Selling Fast and Buying Slow: Heuristics and Trading Performance of Institutional Investors[*]

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Most research on heuristics and biases in financial decision-making has focused on non-experts, such as retail investors who hold modest portfolios. We use a unique data set to show that financial market experts – institutional investors with portfolios averaging $573 million – exhibit costly, systematic biases. A striking finding emerges: while investors display clear skill in buying, their selling decisions underperform substantially – even relative to strategies involving no skill such as randomly selling existing positions – in terms of both benchmark-adjusted and risk-adjusted returns. We present evidence consistent with limited attention as a key driver of this discrepancy, with investors devoting more attentional resources to buy decisions than sell decisions. When attentional resources are more likely to be equally distributed between prospective purchases and sales, specifically around company earnings announcement days, stocks sold outperform counterfactual strategies similar to buys. We document managers' use of a heuristic that overweights a salient attribute of portfolio assets – past returns – when selling, whereas we do not observe similar heuristic use for buys. Assets with extreme returns are more than 50% more likely to be sold than those that just under- or over-performed. Finally, we document that the use of the heuristic appears to a mistake and is linked empirically with substantial overall underperformance in selling.

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THIS IS A PRELIMINARY DRAFT. ALL COMMENTS VERY WELCOME!

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1 Introduction

In developing the efficient market hypothesis, Fama (1970) argued that prices reflect the true fundamental values of assets because rational investors trade away any opportunities to purchase undervalued stocks or sell stocks at inflated prices. Even if some investors do trade irrationally, sophisticated *experts* would trade against them and eliminate any temporary mispricing. Since then, a large literature has demonstrated that investors do indeed use heuristics and are prone to systematic biases. Individual investors have been shown to be overconfident (Barber and Odean 2001), sensation-seeking (Grinblatt and Keloharju 2009), and to have limited attention (Barber and Odean 2008). However, the majority of evidence documenting biased behavior of individual investors comes from data on retail investors (Barber and Odean 2011) or day traders (Barber, Lee, Liu, and Odean 2014), who generally hold modest portfolios.[1] It remains important to better understand the extent to which the decisions of market experts are prone to behavioral biases, and, if so, the effect of the resulting biases on performance.

This paper examines the trade decisions of sophisticated market participants – experienced institutional portfolio managers (PMs) – using a rich data set containing their *daily* holdings and trades. Our data is comprised of 783 portfolios, with an average portfolio (managed on behalf of a single institutional client) valued at approximately $573 million. More than 89 million fund-security-trading dates and 4.4 million trades (2.0 and 2.4 million sells and buys, respectively) are observed between 2000 and 2016. We evaluate performance by constructing counterfactual portfolios, and compare PMs' actual decisions to returns of the counterfactual. Since PMs often need to raise capital by selling existing positions in order to buy, evaluating a selling decision relative to a counterfactual which is unrelated to existing holdings (e.g., a benchmark index) is not an appropriate comparison.[2] Instead, we evaluate selling decisions relative to a conservative counterfactual that assumes no skill: *randomly* selling an alternative position that was not traded on the same date.

We document a striking pattern: while the investors display clear skill in buying, their selling decisions underperform substantially. Positions added to the portfolio outperform

[1] There are several notable exceptions: Frazzini (2006) and Jin and Scherbina (2010) present evidence for the disposition effect using data from SEC mutual fund filings. Coval and Shumway (2005) and Liu, Tsai, Wang, and Zhu (2010) present evidence for history-dependent risk-taking from market makers on the Chicago Board of Trade and the Taiwan Futures Exchange, respectively. Work has also documented behavioral biases amongst experts in corporate finance settings (see Malmendier (2018) for review).

[2] An asset sold may outperform a benchmark index, but the sale may still be optimal depending on what is bought with that capital and what other assets could have been sold (e.g. an alternative may have gone up even more). In turn, a counterfactual for selling in a long-only portfolio must consider current holdings.

both the benchmark and a strategy which randomly buys more shares of assets already held in the portfolio. This result holds both in terms of raw returns and adjusted for risk. In contrast, selling decisions not only fail to beat a no-skill strategy of selling another randomly chosen asset from the portfolio, they consistently underperform it by substantial amounts. PMs forgo between 50 and 100 basis points over a 1 year horizon relative to this random selling strategy, depending on the specification.[3] As with buys, the selling result is robust when adjusting for systematic risk of the assets sold.[4]

We present evidence consistent with the discrepancy in performance between buy and sell decisions being driven by an asymmetric allocation of cognitive resources, particularly attention. When selling decisions coincide with exogenous releases of salient and portfolio-relevant information – company earnings announcements – sales also outperform the counterfactual. Buying and selling decisions are fairly similar in their underlying fundamentals: both require incorporating information to forecast the future performance of an asset. Forecasting returns with greater accuracy should improve the performance of purchases and sales. Skill in both decisions requires the investor to look for relevant information and integrate it into the forecast. Paying relatively little attention to selling would hinder the first step. But if the investor attends to the relevant information, then skill in buying should translate to skill in selling. Specifically, if decision-relevant information is salient and readily available, such as in the case of earnings announcements, differences in performance between buys and sells should be mitigated.

Indeed, it does not appear that the investors lack fundamental skills for selling: selling decisions appear to capitalize on information during earnings announcements and outperform the counterfactual by between 90 and 120 basis points annually. This performance is in stark contrast to sales on non-announcement days, which consistently trail the random selling strategy by up to 200 basis points annually. On the other hand, the performance of purchases around announcement days does not meaningfully differ from those on non-announcement days. This is consistent with attention being generally allocated to buying decisions; in this case, the relevant information shock does not add much to the attention already devoted to making purchases.

Moreover, we find an empirical link between the underperformance in selling and PMs' use of salient information in choosing what to sell. Various measures of prior returns are

[3] As a benchmark, 100 basis points is double the typical annual management fee charged to investors in actively-managed mutual funds.

[4] Section 6 demonstrates that our results are robust to risk adjustment by replacing raw counterfactual returns with those of beta-neutral strategies that take out exposure to risk factors in the Fama-French/Carhart 4 factor model. We also show that the results hold for PMs who trade in developed and developing markets.

among the most readily available sources of information about any stock and, for reasons we discuss below, are likely to be highly salient. Prior work has shown that the salience of prior returns can affect investment decisions above and beyond the informational content itself (Frydman and Rangel 2014; Frydman and Wang 2018). Indeed, we find that prior returns factor significantly into which assets are sold. PMs in our sample have substantially greater propensities to sell positions with extreme returns: both the worst and best performing assets in the portfolio are sold at rates more than 50% percent higher than assets that just under or over performed. Importantly, no such pattern is found on the buying side – unlike with selling, buying behavior correlates little with past returns and other observables. This suggests that PMs are purchasing assets based on private information not available to the researchers.

The tendency to sell positions with extreme returns is robust to numerous alternative specifications. Using annual, quarterly, weekly, or since-initial purchase cumulative returns yields the same U-shaped selling pattern. The pattern emerges regardless of how the assets are grouped; PMs are more likely to sell assets with extreme returns when considering 6 bins of past returns (1st and 6th bins are most likely to be sold), or 20 bins of past returns (1st and 20th bins are most likely to be sold). Moreover, assets with extreme returns are more likely to be sold even when conditioning on other, less salient, attributes such as position size. We find the same U-shaped selling strategy regardless of the assets' weights in the portfolio or how long they have been held. Similar to a test proposed in Hartzmark (2014), the pattern persists even after the inclusion of stock-date fixed effects which absorb a number of time-varying stock-specific unobservables. Moreover, the vast majority of portfolios in our sample are tax-exempt, meaning that tax considerations are unlikely to explain the selling of extreme performers.

Importantly, this strategy is costly to the PMs and is predictive of much of the underperformance in selling. The tendency to sell extreme positions forecasts substantially lower returns than the counterfactual of a random selling strategy both *between* and *within* manager. Comparing managers based on their proclivity to sell positions with extreme returns, PMs who have a more pronounced U-shaped selling pattern have substantially worse selling outcomes than those with a less pronounced pattern; PMs with the most pronounced U-shaped pattern (top quartile) forgo between 110 and 200 basis points annually relative to a random selling strategy. Changes in the proclivity to sell extremes within manager are associated with similar magnitudes of differences in expected performance. In Section 6 we demonstrate that the results documenting the selling strategy and its affect on performance are robust to risk adjustments. For PMs most prone to sell extreme positions relative to those with moderate returns, simply adopting a random selling strategy would generate substantially greater earnings than the average management fees charged to clients.

Why would selling performance differ so dramatically from buying performance? In a review of the literature on individual investor behavior, (Barber and Odean 2013) postulate that buying and selling assets are driven by different psychological processes. Recent experimental work by Grosshans, Langnickel, and Zeisberger (2018) suggests that this is indeed the case: buying decisions appear to be more forward-looking and belief-driven than selling decisions. We conjecture that PMs in our sample focus primarily on finding the next great idea to add to their portfolio and view selling largely as a way to raise cash for purchases.[5] In order to quickly choose between alternatives to sell, PMs look for salient reasons to unload one asset over another. Given the ubiquity of information on prior returns, extreme deviations of returns in either the positive or negative domain are readily accessible at multiple horizons (e.g. weekly, quarterly, since purchase). According to models of salience (Bhatia 2013; Bordalo, Gennaioli, and Shleifer 2013), extreme returns may increase the weight placed on this attribute as a reason to sell one asset over another. Indeed, the theory of reason-based choice (Shafir, Simonson, and Tversky 1993) suggests that people are more likely to reject – or in our case, sell – options with attributes that are extreme on some dimensions than more moderate options because the individual has salient reasons to psychologically rationalize her choice. Similarly, in our setting extreme returns offer investors salient reasons to rationalize their sell decisions: assets with extreme gains may mean revert or have already realized their anticipated upside potential, assets with extreme losses may suggest the investment thesis has changed, or extreme returns may signal greater price volatility.

Consistent with salience theory as formalized by Bordalo et al. (2013), these reasons are not without merit and carry a 'kernel of truth.' However, as noted above, the systematic selling of assets with extreme returns is costly even relative to a no-skill random selling strategy. While a formal explanation why the use of heuristics is associated with particularly poor performance is beyond the scope of this paper, one possibility is that high conviction ideas – stocks for which managers had the strongest beliefs were likely to increase in value – are also salient and thus more likely to be considered for potential selling choices. For instance, it may be particularly easy to justify selling a stock which was strongly expected to and, in line with ex-ante expectations, subsequently did appreciate relative to the benchmark.

[5]The following quotes from PMs in our sample are illustrative of this attitude: "When I sell, I'm done with it. In fact, after I sell, I go through and delete the name of the position from the entire research universe." "Selling is simply a cash raising exercise for the next buying idea." "Buying is an investment decision, selling is something else."

Prior work has shown that reliance on heuristics often increases when cognitive resources are in greater demand (Kahneman 2003). Consistent with the hypothesis of sells being heuristic-driven, we find that sale decisions are particularly poor when attentional resources are likely to be stretched – specifically, in times of potential stress and during periods when investors are likely to be selling to raise cash. We document a strong relationship between quarterly performance of the PM's overall portfolio and the quality of their sells: the worse the overall portfolio return the lower the quality of sells relative to a random-sell counterfactual. There does not seem to be a similar relationship on the buying side, where the quality of decisions does seem to depend on portfolio performance. We also create several proxies to examine performance when PMs are likely to be selling in order to raise cash rather than focusing on sales as investment decisions. Sales of solitary assets are likely to be driven by forecasts of the relevant performance metrics; on the other hand, large sales of asset bundles may be more emblematic of selling to raise cash. Based on this conjecture, we find that periods when large bundles of distinct assets are sold, both overall and relative to the number of distinct assets being bought (measured over time within-manager), are associated with a marked decrease in selling performance.

Lastly, the robustness of the U-shaped selling pattern to alternative specifications, the costs associated with this behavior, and the decrease in selling performance when attentional resources are likely to be stretched all suggest that pecuniary motives such as agency concerns are unlikely to be driving the selling of positions with extreme returns. Rather, these results are quite consistent with limited attention and the accompanying use of costly heuristics as the driver of poor selling performance.

The unique aspect of our analysis is examining buying strategies separately from selling strategies. The findings shed light on the nature of expertise in financial markets. While a large fraction of fund managers use a distinct heuristic when selling that hurt performance, we find no evidence of such heuristic use in their buying decisions. This is surprising given that the two decisions are similar operationally – the outcomes of both are a function of future asset returns of the asset. They also have equivalent consequences for trading profits: the 'quality' of a buy decision is evaluated relative to alternatives in the choice set (not purchasing, purchasing other assets), as is a sell decision (not selling, selling other assets). Yet we do not observe traces of heuristic use in buy decisions, which unlike sell decisions, outperform counterfactuals such as the benchmark.

Related Literature. Our results suggest that PMs systematically fail in porting their expertise in buying to selling decisions. Prior work has documented the fractionation of expertise (Kahneman and Klein 2009), where individuals who attain expertise in one domain fail to successfully port these skills to other related domains (Green, Rao, and Rothschild 2017). Our setting differs from these results in that investors buy and sell at approximately the same rate and are likely to have been doing so since they started in the field. Given the substantial foregone earnings even relative to a no-skill selling strategy, it is natural to ask why the investors do not appear to recognize their underperformance and learn to sell better. While a full analysis of the learning environment is beyond the scope of the paper, recent theoretical work by Gagnon-Bartsch, Rabin, and Schwartzstein (2018) provides insight for this question. The authors show that a mistaken theory such as the favorability of selling positions with extreme returns may persist in the long run because people channel their attention through the lens of this theory. As in Schwartzstein (2014), errors persist due to the person ignoring information that seems irrelevant and only updating her beliefs based on information that is attended to. Anecdotal evidence suggests that PMs extensively track both absolute and relative portfolio returns (required to evaluate buys) but rarely, if ever, calculate foregone returns from selling decisions. In Section 7 we further discuss the potential role of learning environments in the development of expertise for buying assets in our setting, and strategies for porting the expertise to selling decisions.

The selling pattern we document is most related to the rank effect described in Hartzmark (2014). There, retail investors appear to exhibit a similar pattern in selling and buying behavior – unloading and purchasing assets with more extreme returns. While it is not clear from the data whether these trading strategies are particularly maladaptive, this set of investors have been found to underperform the market in general and display a host of heuristics and bias such as the disposition effect (Odean 1998), overconfidence (Odean 1999), and narrow bracketing (Frydman, Hartzmark, and Solomon 2017).[6] Our results also relate to the analysis of Di Mascio, Lines, and Naik (2017), who used the Inalytics dataset of institutional investors to test theoretical models of optimal strategic trading with private information. Most of their analyses aggregate information across managers to examine the speed at which managers trade and, in turn, the rate at which private information is incorporated into prices. The authors argue that the results support models of optimal trading strategies: stocks with above average buying and selling volume tend to outperform the benchmark. Given the different focus of their paper (aggregate metrics rather than individual decision-making), they do not explore individual-level determinants of trading behavior nor use existing holdings to

[6]Though Hartzmark (2014) focuses on the behavior of retail investors, he also present evidence that mutual funds are prone to such behavior as well. However, due to the limitations of the data, which comes from quarterly holdings reports, he notes that the behavior can be driven by strategic concerns in response to investor preferences.

compare performance of strategies to feasible alternatives (e.g. evaluating quality of actual selling strategies relative to counterfactual strategies).

Our findings contribute to the literature in finance documenting biased decision-making in individual investors (see Barber and Odean (2011) for review). While prior work has documented biases amongst experts in corporate finance settings, e.g. CEOs in charge of merger (Malmendier, Tate, and Yan 2011) or other restructuring decisions (Camerer and Malmendier 2007), substantially less research exists on the biases of expert investors.[7] In fact, for the most part the behavioral finance literature has assumed unbiased institutional investors exploiting the behavioral biases of retail investors (Malmendier 2018). Our documented findings suggest that this assumption may not be a valid one. Lastly, our results contribute to the literature demonstrating heuristics and biases amongst experts in domains such as sports (Green and Daniels 2017; Massey and Thaler 2013; Pope and Schweitzer 2011; Romer 2006), judges (Chen, Moskowitz, and Shue 2016), professional forecasters (Coibion and Gorodnichenko 2015), and retail markets (DellaVigna and Gentzkow 2017). This line of work highlights the persistence of behavioral biases despite significant experience and exposure to market forces.

The paper proceeds as follows. Section 2 describes the data. Section 3 presents results on performance of buying and selling decisions, while Sections 4 and 5 present results on the use of heuristics in trading strategies and how those strategies affect performance, respectively. Section 6 demonstrates the robustness of the results to risk-adjustment and other factors. Section 7 discusses our results and concludes.

2 Data

This section discusses the data sources which are assembled for our analysis, presents descriptive statistics, and discusses a number of portfolio and position-specific variables which we use throughout the analysis.

2.1 Data sources and sample selection

Our primary source of data for this analysis is compiled by Inalytics Ltd. These data include information on the portfolio holdings and trading activities of institutional investors. Inalytics acquires this information as part of one of its major lines of business, which is to offer

[7] One exception to this is a literature which emphasizes slow/inefficient incorporation of certain types of *aggregate* signals into asset prices; see, e.g., Chang, Hartzmark, Solomon, and Soltes (2016); Giglio and Shue (2014); Hartzmark and Shue (2017); Hong, Torous, and Valkanov (2007).

portfolio monitoring services for institutional investors that analyze the investment decisions of portfolio managers.[8] The majority of portfolios in our sample are sourced from asset owners – institutional investors such as pension funds who provide capital to PMs to allocate on their behalf. In these cases, we see holdings and trades related to the specific assets owned by the client. The remainder of the portfolios are submitted by PMs themselves who seek to benchmark their own performance; in these cases, data will frequently correspond with holdings and trades aggregated over multiple clients. These data are typically associated with a single strategy, so we do not observe assets managed by the same PMs in alternative strategies. Thus, while we cannot compute the exact amount of total capital managed by these PMs, the account sizes we report provide a lower bound on the scale of assets managed by PMs in our sample. Our dataset includes both active and inactive portfolios, and the vast majority of the data are collected essentially in real-time, suggesting that incubation and survivorship biases are unlikely to be a substantial concern for our analysis.

For purposes of this study, Inalytics assembled an extract of data of long-only equity portfolios spanning from January 2000 through March of 2016. In our data, the names of funds and managers are anonymized – only a numerical identifier for each fund is provided. These portfolios are internationally diversified, including data from a large number of global equity markets. Data are only collected during periods for which Inalytics' monitoring service is performed. This leaves us with an unbalanced panel.

For each portfolio, we have a complete history of holdings and trades at the daily level throughout the sample period. Inalytics collects portfolio data on a monthly basis and extends them to a daily basis by adjusting quantities using daily trades data. As a result, we observe the complete equity holdings of the portfolio at the end of each trading day (quantities, prices, and securities held), as well as a daily record of buy and sell trades (quantities bought/sold and prices) and daily portfolio returns, though we do not observe cash balances. Further, each portfolio is associated with a specific benchmark (usually a broad market index) against which its performance is evaluated – a feature we exploit heavily throughout our analysis.

To complement these data, which characterize portfolios and trades at specific points in time, we merge in external information on past and future returns (including periods before and/or after we have portfolio data). When possible, we use external price and return series from CRSP; otherwise, we use price data from Datastream. When neither of these sources are available, Inalytics provided us with the remaining price series which are sourced (in order of priority) from MSCI Inc. and the portfolio managers themselves.

[8]We will use the terms fund and portfolio interchangeably throughout our discussion.

Table 1. Summary statistics

This table reports summary statistics of the analysis dataset for 783 portfolios at various levels of aggregation. The position level summary statistics include various holding lengths, portfolio weights, future return measures and the number of trades (indicator for buy and sell trades). Future returns are reported in percentage points over specified horizons. The fund-level and position-level summary statistics are reported at monthly and daily frequencies, respectively. See Table 2 and text for additional details on variable construction.

Variable	Count	Mean	Std	25th	50th	75th
Panel A: Fund level Summary (monthly)						
Assets under management ($million)	51228	573.6	1169.3	71.70	201.8	499.0
Number of stocks	51229	78.49	68.46	40.95	58.60	86.58
Turnover(%)	51223	4.10	5.76	0.927	2.54	5.03
Fraction of distinct stocks sold over all holdings (%)	51221	10.14	12.13	1.923	5.695	13.70
Fraction of distinct stocks bought over all holdings (%)	51221	14.86	17.68	3.788	8.820	19.23
Fraction of distinct stocks bought minus fraction of distinct stocks sold over all holdings (%)	51221	4.675	16.87	-0.691	1.852	7.030
Monthly benchmark-adjusted returns (%)	48786	0.217	1.767	-0.599	0.165	1.010
SD of daily benchmark-adjusted returns (%)	48041	0.348	0.208	0.205	0.293	0.431
Loading on Market	48705	0.971	0.259	0.807	0.943	1.121
Loading on SMB	48705	0.00669	0.497	-0.320	-0.0624	0.271
Loading on HML	48705	-0.0636	0.503	-0.358	-0.0655	0.215
Loading on Momentum	48705	0.0447	0.336	-0.133	0.0430	0.221
Heuristics Intensity	47335	0.404	0.240	0.267	0.385	0.522
Panel B : Position Level Summary (daily)						
Buying indicator	89.8M	0.0264	0.160	0	0	0
Selling indicator	89.8M	0.0226	0.149	0	0	0
Holding length since position open (days)	89.8M	484.4	512.9	119	314	679
Holding length since last trade (days)	89.8M	73.36	113.5	10	32	88
Holding length since last buy (days)	89.8M	112.3	152.4	18	57	144
Portfolio weight(%)	89.7M	1.2	1.61	.24	.79	1.65
1-day return (%)	82.1M	0.0511	4.15	-1.11	0.0115	1.17
Future 7-day return (%)	82.9M	0.205	5.830	-2.454	0.179	2.833
Future 28-day return (%)	82.8M	0.781	11.04	-4.634	0.810	6.181
Future 90-day return (%)	82.6M	2.561	20.16	-7.711	2.308	12.30
Future 180-day return (%)	81.5M	5.315	30.51	-10.46	4.164	18.88
Future 270-day return (%)	80.3M	7.873	38.54	-13.10	5.562	24.47
Future 365-day return (%)	78.9M	10.37	44.84	-15.08	7.241	29.73
Future 485-day return (%)	76.9M	13.43	51.12	-16.81	9.006	35.60
Future 605-day return (%)	74.9M	16.73	58.82	-18.73	9.871	41.01
Future 665-day return (%)	73.9M	18.53	62.94	-19.55	10.32	43.66
Future 730-day return (%)	72.7M	20.40	66.82	-20.13	10.86	46.43
Earnings announcement day indicator	49.3M	0.007	0.08	0	0	0

We apply two primary filters to select the set of portfolios to include in our analysis. First, daily trading data are unavailable for a subset of portfolios or appear to be incomplete.[9] Second, we exclude funds that do not have a sufficient fraction (at least 80%) of portfolio holdings which could be reliably matched with CRSP or Datastream.After applying these screening procedures, our final sample includes about 51 thousand portfolio-months of data, which are compiled from a set of 783 institutional portfolios. Summary statistics are presented in Table 1. We have an average of just over 5 years (65 months) of data per portfolio. During this time frame, we observe 89 million fund-security-trading date observations and 4.4 million (2.4 million buy and 2 million sell) trades. We convert all market values to US dollars at the end of each trading day.[10]

Differences from other datasets This sample offers some unique opportunities for the study of expert decision-making relative to other datasets in the literature. First, in contrast to the Large Discount Brokerage dataset of Barber and Odean (2000), which features portfolio holdings and trades of individual retail investors and has been used in numerous studies[11], our data include complete portfolio and trade-level detail for a population of professional investors managing large pools of assets. Illustrative of this distinction, while Barber and Odean (2000) report that the value of the average portfolio is $26,000 and that the *top quintile* of investors by wealth had account sizes of roughly $150,000, the average portfolio in our sample is almost four *thousand* times larger. Second, unlike other datasets which characterize institutional portfolios, such as mutual fund portfolio holdings reports and 13-F filings, we are able to observe changes in portfolio holdings at a *daily* level.[12] This facilitates the testing of hypotheses on individual decision-making that is infeasible with quarterly data. Additionally, most other datasets with institutional trading information often lack timely information on portfolio holdings.

2.2 Fund and position-level characteristics

With these data in hand, we construct a wide array of measures at the portfolio-time and portfolio-stock-time (position) level. Formulas for many of these variables are presented in

[9] Trades are sometimes imputed at month-end because Inalytics receives portfolio snapshots in adjacent months which do not fully match with the portfolio which would be expected from aggregating the trade data, which necessitates a reconciliation process. We exclude funds that have a large fraction of trades occurring at the end of each month.

[10] We compile data on exchange rates from three sources: Datastream, Compustat Global, and Inalytics' internal database, with Datastream being our primary source. In the vast majority of cases, at least two of these sources have identical exchange rates.

[11] See Barber and Odean (2011) for a survey of studies using this and other similar datasets.

[12] See Frazzini (2006) for example of such a dataset.

Table 2. Summary of characteristics

This table describes how we construct several characteristics for use in our analysis. The first column reports the variables, the second column reports the frequency that we compute the variables and the type of sorting methods (across-fund or within-fund) used in the analysis. The third column reports the formula or the description of the sorting variable construction.

Characteristics	Sorting	Construction
Cumulative Returns capped at 1-year	Within Fund-date across stocks	$r^{cum}_{s,f,t} = \Pi^{i=t}_{i=t-\min\{365,d\}}(1+r_{s,f,t}) - 1$, where d is the time since a position is open.
Position past k day returns	Within Fund-date across stocks	$r^{past\ k}_{s,f,t} = \Pi^{i=t-1}_{i=t-k}(1+r_{s,f,t}) - 1$.
Fund past k day returns	Across funds on daily basis	$r^{k}_{f,t} = \Pi^{i=t-1}_{i=t=k-1-1}(1+r_{,f,t}) - 1$.
Heuristics Intensity	Across/Within funds on weekly/monthly basis	$\frac{\text{Total \# of Positions sold in Bin 1 or Bin 6 of past returns}}{\text{Total \# of Positions Sold}}$.
Gross Sell	Within funds on weekly basis	# of Positions sold.
Net Buy	Within funds on weekly basis	# of stocks bought - # of stocks sold.
Monthly Turnover	Across funds on monthly basis	$turnover_{f,m} = \frac{\min\{total\ MarketValue^{buy}_{f,m} total\ MarketVvalue^{sell}_{f,m}\}}{MarketValue_{f,m}}$.
Position Size	Within Fund-date across stocks	$PositionSize_{s,f,t} = \frac{Quantity^{beginiing\ t}_{s,f,t} \times P_{s,f,t}}{Fund\ AUM_{s,f,t}}$.
Holding length last buy	Within Fund-date across stocks	# of trading days from last day on which a position was bought

Table 2. We begin by discussing some characteristics of fund portfolios in our sample; these are summarized in Panel A of Table 1 on a monthly basis. All portfolios are large, and there is considerable heterogeneity in portfolio size. In addition, funds differ noticeably in terms of their trading activity levels. Average monthly turnover is about 4% of assets under management, but some funds are considerably more active in their trading behavior than others (the standard deviation is 5.7%).

While holding fairly diversified portfolios (average number of stocks is about 78 with a standard deviation of 68), funds in our sample remain active, with positions that deviate substantially from their benchmarks. The average tracking error – the standard deviation of the difference between the daily portfolio return and the benchmark – is about 0.35% per day, or about 5.7% on an annualized basis. On average, a manager will initiate a sell trade for about 10% and a buy trade for about 15% of the stocks in his/her portfolio each month. We also characterize fund portfolios in terms of factor exposures by computing rolling Carhart 4-factor regressions (using the prior 1 year of daily data with the Fama-French international factors), adjusted for asynchronous trading.[13] The average market beta is about 1, and

[13]Following Dimson (1979), we adjust for asynchronicity by including 1 lag and 1 forward returns of each

average exposures to the SMB, HML, and Momentum factors are fairly close to zero.

Panel A also reports the average benchmark-adjusted return that uses each portfolio-specific return series. The average fund in our sample beats its respective benchmark by about 0.22% per month, or 2.6% per year. This, in conjunction with the fact that funds' average betas are close to 1 and have little average exposure to the 3 other priced risk factors, suggests that these managers are highly skilled, earning returns above and beyond exposure to known risk factors.

Next, we turn to our position-level data. Our simplest position-level variable is an indicator variable which equals 1 if the manager buys or sells a given stock on a given date. Of the 89 million position-date combinations in our sample where a stock was in the portfolio at either the start or end of the day, about 2.4 million of them involved an active purchase decision on that same day and 2 million of them involved active sell decisions, or about 2.6% and 2.2% of the time, respectively.

We compute three other primary measures at the position level. First, we construct several different measures of the holding length associated with a given position. Specifically, we consider the length of time (in calendar days) elapsed since the position was first added to the portfolio. In many case, this measure will be censored because a stock may have been in the portfolio since it was first added to our sample. The average holding length is 485 calendar days (or about 15 months), though this measure is downward-biased. As such, we also examine holding length measures which consider the time elapsed since a stock was most recently bought (or traded). The average position was last purchased about 112 calendar days (a bit less than 4 months) ago and was last traded about 10 weeks ago. In much of the analysis that follows, we will exclude stocks which were very recently bought to avoid having our results being driven by predictable buying (and lack of selling) behavior as managers split trades over several days while building up positions over time. Second, we compute the portfolio weight as a fraction of market value associated with each position on each date. The average stock has a weight of about 1.2% with a standard deviation of 1.6%.

Finally, we compute a number of measures of backward or forward-looking returns at the position level over various horizons, both overall and relative to the benchmark return. With the exception of 1-day measures (which refer to the prior trading day), we measure horizons in calendar days.[14] For brevity, we only report summary statistics for forward-looking returns

factor.

[14]This choice is, in part, motivated by the fact that trading calendars differ slightly across exchanges. We take a number of precautions to reduce the potential influence of measurement errors in prices, including winsorizing 0.1% of returns in either tail by date. These steps are discussed at greater length in the Appendix.

that are not adjusted for the benchmark. Volatilities of individual stocks are quite large, with a standard deviation of 45% at a 1 year horizon. As we discuss further below, we also consider several measures of prior position performance that are computed using periods of time which depend on holding period length.

3 Overall Trading Performance

Having described the basic properties of our dataset and variable construction procedures, we now begin to analyze PMs' decision-making. We begin by discussing our methodology for computing counterfactual portfolio returns and, accordingly, value-added measures. We then present the first of our empirical results, which calculates the average value-added (or lost) associated with managers' active buying and selling decisions.[15]

3.1 Constructing counterfactuals

This section outlines how we construct counterfactual strategies in order to evaluate trade performance, which is greatly facilitated by the availability of daily holdings information.

Given that the portfolio managers in our sample tend to hold limited cash positions and are not generally permitted to use leverage, the primary mechanism for raising money to purchase new assets is selling existing ones. Since the portfolios already include stocks that are carefully selected to outperform their respective benchmarks, the choice of which asset to sell may be far from innocuous. Precisely if managers have useful private information that makes them skilled at picking stocks, biased selling strategies have the potential to cannibalize existing, still viable investment ideas and to reduce the potential value for executing new ones. It is therefore important to construct the appropriate benchmark to serve as the counterfactual for evaluating buying and selling decisions. Note that this issue is less important when considering unskilled investors; there, we would expect them neither to gain nor lose money (on a risk-adjusted basis) by relying on a simple rule of thumb for selling existing positions.

The ability to observe daily transactions allows us to compare observed buy and sell decisions to counterfactual strategies constructed using portfolio holdings data. Our measures correspond to the relative payoffs from two hypothetical experiments: one for evaluating buying decisions and one for evaluating selling decisions. For evaluating buys, suppose that we learned that a manager was planning to invest $1 to purchase a stock tomorrow and to

[15] We will return to this analysis in more depth in Section 5 below, which will link other position and fund-characteristics with predictable differences in trading performance.

hold it for a fixed period of time. We then suggest that instead of executing the proposed idea, the manager invests that money in a randomly selected stock from his other holdings. For evaluating sells, suppose that we learned that the manager was planning to sell a given stock tomorrow and hold the rest of the portfolio for a fixed period of time. We then suggest that instead of executing this trade, the manager randomly sells one of his/her other positions to raise the same amount of cash, holding the stock that was to be sold for the same period.

Since the information being used by us was also available to the manager, we would expect the decisions of a skilled PM to outperform our suggested strategies; this is due to the fact that, on the margin, our strategies are always feasible.[16] Note that the expected payoff from the counterfactual strategy (integrating out uncertainty about which stock is randomly selected) simply corresponds to the equal-weighted mean of realized returns across stocks held in the portfolio, which we denote by R_{hold}. The manager's selection adds value relative to the random counterfactual if $R_{buy} - R_{hold} > 0$ in the first example and if $R_{hold} - R_{sell} > 0$ in the second example. Following this logic, we compute $R_{buy} - R_{hold}$ and $R_{hold} - R_{sell}$ over horizons ranging from 1 week to 2 years for all buy and sell trades, respectively, to characterize the value-added associated from each.

Note that these measures can be interpreted as changes in benchmark-adjusted returns associated with different trading strategies. According to our discussions with clients and managers this is the primary manner in which these managers are evaluated. That said, they also have an alternative interpretation to the extent that buy and sell trades are not motivated by a desire to change a portfolio's systematic risk exposures. In that case, we would expect loadings on priced factors of the assets being traded and the hold portfolio to be similar and these measures would also correspond to differences in risk-adjusted returns (i.e., "alpha"). Empirically, this appears to be the case at least to a first approximation, in the sense that our main results are quite similar when we introduce more elaborate adjustments for systematic risk. For brevity, we present the main results using this simple procedure. In Section 6 we demonstrate their robustness in to a construction procedure which adjusts for differences in exposures to the Fama-French/Carhart four factor model.[17]

[16] In contrast, selling the benchmark to finance a purchase, which implicitly corresponds to the counterfactual in measuring benchmark-adjusted returns of stocks sold, is likely infeasible for a long-only manager who, similar those in our sample, holds a portfolio with a small (relative to the number of assets in the benchmark) number of high conviction positions and thus deviates substantially from the benchmark. Purchasing the benchmark is feasible on the other hand.

[17] In additional unreported results, we have used additional information to construct a potentially "more intelligent" counterfactual. As we show in Figure 4 below, very few managers elect to sell stocks that were very recently purchased. Thus, we have also considered a counterfactual which exclude stocks which are in the bottom quintile of the distribution of holding length since last purchase. Since results are similar between the two approaches, we elected to use the simpler one.

We aggregate across trades in the following manner. If multiple stocks are bought or sold on a given day, we average these measures for buy and sell trades separately. Since not all funds trade every day and are not necessarily present throughout our sample period, this averaging procedure yields a portfolio-day unbalanced panel. Because some funds trade much more frequently than others – see the dispersion in monthly turnover in Table 1 – we weight observations inversely to a measure of trading frequency.[18]

Note that one disadvantage of this value-added measure is that our use of long horizon returns introduces an overlapping structure in the error term of each fund's value-added time series. To address this concern, we compute heteroskedasticity and autocorrelation robust standard errors using a panel version of the Hansen-Hodrick (1980) correction using a lag of the horizon minus 1.[19] This allows for individual fund time series to be serially correlated but assumes that these value-added measures are cross-sectionally independent across funds and across non-overlapping periods of time within funds.

3.2 Overall performance relative to counterfactuals

Figure 1, Panel A shows average counterfactual returns for buying decisions. As will turn out to be the case across the vast majority of our specifications, we find very strong evidence that buy trades add value relative to our random buy counterfactual, $R_{buy} - R_{hold}$. The average stock bought outperforms stocks held by 60 basis points over one year and 87 basis points over two years.

Figure 1, Panel B presents the average value-added, $R_{hold} - R_{sell}$, for sell trades. Recall that our measure is already signed so that positive values indicate that a trade helps portfolio performance relative to the counterfactual and negative values point to a trade hurting performance. In stark contrast to Panel A, these estimates suggest that managers' actual sell trades underperform a simple random selling strategy. Magnitudes are quite substantial: the value lost from an average sell trade is on the order of 100 basis points at a 1 year horizon relative to a simple counterfactual which randomly sells other stocks held on the same day.

As we will discuss and further justify below, the interpretation that we find most plausible is that the results in Panel B are due to managers' allocation of cognitive resources rather than a fundamental difference between buying and selling decisions. The latter explanation seems

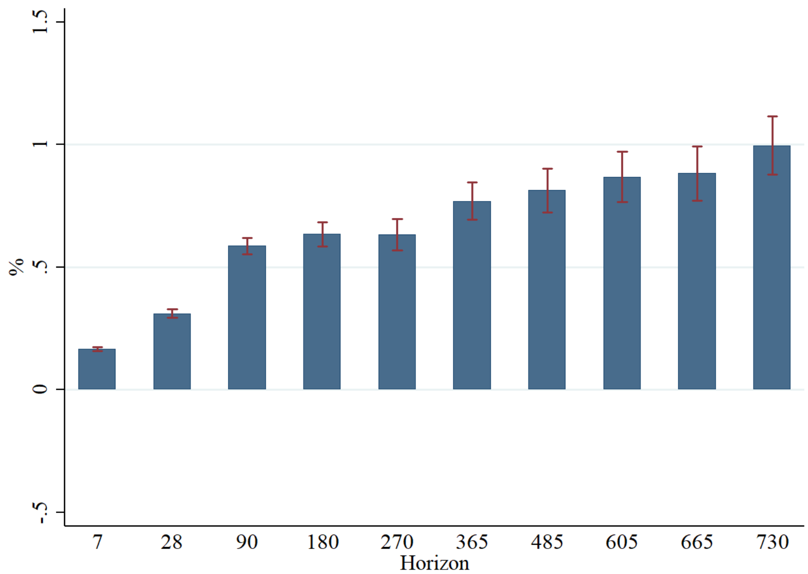
[18] In our baseline analysis, we weight observations inversely to the number of trading days in a calendar year that the fund buys a stock. For easier comparison across buys and sells, we use the same weights across buys and sell trades. Unweighted results are reported in the Appendix. They are qualitatively similar in terms of direction and statistical significance as the weighted results.

[19] We compute these standard errors using the ivreg2 package in Stata.

Figure 1. Post-trade returns relative to counterfactual

This figure presents average returns relative to random buy/sell counterfactuals for buy and sell trades. For buy trades, we compute average returns of stocks bought minus returns of stocks held on each day. For sell trades, we compute average returns of stock held minus returns of stocks sold. We then compute the average of these performance measures across all portfolios and dates, weighted inversely to funds' trading activity. Each bar represents average counterfactual returns in percentage over specified horizons on the x axis. The range on the top of each bar is the confidence interval of the average returns of a portfolio at each horizon. The standard errors are computed using Hansen-Hodrick standard errors with number of lags equal to the horizon -1.

Panel A: Buy Trades, weighted



Panel B: Sell Trades, weighted

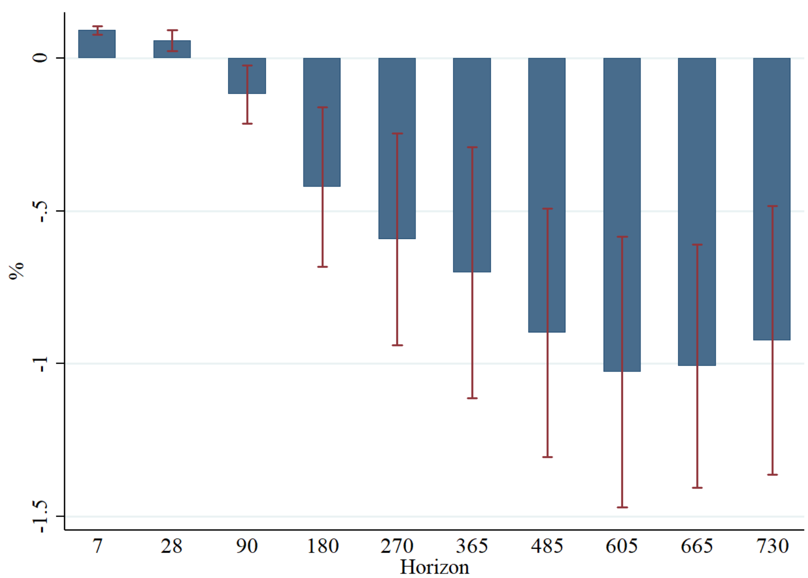
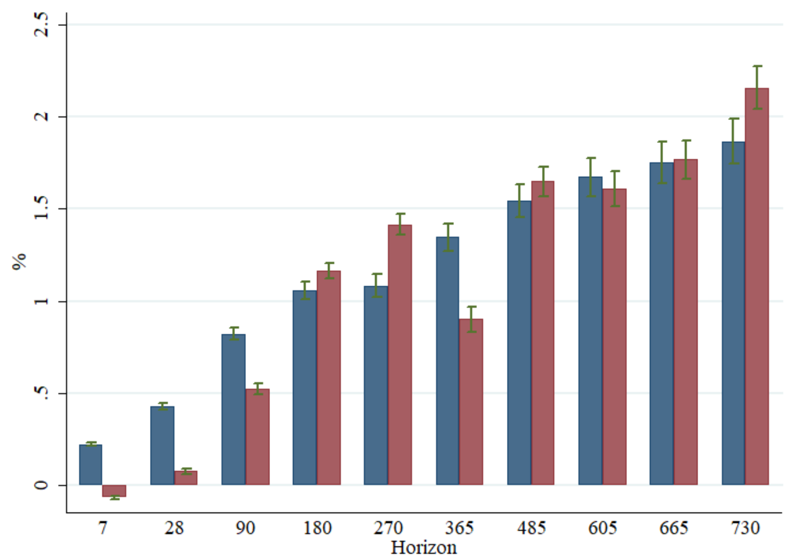


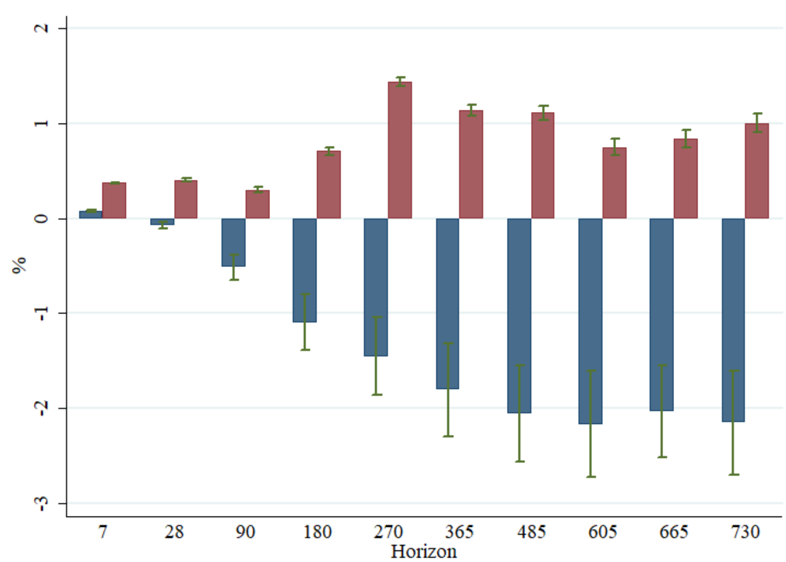
Figure 2. Trading performance on earnings announcement days vs other days

This figure presents average returns relative to random buy/sell counterfactuals for overall buy and sell trades that take place on firm's earning announcement days (red bars) vs trades that are executed on all other days (blue bars). Earning announcement dates are taken from the I/B/E/S database. For buy trades, we compute average returns of stocks bought minus returns of stocks held on each day. For sell trades, we compute average returns of stocks held minus returns of stocks sold. We then compute the average of these performance measures across all portfolios and dates, weighted inversely to funds' trading activity. Each bar represents average counterfactual returns in percentage over specified horizons on the x axis. The range on the top of each bar is the confidence interval of the average returns of a portfolio at each horizon. The standard errors are computed using Hansen-Hodrick standard errors with number of lags equal to the horizon -1.

Panel A: Buy Trades



Panel B: Sell Trades



quite unlikely given that payoffs from buying and selling are mirror images of one another. To provide initial evidence for this conjecture, we examine performance on days when decision-relevant information is salient and readily available – earnings announcement days. We gather earnings announcement dates from the I/B/E/S database and recompute our counterfactual return strategies for stocks which are bought/sold on earnings announcement days, relative to all other trading days. Managers have a strong incentive to pay close attention to stocks in their portfolios on these dates for several reasons. The information in financial statements, associated press releases and conference calls (which even offer opportunities for managers to directly ask questions to the company), provide a wealth of new pieces of hard and soft information that are likely to be relevant for firm valuations. This information is both freely available and salient, since earnings announcements are heavily covered by the financial press.

Figure 2 depicts the outcomes of buy and sell decisions on announcement and non-announcement days. Figure 2, Panel A looks at the value-added of buy trades executed on earnings announcement days compared to other days. In both cases, averages are positive, and, consistent with attentional resources already being devoted towards purchase decisions, magnitudes are similar on both types of days. Panel B demonstrates the stark contrast in the performance of selling decisions on announcement versus non-announcement days. On non-announcement days, results are similar to Panel B of Figure 1: observed sells substantially underperform a random sell strategy.[20] However, stocks sold on announcement days are associated with substantial value-added, especially at longer horizons. When decision-relevant information is salient and readily available, we observe little asymmetry between buy and sell trades. This provides initial evidence that poor selling performance is likely due to a lack of attentional resources devoted to the task rather than a fundamental inability to sell. All results in this section are summarized in Table 8 below.

4 Heuristic Use and Trading Performance

Why might the performance of buying and selling decisions diverge to the extent documented in the preceding section? Here, we provide evidence on one potential mechanism: limited attention to selling decisions, which leads managers to rely in part on simple heuristics. We begin by motivating our proposed empirical measures of heuristic use and then proceed to provide evidence for the use of a salience heuristic based on past returns.

[20]Magnitudes differ somewhat because the sample composition is limited to stocks that can be linked with I/B/E/S for this exercise.

4.1 Motivation

Prior work has argued that selling and buying decisions are driven by different psychological processes (Barber and Odean 2013; Grosshans et al. 2018). We conjecture that the discrepancy in buying and selling performance is due to unequal allocation of limited attention. Our discussions with PMs indicate that they typically focus more on what to add to the portfolio rather than what to unload; as discussed further in Section 7, PMs appear to largely view selling as a cash raising exercise to fund purchases. The results from Section 3.2 provide initial support for this hypothesis. The underlying fundamentals between buying and selling decisions are fairly similar: in both cases, the investor attempts to make the best trade given her forecasts of expected returns. More accurate forecasts should improve the outcomes of decisions in both cases. And in both cases, this requires skill in gathering relevant information and incorporating it into the forecast. Our findings suggest that a lack of attention precludes the first step in the case of selling decisions. When the relevant information is salient and readily available – such as in the case of earnings announcements – sales no longer underperform a no-skill strategy, and in fact do almost as well as buys.

If limited attention is responsible for the discrepancy in performance between buying and selling decisions, then selling strategies will be more prone to heuristics that typify a lack of attentional resources, such as those that overweigh salient features of the choice environment. Relative to other forms of information relevant to the decision problem, such as forecasted returns, data on past returns is ubiquitously available to PMs in our setting. This information is prominently featured on trading terminals, which typically break down past returns by year, quarter, month, day and since last purchase. Most news programs and popular webpages that cover financial markets include a segment which covers the stocks which experienced the largest moves on a given (both positive and negative).[21] The availability of this information, as well as the large range of values past returns take relative to the portfolio average (as captured by their standard deviation, 51% over the average holding period in our sample), makes it highly likely that past returns are a particularly salient attribute of a given asset.

Bordalo, Gennaioli, and Shleifer (2012) and Bordalo et al. (2013) develop a theoretical framework where individuals attach disproportionately high weights to salient attributes of a good or lottery. An attribute's salience is a function of the availability of the relevant information, either from the environment or from memory (Bordalo, Gennaioli, and Shleifer 2017), and the extent to which the values of this attribute deviate from the attribute's average value in the choice set. If investors are prone to overweigh salient attributes of assets, then

[21] See Kumar, Ruenzi, and Ungeheur (2018) for discussion of media focus on past returns.

prior returns are predicted to play a larger role in decisions of what to sell than would otherwise be optimal. Prior returns also generate rationalizable reasons for why a particular asset should be sold. These reasons are not without a 'kernel of truth.' If returns are lower relative to the rest of the portfolio, then this may suggest that the original investment thesis was wrong and the position in the stock should be reduced; if returns are higher relative to the rest of the portfolio, then the original idea did pan out – the stock should be sold to lock in the gains since the upside potential has been realized. This pattern is consistent with the framework of reason-based choice outlined in Shafir et al. (1993). There, the authors argue that attributes with extreme values provide rationalizable reasons to reject or deny a particular option.

In our setting, applying a salience heuristic to generate reasons for unloading assets is predicted to result in a greater propensity to sell stocks with extreme prior returns. If prior returns are overweighed in selling decisions, then this heuristic may be costly relative to a more uniform selling strategy, a possibility we investigate in section 5 below. Moreover, the underperformance of sales should be particularly pronounced during episodes when attentional resources are stretched or otherwise occupied, such as during periods of stress or when the investor is selling to raise cash (as opposed to selling based on forecasted performance metrics of the asset).

4.2 Measuring heuristic use

We construct the following empirical measure of heuristic use. For each portfolio-date, we identify a set of stocks (a subset of holdings in the prior day's portfolio) potentially under consideration to be bought or sold, rank existing holdings according to an empirical proxy for salience (past benchmark-adjusted returns), then ask whether managers are more likely to trade the holdings based on past returns.

Given the size of our dataset, we adopt a fairly flexible, non-parametric approach to measuring managers' tendency to buy and sell positions based on past returns. Specifically, for the set of prior holdings which are included in the analysis, we compute a measure of returns, usually relative to the benchmark over the same horizon. We also emphasize within-manager rankings, rather than absolute levels of these measures, since the definition of "extreme returns" may depend on the types of assets in a given PM's investment opportunity set. Then, on each trading date, we sort stocks into N_{bin} bins using these relative rankings. We always choose an even number of bins and always set the breakpoint between bins $N_{bin}/2$ and $N_{bin}/2 + 1$ equal to zero. This ensures that all stocks in bins $N_{bin}/2$ have declined relative to the benchmark. We choose all remaining breakpoints so that (ignoring issues related to discreteness) there are equal numbers of stocks in bins $1, \ldots, N_{bin}/2$ and bins $N_{bin}/2 + 1, \ldots, N_{bin}$. As a baseline, we consider $N_{bin} = 6$ and name the first three bins "Worst loser", "Loser", "Slight Loser", respectively, and adopt analogous naming conventions for bins three through six.

Our preferred measure of prior returns is computed as follows. For positions which were opened more than 1 year prior to the date of interest, we use the benchmark-adjusted return of the stock from 365 calendar days prior through the trading day before the date of interest. For positions with shorter holding periods, we change the starting point for computing the benchmark adjusted return to the opening date. We use this as our preferred measure because it is unclear whether large returns relative to benchmarks more than 1 year in the past are likely to be salient attributes for the PMs. From a more pragmatic perspective, this construction is less sensitive to the censoring issues for holding length discussed above. However, as we show in Section 4.3, results are robust to alternative definitions of past returns.[22]

We make one substantive restriction on the sample of stocks which are under consideration for this analysis. In predicting the probability that a manager will add to/reduce an existing position, we exclude stocks that were bought in the very recent past. Specifically, we sort positions into 5 bins based on the holding length since the last buy trade, and exclude the bottom bin (shortest time elapsed since last purchase) from our calculations. We elect to do this to avoid a fairly mechanical relationship between our prior return measure, which has a variance which shrinks with the holding period, and the probability of buying/selling that can be generated if managers build up positions by splitting buy trades over short windows of time in order to minimize price impacts.[23] Such trades likely originate from a single purchase decision being executed over time, and so we construct our measures to treat them as such. Further, to ensure meaningful distinctions between bins, we exclude fund-dates which include fewer than 40 stocks in the portfolio throughout the analysis in this section, though results do not meaningfully change without such a restriction.

[22]We find nearly identical results if we restrict attention to stocks with opening dates that are observed during our sample.

[23]This phenomenon mechanically tends to increase the likelihood that positions with non-extreme returns are bought and decrease the likelihood that they are sold, since a manager is unlikely to sell an asset immediately after or while actively building a position in it. Related to this concern, in addition to imposing this selection criterion, our regression analyses below always control for the holding period since the position was opened and the holding period since last buy, as well as squared terms of each.

Table 3. Probability of buying and selling stocks based on prior returns

This table reports the buying and selling probabilities (in percentage points) at the stock-level for six bins of past benchmark-adjusted returns capped at one year. We create bins based on past cumulative returns of a position capped at one year. The three bins on the left are positions with negative benchmark adjusted returns and the three bins on the right are positions with positive benchmark-adjusted returns. The selling (buying) probability is computed by the number of stocks sold (bought) in a particular bin divided by the total number of stocks in that bin. We exclude recently bought stocks by sorting based on the holding length from last buy on each day within a portfolio and dropping the bottom quintile of holding length since last buy. For buying probability, we only consider stocks that a portfolio manager has already held as of the prior day when computing the probability in order to avoid mechanical zero returns for newly bought stocks. The first row reports buying probabilities and the second row represents selling probabilities.

Trade	Bins of Cumulative Returns capped at 1-year					
	Worst Loser	Moderate Loser	Slight Loser	Slight winner	Moderate Winner	Best Winner
Buy	0.91	1.04	0.96	1.11	1.08	1.00
Sell	2.68	2.36	2.15	2.27	2.41	2.83

4.3 Evidence of Heuristic Use

Table 3 summarizes our primary result on PMs' heuristic use. Each row reports the fraction of existing positions that are bought or sold within each of the six bins formed on prior position returns, so that positions with the least extreme returns according to our measure appear in the center of the table and the most extreme ones appear at the edges.[24] The fraction of assets bought in each bin is the first row, and the fraction of assets sold in each bin is depicted in the second row.

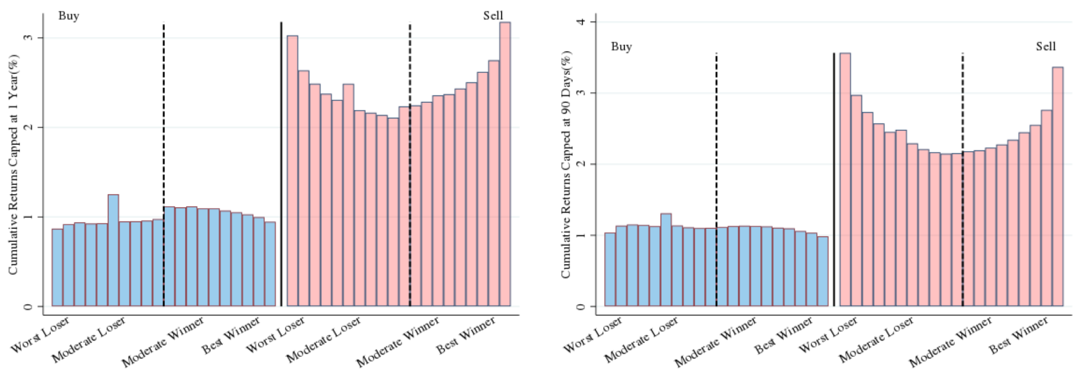
We begin with the buying probabilities. Consistent with the discussion above, the probability of purchasing a stock already held is quite flat across the bins of prior returns. Figure 3, which we discuss further below, depicts this result graphically using a variety of different prior return measures with 20 bins formed on each measure, where bins are sorted from left to right according to prior returns. These results hold across prior return measures and no pronounced patterns appear as we move towards extreme bins in all cases.

[24] These fractions, which can be interpreted as probabilities, are computed by first calculating the proportion of stocks sold within each bin at the fund-date level, then averaging across all fund-dates in the sample.

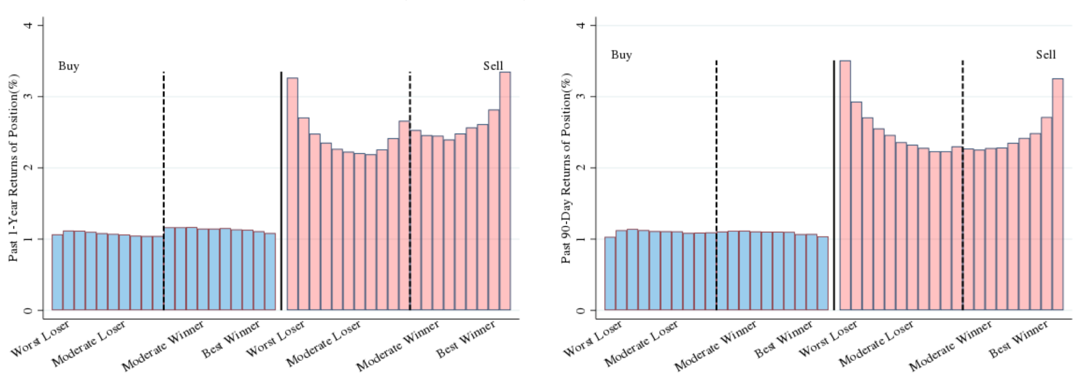
Figure 3. Probability of buying and selling asset based on past returns

This set of figures reports buying and selling probabilities for stocks in the portfolio sorted into 20 bins of various past return measures. Panel A sorts on cumulative past benchmark-adjusted returns since the purchase date or one year/quarter, whichever is shortest. Panel B sorts on past benchmark-adjusted returns of a position over one year and one quarter. Panel C sorts on past raw returns of a position over one week and one day. The ten bins on the left are positions with negative returns and the ten bins on the right are positions with negative returns. The selling (buying) probability is computed as the number of stocks sold (bought) in a particular bin divided by the total number of stocks in that bin. We exclude recently bought stocks by sorting based on the holding length from last buy on each day within a portfolio and dropping the bottom quintile of holding length since last buy. For the buying probability, we only consider stocks that a portfolio manager has already held before when computing the probability in order to avoid mechanical zero returns for newly bought stocks. Blue bars represent buying probabilities and the red bars represent selling probabilities.

Panel A: Cumulative returns capped at 1-year and 1-quarter



Panel B: Past benchmark-adjusted 1-year and 1-quarter returns of a position



Panel C: Short-horizon 1-week and 1-day returns

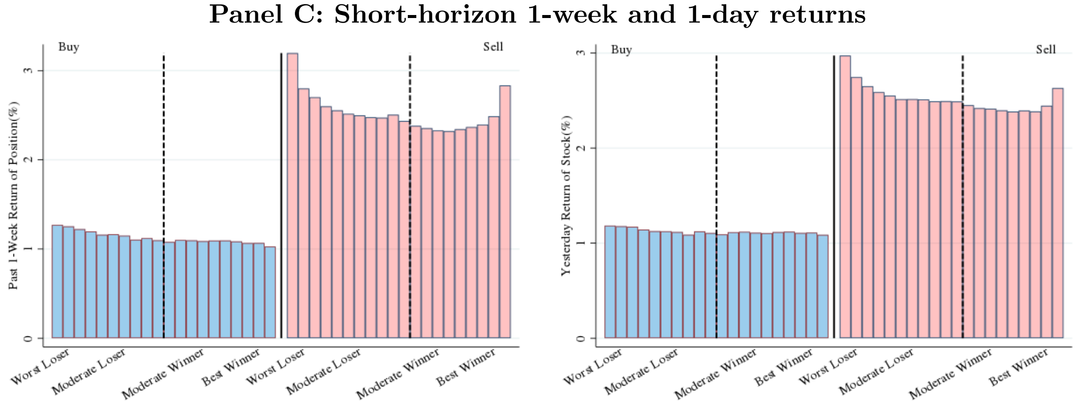
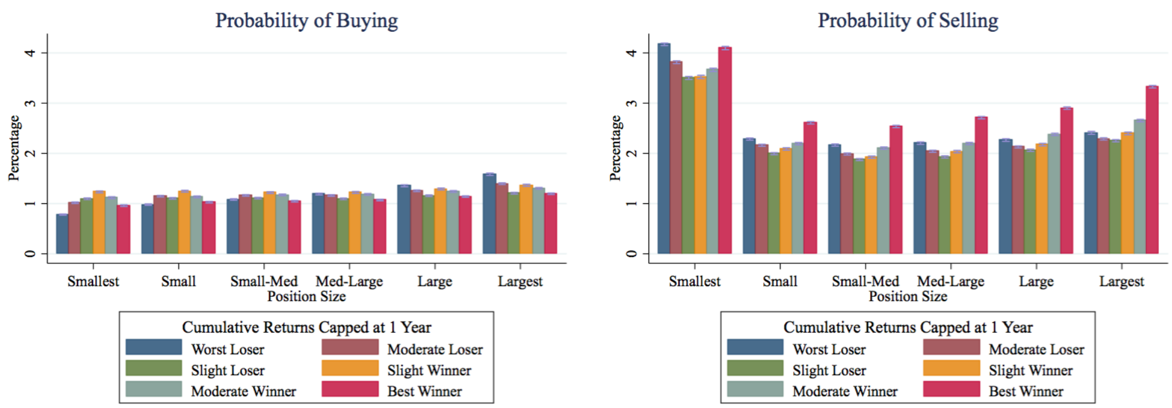


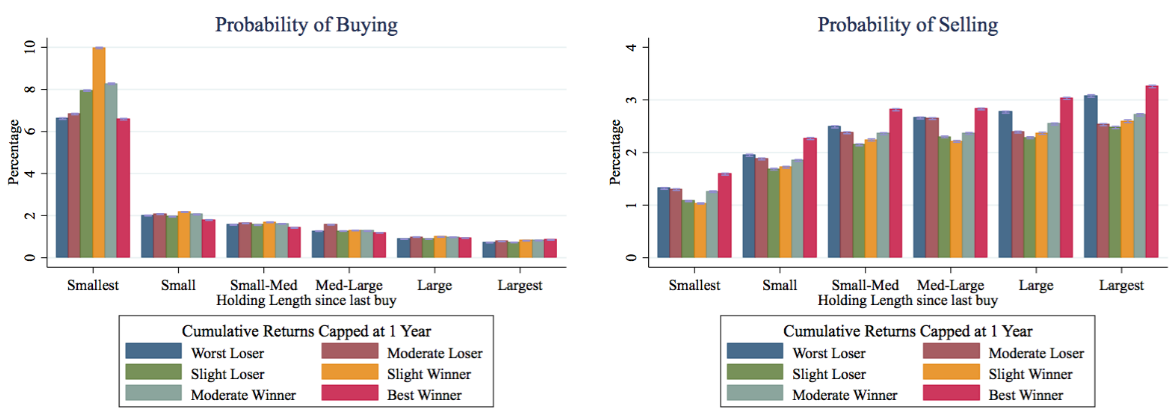
Figure 4. Probability of selling asset by prior returns and holding characteristics

This set of figures reports probabilities, in percentage points, of buying/selling by 6 bins of past benchmark-adjusted returns double sorted with bins of holding characteristics including position sizes and holding lengths. The left panel plots probabilities of buying and the right panel plots probabilities of selling. The x axis represents different position sizes in Panel A and holding length in Panel B. 6 bins of past position returns are plotted within each section on the horizontal axis. The selling (buying) probability is computed by the number of stocks sold (bought) in a particular bin divided by the total number of stocks in that bin. For Panel A, we exclude recently bought stocks by sorting based on the holding length from last buy on each day within a portfolio and dropping the bottom quintile of holding length since last buy. For Panel B, we do not exclude the bottom quintile of holding length since last buy when computing buying probabilities.

Panel A: Position Size



Panel B: Holding Length



A very different picture emerges for the selling probabilities. In Table 3, which sorts past returns into 6 bins, a U-shaped pattern appears. Stocks with more extreme relative returns are substantially more likely to be sold relative to stocks in the central bins. A stock with a more extreme return (bins 1 and 6) is 25% more likely to be sold than a stock with a less extreme return (bins 3 and 4). As depicted in Figure 3, this result is even more pronounced when sorting into 20 bins, with probabilities of selling stocks with more extreme returns nearly 50% higher than stocks with less extreme returns. Despite the fact that each specification is associated with prior return measures that are calculated over a variety of horizons, a very pronounced U-shape appears across all specifications.

Panel A of Figure 3 considers our baseline measure and an analogous one that caps relative returns at the shorter horizon of 90 calendar days instead of 1 year. In this second specification, the difference between central and extreme bins is even more pronounced than when using the baseline measure. Panels B and C look at benchmark-adjusted returns over fixed horizons of 1 year, 90 days, and returns over 1 week and 1 day, respectively. Across all horizons, there is a strong increase in selling probabilities as one moves from intermediate to more extreme bins. This is in stark contrast to buying probabilities which remain relatively flat both for intermediate and extreme returns. Our finding that extremes in terms of both very long and very short horizon returns also points very strongly to attention as a likely mechanism as opposed to agency-based stories (e.g. concerns about reporting realized losses).

Figure 4 considers the extent to which our observed pattern can be explained by two potential omitted variables which may be correlated with our prior return measures: position size and holding length. We use the same prior return sorting procedure as Table 3 for the remaining analyses in this section, though results are similar with different numbers of bins. As a step towards addressing these concerns, we conduct simple double-sorting analyses. We assign each stock into one of 6 bins based on prior returns and the other sorting variable, respectively. Since the breakpoints used for the second characteristic are the same regardless of the bin associated with the first characteristic, there will be unequal numbers of observations in each bin. We then compute the buying (left panel) or selling (right panel) probabilities within each group.

First, even if initial positions all begin at the same size, portfolio drift will imply that stocks that experience extreme relative returns will tend to have very large or very small portfolio weights in the absence of trading. Therefore, simple rebalancing motives (e.g., to reduce portfolio exposures to idiosyncratic risk) could motivate managers to sell positions with extreme positive returns that have become too large.[25] As shown in Panel A, we observe that buying probabilities are relatively flat in position size, while selling probabilities feature a pronounced U-shape for all position sizes.

Second, as discussed above, positions which have only been held for a short period of time will tend to have less dispersion in returns and also be more likely to be bought and less likely to be sold. Panel B double sorts on 6 bins based on time elapsed since last buy (the variable we filter on) and prior returns. For this analysis only, we do not discard any stocks from the analysis based on this holding period measure. One can observe the mechanical patterns discussed in Section 4.2 when looking at the buying probabilities of assets in the bin with the shortest holding length; buying probabilities are flat in prior returns for all other holding periods. In contrast, the U-shaped pattern of selling probabilities persists across all holding lengths.

Finally, Tables 4 and 5 report estimates from a series of linear probability models for the likelihood of selling or buying, which allow us to control for a number of time-varying fund characteristics (either via controls, fund fixed effects, or fund-date fixed effects), calendar time effects, as well as other position characteristics. All specifications include linear and quadratic controls for holding length since the position was opened, holding length since last buy, and position-level portfolio weight (as a fraction of total portfolio assets under management). The key regressors of interest are dummies for each of the prior return categories, which have the same interpretation as differences across rows in Table 3, where the omitted category is bin 3 (slight loser positions). Again, results are similar with different prior return measures and different numbers of bins.

We begin with Table 4, which characterizes selling probabilities. Coefficients are quite similar across columns 1-4, which include different types of fixed effects. Across all of these specifications, the difference in the predicted probability of selling a stock in bin 1 is at least 0.44% higher than the probability of selling a stock in either bin 3 or 4. The final column includes stock-date fixed effects, so the main coefficients of interest are identified off of variation in the relative return categories across portfolio managers who hold the same stock on the same date. Even when coefficients are only identified using this narrow source of variation, we find that positions in the most extreme returns are substantially more likely to be sold.

Turning to Table 5, the relationship between buying probabilities and prior return mea-

[25]Note, however, that similar logic would potentially imply that we would see more buying of positions that have became small due to portfolio drift, which we do not observe.

Table 4. Probability of selling asset based on prior returns

This table presents position-level estimates of a linear probability model (in percentage points) for the likelihood of selling a given stock. The key explanatory variables of interest are indicators corresponding to six bins of past benchmark-adjusted returns capped at one year, where the Slight Loser bin is the omitted category. We control for fund characteristics including log(yesterday's assets under management), prior-month turnover, the volatility of a fund benchmark-adjusted returns over the past year, and prior month loadings on Fama-French Cahart regressions (calculated using the Dimson (1979) procedure using 1 year of prior daily returns). We control for position-level characteristics including linear and quadratic terms in holding lengths (overall and since last buy) and position sizes(% AUM) at the beginning of the day. Columns consider various fixed effects including Fund, Date, Fund x Date and Stock x Date for different comparisons. We exclude recently bought stocks by dropping the bottom quintile of holding length since last buy from the analysis. The coefficients and t-statistics are reported for the variables included for each model. The standard errors for each model are clustered at fund level. * denotes statistical significance at 5% level , ** denotes statistical significance at 1% level and *** denotes statistical significance at 0.1% level.

	(1) No FE	(2) Fund FE	(3) date FE	(4) Fund x Date	(5) Stock x Date
Worst Loser	0.493^{***}	0.418^{***}	0.497^{***}	0.359^{***}	0.203^{***}
	(9.705)	(8.732)	(9.733)	(7.684)	(5.289)
Loser	0.108^{***}	0.065^{**}	0.114^{***}	0.022	0.128^{***}
	(4.042)	(2.973)	(4.298)	(1.076)	(5.406)
Slight Loser	0.000				
	(.)				
Slight Winner	-0.009	-0.081^{***}	0.013	-0.083^{***}	-0.037
	(-0.338)	(-3.992)	(0.423)	(-4.722)	(-1.551)
Winner	0.151^{***}	0.061^{*}	0.176^{***}	0.003	0.169^{***}
	(4.026)	(2.115)	(4.361)	(0.117)	(5.057)
Best Winner	0.631^{***}	0.529^{***}	0.648^{***}	0.450^{***}	0.405^{***}
	(12.790)	(12.263)	(12.643)	(10.471)	(8.553)
Fund Control	Yes	Yes	Yes	No	Yes
FE	None	Fund	Date	Fund x Date	Stock x Date
r2	0.005^{***}	0.018^{***}	0.009^{***}	0.179^{***}	0.317^{***}
N	54.2M	54.2M	54.2M	56.2M	45.5M

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

sures is much more muted. Most of the coefficients are insignificant despite being estimated on a sample of over 50 million observations. Even the significant coefficients are substantially smaller in magnitude than the coefficients associated with selling probabilities. In the saturated specification presented in column 5, none of the coefficients in the Loser categories are statistically distinguishable. Taking stock, the regression specifications, in conjunction with the nonparametric evidence in Figure 4, suggest that the considered sources of omitted variable bias are unlikely to explain our results.[26] Together, these results are consistent with

[26] Increases in selling probabilities for very extreme bins are even larger in additional unreported results with more bins (or dummies for being in the bottom 5%, 5-10%, 90-95%, or top 95%) and other measures of prior return rankings. We elected not to report these estimates since magnitudes are quite similar to Figure 3.

Table 5. Probability of buying asset based on prior returns

This table presents position-level estimates of a linear probability model (in percentage points) for the likelihood of buying a given stock. The key explanatory variables of interest are indicators corresponding to six bins of past benchmark-adjusted returns capped at one year, where the Slight Loser bin is the omitted category. We control for fund characteristics including log(yesterday's assets under management), prior-month turnover, the volatility of a fund benchmark-adjusted returns over the past year, and prior month loadings on Fama-French Cahart regressions (calculated using the Dimson (1979) procedure using 1 year of prior daily returns). We control for position-level characteristics including linear and quadratic terms in holding lengths (overall and since last buy) and position sizes(% AUM) at the beginning of the day. Columns consider various fixed effects including Fund, Date, Fund x Date and Stock x Date for different comparisons. We exclude recently bought stocks by dropping the bottom quintile of holding length since last buy from the analysis. The coefficients and t-statistics are reported for the variables included for each model. The standard errors for each model are clustered at fund level. * denotes statistical significance at 5% level , ** denotes statistical significance at 1% level and *** denotes statistical significance at 0.1% level.

	(1) No FE	(2) Fund FE	(3) date FE	(4) Fund x Date	(5) Stock x Date
Worst Loser	0.033*	0.050**	0.031*	0.034*	0.021
	(2.150)	(3.119)	(1.980)	(2.118)	(1.004)
Loser	0.012	0.031***	0.012	0.019*	0.009
	(1.563)	(3.946)	(1.470)	(2.561)	(0.859)
Slight Loser	0.000				
	(.)				
Slight Winner	-0.026	-0.004	-0.022	0.008	-0.036*
	(-1.831)	(-0.335)	(-1.742)	(1.085)	(-2.390)
Winner	-0.073***	-0.038**	-0.069***	-0.045***	-0.055**
	(-3.853)	(-2.704)	(-4.047)	(-3.998)	(-2.876)
Best Winner	-0.149***	-0.116***	-0.146***	-0.131***	-0.135***
	(-6.199)	(-5.483)	(-6.516)	(-6.938)	(-4.827)
Fund Control	Yes	Yes	Yes	No	Yes
Fixed Effect	None	Fund	Date	Fund x Date	Stock x Date
r2	0.022***	0.028***	0.028***	0.283***	0.281***
N	54.2M	54.2M	54.2M	56.2M	45.5M

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

a salience heuristic being used for selling decisions but not buying decisions.

5 Fund characteristics and trading performance

Above, we provide evidence suggesting that PMs asymmetrically allocate attentional resources between buying and selling trading strategies. In this section, we exploit the panel nature of our dataset in order to illustrate a more direct link between the performance of selling strategies and fund characteristics that are likely associated with differential allocation of attention. To do so, as in Section 3, we compare the returns of the actual stocks traded with

These pronounced increases in probabilities of selling extremes are not matched for buys.

counterfactual random selling strategies. Here, we ask whether patterns in funds' actual trading strategies are associated predictable differences in performance. To operationalize this, we compute several fund and position-level characteristics and sort trades into categories based on relative levels of these characteristics, then compute the average value-added associated with each bin.

Before proceeding, we note that this analysis is only able to identify correlations in the data, so it it is not feasible via these designs to rule out other all other types of time-varying fund-characteristics which simultaneously drive performance and observable properties of trading behavior. However, we will be able to use within-manager time series variation in these characteristics to compare the relative performance of selling strategies for the same individual at different points in time. Such an approach allows us to at least difference some types of time-invariant, between-manager sources of heterogeneity from the analysis.

We begin by considering the potential implications for performance (or lack thereof) of the heuristic strategies documented in Section 4. To capture heuristic intensity, we calculate the fraction of stocks sold that are located in the extreme bins (worst loser and best winner) for each fund-week.[27] We then rank fund-weeks into 4 categories according to this measure to calculate relative performance of the associated selling decisions. Our primary rationale for a weekly frequency is that it provides a nice balance between reducing potential noise in the sorting variable (by averaging over multiple trades), while still operating at a high enough frequency so as to capture within-manager variation in attention allocation.

Table 6 presents sample averages of counterfactual returns where funds are sorted into four bins based on heuristic intensity. Different panels correspond to three alternative ranking schemes and different columns correspond with different holding period lengths. Panel A corresponds to a between-manager measure of heuristics intensity. In each week, we sort each portfolio into one of four categories based on its level of heuristic intensity. In Panel B, we use a within-manager measure, comparing trades that a manager makes during weeks in which heuristic intensity is relatively high or relatively low. Panel C repeats this analysis using a monthly measure of heuristics instead. The left panel plots average performance of buy trades, while the right panel plots average performance of sell trades.

To the extent that increased reliance on heuristics is suboptimal, we would expect trades

[27]For instance, the mean of this heuristics intensity measure is 0.4 on a monthly basis, which would imply (through a simple application of Bayes' rule) that the likelihood of a stock being sold in the extreme bin is 4/3 the likelihood of a stock being sold in one of the central bins. In Appendix Table **??**, we use a variety of fund sorts to show that, perhaps surprisingly, our measure of heuristics intensity is nearly uncorrelated with a variety of observable fund characteristics.

Table 6. Post-trade returns relative to counterfactual by heuristics intensity

This table presents the average returns relative to random buy/sell counterfactuals for buy and sell portfolios sorted by heuristics intensity. For buy trades, we compute average returns of stocks bought minus returns of stocks held on each day. For sell trades, we compute average returns of stock held minus returns of stocks sold. The heuristics intensity is computed by measuring the fraction of sells in the lowest and highest of 6 bins of cumulative returns capped at 1-year at weekly or monthly horizons. We rank the heuristics intensity both in the cross section of funds and within-fund time series and sort funds into four bins from Lowest, Low-Med, Med-High to Highest heuristics use. Columns represent buy or sell performance measures at the following horizons: 1 month, 3 months, and 1 year. We report point estimates of average counterfactual returns for each portfolio at different horizon as well as their standard errors in parenthesis (below the point estimate), where we weigh observations inversely to the number of trades per year of a fund. Standard errors are computed using Hansen-Hodrick standard errors with number of lags equal to the horizon -1.

Heuristics Intensity	Bin	Buy			Sell		
		Horizon			Horizon		
		28 days	90 days	1 year	28 days	90 days	1 year
Panel A: fraction, across-fund weekly	Lowest	0.34	0.67	0.73	0.14	0.20	-0.10
		(0.02)	(0.03)	(0.06)	(0.03)	(0.03)	(0.10)
	Low-Med	0.30	0.46	0.64	-0.05	-0.20	-0.91
		(0.01)	(0.02)	(0.04)	(0.04)	(0.06)	(0.20)
	Med-High	0.33	0.51	0.56	0.03	-0.12	-0.65
		(0.01)	(0.02)	(0.05)	(0.01)	(0.03)	(0.10)
	Highest	0.40	0.59	0.88	0.07	-0.22	-1.71
		(0.02)	(0.03)	(0.06)	(0.04)	(0.06)	(0.20)
Panel B: fraction, within-fund weekly	Lowest	0.32	0.65	0.73	0.10	0.16	-0.08
		(0.01)	(0.03)	(0.06)	(0.02)	(0.03)	(0.09)
	Low-Med	0.29	0.41	0.47	-0.02	-0.25	-1.06
		(0.01)	(0.02)	(0.05)	(0.04)	(0.09)	(0.25)
	Med-High	0.35	0.58	0.63	0.02	-0.07	-0.63
		(0.01)	(0.02)	(0.05)	(0.02)	(0.03)	(0.13)
	Highest	0.40	0.59	0.97	0.09	-0.21	-1.69
		(0.01)	(0.03)	(0.06)	(0.03)	(0.05)	(0.15)
Panel C fraction, within-fund monthly	Lowest	0.26	0.45	0.66	0.12	0.17	0.22
		(0.01)	(0.03)	(0.06)	(0.03)	(0.05)	(0.21)
	Low-Med	0.29	0.56	0.63	-0.03	-0.20	-1.24
		(0.02)	(0.03)	(0.06)	(0.05)	(0.10)	(0.42)
	Med-High	0.34	0.59	0.87	0.09	-0.01	-0.23
		(0.01)	(0.03)	(0.06)	(0.02)	(0.04)	(0.10)
	Highest	0.38	0.59	1.06	0.07	-0.43	-2.30
		(0.02)	(0.03)	(0.08)	(0.04)	(0.14)	(0.49)

Table 7. Post-trade returns relative to counterfactual by fund behavior

This table presents the average returns relative to random buy/sell counterfactuals for buy and sell portfolios sorted by cumulative benchmark-adjusted fund returns since the beginning of a quarter, and weekly trading activities (Gross Sell and Net Buy). For buy trades, we compute average returns of stocks bought minus returns of stocks held on each day. For sell trades, we compute average returns of stock held minus returns of stocks sold. The weekly gross sell is computed by counting the number of unique positions sold within a week. Weekly net buy is computed by the unique number of positions bought per week minus the unique number of positions sold per week. For the fund cumulative returns since the beginning of a quarter, we rank it across funds for each date in the sample. For trading activities, we rank these measures within portfolios across all weeks in the sample. We divide these measures into four bins from Lowest, Low-Med, Med-High and Highest, based on their rankings. Columns represent buy or sell performance measures at the following horizons: 1 month, 3 months, and 1 year. We report point estimates of average counterfactual returns for each portfolio at different horizon as well as their standard errors in parenthesis (below the point estimate), where we weigh observations inversely to funds' trading activity. Standard errors are computed using Hansen-Hodrick standard errors with a lag equal to the number of horizon -1.

Fund Characteristics	Bin	Buy			Sell		
		Horizon			Horizon		
		28 days	90 days	1 year	28 days	90 days	1 year
Panel A: Cumulative Benchmark-adjusted Fund Returns since the beginning of a quarter (sorted across funds)	Lowest	0.31	0.50	0.90	-0.02	-0.63	-2.80
		(0.01)	(0.02)	(0.04)	(0.04)	(0.10)	(0.49)
	Low-Med	0.32	0.67	0.83	0.01	-0.09	-0.44
		(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.04)
	Med-High	0.34	0.52	0.72	-0.01	-0.15	-0.59
		(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.04)
	Highest	0.34	0.65	0.94	0.05	-0.11	-0.49
		(0.01)	(0.02)	(0.04)	(0.01)	(0.02)	(0.04)
Panel B: Gross Sell Weekly Number of distinct stocks sold (sorted within fund)	Lowest	0.38	0.75	1.30	-0.14	0.07	-0.74
		(0.01)	(0.02)	(0.06)	(0.01)	(0.02)	(0.10)
	Low-Med	0.35	0.68	0.96	0.23	0.11	-0.80
		(0.01)	(0.03)	(0.05)	(0.01)	(0.02)	(0.06)
	Med-High	0.40	0.64	0.68	0.13	0.01	-0.42
		(0.01)	(0.02)	(0.05)	(0.01)	(0.03)	(0.06)
	Highest	0.18	0.39	0.49	-0.02	-0.39	-1.58
		(0.01)	(0.02)	(0.05)	(0.07)	(0.17)	(0.75)
Panel C: Net Buy Weekly Number of stocks bought minus Number of stocks sold (sorted within fund)	Lowest	0.36	0.57	0.45	0.00	-0.54	-2.41
		(0.01)	(0.02)	(0.05)	(0.08)	(0.21)	(0.93)
	Low-Med	0.39	0.96	1.08	0.16	0.07	-0.91
		(0.01)	(0.02)	(0.05)	(0.01)	(0.03)	(0.07)
	Med-High	0.35	0.59	0.81	0.02	0.10	-0.19
		(0.01)	(0.02)	(0.05)	(0.01)	(0.02)	(0.06)
	Highest	0.24	0.43	0.82	0.10	0.07	0.28
		(0.01)	(0.03)	(0.06)	(0.01)	(0.02)	(0.05)

occurring during periods with high heuristic use to add the least value. Our calculations suggest that this is indeed the case: selling strategies that overweigh salient attributes appear to be quite costly. Across the majority of the specifications, the highest levels of heuristic intensity are associated with the worst performance, especially at the long horizons. Magnitudes are quite substantial: at a 1 year frequency, the highest level of heuristic intensity predicts an average of around 170 foregone basis points relative to a random sell counterfactual.

The literature on heuristics and biases documents that people are more likely to rely on heuristics during situations when cognitive resources are in higher demand, such as in times of stress or when attention is otherwise occupied (see Kahneman (2003) for review). Table 7 considers three alternative empirical proxies intended to capture periods emblematic of such episodes. As in Panels B and C of Table 6, the three measures are computed on a weekly basis and sort fund-weeks into 4 categories to capture either between or within-manager variation.The first aims to capture performance when the PM is likely to be stressed. Institutional investors are known to be evaluated or take stock of their own performance based on calendar time, e.g. on a quarterly or yearly basis. Based on the conjecture that the PMs are more likely to be stressed when their overall portfolio is underperforming, we construct a measure that captures portfolio performance relative to the beginning of the preceding quarter. Table 7, Panel A demonstrates that selling quality is worst (relative to a random-sell counterfactual) when the PM's overall portfolio is underperforming the most – consistent with the notion that stress exacerbates suboptimal decision-making. We do not observe a similar relationship between portfolio performance and quality of buying decisions.

Next, we consider two measures aimed to proxy for sales that are more driven by cash raising considerations rather than forecasts of relevant performance metrics. We posit that sales of solitary assets are more likely to be driven by the latter motives than sales of asset bundles, and that observing larger bundles being sold (relative to being bought) is emblematic of the manager being in "cash-raising mode." Intuitively, executing purchases likely involves reducing the size of a number of positions in order to free up capital to prepare to invest in a small number of new positions. Therefore, a low number of buys relative to sells would likely be consistent with periods of time where the manager is engaging in "cash-raising" activities. In Table 7, Panel B considers the number of distinct names being sold in a given week relative to the total number of names in the portfolio. We find that sell trades underperform most during weeks when a larger number of distinct names are being sold. In Panel C, we compute the difference between the number stocks bought and the number of stocks sold, where both measures are expressed as fractions of the number of stocks in the portfolio. We find that the number of sell trades relative to buy trades predicts greater underperformance of the selling decisions. Consistent with attentional resources being allocated away from selling decisions, we do not find that the quality of buying decisions is affected by these measures.

Together, the results of this section paint a stark picture: greater heuristic use amongst expert investors is associated with substantial underperformance in their selling decisions. Moreover, periods when attentional resources are likely to be stretched or otherwise occupied, such as when the investor is stressed or focused on purchase decisions, are associated with the worst underperformance in investors' selling decisions.

6 Robustness Checks for Performance Results

In this section, we consider two main tests to verify the robustness of our main results related to buying/selling performance relative to counterfactuals. First, we consider a more explicit adjustment for systematic risk and confirm that our main results are not driven by differential exposures to known, priced risk factors between stocks traded versus those held (which are constituents of the random sell counterfactual portfolios). Second, to address potential issues about measurement errors (e.g., stale prices) and/or liquidity, we re-run our main counterfactual analyses excluding stocks which are traded in developing and emerging markets.[28] Again, our key results are unchanged for this subsample.

The performance measures described above estimate the value-added that a given trade would create/lose relative to a randomly-selected, feasible alternative, where value-added can be interpreted as the expected change in benchmark-adjusted returns over a given horizon per dollar traded. We demonstrate that stocks bought tend to increase more than randomly selected alternatives, and stocks sold *also* tend to increase more than these alternatives. Whereas the former helps performance, the latter acts as a drag on performance. A natural concern, therefore, is that stocks traded tend to have above average exposures to systematic risk, meaning that our estimates could be driven by risk compensation rather than skill. If this were the case, we would tend to overstate positive performance of buy trades and understate performance of sells, which is directionally consistent with our results above.

To address this concern, we modify our counterfactual construction procedure so as to form "factor-neutral" portfolios. Specifically, we estimate stock-level exposures to the Fama-

[28]Similar to Fama and French (2015), we re-run our analyses restricting attention to developed countries in four regions: (i) North America (NA), including the United States and Canada; (ii) Japan; (iii) Asia Pacific, including Australia, New Zealand, Hong Kong, and Singapore; and (iv) Europe, including Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom.

Table 8. Post-trade returns relative to counterfactual, overall and robustness checks

This table presents the average value added measures (post-trade returns relative to a random sell counterfactual) for buy and sell trades under two measures of returns 1) returns and 2) factor-neutral returns, for the whole sample and the subsample of stocks from developed markets (see text for further details). We first present the overall average counterfactual returns, and then report the average counterfactual returns for trades on earnings announcement days (A-day) and non-earnings announcement days (N-day), where we weigh observations inversely to a fund's trading activity. Standard errors are computed using Hansen-Hodrick standard errors with number of lags equal to the horizon -1.

Sorting	Return Measures	Bins	Panel A: Buy			Panel B: Sell		
	Horizon		28	90	365	28	90	365
	Baseline		0.31	0.59	0.77	0.06	-0.12	-0.70
			(0.01)	(0.02)	(0.04)	(0.02)	(0.05)	(0.21)
I.	Baseline (Developed)		0.34	0.67	0.96	0.02	-0.25	-0.94
			(0.01)	(0.02)	(0.04)	(0.02)	(0.05)	(0.23)
Overall	Betaneutral		0.27	0.47	0.59	0.03	-0.21	-0.80
			(0.01)	(0.02)	(0.04)	(0.01)	(0.05)	(0.19)
	Betaneutral (Developed)		0.28	0.47	0.45	-0.09	-0.32	-0.91
			(0.01)	(0.02)	(0.04)	(0.01)	(0.03)	(0.10)
	Baseline	N-day	0.43	0.82	1.35	-0.08	-0.52	-1.81
			(0.01)	(0.02)	(0.04)	(0.02)	(0.07)	(0.25)
		A-day	0.08	0.52	0.90	0.40	0.30	1.14
			(0.01)	(0.02)	(0.03)	(0.01)	(0.01)	(0.03)
II.	Baseline(Developed)	N-day	0.43	0.82	1.35	-0.14	-0.45	-1.71
			(0.01)	(0.02)	(0.04)	(0.02)	(0.03)	(0.12)
Earning		A-day	0.01	1.01	0.20	0.57	0.43	0.84
			(0.01)	(0.02)	(0.03)	(0.01)	(0.01)	(0.03)
Announcement	Betaneutral	N-day	0.39	0.75	1.57	-0.08	-0.58	-2.03
			(0.01)	(0.02)	(0.04)	(0.02)	(0.06)	(0.23)
		A-day	0.06	0.26	0.92	0.38	0.09	0.95
			(0.01)	(0.01)	(0.04)	(0.01)	(0.01)	(0.03)
	Betaneutral (Developed)	N-day	0.40	0.79	1.73	-0.12	-0.54	-1.90
			(0.01)	(0.02)	(0.04)	(0.01)	(0.03)	(0.09)
		A-day	-0.05	0.52	-0.46	0.54	0.27	1.03
			(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.03)

French/Carhart 4 factors using data from prior to the trade, then use these estimates to adjust our long short portfolios for ex-ante differences in these exposures.[29] For each stock-date, we subtract off the inner product of factor loadings and factor realizations, so

$$R_{i,t}^{FN} \equiv R_{i,t} - \Lambda'_{i,q(t)-1} F_t,$$

where $R_{i,t}$ is stock i's excess return on date t and F_t is a (4×1) vector of factor realizations. $\Lambda_{i,q(t)-1}$ is a (4×1) vector of factor loadings which are estimated 1 year of daily data using data up to the end of the previous calendar quarter. $R_{i,t}^{FN}$ thus captures return of a self-financing portfolio which, if factor loadings are estimated correctly and are stable, has zero exposure to the priced risk factors on each date. Thus, if the asset pricing model holds, all $R_{i,t}$ should earn zero excess return in expectation and, accordingly, randomly sold portfolios should have the same factor-neutral returns period-by-period as actual stocks sold. Next, we compute value-added as before, by compounding factor neutral returns and compare cumulative factor-neutral returns of stocks traded with the average of cumulative factor-neutral returns of stocks held.

Table 8 reports estimated return measures from the analysis in Figures 1-2 for our baseline specification as well as three alternatives. Our first alternative is the factor-neutral performance measure described immediately above. Our second two alternatives recompute baseline and factor-neutral performance measures for the subsample of developed countries only. Therefore, any stocks from outside of these developed markets are excluded from both the R_{buy}, R_{sell}, and R_{hold} portfolios. In all cases, magnitudes are fairly similar between the baseline model and the three alternatives. At long horizons, factor-neutral and overall measures are within 10-20 bp of one another. Consistent with much trading activity not being concentrated among stocks with above-average systematic risk exposure, we find fairly similar estimates of value-added for factor-neutral portfolios as the baseline estimates. Results also are quite similar in the developed only sample as in the full sample.

Table 9 also demonstrates the robustness of our results relating funds' use of heuristics and performance. Once again, magnitudes vary somewhat, but our main result that the highest level of heuristic use is associated with the worst performance is quite similar across all of the specifications. If anything, magnitudes are somewhat larger for the alternative specifications relative to the baseline.

[29] The four factors are the market excess return, the Fama-French (1993) size and value factors, as well as the Carhart momentum factor. As above, we compute loadings using data for the global factors from Ken French's website.

Table 9. Post-trade returns relative to counterfactual by heuristics intensity, overall and robustness checks

This table presents the average counterfactual returns for buy and sell trades under two return measures (raw, factor-neutral) for the whole sample and the subsample of developed market, sorted into four bins based on our measure of heuristics intensity. Heuristics intensity is computed by measuring the fraction of sell trades in the lowest and highest of 6 bins of cumulative returns capped at 1-year, sorted weekly across funds. See text for further details on variable definitions. Panel A and B report mean counterfactual returns of each measure for buy and sell trades respectively, weighted by a fund's trading activity, as well as their standard errors in parenthesis (below the point estimate). Each cell represents the average counterfactual returns in percentage over specified horizons and levels of heuristics intensity. Standard errors are computed using Hansen-Hodrick standard errors with number of lags equal to the horizon -1.

Return Measures	Bins	**Panel A: Buy**			**Panel B: Sell**		
Horizon		28	90	365	28	90	365
Baseline	Lowest	0.34	0.67	0.73	0.14	0.20	-0.10
		(0.02)	(0.03)	(0.06)	(0.03)	(0.03)	(0.10)
	Low-Med	0.30	0.46	0.64	-0.05	-0.20	-0.91
		(0.01)	(0.02)	(0.04)	(0.04)	(0.06)	(0.20)
	Med-High	0.33	0.51	0.56	0.03	-0.12	-0.65
		(0.01)	(0.02)	(0.05)	(0.01)	(0.03)	(0.10)
	Highest	0.40	0.59	0.88	0.07	-0.22	-1.71
		(0.02)	(0.03)	(0.06)	(0.04)	(0.06)	(0.20)
Baseline (Developed)	Lowest	0.33	0.70	0.50	0.00	0.10	-0.06
		(0.02)	(0.03)	(0.07)	(0.03)	(0.04)	(0.09)
	Low-Med	0.31	0.56	0.73	-0.02	-0.21	-1.08
		(0.01)	(0.02)	(0.05)	(0.04)	(0.06)	(0.21)
	Med-High	0.33	0.51	0.61	0.04	-0.13	-0.82
		(0.01)	(0.02)	(0.05)	(0.02)	(0.03)	(0.10)
	Highest	0.33	0.53	0.61	-0.09	-0.37	-1.94
		(0.02)	(0.03)	(0.07)	(0.05)	(0.09)	(0.16)
Betaneutral	Lowest	0.25	0.46	0.66	0.19	0.15	-0.07
		(0.02)	(0.03)	(0.06)	(0.02)	(0.03)	(0.09)
	Low-Med	0.23	0.35	0.49	0.00	-0.19	-0.57
		(0.01)	(0.02)	(0.04)	(0.03)	(0.06)	(0.15)
	Med-High	0.29	0.46	0.31	0.02	-0.19	-0.61
		(0.01)	(0.02)	(0.05)	(0.02)	(0.04)	(0.09)
	Highest	0.34	0.46	0.73	-0.10	-0.54	-2.11
		(0.02)	(0.03)	(0.07)	(0.03)	(0.06)	(0.21)
Betaneutral (Developed)	Lowest	0.25	0.47	0.36	0.07	0.05	-0.05
		(0.02)	(0.03)	(0.07)	(0.02)	(0.04)	(0.08)
	Low-Med	0.23	0.45	0.67	0.02	-0.21	-0.65
		(0.01)	(0.02)	(0.05)	(0.03)	(0.05)	(0.15)
	Med-High	0.31	0.45	0.38	0.05	-0.19	-0.68
		(0.01)	(0.02)	(0.05)	(0.02)	(0.04)	(0.09)
	Highest	0.26	0.41	0.42	-0.17	-0.67	-2.14
		(0.02)	(0.03)	(0.07)	(0.05)	(0.07)	(0.17)

7 Discussion and Conclusion

We use a unique data set to show that financial market experts – institutional investors managing portfolios averaging $573 million – display costly, systematic biases. A striking finding emerges: while investors display skill in buying, their selling decisions underperform substantially – even relative to random sell strategies. A salience heuristic explains the underperformance: investors are prone to sell assets with extreme returns. This strategy is a mistake, resulting in substantial losses relative to randomly selling assets to raise the same amount of money.

Why would the performance of buying and selling decisions diverge to the extent documented in the proceeding sections? Barber and Odean (2013) argue that buying and selling are driven by two distinct psychological processes: purchase decisions are forward looking while sales are backward looking. Grosshans et al. (2018) find some supporting evidence for this conjecture, demonstrating that choices of what to buy are more belief-driven than choices of what to sell. While we do not have direct evidence for why PMs take different approaches to the two decisions, interviews with the investors offer anecdotal evidence that they view buying and selling as distinct processes and do not allocate resources (cognitive or otherwise) equally between the two. A skilled manager of a long-only (short-sale constrained) portfolio can add value in two ways: 1) by identifying and increasing positions in undervalued assets and 2) by identifying assets within his/her portfolio which offer less attractive upside potential, reducing these positions in favor of more attractive alternatives. PMs seem to view the first as central: identifying new investment opportunities is seen as perhaps the most critical aspect of a PM's role. Moreover, the decision to add an asset to the portfolio or substantially increase the size of an existing position often follows lengthy periods of research and deliberation. In contrast, there is substantially less emphasis on decisions of what to sell. PMs mostly discussed selling decisions in the context of raising money for the next purchase; they viewed selling as necessary in order to buy. Quoting two PMs: "Selling is simply a cash raising exercise for the next buying idea" and "Buying is an investment decision, selling is something else." Additionally, many readily admit that sell decisions are made in a rush, particularly when attempting to time the next purchase.

As shown in Section 3, the performance of buy decisions is vastly superior to the performance of sell decisions. Moreover, the PMs do not lack the fundamental skills to sell well, they are just not paying attention. When relevant information is salient and readily available – on earnings announcement days – the investors are able to effectively incorporate it into their selling decisions which end up outperforming the counterfactual. We find that the majority of the general underperformance in selling can be explained by a heuristic where PMs overweigh salient information (prior returns) in generating reasons to sell a particular asset. This heuristic results in a U-shaped selling pattern and leads to substantial losses relative to a no-skill random selling strategy.

Perhaps more surprising than the fact that sell trades appear to add less value than buy trades is our empirical finding that sell trades also substantially underperform a random selling strategy, which requires no skill. While formal modeling of this question is beyond the scope of this paper, we suggest one potential explanation here. All else constant, PMs' highest conviction ideas – those for which managers' ex-ante estimates of expected risk-adjusted returns are the largest – may also be more easily accessible in PMs' minds. Moreover, high conviction ideas which recently experienced large price movements may be particularly salient relative to ideas about which the manager was less confident prior to observing these signals. If so, he or she may be especially likely to select these stocks when using the salience heuristic documented above. If this were indeed the case, periods with large fractions of extreme positions sold might actually be expected to underperform more neutral strategies such as our random sell counterfactual, consistent with our empirical results. We leave the further exploration of such interactions for future research.

The question remains of why professional PMs have not learned that their selling decisions are underperforming simple no-skill strategies. While we can only speculate here, the environment in which fund managers make decisions offers several clues. As Hogarth (2001) notes, the development of expertise requires frequent and consistent feedback. While it is feasible to generate this type of feedback for both buy and sell decisions, in practice the environment in which fund managers make decisions is overwhelmingly focused on one domain over the other. The vast majority of the investors' research resources are devoted to finding the next winner to add to the portfolio. Purchased assets are tracked, providing salient and frequent feedback on the outcomes of buying decisions. This process appears successful in producing expertise – purchased assets consistently outperform the benchmark. In comparison, paltry resources are devoted to decisions of what to sell. From our interviews with the PMs, the relevant feedback is largely lacking: assets sold are rarely, if ever, tracked to quantify returns relative to potential alternatives such as our random sell counterfactual.

Given this imbalance in feedback, the theoretical framework of Gagnon-Bartsch et al. (2018) suggests that PMs may fail to recognize their underperformance in selling even in the long run. Our findings imply significant benefits to creating environments where learning can occur more effectively. Given the heterogeneity in selling skills – managers who do not use the extreme-selling heuristic outperform those who do – fund managers who are underperforming can adopt learning tools and simple alternative selling strategies to substantially improve performance.

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A Appendix

This appendix provides additional detail about how we construct and clean our dataset, then presents some supplemental tables/figures referenced in the main text. The primary source of our analysis is Inalytics' holding data and changes in holdings. After we clean the holdings data, we convert all the prices into USD using exchange rates mainly from Datastream. To ensure accuracy in exchange rates, we compare the exchange rate in Datastream with two other sources of exchange rates from Compustat and Inalytics. In the event of a discrepancy, we pick the two out of three that are the same, and this procedure takes care of discrepancy in all cases. We then augment the holding data by merging in external prices series and forward and backward returns from CRSP (US stocks), Datastream (International stocks) and Inalytics' provided price series in this order. The external price series allow us to compute the market value of each holding precisely. There are instances where the market value of a stock (likely due to a measurement error in price/quantity) seems implausibly high, so we employ an iterative weight cleaning algorithm to eliminate these positions from the analysis. We provide additional details about these steps below.

We begin by outlining the key steps of our data cleaning procedure:

1. **Cleaning identifiers**: Inalytics has four main types of identifiers for stocks: SEDOL, ISIN CUSIP, and LOCAL. For the first three types of identifiers, they are distinguishable by the number of digits. SEDOL has 6-7 digits, CUSIP has 8-9 digits, and ISIN has 12 digits. In a few instances one type of identifier is mislabeled by the clients, so we correct them according to the number of digits.

2. **Merging in liquidated stocks with holdings data**: There are instances when a fund completely closes a position, so a stock disappears from the holding data. Since our main trade measure is computed from the change in stock?s holding, a position-closing trade will not be observed in the holdings. To do so, we first measure the minimum date of a fund and maximum date. Then, we compute tag the instance when the stocks disappear on some date between the minimum and maximum dates of each fund. We then append those stocks back to the holding data in order to measure trading activities, from the changes in holdings accurately.

3. **Dropping portfolios without daily trades**: Some of the portfolios in the dataset do not receive daily time-stamped trade data. In these cases, only monthly holdings are reported and trades are imputed at the end of the month. To filter out these portfolios, we count the fraction of trades after the 27th of the month for each fund. If a fraction of trades after the 27th for a fund is over 50% or missing (in case of no trades observed), we drop the portfolio from the analysis sample. In addition, Inalytics independently provided a list of these portfolios from their internal records, essentially all of which were filtered out by this criterion. We also remove these manually flagged portfolios.

Next, we discuss some potential issues related to measurement errors in the price data. We use external price series from CRSP and Datastream, and we additionally have data provided by Inalytics. Inalytics relies on multiple data vendors such as MSCI or Thompson, as well as clients themselves, for price series in the holding data. Since these prices are collected for thousands of unique securities, they inevitably will be occasionally subject to measurement errors. In some cases, reported prices may be overstated, which may lead us to incorrectly characterize portfolio weights and potentially introduce measurement errors in various counterfactual return calculations. We rely on our external price series as the primary measure for a price when computing returns and portfolio weights throughout the analysis, though we take precautions to limit the potential influence of outliers.

When we compute cumulative returns for purposes of evaluating trading performance, we winsorize extremely small and large return realizations, some of which may be due to measurement errors in the price data. To mitigate the effect of the extreme returns when computing the average returns, we winsorize returns in the holding dataset across all measures (raw,betaneutral) before forming portfolios. In our baseline results that we present here, we employ two winsorizing thresholds. First, we winsorize the cumulative return measures on each date across all positions at 0.1% on either tail. As an additional precaution, we winsorize large positive returns in the whole sample at the 99.99% threshold on the right tail of the distribution for raw returns and 0.01% on either tail for beta-neutral returns. The rationale is that beta-neutral returns can have also have extreme negative returns after adjusting for risks, so it is necessary to winsorize on both tails for risk-adjusted returns measures. We have also considered larger thresholds for winsorizing such as 0.3%, 0.5%, and 1% and obtain similar results.

In a handful of cases (e.g., because a stock split has led to an incorrectly high market value), the market value of a single position appears to be extremely large relative to the rest of the portfolio, which is indicative of a likely measurement issue. In order to flag situations when one errant price could cause our estimates of portfolio weights to be substantially biased, we employ an iterative procedure to drop potentially problematic positions. The idea of the procedure is to look for situations where the entire portfolio is concentrated in a single, extremely large position. For these purposes, we compute the market value of a position as the minimum of raw Inalytics price and raw external prices times the quantity of stocks. Then, we compute the position-level weight by dividing through by the dollar value of all positions. With these weights in hand, the procedure proceeds as follows. First, we compute the first three largest weights at a portfolio-date level. We then compute two measures 1) the difference between weights of the largest and second largest-held stocks and 2) the Difference between weights of the second and third largest-held stocks. If the first difference minus the second difference is over 15%, the largest weight is over 10% and the second difference is less than 5%, we flag the stock with the largest weight to exclude from the analysis and the weight calculation. We then recompute stock?s weights after the largest-held stocks are dropped and repeat the procedure to flag other stocks with unusually high weight in a portfolio. We repeat this algorithm until there is no stock with an unusually large weight in portfolios. This iterative weight-dropping algorithm finishes in 5 runs. There are 57,982 stock-date observations to be excluded from weight calculation. 84.3M observations (94.12%) in the holding data have no weight errors. The first run of this algorithm cleans up weight for 4.1M observations (4.62%) in the holding data. After five runs of this algorithm, whereby we exclude five stocks at most, 99.86% of holding observations have no weight problems. There are two portfolios for which this procedure still indicates the presence of a handful of extremely concentrated positions but their total number of associated observations is only 39,128 out of 89M holdings observations.

Table A.1. Average post-trade returns relative to counterfactual by heuristics intensity, unweighted

This table presents the average returns relative to random buy/sell counterfactuals for buy and sell portfolios sorted by heuristics intensity. For buy trades, we compute average returns of stocks bought minus returns of stocks held on each day. For sell trades, we compute average returns of stock held minus returns of stocks sold. The heuristics intensity is computed by measuring the fraction of sells in the lowest and highest of 6 bins of cumulative returns capped at 1-year at weekly or monthly horizons. We rank the heuristics intensity both in the cross section of funds and within-fund time series and sort funds into four bins from Lowest, Low-Med, Med-High to Highest heuristics use. Columns represent buy or sell performance measures at the following horizons: 1 month, 3 months, 1 year, and 2 years. We report point estimates of unweighted average counterfactual returns for each portfolio at different horizon as well as their standard errors in parenthesis (below the point estimate). Standard errors are computed using Hansen-Hodrick standard errors with number of lags equal to the horizon -1.

Heuristics Intensity	Bin	Buy				Sell			
		Horizon				Horizon			
		28 days	90 days	1 year	2 year	28 days	90 days	1 year	2 year
Panel A: fraction, across-fund weekly	Lowest	0.33	0.61	0.94	1.35	0.19	0.29	0.20	0.14
		(0.01)	(0.02)	(0.06)	(0.09)	(0.01)	(0.02)	(0.06)	(0.09)
	Low-Med	0.36	0.51	0.49	0.24	0.06	0.03	-0.09	0.08
		(0.01)	(0.02)	(0.05)	(0.08)	(0.01)	(0.02)	(0.05)	(0.08)
	Med-High	0.40	0.53	0.52	0.25	0.07	-0.03	-0.21	-0.65
		(0.01)	(0.02)	(0.05)	(0.08)	(0.01)	(0.02)	(0.05)	(0.09)
	Highest	0.42	0.56	0.58	0.69	-0.02	-0.16	-0.55	-1.10
		(0.01)	(0.02)	(0.05)	(0.09)	(0.02)	(0.03)	(0.08)	(0.12)
Panel B: fraction, within-fund weekly	Lowest	0.32	0.56	0.73	0.90	0.15	0.20	0.14	0.20
		(0.01)	(0.02)	(0.05)	(0.08)	(0.01)	(0.02)	(0.05)	(0.09)
	Low-Med	0.37	0.49	0.54	0.15	0.07	0.04	-0.16	0.00
		(0.01)	(0.02)	(0.05)	(0.08)	(0.01)	(0.02)	(0.05)	(0.08)
	Med-High	0.41	0.59	0.56	0.54	0.08	0.01	-0.14	-0.67
		(0.01)	(0.02)	(0.05)	(0.08)	(0.01)	(0.02)	(0.06)	(0.09)
	Highest	0.42	0.55	0.63	0.72	-0.02	-0.16	-0.54	-0.97
		(0.01)	(0.02)	(0.05)	(0.08)	(0.02)	(0.03)	(0.07)	(0.11)
Panel C fraction, within-fund monthly	Lowest	0.31	0.56	0.69	0.74	0.13	0.13	-0.11	-0.21
		(0.01)	(0.03)	(0.06)	(0.10)	(0.01)	(0.03)	(0.06)	(0.10)
	Low-Med	0.36	0.47	0.64	0.33	0.11	0.18	-0.07	0.15
		(0.01)	(0.03)	(0.06)	(0.09)	(0.01)	(0.03)	(0.06)	(0.10)
	Med-High	0.38	0.58	0.64	1.08	0.08	-0.03	0.04	-0.26
		(0.01)	(0.02)	(0.06)	(0.10)	(0.01)	(0.03)	(0.07)	(0.11)
	Highest	0.41	0.55	0.57	0.50	-0.02	-0.19	-0.58	-1.24
		(0.01)	(0.03)	(0.06)	(0.10)	(0.02)	(0.03)	(0.08)	(0.13)

Table A.2. Average post-trade returns relative to counterfactual by fund behavior, unweighted

This table presents the average returns relative to random buy/sell counterfactuals for buy and sell portfolios sorted by cumulative benchmark-adjusted fund returns since the beginning of a quarter, and weekly trading activities (Gross Sell and Net Buy). For buy trades, we compute average returns of stocks bought minus returns of stocks held on each day. For sell trades, we compute average returns of stock held minus returns of stocks sold. The weekly gross sell is computed by counting the number of unique positions sold within a week. Weekly net buy is computed by the unique number of positions bought per week minus the unique number of positions sold per week. For the fund cumulative returns since the beginning of a quarter, we rank it across funds for each date in the sample. For trading activities, we rank these measures within portfolios across all weeks in the sample. We divide these measures into four bins from Lowest, Low-Med, Med-High and Highest, based on their rankings. Columns represent buy or sell performance measures at the following horizons: 1 month, 3 months, 1 year, and 2 years. We report point estimates of the average counterfactual returns for each portfolio at different horizon as well as their standard errors in parenthesis (below the point estimate). Standard errors are computed using Hansen-Hodrick standard errors with a lag equal to the number of horizon -1.

Fund Characteristics	Bin	Buy				Sell			
		Horizon				Horizon			
		28 days	90 days	1 year	2 year	28 days	90 days	1 year	2 year
Panel A: Cumulative Benchmark-adjusted Fund Returns since the beginning of a quarter (sorted across funds)	Lowest	0.33	0.46	0.94	0.88	0.01	-0.07	-0.39	-0.61
		(0.01)	(0.02)	(0.05)	(0.01)	(0.01)	(0.02)	(0.06)	(0.01)
	Low-Med	0.36	0.56	0.52	0.65	0.05	0.02	-0.13	-0.23
		(0.01)	(0.02)	(0.04)	(0.00)	(0.01)	(0.02)	(0.04)	(0.00)
	Med-High	0.35	0.52	0.45	1.01	0.07	-0.02	-0.11	-0.25
		(0.01)	(0.02)	(0.04)	(0.00)	(0.01)	(0.02)	(0.04)	(0.00)
	Highest	0.41	0.60	0.79	0.46	0.13	0.04	-0.21	-0.49
		(0.01)	(0.02)	(0.05)	(0.01)	(0.01)	(0.02)	(0.05)	(0.01)
Panel B: Gross Sell Weekly Number of distinct stocks sold (sorted within fund)	Lowest	0.39	0.63	1.03	1.00	0.12	0.27	0.81	1.43
		(0.01)	(0.02)	(0.05)	(0.08)	(0.01)	(0.02)	(0.05)	(0.08)
	Low-Med	0.34	0.55	0.80	1.31	0.13	0.15	-0.06	-0.51
		(0.01)	(0.02)	(0.05)	(0.08)	(0.01)	(0.02)	(0.06)	(0.09)
	Med-High	0.43	0.58	0.67	0.58	0.07	0.03	-0.26	-0.36
		(0.01)	(0.02)	(0.05)	(0.08)	(0.01)	(0.02)	(0.06)	(0.09)
	Highest	0.31	0.44	0.30	0.22	0.04	-0.12	-0.43	-0.81
		(0.01)	(0.02)	(0.05)	(0.08)	(0.01)	(0.03)	(0.06)	(0.11)
Panel C: Net Buy Weekly Number of stocks bought minus Number of stocks sold (sorted within fund)	Lowest	0.38	0.57	0.34	-0.13	0.06	-0.19	-0.80	-1.47
		(0.01)	(0.02)	(0.05)	(0.08)	(0.01)	(0.03)	(0.06)	(0.11)
	Low-Med	0.41	0.73	0.76	0.62	0.12	0.10	-0.45	-0.85
		(0.01)	(0.02)	(0.05)	(0.07)	(0.01)	(0.02)	(0.06)	(0.09)
	Med-High	0.39	0.52	0.54	0.75	0.10	0.21	0.31	0.47
		(0.01)	(0.02)	(0.05)	(0.08)	(0.01)	(0.02)	(0.05)	(0.08)
	Highest	0.32	0.43	0.84	1.21	0.03	0.06	0.41	0.63
		(0.01)	(0.02)	(0.05)	(0.09)	(0.01)	(0.02)	(0.05)	(0.08)

Table A.3. Average heuristics intensity by bins of fund characteristics

This table reports the average measure of heuristic intensity at the fund-level, where funds are sorted into four bins according to various fund characteristics. We measure heuristics intensity by the fraction of positions sold in extreme bins of past position returns. We report this for a variety of fund characteristics, sorted in ascending order. For each bin of fund characteristics denoted by b, we measure heuristics intensity by fraction of position sold by computing :

$$HI_b^{frac} = \frac{\text{\#position sold in past return bin 1 or 6 given bin of fund characteristics b}}{\text{\# positions sold in bin of fund characteristics b}}.$$

Fund Characteristics	Lowest	Low-Medium	Medium-High	Highest
Panel A: Trading Style				
Weekly Gross sell	41.067	40.397	40.333	38.529
Monthly Turnover	39.354	38.892	39.995	39.224
Median Holding Length	38.926	39.601	39.86	38.978
Panel B: Past Fund Returns				
Fund past 2-day return	39.985	39.843	39.821	40.396
Fund past 7-day return	40.121	39.536	39.819	40.513
Fund past 30-day return	39.74	39.677	39.642	40.972
Fund past 60-day return	39.681	39.745	39.59	40.971
Fund past 90-day return	39.672	39.616	39.678	41.001
Fund past-year return	39.407	39.719	39.286	40.715
Fund past 2 year returns	39.985	39.843	39.821	40.396

Table A.4. Post-trade returns relative to counterfactual, overall and robustness checks, unweighted.

This table presents the average value added measures (post-trade returns relative to a random sell counterfactual) for buy and sell trades under two measures of returns 1) returns and 2) factor-neutral returns, for the whole sample and the subsample of stocks from developed markets (see text for further details). Panel A, B presents the average counterfactual returns on buy and sell trades respectively, along with their standard errors in parenthesis (below the point estimate). We first present the overall average counterfactual returns, and then report the average counterfactual returns for trades on earnings announcement days (A-day) and non-earnings announcement days (N-day). Standard errors are computed using Hansen-Hodrick standard errors with number of lags equal to the horizon -1

Sorting	Return Measures	Bins	Panel A: Buy			Panel B: Sell		
	Horizon		28	90	365	28	90	365
	Baseline		0.36	0.54	0.65	0.07	0.02	-0.19
			(0.01)	(0.03)	(0.07)	(0.01)	(0.03)	(0.07)
I.	Baseline (Developed)		0.39	0.63	0.93	0.04	-0.11	-0.44
			(0.01)	(0.03)	(0.07)	(0.01)	(0.03)	(0.08)
Overall	Betaneutral		0.34	0.46	0.51	0.06	-0.03	-0.26
			(0.01)	(0.02)	(0.07)	(0.01)	(0.03)	(0.07)
	Betaneutral (Developed)		0.34	0.47	0.36	0.08	-0.05	-0.37
			(0.01)	(0.03)	(0.07)	(0.01)	(0.03)	(0.07)
	Baseline	N-day	0.41	0.71	1.18	0.01	-0.17	-0.51
			(0.01)	(0.02)	(0.07)	(0.01)	(0.03)	(0.07)
		A-day	0.16	0.51	0.08	0.36	0.31	1.20
			(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.03)
II.	Baseline(Developed)	N-day	0.44	0.75	1.11	0.02	-0.19	-0.74
			(0.01)	(0.03)	(0.08)	(0.01)	(0.03)	(0.08)
Earning		A-day	0.03	0.65	0.14	0.47	0.39	0.93
			(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.03)
Announcement	Betaneutral	N-day	0.40	0.69	1.44	-0.02	-0.29	-0.96
			(0.01)	(0.03)	(0.07)	(0.01)	(0.03)	(0.08)
		A-day	0.13	0.32	-0.06	0.32	0.14	1.05
			(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.03)
	Betaneutral (Developed)	N-day	0.43	0.76	1.43	-0.01	-0.37	-1.26
			(0.01)	(0.03)	(0.07)	(0.01)	(0.03)	(0.08)
		A-day	0.00	0.30	0.04	0.43	0.29	0.98
			(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.03)

Table A.5. Post-trade returns relative to counterfactual by heuristics intensity, overall and robustness checks, unweighted.

This table presents the average counterfactual returns for buy and sell trades under two return measures (raw, factor-neutral) for the whole sample and the subsample of developed market, sorted into four bins based on our measure of heuristics intensity. Heuristics intensity is computed by measuring the fraction of sell trades in the lowest and highest of 6 bins of cumulative returns capped at 1-year, sorted weekly across funds. See text for further details on variable definitions. Panel A and B report mean counterfactual returns of each measure for buy and sell trades respectively, weighted by a fund's trading activity, as well as their standard errors in parenthesis (below the point estimate). Each cell represents the average counterfactual returns in percentage over specified horizons and levels of heuristics intensity. Standard errors are computed using Hansen-Hodrick standard errors with number of lags equal to the horizon -1

Return Measures	Bins	**Panel A: Buy**			**Panel B: Sell**		
Horizon		28	90	365	28	90	365
Baseline	Lowest	0.33	0.61	0.94	0.19	0.29	0.20
		(0.01)	(0.02)	(0.06)	(0.01)	(0.02)	(0.06)
	Low-Med	0.36	0.51	0.49	0.06	0.03	-0.09
		(0.01)	(0.02)	(0.05)	(0.01)	(0.02)	(0.05)
	Med-High	0.40	0.53	0.52	0.07	-0.03	-0.21
		(0.01)	(0.02)	(0.05)	(0.01)	(0.02)	(0.05)
	Highest	0.42	0.56	0.58	-0.02	-0.16	-0.55
		(0.01)	(0.02)	(0.05)	(0.02)	(0.03)	(0.08)
Baseline (Developed)	Lowest	0.34	0.63	0.88	0.16	0.26	0.09
		(0.01)	(0.02)	(0.06)	(0.01)	(0.02)	(0.06)
	Low-Med	0.38	0.59	0.51	0.06	-0.01	-0.35
		(0.01)	(0.02)	(0.06)	(0.01)	(0.02)	(0.06)
	Med-High	0.42	0.53	0.47	0.07	-0.08	-0.50
		(0.01)	(0.02)	(0.06)	(0.01)	(0.02)	(0.06)
	Highest	0.40	0.53	0.50	0.04	-0.15	-0.67
		(0.01)	(0.03)	(0.06)	(0.02)	(0.03)	(0.08)
Betaneutral	Lowest	0.32	0.55	0.80	0.17	0.21	0.14
		(0.01)	(0.02)	(0.06)	(0.01)	(0.02)	(0.06)
	Low-Med	0.34	0.41	0.41	0.07	0.01	0.01
		(0.01)	(0.02)	(0.05)	(0.01)	(0.02)	(0.05)
	Med-High	0.37	0.47	0.37	0.06	-0.03	-0.23
		(0.01)	(0.02)	(0.05)	(0.01)	(0.02)	(0.05)
	Highest	0.40	0.49	0.49	-0.04	-0.27	-0.83
		(0.01)	(0.02)	(0.06)	(0.02)	(0.03)	(0.08)
Betaneutral (Developed)	Lowest	0.34	0.57	0.70	0.14	0.15	0.01
		(0.01)	(0.03)	(0.06)	(0.01)	(0.03)	(0.06)
	Low-Med	0.35	0.49	0.37	0.07	-0.04	-0.22
		(0.01)	(0.02)	(0.06)	(0.01)	(0.02)	(0.06)
	Med-High	0.39	0.46	0.26	0.07	-0.05	-0.40
		(0.01)	(0.02)	(0.06)	(0.01)	(0.02)	(0.06)
	Highest	0.38	0.46	0.37	0.03	-0.24	-0.82
		(0.01)	(0.03)	(0.06)	(0.02)	(0.03)	(0.08)