Risk Management and Price Pressure*

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ABSTRACT

Many asset managers limit the weights of their asset positions in order to ensure the diversification of active bets. Consequently, an individual manager will strongly react to positive returns in his *biggest* positions by rebalancing into other assets; and react less so to positive returns in the rest of his portfolio. I show that this behavior from asset managers can substantially explain the disposition effect in mutual fund portfolios. I further document the pervasiveness of this practice, and how trading to rebalance high exposure positions collectively leads to return predictability. This return predictability is consistent with trading price pressure. Since stocks with large market capitalization are generally held in large proportion across investors, this price pressure affects a large cross section of equity assets.

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In this paper, I argue that portfolio rebalancing for risk management by individual managers leads to trading coordinated by an asset's past returns, generating significant non-fundamental demand. This demand channel can be dramatic for stocks that are held widely and in large weights across risk-managed portfolios. For example, consider the case of Apple stocks. Between 2011 and 2012, Apple became the highest valued public company in the world. Apple's outperformance significantly increased its weight in existing investor portfolios. Funds that once had a moderate position in Apple, now contain a position larger in weight than any of their other assets. In an interview on Apple's heavyweight status by the New York Times, a portfolio manager commented, "we're sensitive to letting a mutual fund get too outsized a position," and when his portfolio's Apple holdings increased to 9 percent of the total assets, the manager decided to "trim a little bit." Furthermore, the trimming of their positions led some investors to act against their own expected returns in Apple. The same portfolio manager lamented, "every sale has been a bad sale," referencing the continued performance of Apple stocks. Consistent with risk management of portfolios, many investment managers decreased their weight in Apple against realized returns, despite losing out on future outperformance. I will show in this paper that the tendency for mutual funds to manage the exposures to their largest holdings, even at a cost, extends far beyond just Apple stocks. Actions to rebalance the exposures to individual companies pervade across professional investors and aggregate into a price pressure that affects a large and important cross section of equities.

Investment managers undoubtedly use a variety of management methods and models to shape their portfolio. However, a simple guideline that captures the heart of many risk management choices is the rule to diversify and limit exposures to individual stock positions. While this heuristic may not match the exact optimization model or behavioral process used by every investor, it is plausible that asset allocation with risk management in mind will exhibit this rule in practice. This paper shows that portfolio diversification through this parsimonious rule explains investors' trading behavior significantly, and that the individual manifestations of this risk management rule in institutional investors collectively generate non-fundamental demand for certain assets.

Although the portfolios studied in this paper are mutual funds managed by dedicated professional investors, whose trading patterns are less susceptible to behavioral bias than retail investors, this pattern of portfolio rebalancing can also be consistent with a combination of behavioral biases: a saliency toward large positions *and* naive prospect theory mental accounting.

This paper makes the following contributions to the finance literature. 1) I show that active professional investors generally rebalance their portfolios away from weight increases that are induced by realized returns, particularly for large initial positions. This rebalancing behavior toward the interaction of returns and holding weights predicts selling and buying of shares of stocks in individual portfolios, and remains after controlling for investor capital flow and size effects (See Pollet and Wilson (2008) for a detailed examination of portfolio management regimes as related to fund size). The rebalancing pattern is consistent with the aforementioned risk management by actively managed funds. 2) The observable disposition effect- the tendency of investors to sell winners and keep losers- in mutual funds can be accounted for substantially by the documented phenomenon. I find that past returns (and winner/loser indicators) only marginally predict trading by fund managers after controlling for the *mechanical* changes in portfolio exposure. 3) Controlling for this effect, I find that investors, even with their existing positions, tend to trend chase on past returns- a pattern consistent with behavioral extrapolation. 4) Summing up rebalancing trades across investors, I show that collective rebalancing leads to return predictability that is consistent with coordinated demand pressure on the largest stocks in the cross section of equities. 5) This price pressure effect is related to the short-term 1 to 6 month momentum, and can explain the lagging predictability of momentum returns.

The paper is mainly related to a large literature that works to explain investor trading behavior. Foremost in this literature is the disposition effect of Shefrin and Statman (1985), which posits and tests the behavioral bias that investors sell winners too early and ride losers too long. This effect has been well documented across investors of different types. Empirical works along this line include Odean (1998), Frazzini (2006), and Ben-David and Hirshleifer (2012). In a complementary literature on extrapolative trading behavior, Grinblatt, Titman, and Wermer (1995) documents that mutual funds appear to chase after stocks that had high historical returns; this work has spawned a large literature on herding and behavioral return extrapolation. Recent works in this area include Greenwood and Shleifer (2014) and Barberis, Greenwood, Jin and Shleifer (2018).

Realized returns cannot unconditionally induce both return chasing *and* profit taking. The reason that both effects have been found in investor portfolios is because portfolio weights are used differently. The literature on disposition effect focus on existing portfolio holdings while works on trend-chasing examines the portfolio averages of new and old positions. The two literatures beg to be reconciled.

As my main contribution, I argue that investors manage at the portfolio level, with particular focus on the exposures toward individual positions- therefore, the return driven changes in positional exposures are naturally predictive of investor trading of their existing holdings. Initial portfolio weights drive a wedge between the positions investors trim and the positions they increase. Unconditionally, investors chase after returns, but the degree to which they sell winners depends largely on the size of these positions *within* their portfolio. I find that the observable disposition effect in professional investors can be attributed significantly to the linear rebalancing of large exposures. After accounting for the rebalancing demand, past positive (negative) returns predict future purchases (sells) in *net*.

The efficient market hypothesis dictates that predictable trading activities should have no effect on asset prices. However, considerable evidences from both theoretical (Duffie (2010)) and empirical literature (Shleifer (1986), Coval and Stafford (2007), Lou (2012), and Chen (2018)) indicate that predictable trading still generates price pressure, due to limited arbitrage. The rebalancing by mutual funds generates price pressure through the coordinated selling by active managers. The price effect due to this rebalancing pressure largely reflects how aggressively arbitrageurs can counteract this demand (Shleifer and Vishny (1992), Shleifer and Vishny (1997), and Greenwood (2005)). Consistent with downward sloping demand curve for stocks, I find that future excess returns reflect aggregate rebalancing demand predicted each quarter. These returns revert at longer holding horizons.

There is also a substantial empirical literature on momentum returns (Jegadeesh and Titman (1993)). Recent works find that intermediate lagged past returns, from 7 to 12 months ago, tend to forecast future returns (Novy-Marx (2013)). In contrast, recent past returns, from 1 to 6 months ago, do not significantly generate such predictability in stock returns. This is puzzling as the finance literature has not specified any substantial reasons for differences between short-term and long-term past returns in the eye of an investor. This paper makes additional contribution by showing that quarterly rebalancing by professional investors tend to generate price pressure in the opposite direction as short-term momentum. Once an econometrician accounts for this missing mechanism in the cross sectional predictability regressions, recent returns gains additional power to forecast future returns. I confirm this novel result on momentum return using double sorted calendar time portfolios.

This is the first paper I am aware of that explicitly documents the repeated rebalancing of asset exposures by portfolio managers, and additionally the cross sectional return predictability associated with this rebalancing. Other recent works on the effect of institutional portfolio managers and cross section of asset prices include Massa, Schumacher and Wang (2016), who observe that there is substantial changes to institutional portfolios after the merger between BlackRock and Barclays Global investors. This rebalancing of concentrated positions is associated with changes in price, liquidity, and volatility. A related paper by Ben-David, Franzoni, Moussawi and Sedunov (2017) finds that institutional holdings tend to be accompanied by their own idiosyncratic volatility. That is, ownership by large institutions imposes a substantial liquidity demand. The documented facts from this paper are also consistent with Blume and Keim (2017), who find that stocks with the highest capitalization are on the whole underweighted in institutional portfolios.

Lastly, the re-diversification mechanism proffered by this paper complements the literature in behavioral finance which has long indicated that investors are under-diversified in their portfolio holdings (See French and Poterba (1991), Coval and Moskowitz (2002), and Goetzmann and Kumar (2008)). This lack of diversification supports certain theories of behavioral biases- biases such as investor over-confidence and local biases. Recent work has also indicated that the lack of diversification may be the rational result of superior information (Nieuwerburgh and Veldkamp, 2009). This paper contributes by examining the re-diversification behavior within investors' existing portfolios- that is given their bias toward a limited set of invested assets, how do investors maintain some level of diversification?

Subsequent to the first versions of this paper, Lines (2016) studies price predictability with respect to the benchmarked weights of the closest indices. He finds that there is also a reversal of portfolio weights toward the passively benchmarked weights and that there is a price predictability associated with this mechanism. While he argues that incentives compel asset managers to rebalance toward the benchmark during periods of volatility, there is very little evidence in the micro data that investors increase their loser portfolios weights. Instead, the most consistent explanation is that active investors persistently rediversify their positions, and with little regard toward he closest benchmarked portfolio. After all, the median active fund portfolio has less than 70 stocks; far less in count than most benchmarking indices. Moreover Lines (2016) argues that there is a premium associated with stock rebalancing; however, I find that trades to rebalance are non-persistent and returns from this channel are short lived. A calendar strategy that takes advantage of this predictability is accompanied by significant quarterly turnover, and would experiences significant reversals if held at horizons longer than a single quarter. I argue that the two building blocks of behavioral finance (1- limits to arbitrage combined and 2- coordinated trading by investors) are simple parsimonious explanations for return predictability associated with rebalancing.

The rest of the paper is organized as follows. Section 1 analyzes individual mutual fund trades and their correlation with past returns. I show that, for mutual funds, the well documented disposition effect in the behavioral finance literature is concentrated among and driven by the respectively large positions. Section 2 decomposes the changes in asset portfolio weights into a *passive* components attributable to realized returns and a residual *active* component due to discretionary rebalancing. I show that the passive component accounts for the bulk of the disposition effect in mutual fund portfolios at the quarterly horizon. Section 3 aggregates the trading induced by a portfolio's exposure rebalancing to the stock level. I show that this demand channel is associated with abnormal volume and abnormal returns in the cross section of equities. Section 4 links the results to the momentum phenomenon. Section 5 finally discusses the results and concludes.

1. Mutual Fund Trading and Past Returns

If some investors actively rebalance their exposures to individual stock positions, then they will likely sell stocks with high price returns. This prediction is consistent with the disposition effect- that investors tend to sell winners and keep loser. However, a distinguishing feature of the risk management hypothesis, beyond this feature, is that investors will rebalance their largest holding positions more strongly than their small to medium sized positions. In this section, I show that returns are only associated with future trades for assets that are held in significant proportion within an individual portfolio.

Quarterly mutual fund holdings from Q1 1990 to Q4 2016 from Thomson-Reuters are joined with fund characteristics from Center for Research in Securities Prices (CRSP) Mutual Fund Database to construct the trading and holdings information used in this analysis. CRSP's Stock Securities Files are used for price and returns. The universe of equity studied is common stocks from the AMEX, NASDAQ, and NYSE exchanges. I contain my analysis to actively[1] managed open-ended equity mutual funds- the data filter procedure is produced in Appendix A1. Summary statistics for stock-portfolio-quarter observations and the mutual funds that own them are reported in the Panel A and Panel B of Table 1.

I begin the analysis on this panel of stock-portfolio-time observations by relating trading activity to past quarterly returns (both total return and price returns). This regression is conducted

[1] Index funds do not display the same behavior.

piecewise, generating trade-return sensitivities for separate ranges of initial portfolio weights. Figure 1 separates the panel of stock-portfolio-time observations into 10 bins each with roughly the same number of observations based on their portfolio weights. Then I regress all of the sample in a single multivariate regression using the piecewise returns (top panels) and piecewise indicators of a winner stock (bottom panels). The resultant coefficients are plotted. The left panels depicts regression of the *Sell* variable ($Y_{i,j,t+1}$ is 1 if portfolio j decreased shares in stock i at $t+1$ and 0 otherwise), while the right panels depicts the regression of *Buy* variable ($Y_{i,j,t+1}$ is 1 if portfolio j increased shares in stock i at $t+1$ and 0 otherwise) on total (blue) and price (red) returns. We observe a visible relationship between the regression coefficients and the range of weights used. The inclusion of dividends has very little effect on this empirical pattern.

Consistent with the risk management hypothesis, large initial positions are particularly sensitive to positive returns- positions with large initial weights are more likely to be sold and less likely to be bought after realizing high returns. Positions that are initially small have the opposite sensitivity- high return positions are more likely to be bought and less likely to be sold. An alternative binning- not based on absolute weights, but based on ranking of position size within each mutual fund portfolio- does not change the results qualitatively (See Appendix F1).

The columns (1) through (6) of Table 2 continues the analysis of trading by mutual fund portfolios with multivariate regressions. The regressors of interest are *Winner* dummies interacted at various initial weight ranges. These indicators have more statistical power than raw returns as can be seen from Figure 1. The regressions control for initial weights, the “rank effects” of Hartzmark (2014), portfolio/time fixed effects, and stock/time fixed effects. Again, I find very little evidence that active fund portfolios sell winners and keep losers for positions with small to medium initial weights. Rather, the tendency of portfolios to sell winners and keep losers rises along with holding size; and is the strongest for positions with large initial sizes. Under the fully specified model in column (3), a fund manager is 23.6% more likely to sell a winner stock in the largest weight bin than a loser stock grouped into the same bin. On the other side of the spectrum, winner stocks binned with the smallest weight bin is less likely of being sold than a loser stock in the same bin. Buying by fund managers follows the opposite direction from the interaction of stocks and portfolio weights. The specification in column (6) indicates that the same manager is 9.03% less likely to increase the position in a winner stock than a loser stock in the same bin. The distinction that portfolio managers sell winners and keep losers in positions with large ex ante weights is consistent with the risk management hypothesis. Interestingly, in the regression specifications that include the bin size fixed effects, the rank effect of Hartzmark switches the direction of its regression coefficient on the selling dummy, confirming that an investors' treatment of an extreme return event may be intrinsically linked to the respective stocks' *ex ante* exposures within his portfolio.

Of course, one major concern is that these empirical facts simply capture size or flow effect in mutual funds. Large inflows from investors are met with diversification (Pollet and Wilson (2014)), which automatically shrinks extant positions relative to the portfolio. However, this can't explain the sensitivity of buying or selling *indicators* to realized returns; that is, mechanical diversification due to inflows will not explain the increased likelihood that an investor sells or buy existing shares. To address this issue formally, I run separate regressions in columns (7) through (10) of Table 2 for positions belonging to mutual funds with positive and negative investor flows at the time of the trading activities. Again, there is a robust increasing pattern in the sensitivity of trading to past returns as the size of the initial position increases. When funds receive investor inflows, their managers invest in new positions, which by construction, decrease the exposures to these large weighted positions. However, these funds still tend to sell shares in existing positions that had mechanically high exposures. We can also observe that funds facing investor outflows are more likely to sell stocks that had large realized returns and high initial positions. In fact, the slope of the sensitivity of trading to returns for mutual funds facing redemptions is higher than that of mutual funds facing inflows. When investors redeem shares, mutual fund managers are more likely to take profit on their largest holdings in order to face these redemptions. The marginal increase in the probability of selling a large position stock is 29.0% for winner in funds facing outflows in the regression specification in Column (7), compared to 27.7% for funds facing inflows in Column (9). These same mutual funds are also less likely to increase the large winning positions even as they face outflows. The marginal decrease in the probability of increasing a large winning position is 79% over a large losing positions. This effect is lower for funds facing inflows. Such inflow funds are 2.63% less likely to increase their largest winning positions over their largest losing positions, indicating that the rebalancing effect isn't simply mechanical diversification from the increasing scales of the portfolio.

In summary, this section describes the correlation between past returns and future trading behavior by actively managed mutual funds. In stock positions with large initial weights, there is a clear negative (positive) relationship between the likelihood that a fund manager will purchase (sell) and this stock's past quarterly return. Otherwise, for small and new positions, this relationship is positive. The pattern for trimming large winners exists for fund portfolios regardless of their capital inflow and redemptions; and is consistent with rebalancing to manage positional exposures by mutual fund managers.

2. Passive Changes in Portfolio Weights

If fund managers actively re-adjust their portfolios in order to limit exposures to individual stocks, then portfolio rebalancing will be predictably associated with the mechanical changes in asset allocation; in particular, portfolio weight adjustments will respond to the changes from realized returns. Following literatures on household and international portfolio rebalancing (Calvet, Campbell and Sodini (2009); and Hau and Rey (2008)), this section decomposes the quarterly weight changes in asset positions into a *passive* mechanical component and an *active* discretionary component. I will show that the *passive* component of quarterly weight changes is a useful and parsimonious way of forecasting trading activities in mutual fund portfolios.

2.1 Quarterly Trading Predictability and the Disposition Effect

This section demonstrates that, in forecasting regressions of quarterly trades, the mechanical component (*Passive*) in portfolio weight changes forecasts active rebalancing by mutual fund managers. This variable accounts substantially for the disposition effect in mutual fund portfolios as observed at quarterly frequencies. That is, the tendency to sell winners is predominantly forecasted by the increases in exposure to this stock due to realized returns, not substantially by the fact that the stock was a "Winner." Once this risk/exposure management effect is incorporated into the regressions, investor portfolios show a substantial trend chasing pattern on their existing holdings.

The quarterly changes in asset weight ($\Delta w_{i,j,t}$) for stock *i* in portfolio *j* can be decomposed as follows:

$$\Delta w_{i,j,t} = w_{i,j,t} - w_{i,j,t-1} = \underbrace{w_{i,j,t} - \widehat{w}_{i,j,t}}_{Active\ Change\ (Active_{i,j,t})} + \underbrace{\widehat{w}_{i,j,t} - w_{i,j,t-1}}_{Passive\ Change\ (Passive_{i,j,t})} . \tag{1}$$

Here $\widehat{w}_{i,j,t}$ is the hypothetical weight of position *i* had there been no active trading in the asset between t-1 and t. Specifically:

$$\widehat{w}_{i,j,t} = \frac{w_{i,j,t-1} \cdot (1 + r_{i,t})}{\sum_k w_{k,j,t-1} \cdot (1 + r_{k,t})}. \tag{2}$$

In the main sections of the paper, $r_{i,t}$ is the ***price return*** of stock *i* between *t-1* and *t*. Therefore, $\widehat{w}_{i,j,t}$ is the weight of asset *i* in portfolio *j*, excluding cash, if the investor had not traded at all. This passive change in portfolio weights can be calculated with only the initial *t-1* holdings and returns from *t-1* to *t* alone. Of course, the reinvestment of dividends is a key mechanism in portfolio management and generates its own source of trading demand due to portfolio reinvestments (see Chen (2018)). In the Appendix A2, total stock returns are used in an alternative construction of $\widehat{w}_{i,j,t}$ to calculate *Passive* under the assumption of automatic reinvestment of dividends by portfolio managers between quarters. It should be not surprising that the results remain almost entirely the same- over 99.5% of the variation in monthly total stocks returns in the CRSP database can be explained by price returns alone.

Table 3 forecasts *Buy* and *Sell* indicators as well as *Active* weight changes (the discretionary change in portfolio weights) with *Passive* (the return driven change in portfolio weights) and

Winner (an indicator for positive returns). In the simple specification with Time X Funds fixed effects (1), *Winner* significantly forecasts *Selling* by portfolio managers. However, once the regression controls for *Passive* and initial *weight* related rebalancing in (2), the magnitude of this coefficient is decreased by 66.6%. Consistent with return chasing, I find that the *Winner* dummy also predict gross increases in positions by mutual fund portfolio. The coefficient of *Winner* against *Buying* is increased by 23.4% from the specification in (4), once this *Passive* variable is included as a control in the multivariate fixed effect model of column (5). This indicates that while return chasing is part of the mechanism in which investors pick which stocks to purchase, this effect is balanced by the investor tendency to maintain against overexposures in large positions. To find the *net* relationship between a *Winner* position and an investor's future trades, I use the discretionary change in weight (*Active*) as the main right hand-side variable in columns (7), (8), and (9). *Winner* forecasts discretionary decreases in position weights only in regression specifications that don't control for *Passive* (including in the untabulated simple bivariate regression that excludes initial portfolio *Weight*). Rather, in the fully specified model (8), the *Winner* indicator for positive stock returns stops predicting decreases through active portfolio rebalancing by fund managers. The fully specified model in column (8) reveals that the *net* trading in mutual fund portfolios against winning stocks can be accounted for entirely by *Passive* changes in portfolio weights. That is, the *net* negative association between trading direction by mutual funds and past stock returns can be entirely explained by the discretionary rebalancing of passive weight changes; not by the isolated tendency of portfolio managers to take profit in individual stocks.

Investors can respond asymmetrically to the changes in portfolio weights: re-diversification of large positions, especially when an investors regularly purchase new stocks outside of her current portfolio, is a mechanism where investors are much more likely to rebalance from the mechanical increases in exposure. As positions become smaller in a portfolio due to relatively lower realized returns, a mechanical diversification occurs. In contrast, when a position becomes large through realized returns, a portfolio's total weight in this position may only decline if the investor actively sells shares, or (if experiencing capital inflows) purchase shares in new positions. In the context of re-diversification, the *Passive* increases in portfolio exposure are more likely to be met with active rebalancing; in contrast to the *Passive* decreases in portfolio weights. I show that this is exactly the case in mutual fund portfolios. Columns (3), (6), and (9) separates *Passive* into two piecewise components, representing mechanical increases and decreases in portfolio weights. That is

$$Passive_{i,j,t}^{+} = Passive_{i,j,t} \cdot \mathbf{1}(Passive_{i,j,t} > 0),$$

and

$$Passive_{i,j,t}^{-} = Passive_{i,j,t} \cdot \mathbf{1}\left(Passive_{i,j,t} < 0\right).$$

We observe that *Sell* (selling of some shares) and *Active* (active weight adjustments) by portfolio managers are mainly predicted by $Passive^{+}$- the passive increases in portfolio exposure; not decreases. Decreases in *Passive* weights are not highly indicative of selling nor active decreases in position weights by mutual fund managers. $Passive^{-}$- the passive decreases in exposure- instead mildly forecasts further discretionary decreases as shown by its correlation with *Active*. This is consistent with the risk management hypothesis- that fund managers actively rebalancing to re-diversify the positions that, due to realized returns, have become more concentrated in their asset portfolios.

Quantitatively, I find that a 1% increase in weights due to *Passive* forecasts a discretionary decrease of about 17 basis points in positional weight by a portfolio manager in the following quarter. This result is extant after controlling for fund level fixed effects and the past returns. Section 3 will aggregate *Passive* to proxy the total rebalancing price pressure as a percentage of shares held in mutual funds.

Interestingly, the *net* discretionary effect in *Active*, and also *Buy* by mutual funds show substantial positive relationship with the *Winner* dummy; especially after accounting for the passive changes in stock portfolio returns. This is consistent with investor extrapolation using past returns in creating his portfolio.

2.2 Horizon of Rebalancing Activities

The previous subsection focuses mainly on mutual fund rebalancing of increases in positional exposures after a single quarter; nevertheless, this specification may not capture key effects that occur at longer horizons or during the contemporaneous quarter. In this subsection, I show that this is the most detectable horizon at which trading activities are associated with *Passive* weight changes. Return driven weight changes from longer lags are mainly subsumed by the most recent available information on portfolio weights. Additionally, I find that there is a significant contemporaneous relationship between *Passive* and *Active* weight changes. The magnitude of this effect as observed through ordinary least square coefficients is about the same as the magnitude forecasted by the weight changes from the past quarter.

Table 4 describes the horizon of trade predictability from rebalancing activities in detail. The sample consists of equity mutual fund portfolios that are observable in all 9 quarters, and therefore is tilted toward larger/more diversified funds with significantly more Total Net Assets and positions than in Table 3. The holdings in the sample are the ones held by the portfolio at time 0. In column (1), I regress *Active* weight changes against the *Passive* weight changes calculated at varying lags- from during the last quarter to 8 quarters in the past. I find that at lags greater than the quarter to quarter horizon, *passive* weight changes, while still significantly predictive of *active* rebalancing in the opposing direction, decline considerably in their forecasting magnitudes. In the full specification, one percent passive increase in portfolio weight indicates a 0.151% (t=-18.73) decrease through active rebalancing in the following quarter, 0.079% (t=-12.22) active decrease in the following quarter, and etc. The power of lagged realized returns to explain future trading activities is almost entirely subsumed by the inclusion of portfolio weights in the regression. That is once I account for a position's portfolio weights in period *t-1*, the

Discovering which horizon predictable rebalancing occurs is an empirical exercise. Nothing prevents a portfolio manager from rebalancing his active bets within each quarter; although nothing says the portfolio manager must rebalance within a quarter. Still, the contemporaneous relationship between returns and investor demand may be potentially a significant source of price friction in the financial markets. Grinblatt and Han (2005) and Frazzini (2006) both argue that contemporaneous profit taking by investors implicitly generates under-reaction in stock returns. To disentangle contemporaneous rebalancing from the predictive rebalancing documented in the previous section, I include the *passive* changes in portfolio weights from the same quarter as the right hand-side variable in the multivariate regression of columns (3) and (4). A projected 1% *passive* weight increase is associated with 19.5 basis points of *active* decrease in the same quarter. This contemporaneous discretionary rebalancing can be attributable to selling by the mutual fund manager at any time within the quarter. That is, the fund manager may have sold his shares after or prior to the realized returns.

Still, while there is a significant contemporaneous relationship between passive weight changes and the direction of trading; the inclusion of contemporaneous *passive* control in the regression specification doesn't substantially change the magnitude of rebalancing at one quarter lag. The magnitude and significant of the coefficient on the *passive* change in portfolio weight at a single lag is almost the same in specification (4) as in specification (2). Even though investors rebalance at lower frequencies than the quarter to quarter horizon used in many of the tests in the paper, the rebalancing demand at the quarterly horizon is an extremely predictable and sizeable source of trading demand in the equity markets.

In summary, this section creates and tests, *Passive*, a measure of return driven mechanical changes in portfolio weights. This measurement strongly predicts buying and selling actions by mutual funds at the quarterly horizon. In fact, once controlling for this measurement, panel regressions stops displaying any negative correlation between positive past returns and future trading activities. In other words, the disposition effect in mutual funds can be attributed almost entirely to the quarterly rebalancing against the mechanical increases in portfolio weights due to returns. The predictability by *Passive* is independent of fund time fixed effects, which subsumes portfolio characteristics such as capital inflows, outflows, and portfolio size.

Accordingly, if such rebalancing activities drive temporary demand originating from portfolio managers and, as demonstrated thoroughly in existing literature, that stock prices are not perfectly elastic (See Shleifer (1986)), then we should observe price pressure associated with these rebalancing trades. I will test this hypothesis in the next section.

3. Aggregating Risk Management Trades

This section aggregates the predictable trading attributable to positional rebalancing into the variable *Rebalancing Demand*. I show that this measurement is associated with 1) decreases in the percent of total shares held by the institutional and mutual fund sector, 2) increases in abnormal volume, and 3) significant abnormal excess returns. The documented correlation between total holdings, volume, abnormal returns and the measurement of forecastable trading demand is consistent with price pressure.

As shown in the previous section, during my sample period between Q1 1990 and Q4 2016, a *passive* increase in weight corresponds with significant discretionary decrease in weight in the following quarter. A scaled proxy of the total forecastable (negative) demand attributable to exposure rebalancing by mutual funds is therefore:

$$Total\ Rebalancing\ Demand_{i,t+1} = \sum_j \underbrace{\left(\widehat{w}_{i,j,t} - w_{i,j,t-1}\right)}_{Passive\ Change} \cdot Holdings_{i,j,t}.$$

Following Lou (2016), I numeraire the trading activities with the total observable mutual fund holdings of stock *i* in order to calculate the price pressure associated with rebalancing trades. That is

$$Rebalancing\ Demand_{i,t+1} = \frac{\sum_j \left(\widehat{w}_{i,j,t} - w_{i,j,t-1}\right) \cdot Holdings_{i,j,t}}{\sum_j Holdings_{i,j,t}}.$$

The rationale for this numeraire is that rebalancing takes place widely for existing stock holders- not just for mutual funds; although Market Capitalization as the numeraire give qualitatively similar results in the regression specifications. Taking out prices per share of stock *i* from both sides of the fraction, the previous is equivalent to:

$$Rebalancing\ Demand_{i,t+1} = \frac{\sum_j \left(\widehat{w}_{i,j,t} - w_{i,j,t-1}\right) \cdot Shares_{i,j,t}}{\sum_j Shares_{i,j,t}}.$$

Mutual fund holdings are commonly unobservable without some lag (of about 5 to 6 weeks from the end of each quarter). I use lagged *t-1* shares as the empirical proxy of time *t* shares. That is in the predictive empirical implementation of this *Rebalancing Demand*, I calculate:

$$Rebalancing\ Demand_{i,t+1} = \frac{\sum_j \left(\widehat{w}_{i,j,t} - w_{i,j,t-1}\right) \cdot Shares_{i,j,t-1}}{\sum_j Shares_{i,j,t-1}}. \tag{3}$$

Equation (3) describes the primary measurement of stock demand used in the analysis of this section. Summary statistics on $Rebalancing\ Demand$ are contained in Table 1. Due to its extreme kurtosis, I winsorize the sample at 5% level in each tail. I'll show in the following subsections that this stock/time panel measurement is robustly predictive of key factors associated with stock demand- factors such as changes in the aggregate holdings by institutional portfolios and abnormal excess returns. Alternative Fama Macbeth regressions using time *t* shares give similar results and are included in the Appendix A4.

3.1 Total Holdings by Funds and Portfolio Managers

The counterparties to the documented trading in the previous section can be a combination of other mutual funds, other institutional investors, and retail investors. Empirically, I find that these rebalancing activities by portfolio managers generate trade transactions between institutions and unobserved portfolios. In the panel of quarterly stock observations between 1990 and 2016, I find that *Rebalancing Demand* is associated with decreases in the total shares held by mutual funds and institutional investors. That is, rebalancing trades generate *net* demand from professional investors.

The simple summary tabulated in the Panel A of Table 5 sorts stocks into 5 quintile portfolios during each calendar quarter based on their predictive *Rebalancing Demand*. Column 1 summarizes the average *Rebalancing Demand* in each portfolio. Coinciding with the proxy of this rebalancing demand is monotonically increasing realized returns- stocks with high realized returns also tend to passively increase in their portfolio weights. Column 2 calculates the value weighted average stock returns from the past quarter in each portfolio. Column 3 shows mutual fund portfolios holding the stock in quarter *t* tend to decrease their holdings between *t* and *t+1* monotonically with respect to higher *Rebalancing Demand*. There is a strict increasing pattern in these portfolios. In this regard, *Rebalancing Demand* captures an expected dimension of selling activities mutual fund. Column 4 is the average percent of mutual fund portfolios holding the stock in *t* that had increased their holdings in *t+1*. We observe a converse effect where funds are *reluctant* to increase their exposure to the stocks whose holding portfolios that had experienced significant increases exposure due to realized returns. Column 5 is the percent of liquidation that occurs between *t* and *t+1* for these same mutual fund portfolios. Interestingly, stocks with high *Rebalancing Demand* are generally not accompanied by higher likelihood of liquidations of their owners. Instead, the trading pattern is consistent with a "trimming" of exposures by the asset managers that hold these stocks. The last two columns (6) and (7) record the change in the percent of total shares held by institutional investors and mutual funds in the following quarter. Generally I find that the stocks with higher expected *Rebalancing Demand* have a lower quarter to quarter change in institutional and mutual fund holdings. With the exception of the lowest ranked quintile portfolio, whose stocks most recently realized significantly negative returns, we observe that both mutual funds and institutional investors tend to decrease their *net* holdings of the stocks in association with higher predicted *Rebalancing Demand*, indicating that a significant portion of the counterparties to these trades are investors outside of my data sample. While, due to parsimony, this panel only tabulates a single dimension of stock characteristic patterns associated with only

Rebalancing Demand, I find that this pattern is independent of size and initial portfolio weights- a characteristic summary of double sorted portfolios on initial average portfolio weights and predicted rebalancing demand will be included in the appendix.

Table 5 Panel B conducts formal regression analysis on rebalancing and institutional demand. Here panel regressions document the association between rebalancing demand and quarterly increases in total mutual fund and institutional holdings. In the first 3 columns, the left hand side variable is *MF_INC*, which indicates whether all of the mutual fund portfolios had in net increased the percent of shares outstanding from the stocks in question's. These regressions control for various existing characteristics and time fixed effects. Under the fully specified linear probability model, *Rebalancing Demand* per quarter has a slope of -12.72 to the probability that the Mutual Fund sector will increase in their percent share of the stock. Given that the unconditional probability that Mutual Funds as a sector will increase their shares outstanding of stock is 53%, a 1% *Rebalancing Demand* decreases this probability by roughly 24%. Regression specifications that examine the likelihood of an increase in the percent of shares held by institutional portfolios (*IN_INC*) produce similar results. The same *Rebalancing Demand* has a slope of -9.12 toward the likelihood that institutional portfolios will increase their holding this stock. This decreases the unconditional likelihood of institutional increases in shares by 17.5%.

An alternative regression takes the percent change in the shares held by Mutual Funds and 13-F institutions as the right hand side variable (Panel C). One limitation of this specification is that it is prone to be driven by extreme outliers; especially for small capitalization stocks. I winsorize the right hand side variables by 2.5% on each tail to alleviate this potential issue. We observe the same pattern as the one recorded in Panel B. The added benefit of this regression is that it implies an aggregate demand schedule for the *Rebalancing Demand* variable. A 1% *Passive* average increase in the mutual fund portfolios implies a 1.88% total decrease in the institutional holdings of the stock, and a 6.32% total decrease in the mutual fund holdings.

Consistent with trading demand originating from portfolio managers, I find that the predicted *Rebalancing Demand* tends to be strongly negatively associated with the amount of assets held in institutional portfolios. That is, when realized returns drives an asset to large weights across active equity fund portfolios, mutual funds and other asset managers tend to underweight this asset on average. These trades are not netted through the increases in portfolio holdings by other mutual funds, and the counterparty to these demand composes substantially of retail and non-institutional investors.

3.2 Abnormal Returns and Rebalancing Demand

The foreseeable rebalancing demand generates excess return predictability on the underlying stocks. The correlation of this demand with returns is in the same direction in the short term and is in opposite direction in the subsequent quarters (untabulated). In other words, the predictable selling activities by mutual fund portfolios is associated with negative abnormal returns during the same quarter; this abnormal return reverts subsequently.

Table 6 documents this effect through Fama Macbeth regressions. In this table, excess returns in individual stocks are regressed on their predicted rebalancing demand, past three, six, and twelve month returns, average portfolio weight, log book equity (*LBE*), log market equity (*LME*), and percentage institutional ownership (*InstOwn*). I use two measures of the rebalancing demand for robustness- *Rebalancing Demand (RebDemand)*, and *Percentile Rebalancing Demand (PRebDemand)*. *Rebalancing Demand* is the exact demand variable aggregated in the previous section. *Percentile Rebalancing Demand* is the percentile of each stock ranked each quarter according to their *Rebalancing Demand*. That is, it is the *Rebalancing Demand* linearized with respect to their cross sectional rank. The cross sectional regressions each quarter are weighted by each stock's market-capitalizations. An equal weighted version of this test is included in the appendix.

Rebalancing Demand, after controlling for short-term returns, negatively forecasts excess future stock returns. 1% in *Rebalancing Demand* forecasts -2.35% return in following quarter in the fully specified regression. A back of the envelop calculation for demand numeraires this return prediction with the associated institutional trading coefficient in Panel C of Table 5. This indicates an elasticity of 1.25 for returns to the amount of net institutional trading. The explanatory power of this variable, *Rebalancing Demand*, can be separated from the average linear effects of the stock characteristic used to construct it; that is, if *Rebalancing Demand* is residualized from past quarter's stock returns, it forecast negative stock returns univariately (untabulated). The cross section percentile of stocks ranked on their respective rebalancing demand, *Percentile Rebalancing Pressure,* also strongly forecasts future stock returns. In the fully specified regression in column (5), this variable forecasts a dispersion of 1.78% excess returns in the following quarter between the stocks with the highest rebalancing demand and the stocks with the lowest rebalancing demand. Column (3) and (6) includes both contemporaneous and lagged Flow Induced Price Pressure (*FIPP*) as control. *FIPP* is calculated as the share weighted average flow into a stock. Flow-induced demand has very little effect on the predictive regressions.

An interesting property of *Rebalancing Pressure* is that the inclusion of this characteristic into a multivariate regression accentuates the positive correlation between recent momentum characteristics and future returns. In all the regression specifications, the coefficients of past 3 month returns on future excess returns switch signs from being negative betas into positive ones. This fact can help reconcile the well-founded fact that momentum returns are driven mainly outside of recent past performances for US equities (Novy-Marx 2012, Goyal and Wahal 2015).

The Fama-Macbeth regression results indicate there are potential calendar time trading strategies associated with rebalancing demand. Table 7 performs additional tests on the tradability of these calendar time portfolios.

In Panel A of Table 7, I sort stocks into 5 quintiles using ranking on the predicted *Rebalancing Demand* calculated using information available at the end of the most recent quarter. Column (1) records the average value weighted monthly returns, in excess of the risk free rate, of these quintile portfolios during the following quarter. We observe that the stocks sorted to the top of the quintile portfolio have the lowest average excess returns. Still, decreasing *Rebalancing*

Demand doesn't monotonically increase the excess returns. The highest excess return portfolio is in the second quintile. As shown in the Panel A of Table 5, these are stocks that had experienced extremely negative returns in the past quarter (returns less than -10%), and are accompanied by increased likelihood of liquidation by their mutual fund owners in the following quarter. Still, after risk adjustments that account for Carthart 4-factors model, a strategy that longs the top quintile portfolio and shorts the bottom quintile portfolio does yield statistically significant negative return; consistent with stock demand.

As an alternative, a back tested strategy that ignores stocks that had extremely negative returns allows a more uniform calendar sort. Panel B focuses on the cross section of assets that recently had returns greater than -10% in the past quarter. I proceed to test the calendar time portfolio returns against various reduced form risk models. The cross section divergence in portfolio excess returns persists and is statistically significant in most of the tested risk factor models. The adjusted returns under the Carhart four-factor model for the rebalancing pressure is 49 basis points per month. The inclusion of a short term reversal factor doesn't significantly change my results. The unadjusted long short excess return is -30 basis points. Annualized, this is -3.7% per annum between 1990 and 2016; comparable to the 3% excess return of value, the 2% of size, 6% of momentum, and 2.7% factors during the same time period.

The excess returns and the time series residual alphas of the long/short portfolios are plotted in Figure 2. We observe that the returns tend to be marginally higher in the second half of the sample, and that no single period account for the significant portion of the excess returns.

Finally, I show that these returns tend to revert at longer horizons. This is consistent with short term non-fundamental price pressure similar to investor flows documented by Coval and Stafford () for extreme mutual fund flow portfolios. Figure 3 plots the cumulative risk adjusted excess returns of holding the long short portfolio from 1 month to 6 months. Most of the cumulative returns occur in the first and second months of the quarter. The abnormal returns start reverting in the second quarter, and disappear 6 months into the holding horizon.

4. Conclusion

How investors trade on past returns is central to behavioral finance. Investors may form extrapolative beliefs based on the recently realized returns. This would empirically appear as trend following and is consistent with speculative trading. However, investors has also shown the tendency to sell winners and keep losers within their existing portfolio. I show that the disposition toward selling winners and keeping losers in mutual fund portfolios is inherently rooted in the size of the asset weights within a portfolio. The active management of large positional exposures is consistent with diversification for risk management. This risk management function may or may not be optimal, and can be also rooted in behavioral biases- biases such as a salience toward large positions and prospect theory mental accounting investors. This paper shows that after accounting for this diversification motive, mutual fund investors display trend chasing behavior toward an asset's past returns- even for existing positions.

Furthermore, diversification motives drive coordination in investors. Realized returns within a short time frame may drive assets to have outsized exposures across existing investors. These investors, in actively managing their positional exposures, will generate demand in the cross section of equity assets. This paper shows that this demand is statistically significant and shows up in a noticeable cross section of equity investors.

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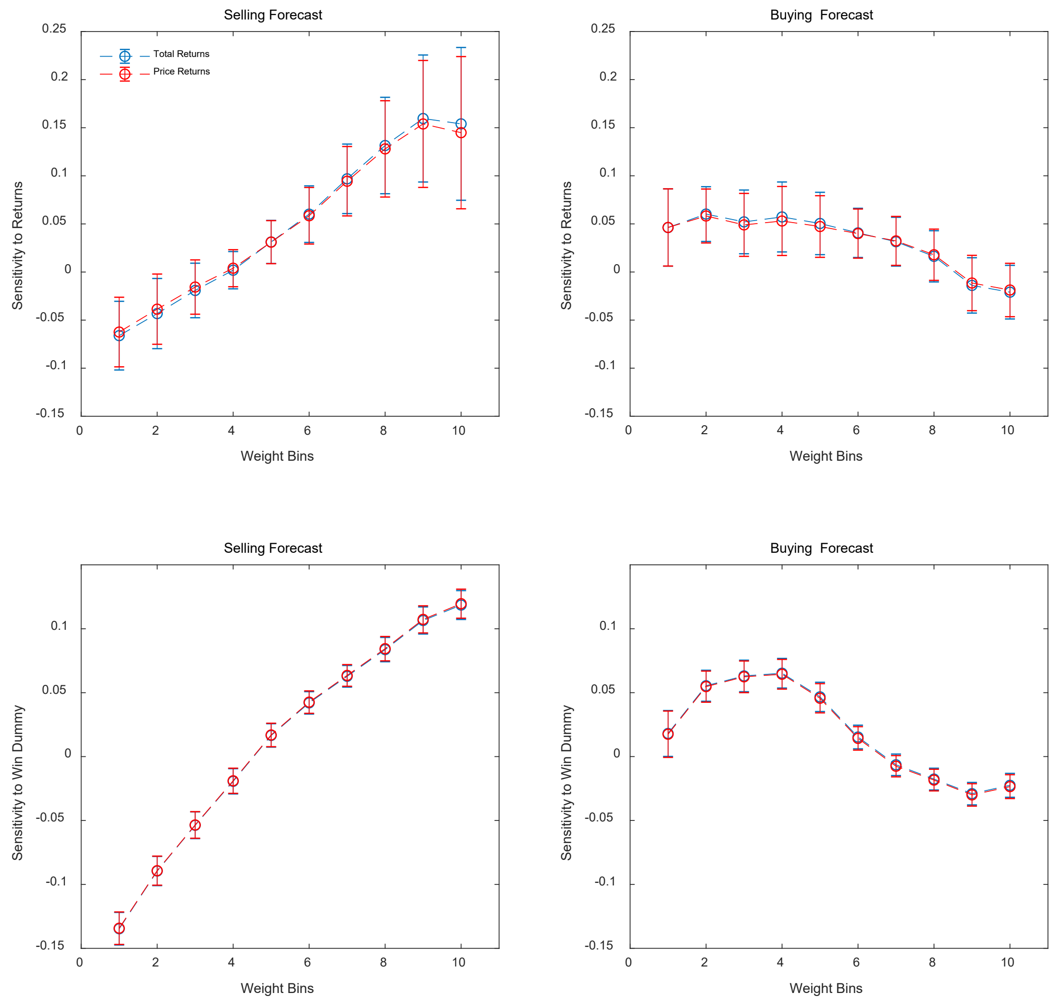

Figure 1. Piecewise regressions of trading on returns using the specifications:

$$Y_{i,j,t+1} = \sum_b \beta_b \cdot r_{i,t} \cdot (w_{i,j,t-1} \in Bin_b) + \epsilon_{t+1,i,j} \qquad \text{(Top)}$$

$$Y_{i,j,t+1} = \sum_b \beta_b \cdot Winner_{i,t} \cdot (w_{i,j,t-1} \in Bin_b) + \epsilon_{t+1,i,j} \qquad \text{(Bottom)}$$

for stock *i* in portfolio *j* at time *t*. $Y_{t+1,i,j}$ is an indictor variable representing the selling or buying of stock *i* by portfolio *j* between *t* and *t+1*. $r_{i,t}$ is stock *i*'s return between *t-1* and *t*. $w_{i,j,t-1}$ is the weight of asset *i* in portfolio *j* at *t-1*. Bin_b are ranges of weights that equally separates all of the observed position into 10 bins- from the smallest to the largest positions (as an alternative, Appendix F1 sorts positions into bins based on their weight within each portfolio/time set). The estimated beta coefficients of returns (top) and winner dummy (bottom) interacted by the initial position weights on next period's selling (left) and buying (right) and their 95% confidence interval are reported for each bin. We observe that large initial positions are particularly sensitive to returns and the winner dummy - stocks with positive returns are more likely to be sold and less likely to be bought by portfolios with large initial weights. Small initial positions have the opposite sensitivity- positive return positions are more likely to be bought and less likely to be sold by portfolios with low initial weights. This is true regardless of using price (red) or total (blue) returns as regressors on the right hand side.

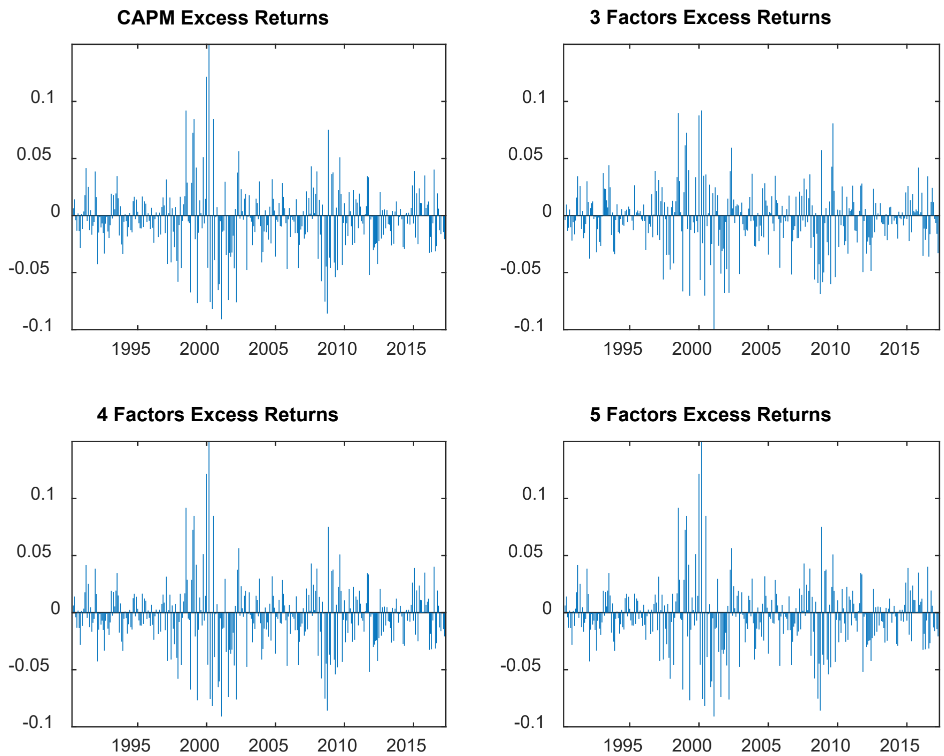

Figure 2. Residual returns of the 5 minus 1 Calendar Portfolios after factor adjustment. The sample consists of stocks with price greater than 5, market cap above the 10 percentile cutoff on the NYSE, and no larger than 10% loss in the past period's stock returns.

Table 1. Summary Statistics

Panel A. Stock x Portfolio x Time Summary

	N	Mean	Std	5th Pctl	25th Pctl	Median	75th Pctl	95th Pctl
$Sell_{i,j,t+1}$	13,027,128	32.98%	47.02%	0.00%	0.00%	0.00%	100.00%	100.00%
$Buy_{i,j,t+1}$	13,027,128	29.49%	45.60%	0.00%	0.00%	0.00%	100.00%	100.00%
$Liquidation_{i,j,t+1}$	13,027,128	9.05%	28.70%	0.00%	0.00%	0.00%	0.00%	100.00%
$Active_{i,j,t+1}$	12,774,250	-0.06%	0.46%	-0.67%	-0.02%	0.00%	0.01%	0.25%
$Passive_{i,j,t+1}$	12,774,250	0.00%	0.19%	-0.20%	-0.01%	0.00%	0.01%	0.20%
$Weight_{i,j,t-1}$	13,027,128	0.74%	1.11%	0.00%	0.06%	0.30%	1.03%	2.83%

Panel B. Mutual Fund x Time Summary

	N	Mean	Std	5th Pctl	25th Pctl	Median	75th Pctl	95th Pctl
$Num\ of\ Stock_{j,t-1}$	96,483	135.08	257.10	27	46	70	112	432
$TNA_{j,t-1}$ (\$Millions)	96,483	977	5,057	8	52	190	687	3,774
$Percentage\ Flow_{j,t-1}$	93,527	4.05%	84.55%	-13.67%	-4.40%	-1.09%	3.60%	27.22%

Panel C. Stock x Time Characteristics Summary

	N	Mean	Std	5th Pctl	25th Pctl	Median	75th Pctl	95th Pctl
$RebDemand_{j,t}$	274,765	0.01%	0.23%	-0.26%	-0.06%	0.00%	0.07%	0.31%
$Ret3m_{i,t}$	274,772	5.78%	25.95%	-28.07%	-7.15%	3.67%	15.45%	44.26%
$\Delta MF\_Hold_{i,t+1}$	221,996	20.05%	81.47%	-60.71%	-12.35%	1.34%	21.88%	178.35%
$\Delta IN\_Hold_{i,t+1}$	221,996	2.28%	10.70%	-13.50%	-2.63%	0.81%	5.33%	23.90%
$LBE_{i,t-1}$	266,686	12.99	8.51	10.60	11.88	12.86	13.99	15.86
$LME_{i,t}$	274,772	13.79	1.57	11.53	12.67	13.60	14.75	16.70
$InstOwn_{i,t-1}$	274,772	53.09%	27.42%	1.26%	32.32%	55.78%	75.74%	93.31%
$FIPP_{i,t}$	274,772	1.60%	8.50%	-4.86%	-1.46%	0.44%	3.14%	11.01%

Table 2. Piece-Wise Regression of Buying and Selling on Past Returns. This table regresses trading dummies on piece-wise returns, initial position weights, rank effect dummy, and fixed effects due to time/fund and time/stock. The main specifications are:

$$Y_{i,j,t+1} = \sum_{b} \beta_b \cdot Winner_{i,t} \cdot (w_{i,j,t-1} \in Bin_b) + \sum_{k} \beta_k \cdot Ctrl\_k_{i,j,t} + \epsilon_{t+1,i,j}$$

$Y_{i,j,t+1}$ is the left hand-side variable indicating Selling (*Sell*) or Buying (*Buy*) of shares by the mutual fund. The variable $Winner_{i,t}$ indicates that stock *i* had positive price returns between periods *t-1* and *t*. Bin_b are ranges of weights that equally separates all of the observed position into 10 bins- from the smallest to the largest positions. Controls used are bin fixed effects, Time X Fund fixed effects, Time X Stock fixed effect, and the Rank Effect of extreme returns. The coefficients are tabulated in percentages. The standard errors are clustered quarterly.

	All Funds						Funds with Outflow		Funds with Inflow	
	$Sell_{i,j,t+1}$			$Buy_{i,j,t+1}$			$Sell_{i,j,t+1}$	$Buy_{i,j,t+1}$	$Sell_{i,j,t+1}$	$Buy_{i,j,t+1}$
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
$Win_{i,t} \cdot Bin_1$	-0.33	-0.35	-0.38	**4.32**	**4.52**	**4.56**	-0.18	**3.61**	-0.46	**5.30**
	(-0.55)	(-0.90)	(-0.97)	**(4.97)**	**(11.76)**	**(11.89)**	(-0.29)	**(9.17)**	(-1.45)	**(10.83)**
$Win_{i,t} \cdot Bin_2$	0.08	0.23	0.24	**2.43**	**2.82**	**3.04**	0.48	**2.70**	-0.04	**3.45**
	(0.15)	(0.75)	(0.79)	**(4.18)**	**(11.00)**	**(12.26)**	(1.15)	**(7.76)**	(-0.18)	**(9.48)**
$Win_{i,t} \cdot Bin_3$	0.19	**0.51**	**0.57**	**1.59**	**2.03**	**2.32**	**0.98**	**2.08**	0.19	**2.56**
	(0.44)	**(2.10)**	**(2.32)**	**(2.82)**	**(7.89)**	**(9.29)**	**(2.55)**	**(7.02)**	(0.90)	**(8.83)**
$Win_{i,t} \cdot Bin_4$	0.20	**0.65**	**0.75**	**1.83**	**2.06**	**2.35**	**1.12**	**1.96**	0.72	**2.20**
	(0.46)	**(3.05)**	**(3.40)**	**(3.17)**	**(7.73)**	**(8.94)**	**(4.32)**	**(7.51)**	**(3.16)**	**(6.05)**
$Win_{i,t} \cdot Bin_5$	0.62	**1.26**	**1.49**	**2.05**	**2.08**	**2.28**	**2.33**	**1.39**	**1.00**	**2.43**
	(1.44)	**(5.38)**	**(6.11)**	**(3.31)**	**(6.29)**	**(6.95)**	**(8.75)**	**(4.63)**	**(3.44)**	**(6.08)**
$Win_{i,t} \cdot Bin_6$	**1.12**	**1.84**	**2.16**	**2.10**	**1.99**	**2.10**	**3.35**	**0.88**	**1.31**	**2.72**
	(2.86)	**(8.13)**	**(9.44)**	**(4.68)**	**(8.15)**	**(8.46)**	**(12.53)**	**(3.45)**	**(5.04)**	**(7.15)**
$Win_{i,t} \cdot Bin_7$	**2.10**	**2.83**	**3.24**	**1.86**	**1.70**	**1.76**	**4.66**	0.36	**2.00**	**2.72**
	(5.93)	**(13.22)**	**(14.55)**	**(5.58)**	**(7.85)**	**(8.20)**	**(20.66)**	(1.64)	**(8.48)**	**(8.66)**
$Win_{i,t} \cdot Bin_8$	**2.61**	**3.38**	**3.96**	**1.36**	**1.21**	**1.18**	**5.45**	-0.32	**2.56**	**2.35**
	(6.84)	**(17.39)**	**(18.51)**	**(4.77)**	**(5.30)**	**(5.02)**	**(24.59)**	(-1.38)	**(11.47)**	**(7.62)**
$Win_{i,t} \cdot Bin_9$	**3.17**	**3.88**	**4.68**	0.25	0.07	0.03	**6.44**	**-1.42**	**3.05**	**1.04**
	(7.49)	**(15.29)**	**(17.48)**	(1.04)	(0.31)	(0.13)	**(23.12)**	**(-5.97)**	**(13.60)**	**(3.42)**
$Win_{i,t} \cdot Bin_{10}$	**2.67**	**3.48**	**4.72**	-0.18	-0.31	-0.51	**7.23**	**-2.30**	**3.40**	-0.36
	(5.56)	**(12.68)**	**(16.95)**	(-0.72)	(-1.13)	(-2.13)	**(21.30)**	**(-8.19)**	**(12.56)**	(-1.01)
$Rank\ Effect_{i,t}$	-0.24	-0.09	**-1.03**	**-7.80**	**-6.87**	**-5.70**	**-3.29**	**-3.25**	**2.20**	**-8.60**
	(-0.80)	(-0.33)	**(-4.13)**	**(-28.84)**	**(-26.52)**	**(-26.45)**	**(-12.58)**	**(-17.13)**	**(8.07)**	**(-25.43)**
Bin Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time X Fund Fixed Effects	NO	YES	YES	NO	YES	YES	YES	YES	YES	YES
Time X Stock Fixed Effects	NO	NO	YES	NO	NO	YES	YES	YES	YES	YES
Adj. R^2	0.027	0.098	0.112	0.006	0.105	0.125	0.125	0.076	0.112	0.199
N	13,007,628	13,007,628	13,002,481	13,007,628	13,007,628	13,002,481	6,835,856	6,835,856	6,153,044	6,153,044

Table 3. Forecasting trades by fund managers using portfolio weights. This table forecasts trading of stock i by mutual fund j between t and $t+1$. The main specification is:

$$Y_{i,j,t+1} = \beta_1 \cdot Winner_{i,t} + \beta_2 \cdot Passive_{i,j,t} + \beta_3 \cdot Weight_{i,j,t-1} + \sum_k \beta_k \cdot Ctrl\_k_{i,j,t} + \epsilon_{t+1,i,j}.$$

$Y_{i,j,t+1}$ describes trading of share i by the mutual fund j between t and $t+1$. $Sell_{i,j,t+1}$ is an indicator variable for a decrease of shares, $Buy_{i,j,t+1}$ indicates an increase in shares, and $Active_{i,j,t+1}$ is calculated as the difference between the actual weight of stock i and the projected weight of stock i assuming no cash reinvestments (or redemptions) by fund j between t and $t+1$. The Time X Stock fixed effect are dropped in favor of the $Winner_{i,t}$ variable, which indicates whether stock i has positive returns between $t-1$ and t. $Passive_{i,j,t}$ is the difference between the project weight of stock i assuming no cash reinvestments (or redemption) by fund j between $t-1$ and t. $Passive^{+}_{i,j,t}$ is calculated as $Passive_{i,j,t} \cdot \mathbf{1}(Passive_{i,j,t} > 0)$, while $Passive^{-}_{i,j,t}$ is $Passive_{i,j,t} \cdot \mathbf{1}(Passive_{i,j,t} < 0)$. $Weight_{i,j,t-1}$ is the initial weight of stock i in portfolio j at $t-1$. The standard errors are clustered quarterly.

	$Sell_{i,j,t+1}$			$Buy_{i,j,t+1}$			$Active_{i,j,t+1}$		
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[10]
$Winner_{i,t}$	2.02%	0.68%	0.77%	1.98%	2.44%	2.33%	-0.02%	0.01%	0.01%
	(15.65)	(4.99)	(5.80)	(12.01)	(14.89)	(15.67)	(-9.45)	(7.58)	(4.51)
$Passive_{i,j,t}$		8.05			-3.15			-0.17	
		(16.19)			(-7.39)			(-20.89)	
$Passive^{+}_{i,j,t}$			11.34			-7.52			-0.29
			(8.72)			(-7.27)			(-14.30)
$Passive^{-}_{i,j,t}$			3.92			2.27			-0.02
			(6.44)			(4.59)			(-1.71)
$Weight_{i,j,t-1}$		4.16	3.81		-0.13	0.34		-0.07	-0.06
		(32.65)	(26.12)		(-1.30)	(3.04)		(-39.31)	(-29.34)
Time X Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.083	0.091	0.091	0.102	0.102	0.102	0.015	0.046	0.047
N	13,007,628	13,001,804	13,001,804	13,007,628	13,001,804	13,001,804	12,749,215	12,749,174	12,749,174

Table 4. Horizon of Rebalancing Predictability. Discretionary rebalancing ($Active_{i,j,t+1}$) is regressed against *Passive* weight change at various lags, contemporaneous *Passive*, and the most recent available portfolio weight information ($Weight_{i,j,t-1}$). Time x Stock and Time x Fund fixed effects are included. The standard errors are clustered quarterly.

	$Active_{i,j,t+1}$			
	[1]	[2]	[3]	[4]
$Passive_{i,j,t+1}$			**-0.20**	**-0.20**
			(-15.96)	**(-15.53)**
$Passive_{i,j,t}$	**-0.17**	**-0.16**	**-0.17**	**-0.17**
	(-18.16)	**(-17.50)**	**(-22.22)**	**(-20.84)**
$Passive_{i,j,t-1}$	**-0.08**	**-0.01**	**-0.08**	**-0.02**
	(-11.52)	**(-2.09)**	**(-12.79)**	**(-2.68)**
$Passive_{i,j,t-2}$	**-0.07**	-0.01	**-0.07**	-0.01
	(-10.65)	(-1.89)	**(-10.64)**	(-1.91)
$Passive_{i,j,t-3}$	**-0.03**	**0.02**	**-0.03**	**0.02**
	(-4.18)	**(3.27)**	**(-4.46)**	**(2.80)**
$Passive_{i,j,t-4}$	**-0.04**	0.00	**-0.04**	0.00
	(-6.14)	(0.60)	**(-6.34)**	(0.16)
$Passive_{i,j,t-5}$	**-0.03**	0.01	**-0.03**	0.01
	(-5.15)	(0.80)	**(-4.76)**	(0.98)
$Passive_{i,j,t-6}$	**-0.03**	0.00	**-0.03**	0.00
	(-5.51)	(0.35)	**(-5.63)**	(0.04)
$Passive_{i,j,t-7}$	**-0.03**	0.00	**-0.04**	0.00
	(-5.67)	(-0.02)	**(-5.80)**	(-0.15)
$Weight_{i,j,t-1}$		**-0.08**		**-0.08**
		(-35.50)		**(-34.75)**
Time X Stock Fixed Effects	YES	YES	YES	YES
Time X Fund Fixed Effects	YES	YES	YES	YES
Adj. R^2	0.0390	0.0656	0.0433	0.0701
N	6,748,265	6,748,265	6,748,265	6,748,265

Table 5. Changes in aggregate portfolio.

Panel A. This Panel sorts stocks each quarter into 5 groups based on their relative ranking of *Rebalancing Demand* each quarter. Stocks with lag prices greater than 5 dollars and market caps greater than the 10th percentile of NYSE firms are sorted equally into 5 portfolios. The values reported are the quarterly averages of the value-weighted portfolio characteristics between Q1 1990 and Q4 2016. Column 2 is the rebalancing demand. Column 3 is the realized return. Column 4 is the percent of mutual funds observed to increase shares in the stocks. Column 5 is the percent of mutual funds observed to decrease shares. Column 6 is the percent of mutual funds observed to liquidate shares. Column 7 is the quarterly percent change in institutional holdings. Column 8 is the quarterly percent change in mutual fund holdings. The values per stock-time observed in the last two columns are winsorized at 2.5% in each tail.

Rank	Rebalancing Demand	Quarter Returns	% of MFs Increase	% of MFs Decrease	% of MFs Liquidated	Δ Institutions Shares	Δ Mutual Funds Shares
1	-0.19%	-10.07%	35.52%	29.30%	8.62%	0.48%	9.43%
2	-0.05%	-1.62%	33.67%	28.07%	8.03%	0.89%	11.99%
3	0.00%	3.22%	32.54%	28.27%	7.56%	0.94%	17.66%
4	0.06%	8.24%	31.45%	30.52%	7.31%	0.81%	10.63%
5	0.22%	19.21%	30.69%	35.29%	6.69%	0.68%	7.26%

Panel B. This panel tabulates the weighted regression of increases in Mutual Fund or Institutional ownership on Rebalancing Demand and stock characteristics. $MF\_INC_{i,t+1}$ ($IN\_INC_{i,t+1}$) is 1 if mutual funds (13-F institutions) increased their share of total stocks outstanding of firm i, and 0 otherwise. The regression weights are stock market capital share ($MktCap_{i,t-1}/\sum MktCap_{j,t-1}$). $RebalancingDemand_{i,t+1}$ is the share weighted average passive increase in portfolio weights across mutual funds. $Ret_{i,t}$ is the quarterly stock return. $Weight_{i,t-1}$ is the shared weighted portfolio weight. $LBE_{i,t-1}$ is the quarterly log book equity. $LME_{i,t-1}$ is the log market equity. $InstOwn_{i,t-1}$ is the percent of shares in stock *i* owned by institutions. The standard errors are clustered quarterly.

	Increase in Mutual Fund Ownership ($MF\_INC_{i,t+1}$)			Increase in Institutional Ownership ($IN\_INC_{i,t+1}$)		
	[1]	[2]	[3]	[4]	[5]	[6]
$RebDemand_{i,t+1}$	**-6.29%**	**-13.65%**	**-12.72%**	**-7.93%**	**-11.98%**	**-9.12%**
	(-2.57)	**(-2.85)**	**(-2.73)**	**(-3.08)**	**(-2.59)**	**(-2.03)**
$Ret3m_{i,t}$		0.10	0.10		0.06	0.03
		(1.84)	(1.87)		(1.19)	(0.60)
$Weight_{i,t-1}$			**-3.89**			**-2.98**
			(-4.99)			**(-4.66)**
$LBE_{i,t-1}$			**2.03%**			**1.26%**
			(3.25)			**(2.70)**
$LME_{i,t}$			-0.52%			-0.90%
			(-0.65)			(-1.47)
$InstOwn_{i,t-1}$			**-0.06**			**-0.12**
			(-2.80)			**(-5.58)**
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.193	0.193	0.198	0.1787	0.1788	0.1843
N	221,989	221,989	215,524	221,989	221,989	215,524

Panel C. This panel tabulates the weighted regression of percent increases in Mutual Fund or Institutional ownership on Rebalancing Demand and stock characteristics. $\Delta MF\_Hold_{i,t+1}$ ($\Delta IN\_Hold_{i,t+1}$) is the percent change in mutual fund (institutional) holdings of firm i. The regression weights are stock market capital share ($MktCap_{i,t-1}/\sum MktCap_{j,t-1}$). Rebalancing Demand ($RebDemand_{i,t+1}$) is the share weighted average passive increase in portfolio weights across mutual funds calculated using information available at *t*. $Ret3m_{i,t}$ is the past quarter's stock return. $Weight_{i,t-1}$ is the shared weighted portfolio weight. $LBE_{i,t-1}$ is the quarterly log book equity. $LME_{i,t-1}$ is the log market equity. $InstOwn_{i,t-1}$ is the percent of shares in stock *i* owned by institutions. The standard errors are clustered quarterly.

	Change in Mutual Fund Ownership ($\Delta MF\_Hold_{i,t+1}$)			Change in Institutional Ownership ($\Delta IN\_Hold_{i,t+1}$)		
	[1]	[2]	[3]	[4]	[5]	[6]
$RebDemand_{i,t+1}$	**-5.32**	**-13.88**	**-6.32**	0.35	**-2.98**	**-1.88**
	(-3.19)	**(-5.04)**	**(-2.57)**	(1.13)	**(-5.32)**	**(-3.54)**
$Ret3m_{i,t}$		**0.12**	0.04		**0.05**	**0.03**
		(3.30)	(1.38)		**(6.70)**	**(5.45)**
$Weight_{i,t-1}$			-1.20			**-0.30**
			(-1.64)			**(-3.59)**
$LBE_{i,t-1}$			**1.26%**			0.08%
			(2.68)			(1.10)
$LME_{i,t}$			**-4.13%**			**-0.41%**
			(-6.24)			**(-5.36)**
$InstOwn_{i,t-1}$			**-0.28**			**-0.04**
			(-5.89)			**(-7.74)**
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.190	0.192	0.195	0.171	0.172	0.176
N	236,843	236,843	229,981	236,843	236,843	229,981

Table 6. Value Weighted Fama Macbeth Regressions of Rebalancing Demand and Stock Returns. The cross sectional regressions are weighted by stock market cap. Rebalancing Demand ($RebDemand_{i,t+1}$) is the share weighted average passive increase in portfolio weights across mutual funds calculated using information available at *t*. Percentile Rebalancing Demand ($PRebDemand_{i,t+1}$) is the cross sectional percentile rank of Rebalancing Demand. $Ret3m_{i,t}$, $Ret4\_6m_{i,t}$, and $Ret7\_12m_{i,t}$ are the stock returns from past quarter, 4 to 6 months, and 7 to 12 months past respectively. $Weight_{i,t-1}$ is the shared weighted portfolio weight. $LBE_{i,t-1}$ is the quarterly log book equity. $LME_{i,t-1}$ is the log market equity. $InstOwn_{i,t-1}$ is the percent of shares in stock *i* owned by institutions. $FIPP_{i,t}$ is the share weighted percent investor flow into the mutual funds that hold stock *i* between *t-1* to *t*; and *t* to *t+1* (contemporaneous as the left hand stock returns).

	Next Quarter's Returns ($Ret3m_{i,t+1}$)					
	[1]	[2]	[3]	[4]	[5]	[6]
$RebDemand_{i,t+1}$	**-4.03**	**-2.84**	**-2.35**			
	(-2.99)	**(-2.31)**	**(-1.96)**			
$PRebDemand_{i,t+1}$				**-2.23**	**-1.68**	**-1.50**
				(-3.58)	**(-3.20)**	**(-2.95)**
$Ret3m_{i,t}$	0.04	0.01	0.00	**0.05**	0.02	0.01
	(1.76)	(0.70)	(0.23)	**(2.07)**	(1.17)	(0.80)
$Ret4\_6m_{i,t}$		0.01	0.01		0.01	0.01
		(0.84)	(0.98)		(0.80)	(0.95)
$Ret7\_12m_{i,t}$		**0.02**	**0.02**		**0.02**	**0.02**
		(2.01)	**(2.18)**		**(1.95)**	**(2.13)**
$Weight_{i,t-1}$		-0.13	-0.09		-0.13	-0.09
		(-0.73)	(-0.51)		(-0.71)	(-0.49)
$LBE_{i,t-1}$		0.00%	-0.03%		0.00%	-0.03%
		(-0.00)	(-0.14)		(-0.00)	(-0.14)
$LME_{i,t}$		-0.07%	0.03%		-0.06%	0.04%
		(-0.27)	(0.12)		(-0.24)	(0.15)
$InstOwn_{i,t-1}$		0.00	0.00		0.00	0.00
		(0.48)	(0.78)		(0.58)	(0.88)
$FIPP_{i,t}$			**-0.45**			**-0.45**
			(-7.62)			**(-7.67)**
$FIPP_{i,t+1}$			**0.74**			**0.74**
			(11.01)			**(10.94)**
Avg. Adj. R^2	0.033	0.121	0.137	0.033	0.121	0.137
Avg. N	2,316	2,244	2,244	2,316	2,244	2,244

Table 7. Calendar Time Portfolios.

Panel A. Calendar sort and adjusted excess returns on *Rebalancing Demand*. Stocks with lag prices greater than 5 dollars and market caps greater than the 10th percentile of NYSE firms are sorted equally into 5 portfolios. The following panel reports the value weighted risk-adjusted excess return of these portfolios. The 3 Factors adjustment uses the Fama French factors. The 4 Factors adjustment uses the Fama French plus the momentum factor. The 5 Factors adjustment adds a short run reversal factor.

Rank	Excess Return	CAPM Adjusted	3 Factors Adjusted	4 Factors Adjusted	5 Factor Adjusted
1	**0.66%**	-0.10%	-0.08%	0.14%	**0.19%**
	(2.16)	(-0.76)	(-0.59)	(1.23)	**(1.96)**
2	**0.86%**	**0.24%**	**0.20%**	**0.29%**	**0.22%**
	(3.60)	**(2.86)**	**(2.58)**	**(4.03)**	**(3.06)**
3	**0.67%**	0.11%	0.05%	0.06%	**0.25%**
	(3.15)	(1.67)	(0.90)	(1.02)	**(3.36)**
4	**0.55%**	-0.04%	-0.06%	-0.16%	-0.05%
	(2.43)	(-0.55)	(-0.82)	(-2.44)	(-0.68)
5	**0.57%**	-0.11%	-0.04%	-0.25%	-0.22%
	(2.06)	(-0.80)	(-0.31)	(-2.36)	(-2.58)
LS	-0.09%	0.00%	0.04%	**-0.39%**	**-0.40%**
	(-0.36)	(-0.02)	(0.16)	**(-1.96)**	**(-2.42)**

Panel B. Calendar sort and adjusted excess returns on *Rebalancing Demand* ignoring low return stocks. Stocks with past quarter returns greater than -10%, lag prices greater than 5 dollars, and market caps greater than the 10th percentile of NYSE firms are sorted equally into 5 portfolios. The following panel reports the value weighted risk-adjusted excess return of these portfolios. The 3 Factors adjustment uses the Fama French factors. The 4 Factors adjustment uses the Fama French plus the momentum factor. The 5 Factors adjustment adds a short run reversal factor to the 4 Factors model.

Rank	Excess Return	CAPM Adjusted	3 Factors Adjusted	4 Factors Adjusted	5 Factor Adjusted
1	**0.90%**	**0.34%**	**0.29%**	**0.28%**	**0.28%**
	(4.10)	**(4.01)**	**(3.73)**	**(3.59)**	**(3.55)**
2	**0.70%**	0.15%	0.08%	0.05%	0.04%
	(3.20)	(1.66)	(0.98)	(0.56)	(0.48)
3	**0.54%**	0.01%	-0.06%	-0.10%	-0.11%
	(2.57)	(0.14)	(-0.71)	(-1.30)	(-1.32)
4	**0.56%**	-0.03%	-0.07%	-0.15%	-0.15%
	(2.44)	(-0.37)	(-0.80)	(-1.86)	(-1.87)
5	**0.60%**	-0.06%	-0.01%	**-0.21%**	**-0.20%**
	(2.26)	(-0.46)	(-0.06)	**(-2.15)**	**(-2.07)**
LS	-0.30%	**-0.39%**	-0.29%	**-0.49%**	**-0.48%**
	(-1.81)	**(-2.41)**	(-1.94)	**(-3.53)**	**(-3.48)**