation." Contrary to the idealistic view that a portfolio manager dreads any robust classification scheme, it is the CRT of corresponding investment management firms that promote such rating. The schemes maintained by research advisors of the consulting firms resemble "the congressman feathering his own nest" through licensing practices. In advisory capture, licensing equates to recommending a portfolio for initial or prolonged investment by a plan sponsor amid responsibility-transfer. This depiction is similar to Stigler's industry-demand for regulation. In issuing responsibility-shielding licenses as ratings, the research advisors evolve to 'regulators under capture' as in Levine and Forrence, 1990. They develop narrow, self-interested goals of job retention, self-gratification from exercise of power, and post-advisory wealth. High tolerance for harassment develops internally, while rating schemes become valid only for small subsets of research, similar to Dal Bo et al., 2003. Symptoms of "repeated extortion" that pertain to such capture as in Choi, 2004, lead to the perpetuation of antiquated technologies, arbitrariness, and unpredictability. Luckily, "larger plans are less likely to retain consultants to assist them in the selection process and have higher post-hiring excess returns than their smaller counterparts" (Goyal, 2008: 1808). Thus, larger institutional investors are less prone to responsibility-transfer, and are less affected by advisory capture. Still, these classification schemes may entail immediacy of portfolio manager contact with the research advisors who maintain them. Such contact is sought-after by the CRT's of portfolio management firms, beyond the scope required for pure strategy evaluation. Through simultaneous contact with plan sponsors, after gaining familiarity with responsibility transfer, the CRT's perceive the void between consultant and research advisor of the same firm and selectively proceed with advisory capture attempts. I measure the effect of capture, using performance and classification data from an anonymous firm. I conclude that rating schemes result in severe loss to investors. Captured research advisors can produce recommendations that are not merely "fruitless," but harmful to the institutional investor.<sup>2</sup>

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<sup>2</sup>Jenkinson, et.al, 2016: 2333, refer to recommendations offered directly to clients. My study uses recommendations implied by classification schemes housed within on-line investment consulting platforms, made available for a fee.

### 3. The Portfolio Performance Model

The challenge in measuring tactical prominence is to preserve terminology of active management but to augment the performance metrics so that tactical and strategic are robustly distinguishable. Tactical allocations take advantage of current market conditions. I model the portfolio manager as a biological “neuron” that gets enticed when the stimulus arises (Trippi and Turban, 1993:5). The stimulus is a tactical opportunity that entices the portfolio manager. It is manifested by the tactical element of portfolio performance relative to a benchmark, and is measured by the common metric of information ratio (*IR*), in a neural network model. Artificial neural networks are mathematical functions inspired by the observation of biological systems, in which myriads of neurons distribute signals to body parts. In these biological systems, the dendritic stimuli cause the neuron to pump sodium/potassium in and out of its body through its membrane, raising or lowering its electrical potential. When this potential exceeds a certain threshold, the neuron fires a signal down its axons to the synapses and to other neurons. This system is mathematically represented by a transfer function that takes as arguments the cell’s electrical potential relative to a threshold (Priddy and Keller, 2005). There is interest in decoding undetected regularities in portfolio returns with transfer-functions. A single-layer hyperbolic tangent response model detects non-linear effects in models originally specified as linear (Franses and Van Dijk, 2000).

#### 3.1 Market Effects Seep into ‘Skill’ in Industry-Standard Performance Metrics

All industry metrics for measuring performance of active managers rely on outmoded linear models that produce *beta* corresponding to strategic elements of portfolios, only. The consulting industry struggles to discern *alpha* by qualitative analysis, adhering to the common intuition that skill is linked to tactical elements. Still, the current appreciation of *alpha* as expensive *beta*, and the emergence of *smart-beta* methods attest to the difficulty in discerning skill. The issue begins at the asset level. A model with a hyperbolic-tangent transfer function disentangles asset returns into the parts of linear and nonlinear returns. The linear return of asset *i* is  $R_{i,t} = \alpha_t + \beta_t I_t$  in an artificial neural network of level-1 model with no learning. Nonlinear return is the hyperbolic tangent function that, together with the linear part, constitutes the estimation model of single-asset returns. The model is shown in (1) for portfolio asset returns  $R_{i,t}$  that get enticed by the market index  $I_t$ . The portfolio manager’s skill or *alpha*, as the weighted sum of  $\alpha_i$  in (2) becomes problematic. Fitting a linear model on an otherwise non-linear relationship inadvertently allows market index  $R_M$  to seep into *alpha* or  $\alpha_P^{NL}$  where it mingles with portfolio manager skill, in (3).

$$R_{i,t} = (\alpha_i + \beta_i \cdot I_t) + \left[ \phi \cdot \frac{e^{\gamma_i + \delta_i I_t} - e^{-\gamma_i - \delta_i I_t}}{e^{\gamma_i + \delta_i I_t} + e^{-\gamma_i - \delta_i I_t}} \right] + \varepsilon_{i,t} = (linear) + [nonlinear] + error \quad (1)$$

$$R_i(t) = \alpha_i + \beta_i \cdot R_M(t) + [0] + \varepsilon_i(t)$$

$$\begin{aligned} R_P(t) &= \sum_{i=1}^N w_i \cdot R_i(t) = \sum_{i=1}^N w_i \cdot [\alpha_i + \beta_i \cdot R_M(t) + \varepsilon_i(t)] = \\ \sum_{i=1}^N w_i \cdot \alpha_i + \sum_{i=1}^N w_i \cdot \beta_i \cdot R_M(t) + \varepsilon(t) &= \alpha_P^L + \beta_P \cdot R_M(t) + \varepsilon_P(t) \end{aligned} \quad (2)$$

$$R_i(t) = \alpha_i + \beta_i \cdot R_M(t) + \phi_i \left[ 1 - \frac{2}{e^{2f_i(R_M(t))} + 1} \right] + \varepsilon_i(t) = \alpha_i + \beta_i \cdot R_M(t) + \varepsilon_i(t)$$

$$R_P(t) = \sum_{i=1}^N w_i \alpha_i + \sum_{i=1}^N w_i \beta_i R_M(t) + \sum_{i=1}^N w_i \phi_i - \sum_{i=1}^N \frac{2w_i \phi_i}{e^{2f_i(R_M(t))} + 1} + \sum_{i=1}^N \varepsilon_i(t)$$

$$E[R_P(t)] = \alpha_P^L + \beta_P \cdot R_M(t) + \phi_P - \sum_{i=1}^N E \left[ \frac{2w_i \phi_i}{e^{2f_i(R_M(t))} + 1} \right] = \alpha_P^{NL} + \beta_P \cdot R_M(t) \quad (3)$$

Where  $f_i(R_M(t)) = \gamma_i + \delta_i \cdot R_M(t)$ , and  $\alpha_P^{NL} = \alpha_P^L + \phi_P - \sum_{i=1}^N E \left[ \frac{2w_i \phi_i}{e^{2f_i(R_M(t))} + 1} \right]$

Standard portfolio theory is based on a linear model that could be viewed as a special case of (1), in which either  $\phi$  is zero, or  $\gamma$  and  $\delta$  are zero, or both. The problematic definition of *alpha* that bewilders consultants, and the need for disentangling returns into tactical and strategic, are illustrated through asset aggregation in (3). In his seminal study, Sharpe, 1963, combines asset returns  $R_i(t)$ , into portfolio returns  $R_P(t)$  as in (2). The market return  $R_M(t)$  in (2) is equivalent to the index return  $I_t$  in (1). Nonlinear asset return in brackets, is zero. Linear portfolio returns (2), are only a special case of (3). Under expectation,  $\beta_P$  conveniently becomes the portfolio sensitivity to the market, capturing non-diversifiable risk in (2). Nonlinearity in asset returns changes the meaning of portfolio *alpha* or skill, as one that also includes market effects, after substituting  $R_i(t)$  from (1) and taking expectation in (3). Deterministic market effects  $f_i(R_M(t))$  escape from the error term of the linear model, and land inside *alpha* of the nonlinear model. If not all of the nonlinear market effects  $f_i(R_M(t))$  are zero, the response-intensity coefficient  $\phi_P$  escapes from linear alpha and the error term into nonlinear alpha, to frustrate any portfolio performance evaluation by the consultant. The non-linear effect incorporates  $f_i(R_M(t))$  of the market index  $R_M$  into expected portfolio returns not accounted for by linear market coefficient  $\alpha_P$ . In (3), ‘skill’ depends on a market coefficient of non-linearity  $\phi_P$  and a term unaccounted for by non-diversifiable  $\beta_P$  that, unfortunately, has  $f_i(R_M(t))$  in it. This market index effect on *alpha* is erroneously perceived as manager skill. This performance evaluation issue with linear metrics gets compounded as portfolio managers “game” their selection of benchmarks.

Ideally, benchmarks should be consistent with the portfolio’s construction. But Bailey et al., 1993:38, reveal the managers’ propensity toward “reducing benchmark holdings of relatively high expected return securities and adding [...] low expected return securities.” For both reasons of betas’ seeping into alpha and benchmark-gaming, my study relies on estimated proxy-benchmarks, obtained from intercept-restricted regressions of portfolio returns against eight indices that pertain to a specific universe. Proxy-benchmarks are used in the estimation of information ratio, (*IR*). I replace  $R_{i,t}$  in (1) with  $IR_{k,m}$ , and break it down into the strategic and tactical elements as in (4), below. This method preserves the *IR* concept but exhumes all market effects from alpha. Here, portfolio managers as perceptron units have a linear mandate  $S$  and a non-linear element  $T$ . Information ratio is the sum of linear (strategic,  $S$ ) and non-linear (tactical,  $T$ ). A partition of a universe into four groups, reveals the relation  $T(S)$  between these characteristics. Starting in partition  $q$ , where a universe is ranked and grouped by performance quartiles, I find that  $S$  and  $T$  are related to each other,  $T = T(S)$ . But the ultimate partition  $r$  by consultant ratings, distorts this  $T(S)$  relation and results in investor loss of *IR*. At a benign level, the research advisors distort the mix of  $S$  and  $T$  across universes, to generate fees. At a severe level, the  $T(S)$  relation is fully inverted from  $q$ , and/or artificially counteracts other universes.

### 3.2 The Regime-Switching Model Isolates Tactical and Strategic Elements

If asset returns (1) are modified as in (4), the institutional investors can still monitor manager performance by information ratio (*IR*), as in Grinold, 1989. In contrast, standard performance measurement relies only on strategic or ‘linear’ *IR*, shown as  $S_{k,m}$  in (4). Everything else falls into either an error term or *alpha*, as in (1). With tactical elements not robustly quantified in industry practice, it is perhaps not curious that plan sponsors prematurely fire an investment manager who would not pander to beliefs, herein represented as *tactical*  $T_{k,m}$ , in (4). Using cash positions as “dry powder” for a tactical move is akin to a perceptron-response described by the hyperbolic-tangent element  $T_{k,m}$  in (4), followed in conjunction with the strategic mandate  $S_{k,m}$ . Vectors (6) and (7) are the linear and nonlinear maximum likelihood coefficients, respectively, using portfolios in  $m$ . These vectors are estimated with one model (4) as below, per each of four groups  $k = k_1, k_2, k_3, k_4$ , in a system of four unrelated equations for each universe  $m = 1 \dots 10$ . This estimation is repeated three times, one for each partition  $q, p$  and  $r$ , as explained below. Generally, the universes are collections of portfolios with similar risk characteristics. In each universe, the average of  $S_{k,m}$  and  $T_{k,m}$  is calculated for each  $k$ -group after substituting (5) in (4), using estimated (6) and (7). The average intercepts and coefficients of (5) in each group  $k = k_1, k_2, k_3, k_4$  are multiplied by the coefficient vectors in (6) and (7) to find average  $S_{k,m}$  and average  $T_{k,m}$  in each  $k$ -group. These four pairs of averages determine *slope-s* of tactical to strategic, denoted as  $s_{q,m}$  and  $s_{r,m}$  for partition  $q$  based on performance, and for  $r$  based on rating schemes by research advisors in the on-line platforms, respectively. The  $p$ -partition is explained below.

$$IR_{k,m} = S_{k,m} + T_{k,m} = \bar{C}_{k,m} \cdot \beta_{k,m}^T + \varphi_{k,m} \cdot \frac{\exp(\bar{C}_{k,m} \cdot \gamma_{k,m}^T) - \exp(-\bar{C}_{k,m} \cdot \gamma_{k,m}^T)}{\exp(\bar{C}_{k,m} \cdot \gamma_{k,m}^T) + \exp(-\bar{C}_{k,m} \cdot \gamma_{k,m}^T)} \quad (4)$$

$$\bar{C}_{k,m} = [1 \ \bar{\alpha} \ \bar{C}_1 \ \bar{C}_2 \ \bar{C}_3 \ \bar{C}_4 \ \bar{C}_5 \ \bar{C}_6 \ \bar{C}_7 \ \bar{C}_8]_{k,m} \quad (5)$$

$$\beta_{k,m}^T = [\beta_0 \ \beta_\alpha \ \beta_1 \ \beta_2 \ \beta_3 \ \beta_4 \ \beta_5 \ \beta_6 \ \beta_7 \ \beta_8]_{k,m} \quad (6)$$

$$\gamma_{k,m}^T = [\gamma_0 \ \gamma_\alpha \ \gamma_1 \ \gamma_2 \ \gamma_3 \ \gamma_4 \ \gamma_5 \ \gamma_6 \ \gamma_7 \ \gamma_8]_{k,m} \quad (7)$$

In the definition of *IR* found in Grinold, 1989, the numerator is the *alpha* plus an error term that becomes zero under expectation. Given the nonlinearity in (1), this zero-error appears as a heroic assumption. Here, performance relative to a benchmark (a.k.a. ‘outperformance’) is assumed to follow a regime-switching model as in (1), with  $IR_{k,m}$  in place of  $R_{i,t}$ , and portfolio betas to eight pertinent indices in the place of index  $I_t$ . But  $IR_{k,m}$  is estimated separately, before it is divided into tactical and strategic: through rolling samples of 36 monthly observations for 499 portfolios over five years for ten fixed-income universes. First, a rolling regression of portfolio returns to indices with intercept restricted to zero provides a time-varying proxy benchmark that exhumes all market effects. Calculation of active returns in a rolling sample is based on the proxy benchmark. The  $IR_{k,m}$  is calculated as the average of active returns divided by their standard deviation, across rolling samples. Then, rolling regression of portfolio returns against the same eight benchmarks, this time unrestricted, provides linear estimates of *alpha* and *betas* as is the industry norm in portfolio performance measurement.

These estimates across rolling samples are used to examine moments in the distribution of portfolio manager responses to the eight indices over time, and to address the problem of multi-collinearity in *betas*. The average of *betas* across rolling samples is used in this study. The result is a table of *IR*’s, *alphas* and *betas* for portfolios in each universe. To resolve

multi-collinearity, I separate the *alphas* and arrange the *betas* in the universe-table into principal components denoted,  $C_1, C_2 \dots C_8$  as in (5), which become the explanatory variables. These are components of the responses of the portfolio managers to index effects in the universe, devoid of direct market effects. The eigenvectors of the covariance matrix of these responses reveal orthogonal patterns of investment available to all portfolio managers in the universe, at the time of the sample. Coefficient vectors  $\beta_{k,m}$  and  $\gamma_{k,m}$  in (6) and (7) measure the linear ( $S$ ) and nonlinear ( $T$ ) response of portfolio managers to these patterns, respectively. Together, the patterns of investment and the responses to them constitute the contributions of component vector  $C_{k,m}$  to  $IR_{k,m}$ , as shown in (4). The latter is independently arrived at, based on proxy benchmarks. Coefficient  $\varphi_{k,m}$  measures the intensity of tactical response to nonlinear stimuli.

Together,  $\varphi_{k,m}$  and the hyperbolic tangent stimulus comprise tactical element  $T_{k,m}$  in (4). Within a universe in each partition, there is a total of four equations (4), one for each of  $k$ -groups  $k = k_1, k_2, k_3, k_4$ . Each of these four equations has its own vectors of coefficients (6) and (7), which are estimated through maximum-likelihood, per Zellner (1962). A universe can be divided into  $k = 4$  quartiles based on performance. Conveniently, there may also be  $k = 4$  classifications in the rating schemes that researcher advisors maintain, in on-line platforms. Transitioning from quartiles to classification schemes is performed in two steps: (1) changing the percentages of the universe in a group from the quartile-based 25% ( $q$ -partition), to the ones implied by classifications ( $p$ -partition), and (2) including in each  $k$ -group, portfolios that research advisors have included ( $r$ -partition), instead of the ones based on performance ( $p$ -partition). There should be gain, or at least no loss of  $IR$ , from these theoretical transitions. Otherwise quality control issues emerge in the classification of portfolios into groups. Research advisors tend to resist such abstract methods. Still, an immediate loss in  $IR$ , ‘today’ at  $t$ , reveals research advisors’ aspiring to be market-timers in recommending underperforming portfolios; a role not only unassigned to them, but detrimental to investor-client wealth. Underperforming portfolios in a universe may not timely mean-revert. If such betting on mean-reversion is a criterion for favorable classification, it could be disclosed to investor-clients, perhaps in a caption such as, ‘caution: these platform classifications cater to portfolio mean-reversion.’

### 3.3 Tactical and Strategic are Related Inversely in a $k$ -Group but Directly Overall

A good strategist should possess the resources to also be, a good tactician. There is no a-priori justification, for tactical and strategic elements, to not affect portfolio performance in a direct relation. It is possible, that once a universe is split into  $k$ -groups, belonging in each group is maintained by tactical-to-strategic tradeoffs. But a generalization, that any and all portfolios in a universe are either tactical or strategic, not both is hardly justified; except for specific reasons, as exemplified by universe  $m = 4$  Credit, and  $m = 2$  US Core Plus, in Table A.1 of Appendix A. These cases are discussed below. Based on the “default option” as in Chalmers et al., 2017, of relying on outperformance quartiles, columns *Quartiles* ( $s_{q,m}$ ) in Tables A.1 and A.2 exhibit a rising *slope-s* with a high  $R$ -squared between  $T_{k,m}$  and  $S_{k,m}$ . By default, as  $IR_{k,m}$  improves, both the tactical element and the strategic mandate of portfolios, go up. Within a group, tactical skill and adherence to mandate may be inversely related ( $q$ -partition, Figure A.1, Appendix A).

- The equation (4):  $IR_{k,m} = S_{k,m} + T_{k,m}$  is estimated through maximum likelihood in a system of seemingly unrelated regressions as in Zellner (1962). Each of the four regressions pertains to the portfolios that fall within a certain  $k$ -group, according to the partition performed. For example, in the  $q$ -partition, the four equations are estimated with  $k$ -groups as quartiles ( $k_1$  is the first quartile;  $k_2$  is the second quartile,

etc.). In the  $r$ -partition,  $k$ -groups are created by the classification schemes or ratings maintained by research advisors, for example,  $k_1 = A, k_2 = B$ , etc.

- The pair of  $S_{k,m}$  and  $T_{k,m}$  averages in each  $k$ -group in any partition is  $(E[S_{k,m}], E[T_{k,m}])$ . Four pair-observations are estimated, one for each  $k = k_1, k_2, k_3, k_4$ . The *slope-s* is derived from the fitted line  $E[T_{k,m}] = intercept + slope(s)E[S_{k,m}]$  and is positive or negative in Table A.1, with  $R$ -Squared in Table A.2. Tables 1, 2 and 3 below, reveal patterns of convergence in the maximum likelihood estimation. Transition into local or non-convergence indicates loss in quality. Row ' $\chi^2$  %' significance is a likelihood ratio test with four restrictions, in the  $p$  and  $r$  partitions.

There are 30 maximum likelihood estimations, ten per each partition of  $q, p$  and  $r$ . Each of the estimations is a system of four seemingly unrelated regressions per Zellner, 1962. Convergence in the  $q$ -partition indicates granularity in a universe. In the  $r$  partition, the lack of convergence across portfolio observations in  $m = 3...7$  indicates lack of quality in the classification scheme, for corresponding portfolios. Model estimation in the  $q$ -partition converges, except in  $m = 7$  Mortgage-Backed Securities. The  $q$ -partition converges to a narrative of a good strategist also being a good tactician, on average. Tables 1, 2 and 3 show the percentages of portfolios in a  $k$ -group, for each of the three partitions. The likelihood ratio tests indicate that the "best" partition is by  $p$ -portions, unobserved in platforms. Deviations  $q$  and  $r$  from  $p$  result in loss of quality.

**Table 1: Percentages in  $k$ -Groups,  $q$ -Partition. Maximum Likelihood and Ratio Test**

$m$ :	1	2	3	4	5	6	7	8	9	10
$k$	Conv ertibl	Core Plus	US Cred.	High Yield	Infl.- Link	Long Cred.	Mtge. Back	Distr essed	Glob. Cred.	Abs. Ret.
$k_1$	25%	25%	25%	25%	26%	24%	24%	26%	26%	27%
$k_2$	25%	25%	25%	25%	26%	24%	24%	26%	26%	27%
$k_3$	25%	25%	25%	25%	26%	24%	24%	26%	26%	27%
$k_4$	25%	25%	25%	26%	23%	29%	27%	22%	23%	20%
$L$	454	698	1088	1624	877	818	<b>-1E</b>	483	2370	441
$\chi^2$ %	1.85	1.75	7.19	3.99	7.86	6.25	<b>+10</b>	1.85	2.34	1.81

**Table 2: Percentages in  $k$ -Groups,  $p$ -Partition. Likelihood and Universe Observations**

$m$ :	1	2	3	4	5	6	7	8	9	10
$k$	Conv ertibl	Core Plus	US Cred.	High Yield	Infl.- Link	Long Cred.	Mtge. Back	Distr essed	Glob. Cred.	Abs. Ret.
$k_1$	18%	9%	15%	9%	8%	21%	16%	15%	21%	30%
$k_2$	21%	43%	27%	32%	18%	35%	10%	19%	38%	33%
$k_3$	11%	8%	4%	14%	3%	3%	6%	11%	15%	7%
$k_4$	50%	39%	54%	45%	72%	41%	67%	56%	26%	30%
$L$	1100	1744	1243	2592	952	1014	1224	1175	5066	1083
$Obs.$	28	76	48	121	39	34	49	27	47	30

**Table 3: Percentages in  $k$ -Groups,  $r$ -Partition, Maximum Likelihood and Ratio Test**

$m:$	1	2	3	4	5	6	7	8	9	10
$k$	Conv ertibl	Core Plus	US Cred.	High Yield	Infl.- Link	Long Cred.	Mtge. Back	Distr essed	Glob. Cred.	Abs. Ret.
$k_1$	18%	9%	15%	9%	8%	21%	16%	15%	21%	30%
$k_2$	21%	45%	27%	32%	18%	35%	10%	19%	38%	33%
$k_3$	11%	8%	4%	14%	3%	3%	6%	11%	15%	7%
$k_4$	50%	38%	54%	45%	72%	41%	67%	56%	26%	30%
$L$	142	209	<b>-3E</b>	<b>-8E</b>	<b>-2E</b>	<b>-4E</b>	<b>-2E</b>	146	1019	119
$\chi^2$ %	0.20	0.17	<b>+13</b>	<b>+09</b>	<b>+14</b>	<b>+14</b>	<b>+09</b>	0.19	0.47	0.15

#### 4. The Consultant and the Institutional Investor

The postponement and cancelation of the Labor Department’s Fiduciary Rule Law raised fears of embarking on the dangerous journey back to deregulation of financial markets. Ensuring that investment advisors adhere to their fiduciary responsibility appears to have shifted from the Department of Labor, to the SEC. Little has been announced on the topic of investment advisors/consultants. In the case of rating schemes, pay-to-play, focusing on the competing relation of advisors to investment managers, does not motivate an ‘inability’ to recommend. It is advisory capture that motivates such apparent inability. It inflates fees generated over a flat rate, distorts tactical prominence in portfolios, forces client-narratives that are either pandering or oxymora, and causes investor losses. Despite the low quality of on-line schemes, the research advisors appear to withhold superior knowledge that would benefit investors, if adhered to in their rating process. It is not. Such knowledge is revealed by the  $p$ -partition, discussed below.

##### 4.1 Classification Schemes Can Increase Fees Earned

In a classical-economics sense, regulation is desirable in cases of market externality, or failure. The literature on investment consulting does not refer to any self-correcting mechanism, which assures quality of recommendations. Fees generated through use of a consulting platform are the means of revenue, for firms that maintain on-line platforms. Classifications housed in platforms can transfer responsibility to the consulting firm on a large scale. These schemes create benefit for the institutional investor who observes them at a current time,  $t$ . Portfolios classified higher (lower) suggest greater (lesser) information ratio in  $t + 24$  months. The flow of assets under management (AUM) in and out of portfolios in any universe is affected by the difference between information ratio at  $t$ , and that suggested by schemes, even as research advisors do not officially or semi-rigorously prepare such numeric forecast. ‘Impact’ is defined as the flow of institutional investor assets in and out of portfolios based on their classification. Research advisors do not have perfect foresight. They cannot impute into the ratings that they maintain, an information ratio two years into the future. Also, they cannot gauge the success of their analysis, if they do not ever produce any numeric estimate by any method. Classifications that imply such estimates are nevertheless available to fee-paying clients via on-line platforms.

Rules, such as “higher than  $k_2$ ,” link schemes to recommendations made to institutional clients. Classifications provide a window into the effect of recommendations on wealth, not twenty-four months into the future, but at month  $t$  (today). This is the time at which advisory capture has permeated research advisors, distorted tactical prominence in generating outperformance, and created loss in  $IR$  on behalf of the investor-client. Outperformance two years into the future, based on today’s ratings is not tracked. Mean-reversion amplifies the

distance in performance between  $t$  and that in two years, as distortions cause fund flows into underperforming portfolios at time  $t$ . Consulting firms have the fee-incentive to ignore distortions. The loss in  $IR$  at time  $t$  is a market externality in the process of researching portfolios and assigning classifications.

Assume that on-line platform  $X$  at month  $t$  involves forward-looking information ratio estimate  $E_t [IR_{t+24, j}]$  for  $j = 1 \dots N$  portfolios evaluated. The research advisors producing the estimates are trusted to have enough foresight to impute these estimates on their ratings, even as the cognition of fiduciary responsibility is unknown, or unenforced. Investors may prefer reliance on  $IR_{t,i}$  when selecting from  $i = 1, \dots, j, \dots, M < N$  portfolios that belong to a particular universe  $m$ . Soon they find that plan sponsors hire and fire portfolio managers prematurely as a result of using  $IR_{t,i}$ , as in Goyal, 2008. Investment manager  $j$  has contacted consulting firm's platform  $X$  and has selected universe  $m$  to have the portfolio included in, together with peers  $i$ , also in  $X$ . It can be assumed, that  $E_t [IR_{t+24, j}]$  is known internally at  $t$  to firm  $x$ , while current  $IR_{t,j}$  is known to both clients and research advisors. Impact  $B_{t,j,m}$  in asset flows to-or-from  $j$  and from-or-to another portfolio, created by advisor schemes on  $j$ , is proportional ( $b_m$ ) to the difference between current and expected  $IR$  in (8). Investor asset flows  $B_{t,j,m}$  instantaneously adjust to such information. Alternatively, if the forecast  $E_t [IR_{t+24, j}]$  is the same as  $IR_{t,i}$  at  $t$ , there is no impact  $B_{t,j,m}$  on asset flows. The investor that relies on platform schemes, and the one who does not, have the same information if  $IR_{t,j}$  follows a random walk in which  $E_t[IR_{t+24,j}] = IR_{t,j}$ . But if non-random and known, the forecast  $E_t [IR_{t+24, j}]$  impacts flows and generates fees, as in (8) and (9).

$$B_{t,j,m} = B_0 + b_m \cdot [E_t [IR_{t+24,j}] - IR_{t,j}] \quad (8)$$

$$F_{t,j} = F_0 + f_1 \cdot [E_t [IR_{t+24,j}] - IR_{t,j}] \quad (9)$$

As long as the difference between current and expected information ratio is different from zero, there is a benefit to investors from obtaining the forecast  $E_t [IR_{t+24, j}]$  if it is different from  $IR_{t,i}$ . In reference to portfolio  $j$ , plan sponsors would be willing to pay a fraction  $f_1 < b_m$  of that difference in the form of fee  $F_{t,j} < B_{t,j}$  above fixed rate  $F_0$ , for access to the forecast  $E_t[IR_{t+24,j}]$ . Thus,  $f_1$  is a fraction of the difference between the current and expected information ratio for portfolio  $j$ , while  $F_0$  is a flat fee.<sup>3</sup> Beyond  $F_0$ , fees  $F_{t,j}$  are assumed proportional to the difference between  $IR_{t,j}$  and  $E_t[IR_{t+24,j}]$ , whether forecasted, or implied. Investors can split universe  $m$  into four performance quartiles using forecasts  $E_t [IR_{t+24, j}]$ . But firm  $x$ , which owns and operates platform  $X$ , may not generate, let alone publicize,  $E_t [IR_{t+24, j}]$ . Conveniently, the partition created by ratings that  $x$  does make available splits universes into four groups like quartiles and implies recommendations for allocation, for clients. This  $r$ -partition then, acts as substitute in place of the nonexistent and/or nonpublic estimates of information ratio  $E_t [IR_{t+24, i}]$  two years hence. An actual, numeric forecast does not need be produced or verified internally, for excess fees to be generated according to (9). Consultants have little incentive to produce  $E_t [IR_{t+24, i}]$ .

The client-facing consultants of firm  $x$  that owns  $X$  are by internal rule bound to abide by the rating scheme of partition  $r$ . Knowing  $r$  and not  $E_t[IR_{t+24,i}]$ , the "trusting" investors monitor the performance of  $j$  in groups  $k$ , by their average information ratio,  $E_t[IR_{t,i}(scheme)]$ . In the

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<sup>3</sup> This study does not use actual fee data. Equation (9) is not estimated, but only stated in mathematical form.

absence of a platform-scheme the investor would look at performance relative to benchmark at  $t$ , with implications about his hiring and firing investment managers. A platform with a classification scheme deters plan sponsors from doing so, as it disentangles the tactical and strategic elements of portfolios. The investor could have partitioned any universe  $m$  into performance quartiles  $q$ , but platforms result in partition  $r$  based on classification schemes. To gauge advisory capture, a plan sponsor who is devoid of responsibility transfer can monitor the difference between  $IR_{k,m}$  by  $q$  estimated at  $t$ , and that by  $r$ , also estimated at  $t$ . If not as pure welfare loss from their own responsibility-transfer, there is no justification for an investor to sacrifice information ratio when switching from  $q$ -performance to the  $r$  platform classification scheme. The consulting industry mantra is to the effect of ‘current performance is no-guarantee of future results [from recommendations].’ Not ‘current performance is no-guarantee of current results.’ As shown, invest-recommendations are a statistical guarantee of current loss in  $IR$  compared to a “default option;” and not-invest recommendations are a statistical guarantee of forgone  $IR$ . Switching from outperformance to rating classifications results in immediate and substantial detriment. Investors bear the consequence of their switch from allocating based on observed performance, to relying on schemes in platforms maintained by consulting firms and their research advisors.

#### 4.2 Classifications Distort the Relation of Tactical Element to Strategic Mandate

The mix of tactical and strategic elements produces information ratio of a portfolio in a specific sample. Intuitively, these two elements should be directly related as ratings and current out performance rise in a universe. The effective portfolio manager should possess an ability to change the mix at any time when tactical elements improve outperformance, including today  $t$ , and to maintain classification in the original  $k$ -group. The research advisor should not reward with a high rating, managers with a strong tactical prevalence at the expense of a strategic focus. Treating tactical as a substitute, not complement for strategic, should not persistently dislocate a manager into a higher  $k$ -group today, and irrespective of what may happen two years into the future. The knowledgeable research advisor should be able to classify a portfolio to a  $k$ -group, separate from generalized narratives on a tactical impact given adherence to a strategic mandate that a universe exhibited, at the time of portfolio evaluation. Irrespective of reflecting outperformance two years hence, or not, ratings impact investor welfare today, immediately.

Except for economic scenarios, and/or the effect of ‘red pumpkins’ as discussed by Rice, et al., 2012, the prominence of tactical over strategic and vice-versa, should not make a portfolio traverse the  $k$ -groups within a universe. On average, portfolio managers in the universe, should exhibit complementarity in tactical and strategic elements, in generating  $IR_{k,m}$ . Performance model (4) helps reveal *slope-s* of tactical to strategic elements across a whole universe. Positive (negative) slope reveals a universe partition in which tactics and strategy are complementary (substitute) in performance (this study uses data between mid-2014 and mid-2017). Consulting platform schemes inconsistently distort this *slope-s*, inverting or exaggerating it, but generally making it less statistically significant. Unaware of lower statistical significance and  $R$ -Squared, the investor may compare  $E[IR_{t,i}(scheme)]$  to  $E[IR_{t,i}(quartile)]$  for  $i = 1 \dots M$ , based on  $k = k_1, k_2, k_3, k_4$ . In partition  $q$ ,  $k$ -groups are quartiles of estimated performance. In partition  $r$ ,  $k$ -groups are rating schemes of investment portfolios, in on-line platforms. After denoting the expected value of  $E[IR_{t,i}(quartile)]$  in quartile  $k$  by  $IR_{k,q}$  and that of  $E[IR_{t,i}(scheme)]$  in the rating that ranks the same as quartile  $k$  by  $IR_{k,r}$ , fees charged,  $F_k$ , are assumed proportional to the difference between quartiles and schemes (subscripts  $j$  and  $m$  are dropped). Tactical elements  $T_{k,q}$  and  $T_{k,r}$  impact  $IR_{k,q}$  and  $IR_{k,r}$ , as functions of the common strategic element  $S_{k,q} = S$  (see equations A.2 and A.3 in Appendix A). For example,  $S_{k,q}$  affects  $IR_{k,q}$  through the *slope-s* of  $T_{k,q} = T_{k,q}(S_{k,q})$ .

$$F_k = F_0 + f_1 \cdot [IR_{k,r} - IR_{k,q}] \quad (10)$$

The unobserved partition  $p$  rests between  $q$  and  $r$ . It preserves the number of portfolios in the universe, which fall in each  $k$ -group through  $r$ ; but it does not rely on performance from the portfolios in a  $k$ -group/rating in the  $r$  partition. Each  $k$ -group in  $p$  has the same number of portfolios in it, as the corresponding  $k$ -rating in  $r$ . But each  $k$ -group in  $p$  includes portfolios as ranked by performance model (4), not as decided upon by the research advisor. The distinction between  $p$  and  $q$  is that  $q$  contains in a  $k$ -group, a fourth of the portfolios in  $m$ , while  $p$  contains the same number of portfolios as  $r$ ; but from the top by performance ranking, similar to  $q$  (see Table 1). In addition to *which*,  $r$ -partition ratings determine *how many* portfolios fall within a  $k$ -group. By itself, the *how many*-part of  $r$  does not reveal distortion, except in  $m = 4$  High Yield (please refer to ‘ $p$ -Partition’ in Figure A.1 of Appendix A). Mysteriously, the  $p$ -partition makes the slope  $s$  of the relation of  $T_{k,q} = T_{k,q}(S_{k,q})$  positive and less dispersed than  $q$  or  $r$ . This finding agrees with the intuition of the good strategist is also a good tactician (see Average of 0.32 and Standard Deviation of 0.67 under ‘Portions ( $s_{p,m}$ )’, in Table A.1). Overall, a portfolio in each universe belongs into one of  $k = 4$  groups, according to the three partitions,  $q$ ,  $p$  and  $r$ :

- $q$ ) Partition  $q$  splits the portfolios in a universe into equal-sized quartiles, based on estimated information ratio for each portfolio in the  $k$ -group. The quartiles  $q$ , are renamed as  $k_1, k_2, k_3, k_4$ . Averages of  $T_q$  and  $S$  in each of four  $k$ -groups determine universe slopes  $s_{q,m}$ . Reliance on platforms can be deemed unnecessary, under this ‘default’ partition  $q$ .
- $p$ ) Partition  $p$  splits a universe by observing through ratings  $r$ , the number of portfolios in each group  $k_1, k_2, k_3, k_4$ , but assigning portfolios based on  $IR_{k,m}$  starting from the top of ranked performance. These unobserved groups in  $p$  maintain portions from scheme  $r$  but reassign  $k$ -group outperformance. Universe slopes  $s_{p,m}$  are derived similarly to  $q$ , above.
- $r$ ) Partition  $r$  uses the number of portfolios in each rating and the information ratio for the portfolios classified within a rating. The scheme uses  $k_1, k_2, k_3, k_4$ , assigned by research advisors, published in on-line consulting platforms. Slopes  $s_{r,m}$  are similar to  $q$  and  $p$ .

In  $q$  and  $p$ , the top group of best-performing portfolios is assigned to  $k_1$ , with the implication that these ‘best’ investment portfolios are suitable for recommendation. The group underneath  $k_1$  is  $k_2$  and would also be recommended. The third group,  $k_3$  is of lesser desirability for further analysis. Finally, group  $k_4$  has portfolios at the bottom of a universe that research advisors would preemptively exclude from analysis, let alone recommendation. Partition  $p$  creates the mysterious at best, ‘correction’ in the slope of tactical to strategic, raising it from  $q$ , as research advisors decide *how many* portfolios to review before even knowing *which*, as at all possible.

Barring a better explanation, research advisors possess some knowledge by the  $p$ -partition, but they systemically misclassify portfolios due to capture in the observed  $r$ -partition. Evidence is in: (i) Table 1 above, where the maximum likelihood in the  $p$ -partition is higher than even the default  $q$ -partition, (ii) Table A.1 of Appendix A, where average universe *slope-s* is greater and more concentrated under  $p$ , even with  $m = 4$  High Yield, (iii) Table A.2 where  $R$ -Squared is similar between  $q$  and  $p$ , except for  $m = 7$  Mortgage-Backed, and (iv) Table B.1, where the first,  $q$ -to- $p$  transition creates a change in *slope-s* of only 0.17 (row A)

and reveals equal positive and negative *slope-s* changes (rows L, M). With the exception of  $m = 4$  High Yield, research-advisors' unobserved  $p$ -partition is 'better' than the default, performance-based  $q$ -partition. Universe  $m = 4$  is particularly arbitrary. The research-advisor splits an otherwise intuitive universe of portfolios under  $q$ , so that portfolios rated as  $k_1$  excessively underperform on strategic mandates, even in unobserved partition  $p$ , let alone  $r$  (Figure A.1, Appendix A).

### 4.3 Classification Schemes Reshuffle Recommended Portfolios

Appendix A delineates the connection of fees, to information ratio and tactical elements in each partition as strategic elements change. The second and third columns in Tables A.1 and A.2 of Appendix A illustrate the *correcting* effect of  $p$  and the *reshuffling* effect of  $r$ , respectively ('Ratings' are the 'Classifications' under partition  $r$ ). Strategic mandate  $S$  is assumed to generate  $IR$  through its relation to tactical ability as far as fees are concerned, in equations A.2 and A.3. In fee-generation, the direct effect of  $S$  is assumed constant, across  $k$ -groups, among all partitions. It is the relation of strategic to tactical that determines *slope-s*, which research advisors assess or distort. The reasoning regarding  $S$  not affecting  $IR$  differently in  $k$ -groups or in partitions rests on the service provided by platforms; that is, determining tactical elements, which based on research advisor knowledge, gauge skill. The portfolio managers reveal *slope-s* of tactical to strategic in qualitative interactions with the research advisors, who then assign classification  $k = k_1, k_2, k_3, k_4$ . The challenge for research advisors is to assess the level of portfolio manager *alpha*-generating potential by tactical ability, when the opportunities for tactical allocation are not fully evident, and/or when the strategic mandate is emphasized in communications. For example, in  $r$  the effect on  $IR_{k,r}$  of tactical allocation  $T_{k,r}$ , denoted as  $\partial IR_{k,r} / \partial T_{k,r}$  in (B.3) of Appendix B, is assumed to be similar in  $k$ -groups across  $l$ -partitions, in the process of generating fees beyond a flat  $F_0$ . Consulting firms cannot charge a different fee depending on the  $IR_l$  effects of the managers that a client accesses in a platform. The effect  $\partial IR_k / \partial T_k$  does not change fees charged across  $k$ -groups and is identical in the  $q, p$  and  $r$  partitions, within a universe. Together with change in strategic  $dS$ , the effect  $\partial IR_l / \partial T_l$  reveals a universe-specific narrative that consultants must present at a client meeting. Narratives stem out of fees charged in excess of a flat rate, as discussed below.

Tactical and strategic can either become directly related (complementary), or inversely related (substitutes). Most of the universes under  $q$  and all but one under  $p$  in Table A.1 adhere to the first narrative, matching the intuitive explanation that on average, a good strategist is also a good tactician and vice-versa. Thus, tactical and strategic elements appear complementary in producing information ratio,  $IR$ . It may be argued that universes where the  $q$ -slope  $s_{q,m}$  is not strongly positive, are not audited often by research advisors. For example, some portfolios that are included in  $m = 3$  Credit, could belong to another universe, but would be placed in  $m = 3$  under loosely defined "universe-gaming" which platforms make possible when a portfolio manager originally registers in the universe of choice. The lack of universe maintenance in the consulting firms' platforms leads to weak or negative relations of tactical to strategic by partition  $q$ , where no interference by research advisors has yet taken place. In painting a pumpkin red and calling it a tomato, per Rice, et al., 2012, tactical elements of portfolios extraneous to a universe may appear as substitute for  $S$ , overpowering a direct slope of  $T_q(S)$  against  $S$ , in  $m$ . Table A.1 shows that red-pumpkins may be present in universes with a strong credit element, such as Credit, and Core Plus. Portfolio managers attempt to squeeze-in their portfolios into a universe that enhances benchmark-relative performance versus peers. The research advisors are concerned with the conundrum of tactical versus strategic, at the universe level. They determine whether an individual portfolio belongs in a universe, at a time the portfolio shows on the radar screen for evaluation. Until

that time, a portfolio is classified as  $k_4$ . As Table 2 and Table 3 show, half of the portfolios in any universe are rated as  $k_4$ , based on ratings assigned. This is disappointing. Compared to quartiles  $q$ , where only a quarter of the portfolios is not considered for investment at all, research advisors “play it safe” by arbitrarily excluding half of the portfolios, for which performance numbers exist, from recommendation. Results in Appendix C show, that outperformers simply fall through the cracks through this practice. Partition  $p$  partly disentangles this problem. It groups red pumpkins in  $k_4$ , a non-recommended classification, where their effects are averaged-out with dissimilar portfolios.

It is also possible to explain the dispersion in slope  $s_{q,m}$  under  $q$  in Table A.1, by the economic conditions during this study. The sample period is roughly from mid-2014 to mid-2017. At that time, the U.S. economy operated in a low-interest-rate, low-volatility environment. Rates and volatility were suppressed due to lack of tightening, with continued central bank intervention through quantitative easing (QE). Mortgage prepayment activity was subdued, and defaults remained high. The manager of a mortgage-backed portfolio would be both a tactician and a strategist as bonds with optionality gravitated near default. It could be hard to distinguish purely prepayment-based, from the default-related portfolios in the mortgage-backed universe. The difficulty in scrubbing this universe is reflected in Table 1,  $m = 7$ . The system of seemingly unrelated regressions fails to converge toward a solution that represents all observations, for  $q$ .

In interpreting the non-convergent Mortgage-Backed  $s_{q,7} = 2.83$  in ‘*Quartiles( $s_{q,m}$ )*’ of Table A.1, it becomes obvious that the research advisor believed after not scrubbing the universe, it was natural for optionality-based portfolios to have 2.83 times as much credit, as prepayment exposure. ‘Mysteriously’ again, the research advisor is able to correct this high value in the  $p$ -partition, to  $s_{p,m} = 0.25$ . This correction indicates that the research advisor compensated for the lack of resources dedicated to cleaning-up a universe, by selecting portfolios to evaluate and classify. In that process, portfolios may completely fall through proverbial cracks. Partition  $p$  raises a question on the possibility of knowing *how many*, without knowing *which* portfolios to classify, except if research advisors simply rated all new registrants as  $k_4$ . This interplay of red pumpkins with economic conditions affects universes  $m = 2$  US Core Plus and  $m = 3$  Credit, as well, but in the opposite direction. Here, portfolio managers must become tacticians as nonlinear, default-based allocations dictate outperformance. Universe-gaming entails painting portfolios with a strong tactical credit element, if consultants favor ‘swinging for the fences’ in an environment where yields are low. But which came first, the bona-fide credit portfolio or the red pumpkin? Research advisors mysteriously weed-out portfolios in partition  $p$ , under *Portions ( $s_{p,m}$ )* on Table A.1. With the notable exception of  $m = 4$  High Yield, tactical  $T_p$  in the  $p$ -partition is directly related to strategic  $S$ , and less dispersed than in  $q$ . Thus, up to the  $p$ -partition, research advisors display an ability to *correct* for the interplay of red-pumpkins with economic conditions. It is the third column, *Ratings ( $s_{r,m}$ )* in Table A.1 that reveals the actual *reshuffling* of portfolios, starting from the unobserved  $p$ -partition. Average *slope-s* and standard deviation among universes rise to the highest levels of 0.56 and 1.67, in this  $r$ -partition. The term ‘reshuffling’ refers to the selection of actual portfolios to include in each  $k$ -group or classification, by the research advisor. As discussed below and illustrated in Appendix C, it is the transition from unobserved  $p$  to publicized  $r$  that creates the market-externality of loss in  $IR$  to the investor-client. It appears that the best service that on-line platforms could provide to clients as far as contemporaneous loss in  $IR$  is concerned would be to:

- (i) Weed-out red pumpkins in reference to economic conditions, when grouping portfolios into classifications or ratings. This is already done by the unobserved  $p$ -partition.

- (ii) Rank portfolios in a universe by model (4) above and include in each  $k$ -group, portfolios based on the ranking. Model (4) is based on a time-varying, regression-based benchmark.
- (iii) Recommend portfolios in  $k$ -groups  $k_1$  and  $k_2$ ; avoid reshuffling among the groups using ‘qualitative’ criteria. However, then clients would consult ratings once in a great while.

With a few exceptions in Table A.2,  $R$ -Square reveals a strong relation that accompanies the  $q$ -slopes listed under column ‘*Quartiles (sq,m)*’ in Table A.1. In column ‘*Portions (sp,m)*’ of Table A.2, only the  $m = 4$  Mortgage-Backed universe ‘destroys’  $R$ -Squared in the transition to the  $p$ -partition, from 81.7% to 4.6%. Again, the question arises, how is it possible to know *how many*, without knowing *which ones* belong in a  $k$ -group? How does the platform, the consulting firm, the research advisor, etc. arrive at the correct *number* of portfolios in each  $k$ -group under  $p$  in a manner that improves upon partition  $q$ , without knowing the exact contents of  $k$ -groups in  $p$ ? It is unlikely that firm  $x$  first partitioned  $r$  as by unobserved  $p$  so that positive aspects of  $p$  accrued to clients of the platform. Ratings simply reshuffle portfolios one-for-one between  $k$ -groups from  $p$ , with the *number* in each group remaining intact. Motivation for reshuffling, is related to advisory capture, and is aligned with excess fee generation.

1. Distortion is from  $q$  to  $p$  and from  $p$  to  $r$ . Except for the conflicting extremes of  $m = 4$  High Yield and  $m = 7$  Mortgage-Backed, the  $q$ -to- $p$  transition supports the narrative of a good tactician also being a good strategist (first column, Table B.1, Appendix B). But the  $r$ -to- $p$  transition almost fully distorts *slope-s*, questioning how  $p$  was possible (second column).
2. Overall distortion in  $IR$  between  $q$  and  $r$  differs across universes as gauged by *slopes-s* (third column, Table B.1). But the first transition from  $q$ -to- $p$  is not a distortion in *slopes-s*, as much as ‘cleaning-up’ of portfolios deemed as review-worthy, in the face of known interplays of ‘red pumpkins’ with the low volatility environment. New portfolios are  $k_4$ .
3. Between  $q$  and  $r$  (third column, Table B.1), overall distortion in slope of tactical to strategic is severe, resulting in loss of  $IR$  to clients when switching to schemes at instantaneous time  $t$ , if they had followed pure outperformance before. Partition  $p$  is unobservable. The investor-client only perceives the  $q$ -to- $r$  transition, with inconsistent distortion in universes.
4. Excess fee-generation accompanies conflicting narratives of manager behavior. Per rating scheme  $r$ , portfolio managers overall raise risk-adjusted returns out of the strategic mandate  $S$ , at a time or universe when tactical  $T$  improves performance. But, this is true only for four out of the ten universes (third column, Table B.1). The other six, show the opposite.

#### 4.4 Classification Schemes Imply Conflicting Client-Narratives

Distortion in the portrayal of tactical ( $T$ ) by research advisors translates into two conflicting narratives, which consultants must present to a client. This can create friction between client-facing consultants and the platform-maintaining research advisors within the consulting firm. One simple question by the investor-client may be, “what should a portfolio manager do to the strategic allocation  $S$ , in a universe or at a time when tactical allocation  $T$  affects information ratio  $IR$ , one way or another?” Advisory capture aligns with the platform’s excess-fee incentive, to generate narratives that conflict between universes, at the time when such study is conducted. Table B.1 in Appendix B shows the first and second transitions, and the overall effect:

- In universes  $m = 2$  Core Plus,  $m = 3$  Credit,  $m = 7$  Mortgage-Backed, and  $m = 9$  Global Credit, the distortion in column ‘Ratings ( $s_{r,m}$ ) – Quartiles ( $s_{q,m}$ )’ reveals that, as tactical ( $T$ ) raises (lowers) information ratio ( $IR$ ), portfolio managers allocate away from (allocate into) strategic ( $S$ ), instead. This narrative agrees with first transition, ‘Portions ( $s_{p,m}$ ) – Quartiles ( $s_{q,m}$ )’ except  $m = 7$ , due to the over-compensating 4.53. This narrative is long-run focused.
- In universes  $m = 1$  Convertible,  $m = 4$  High Yield,  $m = 5$  Inflation-Linked,  $m = 6$  Long Credit,  $m = 8$  Distressed Debt, and  $m = 10$  Absolute Return, *slope-s* distortion in the column ‘Ratings ( $s_{r,m}$ ) – Quartiles ( $s_{q,m}$ )’ shows that, as tactical ( $T$ ) raises (lowers) information ratio ( $IR$ ), managers allocate away from (allocate into) strategic ( $S$ ). This narrative appears too matter-of-fact, short-run focused, and client-pandering, especially for  $m = 4$  High Yield.

There is no discernible justification among universes between these two narratives, in Table B.1. The direction of the distortion due to advisory capture, combined with the excess-fee incentive, dictates which narratives a consultant must portray to an investor, in place of the consultant’s own, independent assessment. The lack of quality control and the excess-fee incentive create doubt in the mind of the investor-client. Doubt has the exact opposite result from that intended: in the long run clients are gone due to lack of confidence in classification schemes, and the on-line platform, overall. In principle, consultants are getting paid fees, to portray: (i) the existence tactical opportunities in a particular universe of portfolios at time  $t$ , and (ii) the tactical ‘*slope-s*’ of a particular portfolio manager, in reference to the revealed strategic mandate. In the generation of excess fees, the first question is universe-specific and is independent of partition methods. The tactical opportunities are available to all peers and have a similar impact on performance, barring red-pumpkins. The mix of tactical and strategic, on the other hand, relates to investor-tolerance for tail-risk that excessively tactical portfolios can impose. In Appendix B, the impact of  $T$  on  $IR$  is stated, in terms of fee-generation equations (B.1) through (B.4). One responsibility of the research advisor is to assess the impact of tactical elements on  $IR$ , in a universe. Irrespective of a partition in  $q$ -quartiles,  $p$ -portions or  $r$ -schemes, the effect of tactical on  $IR$  is the same, in (11). Tactical opportunities arise at discrete points in time, whereas strategic mandates are consistently revealed. A research advisor of portfolios in a universe has frequent opportunity to observe the changes in mandate  $dS \geq 0$ , out of which the impact of tactical  $\vartheta = \partial IR / \partial T$  is discerned, before changes in tactical  $dT \geq 0$  are observed. The combined effect,  $\vartheta \cdot dS$  applies across the whole universe. Two client narratives accompany  $\vartheta \cdot dS \leq 0$  for fees to go up. They are in Appendix B, and elaborated upon, below:

$$\partial IR_{k,r} / \partial T_{k,r}(S) = \partial IR_{k,p} / \partial T_{k,p}(S) = \partial IR_{k,q} / \partial T_{k,q}(S) = \vartheta \quad (11)$$

1. Portfolio managers in universe  $m$  exhibit a ‘long run’ focus in their ability to increase  $IR$  by greater tactical allocation. The resulting narrative is, that it is possible to increase (decrease) strategic mandate  $S$  in these portfolios, even at a time when tactical element  $T$  raises (lowers) information ratio  $IR$  in that universe. Thus,  $\vartheta \cdot dS > 0$  and  $dF = (\vartheta \cdot dS)(s_r - s_q) > 0$ . Distortion of tactical toward the positive can result in fees above a flat rate when the narrative is of a ‘long run’ focus (e.g.  $m = 7$  Mortgage-Backed).
2. Alternatively, universes are portrayed through the fee incentive, to have a ‘short run’ focus. The narrative is, it is desirable to lower (raise) strategic mandate  $S$  in portfolios such as  $m = 1, 4, 5, 6, 8$  and  $10$ , at a time when tactical element  $T$  raises (lowers)  $IR$ . This

narrative is “matter of fact.” It relies on assertion  $\vartheta \cdot dS < 0, (s_r - s_q) < 0$  and  $dF = (\vartheta \cdot dS)(s_r - s_q) > 0$ . *Slope-s* distortions toward the negative result in excess fees, only with narratives of a ‘short run’ focus (e.g.  $m = 4$ , which fully counteracts  $m = 7$ ).

There are pros and cons with each narrative. The first one is contradictory to the definition of tactical ability. It implies that adherence to strategic mandate increases, at a time when tactical elements have a positive effect on *IR*; or, that the tactical elements miraculously rise, when portfolio managers tend to strategic mandates. In that regard, narrative 2 only appears to make more sense. But narrative 2, that portfolio managers should go as far as reduce mandated *S* and substitute *T* in its place when tactical opportunities arise, sounds client-pandering. It is the research advisor who attempts to pander to a client in yet another role unassigned, referred to as pseudo-pandering. It is the fee incentive above a certain level, which dictates which narrative is adopted, depending on the direction of the distortion of tactical prominence in a universe, which in turn is determined by advisory capture. To the extent that only few portfolio managers exert capture on research advisors, the client-narrative does not describe the universe but adheres to interests of select investment management firms. There is no inherent reason why the narratives should differ across universes or across partitions. To detect whether narrative 1 or 2 is more likely, I devise the hypothesis test  $H_0: \mu_1 - \mu_2 = 0$  on the equality of two means, with variances assumed known (Hines and Montgomery, 1990: 301). The means pertain to the two samples from ‘populations’ in which (i) the transition from *q* to *r* raises tactical prominence ( $s_r - s_q > 0$ ), or (ii) the transition from *q* to *r* lowers tactical prominence ( $s_r - s_q < 0$ ), as portrayed by portions-*p*, and rating schemes-*r*. The test statistic is shown in (12) below.

$$Z_0 = \frac{\mu_1 - \mu_2}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}} \quad (12)$$

Results show, that it is not the first transition that causes systemic distortion in the prominence of tactical elements (Appendix B), or losses in *IR* (Appendix C). Other than the  $s_{p,4} - s_{q,4} = -2.44$  for High Yield and the  $s_{p,7} - s_{q,7} = -2.58$  for Mortgage-Backed, the transition into *p* raises *slope-s*. In the context of fee-generation, this alludes to long run narrative 1, of taking advantage of tactical opportunities without sacrificing strategic mandates. On the other hand, the transition into *r* reshuffles portfolios one for one between *k*-groups causing systemic loss in *IR*. With the notable exceptions of  $s_{r,7} - s_{p,7} = 4.53$  for Mortgage-Backed and  $s_{r,9} - s_{p,9} = 1.30$  for Global Credit, this second transition reverses the narrative to short-term, ‘pseudo-pandering’. Especially in  $m = 7$  Mortgage-Backed, it appears that ‘manager action’ counteracts the research advisory capture.

Rows *D* through *O* in Table B.1 analyze the value of statistic (12) for narratives 1, and 2. In (12),  $\mu_1$  and  $\mu_2$  are the sample means of distortion in narratives 1 and 2, using universes in which the distortion is positive, and those in which it is negative, respectively. In the first transition *q*-to-*p*, for example, seven universes fall into narrative 1, and three into narrative 2. Additionally, it is assumed that  $\sigma_1$  and  $\sigma_2$  are known standard deviations of populations 1 and 2, which correspond to narratives 1 and 2. In this first *q*-to-*p* transition, row ‘*M*. Cumulative Normal Distribution’ has a value of 0.23, revealing low significance on the null hypothesis of equality between  $\mu_1$  and  $\mu_2$ . Therefore, the first transition from *q* to the *p*-partition does not reveal systemic tendency toward either narrative, or an attempt to generate extra fees. The result to the right of the 0.23 number on row *M* in the same table reveals that test-significance rises to almost  $\alpha = 10\%$ , pertaining to the second transition from *p* to *r*. This second transition

from  $p$ -portions to  $r$ -ratings points to systemic distortion in tactical prominence. On one hand, most universes support a ‘pseudo-pandering’ narrative. On the other, the  $s_{r,7} - s_{p,7} = 4.53$  of Mortgage-Backed helps portray tactical ability as complementary to a strategic mandate, on average. Thus,  $\mu_1 = 2.09$  pertains to narrative 1, and is statistically larger than  $\mu_2 = 0.55$  pertaining to narrative 2 (please see rows  $D$  and  $G$  in the second column of Table B.1). Ratings are coerced into pointing toward narrative 1, which is described as having a ‘long run’ focus.

Finally, the result to the right of 0.89 on row  $M$  reveals that the overall  $q$ -to- $r$  transition has a high significance, at the level of 1%. In generating fees then, the ratings distort tactical prominence toward client-narrative 1 with an ambivalent interpretation, the desirability of which differs among and between institutional investors and portfolio managers. Given results of this study, an ideal situation may have been one in which changes in the slope in second column ‘Ratings ( $s_{r,m}$ ) – Portions ( $s_{p,m}$ )’ in Table B1, were all zero, after having investigated contradicting outliers  $m = 4$  and  $m = 7$ . In that case, the only distortion would have been in selecting the portfolios to review in lieu of cleaning up these universes, particularly in the case of  $m = 7$ . Perhaps extra fees should be generated by transition ‘Portions ( $s_{p,m}$ ) – Quartiles ( $s_{q,m}$ )’ because it partly alleviates the red pumpkin problem. But after the reshuffling transition to the  $r$ -partition, the overall narrative becomes that portfolio managers do not discern an appropriate opportunity to go as far as lower (raise) mandate  $S$ , when markets or universes are such that raising (lowering) tactical  $T$  results in outperformance. There are several ways to interpret the sign of  $\vartheta \cdot dS$ , none of which rest on consultant assessment. It may be argued that supporting narrative 1 in the interest of excess fees amounts to condemnation of tactical ability of portfolio managers. Or, that not-lowering strategic elements  $S$  at a time when tactical  $T$  raises  $IR$ , points to an oxymoron that is hard for client-facing consultants to explain.

Narrative 2, on the other hand, appears as too obvious, unexamined, and at times arbitrary, as in  $m = 4$ , High Yield, where the distortion uncharacteristically occurs in the  $p$ -partition ( $s_{p,m} = -1.45$  in Table A.1). Asserting that recommended portfolio managers always reduce strategic elements to take advantage of tactical opportunities is dangerously general. The narratives are not determined through bona-fide analysis of a universe by the client-facing consultant, or by the platform-maintaining research advisor. They are determined by the fee incentive, as it interacts with unchecked advisory capture, which distorts tactical elements in all portfolios recommended. Consulting firms see little incentive to fix the problem as it is aligned with excess fee generation. Inconsistent narratives delivered to investor-clients are detrimental.

## 5. Disclosure of Full Cost of Recommendations

The loss in  $IR$  to investors, as a result of advisory capture, is a market-externality that should concern U.S. regulators. The combined, systemic effect of loss in  $IR$  due to hiring or maintaining all managers recommended; plus sacrifice in  $IR$  from firing or avoiding those not recommended, is estimated at 47.8% (see Appendix C). Classifications create this externality, compared to the ‘default’ case. In assessing the full cost of recommendations, the service to institutional investors offered by consulting firms is split into two processes (see Appendix B):

- $p$ ) Weeding-out of red-pumpkins in each universe, represented by the  $q$ -to- $p$ -transition.
- $r$ ) The reshuffling of portfolios into schemes, represented by the  $p$ -to- $r$ -transition.

These processes correspond to the two partitions  $p$  and  $r$ . They are conditional upon each other, in the sense that a rating- $r$  process cannot occur until universes are ‘scrubbed’ in the  $p$ -partition, in addition to selecting a number of portfolios to review. Otherwise, deficiencies in the scrubbing step will be ‘fixed’ by rating practices. Universe  $m = 7$  Mortgage-Backed is an example of this potential. Slope  $s_{q,7} = 2.83$  points to credit-based portfolios that appear in a prepayment-based universe, while the ‘fix’ of ratings causes  $s_{r,7} = 4.78$  by lack of universe convergence, in Table 1. Also, process  $p$  must introduce no bias or distortion in the characteristics of portfolios selected for review. Phenomena as in Figure A.1 of Appendix A could be observed. In Figure A.1, portfolios selected for review and recommendation as  $k_1$ , deviate from the default partition  $q$  by an exaggerated tactical element and a severely negative strategic mandate. Questionably, both the un-scrubbed universe  $m = 7$ , and the arbitrarily distorted  $m = 4$ , result in negative  $p$ -distortion (see -2.58 and -2.44 in the first column of Table B.1). Tail-chasing in controlling this process could be avoided, by realizing that the extreme 4.53 fix in  $m = 7$  is an attempt to counteract the arbitrary -2.44 in  $m = 4$ . Extreme ratings in un-scrubbed universe  $m = 7$  counterbalance arbitrary selections in  $m = 4$ . Neglecting mandates, in favor of undifferentiated tactical elements, appears as un-recommended, on average.

Consulting firms should disclose to investor-clients the transition from unobserved partition  $p$  to observed partition  $r$ . The transition from  $q$ -quartiles to  $p$ -portions is not of main concern, as it does not cause the distortions. This first partition seems to correct for extraneous portfolios in a universe, making relations of tactical to strategic robust. For reasons ‘mysterious’, the  $p$ -partition is effective in splitting universes into  $k$ -groups of unequal size, from  $q$  which splits them into equal-sized quartiles (see Appendix C, C2: Second Transition from  $p$ -portions to  $r$ -schemes). But starting from  $p$ , the  $r$ -partition creates distortion, reshuffling, and losses in  $IR$ .

The rationale for requiring disclosure of the full cost of recommendations is based on a simple present value of expected cash flows above fees, incurred by the client. The full cost to the investor is the loss in  $IR$ , at time  $t$  of switch from performance  $q$ , to schemes  $r$ . The benefit is the present value of expected cash flow streams from performance above a ‘default’ set of strategies, adjusted for flat fees. Investor mandates may require reliance on consultants, in which case, the alternative portfolio selection set would depend on  $k$ -groups by partition  $r$  but performance ranking from model (4). That’s the  $p$ -partition. The decision to rely on schemes in the platform depends on the difference between ‘full cost’ and present value of expected performance above the alternative. This full-cost applies one-on-one to investors when a client-facing consultant is involved; but has the potential of undisclosed systemic impact, when an on-line platform, supported by research advisors, is made available. The gauging of systemic risk by regulators should involve the full cost created by all possible recommendations, across all universes, as illustrated in Appendix C.

## 6. Conclusion

Through classification schemes, on-line platforms reshuffle portfolios in a way that entails large losses or forgone gains in  $IR$  to the investor, who could have followed the default option of performance quartiles, instead. Investment managers exert pressure on advisors by fostering the potential reshuffling toward their own firm’s favor, and away from estimated performance. This phenomenon is termed “advisory capture.” It is caused by rating schemes devoid of direct client-contact by the research advisors who maintain them, and it is manifested in distortions of the prominence of tactical versus strategic elements. Schemes favorable to some, provide to plan sponsors a license that shields them from responsibility, as

consulting firms can propagate unverified claims that ratings represent future outperformance. Information ratio loss is created today (at the time of switching to schemes), and it stays unregulated and unreported. The inconsistent distortion of tactical and strategic elements across universes aligns with the short-sighted incentive for fees. By arbitrary selection, the portrayal of tactical elements as substitute for strategic mandates panders to potential investor beliefs, but not without severe distortion in tactical prominence. Quality control would alleviate issues in selection and rating.

In the absence of classification platforms, plan sponsors would rely on performance through the information ratio (*IR*), in selecting their portfolios. This ‘default’ option partitions all universes into four equal-sized quartiles based on outperformance, the top two of which are recommended. Research advisors reveal an ability to weed-out portfolios that do not belong in a universe, just by selecting how many portfolios to review. The results of that process are not observed by the investor-client. From that unobserved point-on, research advisors proceed with reshuffling due to capture. Had research advisors merely grouped portfolios in a universe away from quartiles by classifying red pumpkins in the non-recommended group, the distortion in tactical-to-strategic, the reshuffling among groups and the loss in *IR* would have been present only in extreme or arbitrary cases. It does not appear as accidental, that results in the *p*-partition are better than quartiles *q*, and much better than ratings *r*. The “mystery” is that research advisors would have to first find the identity of the portfolios across a scheme, before they found the number of portfolios in the scheme’s groups. This fact raises the possibility that research advisors have ways to augment the benefit to their clients, but chose not to. Due to pressure related to capture, the research advisors persist in reshuffling portfolios through assignment of a rating classification, using qualitative factors. They could simply rate newly registered portfolios as non-recommended, until capture-induced processes thrust specific strategies onto their radar screen. As in regulatory capture, arbitrariness in research impacts investor confidence in rating-scheme credibility and erodes trust in client-consulting practice.

The impact of research advisors through rating schemes is that the recommended portfolios are ones for which tactical elements are portrayed as complementary to strategic, only on average. On a case-by-case basis, distortions lead to differing narratives that spring out of the fee-generation incentive, not based on bona-fide universe analysis by either research advisors, or consultants. The latter are required to reluctantly propagate such low *R*-Squared narratives in client-meetings. But these narratives indiscriminately over-generalize on the ability of a portfolio manager as tactician rather than a strategist, at opportune times. As not arrived at by client-facing consultants themselves, such narratives either appear as pseudo-pandering, or sound as outright oxymora. Presented with the fee incentive, the consulting firms prefer an awkward narrative to improving the quality of classifications. Nevertheless, even that awkward client-narrative, is inconsistent across universes. In High Yield, the pattern of distortion egregiously points to an arbitrary direction. In aiming at raising fees earned by the platform, the consultant would have to narrate that high yield portfolio managers were encouraged by ratings, to go as far as set aside strategic mandates if tactical opportunities raised *IR*. It appears that plan sponsor responsibility-transfer has traveled full-circle back to the plan sponsor, who is asked to pay higher fees, to hear two inconsistent narratives. Consulting firms that support on-line platforms may not perceive the long term need to improve the quality of classification schemes made available to clients. What serves excess fee-generation, is that the prominence of tactical ability gets blurred on-line with strategic mandates at a low *R*-Squared, even as these two elements would be clearly delineated in ‘default-option’ investor-reliance on performance quartiles. Interests served in misclassifying portfolios are aligned with incentives to raise fees. Since there is no apparent

correction mechanism, capture results in a market externality. To the degree that loss in *IR* to the investor becomes substantial, the regulatory authorities should be intently involved with investment platform supervision.

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### Appendix A: Excess Fees and the Distortion by Schemes

Beyond a flat  $F_0$ , which clients of firm  $x$  incur for access to platform  $X$ , fees  $F$  are proportional to differences between quartile-performance  $q$  and that implied by scheme  $r$ , in (A.1). Element  $S$  is assumed common in partitions  $q$  and  $r$ . Tactical elements in quartiles  $T_q$  could rise and those in  $T_r$  could remain indeterminate as  $S$  increases in A.2 and A3, respectively. The consulting firm's goal to increase fees beyond  $F_0$  as strategic  $S$  goes up, rests on the value in square brackets of A.4, holding  $f_1 = 1$  for simplicity. Assumptions are ( $k$  is suppressed):

1. Information ratio  $IR$  estimated in  $q$ ,  $p$ , or  $r$  is a function of tactical elements  $T_q$ ,  $T_p$  and  $T_r$ , respectively, which are stated as functions of the common element  $S$  across partitions. Only the relation of  $S$  to  $T_q(S)$ ,  $T_p(S)$  and  $T_r(S)$  changes, not because of the performance model estimated, but because of the way the partitions classify portfolios in universes. Excess fees  $dF$  are not possible if relations  $T_q(S)$  and  $T_r(S)$  are identical,  $[s_r - s_q] = 0$ .
2. The derivative of  $IR$  with respect to tactical  $\partial IR/\partial T$  is identical in  $q$ ,  $p$ , and  $r$ . Partition  $p$  is unobserved, but can be replicated. Be it through performance or schemes, the effect of tactical on  $IR$  is the same, as far as fee generation is concerned. Presenting  $\partial IR_r/\partial T_r$  as distinct from  $\partial IR_q/\partial T_q$  could impact the credibility of the scheme, in fee generation. Fees do not change, across varying tactical effects:  $\partial IR_q/\partial T_q \approx \partial IR_r/\partial T_r \equiv \vartheta$

$$F = F_0 + f_1 \cdot [IR_r - IR_q] \tag{A.1}$$

$$IR_q = IR_q[T_q(S), S], s_q = \left( \frac{\partial T_q}{\partial S} \right) \geq 0 \tag{A.2}$$

$$IR_r = IR_r[T_r(S), S], s_r = \left( \frac{\partial T_r}{\partial S} \right) \leq 0 \tag{A.3}$$

$$dF = \left[ \frac{\partial IR_q}{\partial T_q} \frac{\partial T_q}{\partial S} - \frac{\partial IR_r}{\partial T_r} \frac{\partial T_r}{\partial S} \right] dS = (\vartheta \cdot dS) \cdot [s_r - s_q] \geq 0 \tag{A.4}$$

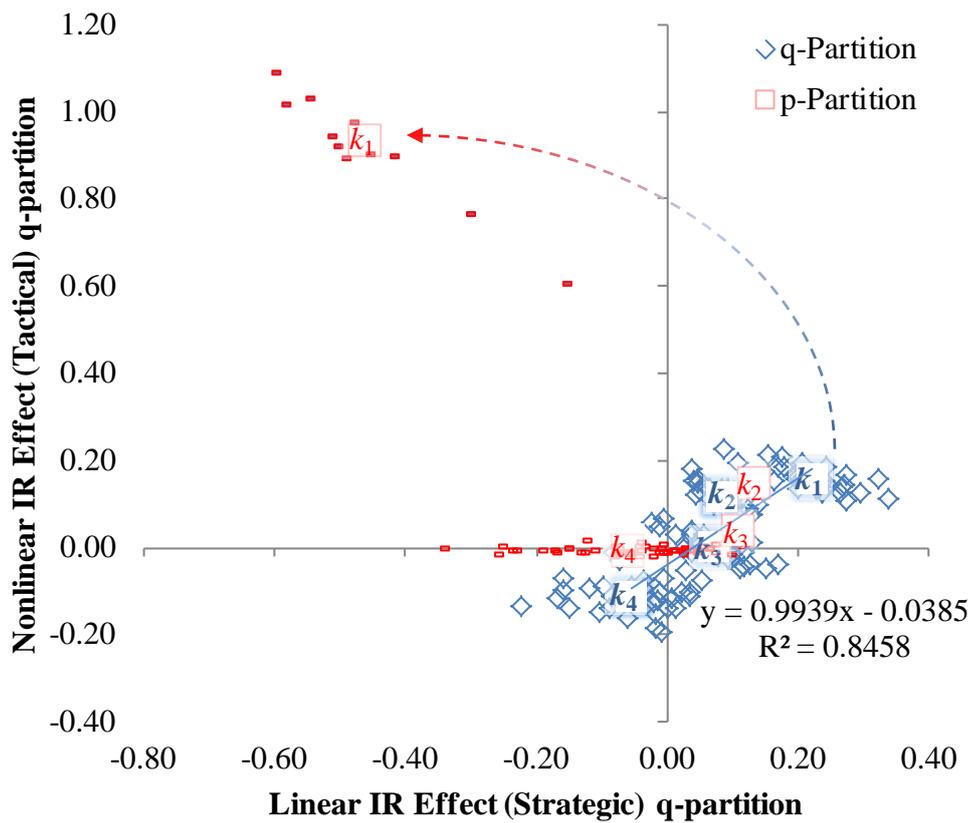
**Table A.1: Slope  $s_{\{q,r,p\}}$  of Tactical to Strategic Elements across Partitions**

$m$	Universe	Quartiles ( $s_{q,m}$ )	Portions ( $s_{p,m}$ )	Ratings ( $s_{r,m}$ )
1	Convertible	0.16	0.26	-0.78
2	Core Plus	-1.13	0.67	0.25
3	US Credit	-2.86	0.82	0.73
4	High Yield	0.99	-1.45	-1.00
5	Inflation-Linked	0.58	1.04	0.03
6	Long Credit	0.29	0.42	-0.35
7	Mortgage-Backed	2.83	0.25	4.78
8	Distressed Debt	0.44	0.42	0.01
9	Global Credit	-0.04	0.44	1.74
10	Absolute Return	0.24	0.32	0.19
	Average	0.15	0.32	0.56
	Standard Deviation	1.45	0.67	1.67

**Table A.2: R-Squared of Tactical to Strategic Elements across Partitions**

<i>m</i>	<i>Universe</i>	<i>Quartiles (s<sub>q,m</sub>)</i>	<i>Portions (s<sub>p,m</sub>)</i>	<i>Ratings (s<sub>r,m</sub>)</i>
1	Convertible	22.8%	49.1%	17.2%
2	Core Plus	96.4%	64.1%	35.4%
3	US Credit	37.4%	83.9%	48.1%
4	High Yield	84.6%	81.5%	100.0%
5	Inflation-Linked	80.9%	53.3%	0.4%
6	Long Credit	99.7%	50.7%	5.4%
7	Mortgage-Backed	81.7%	4.6%	7.6%
8	Distressed Debt	86.3%	80.9%	0.0%
9	Global Credit	12.1%	93.1%	97.2%
10	Absolute Return	93.9%	99.7%	34.8%
Average		69.6%	66.1%	34.6%
Standard Deviation		32.5%	28.1%	37.4%

**Figure A.1: Relation of (T) to (S) in High Yield: Default-*q* and Portion-*p* Partitions**



## Appendix B: Client-Pandering versus Narrative-Oxymora

Due to advisory capture, the fee-incentive from platforms can become incompatible with the apparent portfolio manager behavior. This incompatibility is expressed in equation (B.4) and illustrated by rows *J-M* in Table B.1. Equations (B.1) and (B.4) are restatements of (A.1) and (A.4) with  $f_l = 1$ , for simplicity. Equation (B.3) is paramount to the interpretation of portfolio manager behavior when a clear determination is made about the effect of tactical elements on the performance of the portfolios. The effect  $\partial IR/\partial T = \vartheta$  in (B.3) is market and time-specific and does not change between partitions. It is the effect of tactical elements on the performance of portfolios in a universe, holding strategic mandate constant. Additionally,  $\partial IR_{k,r} = \partial IR_{k,q}$  implies that a separate effect of  $S$  on  $IR$  is identical between the  $q$  and the  $r$  partitions. It cancels out between (B.2) and (B.4). Alternatively, it can be assumed that  $S$  does not affect  $IR$ , except through  $T(S)$ . In other words, strategic mandates do not affect  $IR$  directly, but through tactical elements. Depending on the sign of the distortion between transitions, only one of the two narratives justifies higher fees. These two narratives are outlined below, as narrative 1 and 2:

1. A portfolio manager mildly portrayed as having a ‘long run’ focus raises strategic element  $S$  (that is,  $dS > 0$ ) as raising tactical  $T$  contributes to  $IR$ . Fee increases necessitate  $(\vartheta \cdot dS) > 0$  in cases where  $(s_r - s_q) > 0$  in (B.4).
2. A portfolio manager portrayed as having a ‘short run’ focus will lower strategic element  $S$  (that is,  $dS < 0$ ) when raising tactical  $T$  contributes to  $IR$ . Fee increases necessitate  $(\vartheta \cdot dS) < 0$  in cases where  $(s_r - s_q) < 0$  in (B.4).

$$F_k = f_0 + [IR_{k,r}(T_{k,r}(S), S) - IR_{k,q}(T_{k,q}(S), S)] \quad (\text{B.1})$$

$$dF_k = \frac{\partial IR_{k,r}}{\partial T_{k,r}(S)} \frac{\partial T_{k,r}(S)}{\partial S} dS + \frac{\partial IR_{k,r}}{\partial S} dS - \frac{\partial IR_{k,q}}{\partial T_{k,q}(S)} \frac{\partial T_{k,q}(S)}{\partial S} dS - \frac{\partial IR_{k,q}}{\partial S} dS \quad (\text{B.2})$$

$$\frac{\partial IR_{k,r}}{\partial T_{k,r}(S)} = \frac{\partial IR_{k,p}}{\partial T_{k,p}(S)} = \frac{\partial IR_{k,q}}{\partial T_{k,q}(S)} = \vartheta, \partial IR_{k,r} = \partial IR_{k,p} = \partial IR_{k,q} \quad \forall k, \forall l \in \{q, p, r\} \quad (\text{B.3})$$

$$dF = \left[ \frac{\partial IR}{\partial T} dS \right] \left[ \frac{\partial T_r}{\partial S} - \frac{\partial T_q}{\partial S} \right] = (\vartheta \cdot dS)(s_r - s_q) > 0 \quad (\text{B.4})$$

**Table B.1: Distortion in Slope of Tactical to Strategic between Transitions**

<i>m</i>	<i>Universe</i>	<i>Portions (<math>s_{p,m}</math>) - Quartiles (<math>s_{q,m}</math>)</i>	<i>Ratings (<math>s_{r,m}</math>) - Portions (<math>s_{p,m}</math>)</i>	<i>Ratings (<math>s_{r,m}</math>) - Quartiles (<math>s_{q,m}</math>)</i>
1	Convertible	0.10	-1.04	-0.94
2	Core Plus	1.79	-0.42	1.38
3	US Credit	3.68	-0.09	3.59
4	High Yield	-2.44	0.45	-1.99
5	Inflation-Linked	0.47	-1.01	-0.55
6	Long Credit	0.13	-0.77	-0.64
7	Mortgage-Backed	-2.58	4.53	1.95
8	Distressed Debt	-0.03	-0.41	-0.43
9	Global Credit	0.49	1.30	1.78
10	Absolute Return	0.08	-0.12	-0.04
A.	Average (Overall)	0.17	0.24	0.41
B.	Standard Deviation	1.81	1.66	1.70
C.	z-score	0.09	0.15	0.24
D.	Average (Long Run)	0.96	2.09	2.18
E.	Standard Deviation	1.34	2.15	0.97
F.	z-score	0.72	0.97	2.23
G.	Average (Short Run)	1.68	0.55	0.77
H.	Standard Deviation	1.44	0.40	0.67
I.	z-score	1.17	1.40	1.15
J.	Diff, in Means (Long run - Short run)	-0.72	1.54	1.41
K.	Difference in Standard Deviation	0.97	1.25	0.56
L.	Z-score (Long run - Short - run)	-0.74	1.23	2.53
M.	Cumulative Normal Distribution	0.23	0.89	0.99
N.	Degrees of Freedom (Long run)	7	3	4
O.	Degrees of Freedom (Short run)	3	7	6

## Appendix C: Transition from $q$ -Quartile Partition and Loss in $IR$

### C1: First transition from the ‘default’ $q$ -quartiles to unobserved $p$ -portions

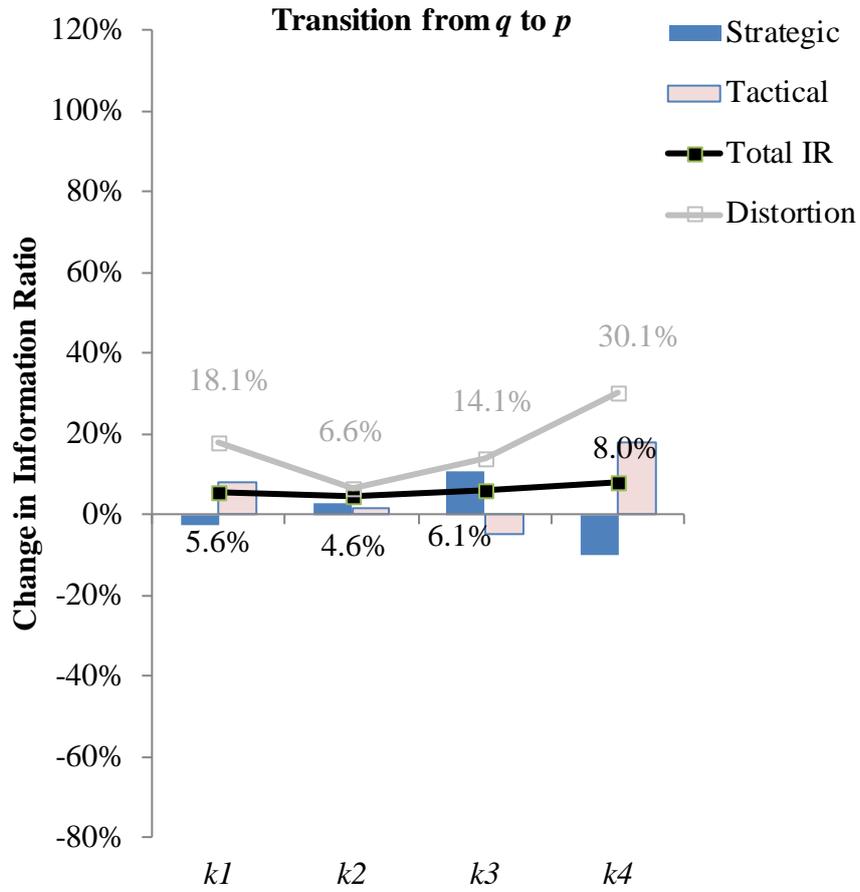
The estimation of  $IR$  loss is based on the original data with the outliers in, as reflected in Tables A.1, A.2, and B.1. Figure C.1 below reflects the full cost of client-reliance on unobserved  $p$ -partition’s  $k$ -groups, on average across all ten universes. This is the  $q$ -to- $p$  transition-gain/loss in  $IR$  by group  $k$ , by Strategic and Tactical, and by Total  $IR$ . These  $k$ -groups are unobserved  $p$ -portions of portfolios in each  $k$ -group. They come into effect in the transition between the first two columns of ‘ $Quartiles(s_{q,m})$ ’ and ‘ $Portions(s_{p,m})$ ’ in Tables A.1 and A.2 of Appendix A. Figure C.1 below shows the first transition, in the column ‘ $Portions(s_{p,m}) - Quartiles(s_{q,m})$ ’ of Table B.1 in Appendix B. Figure C.1 shows the  $IR$  gain and loss going from quartiles  $q$  to portions  $p$ , by strategic and tactical averages across all ten universes. Results point to correction for extraneous portfolios by this transition. Portfolios that would have not been recommended under  $q$ , mostly are not under  $p$ , either. Partition  $p$  appears to merely weed-out the ‘red-pumpkin’ portfolios, grouping them as either  $k_3$ , or  $k_4$ . Partition  $p$  is implied by platform-observed scheme  $r$  and determines *how many* portfolios should be included in a  $k$ -group. There is hardly any loss in  $IR$  through the transition  $q$ -to- $p$ . In fact, there appears to be a mild gain in  $IR$  across all  $k$ -groups for  $k = k_1, k_2, k_3, k_4$ . Still, classifications  $k_1, k_2$  ( $k_3, k_4$ ) contain portfolios recommended (not recommended). Non-recommended portfolios represent forgone  $IR$ , as is the case of  $k_3, k_4$ .

- C1-i. For classifications  $k_1$  and  $k_2$ , which are recommended to clients, the plan sponsors who abandon partition  $q$  and hire/keep managers based on  $p$ , gain 5.6% and 4.6% in average  $IR$ , respectively.
- C1-ii. For classifications  $k_3$ , and  $k_4$ , not recommended to institutional clients, plan sponsors who abandon  $q$  and fire/avoid managers based on  $p$  forgo 6.1% and 8.0% of  $IR$ , respectively.
- C1-iii. Viewed as a combined effect of loss and opportunity cost, the plan sponsors who follow recommendations by  $p$ , incur a small,  $5.6\% + 4.6\% - 6.1\% - 8.0\% = - 3.9\%$  loss in  $IR$  (see ‘Total  $IR$ ’ in Figure C.1, below).
- C1-iv. Distortion  $D_{k, (p - q)}$  in Equation C.1 is the average across  $m$ , of the square root of squared difference in strategic  $S$  plus the squared difference of tactical  $T$  between  $q$  and  $p$ , for  $k = k_1, k_2, k_3, k_4$ . The partition  $p$  exhibits very low  $IR$  distortion, ranging from a low 6.6% to a high 30.1% across schemes. Universe of  $m = 4$  High Yield, does not raise distortion, even as the research advisor piled-up all managers with low tactical element, in the  $k_4$  group. This reveals that the researcher-advisor specifically picked portfolios that distorted the tactical-to-strategic relation in  $r$ . Based on C.1, the contribution of  $m = 4$  to  $p$ -distortion for  $R$  is merely:

$$\sqrt{[(S_p - S_q)_{R,4}^2 + (T_p - T_q)_{R,4}^2]} = \sqrt{[(10.8\% - 7.1\%)_{R,4}^2 + (3.8\% - 0.1\%)_{R,4}^2]} = 5.2\%$$

$$D_{k,(p-q)} \equiv \frac{\sum_{m=1}^{10} \sqrt{[(S_p - S_q)_{k,m}^2 + (T_p - T_q)_{k,m}^2]}}{m} \quad (C.1)$$

Figure C.1: IR Impact of First Transition from  $q$ -quartiles to  $p$ -portions



### Appendix C: Transition from $q$ -Quartile Partition and Loss in $IR$ (continued)

#### C2: Second transition from unobserved $p$ -portions to classification-scheme $r$ -schemes

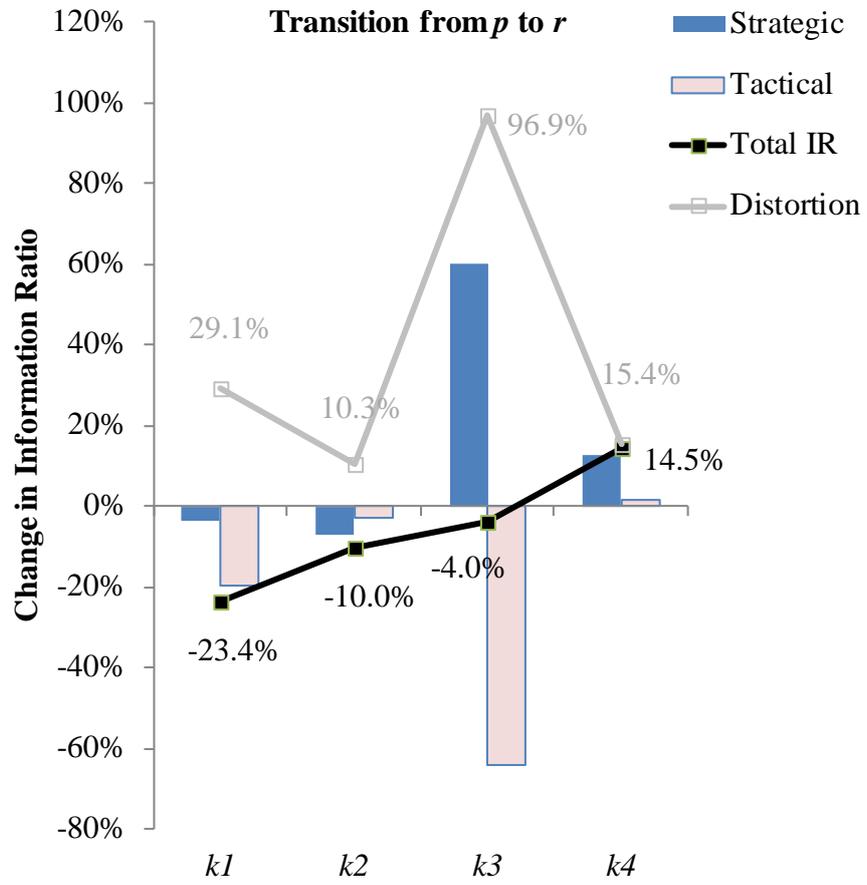
Estimation of  $IR$  loss is based on original data with outliers in, as reflected in Tables A.1, A.2, and B.1. Figure C.2 reflects full cost of client-reliance on platform  $k$ -ratings, which unobserved partition  $p$  transitions into. This is the gain and loss in  $IR$  from  $p$ -to- $r$  by group  $k$ , by Strategic and Tactical, with Total  $IR$ . The number of portfolios in each  $k$ -group of  $r$  is the same as that in each  $k$ -group of  $p$ . The transition from  $p$ -to- $r$  is between the second column, ‘Portions( $s_{p,m}$ ),’ and third, ‘Schemes( $s_{r,m}$ ),’ in Table A.1 and A.2 of Appendix A. Figure C.2 of this second transition pertains to the second column ‘Schemes( $s_{r,m}$ ) - Portions( $s_{p,m}$ )’ in Table B.1 of Appendix B. The figure shows  $IR$  gain and loss by strategic and tactical averages across all universes. Compared to ‘C1: First Transition from  $q$ -quartiles to  $p$ -portions’ above, the results point to reshuffling. There is no other explanation, given that the number of portfolios in each  $k$ -group remains the same, between  $p$  and  $r$ . Had research advisors been required to construct partition- $p$ , they would most likely go through an  $r$ -partition that coincided with  $p$ , initially. As it stands at this time, portfolios not recommended under  $p$  are recommended under  $r$  and vice-versa. This full distortion of  $k$ -groups under  $p$  after they fall under scheme  $r$ , takes place even as the red-pumpkin problem would have been partly addressed, by  $p$ . The distortion “defies a rational explanation,” similar to Stigler, 1971. Regulators should require disclosure to clients, of the  $p$ -to- $r$  transition.

- C2-i. For classifications  $k_1$  and  $k_2$ , which are recommended to clients, plan sponsors who abandon unobserved partition  $p$  and hire/keep managers based on scheme  $r$ , lose - 23.4% and -10.0% in average  $IR$ , respectively.
- C2-ii. For classifications  $k_3$ , and  $k_4$ , not recommended to institutional clients, the plan sponsors who abandon unobserved  $p$  and fire/avoid managers based on  $r$  save 4.0% and forgo -14.5% of  $IR$ , respectively.
- C2-iii. Viewed as a combined effect of loss and opportunity cost, the plan sponsors who follow recommendations by scheme  $r$ , incur a very large, - 23.4% - 10.0% + 4.0% - 14.5% = - 43.9% loss in  $IR$  (Figure C.2, below).
- C1-v. Distortion  $D_{k,(r-p)}$  shown in C.2 is the average across  $m$ , of the square root of squared difference in strategic  $S$  plus the squared difference of tactical  $T$  between  $p$  and  $r$ , for each group  $k = k_1, k_2, k_3, k_4$ . The partition  $r$  exhibits very high  $IR$  distortion, ranging from a low 10.3% to the arbitrary, 96.9%. A special case is  $m = 4$  High Yield. After having distorted even the  $p$ -partition, the research advisor for  $m = 4$  reshuffles the portfolios among  $k$ -groups and ratings, to the point that model estimation does not converge for all portfolios in the universe. Based on equation C.1, the contribution of  $m = 4$  to the  $k_3$ -distortion in  $r$  is an outrageous 905.7%:

$$\sqrt{[(S_r - S_p)_{R,4}^2 + (T_r - T_p)_{R,4}^2]} = \sqrt{[(649.9\% - 10.8\%)_{R,4}^2 + (638.0\% - 3.8\%)_{R,4}^2]} \\ = 905.7\%$$

$$D_{k,(r-p)} \equiv \frac{\sum_{m=1}^{10} \sqrt{[(S_r - S_p)_{k,m}^2 + (T_r - T_p)_{k,m}^2]}}{m} \quad (C.2)$$

Figure C.2: IR Impact of Second Transition from  $p$ -portions to  $r$ -schemes



### Appendix C: Transition from $q$ -Quartile Partition and Loss in $IR$ (Continued)

#### C3: Overall transition from the ‘default’ $q$ -quartiles to classification-scheme $r$ -schemes

Estimation of  $IR$  loss is based on original data with outliers in, as reflected in Tables A.1, A.2, and B.1. Figure C.3 reflects full cost of client-reliance on platform  $k$ -groups in  $r$ , starting from the ‘default’ option of the  $q$ -partition. It is the overall gain and loss in  $IR$  from  $q$ -to- $r$  by  $k$ -group, by Strategic and Tactical, with Total  $IR$ . The number of portfolios in each  $k$ -group of  $r$  is not the same as that in each  $k$ -group of  $q$ . The transition from  $q$ -to- $r$  is between the columns ‘*Quartiles* ( $s_{q,m}$ )’ and ‘*Schemes*( $s_{r,m}$ )’ in Tables A.1 and A.2 of Appendix A. This transition is shown in the third column ‘*Schemes*( $s_{r,m}$ ) - *Quartiles*( $s_{q,m}$ )’ in Table B.1, in Appendix B. Figure C.3 shows  $IR$  gain and loss by strategic and tactical averages across all universes. Results are similar to ‘C2: Second Transition from  $p$ -portions to  $r$ -schemes’ above. The reshuffling of portfolios takes place in the second,  $p$ -to- $r$  transition. The size of each  $k$ -group in  $q$ , in number of portfolios, differs from that in  $r$ , but the overall transition from  $q$ -to- $r$  has a similar distortion effect to the second transition from  $p$ -to- $r$ . In other words, the  $p$ -partition is challengeable on the grounds that it is unobserved. The  $q$ -partition is replicated based on quartiles, while the  $r$ -partition is observable by the classification schemes available in on-line platforms. However, the distortion in the overall  $q$ -to- $r$  transition is accounted for by unobservable  $p$ -to- $r$  transition. Unequivocally, the loss in  $IR$  is created by specific inclusion of portfolios within each of the  $k$ -groups by research advisors, in  $r$ . The fact that  $p$  is unobservable, is not of crucial importance.

- C3-i. For classifications  $k_1$  and  $k_2$ , which are recommended to clients, plan sponsors who abandon the default  $q$ -partition and hire/keep managers based on schemes  $r$ , lose - 17.8% and -5.4% in average  $IR$ , respectively.
- C3-ii. For classifications  $k_3$ , and  $k_4$ , not recommended to institutional clients, plan sponsors who abandon default partition  $q$  and fire/avoid managers based on  $r$  forgo -2.1% and - 22.5% of  $IR$ , respectively.
- C3-iii. Viewed as a combined effect of loss and opportunity cost, the plan sponsors who follow recommendations by schemes  $r$ , incur a very large, - 17.8% - 5.4% + 2.1% - 22.5% = - 47.8% loss in  $IR$  (Figure C.3, below).
- C3-iv. Distortion  $D_{k,(r-q)}$  shown in C.3 is the average across  $m$ , of the square root of squared difference in strategic  $S$  plus squared difference of tactical  $T$  between  $p$  and  $r$ , for each group  $k = k_1, k_2, k_3, k_4$ . The partition  $r$  exhibits very high  $IR$  distortion, ranging from a low 9.0% to the arbitrary, 104.3%. A special case is one of  $m = 4$  High Yield, in which the distortion for scheme  $R$  rises to 905.6%, estimated, similar to C2 above. This is a matter of problematic lack of quality control. The  $r$ -partition in  $m = 4$  wreaks havoc in  $D_{k,(r-q)}$ . The research advisor for  $m = 4$  reshuffles the portfolios among  $k$ -groups, to the point that model estimation does not converge. Based on the last column, ‘*Schemes* ( $s_{r,m}$ ) - *Quartiles* ( $s_{q,m}$ )’ in Table B.1, the change in *slope-s* of -1.99 appears as an attempt to raise fees while arbitrarily adhering to ‘client-pandering’ narrative 2, according to which portfolio managers must lower (raise)  $S$ , when  $T$  has a positive (negative)  $IR$  impact.

$$D_{k,(r-q)} \equiv \frac{\sum_{m=1}^{10} \sqrt{[(S_r - S_q)_{k,m}^2 + (T_r - T_q)_{k,m}^2]}}{m} \quad (C.3)$$

Figure C.3: IR Impact of Overall Transition from  $q$ -quartiles to  $r$ -schemes

