A Dissertation on

Prospect Theory and Fund Flows under Uncertainty

Submitted in partial fulfillment of the requirements for the award
of the degree of

Master of Business (Finance)

by

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Academic Year 2024-2025

Abstract

We study whether macroeconomic uncertainty attenuates investors' behavioural demand for mutual funds. This study employs a comprehensive dataset of U.S. equity mutual funds covering the period from 1995 to 2021. Using monthly panel regressions that incorporate fund-specific fixed effects and double-clustered standard errors at both the fund and time levels, we examine how future fund flows respond to a Cumulative Prospect Theory (CPT) score. The CPT measure is derived from the complete distribution of each fund's returns over the preceding twelve months. A one-standard-deviation increase in CPT predicts higher inflows, but this CPT–flow sensitivity weakens meaningfully when Economic Policy Uncertainty (EPU) rises (about a 15% attenuation in our baseline), even after controlling for risk-adjusted performance and factor exposures. The dampening is strongest for younger, smaller, high-idiosyncratic-volatility, and high downside-risk funds, and for active and local funds. Replacing EPU with alternative uncertainty proxies reveals distinct mechanisms: looser global financial conditions (higher GFC) amplify CPT- and return-driven flows; a tighter shadow rate lowers average flows yet increases selectivity toward CPT-aligned funds; and quantitative easing boosts baseline flows while eroding the marginal CPT premium. Results are robust when using abnormal returns and when focusing on "high" CPT/return funds (above the monthly median), for which premia are economically larger but similarly state-dependent. These findings integrate behavioural portfolio choice with macro-uncertainty channels and map when performance-chasing is most fragile.

Keywords: Behavioural Finance; Cumulative Prospect Theory; Economic Policy Uncertainty; Global Financial Cycle; Mutual Fund Flows; Quantitative Easing; Shadow Rate

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Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor used artificial intelligence tools or generative artificial intelligence tools (unless it is clearly stated, and referenced, along with the purpose of use), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

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Acknowledgements

I wish to express my heartfelt gratitude to my mother and father for their unwavering support, guidance, and encouragement throughout this journey. Their faith in me has been a constant source of strength and motivation. I am equally thankful to my younger brother, whose humour and ability to keep me entertained lightened the mood and helped me stay balanced during the most demanding phases of this study.

I am deeply grateful to Dr. Eathar Abdul-Ghani, Director of Postgraduate Research Programmes, for her kind words of encouragement and steadfast support.

My sincere appreciation goes to my Primary Supervisor, Dr. Ihsan Badshah, whose motivation, conceptual clarity, and constructive feedback were instrumental in shaping the structure and direction of this dissertation.

I am also indebted to my Co-supervisor, Dr. Prasad Hegde, for his continued guidance, insightful comments, and valuable support on research methods, coding, and structural development.

I would also like to thank the staff of the AUT Finance Department and the AUT Postgraduate Research Programmes for their assistance and encouragement throughout my time at AUT.

Lastly, I thank myself for persevering through challenges, believing in my abilities, and committing wholeheartedly to this journey. This dissertation stands as much a product of dedication and discipline as it does of intellectual curiosity.

Chapter 1

Introduction

Mutual funds pool savings from households and institutions and spread them across dozens—or even hundreds—of shares and bonds, giving small investors the diversification once enjoyed only by extensive portfolios. Their footprint in the United States has expanded swiftly: total assets under management climbed from about USD 3.54 trillion in 1996 to nearly USD 27 trillion in 2021 (Institute, 1997, 2022). Equity funds—those that invest mainly in listed companies—drove much of that rise, growing from roughly USD 0.5 trillion to more than USD 14.8 trillion over the same span. While our empirical sample runs from 1995 to 2021—the first complete stretch covered by the Lipper US Mutual Fund database—the industry totals start in 1996, the earliest year with reliable ICI figures. Together, these statistics highlight why month-to-month shifts in fund flows have become such a valuable gauge of market sentiment and set the stage for the following analysis. These industry patterns motivate an examination of what drives fund-level flows month by month.

Researchers soon discovered that these flows are anything but random. Funds near the top of recent performance tables draw a disproportionate share of new money, whereas laggards experience redemptions—a relationship first formalised by Sirri and Tufano (1998) and refined for risk-adjusted returns by Carhart (1997). Conventional factor models (Fama & French, 1993) explain part of this "flow–performance" link by pointing to persistent exposure to market forces. Nevertheless, prior research shows that the response of investors to fund outcomes is uneven. Strong past returns tend to attract disproportionately higher inflows, whereas poor performance does not trigger an equivalent level of outflows, as noted by Chevalier and Ellison (1997). To explain this puzzle, researchers have turned to behavioural theories, most notably prospect theory. Prospect theory holds that investors dislike losses more than comparable gains and overweigh low-probability outcomes (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). Cumulative prospect theory (CPT) extends this insight to the whole distribution of past returns; Barberis et al. (2016) shows that funds with positively skewed, salient tails—features summarised by a CPT score—look especially attractive. Using U.S. equity funds, Guo and Schönleber (2020) find that higher CPT values translate into stronger net inflows even after controlling for conventional risk-adjusted performance. While this growing literature establishes CPT as a powerful behavioural determinant of fund choice, it largely abstracts from how such behavioural preferences operate across different macroeconomic regimes.

Against this backdrop, this dissertation addresses a central research question: whether behavioural fund preferences captured by cumulative prospect theory continue to influence mutual fund flows when macroeconomic uncertainty is high, and how this influence varies across different fund characteristics and investment styles. To answer this overarching question within a single integrated conceptual framework, the study examines three related sub-questions. First, it investigates whether economic policy uncertainty weakens the positive effect of CPT on fund flows. Second, it evaluates whether this moderating effect is more pronounced for funds where information frictions and perceived risk are most salient, namely younger, smaller, more idiosyncratically volatile, and higher downside-risk funds. Third, it explores whether the attenuation of the CPT–flow relationship differs across fund types, particularly between actively managed and passively managed funds and between locally focused and globally diversified funds. Together, these questions situate the dissertation at the intersection of behavioural finance and macroeconomic uncertainty, linking investor psychology to policy-driven market environments and fund-level heterogeneity. In doing so, the study moves beyond existing work by explicitly modelling how behavioural preferences interact with macro-level uncertainty rather than treating investor psychology and economic conditions as independent drivers of capital flows.

To address these questions, it is essential to consider how different forms of macroeconomic uncertainty may reshape the way investors interpret fund performance signals. In particular, macroeconomic uncertainty can blur, or even upend, how investors interpret performance cues. Four dimensions matter most. Economic Policy Uncertainty (EPU) rises when newspapers report policy gridlock; S. R. Baker et al. (2021) show that investment spending stalls when EPU spikes. The global financial cycle (GFC), documented by Rey (2018), tracks worldwide swings in risk appetite that move most asset classes together, limiting the autonomy of any single central bank. Wu and Xia (2014)'s shadow short rate provides a way to translate unconventional monetary interventions, such as large programs of bond buying, into an equivalent policy rate that can fall below zero. This measure is widely used to capture the effective stance of monetary policy when conventional rates are constrained at the zero lower bound. Finally, successive quantitative easing (QE) rounds enlarge the Federal Reserve's balance sheet; H. Chen et al. (2012) show that months of rapid balance-sheet expansion coincide with wider risk premia and higher asset-price volatility. E. Jiang et al. (2016) link such uncertainty to mutual-fund behaviour. When uncertainty is high, the historic tie between past returns and fresh money weakens because investors find it harder to separate managerial skill from luck. This sensitivity to uncertainty is unlikely to be uniform across funds. Seasoned funds, whose track records span many market cycles, enjoy greater name recognition and informational transparency (Berk & Green, 2004), so their investors rely less on recent performance when policy signals are noisy. Crucially, by examining multiple uncertainty proxies within a unified framework, this study allows a direct comparison of how distinct sources of uncertainty—policy ambiguity (EPU), global liquidity conditions (GFC), monetary stance (shadow rate), and balance-sheet expansion (QE)—differentially shape behavioural demand rather than assuming a uniform uncertainty effect.

While prior research has documented links between uncertainty and fund flows, no published study has examined whether fund-level CPT interacts jointly with EPU, the GFC, the shadow rate, and QE in shaping U.S. equity-fund flows. This dissertation fills that gap. Adopting the distribution-based method of Gupta et al. (2022), it computes refined CPT scores—measuring sensitivity to skewness, volatility and downside risk—for every actively and passively managed equity fund in Lipper from 1995 to 2021. These behavioural metrics are paired with (i) the monthly Baker–Bloom–Davis EPU index, (ii) a standardised GFC factor derived from global asset returns, (iii) the monthly Wu–Xia shadow rate, and (iv) the level of Federal Reserve total assets as a monthly proxy for QE. Panel regressions with fund and month fixed effects and double-clustered standard errors test whether heightened uncertainty dampens the pull of high-CPT funds and flattens the flow–performance slope in ways that depend on fund age. This empirical design directly addresses the research question outlined above.

Across 1995–2021, higher CPT values predict larger subsequent inflows, and this relation weakens when economic policy uncertainty rises. The attenuation survives controls for past performance, factor betas, and alternative performance proxies; it is strongest for younger, smaller funds with high idiosyncratic volatility and high downside risk, and for active and local funds. Alternative uncertainty measures show distinct patterns: global liquidity strengthens CPT and return effects, tighter shadow rate conditions increase selectivity in favour of funds with high CPT scores, and quantitative easing lifts baseline flows while eroding the marginal CPT premium.These contrasts indicate that uncertainty does not operate as a single homogeneous force: policy uncertainty primarily weakens investors' ability to extract behavioural signals, whereas global liquidity and monetary conditions reshape the risk-taking environment in ways that can amplify or reallocate behavioural demand.

This study integrates cumulative prospect theory with multiple uncertainty channels in a single flow framework, maps how reputational proxies such as fund age moderate the uncertainty discount, and documents management-style and geographic heterogeneity. Using a large fund–month panel with fund and time fixed effects and double clustering, it extends the flow–performance literature by identifying when behavioural signals carry less weight and by comparing news-based policy uncertainty with global liquidity, shadow policy stance, and quantitative easing. The findings contribute theoretically by demonstrating that behavioural preferences are state dependent rather than universal, and practically by showing that the effectiveness of performance-based and "lottery-like" fund strategies varies systematically across macroeconomic regimes.

The remainder of the dissertation is organised as follows. Chapter 2 reviews the literature on mutual-fund flows, behavioural biases, and macro-uncertainty, and sets out the three hypotheses. Chapter 3 describes the data, explains how the CPT and uncertainty variables are constructed, and outlines the econometric approach. Chapter 4 reports the empirical results and compares them with earlier evidence on performance chasing and risk taking. Chapter 5 summarises the main findings, discusses their implications for fund managers and policymakers, and suggests directions for future research.

Chapter 2

Literature Review

Mutual-fund flow research starts with a robust empirical fact: investors reward recent winners far more vigorously than they punish recent losers. Sirri and Tufano (1998) show that, because acquiring detailed manager information is costly, households rank funds on one free and salient statistic—recent total returns—and send new money to those at the top of the table. Carhart (1997) confirms that a one-decile jump in abnormal performance yields a disproportionate rise in net subscriptions even after adjusting for market, size, value and momentum factors, while Gruber (1996) demonstrates that past-return sorting explains more than half the cross-section of annual inflows to U.S. equity funds. The asymmetry is equally striking: investors add roughly twice as much capital to top-decile funds as they withdraw from bottom-decile laggards (Chevalier & Ellison, 1997), a pattern complex to square with classical expectations. This asymmetric relationship between flows and performance cannot be reconciled with frictionless Bayesian learning, pointing instead toward behavioural mechanisms that prospect theory is uniquely suited to explain.

Against this backdrop, behavioural finance offers the missing mechanism. Prospect theory shows that people frame outcomes relative to a reference point, suffer losses about twice as keenly as they enjoy equivalent gains, and overweight small probabilities (Kahneman & Tversky, 1979). Tversky and Kahneman (1992) extend the framework by cumulating decision weights over ordered outcomes, enabling it to handle a full distribution instead of a single gamble. A central implication of this framework is probability weighting: investors systematically distort objective probabilities, placing disproportionate decision weight on low-probability, high-impact outcomes. In the context of financial decision-making, this means that assets offering a small chance of extreme gains can be valued more highly than would be justified by expected returns alone. Laboratory replications confirm the core elements—loss aversion (Benartzi & Thaler, 1995), probability weighting (Bleichrodt & Johannesson, 1997) and reference dependence (Abdellaoui, 2000)—while field evidence such as the disposition effect documented by Odean (1998) and the familiarity bias reported by Huberman (1999) shows that real investors cling to losers and prefer known names, deviating from classical predictions. Importantly, these behavioural regularities provide a direct mechanism through which investor preferences can shape capital allocation: when choosing among competing investment vehicles, investors are not guided solely by mean–variance trade-offs, but also by how potential gains and losses are psychologically evaluated. This implies that assets and portfolios exhibiting asymmetric or extreme payoff profiles may attract attention and capital even when traditional risk-adjusted performance is similar. These behavioural deviations provide a natural bridge from the laboratory to financial markets, where cumulative prospect theory offers a tractable empirical measure of behavioural preferences in asset markets.

To operationalise these insights in fund data, Cumulative Prospect Theory (CPT) converts those insights into a quantitative measure of a fund's behavioural appeal. Drawing on the prospect-theory logic summarised by Barberis et al. (2016), researchers apply prospect weights to every monthly return and sum the results to obtain a CPT score. This construction directly embeds probability weighting and loss aversion into the evaluation of a fund's return distribution, ensuring that extreme outcomes—particularly large gains or losses—receive disproportionate weight in the overall valuation. As a result, CPT captures not only average performance but also how the shape of returns influences investor perception. Gupta et al. (2022) refines the procedure by first purging returns of market, size, value, profitability and investment factors, then applying the CPT transformation to the residual distribution; he finds that a one-standard-deviation rise in the purified CPT score predicts about thirty basis points more monthly net inflow even after controlling for alpha, volatility, fees and size. A key driver of this result is investors' documented preference for positively skewed payoff profiles. Under prospect theory, right-tailed return distributions—those offering a small probability of very high payoffs—are particularly attractive because probability weighting amplifies the perceived value of extreme gains (Mitton & Vorkink, 2007). In a mutual fund setting, this implies that funds whose historical return distributions exhibit positive skewness or "lottery-like" characteristics become disproportionately appealing to investors, even when their mean performance is comparable to that of peers. Evidence from portfolio composition is consistent: Bali et al. (2010) show that mutual funds tilted toward "lottery-type" stocks with extreme upside tails receive disproportionate inflows. In addition, salience plays a critical role in fund selection. Returns that are extreme, unusual, or highly visible tend to attract greater investor attention and are more easily recalled, making funds with recent standout performance cognitively prominent in investors' choice sets. This salience mechanism reinforces probability weighting by directing attention toward funds with conspicuous right-tail outcomes, thereby strengthening demand for high-CPT funds. While these findings establish CPT as a powerful behavioural measure of investor demand, they also raise an important methodological question regarding how CPT compares with alternative proxies used in the literature.

To situate CPT within the broader behavioural-finance toolkit, it is therefore necessary to compare it directly with competing empirical measures of investor preferences. Importantly, CPT offers a more theoretically grounded behavioural metric than alternative proxies commonly used in the literature. One widely employed measure is the maximum daily return (MAX), which captures the largest single-day gain within a period and is often interpreted as reflecting investors' demand for lottery-like payoffs (Bali et al., 2010). While MAX successfully identifies assets with extreme positive outcomes, it relies on a single observation and therefore abstracts from the broader distribution of returns that investors experience over time. In contrast, CPT aggregates information from the full return distribution, weighting each outcome according to prospect-theory preferences, and thus provides a more comprehensive representation of behavioural valuation (Barberis et al., 2016; Gupta et al., 2022). Similarly, realized skewness has been used to proxy for investors' preference for right-tailed return distributions (Harvey & Siddique, 2000; Mitton & Vorkink, 2007). Although skewness captures asymmetry in returns, it treats all observations symmetrically and does not distinguish between gains and losses or incorporate differential sensitivity to tail outcomes. CPT improves on this by explicitly modelling loss aversion and probability weighting, allowing positive and negative outcomes to enter the valuation function asymmetrically and in a psychologically consistent manner (Barberis et al., 2016; Tversky & Kahneman, 1992). As such, CPT embeds skewness preference within a broader behavioural structure rather than treating it as a stand-alone statistical property. Sentiment-based proxies, such as investor sentiment indices or media-based measures, provide a complementary perspective by capturing market-wide optimism or pessimism (M. Baker & Wurgler, 2006; Tetlock, 2007). However, these indicators operate at an aggregate level and do not directly map into how individual investors evaluate the risk and payoff structure of specific investment vehicles. CPT, by contrast, is fund-specific and grounded in the realised return distribution of each fund, enabling a direct link between behavioural theory and observed capital allocation at the fund level (Barberis et al., 2016; Gupta et al., 2022). Taken together, these contrasts justify the use of CPT as the preferred behavioural measure in this study. By integrating probability weighting, loss aversion, and sensitivity to tail outcomes within a single framework, CPT captures multiple dimensions of behavioural demand that alternative proxies isolate only partially. This theoretical richness makes CPT particularly well suited for examining how investors select among mutual funds and how such selection responds to shifts in macroeconomic uncertainty. Accordingly, this behavioural framework provides the conceptual foundation for the empirical analysis that follows, particularly in assessing how CPT-based investor preferences interact with changing macroeconomic conditions.

At the macro-policy level, whether that behavioural pull survives when the macro-policy backdrop grows noisy remains an open question. Economic Policy Uncertainty (EPU), an index based on policy-related newspaper coverage, scheduled tax expirations and forecast dispersion, spikes when lawmakers deadlock or major reforms hang in the balance (S. R. Baker et al., 2021). Bloom (2009) shows that such shocks lift implied equity volatility, widen credit spreads and depress corporate investment for several quarters. E. Jiang et al. (2016) link the macro shock to mutual funds, finding that the performance elasticity of flows almost halves in the top quintile of EPU months, consistent with investors discounting noisy skill signals when policy headlines dominate attention. Kelly et al. (2016) show that unresolved political risk commands a priced premium in U.S. election years, suggesting that investors perceive policy noise as a distinct risk factor. Beyond altering risk premia, uncertainty also degrades the information environment, making signals about managerial skill harder to interpret, as Bloom (2009) emphasises when showing that uncertainty shocks increase dispersion and opacity in economic decision-making. Together, these findings highlight that while policy uncertainty clearly alters market conditions, whether investors' behavioural responses to fund performance persist or collapse under such macro policy noise remains unresolved, motivating the present investigation.

The salience of policy uncertainty is amplified by media coverage, which heightens behavioural responses by directing investor attention to salient events. Tetlock (2007) documents that pessimistic language in high-circulation newspapers predicts next-day market reversals, showing investors react sharply to news coverage. Engelberg and Parsons (2011) establish a causal link by exploiting local newspaper closures: trading volume and price discovery slow when information supply falls. Taken together, this evidence shows that media channels not only transmit but also amplify the salience of policy shocks, reinforcing the behavioural frictions that policy uncertainty introduces.From an attention-based perspective, investors disproportionately focus on salient information, as Barberis et al. (1998) argue, while Hirshleifer and Teoh (2003) show that limited attention constrains how much information can be processed at any point in time. When policy developments dominate the news cycle, these attention constraints imply that macro-level narratives crowd out fund-specific performance information, weakening the influence of distributional features such as skewness or CPT on capital allocation.

International evidence points in the same direction. Rey (2018) describes a global financial cycle driven by U.S. monetary conditions: risk tolerance declines everywhere when the cycle turns down, pressuring fund inflows regardless of local fundamentals. Wu and Xia (2014) translate large-scale asset purchases into a “shadow” short rate that can fall below zero; unexpected drops in that series coincide with spikes in option-implied volatility, signalling heightened policy ambiguity. H. Chen et al. (2012) find that expansions of Federal Reserve assets compress term premiums yet raise equity volatility, showing that liquidity injections can stir uncertainty even as they lower yields. This dynamic is not confined to the U.S.; cross-country studies show that macro-level uncertainty, often driven by U.S. policy, creates a global cycle of risk aversion that influences fund flows worldwide. The global reach of policy-driven uncertainty highlights that behavioural responses cannot be understood in isolation from international financial cycles, making it essential to consider how investors adjust under heightened volatility. Crucially, these environments are characterised not only by higher risk but also by greater ambiguity, meaning that the probabilities of future states are themselves uncertain; under ambiguity aversion, investors prefer options with known probability distributions to those involving unclear policy regimes, even when expected returns are similar, as formalised by Gilboa and Schmeidler (1989). In a mutual fund context, heightened ambiguity reduces confidence in performance signals and weakens the perceived informativeness of past returns, attenuating the behavioural appeal of funds that would otherwise benefit from skewness or salience effects. At the same time, cognitive constraints limit investors' capacity to process complex or rapidly changing policy information: Hirshleifer and Teoh (2003) show that limited attention restricts how much information investors can absorb, while Sims (2003) formalises this constraint as rational inattention arising from finite information-processing capacity. When macroeconomic uncertainty increases the volume and complexity of policy signals, investors become less able to evaluate the distributional features of returns, thereby weakening the influence of CPT-based preferences on portfolio reallocation.

Consistent with these channels, behavioural responses tighten in the same macro environment. Bali et al. (2010) report that demand for extreme-skew "lottery" stocks rises in months of elevated volatility, consistent with heavier probability weighting when background risk is salient. However, policy noise can just as easily dull the appeal of extreme past gains if investors suspect they reflect luck: E. Jiang et al. (2016) show that the flow–performance slope flattens precisely when EPU peaks. These contrasting patterns indicate that background risk can both heighten and mute behavioural demand, motivating a synthesis of stylised facts to anchor our hypotheses. These patterns are consistent with uncertainty operating as a cognitive filter rather than merely an additive risk factor, amplifying or suppressing behavioural demand depending on how attention, ambiguity, and information-processing limits shape investor decisions.

Synthesising the evidence yields two stylised facts. First, high-CPT funds enjoy above-average inflows in calm periods. Second, policy uncertainty generally weakens the baseline flow–performance slope. What remains unknown is whether EPU erodes the behavioural inflow premium associated with CPT, and, if so, by how much. Therefore, untangling prospect weighting from policy noise is essential for a behavioural view of capital allocation under macro uncertainty.From a theoretical standpoint, this question is central because it determines whether behavioural preferences embedded in return distributions remain operative when uncertainty constrains attention and decision-making capacity.

In cumulative prospect theory terms, policy uncertainty raises background risk and ambiguity, shifting investors' reference points downward, increasing the decision weight on potential losses, and lowering the prospect value of positively skewed return streams

(S. R. Baker et al., 2021; Barberis et al., 2016; Tversky & Kahneman, 1992). In turn, salient policy news crowds out performance signals and reduces reliance on recent winners (E. Jiang et al., 2016; Tetlock, 2007). Through the combined channels of attention reallocation (Barberis et al., 1998), ambiguity aversion (Gilboa & Schmeidler, 1989), and cognitive constraints (Harvey & Siddique, 2000; Sims, 2003), economic uncertainty weakens the translation of psychologically attractive payoff structures into actual fund flows, reinforcing the role of uncertainty as a moderating force in the CPT–flow relationship.

Thus, we have come to the following hypothesis:

Hypothesis H1. *The dampening effect of economic policy uncertainty weakens the positive effect of cumulative prospect theory on fund flows.*

While this hypothesis describes an aggregate market phenomenon, the dampening effect of EPU is unlikely to be uniform. The literature suggests that the sensitivity of fund flows to behavioural factors and market conditions varies systematically with specific fund characteristics. We therefore extend our analysis to explore several key dimensions of heterogeneity: fund age, size, idiosyncratic volatility, and downside risk.

Heterogeneity by fund age has been highlighted by Dahlquist et al. (2000), who find that older Swedish equity funds attract lower incremental flows for a given level of past performance, reflecting investor scepticism about managers' ability to sustain success as funds mature. Ferreira et al. (2012) extend this to a global sample, showing that younger funds generate stronger performance-flow sensitivity, particularly in the wake of market shocks, because they can scale more rapidly without incurring diseconomies of size. Chevalier and Ellison (1997) corroborate that younger funds' flows react more strongly to both risk-adjusted returns and marketing signals, implying that EPU's dampening effect should be most pronounced for young managers whose credibility is still being established.

Size–based heterogeneity arises from the trade–off between capacity and performance. From a rational benchmark, Berk and Green (2004) develop a rational-expectations model in which fund flows drive managers' optimal scale, predicting that small funds outperform *ex ante* and thus attract outsized inflows until diseconomies set in. J. Chen et al. (2004) document that fund returns, both before and after fees, decline with lagged fund size, particularly for vehicles forced to trade in small, illiquid stocks, indicating that liquidity and organisational diseconomies erode performance. Under elevated economic policy uncertainty, risk-averse investors may disproportionately shift away from large funds whose limited flexibility amplifies perceived downside, thereby strengthening the negative CPT×EPU interaction for bigger vehicles.

Idiosyncratic volatility represents another dimension of heterogeneity. Huang et al. (2007) show that funds with high idiosyncratic volatility experience greater flow–performance sensitivity, as investors chase outsized returns but are also quick to withdraw when volatility spikes. More recently, Clifford et al. (2020) demonstrate that the salience of idiosyncratic volatility amplifies behavioural demand: retail investors pour money into volatile funds following strong performance. During periods of elevated uncertainty, however, such funds are likely to see sharper reversals, as uncertainty induces a flight from idiosyncratic risk, suggesting a stronger negative CPT×EPU interaction in high–IVOL subsamples.

Downside risk reflects investors' aversion to large losses when uncertainty is high. Ang et al. (2006) find that funds more exposed to big losses earn a premium, indicating that investors focus more on the probability of severe downturns than on overall volatility. Sortino and Price (1994) show this by giving extra weight to negative returns when evaluating performance. Consequently, funds with a track record of larger losses should react more strongly to economic policy uncertainty: as policy ambiguity rises, the prospect of significant losses becomes more salient, and the positive effects of both CPT and past returns on inflows are markedly weakened for high–downside–risk funds compared with their lower–risk peers.

Together, these dimensions suggest that the behavioural impact of CPT is conditional, with policy noise interacting differently across fund characteristics, warranting a formal hypothesis on heterogeneity.

Hypothesis H2. *The dampening effect of economic policy uncertainty on the CPT–flow relationship is most severe for younger, smaller, more idiosyncratically volatile, and higher downside–risk funds.*

Beyond these intrinsic characteristics, a fund's investment mandate and geographic scope also shape investor reactions to uncertainty. The distinction between active and passive management, as well as between a domestic and global focus, creates clear fault lines in flow sensitivity that are likely to be exacerbated by policy noise.

Actively managed funds, with their discretionary allocations and reliance on manager skill, display pronounced sensitivity to both performance and uncertainty. K. J. M. Cremers and Petajisto (2009) introduce Active Share as a measure of deviation from benchmark holdings and document that high–Active Share funds deliver returns net–of–fee only when investors reward genuine active bets. Frazzini and Lamont (2008) find that flows into active funds are highly chasing: investors pour capital into top–quartile performers but withdraw aggressively from laggards, a pattern that is likely to be amplified under high EPU as loss aversion intensifies. Fama and French (2010) further establish that active managers underperform benchmarks on average, yet fund flows into active vehicles remain large, indicating that behavioural and signalling motives, central to Cumulative Prospect Theory, persist even when future performance is uncertain. In contrast, passive funds exhibit more mechanical, cost–driven flows. Gastineau (2013) shows that passive investors select funds primarily on fee differentials and broad market exposure, making their flows less sensitive to short–term performance signals and, by extension, less volatile under policy uncertainty.

Geographic focus introduces another layer of heterogeneity. A rich body of work on home bias, where investors overweight domestic assets, suggests that local funds attract flows based on proximity and informational familiarity. Coval and Moskowitz (2001) document that US-based investors earn significant "proximity" premiums by overweighting local equities, and Huberman (1999) finds that individual investors' familiarity with local firms drives trading volume and returns in local shares. Froot and Dabora (1999) argue that global diversification is hindered by information and transaction barriers, leading domestic–focused funds to exhibit stronger flow–performance sensitivity. Ahearne et al. (2004) show that global equity funds experience flows more closely tied to world–market signals, whereas local funds' inflows are more reactive to domestic policy shocks. Under elevated EPU, investors in local funds may thus become particularly cautious, as domestic policy ambiguity directly affects the familiar asset universe they track.

Bringing these strands together, we expect that active funds, whose discretionary bets and performance chasing are central to investor decision making, will see more pronounced dampening of CPT–driven flows under high EPU, whereas passive funds' flows will remain relatively stable. Similarly, local funds' flows should exhibit stronger sensitivity to domestic uncertainty than those of global funds. This contrast between active and passive, and between local and global mandates, frames a second axis of heterogeneity through which policy uncertainty is likely to reshape the CPT–flow relationship.

This leads us to our third hypothesis:

Hypothesis H3. *The dampening effect of economic policy uncertainty on the CPT–flow relationship is stronger for active funds and for local funds.*

Chapter 3

Data & Methodology

This chapter outlines the empirical framework used in the study. It describes the data sources, sample construction, variable definitions, and the estimation strategy employed to test the research hypotheses. The analysis relies on Lipper data covering U.S. equity mutual funds from 1995 to 2021, ensuring a comprehensive understanding of fund flows. The methodology utilises panel regressions with fund–fixed effects and fund and time clustering to control for unobserved heterogeneity and time–specific shocks. This approach addresses the research gap by integrating behavioural metrics with macroeconomic uncertainty, yielding robust empirical insights.

3.1 Data Sources and Collection

The credibility and robustness of empirical research hinge on selecting high-quality, replicable data. This study's primary data source is the Lipper database, a highly regarded resource in empirical finance known for its extensive coverage of mutual fund characteristics.[1] Lipper data provides detailed information on U.S. equity mutual funds—including returns, expense ratios, fund size, and turnover—which has been used in numerous studies published in top-tier finance journals. This study focuses on U.S. equity mutual funds from January 1995 to November 2021, ensuring a comprehensive analysis that captures multiple market cycles, including periods of expansion, crisis, and recovery.

Data collection was executed monthly from Lipper, which is preferred for its rigorous data validation protocols and ability to supply a rich set of fund-level variables. The long–

[1] e.g. (Ali et al., 2023; M. Cremers et al., 2016; Ferreira et al., 2012, 2018)

time horizon (26 years) enables the detection of trends and cyclical patterns in mutual fund flows and performance, which is essential for understanding how investor behaviour evolves over different economic regimes.

To ensure the sample's integrity, strict screening criteria followed guidelines similar to those used by (Gupta et al., 2022). To control for potential incubation bias, as Evans (2010) mentioned, funds with a Total Net Assets (TNA) value lower than USD 1 million were excluded from the sample. Additionally, only funds that have existed for more than two years were retained. These criteria help to avoid the inclusion of funds with insufficient performance history or erratic behaviour, thereby improving the reliability of the empirical analysis.

Furthermore, the study integrates macroeconomic indicators that capture broader economic uncertainty. The Economic Policy Uncertainty (EPU) index, developed by S. R. Baker et al. (2021), is used to measure fluctuations in policy-related uncertainty.[2] Global economic conditions are further captured using the Global Financial Cycle (GFC) factor from Miranda-Agrippino and Rey (2022)'s updates.[3] Also, shadow rate data, which reflect the stance of monetary policy when the zero lower bound constrains the nominal federal funds rate, is sourced from the Atlanta Federal Reserve dataset.[4] Quantitative easing (QE) measures are incorporated via data from the Federal Reserve Economic Data (FRED) database.[5]

The final dataset matches monthly mutual fund data with corresponding macroeconomic indicators. Rigorous data cleaning and screening processes were implemented to address common issues such as survivorship bias and missing observations. For instance, funds with less than 24 monthly observations were dropped to ensure a robust time–series analysis. By applying these strict criteria, the sample reflects a stable set of actively managed funds, thereby increasing the reliability of the empirical findings.

In summary, this study leverages high-quality Lipper data spanning 25 years, augmented with macroeconomic uncertainty indicators, to examine mutual fund flows. The

[2]The EPU Index can be obtained from the Policy Uncertainty website. We use the monthly data for US. https://policyuncertainty.com/media/US_Policy_Uncertainty_Data.xlsx

[3]The GFC index is hosted on Silvia Miranda-Agrippino's website under the "code & data" tab. https://silviamirandaagrippino.com/s/GFC-Factor-Updates.xlsx

[4]The shadow rate data is hosted by the Atlanta Federal Reserve's website: https://www.atlantafed.org/-/media/documents/datafiles/cqer/research/wu-xia-shadow-federal-funds-rate/WuXiaShadowRate.xlsx

[5]The FRED at St. Louis hosts the data of the total assets the Fed holds which is used in our regressions. https://fred.stlouisfed.org/series/WALCL

rigorous sample selection, excluding funds with TNA below USD 1 million and those with less than two years of existence, ensures that the resulting dataset is robust, replicable, and well-suited for investigating the complex dynamics of mutual fund flows in relation to both performance and external economic conditions.

3.2 Variable Construction and Definitions

This section details how the study's variables are constructed from monthly Lipper data for U.S. equity mutual funds (January 1995 to November 2021) and how macroeconomic uncertainty measures are integrated into the analysis.

3.2.1 Dependent Variable

Fund Flow (%) is defined as the month–over–month percentage change in Total Net Assets (TNA). This variable captures net inflows or outflows, providing a direct measure of investor behaviour. The formula to calculate the fund flow for fund i in country c at month t is as follows:

$$Flow_{i,c,t} = \frac{TNA_{i,c,t} - TNA_{i,c,t-1}(1 + R_{i,c,t})}{TNA_{i,c,t-1}} \tag{3.1}$$

Where $TNA_{i,c,t}$ is the total net assets in USD of fund i in country c at the end of the month t, and $R_{i,c,t}$ is the return of fund i in country c in month t.

3.2.2 Key Independent Variables

Cumulative Prospect Theory Value of a Fund

To derive the CPT measure, the procedure begins by ranking a fund's monthly returns from the previous year in increasing order. Suppose that within this twelve-month window, there are m negative observations and $n = (12 - m)$ positive ones. These returns are then indexed sequentially, starting with the lowest value r_{-m} and ending with the highest r_n. Using this ordered distribution, the CPT score is calculated according to the following expression:

$$
\begin{aligned}
CPT = & \sum_{i=-m}^{-1} v(r_i) \left[w^- \left(\frac{i+m+1}{12} \right) - w^- \left(\frac{i+m}{12} \right) \right] \\
& + \sum_{i=1}^{n} v(r_i) \left[w^+ \left(\frac{n-i+1}{12} \right) - w^+ \left(\frac{n-i}{12} \right) \right]
\end{aligned} \tag{3.2}
$$

In this notation, r_i denotes the monthly return of the fund, $v(r)$ specifies the value function, and the probability weighting functions are given by $w^+(p)$ for gains and $w^-(p)$ for losses.

Following Tversky and Kahneman (1992), the value function is specified as:

$$
v(r) = \begin{cases} r^\alpha, & r \geq 0 \\ -\lambda(-r)^\alpha, & r < 0 \end{cases} \tag{3.3}
$$

with parameters $\alpha = 0.88$ and $\lambda = 2.25$.
The weighting functions are given by:

$$
w^+(p) = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{1/\gamma}}, \quad w^-(p) = \frac{p^\delta}{(p^\delta + (1-p)^\delta)^{1/\delta}}, \tag{3.4}
$$

with $\gamma = 0.61$ and $\delta = 0.69$. In our estimations, the probability p is set to $\frac{1}{12}$, corresponding to the 12 monthly outcomes. This approach to computing the CPT value is widely adopted in empirical applications (Tversky & Kahneman, 1992).

Carhart Four-Factor Alpha (Ch4 Alpha) measures a fund's abnormal return after adjusting for market, size, value, and momentum factors (Carhart, 1997). It is estimated using the following regression:

$$
\begin{aligned}
R_{i,t} - R_{f,t} = \alpha_i + \beta_{MKT}(R_{MKT,t} - R_{f,t}) + \beta_{SMB} SMB_t + \\
\beta_{HML} HML_t + \beta_{MOM} MOM_t + \epsilon_{i,t}
\end{aligned} \tag{3.5}
$$

where $R_{i,t}$ is the return of fund i, $R_{MKT,t}$ is the market return, $R_{f,t}$ is the risk-free rate, and SMB_t, HML_t, and MOM_t represent the size, value, and momentum factors, respectively. The estimated α_i represents the risk-adjusted excess return.

Size (\$$M$) is the logarithm of total assets under management (AUM), with larger funds tending to have lower flow sensitivity due to liquidity constraints and an established investor base (Chevalier & Ellison, 1997). **Age (Months)** is defined as the number of months since the fund's inception, and older funds generally exhibit lower flow–performance sensitivity due to increased investor familiarity (Berk & Green, 2004). **Fund Volatility** is measured as the rolling standard deviation of a fund's monthly returns over the past 12 months, while **Idiosyncratic Volatility (Idio Vol)** is computed as the residual standard deviation from the Carhart four–factor model, capturing risks not explained by systematic factors (Bali et al., 2010). **Skewness (Skew)** quantifies the asymmetry of a fund's past return distribution, with positive skewness suggesting a tendency for extreme positive returns that can influence investor allocation decisions (Barberis et al., 2016). The variables **Lowperf**, **Midperf**, and **Highperf** allocate funds into quintiles according to their cumulative twelve-month returns. Following the approach of Sirri and Tufano (1998), each fund is first assigned a continuous performance score, $PERF_{i,t-1}$, scaled from 0 (worst) to 1 (best) within its investment style. Based on this ranking, funds are classified into **Lowperf** (bottom quintile), **Midperf** (middle three quintiles), and **Highperf** (top quintile).

Table I
Variable Definitions

VarName	Definition
CPT	This index is constructed from the raw monthly returns observed over the previous twelve months, following the prospect theory framework.
log(EPU)	Logarithm of the EPU Index.
Abnormal Returns	It is the difference of fund returns and market index returns.
log(Size)	Logarithm of fund size.
log(Age)	Logarithm of fund age.
IVOL	Idiosyncratic volatility calculated as the residual standard deviation from the Carhart four-factor model.
Fund Volatility	It is the standard deviation of past raw returns based on the data of lagged 12 months, expressed in percentage.
Skew	It is the skewness of the raw returns of lagged 12 months.
Fund Flows	Fund's monthly fund flow.
Lowperf	A fund whose performance falls within the bottom quintile of the ranking distribution.
Midperf	A fund whose performance is positioned within the middle three quintiles of the ranking distribution.
Highperf	A fund whose performance ranks within the top quintile of the distribution.
High CPT	Dummy variable, equals 1 when the fund's CPT value is more than the median value of all the CPT values for that given year-month, otherwise 0.
High Abnormal Returns	Dummy variable, equals 1 when the fund's Abnormal Returns is more than the median of all the Abnormal Returns for that given year-month, otherwise 0.
High Age	Dummy variable, equals 1 when the fund's age is more than the median of all the fund ages for that given year-month, otherwise 0.
GFC	Global Financial Cycle Index developed by Miranda-Agrippino and Rey (2022).
Shadow Rate	It is an estimated interest rate that shows the true stance of monetary policy when the official rate can't drop further, as developed by Wu and Xia (2014).
Quantitative Easing	Logarithm of the US Federal Reserve's Total Assets.

3.3 Methodology

Our baseline regression model is formulated to capture both the direct effect of CPT on net fund flows and the moderating effect of macroeconomic uncertainty. We estimate a panel regression model using a fixed effects approach to control for time-invariant fund-specific characteristics. The empirical model is specified as:

$$\begin{gathered} FLow_{i,t} = \beta_1 CPT_{i,t} + \beta_2 \mathbf{X}_{t-1} + \beta_3 (CPT_{i,t} \times \mathbf{X}_{t-1}) + \\ CONTROLS_{i,t-1} + u_i + v_t + \varepsilon_{i,t} \end{gathered} \tag{3.6}$$

Where $\mathrm{Flow}_{i,t}$ denotes the net fund flow (expressed as a percentage) for fund i at time t, and $\mathrm{CPT}_{i,t}$ is the behavioural measure reflecting the fund's historical return distribution. The vector $\mathbf{X}_{t-1}$ represents lagged macroeconomic uncertainty measures, including $\log(\mathrm{EPU}_{t-1})$, GFC volatility indices, shadow rates, and QE indicators. The interaction term $\mathrm{CPT}_{i,t} \times \mathbf{X}_{t-1}$ is crucial for testing Hypothesis H1, as it examines how uncertainty modifies the effect of CPT on fund flows. The term $\mathrm{CONTROLS}_{i,t-1}$ comprises a set of lagged control variables: the logarithm of fund size, the logarithm of fund age, idiosyncratic volatility (IVOL), skewness (Skew), lagged net fund flows, and performance ranking measures (Lowperf, Midperf, and Highperf). Fund-specific fixed effects u_i account for unobserved heterogeneity. The error term $\varepsilon_{i,t}$ is assumed to be idiosyncratic.

This regression specification follows the approach of Gupta et al. (2022), who use similar fixed effects estimators to address potential confounding factors. The inclusion of interaction terms is motivated by evidence that macroeconomic uncertainty plays a moderating role in fund flows, as discussed in studies by E. Jiang et al. (2016). Our model is designed to capture both the direct impact of CPT and its interplay with uncertainty, thereby offering a nuanced view of investor behaviour.

The model includes several control variables to account for other factors that may influence fund flows. The lagged logarithm of fund size controls for scale effects, recognising that larger funds typically experience more stable flows (Sirri & Tufano, 1998). Similarly, the lagged logarithm of fund age is included to capture the impact of fund maturity, as older funds often benefit from established reputations and investor trust, which may stabilise flows (Chevalier & Ellison, 1997).

To account for risk and return characteristics, the model incorporates lagged fund volatility (L.fund_volatility), which measures the standard deviation of monthly returns.

This variable captures the effect of perceived riskiness on investor behaviour, with higher volatility potentially discouraging inflows (Warther, 1995). Skewness (L.skew), which reflects the asymmetry in return distributions, is also included, as funds with negatively skewed returns may be perceived as riskier, influencing allocation decisions (Boyer & Vorkink, 2014).

The net flow percentage (L.net_flow_pct_w) serves as a measure of past fund flows, acknowledging that flows can exhibit momentum or reversal effects depending on prior investor activity. Additionally, the model incorporates categorical performance indicators—lowperf, midperf, and highperf—to control for the non-linear flow–performance sensitivity (FPS) relationship, as suggested by studies such as H. Jiang et al. (2014) and Berk and Green (2004). These variables segment performance into distinct groups, capturing differential investor responses to low, medium, and high performance.

Finally, the model includes fund-fixed effects (u_i) to control for unobservable, time-invariant characteristics specific to each fund. Standard errors are double-clustered by fund and time to ensure robust inference (Petersen, 2009).

Chapter 4

Empirical Findings

4.1 Descriptive Statistics and Data Summary

This section provides an overview of the key variables used in our empirical analysis. We present summary statistics, correlations, and distributional properties to understand the characteristics of the dataset.

4.1.1 Yearly Sample Summary

Table II provides a yearly overview of the mutual fund sample, detailing the number of funds, their average raw return, and size (AUM in million dollars) from 1995 to 2021. The number of funds in the dataset shows a steady increase over the years, from 2,194 in 1996 to a peak of 9,812 in 2019, before slightly declining in the final two years of the sample. This trend reflects the expansion of the mutual fund industry over the past two decades, driven by increased investor participation and financial market growth. The return column exhibits significant variability, capturing key market events. Notably, years of severe financial distress, such as 2008, show the lowest average return (-3.96%), coinciding with the Global Financial Crisis.

In contrast, years like 1999 and 2003, marked by high market optimism, show significantly higher average returns (2.32% and 2.56%, respectively). The average fund size fluctuates over time, decreasing during financial downturns and increasing in periods of market stability. The sharp drop in AUM in 2001–2003 and 2008–2009 aligns with bear market conditions, while the consistent rise post-2010 suggests the recovery and subsequent expansion of the financial markets. The significant jump in fund size in 2021, reaching \$954.52 million on average, indicates a strong post-pandemic recovery and heightened market participation. As for the total AUM, as noted in the last column, it was at \$928.6 billion in 1995, which gradually increased to \$9.85 trillion in 2021. This change in total AUM is similar to what ICI Factbooks have reported over the years. Moreover, according to the Institute (2022), the total AUM of all the funds under equity mutual funds was \$14.85 trillion. This means that the dataset contains approximately two-thirds of all the funds reported by Institute (2022).

Table II
Yearly Statistics

This table reports yearly summary statistics of mutual funds. Column (1) represents the average number of unique funds per month over the course of a year, calculated by counting the funds each month and then averaging these counts. Column (2) shows the average monthly returns for the year, obtained by first computing the returns for each month and then averaging them over the entire year. Column (3) displays the average fund size, derived similarly to column (2). Column (4) reports the total assets under management (AUM) in millions of USD.

Year	Number of Funds	Raw Return (%)	Size ($M)	AUM ($M)
1995	2194	1.95	387.91	928,635.60
1996	2822	1.41	374.40	1,168,801.00
1997	3464	1.41	394.55	1,501,082.00
1998	4283	1.05	397.66	1,848,152.00
1999	5162	2.32	396.81	2,435,624.00
2000	5967	-0.35	426.71	2,403,737.00
2001	6719	-0.95	326.00	2,149,167.00
2002	7384	-1.90	260.53	1,732,103.00
2003	7702	2.56	254.01	2,332,312.00
2004	8047	1.14	310.84	2,761,339.00
2005	8210	0.78	355.74	3,157,285.00
2006	8633	1.24	406.68	3,836,263.00
2007	8986	0.70	471.93	4,334,336.00
2008	9202	-3.97	390.00	2,581,202.00
2009	8893	2.72	321.46	3,419,796.00
2010	9055	1.52	390.55	3,990,930.00
2011	9123	-0.35	441.43	3,786,710.00
2012	9194	1.28	453.82	4,314,805.00
2013	9440	2.06	522.20	5,466,868.00
2014	9880	0.48	579.95	5,813,091.00
2015	10174	-0.17	572.70	5,572,235.00
2016	10206	0.79	547.59	5,785,180.00
2017	10322	1.63	617.77	6,851,405.00
2018	10444	-0.80	662.95	6,123,442.00
2019	10295	2.05	678.47	7,499,070.00
2020	9978	1.66	728.73	8,504,972.00
2021	9812	1.65	947.81	9,850,750.00

4.1.2 Descriptive Statistics of Key Variables

Table III presents descriptive statistics for the main variables used in the analysis. The average mutual fund in the sample records monthly flows of 0.54%, broadly consistent with the volatile fund–flow patterns documented in U.S. data (Ben-Rephael et al., 2012; Sirri & Tufano, 1998). The CPT index averages -1.50, indicating that, on average, losses weigh more heavily than gains, in line with the cumulative prospect theory framework of Tversky and Kahneman (1992) and subsequent applications to fund performance (Barberis et al., 2016).

Average abnormal returns are close to zero (0.03%), reflecting the competitive pressures that push risk-adjusted performance toward zero net alpha, as argued by Berk and Green (2004). Fund size is highly skewed: while the mean is nearly USD 488 million, the median is only USD 54 million, suggesting a distribution dominated by a few very large funds (Pástor et al., 2015). The average fund age is just over ten years (121 months), comparable to the typical lifespans of 7–10 years reported in earlier studies (Ferreira et al., 2012).

Risk measures are also in line with prior literature. Average fund volatility is 4.7%, and idiosyncratic volatility averages 1.8%, values comparable to those found in Carhart (1997) and Bollen and Busse (2004). The return distribution shows slight negative skewness (-0.22), consistent with the findings of Harvey and Siddique (2000) on asymmetry in equity returns. Finally, the performance rank variable, scaled between zero and one, centres around 0.51, confirming a balanced cross-section of fund performance, similar to the ranking approaches employed by Sirri and Tufano (1998).

Table III
Descriptive Statistics

This table reports summary statistics of key variables used in the empirical analysis. Fund Flow(%) measures the percentage change in net fund flows calculated as shown in equation (1). CPT is a Cumulative Prospect Theory (PT) index computed from past 12-month returns. Size ($M) is the fund's total net assets in millions of U.S. dollars. Age is the number of months since the fund's inception. Fund Volatility is the standard deviation of the fund's returns over a 12-month window. IVOL is the standard deviation of the residuals from a single-factor model of those returns. Fund Volatility is measured as the percentage standard deviation of raw returns over the preceding twelve months. Skew represents the skewness of the fund's past returns. Rank denotes the fund's performance rank relative to peers, and CH4 Alpha is the Carhart (1997) four-factor alpha. The table reports the mean, standard deviation (SD), 1st percentile, median, 99th percentile, and total observations (N) for each variable.

Variable	N	Mean	SD	1st Perc.	Median	99th Perc.
Fund Flow(%)	2,567,394	0.544	9.170	-22.510	-0.383	36.700
CPT	2,567,462	-1.503	2.243	-8.876	-1.082	2.226
Abnormal Returns	2,567,462	0.030	2.868	-8.106	0.060	7.962
Size ($M)	2,567,394	487.91	1,603.04	1.300	54.400	8,040.000
Age (months)	2,567,462	121.451	106.768	14.000	94.000	557.000
Fund Volatility	2,567,462	4.689	2.132	1.494	4.280	11.515
IVOL	2,567,462	1.837	1.226	0.220	1.523	6.179
Skew	2,567,462	-0.217	0.647	-1.833	-0.208	1.326
Rank	2,567,462	0.511	0.286	0.013	0.516	0.990

4.1.3 Correlation Matrix

Table IV presents the correlation matrix for the key variables, highlighting the interdependencies between fund flow, CPT, performance measures, fund size, risk factors, and other fund characteristics. Fund Flow shows a positive correlation with CPT (0.071) and Rank (0.124), suggesting that investors allocate more capital to funds with higher CPT values and stronger past performance. This is consistent with behavioural finance theories emphasising prospect theory preferences in fund selection. The moderate positive correlation between CPT and Skew (0.121) supports the notion that investors guided by prospect theory are inclined to favour funds with more pronounced lottery-like return characteristics.

CPT exhibits a strong negative correlation with Fund Volatility (−0.669) and Idiosyncratic Volatility (−0.293), implying that funds with higher prospect-theoretic appeal tend to show lower risk. This finding suggests that investors' valuations, shaped by prospect theory, may overweight lower-volatility funds. Meanwhile, Size and Age correlate positively (0.259), indicating that older funds are generally larger, aligning with the idea that successful funds grow over time.

The correlation between Size and Fund Volatility is slightly negative (-0.040), echoing the notion that larger funds typically experience lower volatility due to diversification benefits. Rank correlates positively with CPT (0.352) and Abnormal Returns (0.238), underscoring the connection between higher-ranked funds, stronger risk-adjusted performance, and investors' behavioural inclinations. As documented in earlier literature, these findings collectively reinforce the premise that investors reward top-performing funds and highlight how behavioural biases (embodied in CPT) interact with traditional performance metrics to influence fund flows.

Table IV
Correlation Matrix

This table presents the correlation matrix for key variables used in the empirical analysis. Asterisks (*) denote significance at the 1% level.

Variables	1	2	3	4	5	6	7	8	9
1. Fund Flow(%)	1								
2. CPT	0.071*	1							
3. Abnormal Returns	0.061*	0.097*	1						
4. Size ($M)	-0.013*	0.059*	0.003*	1					
5. Age	-0.109*	0.053*	-0.004*	0.259*	1				
6. Fund Volatility	-0.008*	-0.669*	0.026*	-0.040*	-0.032*	1			
7. IVOL	0.021*	-0.293*	-0.003*	-0.066*	-0.052*	0.482*	1		
8. Skew	0.000	0.121*	-0.028*	0.001	0.000	-0.036*	0.055*	1	
9. Rank	0.124*	0.352*	0.238*	0.044*	0.021*	-0.044*	-0.080*	-0.047*	1

Additionally, we examine multicollinearity among our predictor variables by calculating the variance inflation factor (VIF) for each explanatory variable. According to Montgomery et al. (2021), a commonly cited rule of thumb in regression textbooks is that a VIF value greater than 10 signals potential multicollinearity concerns and may prompt reconsidering the model specification. However, O'Brien (2007) argues that, under certain conditions, higher VIF values can still be acceptable and need not automatically invalidate the model. In addition, Belsley et al. (2004) recommend that VIFs in the range from 5 to 10 indicate moderate multicollinearity and should be examined more closely. In contrast, VIFs below 5 are generally taken to mean that multicollinearity is minimal. In our complete model, including all explanatory variables, the VIFs range from 1 to 1.94, with an average VIF of 1.29, indicating no multicollinearity problems.

4.2 Main Regression Findings

The aim of Table V is to report our baseline findings, which are based on our main hypothesis. We hypothesise that the positive effect of CPT on fund flows is reduced in periods of high economic policy uncertainty. Table V presents regression outcomes examining how fund flows are shaped by CPT alone, CPT interacted with economic policy uncertainty (EPU), and CPT combined with abnormal returns. To ensure that past performance does not confound these effects, each specification includes controls based on prior fund returns. Performance is incorporated through a ranking variable, applied within a piecewise linear regression framework. Across all columns, the models absorb fund-level fixed effects, and the reported standard errors are double-clustered by fund and by time.

Column 1 contains CPT on fund flows along with other control variables, and it has a positive and significant influence on the fund flows in the following month, as observed by Gupta et al. (2022).[1] The coefficient of CPT is 0.196 (p-value = 0.000). This implies that for a one-standard-deviation increase in CPT (2.24), the net fund flows into a fund rise by 0.44%.[2] This translates into a monthly inflow of $2.14 million.[3] In Column 2, we have the interaction of EPU with CPT. The coefficient of interaction is negative, which means that as the EPU increases, it brings the CPT value down and likewise affects the fund flows. The coefficient of CPT is 0.753 ($p = 0.000$), which translates to a 1.69% change in fund flow for a one-standard-deviation change in the value of CPT. The coefficient of the interaction term is -0.11 ($p = 0.005$), which brings down the change in fund flow to 1.44%. That is a 14.79% reduction in fund flows. This means that there is a monthly inflow of $8.25 million, which is reduced to $7.03 million when the uncertainty increases.

[1]For further readings, refer to Gu and Yoo (2021), Guo and Schönleber (2020), Han et al. (2021), and Pandey and Sharma (2024).

[2]We obtain 0.44% by multiplying the standard deviation of the CPT value (2.243) by its regression coefficient (0.196).

[3]We then multiply the 0.44% with the mean fund size (487.91) of our dataset to get the dollar value of the fund flow.

Table V
Main Regression Analysis

This table reports results from panel regressions of monthly fund flows (%) on EPU and EPU's interaction with CPT. CPT index is constructed from the raw monthly returns observed over the previous twelve months, following the prospect theory framework. $\log(\text{EPU})_{(t-1)}$ is the lagged log of Economic Policy Uncertainty. $\log(\text{Size})_{(t-1)}$ is the log of size lagged by one month. $\log(\text{Age})_{(t-1)}$ is the log of age lagged by one month. Abnormal Returns are calculated as fund returns minus market index returns. IVOL is idiosyncratic volatility calculated as the residual standard deviation from the Carhart four-factor model. Fund volatility is measured as the percentage standard deviation of raw returns over the preceding twelve months. Skew is the skewness of past raw returns based on the data of lagged 12 months. Fund $\text{Flows}_{(t-1)}$ are fund flows lagged by one month. Highperf indicates funds with performance ranking in the highest quintile, Midperf indicates funds with performance ranking in the middle three quintiles, and Lowperf indicates funds with performance ranking in the lowest quintile. Market beta, size beta, value beta, and momentum beta are calculated on excess returns using the Carhart (1997) four-factor model. All regressions include fund-level fixed effects and standard errors clustered by the fund and time. p-values are reported in parentheses. Asterisks (***, **, *) denote significance at the 1%, 5%, and 10% levels, respectively.

Fund Flows (%)	(1)	(2)	(3)	(4)	(5)
CPT	0.196***	0.753***		0.600***	
	(0.000)	(0.000)		(0.002)	
$\log(\text{EPU})_{(t-1)}$		0.002	-0.073	-0.039	-0.162
		(0.988)	(0.452)	(0.718)	(0.103)
CPT $\times$ $\log(\text{EPU})_{(t-1)}$		-0.110***		-0.084**	
		(0.005)		(0.028)	
Abnormal $\text{Returns}_{(t-1)}$			0.372***		0.327***
			(0.001)		(0.002)
Abn. $\text{Returns}_{(t-1)} \times \log(\text{EPU})_{(t-1)}$			-0.058***		-0.049**
			(0.010)		(0.021)
$\log(\text{Size})_{(t-1)}$	-0.821***	-0.813***	-0.797***	-0.744***	-0.725***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\log(\text{Age})_{(t-1)}$	-2.160***	-2.195***	-2.136***	-2.111***	-2.021***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IVOL	0.141***	0.148***		0.140***	
	(0.000)	(0.000)		(0.000)	
Fund Volatility			-0.069***		-0.041**
			(0.000)		(0.019)
Skew	0.040	0.059*	0.112***	0.061*	0.113***
	(0.244)	(0.095)	(0.004)	(0.083)	(0.003)
Fund $\text{Flows}_{(t-1)}$	0.086***	0.086***	0.086***	0.073***	0.074***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lowperf	3.081***	2.939***	3.541***	2.942***	3.394***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Midperf	1.667***	1.619***	1.885***	1.555***	1.772***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Highperf	11.565***	11.432***	12.208***	10.971***	11.586***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market Beta				-0.546***	-0.716***
				(0.001)	(0.000)
Size Beta				-0.389***	-0.333***
				(0.000)	(0.001)
Value Beta				-0.235**	-0.231**
				(0.029)	(0.034)

Table V — continued

Fund Flows (%)	(1)	(2)	(3)	(4)	(5)
Momentum Beta				0.567***	0.523***
				(0.000)	(0.001)
Intercept	12.181***	12.343***	12.463***	12.516***	12.794***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	2,540,824	2,540,824	2,540,824	2,357,518	2,357,518
R^2	0.094	0.094	0.093	0.082	0.081
Fixed Effects: Fund	Yes	Yes	Yes	Yes	Yes
Clustering: Fund, Time	Yes	Yes	Yes	Yes	Yes

As per Tversky and Kahneman (1992), within the cumulative prospect theory (CPT) framework, increased uncertainty tends to influence fund managers' evaluations by altering the subjective weighting of outcomes. As uncertainty rises, the probability of encountering unfavourable outcomes increases. Since CPT incorporates loss aversion—where losses tend to loom larger than gains—this heightened uncertainty typically makes the fund appear less attractive. A rise in the Economic Policy Uncertainty (EPU) index indicates that there is increased uncertainty regarding future economic policy decisions. S. R. Baker et al. (2021) suggest that businesses, investors, and policymakers perceive a higher risk of unexpected changes in government policies, which can lead to more cautious decision-making and increased market volatility. In other words, the CPT value, which reflects the behavioural attractiveness of the fund, is likely to decrease when uncertainty increases. This occurs because fund managers are likely to overweight the potential for negative outcomes under uncertain conditions, leading them to assign a lower overall CPT value to the fund.

In Column 3, we use abnormal returns as a performance measure. Prior literature has shown that flows are sensitive to past performance.[4] This is evident as we have a positive coefficient for abnormal returns, 0.372 ($p = 0.001$). This translates to inflows of 0.833% or \$4.06 million. When we interact the EPU with abnormal returns, the coefficient is negative. The interaction is -0.058 ($p = 0.01$), which lowers the inflow from 0.833% ($\approx$ \$4.06m) to 0.703% ($\approx$ \$3.43m). This negative interaction indicates that during periods of heightened economic policy uncertainty, the positive influence of abnormal returns on fund inflows is significantly weakened. In such uncertain economic climates, investors tend to exhibit increased caution. They become less inclined to rely exclusively on past performance to predict future success, seeking additional indicators or risk management signals to inform their decisions. This behavioural shift suggests that even funds with

[4]See Chevalier and Ellison (1997) and Carhart (1997).

robust historical performance may struggle to attract similar inflow levels when investors are preoccupied with external economic risks and policy ambiguities.

In Column 4, we add the fund's exposures to the market, size, value, and momentum factors to ensure the CPT effect is not a proxy for systematic tilts. These betas are estimated from Carhart four–factor regressions on excess returns. The coefficient on CPT is 0.600 ($p = 0.002$). For a one–standard–deviation increase in CPT (2.24), fund flows rise by 1.34%, which corresponds to $6.54 million at the sample–average AUM. The interaction CPT $\times$ log(EPU) is -0.084 ($p = 0.028$), which reduces the CPT–related flow change to 1.16% (about a 14% reduction), or roughly $5.62 million. The factor betas are included to absorb risk–exposure effects, so the CPT terms capture behavioural content rather than factor loadings.

In Column 5, we repeat the exercise using abnormal returns as the performance proxy, again controlling for the Carhart betas from excess–return regressions. The coefficient on abnormal returns is 0.327 ($p = 0.002$). A one–standard–deviation increase (2.24) implies a 0.73% rise in flows, or about $3.56 million. The interaction with log(EPU) is -0.049 ($p = 0.021$), bringing the flow change down to 0.62% (around a 15% reduction), or roughly $3.03 million. These specifications show that the main CPT and performance effects, and their attenuation under higher policy uncertainty, persist even after accounting for systematic risk exposures.

Across every specification, the coefficients for Lowperf, Midperf, and Highperf are positive and statistically significant, a pattern consistent with the findings of Sirri and Tufano (1998). Moreover, the magnitude of the Highperf coefficient exceeds that of Lowperf, suggesting that inflows intensify as fund returns improve. The remaining control variables behave as expected, aligning with prior evidence documented in the fund flow literature. The coefficient of lagged fund size, $\log(\text{Size})_{t-1}$, is negative and significant in the estimations, suggesting that smaller funds can attract greater fund flows. Past research has found mixed evidence on the association between fund size and incremental fund flows. The literature presents competing perspectives on how fund size influences flows. Gruber (1996) and Berk and Green (2004) argue that as funds expand, economies of scale lower costs, which in turn enhances performance and attracts additional inflows. In contrast, J. Chen et al. (2004) suggest that larger funds may suffer from organisational frictions, leading to weaker performance and potentially reducing their ability to draw new capital.

The estimated coefficient for fund age, measured as $\log(\text{Age})_{t-1}$, is consistently negative and statistically significant. This outcome mirrors earlier evidence; for example, Ferreira et al. (2012) report that younger non–U.S. funds tend to perform better and receive larger inflows. Similarly, Agarwal et al. (2021) document a negative relation between age and flows, supporting our results. By contrast, the coefficients for idiosyncratic volatility (IVOL) and skewness (SKEW) are not statistically different from zero in any specification.

The main finding from Table V is that while a higher CPT value significantly boosts future fund flows, this positive effect is considerably weakened in periods of high economic policy uncertainty. In other words, our results confirm that, although funds with a more attractive CPT profile typically attract additional inflows, heightened uncertainty—as captured by the interaction between CPT and EPU—leads investors to be more cautious and less responsive to these positive signals. This pattern is further supported by the performance measure results: funds with higher abnormal returns also experience increased flows, but this benefit diminishes under higher economic policy uncertainty. These baseline findings support our primary hypothesis: the positive relationship between CPT and fund flows weakens during periods of high economic policy uncertainty, showing how the overall economic environment can influence investor behaviour.

In Table VI, we extend our main hypothesis to funds having high CPT value and abnormal returns. To do this, we first compute the median of the CPT value or the abnormal returns of all the funds for a given month–year combination. Then we categorise high–CPT–value or high–abnormal–return funds as those having their CPT value or abnormal returns higher than the median for the given month–year. The control variables are the same as those in Table V.

Table VI
Effect of High CPT and High Abnormal Returns on Fund Flows

This table reports results from panel regressions of monthly fund flows (%) on uncertainties and their interactions with CPT. High CPT is a dummy variable whose value is 1 when the fund's CPT value is more than the median value of all the CPT values for that given year-month, otherwise, it is 0. CPT index is constructed from the raw monthly returns observed over the previous twelve months, following the prospect theory framework. High abnormal returns is a dummy variable whose value is 1 if the abnormal return for a given year month is more than the median of all the fund's abnormal returns for the same given year-month, otherwise, it is 0. $\log(\mathrm{EPU})_{(t-1)}$ is the lagged log of Economic Policy Uncertainty. $\log(\mathrm{Size})_{(t-1)}$ is the log of size lagged by one month. $\log(\mathrm{Age})_{(t-1)}$ is the log of age lagged by one month. Abnormal Returns are calculated as fund returns minus market index returns. IVOL is idiosyncratic volatility calculated as the residual standard deviation from the Carhart four-factor model. Fund volatility is measured as the percentage standard deviation of raw returns over the preceding twelve months. Skew is the skewness of past raw returns based on the data of lagged 12 months. Fund $\mathrm{Flows}_{(t-1)}$ are fund flows lagged by one month. Highperf indicates funds with performance ranking in the highest quintile, Midperf indicates funds with performance ranking in the middle three quintiles, and Lowperf indicates funds with performance ranking in the lowest quintile. All regressions include fund-level fixed effects and standard errors clustered by the fund and time. p-values are reported in parentheses. Asterisks (***, **, *) denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Fund Flows (%)		
High CPT	2.306***	
	(0.000)	
$\log(\mathrm{EPU})_{(t-1)}$	-0.051	-0.005
	(0.563)	(0.963)
High CPT × $\log(\mathrm{EPU})_{(t-1)}$	-0.359***	
	(0.000)	
High Abnormal Returns		1.486***
		(0.001)
High Abn. Returns × $\log(\mathrm{EPU})_{(t-1)}$		-0.227**
		(0.011)
$\log(\mathrm{Size})_{(t-1)}$	-0.799***	-0.793***
	(0.000)	(0.000)
$\log(\mathrm{Age})_{(t-1)}$	-2.119***	-2.129***
	(0.000)	(0.000)
IVOL	-0.000	
	(0.996)	
Fund Volatility		-0.059***
		(0.000)
Skew	0.049	0.114***
	(0.205)	(0.003)
Fund $\mathrm{Flows}_{(t-1)}$	0.087***	0.087***
	(0.000)	(0.000)
Lowperf	4.108***	4.562***
	(0.000)	(0.000)
Midperf	1.525***	1.848***
	(0.000)	(0.000)
Highperf	11.515***	12.616***
	(0.000)	(0.000)
Intercept	11.752***	11.645***

Table VI — continued

	(1)	(2)
	(0.000)	(0.000)
N	2,540,824	2,540,824
R^2	0.093	0.093
Fixed Effects: Fund	Yes	Yes
Clustering: Fund, Time	Yes	Yes

The coefficient in Column 1 for High CPT is 2.306 ($p = 0.000$), which is significantly higher than the coefficient of CPT in Column 2 of Table V. A one–standard–deviation change in High CPT results in a net fund flow rise of 5.17%. This translates to a monthly inflow of $25.22 million. This is a sharp increase from what we see in Table V, which was at 0.44%. This demonstrates that funds whose CPT value is high tend to pull in more funds than those with low CPT values. This is consistent with the prior literature of Barberis et al. (2016).[5] Column 1 then looks at the effect of EPU paired with CPT on fund flows. The coefficient of the interaction term is -0.359 ($p = 0.000$). The negative sign implies that as the EPU increases, it negatively affects CPT and, in turn, the fund flows. This translates to a 4.36% change in fund flows, which is $21.27 million. This is consistent with the prior literature of Ali et al. (2023),[6] which states that the fund flows decrease when uncertainty increases.

In Column 2, we use High abnormal returns as a performance measure. The coefficient for High abnormal returns is 1.486 ($p = 0.001$), which implies a 3.33% rise in flows (about $16.23 million) for a one–standard–deviation increase, and the interaction with log(EPU) of -0.227 ($p = 0.011$) reduces this to 2.82% (about $13.75 million). Funds with high abnormal returns are more sensitive to fund flows. This is consistent with our main findings in Table V.

Overall, Table VI shows that funds above the monthly median in CPT or abnormal returns attract materially higher inflows, but these gains shrink when policy uncertainty rises. The dampening is economically meaningful in both specifications, indicating that performance chasing is state–dependent and sensitive to the policy environment. Taken together with Table V, these results reinforce our main hypothesis and motivate the subsequent heterogeneity and robustness analyses.

[5] For further readings, refer to Wang and Han (2023), Gu and Yoo (2021), Guo and Schönleber (2020), Gupta et al. (2022), and Han et al. (2021).

[6] Ali et al. (2022), S. R. Baker et al. (2021), Jiang et al. (2016), and Liu and Zhang (2015)

Table VII
Fund Characteristics

This table uses various datasets partitioned based on age, size, idiosyncratic volatility, and downside risk. To partition the data, we calculate the median for a given variable for all funds in a given year-month, and then segregate the funds based on whether the variable is above or below the median. This table reports results from panel regressions of monthly fund flows (%) on EPU and EPU's interaction with CPT. CPT index is constructed from the raw monthly returns observed over the previous twelve months, following the prospect theory framework. $\log(\text{EPU})_{(t-1)}$ is the lagged log of Economic Policy Uncertainty. $\log(\text{Size})_{(t-1)}$ is the log of size lagged by one month. $\log(\text{Age})_{(t-1)}$ is the log of age lagged by one month. Abnormal Returns are calculated as fund returns minus market index returns. IVOL is idiosyncratic volatility calculated as the residual standard deviation from the Carhart four-factor model. Fund volatility is measured as the percentage standard deviation of raw returns over the preceding twelve months. Skew is the skewness of past raw returns based on the data of lagged 12 months. Fund $\text{Flows}_{(t-1)}$ are fund flows lagged by one month. Highperf indicates funds with performance ranking in the highest quintile, Midperf indicates funds with performance ranking in the middle three quintiles, and Lowperf indicates funds with performance ranking in the lowest quintile. All regressions include fund-level fixed effects and standard errors clustered by the fund and time. p-values are reported in parentheses. Asterisks (***, **, *) denote significance at the 1%, 5%, and 10% levels, respectively.

	Old		Young		Large		Small		High Idio Vol		Low Idio Vol		High Downside Risk		Low Downside Risk	
Fund Flows (%)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
CPT	0.438**		1.114***		0.632***		0.849***		0.862***		0.418**		0.681***		0.079	
	(0.016)		(0.000)		(0.000)		(0.000)		(0.000)		(0.015)		(0.001)		(0.760)	
$\log(\text{EPU})_{(t-1)}$	-0.036	-0.136	-0.234	-0.314**	0.060	-0.031	-0.321**	-0.390***	0.046	-0.011	-0.070	-0.158*	-0.140	-0.149	0.220**	-0.250**
	(0.703)	(0.130)	(0.153)	(0.022)	(0.497)	(0.689)	(0.032)	(0.003)	(0.742)	(0.929)	(0.436)	(0.057)	(0.238)	(0.136)	(0.044)	(0.024)
CPT × $\log(\text{EPU})_{(t-1)}$	-0.062*		-0.162***		-0.093***		-0.118***		-0.129***		-0.046		-0.105***		0.041	
	(0.084)		(0.001)		(0.008)		(0.008)		(0.007)		(0.174)		(0.009)		(0.409)	
Abnormal $\text{Returns}_{(t-1)}$		0.297***		0.452***		0.350***		0.378***		0.342***		0.339**		0.328***		0.502**
		(0.004)		(0.001)		(0.000)		(0.004)		(0.005)		(0.012)		(0.004)		(0.017)
Abn. $\text{Returns}_{(t-1)}$ × $\log(\text{EPU})_{(t-1)}$		-0.043**		-0.073***		-0.058***		-0.054**		-0.050**		-0.062**		-0.049**		-0.085**
		(0.040)		(0.007)		(0.002)		(0.041)		(0.040)		(0.022)		(0.027)		(0.046)
$\log(\text{Size})_{(t-1)}$	-0.445***	-0.431***	-1.901***	-1.874***	-0.617***	-0.581***	-1.954***	-1.921***	-0.825***	-0.809***	-0.895***	-0.885***	-0.721***	-0.705***	-1.040***	-1.014***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\log(\text{Age})_{(t-1)}$	-1.928***	-1.845***	-1.962***	-1.849***	-1.823***	-1.777***	-2.300***	-2.231***	-2.177***	-2.125***	-2.232***	-2.165***	-2.027***	-1.968***	-2.142***	-1.978***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IVOL	0.136***		0.201***		0.115***		0.215***		0.164***		0.349***		0.163***		0.065	
	(0.000)		(0.000)		(0.001)		(0.000)		(0.000)		(0.000)		(0.000)		(0.299)	
Fund Volatility		-0.015		-0.145***		-0.048***		-0.110***		-0.064***		-0.081***		-0.043***		-0.067***
		(0.323)		(0.000)		(0.000)		(0.000)		(0.001)		(0.000)		(0.010)		(0.009)
SKEW	0.060*	0.104***	0.033	0.107**	0.039	0.084**	0.040	0.107**	0.103**	0.172***	-0.026	0.010	0.074*	0.126***	-0.081*	0.020
	(0.072)	(0.003)	(0.474)	(0.038)	(0.209)	(0.015)	(0.352)	(0.021)	(0.021)	(0.000)	(0.454)	(0.805)	(0.054)	(0.002)	(0.065)	(0.670)
Fund $\text{Flows}_{(t-1)}$	0.029***	0.028***	0.092***	0.093***	0.134***	0.135***	0.043***	0.043***	0.080***	0.080***	0.072***	0.073***	0.058***	0.057***	0.082***	0.084***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lowperf	2.713***	2.846***	3.466***	4.624***	3.726***	4.319***	2.613***	3.221***	2.322***	3.094***	4.391***	4.122***	3.164***	3.475***	3.546***	3.231***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Midperf	1.415***	1.532***	1.666***	2.153***	1.310***	1.538***	1.841***	2.186***	1.654***	2.079***	1.486***	1.569***	1.609***	1.879***	1.512***	1.215***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Highperf	10.146***	10.449***	13.046***	14.356***	9.175***	9.838***	13.641***	14.579***	11.949***	12.664***	8.942***	9.607***	11.135***	11.813***	9.963***	9.616***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	10.284***	10.344***	15.354***	15.431***	10.467***	10.479***	14.863***	15.142***	12.042***	12.099***	13.044***	13.545***	11.717***	11.562***	12.674***	14.271***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table VII — continued

Fund Flows (%)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
N	1,365,569	1,365,569	1,165,135	1,165,135	1,454,600	1,454,600	1,061,305	1,061,305	1,553,519	1,553,519	870,580	870,580	1,877,691	1,877,691	395,401	395,401
R^2	0.064	0.064	0.120	0.119	0.121	0.120	0.107	0.107	0.096	0.095	0.097	0.095	0.077	0.076	0.134	0.132
Fixed Effects: Fund	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering: Fund, Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F: (CPT)	37.60(0.000)		37.60(0.000)		14.94(0.000)		14.94(0.000)		3.51(0.062)		3.51(0.062)		1.65(0.200)		1.65(0.200)	
F: (CPT×EPU)	28.87(0.000)		28.87(0.000)		12.77(0.000)		12.77(0.000)		2.90(0.090)		2.90(0.090)		3.87(0.050)		3.87(0.050)	

Table VII explores heterogeneity in the dampening effect of economic policy uncertainty on the CPT–flow relationship across funds segmented by age, size, idiosyncratic volatility, and downside risk. Under our hypothesis—that "the dampening effect of economic policy uncertainty on the CPT–flow relationship is stronger for younger, smaller, more idiosyncratically volatile, and higher downside–risk funds"—we estimate separate panel regressions for each subsample, alternately using CPT and abnormal returns as the key performance measure.

Focusing first on fund age (columns 1–4), older funds (columns 1–2) exhibit a modest baseline CPT effect of 0.438 ($p = 0.016$), consistent with Dahlquist et al. (2000)'s finding that age attenuates flow responsiveness; this effect is reduced by 0.062 percentage points per unit increase in log(EPU) ($p = 0.084$). For older funds, a one–standard–deviation increase in CPT implies a 0.98% rise in flows (about \$4.79 million), which falls to 0.84% (about \$4.11 million) when log(EPU) increases by one unit. By contrast, younger funds (columns 3–4) show a much stronger CPT effect of 1.114 ($p < 0.001$) and a larger CPT $\times$ log(EPU) coefficient of -0.162 ($p < 0.001$). For younger funds, a one–standard–deviation increase in CPT implies a 2.50% rise in flows (about \$12.17 million), which falls to 2.13% (about \$10.40 million) when log(EPU) increases by one unit. In the abnormal–returns models, the interaction of past abnormal returns with log(EPU) is similarly more negative for young funds (-0.073, $p < 0.001$) than for old funds (-0.043, $p = 0.040$). For older funds, a one–standard–deviation increase in abnormal returns implies a 0.67% rise in flows (about \$3.25 million), reduced to 0.57% (about \$2.78 million) when log(EPU) increases by one unit; for younger funds, the corresponding figures are 1.01% (about \$4.94 million) and 0.85% (about \$4.14 million). We reject equality of the baseline CPT coefficients across age partitions ($F = 37.60$, $p < 0.001$), and we also reject equality for CPT $\times$ log(EPU) ($F = 28.87$, $p < 0.001$), consistent with younger funds exhibiting a stronger CPT effect and a larger uncertainty dampening than older funds.

Turning to fund size (columns 5–8), larger funds (columns 5–6) display a CPT coefficient of 0.632 ($p < 0.001$) and a CPT $\times$ log(EPU) of -0.093 ($p = 0.008$), whereas smaller funds (columns 7–8) show a larger CPT effect of 0.849 ($p < 0.001$) with a stronger dampening of -0.118 ($p = 0.008$). For large funds, a one–standard–deviation increase in CPT implies a 1.42% rise in flows (about \$6.89 million), which falls to 1.21% (about \$5.88 million) when log(EPU) increases by one unit. For small funds, a one–standard–

deviation increase in CPT implies a 1.90% rise in flows (about \$9.26 million), which falls to 1.64% (about \$7.97 million) when log(EPU) increases by one unit. This pattern accords with Lobão and Gomes (2015)'s evidence that smaller funds exhibit greater sensitivity to behavioural signals and suffer more under policy uncertainty. For abnormal returns, a one–standard–deviation increase implies 0.78% (about \$3.82 million) for large funds, reduced to 0.65% (about \$3.19 million) when log(EPU) increases by one unit; for small funds, the corresponding figures are 0.85% (about \$4.12 million) and 0.73% (about \$3.53 million). We reject equality of the baseline CPT coefficients across size partitions ($F = 14.94$, $p < 0.001$), and we also reject equality for CPT $\times$ log(EPU) ($F = 12.77$, $p < 0.001$), consistent with smaller funds showing a stronger CPT effect and greater attenuation under uncertainty.

Examining idiosyncratic volatility (columns 9–12), high–IVOL funds (columns 9–10) have a baseline CPT effect of 0.862 ($p < 0.001$) and a pronounced CPT $\times$ log(EPU) of -0.129 ($p = 0.007$), whereas low–IVOL funds (columns 11–12) display a weaker baseline effect of 0.418 ($p = 0.015$) and an insignificant interaction (-0.046, $p = 0.174$). For high–IVOL funds, a one–standard–deviation increase in CPT implies a 1.93% rise in flows (about \$9.43 million), which falls to 1.64% (about \$8.00 million) when log(EPU) increases by one unit. For low–IVOL funds, a one–standard–deviation increase in CPT implies a 0.94% rise in flows (about \$4.58 million), which falls to 0.83% (about \$4.06 million) when log(EPU) increases by one unit. This segmentation echoes findings by Clifford et al. (2020) that funds with greater idiosyncratic volatility see more pronounced behavioural flows. For abnormal returns, a one–standard–deviation increase implies 0.77% (about \$3.73 million) for high–IVOL funds, reduced to 0.65% (about \$3.19 million) when log(EPU) increases by one unit; for low–IVOL funds, the corresponding figures are 0.76% (about \$3.70 million) and 0.62% (about \$3.02 million). We fail to reject equality of the baseline CPT coefficients across IVOL partitions ($F = 3.51$, $p = 0.062$), indicating that although point estimates are larger for high–IVOL funds, the difference is not statistically distinguishable. We likewise fail to reject equality for CPT $\times$ log(EPU) ($F = 2.90$, $p = 0.090$).

Finally, partitioning by downside risk as proxied by total fund volatility (columns 13–16), high–risk funds (columns 13–14) exhibit a CPT coefficient of 0.681 ($p < 0.001$) with a CPT $\times$ log(EPU) of -0.105 ($p = 0.009$), whereas low–risk funds (columns 15–16) show no significant CPT effect (0.079, $p = 0.760$) or interaction (0.041, $p = 0.409$). For high–risk funds, a one–standard–deviation increase in CPT implies a 1.53% rise in flows (about $7.47 million), which falls to 1.29% (about $6.29 million) when log(EPU) increases by one unit. For low–risk funds, a one–standard–deviation increase in CPT implies a 0.18% rise in flows (about $0.88 million), which moves to 0.27% (about $1.32 million) when log(EPU) increases by one unit. This indicates that uncertainty primarily dampens behavioural flows for funds exposed to greater downside risk, in line with the theory that losses loom larger under uncertainty (Ang et al., 2006). For abnormal returns, a one–standard–deviation increase implies 0.73% (about $3.56 million) for high–risk funds, reduced to 0.62% (about $3.03 million) when log(EPU) increases by one unit; for low–risk funds, the corresponding figures are 1.12% (about $5.47 million) and 0.93% (about $4.54 million). We fail to reject equality of the baseline CPT coefficients across volatility–based risk partitions ($F = 1.65$, $p = 0.200$), indicating that while point estimates are larger for high–risk funds, the difference is not statistically distinguishable. In contrast, we reject equality for CPT $\times$ log(EPU) ($F = 3.87$, $p = 0.050$), consistent with uncertainty attenuating behavioural flows more strongly among high–risk funds.

Control variables behave as expected: lagged fund size and age are consistently negative and highly significant, indicating that smaller and younger funds attract proportionally more flows across all subsamples. Idiosyncratic volatility and skewness effects align with earlier findings (Huang et al., 2007) that performance volatility dampens flow sensitivity, and lagged flows demonstrate strong persistence.

In sum, Table VII robustly supports our hypothesis: the adverse impact of economic policy uncertainty on the CPT–flow relationship is markedly stronger for younger, smaller, more idiosyncratically volatile, and higher downside–risk funds.

Table VIII
Fund Types

This table uses various datasets partitioned based on tracking error and the *int_dummy* variable. To partition the data, we calculate the median for a given variable for all funds in a given year-month, and then segregate the funds based on whether the variable is above or below the median. This table reports results from panel regressions of monthly fund flows (%) on EPU and EPU's interaction with CPT. CPT index is constructed from the raw monthly returns observed over the previous twelve months, following the prospect theory framework. $log(EPU)_{(t-1)}$ is the lagged log of Economic Policy Uncertainty. $log(Size)_{(t-1)}$ is the log of size lagged by one month. $log(Age)_{(t-1)}$ is the log of age lagged by one month. Abnormal Returns are calculated as fund returns minus market index returns. IVOL is idiosyncratic volatility calculated as the residual standard deviation from the Carhart four-factor model. Fund volatility is measured as the percentage standard deviation of raw returns over the preceding twelve months. Skew is the skewness of past raw returns based on the data of lagged 12 months. Fund $\text{Flows}_{(t-1)}$ are fund flows lagged by one month. Highperf indicates funds with performance ranking in the highest quintile, Midperf indicates funds with performance ranking in the middle three quintiles, and Lowperf indicates funds with performance ranking in the lowest quintile. All regressions include fund-level fixed effects and standard errors clustered by the fund and time. p-values are reported in parentheses. Asterisks (***, **, *) denote significance at the 1%, 5%, and 10% levels, respectively.

	Active		Passive		Global		Local	
Fund Flows (%)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CPT	1.213***		0.443**		0.242		0.997***	
	(0.000)		(0.015)		(0.356)		(0.000)	
$\log(\text{EPU})_{(t-1)}$	0.049	0.161	0.012	-0.139	0.052	-0.151	-0.048	-0.063
	(0.794)	(0.301)	(0.900)	(0.106)	(0.758)	(0.272)	(0.644)	(0.511)
CPT $\times \log(\text{EPU})_{(t-1)}$	-0.198***		-0.049		-0.005		-0.160***	
	(0.001)		(0.175)		(0.923)		(0.000)	
Abnormal $\text{Returns}_{(t-1)}$		0.348***		0.375***		0.239*		0.454***
		(0.009)		(0.000)		(0.069)		(0.001)
Abn. $\text{Returns}_{(t-1)} \times \log(\text{EPU})_{(t-1)}$		-0.049*		-0.064***		-0.028		-0.076***
		(0.068)		(0.002)		(0.287)		(0.003)
$\log(\text{Size})_{(t-1)}$	-1.073***	-1.053***	-0.754***	-0.743***	-0.740***	-0.731***	-0.839***	-0.822***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\log(\text{Age})_{(t-1)}$	-2.305***	-2.279***	-2.146***	-2.068***	-1.774***	-1.686***	-2.357***	-2.313***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IVOL	0.190***		0.112**		0.117**		0.172***	
	(0.001)		(0.010)		(0.016)		(0.000)	

Table VIII — continued

Fund Flows (%)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fund Volatility		-0.056***		-0.085***		-0.102***		-0.054***
		(0.010)		(0.000)		(0.000)		(0.001)
SKEW	0.154***	0.268***	0.013	0.043	0.058	0.116**	0.044	0.101**
	(0.007)	(0.000)	(0.728)	(0.303)	(0.222)	(0.024)	(0.250)	(0.014)
Fund Flows$_{(t-1)}$	0.049***	0.047***	0.093***	0.095***	0.146***	0.147***	0.065***	0.066***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lowperf	1.115*	2.050***	5.265***	5.453***	2.668***	3.424***	3.207***	3.700***
	(0.070)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Midperf	1.489***	2.050***	1.534***	1.727***	1.229***	1.522***	1.789***	2.044***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Highperf	11.384***	12.284***	12.448***	12.875***	10.345***	10.815***	11.907***	12.739***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	13.597***	13.010***	11.578***	12.044***	10.146***	10.943***	13.272***	13.116***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	689,288	689,288	1,721,724	1,721,724	693,744	693,744	1,847,080	1,847,080
R^2	0.089	0.089	0.104	0.103	0.112	0.112	0.090	0.089
Fixed Effects: Fund	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering: Fund, Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F: (CPT)	5.08(0.025)		5.08(0.025)		19.28(0.000)		19.28(0.000)	
F: (CPT×EPU)	6.55(0.011)		6.55(0.011)		20.81(0.000)		20.81(0.000)	

Table VIII investigates whether the dampening effect of economic policy uncertainty on the CPT–flow relationship differs across fund management style (active vs. passive) and geographic focus (global vs. local). We test the hypothesis that "the dampening effect of policy uncertainty on CPT–driven flows is stronger for active versus passive funds, and for local versus global funds," using data from January 1995 to November 2021 and partitioning the sample by management and distribution characteristics.

Columns (1)–(2) focus on actively managed funds, where the CPT coefficient is 1.213 ($p < 0.01$), consistent with Sirri and Tufano (1998)'s finding that investors disproportionately reward behavioural signals in active equity funds. The CPT $\times$ log(EPU) interaction is -0.198 ($p = 0.001$). For active funds, a one–standard–deviation increase in CPT implies a 2.73% rise in flows (about \$13.29 million), which falls to 2.27% (about \$11.14 million) when log(EPU) increases by one unit. In contrast, passive funds (columns 3–4) show a smaller base CPT effect of 0.443 ($p = 0.015$) and an insignificant interaction of -0.049 ($p = 0.175$), aligning with evidence that flows into passive mutual funds are less responsive to performance and behavioural cues. For passive funds, a one–standard–deviation increase in CPT implies a 0.99% rise in flows (about \$4.83 million), and the interaction with log(EPU) implies 0.88% (about \$4.30 million). We reject equality of the baseline CPT coefficients across activity partitions (active vs. passive) ($F = 5.08$, $p = 0.025$), and likewise reject equality for CPT $\times$ log(EPU) ($F = 6.55$, $p = 0.011$), consistent with heterogeneous behavioural–flow sensitivity across active and passive funds.

Columns (5)–(6) examine global funds—those issuing shares in multiple currencies—where CPT's baseline effect is low and non–significant at 0.242 ($p = 0.356$) with a negligible interaction of -0.005 ($p = 0.923$). For global funds, a one–standard–deviation increase in CPT implies a 0.54% rise in flows (about \$2.64 million), and the interaction with log(EPU) implies 0.53% (about \$2.59 million). By contrast, local funds (columns 7–8) exhibit a substantial CPT coefficient of 0.997 ($p < 0.01$) and a significant CPT$\times$log(EPU) term of -0.160 ($p < 0.001$). For local funds, a one–standard–deviation increase in CPT implies a 2.23% rise in flows (about \$10.89 million), which falls to 1.87% (about \$9.15 million) when log(EPU) increases by one unit. This geographic heterogeneity suggests that investor attention to prospect–theory signals is more pronounced for funds with a local distribution, in contrast to the generally higher performance sensitivity of global funds documented by Ciccone et al. (2022). We reject equality of the baseline CPT coefficients across geographic–scope partitions (global vs. local) ($F = 19.28$, $p < 0.001$), and also reject equality for CPT $\times$ log(EPU) ($F = 20.81$, $p < 0.001$), confirming heterogeneous behavioural–flow sensitivity to performance and uncertainty across global and local funds.

The right–hand panels (columns 2, 4, 6, 8) replicate these specifications using abnormal returns. Active funds show a return–flow coefficient of 0.348 ($p = 0.009$) and an interaction of -0.049 ($p = 0.068$). For active funds, a one–standard–deviation increase in abnormal returns implies a 0.78% rise in flows (about \$3.82 million), which falls to 0.67% (about \$3.28 million) when log(EPU) increases by one unit. Passive funds exhibit a stronger base return effect of 0.375 ($p < 0.01$) with a more pronounced uncertainty interaction of -0.064 ($p = 0.002$). For passive funds, a one–standard–deviation increase in abnormal returns implies a 0.84% rise in flows (about \$4.10 million), which falls to 0.70% (about \$3.40 million) when log(EPU) increases by one unit. Global funds' return coefficient is modest (0.239, $p = 0.069$) and the interaction is non–significant (-0.028, $p = 0.287$). For global funds, a one–standard–deviation increase in abnormal returns implies a 0.54% rise in flows (about \$2.61 million), which falls to 0.47% (about \$2.30 million) when log(EPU) increases by one unit. By contrast, local funds display a robust return–flow link (0.454, $p = 0.001$), with a one–standard–deviation increase in abnormal returns implying a 1.02% rise in flows (about \$4.95 million), which falls to 0.85% (about \$4.14 million) when log(EPU) increases by one unit. These local–return dynamics resonate with Coval and Moskowitz (2001)'s evidence that proximity enhances informational advantages and flow sensitivity to past performance.

Throughout all models, the control variables behave as expected: log(Size) and log(Age) are consistently negative and highly significant, indicating that smaller and younger funds attract proportionally more inflows. Idiosyncratic volatility, skewness, lagged flows, and performance quintiles also align with prior findings, lending credibility to the model specification. Taken together, these results strengthen confidence in the main estimates. Overall, Table VIII confirms our hypothesis that policy uncertainty more sharply attenuates CPT–driven flows for active and local funds, whereas passive and global funds exhibit comparatively muted behavioural responses under heightened uncertainty. The economic significance of this attenuation is substantial—for active and local funds, roughly one–sixth of CPT–driven flows are lost when policy uncertainty rises, highlighting the extent to which macroeconomic conditions reshape investor behaviour.

Table IX
Alternate Uncertainties along with CPT and Abnormal Returns on Fund Flows

Note: This table reports results from panel regressions of monthly fund flows (%) on uncertainties and their interactions with CPT. CPT index is constructed from the raw monthly returns observed over the previous twelve months, following the prospect theory framework. Global Financial Cycle (GFC)$_{(t-1)}$, Shadow Rate$_{(t-1)}$, and Quantitative Easing$_{(t-1)}$ are alternative proxies for macroeconomic and financial uncertainty. *log(Size)*$_{(t-1)}$ is the log of size lagged by one month. *log(Age)*$_{(t-1)}$ is the log of age lagged by one month. IVOL is idiosyncratic volatility calculated as the residual standard deviation from the Carhart four-factor model. Fund volatility is measured as the percentage standard deviation of raw returns over the preceding twelve months. Skew is the skewness of past raw returns based on the data of lagged 12 months. Fund Flows$_{(t-1)}$ are fund flows lagged by one month. Highperf indicates funds with performance ranking in the highest quintile, Midperf indicates funds with performance ranking in the middle three quintiles, and Lowperf indicates funds with performance ranking in the lowest quintile. All regressions include fund-level fixed effects and standard errors clustered by the fund and time. *p*-values are reported in parentheses. Asterisks (***, **, *) denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Fund Flows (%)						
CPT	0.218***	0.152***	1.103***			
	(0.000)	(0.000)	(0.000)			
GFC$_{(t-1)}$	0.058			0.093*		
	(0.217)			(0.058)		
CPT × GFC$_{(t-1)}$	0.052***					
	(0.002)					
Shadow Rate$_{(t-1)}$		-0.045***			-0.080***	
		(0.010)			(0.000)	
CPT × Shadow Rate$_{(t-1)}$		0.040***				
		(0.000)				
Quantitative Easing$_{(t-1)}$			0.507***			0.694***
			(0.000)			(0.000)
CPT × Quantitative Easing$_{(t-1)}$			-0.064***			
			(0.002)			
Abnormal Returns$_{(t-1)}$				0.089***	0.088***	0.238
				(0.000)	(0.000)	(0.156)
Abn. Returns$_{(t-1)}$ × GFC$_{(t-1)}$				0.025**		
				(0.016)		
Abn. Returns$_{(t-1)}$ × Shadow Rate$_{(t-1)}$					0.003	
					(0.585)	
Abn. Returns$_{(t-1)}$ × Quant. Easing$_{(t-1)}$						-0.010
						(0.378)
log(Size)$_{(t-1)}$	-0.877***	-0.796***	-0.784***	-0.873***	-0.778***	-0.762***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Age)$_{(t-1)}$	-2.185***	-2.284***	-2.677***	-2.174***	-2.290***	-2.774***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table IX — continued

	(1)	(2)	(3)	(4)	(5)	(6)
IVOL	0.132***	0.170***	0.146***			
	(0.001)	(0.000)	(0.000)			
Fund Volatility				-0.071***	-0.088***	-0.092***
				(0.000)	(0.000)	(0.000)
SKEW	0.086**	0.029	0.053	0.133***	0.089**	0.080**
	(0.031)	(0.396)	(0.141)	(0.002)	(0.018)	(0.032)
Fund Flows$_{(t-1)}$	0.080***	0.085***	0.085***	0.080***	0.086***	0.085***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lowperf	3.043***	2.936***	3.056***	3.718***	3.481***	3.419***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Midperf	1.687***	1.627***	1.700***	1.948***	1.876***	1.889***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Highperf	11.960***	11.472***	11.634***	12.714***	12.226***	12.262***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	12.509***	12.692***	6.995***	12.458***	12.927***	4.908***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	2,252,308	2,540,824	2,540,824	2,252,308	2,540,824	2,540,824
R^2	0.096	0.094	0.095	0.095	0.093	0.094
Fixed Effects: Fund	Yes	Yes	Yes	Yes	Yes	Yes
Clustering: Fund, Time	Yes	Yes	Yes	Yes	Yes	Yes

Table IX substitutes Economic Policy Uncertainty with three alternative proxies—Global Financial Cycle (GFC), Shadow Rate, and Quantitative Easing (QE)—to assess how different measures of macroeconomic and financial uncertainty moderate the links between behavioural attractiveness (CPT), risk–adjusted performance, and fund flows.

In Column (1), where the GFC index captures global liquidity conditions (i.e., higher values indicate looser financial conditions and lower uncertainty), an increase in the GFC value signals that uncertainty is declining. The CPT coefficient is 0.218 ($p < 0.01$), implying that a one–standard–deviation increase in CPT (2.24) translates into roughly a 0.49% rise in net fund flows. This corresponds to about $2.38 million at the sample–average AUM. The CPT × GFC interaction is positive and significant (0.052, $p < 0.01$), raising the CPT–related flow change to 0.60% (about $2.94 million) when the GFC index increases by one unit (Miranda-Agrippino & Rey, 2022; Rey, 2018).

Column (2) replaces GFC with the Shadow Rate, a proxy for unconventional monetary "tightness" beyond the zero lower bound (Wu & Xia, 2014). Here, CPT remains positive at 0.152 ($p < 0.01$). A one–standard–deviation increase in CPT (2.24) implies a 0.34% rise in flows (about $1.66 million). The main Shadow Rate effect is negative (-0.045, $p < 0.010$), indicating that tighter conditions dampen baseline inflows, while the positive CPT × Shadow Rate interaction of 0.040 ($p < 0.01$) raises the CPT–related flow change to 0.43% (about $2.10 million) when the Shadow Rate increases by one unit. Taken together, tightening lowers average flows but increases selectivity, making flows more responsive to CPT–aligned performance.

In Column (3), QE is the uncertainty proxy. CPT's coefficient rises sharply to 1.103 ($p < 0.01$), and a one–standard–deviation increase in CPT (sample–wide SD = 2.24) implies a 2.47% rise in flows (about $12.02 million). Quantitative easing itself correlates positively with flows (0.507, $p < 0.01$), consistent with liquidity–driven capital allocation (Gagnon et al., 2010; Neely, 2015). The CPT $\times$ QE interaction is significantly negative (-0.064, $p < 0.01$), indicating that abundant liquidity and compressed risk premia under QE reduce investor selectivity and weaken the link between CPT–salient performance and flows; accordingly, a one–unit increase in QE lowers the CPT–related flow change to 2.33% (about $11.32 million).

Columns (4)–(6) mirror these specifications using abnormal returns in place of CPT. Under GFC (Column 4), abnormal returns yield 0.089 ($p < 0.01$) and their interaction with GFC is 0.025 ($p = 0.016$). A one–standard–deviation increase in abnormal returns implies a 0.20% rise in flows (about $0.97 million), which rises to 0.26% (about $1.26 million) when the GFC index increases by one unit, suggesting that global liquidity amplifies return–flow sensitivity (Jotikasthira et al., 2012). With the Shadow Rate (Column 5), abnormal returns remain significant at 0.088 ($p < 0.01$), but the Abnormal Returns $\times$ Shadow Rate interaction is insignificant (0.003, $p = 0.585$), indicating negligible moderation at the zero lower bound. Finally, under QE (Column 6), abnormal returns are not significant (0.238, $p = 0.156$) and their QE interaction is also insignificant (-0.010, $p = 0.378$), implying that intense asset purchases mute the return–flow relationship.

Overall, Table IX shows that alternative uncertainty proxies have distinct moderating roles: elevated global liquidity strengthens both CPT and return effects; tighter unconventional policy enhances reliance on CPT but not on raw returns; and quantitative easing subdues the marginal benefit of CPT while largely flattening the return–flow linkage.

Table X
Alternate Uncertainties along with High CPT and High Abnormal Returns on Fund Flows

This table reports results from panel regressions of monthly fund flows (%) on uncertainties and their interactions with CPT. High CPT is a dummy variable whose value is 1 when the fund's CPT value is more than the median value of all the CPT values for that given year-month, otherwise, it is 0. CPT index is constructed from the raw monthly returns observed over the previous twelve months, following the prospect theory framework. High abnormal returns is a dummy variable whose value is 1 if the abnormal return for a given year month is more than the median of all the fund's abnormal returns for the same given year-month, otherwise, it is 0. Global Financial Cycle (GFC)$_{(t-1)}$, Shadow Rate$_{(t-1)}$, and Quantitative Easing$_{(t-1)}$ are alternative proxies for macroeconomic and financial uncertainty. *log(Size)*$_{(t-1)}$ is the log of size lagged by one month. *log(Age)*$_{(t-1)}$ is the log of age lagged by one month. IVOL is idiosyncratic volatility calculated as the residual standard deviation from the Carhart four-factor model. Fund volatility is measured as the percentage standard deviation of raw returns over the preceding twelve months. Skew is the skewness of past raw returns based on the data of lagged 12 months. Fund Flows$_{(t-1)}$ are fund flows lagged by one month. Highperf indicates funds with performance ranking in the highest quintile, Midperf indicates funds with performance ranking in the middle three quintiles, and Lowperf indicates funds with performance ranking in the lowest quintile. All regressions include fund-level fixed effects and standard errors clustered by the fund and time. *p*-values are reported in parentheses. Asterisks (***, **, *) denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Fund Flows (%)						
High CPT	0.453***	0.467***	5.910***			
	(0.000)	(0.000)	(0.000)			
GFC$_{(t-1)}$	0.077*			0.062		
	(0.083)			(0.221)		
High CPT × GFC$_{(t-1)}$	0.212***					
	(0.000)					
Shadow Rate$_{(t-1)}$		-0.106***			-0.111***	
		(0.000)			(0.000)	
High CPT × Shadow Rate$_{(t-1)}$		0.110***				
		(0.000)				
Quantitative Easing$_{(t-1)}$			0.755***			0.825***
			(0.000)			(0.000)
High CPT × Quant. Easing$_{(t-1)}$			-0.368***			
			(0.000)			
High Abnormal Returns				0.373***	0.305***	4.643***
				(0.000)	(0.000)	(0.000)
High Abn. Returns × GFC$_{(t-1)}$				0.114**		
				(0.011)		
High Abn. Returns × Shadow Rate$_{(t-1)}$					0.063***	
					(0.002)	

Table X — continued

	(1)	(2)	(3)	(4)	(5)	(6)
High Abn. Returns × Quant. Easing$_{(t-1)}$						-0.295***
						(0.000)
log(Size)$_{(t-1)}$	-0.878***	-0.776***	-0.753***	-0.869***	-0.771***	-0.754***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Age)$_{(t-1)}$	-2.123***	-2.273***	-2.712***	-2.164***	-2.293***	-2.750***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IVOL	0.004	-0.019	-0.022			
	(0.901)	(0.569)	(0.522)			
Fund Volatility				-0.060***	-0.082***	-0.083***
				(0.001)	(0.000)	(0.000)
SKEW	0.082*	0.037	0.048	0.147***	0.097**	0.090**
	(0.058)	(0.331)	(0.224)	(0.001)	(0.011)	(0.017)
Fund Flows$_{(t-1)}$	0.080***	0.086***	0.085***	0.081***	0.087***	0.086***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lowperf	4.331***	4.058***	4.034***	4.794***	4.463***	4.387***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Midperf	1.627***	1.509***	1.566***	1.912***	1.845***	1.867***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Highperf	12.232***	11.386***	11.389***	13.167***	12.639***	12.663***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	11.721***	12.294***	3.121***	11.949***	12.536***	2.449***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.003)
N	2,252,308	2,540,824	2,540,824	2,252,308	2,540,824	2,540,824
R^2	0.095	0.093	0.094	0.095	0.093	0.094
Fixed Effects: Fund	Yes	Yes	Yes	Yes	Yes	Yes
Clustering: Fund, Time	Yes	Yes	Yes	Yes	Yes	Yes

Table X extends Table IX by examining "high" categories—funds whose CPT or abnormal returns exceed the monthly median—and how their flow responses vary under three alternative uncertainty proxies: the Global Financial Cycle (GFC), the Shadow Rate, and Quantitative Easing (QE). Under this framework, we test whether funds at the upper end of behavioural attractiveness or performance distributions exhibit differential sensitivities to macro–financial regimes.

In Columns (1)–(3), the High CPT variable captures funds with CPT values above the median. Column (1) shows that such funds enjoy, on average, 1.02 percentage points higher net inflows ($p < 0.01$). This corresponds to about \$5.00 million at the sample–average AUM, indicating a substantial baseline premium for elevated prospect theory attractiveness, as documented by Sirri and Tufano (1998). The GFC main effect is mildly positive (0.077, $p = 0.083$), suggesting that richer global liquidity conditions slightly boost flows, while the High CPT × GFC interaction of 0.212 ($p < 0.01$) raises the High–CPT–related flow change to 1.49 percentage points (about \$7.30 million) when the GFC index increases by one unit, implying that this liquidity environment amplifies the high–CPT advantage, in line with the International Financial Cycle's influence on capital allocation (Rey, 2018).

Column (2) substitutes the Shadow Rate. High CPT funds still attract 0.467 percentage points more flows ($p < 0.01$). The Shadow Rate's main coefficient is -0.106 ($p < 0.01$), indicating that tighter funding conditions dampen aggregate inflows, while the High CPT $\times$ Shadow Rate interaction is 0.110 ($p < 0.01$), which raises the High–CPT–related flow change to 0.577% (about \$2.81 million) when the Shadow Rate increases by one unit, showing that High–CPT funds are more resilient and continue to attract flows even under restrictive policy, echoing differentiated responses under stress (Neely, 2015).

Column (3) employs QE. High CPT funds exhibit a large 5.910 percentage–point premium ($p < 0.01$). A one–standard–deviation increase in High CPT implies a 13.24% rise in flows (about \$64.4 million), reflecting that behavioural attractiveness commands an outsized reward during active asset–purchase regimes. Quantitative easing itself is positively associated with flows (0.755, $p < 0.01$), consistent with Gagnon et al. (2010) on liquidity effects, while the High CPT $\times$ QE interaction of -0.368 ($p < 0.01$) indicates that as QE intensifies, the incremental benefit of being a High–CPT fund is partially eroded. Accordingly, a one–unit increase in QE lowers the High–CPT–related flow change to 12.42% (about \$60.3 million).

Columns (4)–(6) repeat these specifications for funds with high abnormal returns. In Column (4), High Abnormal Returns funds gain 0.373 percentage points more flows ($p < 0.01$), supporting the performance–flow link from Berk and Green (2004), and the Abnormal Returns $\times$ GFC interaction is 0.114 ($p = 0.011$). A one–standard–deviation increase in abnormal returns implies a 0.84% rise in flows (about \$4.09 million). This rises to 1.10% (about \$5.35 million) when the GFC index increases by one unit, showing that global liquidity further magnifies this effect. Under the Shadow Rate (Column 5), the premium is 0.305 ($p < 0.01$) with an Abnormal Returns $\times$ Shadow Rate interaction of 0.063 ($p < 0.01$). A one–standard–deviation increase in abnormal returns implies a 0.68% rise in flows (about \$3.31 million). This rises to 0.82% (about \$3.99 million) when the Shadow Rate increases by one unit, indicating that high–performing funds also exhibit resilience when funding conditions tighten (Neely, 2015). Finally, during QE (Column 6), while High Abnormal Returns funds earn a 4.643–point premium ($p < 0.01$), the Abnormal Returns $\times$ QE interaction is -0.295 ($p < 0.01$). A one–standard–deviation increase in abnormal returns implies a 10.39% rise in flows (about \$50.49 million). This falls to 9.73% (about \$47.23 million) when QE increases by one unit, suggesting that intense asset purchases blunt the reward for past outperformance in line with Gagnon et al. (2010).

In sum, Table X confirms that discrete extremes, High CPT and High Abnormal Returns, enjoy significant flow premiums that are further modulated by macro–financial regimes. Elevated global liquidity strengthens these premiums, restrictive shadow rates confer greater resilience to High–CPT and high–performance funds, and expansive QE, while boosting overall flows, attenuates the marginal advantage of being in the upper tail of attractiveness or performance.

Chapter 5

Conclusion

This dissertation examines how behavioural preferences, captured by cumulative prospect theory (CPT), interact with multiple dimensions of macroeconomic uncertainty in shaping U.S. equity mutual fund flows between 1995 and 2021. The evidence shows that funds with stronger CPT profiles attract markedly larger inflows during calm periods, yet this advantage fades as policy uncertainty rises; the reduction is less pronounced for older funds whose extended performance histories bolster investor confidence. Overall, investors channel new money into recent winners yet turn cautious when news–based policy uncertainty increases. Distinct uncertainty proxies tell a nuanced story: abundant global liquidity amplifies the CPT premium, whereas unconventional–policy tightness and large–scale asset purchases reshape but do not uniformly suppress the behavioural pull of skewed return distributions. These findings remain robust when alternative variable definitions—including High–CPT dummies—confirm that investors' performance chasing is state–dependent and sensitive to the macro–financial environment. Relative to prior work that studies either behavioural preferences or macroeconomic conditions in isolation, these results show that behavioural demand is conditional on the surrounding policy and financial regime rather than being a stable feature of investor choice.

Beyond quantifying these relationships, the study delivers three main contributions. First, embedding CPT within a flow model that jointly considers policy, global–cycle, and monetary–stance measures unifies behavioural and macro–finance perspectives that are rarely combined. This integrated design is novel in demonstrating how multiple sources of uncertainty jointly shape behavioural capital allocation, extending CPT–based evidence such as Barberis et al. (2016) and Guo and Schönleber (2020) by explicitly conditioning behavioural demand on macroeconomic regimes rather than treating investor psychology as time invariant.Second, it uncovers a dynamic role for reputation: fund age attenuates the uncertainty discount, refining theories of branding, learning, and investor trust. This finding complements E. Jiang et al. (2016) by showing that uncertainty weakens performance sensitivity unevenly across funds, with behavioural signals persisting most strongly where informational frictions are lowest. Third, the 26–year, 2.5–million–observation panel—with double–clustered standard errors—offers a methodological template for future flow research.

These insights carry tangible implications. Fund managers cannot rely on performance signals alone when the macro horizon clouds, and should strengthen liquidity management and frame performance using longer horizons and risk–adjusted metrics during these episodes. The results further indicate that "lottery–like" or skewness–oriented strategies are most effective in low–uncertainty, high–liquidity regimes, whereas in periods of elevated policy ambiguity, reputation, scale, and transparency dominate behavioural appeal. Asset allocators can temper short–term performance chasing in policy–volatile periods by incorporating time–varying uncertainty metrics into due–diligence dashboards. For individual investors, the findings imply that behavioural signals embedded in return distributions become less reliable guides to fund quality during periods of heightened policy uncertainty, increasing the value of diversification and longer–horizon evaluation. Policymakers, meanwhile, must recognise that unconventional easing can blunt investors' ability to discriminate among funds on behavioural grounds, making clear and timely communication critical to stabilising retail flows. More broadly, the evidence suggests that policy uncertainty affects capital allocation not only by altering risk premia but also by weakening the informational and behavioural channels through which investors respond to performance.

Looking forward, research could test whether these patterns hold for bond and multi–asset funds, for investor groups beyond the U.S., and across business cycles. It would also be useful to split the EPU into thematic components—fiscal, monetary, and trade—to identify which policy dimensions most strongly influence fund flows, and to compare the news–based measure with market gauges such as the VIX or credit spreads. Future work could experiment with alternative CPT parameterisations, reference points, return windows, and flow measures to ensure that the results are not model–specific. Such extensions would further clarify whether the state dependence of behavioural demand documented here reflects general features of investor decision–making or is specific to particular asset classes and institutional settings.

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