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Martin Hodula, Milan Szabo, and Josef Bajzík *

Abstract

This paper explores flow patterns in retail equity mutual funds related to past and future performance. We employ supervisory data of monthly fund inflows and outflows in the Czech Republic and produce several key findings that shed light on the behavior of households as investors in an emerging market economy. First, we show that investor flows chase past performance and tend to underreact to poor performance – a typical finding in the literature. However, we find that retail investors are very sensitive to poor performance in times of aggregate illiquidity and when investing in funds that hold more illiquid assets. Second, we document that when facing illiquidity and a deteriorating performance, underperforming equity-investing funds experience lower investor purchases and a larger share of redemption requests. We observe similar investor behaviour in periods when retail investors face constraints on their disposable income. At such times, mutual fund inflows are found to decrease significantly and fund outflows to increase. Third, we document the presence of the smart money effect, while finding that it is caused by the buying (but not selling) decisions of retail investors.

Abstrakt

Tento článek se zabývá vývojem toků v retailových akciových podílových fondech ve vztahu k jejich minulé a budoucí výkonnosti. S využitím dohledových dat o měsíčních přílivech a odlivech prostředků do/z fondů v České republice docházíme k několika klíčovým zjištěním, která osvětlují chování domácností v roli investorů v rozvíjející se tržní ekonomice. Zaprvé ukazujeme, že toky investovaných prostředků sledují minulou výkonnost a mají tendenci nedostatečně reagovat na špatné výsledky, což je v literatuře obvyklé zjištění. Zjišťujeme však, že retailoví investoři jsou velmi citliví na špatné výsledky v dobách celkového nedostatku likvidity a při investicích do fondů, které drží méně likvidní aktiva. Zadruhé dokládáme, že při nedostatku likvidity a zhoršujících se výsledcích zaznamenávají méně výkonné fondy investující do akcií nižší nákupy podílů ze strany investorů a více žádostí o odkup podílů. Podobné chování investorů pozorujeme také v obdobích, kdy retailoví investoři čelí omezením disponibilního důchodu. V těchto dobách příliv prostředků do podílových fondů výrazně klesá a naopak roste jejich odliv. Zatřetí dokládáme přítomnost efektu chytrých peněz, přičemž zjišťujeme, že jej způsobují nákupní (ale nikoli prodejní) rozhodnutí retailových investorů.

JEL Codes: G11, G23.
Keywords: Equity funds, liquidity, retail investors, smart money.

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1. Introduction

Understanding how investors allocate capital is important in the study of financial markets. Because of the wealth of data on both fund performance and flows in and out of those funds, the actively managed mutual fund industry has been used extensively as a window to understand investor behavior. Economic research in this area focuses predominantly on the relation of fund flows to the cross sections of a fund's past and future performance (for a review, see Christoffersen et al., 2014). The relation of fund flows to past performance is of both practical and theoretical interest. Practical, because if investors tend to rush into taking their money out of funds following negative developments, then one may be concerned about the negative implications of large funds outflows increasing financial fragility (Goldstein et al., 2017; Falato et al., 2021) and possibly having spillover effects to the real economy.[1] And theoretical, because the efficient markets theory casts doubts on the existence of abnormal return persistence and cautions against banking on performance. The relation of flows to future performance (sometimes referred to as the smart money effect) also touches upon the validity of the efficient markets theory as it attempts to verify the existence of performance persistence and investors' ability to seize it and capitalize on it.

A dominant share of the literature is focused on the behavior of US mutual funds investors. In the first group of studies, which focus on the relation of flows to past performance, Chevalier and Ellison (1997) show that US investors tend to react to changes to the performance of well-performing funds more forcefully than they do for poorly-performing funds. Investors thus behave as if the difference between two well-performing funds is more informative about the future than the difference between two poorly-performing ones.[2] However, as shown in Ferreira et al. (2012), US-based findings concerning the shape of the flow-performance relationship do not apply universally and there is a gap as regards the study of investor behaviour in emerging market economies. The second group of studies is focused on the relation of flows to future performance and posits that, under certain circumstances, investors may succeed in identifying superior funds as flows are found to predict future fund performance (Gruber, 1996; Zheng, 1999). In this stream of literature, the US evidence is far less conclusive. While Sapp and Tiwari (2004) find that the smart money effect in the US no longer holds when controlling for stock momentum, others document a robust smart money effect in the United Kingdom (Keswani and Stolin, 2008) and partially in Brazil (Berggrun and Lizarzaburu, 2015).

In this paper, we re-examine the relation of fund flows to past and future performance using detailed supervisory data on the mutual funds industry in an emerging market economy – the Czech Republic. To this end, we construct a monthly sample of actively managed equity-investing funds over the period 2009–2022. In our exploration, we aim to benefit from our ability to observe exact gross flows, e.g. we are able to distinguish between investor purchases and sales. This feature of our data, alongside our focus on an emerging market economy, give us an important advantage over the existing literature which largely relies on aggregate money flows approximated using the total net assets of funds and fund returns, studied at a quarterly frequency. Our data allow us to perform more robust tests for the shape of the flow-performance relationship and to better identify the presence of smart money. The use of supervisory data allows us to gain greater insight

[1] A strong relation to past performance may also encourage higher risk-taking by managers under certain conditions (Hu et al., 2011).

[2] Why would investors behave like this? The literature offers both rational and behavioural explanations. Lynch and Musto (2003) show that investors tend to expect management companies to abandon poor strategies (or managers) and hold on to good ones. Huang et al. (2007) argue that the power of search costs is an important factor in explaining the convex flow-performance relationship. Using the behavioral approach, Goetzmann and Peles (1997) show that investors resist processing bad news related to performance.

into investors' decisions and to get a better understanding of the potential threats to financial stability posed by mutual funds.

We produce several key findings. First, we confirm a convex shape for the flow-performance relationship of equity funds over the period of our study: Money inflows as well as outflows are found to be more sensitive to good performance than they are to bad performance. Thus, investors are found to chase winners who receive larger inflows but, as performance declines, they do not punish poorly performing funds by making larger withdrawals. This finding is robust to different measures of fund performance. Various subsample analyses show that the convex shape of the flow-performance relationship is pervasive. This is in contrast to the US evidence in Spiegel and Zhang (2013) who argue that the convexity disappears within the subsamples due to heterogeneity.

Second, while we find that the convex shape of the flow-performance relation holds (on average) for our sample of equity-investing funds, we show that – under certain conditions – the relationship may take on a concave shape. Specifically, we find that the sensitivity of fund flows to bad performance is high in times of aggregate illiquidity and among funds that hold more illiquid assets. Our findings echo the arguments raised in Chen et al. (2010) who show that US fund flows are more sensitive to the poor performance of illiquid funds. They relate this behavior to a first-mover advantage in the redemption decision, as withdrawing money from the funds leads to negative externalities on those investors who keep their investment position unchanged. We also show that such investor behavior can be observed during periods of higher illiquidity when the liquidation costs imposed on funds due to large outflows are likely to be more severe (Zeng, 2017).[3] In fact, we find that the concave shape of the flow-performance relationship is strongest during rare stressful events such as the Covid-19 outbreak. This is in line with the arguments raised in Chen and Dai (2020) who use terrorist attacks and Covid-19 as exogenous shocks to the investor fear level and find that fund flows become increasingly sensitive to tail risk following the shocks.

While Chen et al. (2010) track implied fund flows and relate the concave shape of the relation to a greater amount of fund redemption, we show that both lower fund inflows and higher fund outflows are the driving force. In another words, when facing illiquidity and a deteriorating performance, under-performing equity-investing funds experience lower investor purchases as well as a larger share of redemptions. Given that Chen et al. (2010) track implied net fund flows, which are based on changes to the total fund assets, their estimates effectively mask large-scale trading activity in fund shares. Our findings highlight the need to use more detailed data to allow exact net fund flows to be tracked and to distinguish between the flows related to asset sales and asset purchases.

Third, we show that retail mutual fund flows are sensitive to time-varying constraints on household disposable income at the aggregate level. Following Gicheva et al. (2010), we use exogenous unanticipated shocks in the prices of energy commodities (including gasoline, natural gas, electricity, etc.) to proxy for short-run financial constraints on potential or current investors. This strategy seems timely in view of the recent developments in the global energy market due to the Russian invasion of Ukraine. Given that an average Czech household spends almost 10% of its income on energy, Czech funds are an appropriate sample for this study. We find that in periods when retail investors face constraints on their disposable income stemming from increased energy

[3] Following a deterioration in market conditions, (retail) investors are assumed to sell what they perceive to be higher-risk investments (equity) and purchase safer investments. This is consistent with the flight-to-safety hypothesis (Barsky, 1989). Adrian et al. (2019) document an economically and statistically strong nonlinear risk-return trade-off by estimating the relationship between stock market volatility as measured by the VIX and future returns. Baele et al. (2020) show that flight-to-safety episodes are characteristics of significant outflows from equity funds into government bond and money market funds.

prices, mutual fund inflows decrease and fund outflows increase. This shows that placing financial constraints on households may discourage prospective investors as well as alter the behavior of those who already hold a share in a mutual fund.

Fourth, we examine whether Czech money flowing into equity mutual funds are "smart", e.g. whether investors can identify superior funds in advance. We offer two pieces of evidence in favour of the smart money effect. One, we follow Keswani and Stolin (2008) and compare the performance of portfolios in which funds are weighted by their money inflows (new money) and portfolios in which funds are weighted by total net assets (old money). We find that mutual fund investors can identify funds that subsequently outperform the market average: new money beats old money. Two, while we confirm this finding in a multivariate regression setup, we find the effect to be rather short-lived and only detectable when using monthly actual net flows.

Our estimates suggest that financial stability concerns related to the mutual fund industry are tightly linked to the level of liquidity, both at a cross-sectional (fund) level and over time. We show that retail investors tend to respond dramatically to bad performance, such as liquidity shortages and extreme events like the Covid-19 outbreak. This is also the case when investing in funds which hold fewer liquid assets. This may create run-like dynamics since investors are prompted to take certain action based on the expectation that other investors will do the same. Thus, a multiplier effect can arise, amplifying the effect of a worsening of fundamentals on investors' behaviour (Shleifer and Vishny, 2011). This may be a pressing concern especially for funds which invest in emerging market assets rather than for funds with large-cap US stocks, as is the case for the Czech Republic. Faced with bad performance, the former are more likely to redeem their fund shares quickly because they know that redemption decisions by others will impose non-negligible costs on the fund, which hurts those who choose to stay in the fund.

The supposed fragility of the mutual fund industry is linked to the fact that open-end funds offer demandable claims on a daily basis. Supervisory (microprudential) activities assessing the stability and interlinkages of mutual funds may thus be an important factor in keeping the industry safe. The former is demonstrated in our finding that periods of aggregate illiquidity are also important, possibly leading to a change in investor behavior towards deteriorating fund performance. A stress-testing framework should take these liquidity dry-ups into account, assessing the stability of the mutual fund industry from a macroprudential perspective.

The rest of the paper is structured as follows. Section 2 presents the institutional background and section 3 shows our hypothesis development. Section 4 presents the data. Section 5 presents our methodology and shows our empirical results concerning the relationship between fund flows and past performance. Section 6 shows the empirical results on the smart money effect. Section 7 concludes.

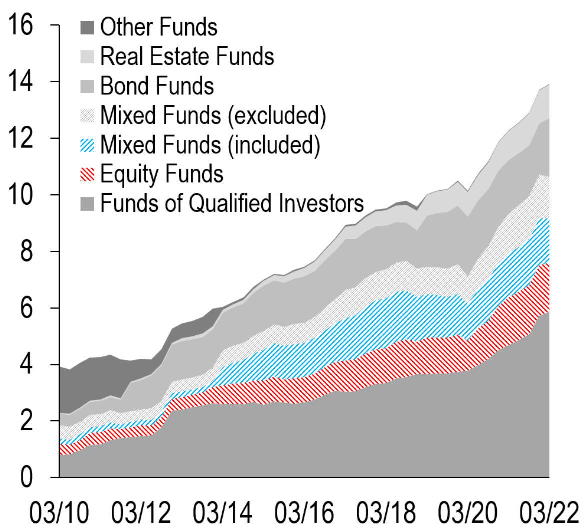
2. Institutional Background

Czech investment funds have seen vibrant growth over the last ten years, taking their place among the most significant components of the Czech financial sector. Investment fund assets have grown by a staggering 400% over the last decade (Figure 1), representing the third most dynamic growth among the EU Member States according to data from the European Central Bank. The substantial growth in assets under management makes the study of cash-flow dynamics in the Czech market an interesting exercise. Czech law recognizes three main categories of investment funds: retail UCITS, retail AIFs, and funds of qualified investors. This paper focuses on retail funds only, i.e.

both UCITS and retail AIFs, which have to adhere to strict rules closely based on UCITS standards. Non-retail AIFs, also known as funds of qualified investors, will not be studied here.

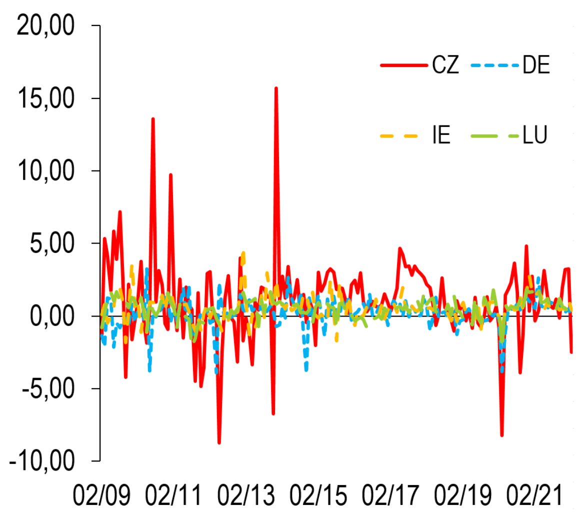
Even though the Czech investment fund sector is relatively small in comparison to the big financial centres located, for example, in Luxembourg, Ireland, and Germany, Czech investment funds provide an interesting case study for the stylized facts in investor flows for two main reasons. First, the Czech funds studied in this paper serve mainly residential households whose share in total investment fund shares/units accounted for 74% in 2022 Q1, the third largest in the EU.[4] The studied funds thus channel a large bulk of funding from domestic households which suits the hypotheses examined in the study. Second, Czech equity funds face more volatile net flows which may be related to the large share of retail household investors (Figure 2).

Figure 1: Total Assets of Czech Investment Funds (% of GDP)



Note: The "Other Funds" category also contains historical money market funds.
Source: Czech National Bank, own processing

Figure 2: Aggregated Net Flows (% of Lagged Assets) for Equity Funds in Selected Countries



Source: European Central Bank, own processing

Under their investment strategy, Czech retail investment funds invest predominantly in equities and bonds. While only a few funds declare themselves to be purely equity funds (see Figure 1, dashed red area), many funds hold a dominant share of their portfolios in equities despite the fact that they declare rather mixed investment strategies which leave asset managers with flexible investment options. In our exploration, we focus both on funds that are purely equity funds and on mixed funds that hold at least 70% of their portfolios in equities (Figure 1, dashed blue area).

[4] The largest share is held in Estonia and Spain. German households hold around 17% in German funds' shares/units. Luxembourg and Irish households hold less than 1% in domestic funds.

3. Related Literature and Hypotheses Development

In this section, we survey the relevant literature related to the flow-performance relationship and the smart money effect. We use the information obtained from the survey to craft our testable hypotheses. The empirical part of the paper will then focus on verifying these hypotheses.

3.1 The Flow-Performance Relationship

Our main hypotheses are centered around the idea that fund flows are strongly correlated with a fund's past performance. Given the study's focus on the retail investor segment that dominates the funding for the Czech mutual fund industry, we expect the flow-performance relationship to be convex. The convex shape of the relationship posits that the sensitivity of fund inflows to good performance would be much higher than that of outflows to bad performance. This relates to the wealth of literature showing that retail investors punish bad performance much less severely than institutional investors (for a review, see Christoffersen et al., 2014).[5] This brings us to our first testable hypothesis.

Hypothesis 1. Retail funds exhibit a stronger sensitivity of net fund flows to good performance than bad performance, leading to a convex flow-to-performance relation.

The 20+ years since the canonical flow-performance studies have seen deep recessions and major market swings. This raises questions as to whether investors respond to performance as they used to. Christoffersen et al. (2014) state that the experience of the 2007–2009 Global Financial Crisis, like the Great Depression in the 1930s, may influence the investment behavior of a generation. The vast improvement in data availability is a somewhat more tangible change that has occurred in the past 10 years. This concerns both market and supervisory data which we use in this paper. For instance, historical studies and much of the present studies are limited to net flows, but our data allows a separate analysis of monthly inflows and outflows. O'Neal (2004) provides early evidence that net flows may actually mask a substantial portion of fund flow dynamics that is only visible when distinguishing between inflows and outflows. He finds that investors reward good performance by reducing outflows rather than punishing poor performance by increasing outflows. The study by Cashman et al. (2012) goes a step further as it provides evidence that outflows increase more aggressively following poor performance, and inflows increase more aggressively following good performance. This leads us to our second hypothesis.

Hypothesis 2. Investors punish poor performance by reducing inflows rather than increasing outflows.

Building on the second hypothesis, we may further expect fund flows (inflows and outflows) to be more sensitive to bad performance during illiquid periods and/or in illiquid funds. Under the flight-to-safety hypothesis, it is assumed that (retail) investors sell what they perceive to be higher-risk investments (equity) and purchase safer investments (Barsky, 1989), leading to a larger share of equity fund redemptions when compared to bond funds or rare commodities. Recently, a couple of studies have confirmed the functioning of the flight-to-safety mechanism in the US (Adrian et al., 2019; Baele et al., 2020). In illiquid funds, outflows impose greater liquidation costs on the fund when readjusting the portfolio (Edelen, 1999; Coval and Stafford, 2007). Withdrawing money from

[5] In this respect, Thaler (2000) consider households as investors to be naive and endowed with limited financial literacy, limited access to information, and a limited ability to process information. Papers documenting this pattern, discussing its origins and consequences, include but are not limited to Ippolito (1992), Brown et al. (1996), Lynch and Musto (2003) and Huang et al. (2007).

the fund leads to negative externalities on other investors who keep their money in the fund. This creates a first-mover advantage in the redemption decision, amplifying the outflows of illiquid funds following bad performance. Using information on net flows, Chen et al. (2010) show that US equity funds tend to have greater sensitivity of outflows to bad performance when they invest in more illiquid assets. In a similar spirit, illiquid funds or under-performing funds are also more likely to receive substantially less money following a decrease in performance. This leads us to the third hypothesis.

Hypothesis 3. During illiquid periods and in a sub-set of less liquid funds, fund flows exhibit greater sensitivity to low past performance.

The third hypothesis deals with both the cross-section and time-specific aspects of illiquidity. This way, it is sympathetic to the fact that performance chasing not only takes place at the intensive margin (across funds), but also at the extensive margin (i.e. in aggregate flows over time into and out of the equity mutual fund space). Funds may thus choose to hold more liquidity to alleviate the tendency of investors to run.

We approach the identification of the relationships mostly by exploiting the differences across mutual funds and periods. For instance, investors who hold their money in illiquid funds should have a higher tendency of run-like behaviour than investors in funds that hold liquid assets. In the same spirit, investor behaviour is likely to differ in, say, normal times versus less tranquil times of high market stress and liquidity shortages.

3.2 The Smart Money Effect

Can investors identify superior mutual funds? The smart money hypothesis postulates that investors exhibit an ex-ante ability to buy shares of future winners and divest shares of future losers. Early studies find just that; e.g. funds that receive larger inflows perform better in the subsequent periods (Gruber, 1996; Zheng, 1999). However, the smart money effect is not clear cut. Sapp and Tiwari (2004) find that after adjusting for the momentum factor in stock returns, net fund flows no longer lead to higher performance. This is explained using the argument that well-performing funds have disproportionate holdings of well-performing stocks. And stocks that perform well tend to hold this momentum (Jegadeesh and Titman, 1993).

The disaggregated nature of our fund flow data allows us to test for the presence of smart money using a set of purely retail-oriented mutual funds. In line with Keswani and Stolin (2008), we expect to find a stronger link between funds' future performance and investors' fund purchases rather than their sales. In this respect, we argue that mutual fund redemptions are more likely to be caused by factors unrelated to future performance, such as liquidity needs (Szabo, 2022). Hence, this brings us to our last hypothesis.

Hypothesis 4. Czech money is "smart" meaning there is a statistically sound and positive relationship between funds' future performance and mutual fund inflows.

Using a UK dataset, which allows fund inflows and outflows to be tracked, Keswani and Stolin (2008) find that the smart money effect holds and it is driven by fund purchases of both individuals and institutions. Similarly, Berggrun and Lizarzaburu (2015) document that flows in small and retail funds in Brazil, which are often considered to be populated by less sophisticated investors, tend to anticipate future fund performance.

4. Data

We drew data on open-end equity mutual funds from supervisory data collected by the Czech National Bank. Our sample period is January 2009 to February 2022. Data prior to 2009 are not available at the required level of detail. Specifically, it is not possible for us to distinguish between fund inflows and outflows prior to 2009. The dataset includes funds that either ceased to exist or merged with other funds and is therefore free of a survivorship-bias. Figure A1 shows the evolving number of active funds and the number of months for which each fund is tracked over the period under review. We do not consider bond or hedge funds in this analysis, as they differ significantly from equity funds (Klapper et al., 2004; Goldstein et al., 2017). This results in a sample of 6,300 fund-month observations from 70 unique funds.

4.1 Measurement of Fund Flows and Performance

The key variables of interest in our analyses are mutual fund flows and fund performance. A standard practice in the literature is to impute net fund flows from the total net assets of each fund share class between consecutive points in time (in our data, between the beginning and the end of the month), and the interim fund return. Nevertheless, this is a mere approximation of actual investor flows when more detailed data are not available.

We take advantage of available *actual* investor flows reported directly from mutual funds, that is, we observe both fund inflows and fund outflows. Fund inflows are defined as investor purchases divided by fund size at the beginning of the month. Fund outflows are sales divided by fund size at the beginning of the month. This is to account for the fact that one would expect buy-ins or withdrawals from a well or poorly performing fund to be proportional to its initial asset level. We then define net flows as investor purchases minus investor redemption requests divided by the size of the fund at the beginning of the month (TNA). Formally, flow for fund i in month t is defined as:

$$Flow_{i,t} = \frac{inflow_{i,t} - outflow_{i,t}}{TNA_{i,t-1}} \tag{1}$$

To mitigate the influence of outliers, which is a standard practice in the related literature, fund flows are winsorized at the 1% and 99% levels.

Important input to our analyses is how the performance of funds is measured. We evaluate fund (managers') performance using the holdings-based measure proposed in Grinblatt and Titman (1993) which does not have to determine factors affecting a fund's returns.[6] The measure also takes advantage of our access to supervisory data which includes monthly security-by-security holdings of the studied funds. Grinblatt and Titman (1993) introduced the *Portfolio Change Measure (PCM)* which measures a fund's performance by how much the fund tilted its portfolio weights over time in favor of assets with increasing expected returns and away from assets with decreasing expected returns. A performing fund whose percentage holdings of an asset is increasing in its conditional expected return will thus exhibit positive covariance between the weight of the given asset (w_j) and its subsequent returns (R_j). In contrast, covariance is negative for an under-performing fund. Following the authors, one can sum up the security-related covariances across each asset j in the fund's portfolio and use the weight from period $t-k$ as a

[6] The measure belongs to the broad holding-based category of fund performance measures, see Elton and Gruber (2020) for a review.

proxy for its expected holdings. Hence we write:

$$\begin{aligned}
\textit{Portfolio Change Measure}_i &= \sum_{j=1}^{J} E\left[\left(w_j - E\left[w_j\right]\right) R_j\right] = \\
&= \sum_{j=1}^{J}\sum_{t=1}^{T} \left(w_{j,t} - \bar{w_j}\right) R_{j,t}/T = \\
&= \sum_{j=1}^{J}\sum_{t=1}^{T} \left(w_{j,t} - w_{j,t-k}\right) R_{j,t}/T
\end{aligned} \tag{2}$$

We allow the performance measure to be time-variant by calculating the sample covariances on a 12-month rolling basis, i.e. not throughout the whole period $t = 1,2,...,T$. Furthermore, we follow the authors in setting $k = 12$. The measure can thus be interpreted as a 12-month rolling mean of monthly returns given by a zero-cost portfolio consisting of short positions according to the prior weights (w_{t-12}) and long positions according to the weights in the current portfolio. If the return on the constructed portfolio is positive, then the manager is performing well in re-balancing the managed portfolio into performing assets and out of underperforming ones. On the other hand, if the return is negative, the manager is doing a poor job in active investment and this might influence investors' decisions.

4.2 Alternative Measures of Fund Performance

We are aware that one of the standard approaches to measuring fund performance in the related literature is to use Jensen's alpha (Jensen, 1968) which is the intercept from a regression of the excess return of the managed portfolio on the excess return of a market index:

$$R_{i,t} - R_t^f = \alpha_i + \beta_i (R_t^M - R_t^f) + \varepsilon_{i,t} \tag{3}$$

where $R_{i,t}$ is the i-th fund's rate of return, R_t^f stands for the risk-free rate in the given month and R_t^M stands for market return. The α_i is a risk-adjusted performance measure. The β_i is the measure of risk which the asset pricing model implies is crucial in determining the prices of risky assets. The theoretical foundation of this model is the capital asset pricing model (CAPM) but other multi-factor models are widely used. Prominent examples are Fama and French (1992) and Carhart (1997).

The choice of the market return (R_t^M) is critical to the measure of excess performance (the fund's 'alpha'), see Roll (1978) and Jensen (1972). The usual choice is to substitute an index that purports to better represent the investment policy of the fund, i.e. the fund's prospectus benchmark, for the market portfolio.[7] Unfortunately, the substitution is not possible for the Czech funds studied here, since they predominantly do not track or disclose their benchmark in their prospectuses. This is in contrast to US mutual funds, where it is mandatory to disclose a fund's benchmark in its prospectus. Nevertheless, as we explain in the next section, we at least attempt to estimate the funds' alpha using information from funds' prospectuses and the Lipper geographical focus. We use these alternative measures as robustness checks to validate the results we obtained when using the PCM.

[7] Sensoy (2009) and Cremers et al. (2019) provided some support that prospectus benchmark-adjusted returns influence fund flows and investors' decisions. See also Angelidis et al. (2013). However, let us also mention that a number of studies have found that the prospectus benchmarks lead to biases in alphas as funds deliberately misclassify themselves to less performing benchmarks, see Chen et al. (2021) and Cremers et al. (2022). These critical points provide ground for the holding-based measures introduced in this section.

Given the prevalence of Jensen's alpha in the literature examining the flow-performance relation, we provide an alternative performance measure based on Jensen's two-factor model as well as the Fama-French three-factor model and Carhart's four-factor model. Returning to the missing prospectus benchmarks, we build our alternative performance measure by assigning the funds studied in this paper to three groups. The groups are created on the basis of the given fund's geographical focus: developed, emerging and the US.[8] The information was obtained from funds' prospectuses and the Lipper geographical focus where available. Each group is then assigned various factors that reflect its geographical focus and which were obtained from Professor Kenneth R. French's website.[9]

The Fama-French three-factor model for a given j-th geographical group and i-th fund is as follows:

$$R_{i,t} - R^f_{t,j} = \alpha_i + \beta_{0,i}(R^M_{t,j} - R^f_{t,j}) + \beta_{1,i} SMB_{t,j} + \beta_{2,i} HML_{t,j} + \varepsilon_{i,t} \quad (4)$$

where SMB_t (small minus big) is the average return on the small capitalization portfolio minus the average return on the large capitalization portfolio; HML_t (high minus low) is the difference in return between a portfolio with high book-to-market stocks and a portfolio with low book-to-market stocks. Previously defined terms are the same. One can expand the factor model with the fourth momentum factor which is the difference in returns between the portfolio with the past 12-month winners and the portfolio with the past 12-month losers UMD_t (Carhart, 1997). Adjusting by the momentum factor has been shown to be important for the examination of the smart-money effect (Sapp and Tiwari, 2004). We therefore also calculate Carhart's alpha to check the robustness of the smart-money effect findings.

We estimate 12-month rolling alphas as in equation 2 for each fund and using market factors based on the group to which the given fund is assigned. Importantly, we measure fund performance in cumulative terms over a one-year period. All returns are thus expressed as year-on-year returns. The obtained αs measure how much better a fund did in comparison to returns implied by the given multi-factor model over the previous 12 months. The choice of a 12-month window corresponds to the slowly moving nature of the *Portfolio Change Measure* and makes the results comparable. Furthermore, the motivation for a longer evaluation window stems from households' extrapolative beliefs, as suggested by Greenwood and Shleifer (2014) and Choi and Robertson (2020). It is assumed that investors base their evaluations on and react to a fund's longer-term performance. Therefore, rather than using month-on-month performance which can be volatile and send noisy signals that may be ignored by retail investors,[10] we prefer to calculate year-on-year performance which manifests our belief that retail investors assess and react to a fund's performance by taking a longer interval into account.

We also consider simple unadjusted funds' returns to capture fund performance to make sure our results are robust and not influenced by the recognition of a fund's geographical focus or the strict assumptions of the alpha-based literature. After all, households are known to be naive investors rather than hyperrational alpha-maximizing agents. In a recent study, Ben-David et al. (2022) argue that mutual fund investors rely on simple signals and likely do not engage in sophisticated learning

[8] In our sample, four funds invest predominantly in US assets, ten focus on emerging markets and the rest focus on developed countries in general.

[9] See `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

[10] Goetzmann and Peles (1997) argue that investors resist digesting the news that a fund that they previously perceived as acceptable is performing poorly and, thus, do not act on the news as they would (or should) otherwise. As evidence, they show that investors exhibit cognitive dissonance by systematically overestimating the performance of their existing mutual fund investments.

about managers' alpha as widely believed. They shows that very simple performance measures best explain aggregate flows to the mutual fund space and flows across funds. The simple unadjusted funds' returns are calculated as the change in NAVs, again, over a one-year period:

$$R_{i,t} = \frac{NAV_{i,t}}{NAV_{i,-12}} - 1 \tag{5}$$

4.3 Descriptive Statistics

Table 1 shows the summary statistics for the funds in our sample from January 2009 to February 2022. Our baseline analysis is run on a sample of 6,300 fund-months, where the number of cross-sectional units is 70. Over our sample period, the active equity-investing funds recorded average unadjusted returns of 0.38%, while the average for the top 10% best-performing funds stood at 3.94%. The annualized PCM fund performance measure shows that the average managed portfolio performance is small and positive (1.19), while it is negative for the bottom 25% of funds. In our sample of funds, the average net aggregate money flow is positive and comes in at 1.37% per month. As it turns out, the net flow masks an annual inflow of 2.91% per month and an outflow of 1.44% per month. This highlights that research based on approximations of net money flows might be a rather noisy indicator of actual investor decisions and observes only a fraction of investor capital moving through mutual funds. The median fund age is about 7 years. On average, the funds hold 8.05% of their assets in cash but the cash holdings vary substantially in the sample with a standard deviation of 6.89. The top 10% of funds hold almost 16% of their assets in cash while the bottom 25% hold no more than 1.58%. A majority of the funds are retail-oriented as the average share of the value of units held by households on the total value of units is 73%. Almost half of all funds are predominantly held by households.

Table 1: Summary Statistics

Variable	Mean	SD	P10	P25	P50	P75	P90	N
$Net\ Flow\ (\%)$	1.37	4.55	-1.58	-0.47	0.45	1.89	4.73	7,021
$Net\ Flow\ Retail\ (\%)$	1.24	4.28	-1.69	-0.62	0.42	1.89	4.35	6,398
$Inflows\ (\%)$	2.91	4.92	0.17	0.73	1.51	3.02	6.09	6,628
$Outflows\ (\%)$	1.44	1.62	0.13	0.54	1.07	1.70	2.82	6,628
$Unadjusted\ Return\ (\%)$	0.38	3.58	-3.45	-0.91	0.43	1.85	3.94	7,041
$Portfolio\ Change\ Measure\ (\%)$	1.19	3.72	-1.87	-0.42	0.50	2.32	4.75	5,340
$Fama-French\ Alpha\ (\%)$	2.11	8.71	-7.34	-2.61	1.20	6.10	13.34	5,501
$Log(TNA)$	20.60	1.23	19.06	19.81	20.58	21.42	22.06	7,102
Age	8.35	5.96	1.57	3.53	6.89	12.33	17.44	7,063
$Cash\ (\%)$	8.05	6.89	1.58	3.35	6.54	11.01	15.90	7,102
$Liquid\ Assets\ (\%)$	10.09	8.52	2.03	4.26	8.08	13.20	19.48	7,102
$Retail\ (\%)$	73	36	0	45	97	100	100	7,069

Note: In this summary statistics table, we report the mean (Mean), standard deviation (SD), 10th percentile (P10), etc., and the total number of observations (N). $Flow\ (\%)$ is the percentage fund flow in a given month, $Return\ (\%)$ is the monthly net fund return in percent, $Log(TNA)$ is the natural log of total net assets, Age is the natural log of fund age in years, $Cash\ (\%)$ is the share of fund assets held in $Cash$ in total assets in percent, $Retail$ is the share of the value of units held by households in the total value of units. The unit of observation is fund-month. The sample includes 73 unique funds.

Before we can start working with our flow data at the fund-month level, we address several data issues. We begin with a winsorized sample of 7,021 fund-months that recorded money flow over our sample period. We then single out those with a dominant share of retail investors, leaving us with 6,398 fund-months observations. There are only 623 fund-months with a dominant share of institutional investors. We then match the cleansed retail flow data with our fund performance measures. The risk-adjusted fund performance measures are calculated on a 12- month rolling basis, leaving us with a baseline sample of fund-months of 5,240. Using unadjusted fund returns would give us 6,300 observations.

5. The Flow-Performance Relationship

In this section, we explore the flow-performance relation for our sample of purely retail-oriented equity-investing funds. We begin with a simple semi-parametric regression of fund flows on past fund performance in the spirit of Chevalier and Ellison (1997). The model is specified as follows:

$$Flow_{i,t} = \alpha Flow_{i,t-1} + f(Performance_{i,t-1}) + \gamma Controls_{i,t} + \varepsilon_{i,t}, \tag{6}$$

where the dependent variable $Flow_{i,t}$ is fund i's net flow in month t, and $Performance_{i,t-1}$ is fund i's performance measure. We gradually consider the Portfolio Change Measure, Fama-French alpha and unadjusted return as our performance measures. We also include the lagged fund flow, the natural log of fund total net assets and the natural log of fund age in years as explanatory variables. The past flow measure we use for each of our flow components is a simple way to account for the presence of seasonality in individual investors' decisions. This seasonality may be due, for example, to scheduled fund purchases that repeat themselves at a fixed point in time.

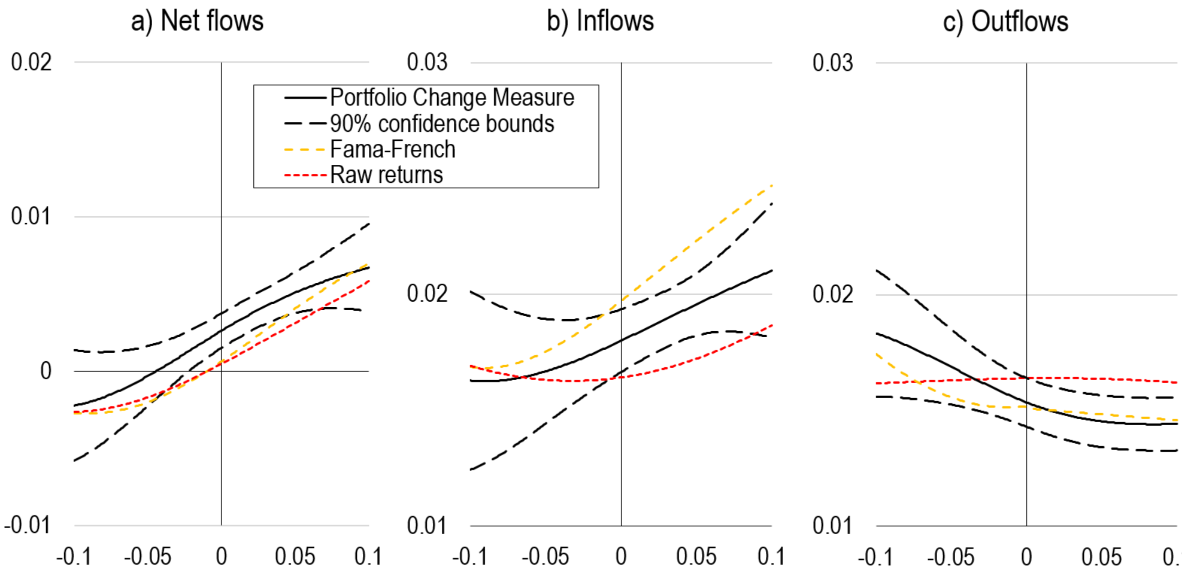
Figure 3 presents a graph of the function $\widehat{f}$ obtained from the set of retail-oriented funds studied in this paper. Given the variable transformations we use, the graph may be interpreted as presenting the expected fund flows in month t as a function of previous month $(t-1)$ performance (assuming that the fund's total assets and age match the geometric mean of our sample). Considering the baseline model using the PCM to measure a fund's performance, a fund would attract net investor inflows of 0.5 percent in month t where its lagged performance is 5%. This is in contrast to the insignificant net outflows of -0.03 percent in month t if a fund's lagged performance was -5%.[11] While we do not develop a model for investor behaviour in the paper, the relation shown in Figure 3 seems broadly consistent with a model in which heterogeneously informed prospective investors assess the quality of various funds. The shape of the estimated function $\widehat{f}$ is visibly convex meaning that retail investors pay little attention to a fund's poor performance. On the contrary, a well-performing fund seems to attract large investor inflows. Very large returns come to the attention of relatively uninformed potential investors who are than more likely to invest in the "winners".

Given the nature of our supervisory data, we can distinguish between fund inflows and outflows. Judging from Figure 3 Panel B, well-performing funds (positive performance region) receive a larger amount of inflows than their worse-performing peers. Panel C then shows that worse performing funds (negative performance region) experience a larger amount of outflows. These statistical facts lend some support to the validity of our first and second hypotheses.

We obtain very similar estimates when using different versions of the fund performance measure. The only time we do not find any difference between the outflow response to a change in performance for worse and better performing funds is when using simple unadjusted fund returns. This would suggest that investors require more precise performance evaluation when deciding on redeeming or exiting a fund.

[11] The interpretation would be slightly different using Fama-French alpha, given that it measures fund performance relative to the market benchmark. Here, a fund would attract a net inflow of approximately 0.4 percent in month t if its previous month $(t-1)$ return matches the return on the market and approximately 0.7 percent if its return is 10 percentage points greater than the market return.

Figure 3: Flow-Performance Relationship $\widehat{f}$ for Equity Funds



Note: The graph shows estimates of the flow-performance relationship for retail equity-investing funds using semi-parametric regressions. We regress monthly a) net fund flows, b) inflows and c) outflows on past fund performance measured using the Portfolio Change Measure (black solid line), Fama-French alpha (yellow dashed line) and unadjusted return (red dotted line). We include the following controls: lagged fund flows, fund size and fund age. The dotted lines represent the 90% confidence intervals.

It is important to bear in mind that the semi-parametric regression has relatively low statistical power due to the flexible functional specification. To formally test *Hypothesis 1* and *Hypothesis 2* and to analyze the flow-performance relationship in a multivariate setting, we conduct a panel regression (within estimation) analysis.[12] The choice of performance measure for our analysis is guided by the missing prospectus benchmark for Czech funds. Therefore, the appropriate fund performance measure is one that does not require us to determine factors affecting a fund's returns. Hence, we focus on the PCM as the fund performance measure in the rest of the paper, but provide estimates using the three-factor geographical-focus based Fama-French alpha in the Appendix. We begin with the following regression:

$$\begin{aligned} Flow_{i,t} = \alpha Flow_{i,t-1} + \beta_1 PCM_{i,t-1} + \beta_2 PCM_{i,t-1} \times I(PCM_{i,t-1} < 0) \\ + \beta_3 I(PCM_{i,t-1} < 0) + \gamma Controls_{i,t} + \zeta_i + \varepsilon_{i,t}, \end{aligned} \tag{7}$$

where $I(PCM_{i,t-1} < 0)$ is a dummy variable that takes the value of one if the fund records a negative performance based on the Portfolio Change Measure (PCM) and takes the value zero otherwise. The previously defined terms remain the same. We include fund fixed effects ζ_i to control for possible confounders. The β_1 and β_2 parameters are of main interest. The interaction term $PCM_{i,t-1} \times I(PCM_{i,t-1} < 0)$ and the associated β_2 parameter verify the existence of the flow-performance relationship when funds exhibit a negative performance, while the β_1 parameter captures the flow-performance relationship when funds show a positive performance. If there is a convex flow-performance relationship, we expect to find a weaker flow-performance relationship for under-performing funds as investors would underreact to bad performance.

[12] Regressions are estimated using the OLS FE estimator which should be a robust estimator given the characteristics of our sample which is heavy on the time dimension. As such, our estimates should be free of the Nickell (1981) bias that might potentially affect estimates of samples with a short time period.

Table 2 shows our baseline set of results concerning the flow-performance relationship. The estimates show that fund flows are, in general, responsive to past performance, a relation typically found in prior literature. In our sample of funds, a one percentage point increase in lagged fund performance is associated with increased net flows of about 5.3% (column 1). The estimates of the interaction term $PCM \times (PCM < 0)$ using the full sample of funds (column 1) as well as purely retail-oriented funds (column 2) suggest that the sensitivity of fund flows to bad performance is much lower than that of fund flows to good performance. In column 1, the slope coefficient for PCM is 0.053 and the slope coefficient for the interaction term, $PCM \times (PCM < 0)$, is -0.036. Thus, the sensitivity of fund flows to negative performance is reduced to 0.017 (=0.053-0.036), which is more than 3.1 times less that the sensitivity of flows to positive performance. Overall, this confirms the convex flow-performance relationship and lends empirical support to *Hypothesis 1*.

In columns 4 and 5 of Table 2, we consider the relationship between fund inflows and outflows as the dependent variable and fund performance. This allows us to obtain a clearer picture of what is driving fund flows following a change in funds' performance. For equity funds with negative performance ($PCM < 0$), a 1 percentage point decrease in performance is associated with a 2.6% (=0.079-0.053) decrease in fund inflows (column 3) but only a 0.3% (=-0.023+0.020) increase in fund outflows (column 4). As regards *Hypothesis 2*, we find that good performance results in large inflows but that poor performance is not mirrored in a larger increase in fund outflows. The documented change in net fund flows thus appears to be driven – for poorly performing funds – by a change in fund inflows, not outflows, which confirms the hypothesis.

Table 2: Flow-Performance Relationship

	Net Fund Flows (1)	Pure Retail (2)	Inflows (3)	Outflows (4)
PCM	0.053***	0.072***	0.079**	-0.023**
	(0.011)	(0.021)	(0.036)	(0.011)
$PCM \times (PCM < 0)$	-0.036***	-0.056***	-0.053**	0.020**
	(0.012)	(0.012)	(0.024)	(0.010)
$PCM < 0$	-0.001	-0.001	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
$Lagged\ Flow$	0.315***	0.219***	0.323***	0.192***
	(0.037)	(0.062)	(0.060)	(0.045)
$Log(size)$	0.005**	0.005*	0.003	-0.003***
	(0.002)	(0.003)	(0.002)	(0.001)
$Log(age)$	-0.016***	-0.021***	-0.011***	0.005***
	(0.002)	(0.003)	(0.002)	(0.001)
Observations	5,280	4,964	5,280	5,280
adj. R^2	0.152	0.110	0.129	0.046

Note: The table shows estimates of the flow-performance relationship for active equity-investing funds from January 2009 to February 2022. The model is estimated using the OLS estimator with fixed effects. Column 1 reports the estimates using monthly net fund flows as the dependent variable. Column 2 considers flows related to purely retail investors. Columns 3 and 4 report the regression estimates for fund inflows and outflows. The unit of observation is fund-month and the estimation is run on a sample of 73 unique funds (70 for retail). We include fund fixed effects, control for aggregate fund flows (unreported) and use bootstrapped standard errors in parenthesis. The statistical significance is denoted as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

An immediate robustness check concerns our choice of fund performance measure. Given the dominant use of fund's alpha to measure fund performance in the literature, we re-estimate the regressions in Table 2 using the geographical-focus based three-factor Fama-French alpha. The resulting coefficients are shown in Table B1 in the Appendix and are very similar in magnitude and significance. While inspecting retail fund flows, the sensitivity of flows to bad performance

(=0.031-0.016) is found to be more than two times less than the sensitivity of flows to good performance (0.031). Further, we re-estimate the PCM using a weighting scheme where the outermost month receives the smallest weight and the nearest the largest. Weights were normalized to be one in total. By doing so, we implicitly assume that retail investors are more likely to consider recent changes to fund performance when making their investment decisions. The estimates are displayed in Table B2 in the Appendix and confirm our baseline set of results.

Table 3: Flow-Performance Relationship for Subsamples of Equity Funds

	Static (1)	Time FE (2)	Young (3)	Old (4)	Low (5)	High (6)	Inst. (7)
PCM	0.039***	0.057***	0.050***	0.015***	0.016***	0.020**	0.023*
	(0.005)	(0.018)	(0.013)	(0.003)	(0.004)	(0.009)	(0.013)
$PCM \times (PCM < 0)$	-0.019**	-0.045**	-0.020*	-0.014***	-0.016***	-0.019**	-0.025*
	(0.008)	(0.023)	(0.011)	(0.002)	(0.006)	(0.008)	(0.014)
$PCM < 0$	0.001*	0.004*	0.003*	-0.001	0.001	0.000	-0.003*
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
$Lagged\ Flow$		-0.085***	0.224***	0.129***	0.056***	0.074	0.080**
		(0.014)	(0.083)	(0.018)	(0.011)	(0.071)	(0.036)
$Log(size)$	0.005***	0.012***	0.003	0.006***	0.001	0.001	0.008
	(0.001)	(0.003)	(0.004)	(0.001)	(0.001)	(0.004)	(0.005)
$Log(age)$	-0.020***	-0.037***	-0.016***	-0.015***	-0.000	-0.014**	-0.012
	(0.001)	(0.007)	(0.006)	(0.002)	(0.001)	(0.006)	(0.009)
N	5,149	5,136	1,975	3,160	2,789	2,347	692
adj. R^2	0.031	0.038	0.103	0.020	-0.008	0.028	0.019

Note: The table shows estimates of the flow-performance relationship for active equity-investing funds from January 2009 to February 2022. The model is estimated using the OLS estimator with fixed effects. The dependent variable is monthly net fund flows related to purely retail investors. The unit of observation is fund-month. Columns 1 and 2 show the results for a static model and a model with month fixed effects. Columns 3 to 6 report results for sub-samples of young, old, low flow and high flow funds. Young and old funds correspond to the funds whose age falls below- and above-median, respectively. Low flows and high flows correspond to periods with aggregate equity fund flows below- and above-median. Column 7 reports the results for a subset of institutional-oriented funds. We include fund fixed effects, control for aggregate fund flows (unreported) and use bootstrapped standard errors in parenthesis. The statistical significance is denoted as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3 reports additional results to check for the convexity across different sub-samples and model specifications. This is to address the issue put forward by Spiegel and Zhang (2013) who claim that heterogeneity among equity funds may lead to a spurious convex flow-performance relationship. Needless to say, the use of fund fixed effects should largely mitigate the heterogeneity bias. First, in column 1, we consider a static model instead of the dynamic specification used in the baseline model. Given the large persistency of fund flows, a static model is the less preferred option of model specification but we continue to report qualitatively the same estimates as in the baseline. We add monthly fixed effects in column 2 mostly to control for foreign developments since we do not record any major changes (economic or regulatory) in the home country. In columns 3 and 4, we examine whether the flow-performance relation is pervasive across young and old funds, e.g. funds with a below- and above-median fund age. We find that while for both sub-samples investors tend to under-react to poor performance, they do so more when investing in older funds. This is in line with Chevalier and Ellison (1997) who also find larger convexity in the case of older funds. In columns 5 and 6, we check for differences between periods with low and high aggregate fund flows (months with above- and below-median aggregate equity fund flows). We find that the shape of the flow-performance relationship is similar in periods with high and low fund flows. Finally, in column 7, we single out funds with a dominant share of institutional investors. Given the low number of purely institutional funds in the Czech mutual fund industry, we follow Goldstein et al. (2017) and classify equity funds as institutional-oriented if more than 80% of fund assets are owned through an institutional share class. We continue to report the under-reaction of investors to poor fund performance, albeit only at the 10% statistical level of confidence.

Overall, our results across different model specifications and sub-samples suggest that the reported flow-performance relationship and the documented under-reaction of investors to poor fund performance should not be spurious as argued by Spiegel and Zhang (2013) in the context of equity mutual funds.

5.1 The Role of Illiquidity for Poorly Performing Funds

Next, we turn to *Hypothesis 3* and assess the importance of liquidity on the given flow-performance relationship. To this end, we estimate the following regression:

$$\begin{aligned} Flow_{i,t} \alpha Flow_{i,t-1} + \beta_1 PCM_{i,t-1} + \beta_2 PCM_{i,t-1} \times Illiquidity_{i,t} \\ + \beta_3 Illiquidity_{i,t} + \gamma Controls_{i,t} + \zeta_i + \varepsilon_{i,t}, \forall\ PCM_{i,t}^{RANK} < p(50) \end{aligned} \tag{8}$$

where the interaction term $PCM_{i,t-1} \times Illiquidity_{i,t}$ captures the flow in or out of funds associated with a change in fund performance when facing illiquidity of some sort. The regression is run on a sub-sample of under-performing funds where changes to investor behaviour due to liquidity shortages are more likely to occur. We first evaluate the performance (PCM) of each fund i at month t and all funds in the given month are ranked from 0 (worse-performing) to 1 (best-performing), captured by variable $PCM_{i,t}^{RANK}$. Our sub-sample of under-performing funds is then formed by funds with a below median performance rank $PCM_{i,t}^{RANK} < p(50)$.[13]

We measure $Illiquidity_{it}$ both at the cross-section (fund) level (i) and through time (t). To measure illiquidity at the fund level, we assess the fund's level of cash holdings. Since we need to make sure that cash holdings are exogenous to fund inflows in month t and to investor decisions in that month[14], we measure the level of cash holdings in the previous month $t-1$. As a robustness check, we also consider (on top of cash holdings) a fund's holdings of money market fund shares and short-term repo lending by funds[15] (liquid assets). We then construct an indicator variable $IlliqFund$ which equals one if the fund has below-median cash holdings (or liquid assets) and zero otherwise. By using the median value as a threshold, we make our two sub-samples relatively comparable in size, which will facilitate our analysis. To identify illiquid periods, we look at the evolution of the VIX index and the term spread. Nagel (2012), Chung and Chuwonganant (2014) and Adrian et al. (2019) show that the VIX index exerts a large market-wide impact on liquidity consistent with theoretical considerations that higher volatility tightens the funding constraints of market makers and thereby reduces their liquidity-provision capacity (Brunnermeier and Pedersen, 2009). The resulting indicator variable *IlliqPeriod* equals one if the corresponding time-series variable is above the sample average. We also manually typeset dummies that capture periods with heightened levels

[13] Note that funds which are categorized as under-performing can still record positive performance so the focus is kept on the entire performance distribution from the baseline model.

[14] Chen et al. (2010) argue that higher cash holdings should endogenously lower the volatility of fund flows since investors may be less or more worried when their fund is holding lots of or very little cash to meet sudden redemption.

[15] We thus assume that funds can opt not to reopen the repo and use cashflow from repurchases to cover redemption requests.

of market-wide stress, such as the 2018 stock market crash (October–November 2018) or the Covid-19 outbreak (February–March 2020).

Table 4: Flow-Performance Relationship: The Role of Illiquidity

$PCM_{i,t}^{RANK} < p(50)$	Illiquid periods				Illiquid funds	
	VIX	Spread	2018 fire-sale	Covid	Low cash	Low liquid assets
	(1)	(2)	(3)	(4)	(5)	(6)
PCM	0.031***	0.014***	0.018***	0.011***	0.015**	0.022***
	(0.004)	(0.007)	(0.009)	(0.004)	(0.006)	(0.005)
$PCM \times IlliqPeriod$	0.015***	0.027**	0.129***	0.172***		
	(0.004)	(0.013)	(0.034)	(0.042)		
$IlliqPeriod$	-0.004***	0.002**	-0.010***	-0.003		
	(0.001)	(0.001)	(0.002)	(0.003)		
$PCM \times IlliqFund$					0.047***	0.041***
					(0.015)	(0.015)
$IlliqFund$					-0.007***	-0.004***
					(0.001)	(0.001)
$Lagged\ Flow$	0.182**	0.184**	0.143**	0.146***	0.177***	0.186***
	(0.076)	(0.076)	(0.068)	(0.022)	(0.020)	(0.020)
$Log(size)$	0.001	0.000	0.007**	0.006***	0.000	0.000
	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)
$Log(age)$	-0.023***	-0.021***	-0.026***	-0.024***	-0.020***	-0.021***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)
N	2,383	2,383	1,932	1,932	2,383	2,383
adj. R^2	0.104	0.101	0.089	0.055	0.085	0.076

Note: The table shows estimates of the flow-performance relationship for under-performing active equity-investing funds from January 2009 to February 2022. The model is estimated using the OLS estimator with fixed effects. In columns 1 to 4, we use dummy variables specified according to different indicators to capture illiquid periods ($IlliqPeriod$). $IlliqPeriod$ equals one if the corresponding time-series variable (VIX index, term spread) is above the sample average. The term spread is the difference between the 10-year government bond yield and the three-month interbank rate (PRIBOR). We further specify fixed periods of high market illiquidity (2018 fire-sale and the Covid-19 outbreak). We use dummy variables to capture funds with low liquidity ($IlliqFund$) in columns 5 and 6. $IlliqFund$ is equal to one if the fund has cash holdings or cash, money market fund shares and repo holdings below the sample median. Otherwise, it is equal to zero. The unit of observation is fund-month and the estimation is run on a sample of 70 purely retail funds. We include fund fixed effects, control for aggregate fund flows (unreported) and report bootstrapped standard errors in parenthesis. The statistical significance is denoted as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4 shows the results. Columns 1 to 4 present the results in which we include the interaction between illiquid periods and fund performance, while columns 5 and 6 consider the relation for illiquid funds. The estimates show that the previously established convexity of the fund-performance relationship does not entirely hold during illiquid periods and/or when the funds invest heavily in less liquid assets. Specifically, for a subset of under-performing funds, we document that investors are highly sensitive to poor performance during less tranquil periods, as captured by high VIX and the term spread or when funds hold low levels of cash or low amounts of liquid assets in general. For instance, during periods with high VIX, the effect of performance on fund flows is 1.5 times greater (=0.031+0.015) than during periods of low VIX (0.031). In economic terms, a one percentage point decrease in fund performance during an illiquid period (high VIX) is associated with a 4.6% decrease in fund flows (column 1). The concave relationship was found to be even more pronounced during the turmoil caused by the 2018 fire-sale and the outbreak of Covid-19. The decrease in performance following the Covid-19 outbreak in February and March 2019 has been associated with a decrease in fund flows of more than 18%. Columns 5 and 6 present results in which we include the interaction terms given by the product of fund performance and a low cash holdings indicator variable. Similarly to illiquid periods, we find that the flow of money in or out of under-performing funds with low liquidity holdings is much more sensitive to changes in performance. A decrease in such a fund's performance is associated with about a two or two and a half times higher decrease in fund flows than for a fund with high liquidity.

To make sure our choice of fund performance measure is not driving the estimates, we repeat the exercise with the geographical-focus based Fama-French three-factor alpha. The estimates are shown in Table B3 in the Appendix and are largely similar, both qualitatively and quantitatively. The relation between fund flows and performance takes on a concave shape during periods of aggregate illiquidity and for illiquid funds. We also re-run the regression using a full sample of funds which yields quantitatively similar estimates, albeit at a lower level of statistical significance. These estimates are available from the authors upon request.

Table 5: Inflows vs. Outflows: The Role of Illiquidity

$PCM^{RANK}_{i,t} < p(50)$	Inflows			Outflows		
	VIX	Stress	Low liquid assets	VIX	Stress	Low liquid assets
	(1)	(2)	(3)	(4)	(5)	(6)
PCM	0.043**	0.021**	0.025**	0.005	0.000	0.003
	(0.021)	(0.010)	(0.011)	(0.005)	(0.004)	(0.007)
$PCM \times IlliqPeriod$	0.011***	0.222***		-0.017**	-0.116***	
	(0.003)	(0.051)		(0.007)	(0.028)	
$IlliqPeriod$	-0.002*	0.002		0.001	0.005***	
	(0.001)	(0.002)		(0.001)	(0.001)	
$PCM \times IlliqFund$			0.010***			-0.009***
			(0.003)			(0.003)
$IlliqFund$			-0.003**			0.004***
			(0.001)			(0.001)
$Lagged\ Flow$	0.297***	0.257***	0.299***	0.228***	0.195***	0.225***
	(0.067)	(0.020)	(0.018)	(0.066)	(0.021)	(0.020)
$Log(size)$	-0.001	0.001	-0.001	0.000	-0.003***	0.000
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
$Log(age)$	-0.013***	-0.010***	-0.011***	0.002	0.003***	0.001
	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
N	2,679	2,170	2,679	2,679	2,170	2,679
adj. R^2	0.138	0.071	0.113	0.054	0.021	0.037

Note: The table shows estimates of the flow-performance relationship for under-performing active equity-investing funds from January 2009 to February 2022. The model is estimated using the OLS estimator with fixed effects. In columns 1 to 4, we use dummy variables specified according to different indicators to capture illiquid periods ($IlliqPeriod$). $IlliqPeriod$ equals one if the corresponding time-series variable (VIX index, term spread) is above the sample average. The term spread is the difference between the 10-year government bond yield and the three-month interbank rate (PRIBOR). We further specify fixed periods of high market illiquidity (2018 fire-sale and the Covid-19 outbreak). We use dummy variables to capture funds with low liquidity ($IlliqFund$) in columns 5 and 6. $IlliqFund$ is equal to one if the fund has cash holdings or cash, money market fund shares and repo holdings below the sample median. Otherwise, it is equal to zero. The unit of observation is fund-month and the estimation is run on a sample of 70 purely retail funds. We include fund fixed effects, control for aggregate fund flows and report bootstrapped standard errors in parenthesis. The statistical significance is denoted as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5 presents the results where we differentiate between fund inflows and fund outflows to see whether the documented higher sensitivity of investors' fund flows to poor performance when facing illiquidity shown in Table 4 is driven by increases in investor redemptions (outflows) or decreases in investor purchases of fund shares (inflows). The estimates show that the documented change in fund flows due to a change in fund performance is driven by both a change in fund inflows and fund outflows. Following a decrease in fund performance during illiquid periods (column 1), under-performing funds experienced a reduction of inflows by 5.4% (=0.043+0.011). While some portion of this effect could be attributed to a general decrease in fund inflows during anxious times that coincide with periods of low liquidity, we still find the reduction to be more pronounced for under-performing funds. While there is no relationship between fund performance and outflows when liquidity is plenty, we identify a statistically significant increase in fund outflows by about 1.7% during illiquid periods (column 4) and by 0.9% (column 6) for illiquid funds. This shows that bad performance is punished not just by a reduction in inflows but also by an increased share of redemptions. This somewhat contrasts with the baseline estimates using the full sample of funds where the documented convex relationship was mainly driven by a change in fund inflows.

The focus on retail-oriented funds means that our estimation should be free of the clientele effect described in Chen et al. (2010). The effect postulates that more sophisticated investors might be driving the observed tendencies to cut and run behaviour following a decrease in fund performance in illiquid funds. Investors, who place their money in less liquid funds, may be monitoring their position and the market more frequently and would thus be more sensitive to bad performance.

5.2 Fund Flows and Performance with Constraints on Investor Income

In this section, we enrich our analytical considerations on the flow-performance relationship by introducing time-varying constraints on investor income. While fund performance was confirmed to be an important factor in investment decisions, many studies argue that consumption investment decisions vary with changes in household disposable income. For instance, Guiso et al. (1996) show that investment in risky financial assets responds negatively to income risk (proxied by the variance of expected inflation and expected income growth). Similarly, Angerer and Lam (2009) find that a permanent income risk significantly shifts a household's portfolio toward risk-free assets. Last but not least, Gupta-Mukherjee (2021), using hikes in retail energy prices as a proxy for shocks to disposable income, discovers that flows to actively-managed US equity funds decreased with the rising constraints on disposable income.

The fluctuations in energy prices are a promising candidate to capture the emergence of short-term financial constraints on household disposable income, since energy costs are a highly inelastic expenditure and households are unable to react swiftly to the price changes. Edelstein and Kilian (2009) note that spikes in energy prices are usually accompanied with concerns about one's financial situation, suggesting that households may cut their expenditures based on their savings motive. Specifically, Edelstein and Kilian (2009) find that: "A one-time 1% increase in energy prices in a given month is associated with a statistically significant decline in real total consumption of -0.15% a year later." Data from the Czech Statistical Office indicate that energy price changes might be a good indicator of the possible disposable income constraints of Czech investors. Note that Czech households hold, on average, 99.5% of retail mutual fund shares. Total energy expenses in 2015-2019 comprised up to 8% of the total household expenditure on average. The differences between the rich and the median-income groups of the population (i.e. those most likely to invest in mutual funds) are not sizeable (Table A1).

Thus, to identify exogenous shocks to income, we exploit fluctuations in energy prices (energy price index) as they are a significant source of financial constraints on households (Edelstein and Kilian, 2009) and are considered to be "exogenous" to other economic factors (Hamilton, 1983, 1996).[16]

First, we investigate whether mutual fund flows are sensitive to short-run variations of household disposable income. We hypothesise that since rising energy prices can be considered as inelastic expenditure and are expected to result in less disposable income, the shock will lead to a reduction in the next month's fund flows. In order to test the hypothesis, we regress a fund's monthly flow on the Czech energy price index:

$$\begin{aligned} Flow_{i,t} = \alpha Flow_{i,t-1} + \beta_1 PCM_{i,t-1} + \gamma Controls_{i,t} + \delta_1 \Delta EP_{t-p} \\ + \delta_2 Large\ EP\ Change_{t-p} + \delta_3 \Delta EP_{t-p} \times Large\ EP\ Change_{t-p} + \zeta_i + \varepsilon_{i,t}, \end{aligned} \tag{9}$$

where ΔEP is the energy price index expressed in first differences and $Large\ EP\ Change$ is a dummy which we specify in two ways. First, we consider it to be equal to one in periods where the month-on-month increase in EP is larger than 0.5 (i.e. the top quartile in the sample period), $Large\ EP\ Increase$. Second, we make it equal to one for periods of large EP decreases, $Large\ EP\ Decrease$. For example, the interaction term $\Delta EP \times Large\ EP\ Increase$ and the related δ_3 parameter would then capture the impact of large energy price shocks on mutual fund flows. We use up to a two-quarter lag in energy price changes to allow sufficient time for a change in investor decisions (as a response to short-term changes in their household disposable income) to materialize.[17]

We run eq. 9 on the dataset of Czech retail equity-investing fund flows over the period January 2009 – February 2022. The development of energy prices over the sample period is shown in Figure A2. The figure highlights the various spikes in energy prices over the years. The largest spike of 20 pp was recorded in late 2021 and in early 2022, first due to the closure of one of the country's largest energy suppliers and then owing to the war in Ukraine .[18]

Estimates of eq. 9 are summarized in Table B4. When inspecting the baseline estimate in column 1, we find a statistically significant negative association between net fund flows and a change in the energy price index at both lags, significant at a level of 1%. The results are explained in more detail in columns 4 and 5. The documented decrease in fund flows appears to be driven by both a decrease in investor purchases of fund shares and a simultaneous increase in fund redemptions. In sum, in periods when retail investors face constraints on their disposable income stemming from increased energy prices, we find sizeable decreases in mutual fund inflows and modest increases in fund outflows. Column 2 clearly shows that this association is driven mainly by periods of large hikes in energy prices. The impact of changes in energy prices on fund flows appears asymmetric since falling energy prices are not significantly related to fund flows (column 3). Economically, the

[16] One may worry that the volatility index VIX denoting the overall fluctuations on the market is highly correlated with changes in energy prices. However, this is not the case as the observed correlation is only 0.2 and is not statistically significant.

[17] The fact that we lack information on the share of households with fixed energy contracts should not pose a great problem. We expect households to be rational agents who expect any major changes to spot prices to be reflected in their current contracts.

[18] The company (Bohemia Energy Ltd.) suffered due to increases in wholesale energy prices in the summer and autumn of 2021, at a time when it was expecting prices to go down. This variance led to huge losses in the futures markets and ended in bankruptcy. A total of 600,000 electricity and 300,000 gas customers consequently had to turn to "suppliers of last resort" where they paid much higher prices, since Bohemia Energy had pushed the prices to below average levels.

estimated coefficients are material. For example, in column 5, flows are 6.9% lower in the quarters following periods when energy prices increased sharply, ceteris paribus.

Second, we test whether investor under-reaction to poor performance (Section 5, Table 2) persists when investors face constraints on their income and, in theory, should feel more risk averse. To this end, we estimate the following regression:

$$\begin{aligned} Flow_{i,t} = \alpha Flow_{i,t-1} + \beta_1 PCM_{i,t-1} + \beta_2 PCM_{i,t-1} \times Large\ EP\ Increase_{i,t-3} \\ + \beta_3 Large\ EP\ Increase_{i,t-3} + \gamma Controls_{i,t} + \zeta_i + \varepsilon_{i,t}, \end{aligned} \quad (10)$$

where the interaction term *PCM* × *Large EP Increase* and the related β_2 parameter verify the nature of the flow-performance relationship during times of large spikes in energy prices.

The estimates are given in Table 6. We observe that placing constraints on investor income may significantly change their behaviour towards fund performance. During such times, the flow-performance relationship takes on a concave shape, suggesting that when facing financial constraints, investors tend to closely monitor and respond to changing fund performance. When focusing on a subsample of funds which underperform the benchmark returns (columns 4-6), we see that investors are more responsive to poor performance. Specifically, following a large spike in energy prices and a worsening of fund performance, we observe a significant decrease in fund inflows (-3.7%) and a significant increase in fund outflows (3.6%).

Table 6: Flow-Performance Relationship When Investors Are Facing Financial Constraints

	Full sample			Under-performing funds		
	Net Flows	Inflows	Outflows	Net Flows	Inflows	Outflows
	(1)	(2)	(3)	(4)	(5)	(6)
PCM	0.037***	0.027**	0.004	0.060**	0.011**	-0.017
	(0.012)	(0.013)	(0.006)	(0.024)	(0.005)	(0.013)
PCM × *Large EP Increase* $(t-3)$	0.031***	0.056***	-0.038**	0.067***	0.037**	-0.036***
	(0.008)	(0.018)	(0.015)	(0.020)	(0.017)	(0.012)
Large EP Increase $(t-3)$	-0.002	0.001	0.003***	-0.001	0.001	0.004***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Lagged Flow	0.203***	0.314***	0.189***	0.152**	0.298***	0.228***
	(0.060)	(0.063)	(0.045)	(0.069)	(0.073)	(0.073)
$Log(size)$	0.005**	0.003	-0.003***	0.002	-0.001	-0.001
	(0.003)	(0.002)	(0.001)	(0.004)	(0.002)	(0.001)
$Log(age)$	-0.021***	-0.011***	0.004***	-0.021***	-0.012***	0.002
	(0.003)	(0.003)	(0.001)	(0.004)	(0.002)	(0.001)
N	4,843	5,159	5,159	2,303	2,522	2,522
adj. R^2	0.097	0.120	0.051	0.082	0.127	0.059

Note: The table shows estimates of the flow-performance relationship for a full sample of active equity-investing funds (columns 1-3) and a sub-sample of under-performing funds (columns 4-6) from January 2009 to February 2022. The model is estimated using the OLS estimator with fixed effects. Column 1 and 4 report estimates using monthly net fund flows as the dependent variable. Column 2 and 5 consider fund inflows, while column 3 and 6 consider fund outflows. The unit of observation is fund-month and the estimation is run on a sample of 70 purely retail funds. We include fund fixed effects, control for aggregate fund flows and report bootstrapped standard errors in parenthesis. The statistical significance is denoted as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6. Smart Money Effect

In the last section, we check for the presence of the smart money effect in Czech mutual fund flows. It is argued that if (at least some) investors can identify superior funds in advance, this should be reflected in the data and materialized into a positive relationship between fund flows and subsequent fund performance. In our exploration, we can benefit from our access to exact new flows for our sample of funds. This allows us to focus our analysis on investments and disinvestments by individual (retail) investors. These important features of our dataset make it possible for us to conduct a more powerful test of the smart money effect than other studies that use mostly US-based quarterly fund flows implied by fund sizes and investment returns.

We use two approaches to test *Hypothesis 4*. First, we follow Keswani and Stolin (2008) who test for the presence of smart money by comparing the performance of "new money" put into mutual funds with the performance of "old money", that is, of assets that are already in place. Second, we conduct a standard multivariate analysis of the fund-flow performance. This is to account for the findings of the large literature on the various predictors of mutual funds performance, such as performance persistence and fund fees (Carhart, 1997) and fund size (Chen et al., 2004). For instance, Chen et al. (2004) find a size effect for US-based mutual funds under which larger funds exhibit poorer performance.

6.1 Performance of Money Flow-Based Portfolios

To obtain the first evidence of the presence of the smart money effect, we evaluate the performance of a hypothetical portfolio of "new money" which constitutes all eligible funds weighted in proportion to their value of the inflow or outflow measure in the preceding month. The new money is then compared to the performance of the "old money". To this end, we form a portfolio from all eligible funds weighted by the funds' TNA after excluding the money put in or taken out during the last month (Keswani and Stolin, 2008). As a performance measure for the constructed portfolios, we gradually consider an annualized PCM, a geographical-focus based three-factor model and a four-factor model which includes Carhart's momentum factor, see Section 4.2. Comparing the performance of new and old money-weighted portfolios informs us whether a "recent" investment decision outperforms the mutual fund industry as a whole.

We show the results in Table 7. Before inspecting the performance of the new money-weighted portfolio, let us discuss the performance of the old money (value-weighted) portfolio shown in the third row (3) of each panel. This portfolio's (baseline) annualized PCM averages at 1.24% over the full sample period. The first row of each panel shows the performance of a portfolio of studied funds weighted by their inflows of money (new money). Its estimated performance, 1.45%, is significantly different from the performance of the old money portfolio (a difference of 0.21 percentage points). The result holds even if we use other measures of fund performance to obtain the constructed portfolios. For instance, the third panel uses the Carhart (1997) four-factor model to measure the funds' performance. With that measure, we can see that none of the constructed portfolios outperforms the market as alpha averages at -0.8%. Nonetheless, the difference between the inflows-weighted portfolio and the old money is always positive and significantly different from zero. Accounting for the momentum factor thus does not invalidate our results.

Table 7: Comparison of Performance of New and Old Money Portfolios

Portfolio description	Portf. perform. (%)	Smart money effect	
		Difference (p.p.)	P-value (%)
Panel A) Portfolio change measure			
(1) Weighted by inflows	1.45	0.21	0.00
(2) Weighted by outflows	1.08	-0.15	0.01
(3) Weighted by fund value	1.24	-	-
Panel B) Three-factor model			
(1) Weighted by inflows	-0.46	0.42	0.00
(2) Weighted by outflows	-0.90	-0.03	72.0
(3) Weighted by fund value	-0.87	-	-
Panel C) Four-factor model			
(1) Weighted by inflows	-0.38	0.42	0.00
(2) Weighted by outflows	-0.84	-0.03	72.0
(3) Weighted by fund value	-0.80	-	-

Note: The table shows the performance of the constructed "new money" and "old money" portfolios from all eligible funds. We show the results based on three different performance metrics as indicated by the three panels. The difference column stands for the comparison of the performance of the new money and old money portfolios given the performance measure. P-value stands for the paired two-sample t-test, i.e. testing the hypothesis that the difference is zero.

This is the first result indicating that Czech mutual fund investors can successfully identify and then invest in funds that subsequently outperform idle money. The second row of each panel also tests for the presence of smart money when deciding on fund redemption requests (outflows). As is apparent though, the performance of the studied funds weighted in proportion to their outflows of investor money is not statistically different from the value-weighted fund population. Money withdrawals from funds, unlike money which is invested, are not smart. The only difference in terms of the statistical significance is when the performance of the constructed portfolios is measured by the PCM. However, note that the difference is negative, meaning that redeemed money underperforms idle money.

6.2 Multivariate Analysis

To verify that the presence of smart money is not driven by other omitted factors, we include the lead of the Portfolio Change Measure (PCM) in eq. 6 and rerun the regression. If mutual fund investors are smart enough to distinguish between good and bad funds, as suggested by the smart-money hypothesis, we should obtain a positive relation between $Flow_{i,t}$ and the lead of the $PCM_{i,t+1}$:[19]

$$Flow_{i,t} = \alpha Flow_{i,t-1} + \beta PCM_{i,t+1} + \gamma Controls_{i,t} + \varepsilon_{i,t}, \tag{11}$$

The results are presented in Table 8. The first regression confirms the existence of the smart money effect as fund performance at $t+1$ is positively associated with the previous month's net aggregate flow t. In the second regression, we introduce our controls, namely the lagged fund flow, the logarithm of fund size and fund age. The fund size effect, as described in Chen et al. (2004), is not present in our sample of funds (column 3). In any case, neither the performance persistence nor the

[19] Related studies typically regress fund performance on past fund flows (Keswani and Stolin, 2008; Jiang and Yuksel, 2017), e.g. they simply reverse the flow-performance regression. However, this introduces the risk of reverse causality bias.

fund size effect affects the documented smart money effect. In the fourth and fifth regression, we confirm that the smart money effect is apparent for fund share purchases only, not for fund redemptions.

Table 8: Testing for the Presence of the Smart Money Effect

		Net Flows		Inflows	Outflows
	(1)	(2)	(3)	(4)	(5)
PCM_{t+1}	0.023***	0.024***	0.038***	0.019***	-0.006
	(0.004)	(0.006)	(0.009)	(0.005)	(0.006)
$PCM_{t+1} \times Log(size)$			-0.001		
			(0.004)		
$Lagged\ Flow$	0.322***	0.294***	0.290***	0.312***	0.208***
	(0.033)	(0.030)	(0.037)	(0.059)	(0.036)
$Log(size)$		0.004***	0.006***	0.002	-0.002**
		(0.001)	(0.002)	(0.002)	(0.001)
$Log(age)$		-0.012***	-0.013***	-0.009***	0.003**
		(0.003)	(0.003)	(0.002)	(0.001)
N	5,408	5,392	5,392	5,344	5,344
adj. R^2	0.104	0.121	0.124	0.107	0.036

Note: The table shows estimates of the flow-performance relationship with the lead of the fund performance for a full sample of active equity-investing funds. The estimation period is from January 2009 to February 2022. The model is estimated using the OLS estimator with fixed effects. We include fund fixed effects and report bootstrapped standard errors in parenthesis. The statistical significance is denoted as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Table 9, we check how long the smart money effect persists. In our analyses up to this point, we searched for the presence of smart money in the month immediately following the flow of money. In the table below, we examine the validity of the smart money effect up to one year ahead. We regress fund flows on future performance and the set of controls where we gradually consider the lead of performance of 1 to 12 months. In the process, we also sort the funds in two ways. First, we distinguish between implied and actual fund flows. Implied fund flows are obtained as the fund's TNA at the end of a given month minus the product of the fund's TNA at the start of the month and its total return during the month. Actual flows are obtained directly from our dataset as inflows net of outflows. Our second distinction is between fund flows measured monthly as against fund flows captured on a quarterly basis. The purpose of this exercise is to verify the advantage of a more precise measurement of fund flows and the ability to observe them at a monthly frequency that stems from our supervisory dataset.

The estimates show that the smart money effect is rather short-lived. When using implied fund flows (those observed by investors), we are unable to detect smart money after the second month. When using actual fund flows, the smart money effect lasts up to three months, somewhat longer than in the case of using implied fund flows. This confirms that investors make good fund choices while the implied fund flows are only an approximation of actual investor behaviour.

Table 9: Smart Money Effect Up to 6 Periods Ahead

	Money Flow Measured Monthly				Money Flow Measured Quarterly			
	Actual flows		Implied flows		Actual flows		Implied flows	
1 *month/quarter lead*	0.045***	(0.011)	0.023***	(0.005)	0.068**	(0.033)	0.044*	(0.026)
2 *month/quarter lead*	0.038***	(0.010)	0.019**	(0.009)	0.040*	(0.023)	0.033	(0.033)
3 *month/quarter lead*	0.022**	(0.011)	0.013	(0.012)	0.028	(0.038)	0.023	(0.041)
4 *month/quarter lead*	0.015	(0.018)	0.008	(0.010)	0.012	(0.029)	0.019	(0.023)
5 *month/quarter lead*	0.009	(0.019)	0.002	(0.015)	0.004	(0.022)	0.011	(0.020)
6 *month/quarter lead*	0.002	(0.015)	-0.004	(0.011)	-0.009	(0.020)	0.002	(0.019)

Note: The table shows estimates of the flow-performance relationship with the lead of the fund performance for a full sample of active equity-investing funds. The estimation period is from January 2009 to February 2022. The model is estimated using the OLS estimator with fixed effects. We include fund fixed effects and report bootstrapped standard errors in parenthesis. The statistical significance is denoted as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Estimates further show that when using fund flows measured at a quarterly frequency, it is somewhat more complicated to detect the presence of smart money, even more so when using implied fund flows. This weakness of using quarterly implied flows to detect smart money can be attributed to at least two factors (on top of the fact that using monthly fund flows multiplies the number of observations in the analysis by a factor of three). First, implied fund flows can be expected to lose accuracy as the span over which they are measured grows. Second, the "prediction" performance of our simple regression model would be much less precise for quarterly data since the lead of fund performance is effectively used to predict flows between 1 and 5 months ahead, and three months ahead on average. This is in stark contrast to a one month ahead prediction when monthly data are used.

7. Concluding Remarks

Our understanding of how mutual fund investors react to changing performance is based primarily on the behavior of US investors. Ferreira et al. (2012) document substantial differences in the flow-performance relationship across countries, meaning that the US findings do not map directly onto other countries. To contribute to the literature, we revisit the flow-performance relationship as well as the smart money effect with a unique supervisory dataset from an emerging market economy – the Czech Republic. We construct a sample of retail-oriented open-end equity funds over the period 2009–2022. While most US-based studies use quarterly flows implied by fund sizes and investment returns, we have access to monthly exact net flows for our sample of funds. Further, we observe the two key components of these net flows: investments by individuals and disinvestments by individuals. These features of the data allow us to conduct robust tests on the flow-performance relation and the smart money effect.

We find a convex flow-performance relationship for the overall sample of funds meaning that Czech investors are more responsive to good past performance than they are to poor performance. We also find that the convex relationship turns to concave during periods of aggregate illiquidity and for funds which invest in less liquid assets. When facing illiquidity and a deteriorating performance, under-performing equity-investing funds are found to experience lower investor purchases as well as a larger share of redemptions. Furthermore, we find evidence that retail-oriented mutual fund flows are sensitive to time-varying constraints on household disposable income at the aggregate level. When facing income shocks and negative fund performance, a significant investor reaction is found for both perspective investors deciding over a fund share purchase and those investors who already hold a mutual fund share and are deciding whether to exit a fund or reduce their fund share.

We further verify that Czech investors display significant fund selection skills. While the smart money effect was questioned in the US (Sapp and Tiwari, 2004), we find conclusive evidence that smart money is present in the Czech Republic, albeit difficult to unravel. The performance difference between new money and old money is found to be statistically significant and robust to the choice of fund performance measure. The smart money effect is found to be driven by fund purchases and not withdrawals.

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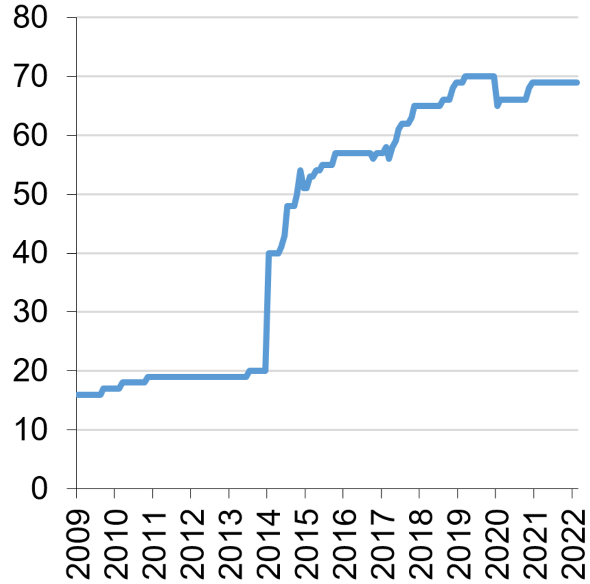
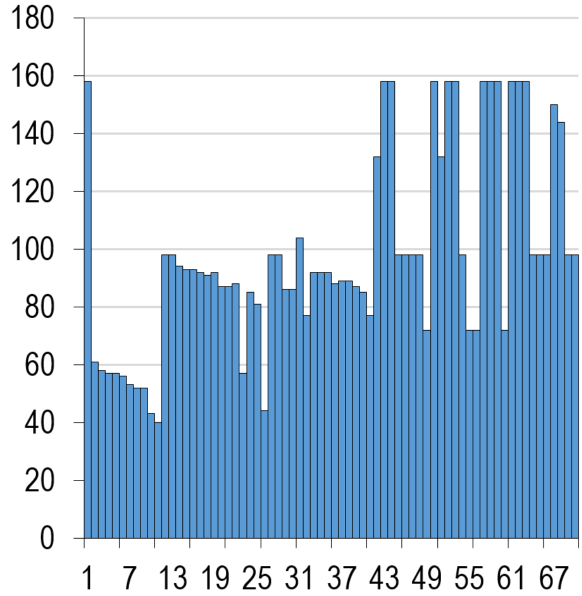
Appendix A: Supporting Data Information

Figure A1: Period and Cross-Section Coverage

(A) Total Number of Active Funds for Each Year

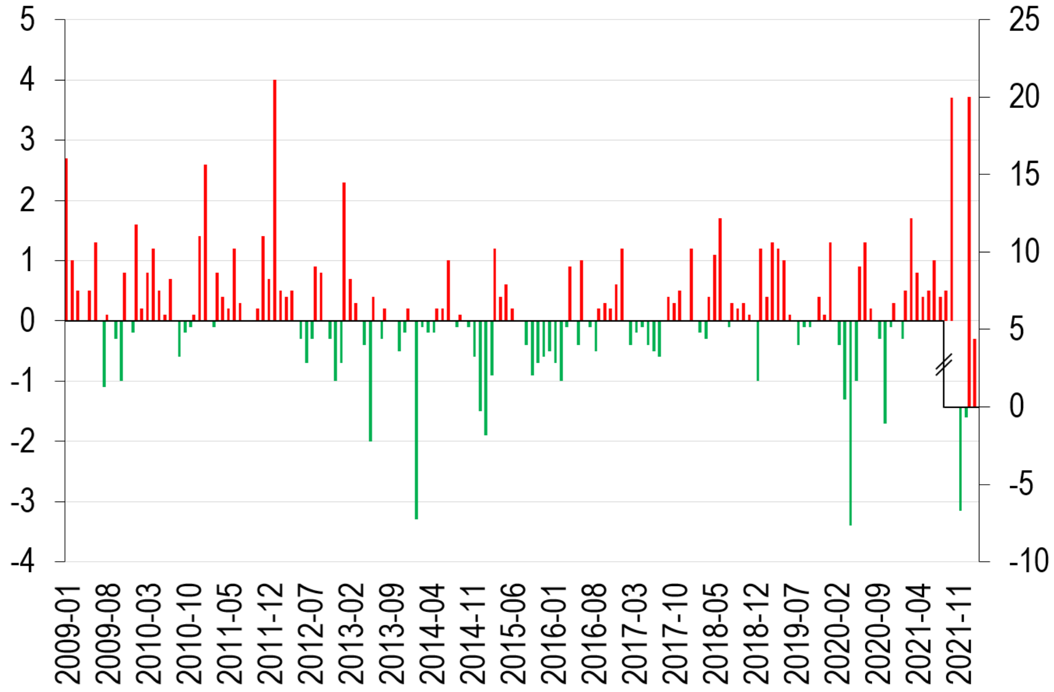


(B) Total Number of Traceable Months for Each Fund



Source: Czech National Bank, own processing

Figure A2: Evolution of the Czech Energy Price Index



Note: The graph shows the first differences in the energy price index in the Czech Republic for the period from January 2009 to February 2022. The surge in energy prices due to the closure of Bohemia Energy and the start of the war in Ukraine is on the right-axis to keep the graph informative.
Source: Czech Statistical Office (2022), own processing

Table A1: Household Energy Expenditure

Year	Total household expenditure	Lowest quintile	Second quintile	Third quintile	Fourth quintile	Fifth quintile
2015	7.96%	12.07%	9.78%	8.49%	7.19%	5.81%
2016	7.79%	11.70%	9.49%	8.33%	7.13%	5,67%
2017	7.46%	10.99%	9.27%	7.93%	6.82%	5,52%
2018	7.07%	10.42%	8.60%	7.58%	6.47%	5,24%
2019	6.72%	10.02%	8.31%	6.97%	6.13%	5.00%

Note: Czech household expenditure on electricity, gas and other fuels as a percentage of total household expenditure based on different income quintiles.
Source: Czech Statistical Office (2022), own processing

Appendix B: Additional Estimates

Table B1: Flow-Performance Relationship when Using Fama-French Alpha

	Net Fund Flows (1)	Pure Retail (2)	Inflows (3)	Outflows (4)
$Alpha$	0.030***	0.031***	0.023***	-0.011***
	(0.006)	(0.008)	(0.006)	(0.003)
$Alpha \times (Alpha < 0)$	-0.017***	-0.016***	-0.010***	0.011**
	(0.003)	(0.003)	(0.002)	(0.005)
$Alpha < 0$	-0.000	0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.000)
$Lagged\ Flow$	0.304***	0.215***	0.315***	0.198***
	(0.035)	(0.061)	(0.056)	(0.041)
$Log(size)$	0.004**	0.004*	0.002	-0.002*
	(0.002)	(0.002)	(0.002)	(0.001)
$Log(age)$	-0.012***	-0.015***	-0.010***	0.002**
	(0.002)	(0.003)	(0.002)	(0.001)
Observations	5,482	5,136	5,450	5,450
adj. R^2	0.134	0.088	0.119	0.046

Note: The table shows estimates of the flow-performance relationship for active equity-investing funds from January 2009 to February 2022. The model is estimated using the OLS estimator with fixed effects. Column 1 reports estimates using monthly net fund flows as the dependent variable. Column 2 considers flows related to purely retail investors. Columns 3 and 4 report regression estimates for fund inflows and outflows. The unit of observation is fund-month and the estimation is run on a sample of 73 unique funds (70 for retail). We include fund fixed effects, control for aggregate fund flows (unreported) and report bootstrapped standard errors in parenthesis. The statistical significance is denoted as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B2: Flow-Performance Relationship when Using Weighted PCM

	Net Fund Flows (1)	Pure Retail (2)	Inflows (3)	Outflows (4)
PCM	0.047***	0.060***	0.072***	-0.023**
	(0.016)	(0.016)	(0.016)	(0.009)
$PCM \times (PCM < 0)$	-0.015***	-0.047***	-0.054**	0.021*
	(0.004)	(0.012)	(0.021)	(0.013)
$PCM < 0$	-0.001	-0.001	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
$Lagged\ Flow$	0.327***	0.249***	0.259***	0.181***
	(0.013)	(0.014)	(0.014)	(0.014)
$Log(size)$	0.004***	0.005***	0.004***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
$Log(age)$	-0.014***	-0.018***	-0.014***	0.003***
	(0.001)	(0.002)	(0.001)	(0.001)
Observations	5154	4804	4969	4969
adj. R^2	0.150	0.108	0.091	0.024

Note: The table shows estimates of the flow-performance relationship for active equity-investing funds from January 2009 to February 2022. The model is estimated using the OLS estimator with fixed effects. Column 1 reports estimates using monthly net fund flows as the dependent variable. Column 2 considers flows related to purely retail investors. Columns 3 and 4 report regression estimates for fund inflows and outflows. The unit of observation is fund-month and the estimation is run on a sample of 73 unique funds (70 for retail). We include fund fixed effects, control for aggregate fund flows (unreported) and use bootstrapped standard errors in parenthesis. The statistical significance is denoted as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B3: Flow-Performance Relationship and Illiquidity when Using Fama-French Alpha

$Alpha < 0$	VIX (1)	Spread (2)	2018 fire-sale (3)	Covid (4)	Low cash (5)	Low liquid assets (6)
$Alpha$	0.017**	0.039***	0.017**	0.016**	0.041***	0.054***
	(0.007)	(0.008)	(0.007)	(0.007)	(0.012)	(0.012)
$Alpha \times IlliqPeriod$	0.017***	0.028***	0.435***	0.442***		
	(0.004)	(0.008)	(0.140)	(0.128)		
$IlliqPeriod$	-0.002**	0.000	0.003	-0.004*		
	(0.001)	(0.001)	(0.006)	(0.003)		
$Alpha \times IlliqFund$					0.031***	0.039**
					(0.009)	(0.015)
$IlliqFund$					-0.007***	-0.003***
					(0.001)	(0.001)
$Lagged\ Flow$	0.159**	0.159**	0.147**	0.151***	0.157***	0.163***
	(0.068)	(0.068)	(0.068)	(0.021)	(0.020)	(0.020)
$Log(size)$	0.000	-0.000	0.005*	0.004**	-0.000	-0.000
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
$Log(age)$	-0.019***	-0.018***	-0.019***	-0.018***	-0.017***	-0.018***
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
N	2,448	2,448	2,051	2,051	2,448	2,448
adj. R^2	0.083	0.084	0.068	0.040	0.065	0.057

Note: The table shows estimates of the flow-performance relationship for active equity-investing funds with negative alpha from January 2009 to February 2022. The model is estimated using the OLS estimator with fixed effects. In columns 1 to 4, we use dummy variables specified according to different indicators to capture illiquid periods ($IlliqPeriod$). $IlliqPeriod$ equals one if the corresponding time-series variable (Vix index, Term spread) is above the sample average. The term spread is the difference between the 10-year government bond yield and the three-month interbank rate (PRIBOR). We further specify fixed periods of high market illiquidity (2018 fire sale and the Covid-19 outbreak). We use dummy variables to capture funds with low liquidity ($IlliqFund$) in columns 5 and 6. $IlliqFund$ is equal to one if the fund has cash holdings or cash, money market fund shares and repo holdings below the sample median. Otherwise, it is equal to zero. The unit of observation is fund-month and the estimation is run on a sample of 70 purely retail funds. We include fund fixed effects, control for aggregate fund flows (unreported) and report bootstrapped standard errors in parenthesis. The statistical significance is denoted as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B4: Mutual Fund Flows and Change in Energy Prices

	(1) Net Flows	(2) Net Flows	(3) Net Flows	(4) Inflows	(5) Outflows
$\Delta EP\ (t-3)$	-0.036***	0.017	-0.022	-0.026***	0.013***
	(0.007)	(0.027)	(0.068)	(0.007)	(0.003)
$\Delta EP\ (t-6)$	-0.046***	-0.025	-0.149**	-0.035**	0.017***
	(0.011)	(0.079)	(0.074)	(0.010)	(0.004)
PCM	0.038***	0.038***	0.036***	0.048***	-0.015**
	(0.011)	(0.010)	(0.011)	(0.011)	(0.007)
$Lagged\ Flow$	0.211***	0.207***	0.198***	0.315***	0.195***
	(0.014)	(0.014)	(0.014)	(0.013)	(0.013)
$Log(age)$	-0.015***	-0.015***	-0.020***	-0.010***	0.003***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
$Log(size)$	0.004***	0.004***	0.005***	0.002*	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\Delta EP\ (t-3) \times Increase\ (t-3)$		-0.069***			
		(0.019)			
$\Delta EP\ (t-6) \times Increase\ (t-6)$		-0.069**			
		(0.031)			
$\Delta EP\ (t-3) \times Decrease\ (t-3)$			0.041		
			(0.077)		
$\Delta EP\ (t-6) \times Decrease\ (t-6)$			0.078		
			(0.149)		
N	5,127	5,124	5,124	5,441	5,441
adj. R^2	0.077	0.077	0.109	0.109	0.035

Note: The table shows estimates of the relationship between fund flows related to purely retail investors and changes to the energy price index for active equity-investing funds from January 2009 to February 2022. The model is estimated using the OLS estimator with fixed effects. Columns 1 to 3 report estimates using monthly net fund flows as the dependent variable. Column 4 and 5 report regression estimates for fund inflows and outflows. The interaction dummies *Increase* and *Decrease* were estimated but are not reported. The unit of observation is fund-month and the estimation is run on a sample of 73 unique funds (70 for retail). We include fund fixed effects, control for aggregate fund flows (unreported) and report bootstrapped standard errors in parenthesis. The statistical significance is denoted as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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