The power of investor flows data to augment performance

A newly developed dataset, Addepar Investor Flows[SM], can be used for performance attribution, risk assessment and to uncover new investment opportunities

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1. Welcome

Investors frequently revise their portfolios in response to evolving market conditions, investment opportunities and return realizations. These flows, which we define as net cash flows investors invest or divest from assets, provide unique insights to understand investors' portfolio and market assumptions. While flows to mutual funds, ETFs and hedge funds are widely covered, little is known about the flows and trading decisions of private wealth investors.

In this Addepar Research Brief (ARB), we use a new data set from the Addepar Research platform to create Addepar Investor Flows[SM], an innovative look at investor flows across asset classes.[1] We use these new data to shed light on three important questions:

1. How much do investors' trading decisions across asset classes affect their performance? We find it to be significant, with large differences across investors.

2. How do investors respond to turbulent market episodes, and how is this behavior influenced by factors such as investors' wealth, trading activity and advisor type? We find that trading activity picks up when the stock market falls and when market volatility spikes.

3. How does investors' turnover relate to risk-adjusted performance (or alphas) in the most commonly held asset class, U.S. equities? We find a negative relationship between turnover

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[1] This ARB summarizes the key insights of an academic research paper published by Gabaix, Koijen, Mainardi, Oh and Yogo (2022). The latest version can be downloaded at https://ssrn.com/abstract=4251972, and will be updated regularly as our research progresses.

and alphas, implying that more frequent rebalancing hurts — rather than improves — investor performance.

We conclude by discussing the ARB-itrage opportunities: how to leverage these findings to benchmark your own performance and derive actionable insights to navigate changing market environments.

2. NTK

Here are the key takeaways you need to know (NTK) from this brief.

- **Trading decisions and investor returns**: Using Addepar Investor Flows, we measure the impact of trading decisions on investor performance. By comparing an investor's actual allocation to the investor's average allocation over time, we find that trading decisions have a significant impact on returns. This implies that analyzing trading decisions is important for performance attribution and to identify new opportunities and potential risks.

- **Trading during market downturns:** Trading activity increases during times of market turmoil, and we find large differences in how investors respond to declines in the stock market. While the average investor sells U.S. equities during market downturns, the wealthiest investors increase their allocation to equities. This includes investors who are advised by a single-family office, because they tend to lean against the market and buy equities when markets fall. Also, investors who are generally more active in the stock market act more pro-cyclically on average.

- **Turnover and investment performance in U.S. equities:** We find a negative relationship between turnover in U.S. equities and investors' risk-adjusted returns. This underscores the importance of assessing whether active rebalancing improves or hurts performance.

- **New benchmarks:** The Addepar Investor Flows dataset provides insights into how an investor revises her portfolio and provides new opportunities for performance attribution. Furthermore, by monitoring Addepar Investor Flows over time, investors better understand how other private wealth investors evaluate risks and opportunities in global financial markets, which can serve as a valuable input in building investment strategies.

3. Significance

The new Addepar Investor Flows provide a benchmark for an investor's own trading strategy. It can also be used to identify important emerging themes in financial markets that come with their own risks and opportunities. This is particularly valuable when economic conditions change quickly, for instance due to new developments related to inflation, monetary policy or geopolitics.

To illustrate the significance of trading decisions across asset classes, we construct two return series for each investor who invests in at least three asset classes (see the appendix for the list of asset classes) and whom we observe for at least 10 quarters. One return series uses the actual allocation across asset classes; it provides the realized return of an investor. The other, which is the benchmark return series, uses the average portfolio shares that we observe for that investor over the same period.

We first provide an example for one investor in our sample in Figure 1. This investor reduces her allocation to equities during the onset of the COVID-19 crisis. As markets rallied in the following quarters, the fixed-share benchmark outperformed.

Figure 1

An illustration of the impact of trading decisions on the cumulative portfolio return
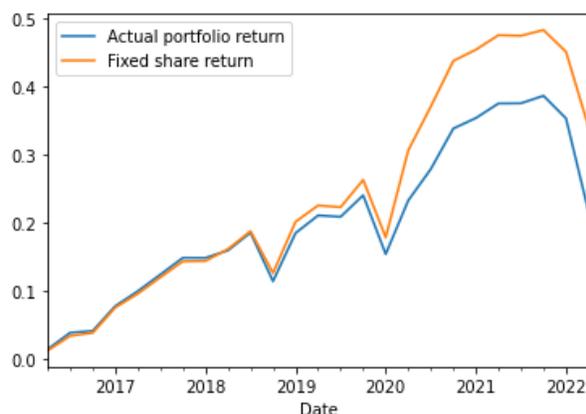
Source: Addepar Research

To show the impact of rebalancing decisions more broadly, we summarize the distribution of quarterly returns across investors in Figure 2. In the left panel, we provide a scatterplot of the actual return series (horizontal axis) and the benchmark return series (vertical axis). In the right

panel, we plot a histogram of the difference in returns. If an investor maintains a fixed-share allocation across asset classes, such as a 60/40 stock/bond allocation, the returns are identical and the difference is zero. In this scenario, the returns will perfectly align along the 45-degree line in the left panel and all return differences would be zero in the right panel.

Figure 2

The impact of trading decisions on the performance of investor portfolios
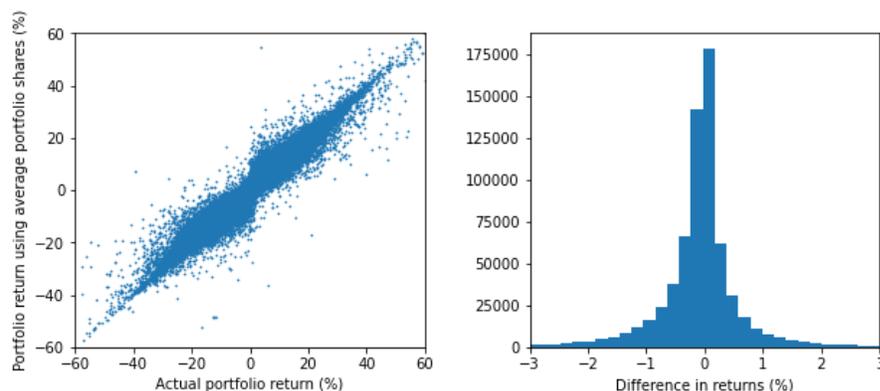
Source: Addepar Research

We find significant deviations from the fixed-share benchmark. **Investors often realize return differences of 1–2% per quarter by deviating from a fixed-share benchmark,** which can accumulate to large performance differentials. These performance differences can be substantial, compared to the typical alpha estimates within asset classes and are best understood by a simple example. If an investor, for instance, decides to move out of equities during the COVID-19 turmoil in March of 2020, she misses out on the sharp recovery that followed. Such decisions significantly impact performance.

For these reasons, it's important to understand investors' trading decisions across asset classes.

4. Context

Flows from institutional investors — such as mutual funds, ETFs and hedge funds — are widely studied to assess how various investor groups adjust their positioning in financial markets.[2]

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[2] See Ben-David, Franzoni and Moussawi (2012).

Likewise, flows from retail investors into various mutual funds and ETFs (both broad-based passive funds as well more thematic funds) are of interest to gauge retail investors' sentiment.[3]

At the level of asset classes, institutional investors typically do not aggressively time the market and many stick closely to a (fixed-share) strategic benchmark (Gabaix and Koijen, 2022). To illustrate this, we repeat the earlier calculation of constructing benchmark series, but this time for pension plans for the period from 2002 to 2022. The results are reported in Figure 3.

Figure 3

The impact of trading decisions on the performance of pension funds
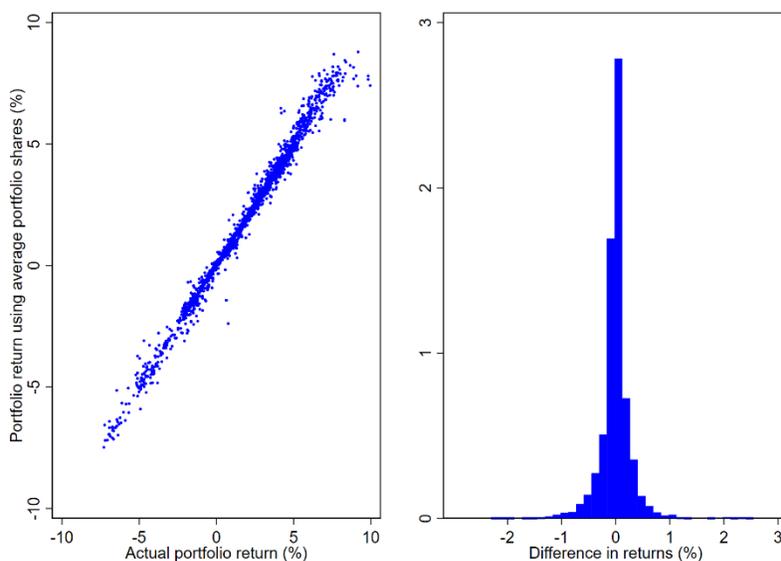
Source: Addepar Research

As expected, the returns are more tightly clustered compared to those of private wealth investors.[4] This reinforces the importance of studying trading decisions of private wealth investors.

5. Approach

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[3] See Ben-David, Franzoni, Kim and Moussawi (2023).
[4]This finding is consistent with the classic article of Brinson, Hood and Beebower (1986), who show that performance differences across pension funds can be traced back largely to differences in the strategic asset allocation.

We now turn to studying the trading decisions of private wealth investors. We first describe the methodology and then discuss the core findings.

Sample construction

We use data from January 2016 to June 2022. We construct quarterly flows and returns at the level of the narrow and broad asset classes listed in the appendix. We restrict the sample to accounts with at least $100,000 in assets and investments in at least three liquid asset classes. This leaves us with 77,794 unique portfolios and more than $1.3 trillion in assets in Q2 2022.

We focus on public, liquid asset classes and cash. We study the flow to cash separately; these flows tend to be excessively volatile as cash is used to absorb temporary liquidity shocks. It also plays a key role as a safe asset, as we show below. For most of the analysis, we do not focus on private assets as those cannot be traded easily in response to changing market conditions given their illiquid nature.

Defining flows

To measure the flow into an asset class, we take the difference between the end-of-period assets and beginning-of-period assets and remove the impact of price effects. This measure of flows captures the pure trading decisions. We then normalize this dollar flow by the average amount of assets at the beginning and the end of the period (again, adjusted for price effects).

Measuring differences across investors

Investors follow vastly different trading strategies that ultimately lead to significant differences in returns. We first measure how different groups of investors revise their portfolios in response to U.S. equity returns. We group investors by wealth as measured by total assets on the platform, by how active they are and whether they are advised by a single-family office.

We form five wealth groups (< $3 million, $3–10 million, $10–30 million, $30–100 million, and >$100 million). To measure how active an investor is, we compute two measures. First, we measure an investor's monthly turnover within U.S. equities, which is the most commonly held asset class. Second, we compute the fraction of stocks within U.S. equities that the investor does not trade (on average) in a given month. We refer to the second measure as inertia.

In Figure 4, we plot how the average turnover (left panel) and inertia (right panel) across investors in a given quarter evolves during our sample period. We find that investors are more likely to trade

during times of stress (for instance, the fourth quarter of 2018, or the first quarter of 2020 during the COVID-19 pandemic). As expected, the two measures are negatively correlated (-58%).

Figure 4

Average turnover (left panel) and inertia (right panel) across investors
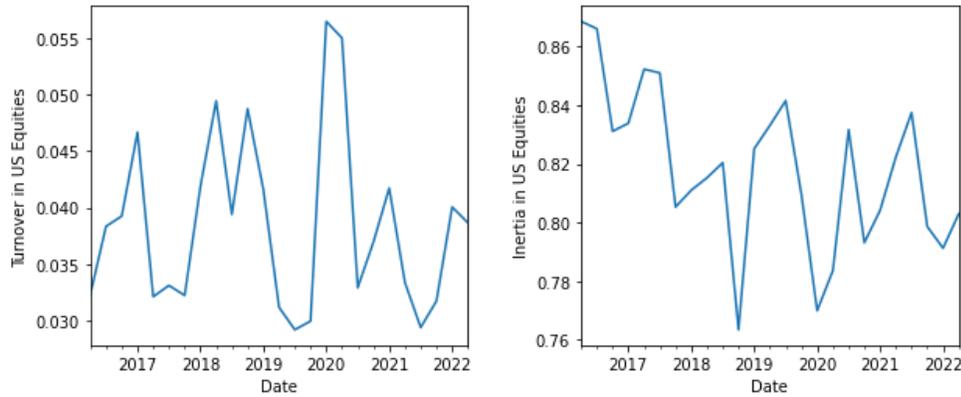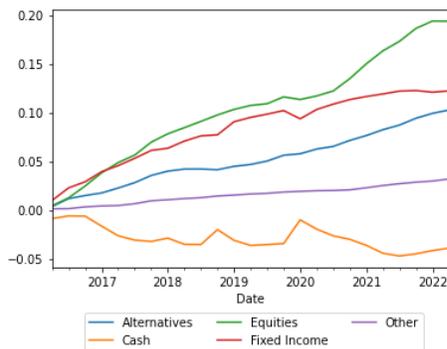

Source: Addepar Research

6. Findings

To lead our analysis, we report the cumulative flows into broad asset classes in Figure 5. During our sample period, the flow out of cash is negative. This is perhaps in part driven by the low-rate environment, while there are significant flows into public equities, fixed income and alternatives. We see two periods during which the allocation to cash increases, Q4 of 2018 and Q1 of 2020, which will be salient periods throughout our analysis.

Figure 5

Cumulative flows into broad asset classes.

In Figure 6, we zoom in on the flow to liquid assets and cash. We find that the two series are strongly negatively correlated (-71%). During times of stress, investors on average reallocate capital from liquid, risky assets to cash — signifying that cash is perceived as a safe asset.

Figure 6

Flows into liquid assets and cash
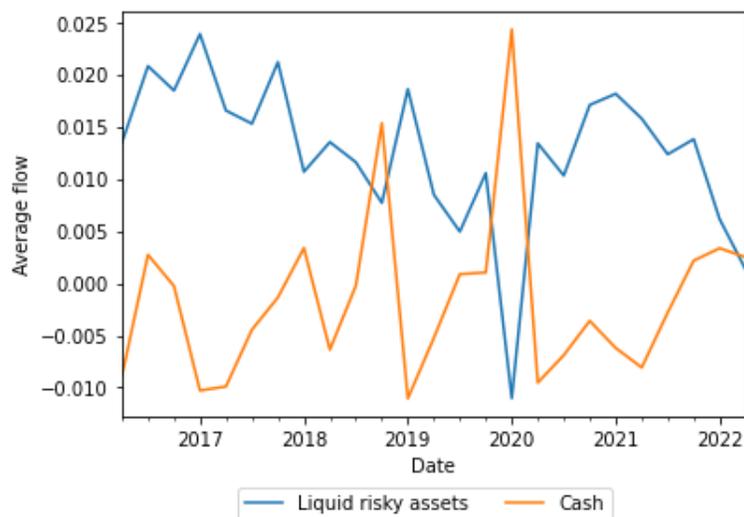
In Figure 7, we align the average flow to liquid assets with the return on the U.S. equity market in the left panel. As already suggested by Figure 5, private wealth investors tend to lower their allocation to liquid, risky assets when equity returns are negative. The correlation between the series is 71%. In the right panel of Figure 6, we compute the dispersion in flows across investors as a measure of investor disagreement. We find that during 2018 and 2020, disagreement increases when the stock market falls, although — interestingly — this doesn't happen during the equity market downturn in 2022.

Figure 7

Average flow, disagreement in flows and U.S. equity returns
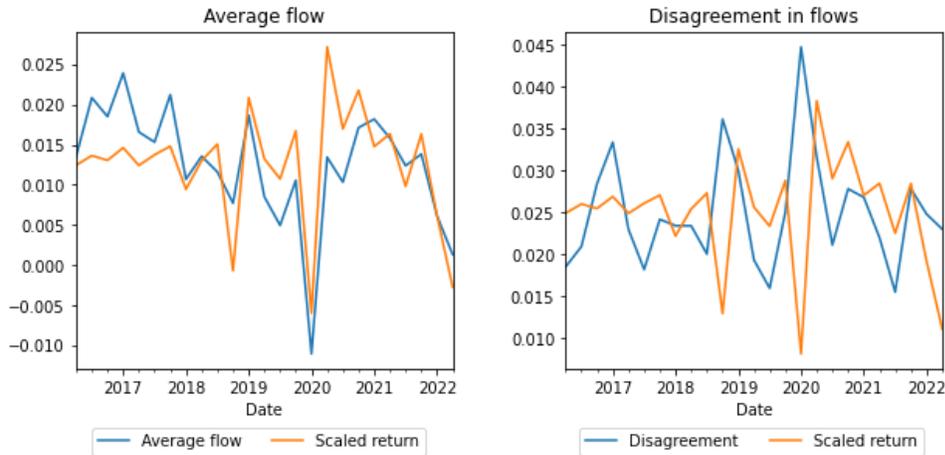
Source: Addepar Research

We then ask how the sensitivity of flows to U.S. stock market returns differs across investor groups. To this end, we estimate an Ordinary Least Squares (OLS) regression, where we regress the flow to liquid assets and the flow to U.S. equities on the U.S. equity market return for different wealth groups. The results are presented in Figure 8.

Figure 8

Sensitivity of flows to U.S. equity returns for different wealth groups
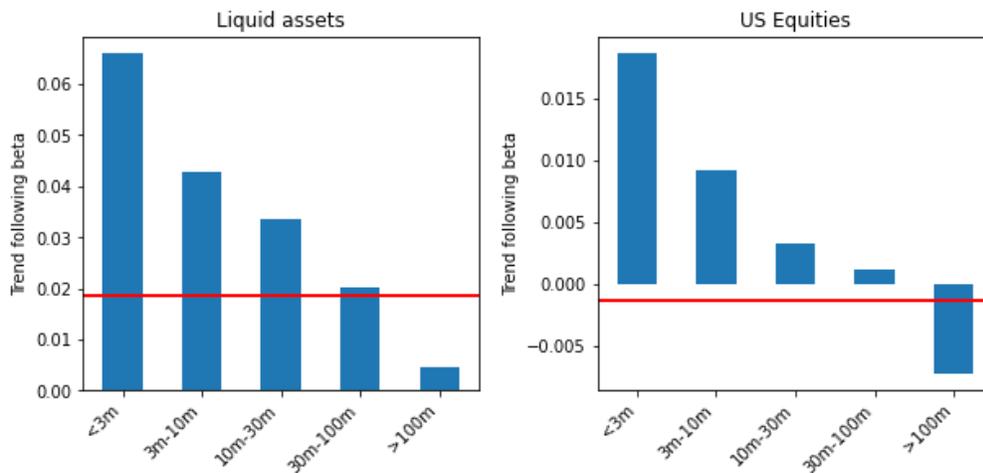
Source: Addepar Research

In the left panel of Figure 8, we summarize the sensitivity of flows to liquid, risky assets. A positive trend following beta means that investors tend to sell when the market falls and buy when the market rallies.

We find that wealthier investors are less sensitive to stock market movements. The horizontal red line corresponds to the wealth-weighted average sensitivity across all investors. Given the concentration of wealth, the weighted average is strongly affected by the behavior of the top wealth group.

It's unclear from the left panel alone whether wealthier investors are generally more passive and less reactive, or whether they truly implement different strategies. In the right panel of Figure 7, we therefore estimate the trend following behavior based only on flows to U.S. equities.

This analysis uncovers a rather striking pattern; while less wealthy households tend to follow the market trend, the opposite is true for the wealthiest investors. Economically, the wealthiest investors therefore help to stabilize financial markets, while the less wealthy households amplify the volatility in the stock market.

In Figure 9, we explore other dimensions of heterogeneity across households. The left column reports the trend following beta based on flows to liquid, risky assets, and the right column based on flows to U.S. equities. The top row groups investors by turnover, the middle row groups investors by inertia, and the bottom row groups investors by whether they're advised by a single-family office or not.

The difference is most salient for turnover. Recall that turnover and inertia are computed using the trading behavior within U.S. equities. Figure 8 shows that those households that are more active within U.S. equities are also more active across asset classes. Given that turnover and inertia are negatively correlated, we find the opposite pattern for inertia as for turnover.

The bottom row shows that grouping households by whether they're advised by a single-family office yields a similar pattern as in Figure 8. This finding is to be expected as access to a family office correlates strongly with wealth.

Figure 9

Sensitivity of flows to U.S. equity returns for different investor groups. The top two panels are for groups with different levels of turnover. The two middle panels are for households with different levels. The bottom two panels are for households that are or are not advised by a single-family office.
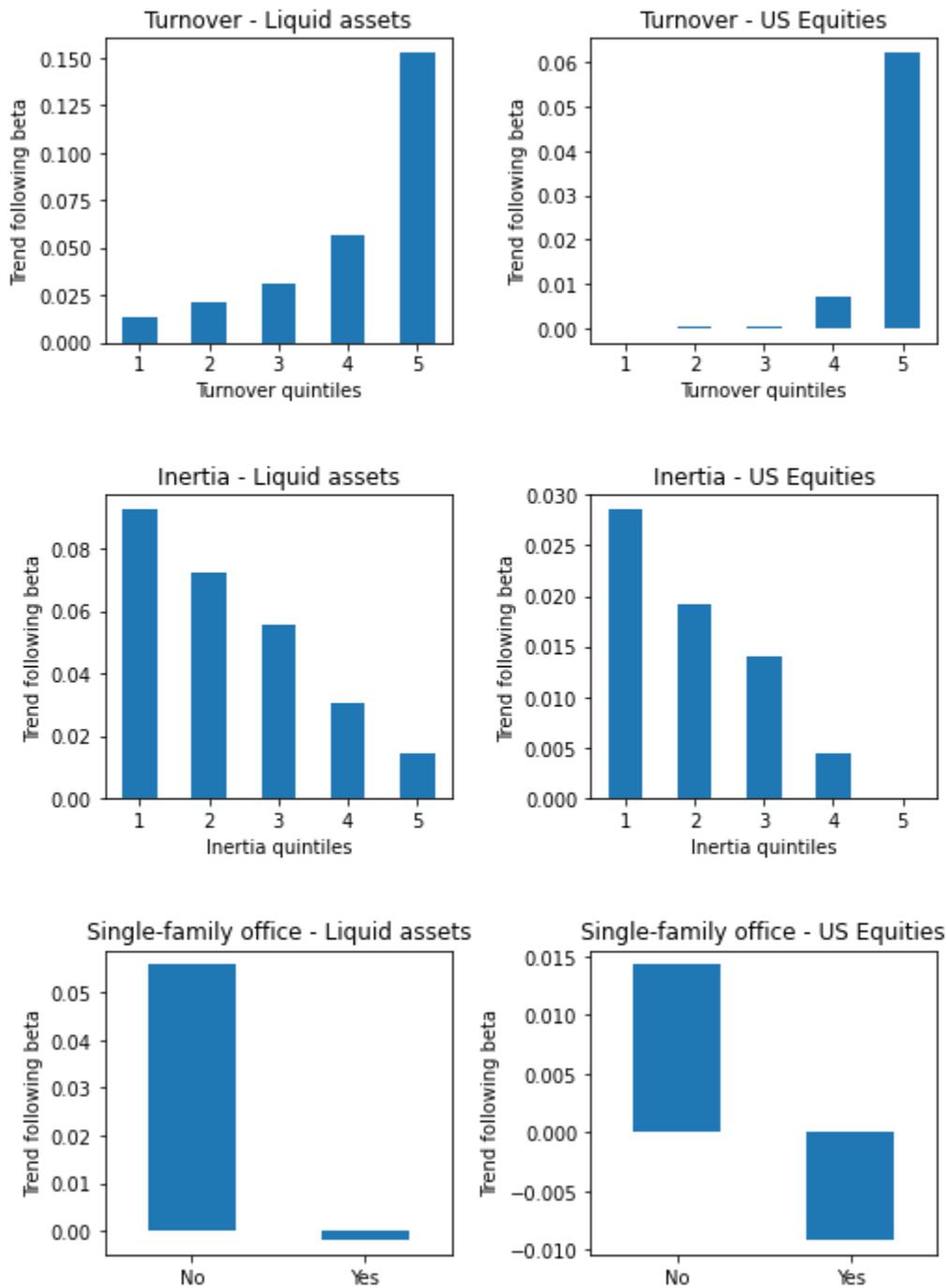
Source: Addepar Research

Figure 10

Risk-adjusted performance in U.S. equities for households grouped by turnover
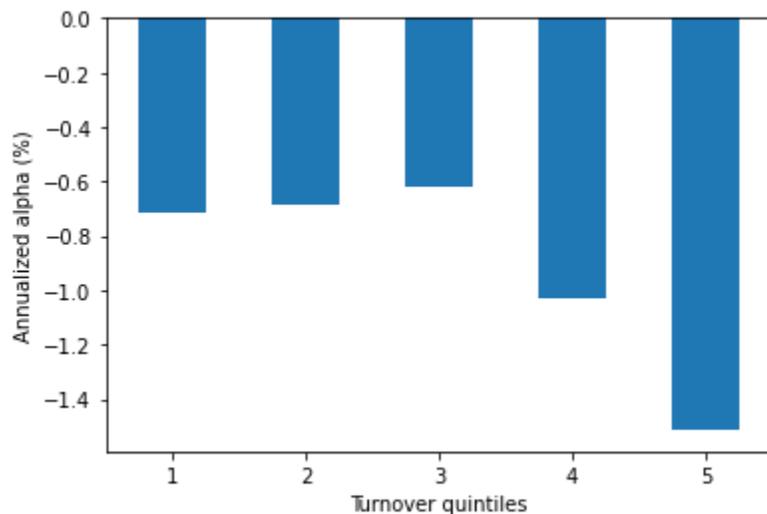
Source: Addepar Research

We have so far focused on rebalancing and returns across asset classes. We conclude our analysis by zooming in on the link between performance and rebalancing within the most commonly held asset class, U.S. equities. In Figure 10, we report the alpha, which is the average risk-adjusted return using the 3-factor Fama and French model, for investors with different levels of turnover within U.S. equities.

While there are no noticeable differences in alphas for the first three groups, the alphas turn more negative for the fourth and fifth quintiles. **This suggests that trading costs negatively affect performance with little improvement in alphas.**

7. The ARB-itrage

- **Trading during market stress:** Be aware of trading decisions during periods of market turmoil as these periods are characterized by large shifts in both risk and expected returns.

The trading decisions during these periods are particularly critical for investors' long-run performance.

- **New benchmarks:** Addepar Investor Flows provide a new reference point to benchmark trading decisions. First, we can compute an investor-specific benchmark by comparing the trading decisions to a fixed-share benchmark. Figure 1 provides an example. This investor moved away from risky assets during the COVID-19 pandemic, which subsequently rallied. Over time, such analytics can be helpful to understand the difference in performance relative to an easily attainable benchmark of maintaining fixed shares.

- **Turnover and performance:** Within U.S. equities, we find a negative relationship between turnover and risk-adjusted performance. Investors who actively rebalance their portfolios should make sure that such additional trading activity indeed comes with higher risk-adjusted returns and that alphas are not lowered by increased trading costs.

8. Coda

This ARB introduces a newly developed dataset, Addepar Investor Flows[SM], and discusses how this data can be used to derive actionable insights. The data is aggregated at the level of broad asset classes, narrow asset classes and core trading factors. We also show how to use these new analytics to benchmark your own performance, discover new investment opportunities and highlight emerging risks.

In ongoing work, we're developing new tools to track common ways in which investors rebalance their portfolios across asset classes. Those flows can be used to provide further insights to navigate changing market environments.

We're also developing more refined, personalized performance benchmarks. Specifically, we've developed an algorithm that selects a peer group for each investor that held a similar portfolio at some point in the past (for instance, one or two years ago). By tracking this group of investors that shared the same capital market assumptions in the past, investors can compare their own trading decisions and performance to this unique peer group to critically assess their own trading decisions and uncover potentially new directions to adjust their portfolios. Please reach out to us at research@addepar.com if you're interested in discussing this further.

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