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SHORT REPORT

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Economic policy uncertainty and fund flow performance sensitivity: Evidence from New Zealand

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Abstract

Utilizing a large sample of actively managed equity funds and a recently developed EPU index for New Zealand, we show that fund flow performance sensitivity decreases with policy uncertainty. The role of policy uncertainty as a determinant of fund flow performance sensitivity is found to be stronger, particularly for funds with global focus, large sized funds, high momentum funds and those with high idiosyncratic volatility and low downside risk. The findings support the argument that high policy uncertainty dampens investors' ability to process information that allows them to distinguish fund manager skill from luck. The results remain strong after accounting for various macroeconomic factors.

KEYWORDS

economic policy uncertainty, fund flow performance sensitivity, investor learning, New Zealand EPU

JEL CLASSIFICATION

G11, G12, C13, E20, E30

1 | INTRODUCTION

Investment flows (both inflows and outflows) of managed funds such as mutual funds and exchange traded funds are often considered as an indicator of investor sentiment about current and future economic conditions (see for e.g., Ben-Rephael et al., 2012; Frazzini & Lamont, 2008). A well-established literature argues that return-chasing investors make inferences regarding fund manager skills using signals from past fund performance, which in turn, creates a domino effect as strong flows to equity funds drive subsequent returns, thereby attracting more investors (Huang et al., 2007). This learning effect by investors about managerial ability in the investment industry contributes to the fund flow-performance relationship that is well documented in the literature (e.g., Berk & Green, 2004; Franzoni & Schmalz, 2017; Huang et al., 2022). Recent evidence, however, suggests that investor learning about managerial skills weakens with policy uncertainty, thus resulting in an inefficient allocation of funds. For example, Jiang et al. (2021) argue that greater economic policy uncertainty (EPU) leads to an inefficient capital allocation (by investors) by hindering the learning process through diminished fund flow-performance sensitivity. This finding supports the evidence by French and Li (2022) that links aggregate equity fund flows to policy uncertainty, thus establishing a novel information channel through which EPU affects the efficient allocation of resources in the economy.

In the current study, we extend this emerging literature to the New Zealand managed fund industry that accounts for about 85% of the equity investments in the country (Ali, Badshah, & Demirer, 2022; Ali, Badshah, Demirer, & Hegde, 2022) by testing the implications of policy uncertainty on the sensitivity of fund flows to past performance. To do so, we utilize a recently developed EPU index for New Zealand that is shown to capture a significant risk premium in the cross-section of fund returns, both statistically and economically. Considering the emerging evidence from the U.S. that policy uncertainty hinders the learning process regarding managerial skills and the fact that equity investments in New Zealand are largely dominated by managed funds, examining the uncertainty-fund flow performance sensitivity nexus in the context of New Zealand is of high interest for investors and market regulators alike regarding the efficient allocation of funds in this market. To the best of our knowledge, ours is the first study to explore the link between policy uncertainty and fund-flow performance sensitivity in such a unique setting wherein managed funds dominate equity investments, thus contributing to the emerging discussion on the effect of uncertainty on investor learning about fund manager ability from a novel perspective.

Previous empirical works on the US mutual fund industry show that flows depend on the past performance of mutual funds and investors reward funds in an asymmetric fashion based on their past performance, that is, they invest in good performers more aggressively than they sell bad performers, thus resulting in a convex flow-performance relationship (e.g., Del Guercio & Tkac, 2002; Sirri & Tufano, 1998, among others). However, the theoretical work by Berk and Green (2004) argues that the empirical flow-performance relationship reflects Bayesian (rational) investor learning about the skill of mutual fund managers such that past performance provides signals to investors, which in turn creates an informational channel. Supporting this argument, Huang et al. (2022) find that the flow-performance relationship is consistent with the Bayesian learning process and show that the flow-performance sensitivity of managed funds is weaker for funds with higher return volatility. This finding is consistent with the investors' learning hypothesis as volatile past performance provides noisy signals regarding managerial ability, thus hindering the learning process. Similarly, Franzoni and Schmalz (2017) determine how uncertainty regarding the risk loadings on benchmark factors affects investors' capital allocation decisions and show that flow-performance sensitivity decreases in extreme markets states. In a study that is more directly related to our context, Jiang et al. (2021) argue that EPU dampens decision makers' ability to process information and so when uncertainty is high, equity investors cannot differentiate investment skill from luck.[1]

Against this backdrop, we build upon the established evidence on the role of EPU as a driver of stock market dynamics and contribute to the emerging literature on investor learning under uncertainty from a novel perspective by examining the effect of EPU on the flow-performance sensitivity for a comprehensive sample of 353 actively managed equity funds in New Zealand, using a recently developed EPU index for New Zealand. The main contribution of this study is that we are able to clearly establish the role of EPU on fund flow-performance sensitivity in a unique market that is largely dominated by managed funds, unlike in other developed markets. Furthermore, our results provide new evidence that certain fund features play a significant role in how policy uncertainty interacts with fund flow-performance sensitivity. We show that funds with global (local) investment focus have high (low) flow-performance sensitivity with EPU. The negative relationship between flow-performance and EPU suggests that high uncertainty dampens investors' ability to process information, thereby hindering investors' ability to differentiate investment skill from luck. The uncertainty effect is also found to be stronger in larger funds and funds that experience high momentum and idiosyncratic volatility, supporting the argument that noisy signals play a significant role in investor learning regarding managerial skills. Further robustness checks confirm that the role of uncertainty on fund flow sensitivity is robust even after we control for macroeconomic factors that capture monetary and fiscal policy actions.

The remainder of the paper is organized as follows. Section 2 describes the data and the methodology. Sections 3 and 4 discuss the empirical results and Section 5 provides our concluding remarks with suggestions for future research.

2 | DATA AND METHODOLOGY

To test our hypothesis, we employ the survivorship bias-free institutional fund dataset that includes all available equity funds in New Zealand (NZ) for the sample period January 1997 through March 2021, obtained from the Refinitiv Lipper for Investment Management (LIM) database.[2] After eliminating funds with missing information on returns and assets under management (AUM), our final sample yields a total of 353 equity funds, among them 218 are alive (surviving) and 135 defunct or dead (liquidated/merged), resulting in 25,212 fund-month observations. Our choice of fund selection is consistent with the flow-performance and mutual fund literature.

Panel A in Table 1 presents the summary statistics for the entire sample of funds and Panel B reports the summary statistics for local and global sub-samples of funds based on each fund's geographical focus as determined by the Lipper Global Classification (LGC) guidelines.[3] Specifically, we classify a fund as "Local" when the fund's geographical focus is New Zealand and "Global" when the fund's stated geographical focus is global. This categorization results in 65 (141) funds classified as local (global).[4] We observe in Table 1 that local funds on average experience positive mean fund flows, whereas the opposite is true for global focused funds. Further, Global funds on average are smaller in size (log assets) although they have been in existence longer (i.e., higher fund age) than their NZ focused counterparts. Both fund groups are similar in terms of their downside risk and idiosyncratic volatility and experience market betas less than unity, highlighting the diversified nature of these funds.

To capture policy uncertainty (i.e., EPU), we utilize the economic policy uncertainty index for New Zealand, recently proposed by Ali, Badshah, and Demirer (2022) and Ali, Badshah, Demirer, and Hegde (2022), that is constructed based on the text-based approach of Baker et al. (2016). Specifically, the index is constructed by parsing the text archives available in Newztext for four major NZ news outlets including NZ-Herald, Fairfax, Stuff and Interest.co.nz. from January 1997 through March 2021. The data is publicly available on policyuncertainty.com. Figure 1 plots the monthly EPU index series for New Zealand and the Global EPU index for comparison. As expected, we observe notable spikes around certain key dates including the Asian Financial Crisis (1998), the NZ Elections (1999), the 2001 terrorist attack (9/11), and 2003 Iraq Invasion. We also observe major spikes in the EPU index values around the Global Financial Crisis (2008) and during the recent COVID-19 period, suggesting that the NZ EPU index is able to capture market shocks from both the global and local perspectives.

To test our hypotheses, we construct monthly net fund flow series for each fund in our sample based on the methodology proposed by Franzoni and Schmalz (2017) as follows:

$$FLOW_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1+R_{it})}{TNA_{i,t-1}}, \tag{1}$$

where, $TNA_{i,t}$ is fund i's total net assets at the end of month t, and R_{it} is the return of fund i in month t. To account for the fund performance, we primarily resort to two widely used performance measures, namely the fund excess returns ($R_{it} - R_f$) where R_f is the risk-free rate, measured by the 1-month bill rate, and Carhart (1997) alphas computed as $R_{it} - \beta_i^{mkt} MKT_m + \beta_i^{smb} SMB_m + \beta_i^{hml} HML_m + \beta_i^{mom} MOM_m$ where R_{it} is the excess fund return.[5] For consistency, we use the risk factors for New Zealand, obtained from Jensen et al. (2021), to compute the risk-adjusted returns for

TABLE 1 Fund statistics.

Variable	Mean	SD	Min	Max
Panel A: Descriptive statistics of fund characteristics				
Flow (%)	0.28	5.72	−18.38	30.98
Raw Return (%)	1.04	5.72	−41.93	37.29
Excess Return (%)	0.99	5.73	−42.05	37.28
Four-Factor Alpha (%)	−2.69	5.76	−54.62	25.96
Abnormal Return (%)	−0.04	4.61	−33.62	35.58
Fund momentum (%)	0.01	0.03	−0.15	0.15
Tracking Error (%)	4.20	1.62	1.07	18.88
Return Volatility (%)	5.27	2.10	0.76	21.57
Fund Size (million)	39.42	82.28	0.01	938.67
Fund age (in months)	170.44	109.05	2.00	459.00
Fund Beta (%)	0.88	0.17	0.20	1.71
Fund Beta Uncertainty (%)	0.20	0.06	0.06	0.64
Sharpe Ratio (%)	0.14	1.00	−3.45	4.18
Idiosyncratic Volatility (%)	2.49	0.85	0.43	11.90
Downside Risk (%)	8.98	5.21	−0.63	41.93
Observations	25,212			
No. of funds	353			

	Local focused		Global focused	
	Mean	SD	Mean	SD
Panel B: Descriptive statistics for equity funds partitioned based on geographical focus				
Flow (%)	0.005	5.897	−0.658	5.415
Raw Return (%)	1.013	5.698	1.053	5.521
Excess Return (%)	0.967	5.706	1.002	5.529
Four-Factor Alpha (%)	−2.978	4.691	−2.254	6.763
Abnormal Return (%)	−0.063	4.718	−0.047	4.267
Fund momentum (%)	0.006	0.033	0.007	0.033
Tracking Error (%)	4.292	1.715	3.920	1.337
Return Volatility (%)	5.244	2.126	5.144	1.899
Fund Size (million)	46	97	35	82
Fund age (in months)	149	107	203	106
Fund Beta (%)	0.899	0.182	0.835	0.151
Fund Uncertainty Beta (%)	0.195	0.063	0.201	0.067
Sharpe Ratio (%)	0.148	1.014	0.133	0.991
Idiosyncratic Volatility (%)	2.427	0.801	2.695	0.870
Downside Risk (%)	8.801	5.069	8.735	4.844
Observations	3578		6755	
No. of funds	65		141	

Note: This table presents the summary statistics for funds in the sample over the period January 1994 through March 2021. Panel A provides the summary statistics for the overall sample of equity funds in New Zealand. Panel B provides the summary statistics for funds based on their geographical focus. Fund Size is log(assets); Fund Age is the average number of months in fund's existence; Sharpe ratio is defined as the excess fund returns (in excess of risk-free rate) per unit of 12-month rolling standard deviation in returns; and Average Tracking Error is the 12-month rolling standard deviation of abnormal returns, where abnormal return is the difference between monthly fund and NZX market index returns. Idiosyncratic volatility (IV) is computed relative to the benchmark Fama–French (1993) 5-factor model via rolling regressions as per Ang et al. (2006); downside risk is measured by the Value at Risk values as per Ali, Badshah, and Demirer (2022) and Ali, Badshah, Demirer, and Hegde (2022); momentum (MOM) is the cumulative return over the trailing 12-month period; monthly fund flows are based on the flow measure of Franzoni and Schmalz (2017). Return Volatility is the time-series standard deviation of the fund's monthly returns over $t-1$ to $t-11$ months. Fund beta uncertainty is the range of the 95% confidence interval of the beta coefficient in the Fama–French five factor model.

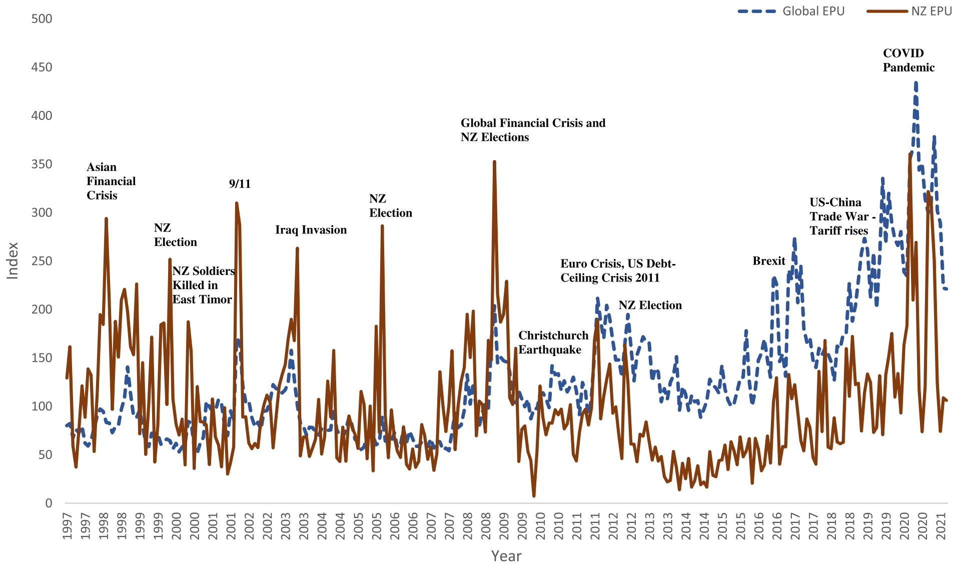

FIGURE 1 Economic policy uncertainty (EPU) index for New Zealand. This figure depicts the monthly NZ EPU index values based on the scaled monthly counts of news articles that contain a trio of terms pertaining to the economy (E), policy (P) and uncertainty (U), along the lines of Baker et al. (2016), compared with the Global EPU of Davis (2016). NZ EPU index is constructed based on the text archives available in Newztext for four major NZ newspapers: NZ-Herald, Fairfax, Stuff and Interest.co.nz in New Zealand. The series is normalized to mean 100 over the sample period of 1997–2021.

local focused funds, while the global risk factor data, obtained Ken French's data library, is used to compute the risk-adjusted alphas for global focused funds.

To test our primary hypothesis that EPU weakens a fund's flow-performance sensitivity, we employ the following regression for the determinants of fund flow:

$$FLOW_{i,t} = b_1 PERF_{i,t-1} + b_2 \log(EPU_{t-1}) + b_3 PERF_{i,t-1} \times \log(EPU_{t-1}) + CONTROLS_{i,t\text{-}1} + u_i + v_t + e_{i,t}, \quad (2)$$

where, $FLOW_{i,t}$ is the monthly percentage flow to the fund as defined in Equation (1). Following Jiang et al. (2021), the explanatory variables include fund i's performance in month $t-1$ ($PERF_{i,t-1}$), and the logarithm of the EPU index in month $t-1$ ($\log(EPU_{t-1})$).[6] Additional control variables include the squared measure of performance (PERF-Squared$_{(t-1)}$) to account for the aforementioned convex flow-performance relationship; fund return volatility (Volatility$_{(t-1)}$) calculated as a time-series standard deviation of the fund's monthly returns over months $t-1$ to $t-11$; fund size (log (Assets)$_{(t-1)}$); fund age (log (Fund Age)$_{(t-1)}$); fund momentum (Momentum$_{(t-1)}$) computed as the cumulative return for months $t-1$ to $t-11$; and tracking error$_{(t-1)}$ calculated as the 12-month rolling standard deviation of abnormal returns, where abnormal return is the difference between monthly fund and NZX index returns. All control variables are lagged by 1-month. u_i and v_t are fund fixed effects and time fixed effects, respectively and standard errors are double clustered by fund and time.

3 | EMPIRICAL RESULTS

Table 2 reports the results for Equation (2) for monthly fund flows regressed on lagged fund performance ($PERF_{i,t-1}$), log EPU index, and the interaction of these variables, in addition to fund level controls. Specifically, Models 1 and

2 use excess fund returns as a measure of performance and Models 3–5 use the risk-adjusted alphas from the Carhart (1997) 4-factor model as a measure of fund performance. We find that the coefficient for $PERF_{i,t-1}$ is positive and significant, suggesting that past performance leads to greater fund flows, consistently for all performance specifications. However, the interaction term between past performance and policy uncertainty, $PERF_{i,t-1} \times \log(EPU_{t-1})$, is negative and highly significant in all model variations, even when EPU is measured by a dummy variable to denote its high levels (Model 5). This finding suggests that high uncertainty dampens investors' learning process regarding managerial ability such that investors do not rely on past performance as a signal to make capital allocation to funds under high policy uncertainty. At the same time, we observe that the squared performance term (PERF-Squared$_{(t-1)}$) is largely insignificant, failing to support a convex flow-performance relationship.

As one of the novel contributions of our study, we next explore whether the relationship between EPU and flow-performance sensitivity has any bearing on the well-known fund anomalies. To that end, we partition the entire sample into above/below median funds based on several anomalies such as fund size, momentum, idiosyncratic volatility (IV), and downside risk in addition to the geographical focus. The findings reported in Table 3 indicate several interesting distinctions along these characteristics. First, we find that $PERF_{i,t-1}$ is positive and significant for funds with global focus as well as large sized funds and funds that experience high momentum returns, high idiosyncratic volatility (IV), and low downside risk, confirming the positive relationship between past performance and fund flow. More importantly, we find that the coefficient for $PERF_{i,t-1} \times \log(EPU_{t-1})$ is negative and significant for these funds. This suggests that certain fund characteristics play an important role when it comes to the interaction of investor learning with policy uncertainty. Specifically, we find that uncertainty plays a stronger role for certain funds with a global focus, larger sized funds and funds with high momentum, idiosyncratic volatility and lower downside risk.

The explanations for these findings are consistent with the argument that uncertainty hinders investor learning by creating noisy signals and these signals could be particularly effective as a hindrance to investor learning depending on fund characteristics. For example, the volatile past performance, experienced by high IV funds, provides noisy signals for investors regarding managerial ability (Huang et al., 2022) or funds with a global focus could expose investors to greater ambiguity during high uncertainty periods compared to their locally focused alternatives. In the case of funds that experience low downside risk, the negative relationship between EPU and flow-performance sensitivity could be driven by fund managers with downside-risk timing skills actively managing their portfolios' downside risk exposures in different market conditions (Bodnaruk et al., 2019). Nevertheless, our findings suggest that the role of policy uncertainty on investor learning could be stronger depending on certain fund features.

4 | ACCOUNTING FOR MACROECONOMIC FACTORS

There is ample evidence in the literature that macroeconomic factors can serve as a significant driver of capital flows to risky assets including managed funds. While studies including Mishkin (2001) and Gilchrist and Leahy (2002) show that conventional monetary policy affects risky asset prices and subsequently fund flows, unconventional monetary policy actions, as observed during the Eurozone sovereign-debt crisis and the recent COVID-19 pandemic, can also have a significant impact on investor flows to risky asset including managed funds (Cortes et al., 2022; Dedola et al., 2021). Therefore, it is important to account for the macroeconomic factors in the models when we explore the role of uncertainty as a driver of fund flow performance sensitivity as uncertainty will be closely related to those macroeconomic factors. For this purpose, we control for the shadow rates similar to Wu and Xia (2016) for the U.S. and Eurozone to capture conventional monetary policy, assuming that these monetary policy actions will be closely linked with those adopted by policy makers in New Zealand. Likewise, to capture unconventional monetary policy, following Cortes et al. (2022), we augment our model by accounting for all the quantitative easing (QE) intervention months by the Reserve Bank of New Zealand. Finally, building on the evidence that fiscal policy responses by governments can also play a role in equity valuations (Gandhi et al., 2020), the issuance of debt

TABLE 2 EPU and flow-performance sensitivity.

	Dependent variable: Net Fund Flow$_t$ (%)				
	Model 1 Excess returns	Model 2 Excess returns	Model 3 4-Factor Alpha	Model 4 4-Factor Alpha	Model 5 4-Factor Alpha
PERF × log (EPU)$_{(t-1)}$	**−0.035****	**−0.034****	**−0.049*****	**−0.052***	
	(−2.28)	**(−2.14)**	**(−2.68)**	**(−1.81)**	
PERF × High EPU					**−0.043***
					(−1.84)
PERF$_{(t-1)}$	**0.180****	**0.175****	**0.238*****	**0.256***	**0.053****
	(2.39)	**(2.24)**	**(2.99)**	**(1.70)**	**(2.35)**
log (EPU)$_{(t-1)}$	−0.240	−0.241	−0.447***	0.539	
	(−1.15)	(−1.42)	(−3.52)	(0.23)	
High EPU dummy					−0.650
					(−0.46)
PERF-Squared$_{(t-1)}$	−0.001	−0.001	0.001	0.001	0.001
	(−0.49)	(−0.54)	(0.80)	(0.88)	(0.90)
Volatility$_{(t-1)}$	0.020	0.024	0.040	−0.101	−0.094
	(0.41)	(0.45)	(0.75)	(−0.39)	(−0.52)
log (Assets)$_{(t-1)}$	−2.140**	−2.143***	−1.287***	−1.392**	−1.401***
	(−2.59)	(−2.69)	(−7.80)	(−2.43)	(−8.24)
log (Fund Age)$_{(t-1)}$	−0.716	−0.716	−1.093***	−1.024	−1.073***
	(−1.41)	(−1.41)	(−4.58)	(−1.33)	(−2.91)
Momentum$_{(t-1)}$	0.010	0.010**	0.005	0.014	0.013*
	(1.62)	(2.24)	(1.15)	(1.24)	(1.74)
Tracking error$_{(t-1)}$	−0.115	−0.115	−0.139*	−0.105	−0.112
	(−1.54)	(−1.60)	(−1.90)	(−0.43)	(−0.58)
Intercept	9.230***	9.225***	10.390***	6.558	9.450***
	(3.01)	(3.11)	(8.98)	(0.49)	(5.01)
Observations	25,212	25,212	17,500	17,500	17,500
Adj. R^2	0.040	0.010	0.028	0.031	0.031
Time (Year-Month) FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Clustered SE	Fund	Fund and Time	Fund	Fund and Time	Fund and Time

Note: This table the reports results for Equation (2) for monthly fund flows regressed on fund performance, PERF; log EPU index, and the interaction of these variables, in addition to fund level controls. Fund performance is measured by excess fund returns and the Fama–French-Carhart alphas. Model 5 replaces log (EPU)$_{(t-1)}$ with a dummy variable that indicates High EPU, taking on the value of 1 for months when the EPU index is greater than past 4 quarters median EPU and zero otherwise. Fund flows are based on Franzoni and Schmalz (2017), tracking error is computed as the standard deviation of abnormal fund returns where abnormal return is the difference between monthly fund returns and monthly NZX market index returns. All explanatory variables are lagged by 1 month. All the models include fund and time fixed effects. Standard errors in Models 2, 4 and 5 are double clustered by fund and time. The *t*-statistics are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Statistical significance at the 1%, 5% and 10% levels are indicated in bold values.

TABLE 3 Fund anomalies, flow-performance sensitivity and EPU.

	Panel A: Geo. Focus		Panel B: Momentum		Panel C: Size		Panel D: Idiosync. Volatility		Panel E: Downside risk	
	Local	Global	High	Low	Large	Small	High	Low	High	Low
PERF × log (EPU)$_{(t-1)}$	−0.011	**−0.146*****	**−0.086*****	−0.020	**−0.098*****	−0.009	**−0.089****	**−0.027***	−0.025	**−0.078****
	(−0.47)	**(−3.13)**	**(−2.84)**	(−0.95)	**(−2.88)**	(−0.55)	**(−2.26)**	**(−1.71)**	(−1.32)	**(−2.42)**
PERF$_{(t-1)}$	0.064	**0.749*****	**0.417*****	0.094	**0.466*****	0.065	**0.457*****	**0.120***	0.112	**0.381*****
	(0.64)	**(3.57)**	**(3.11)**	(1.04)	**(3.08)**	(0.88)	**(2.60)**	**(1.76)**	(1.36)	**(2.68)**
log (EPU)$_{(t-1)}$	0.680	6.845	1.549	**3.672***	6.284	**3.041***	**−0.823*****	−0.096	**−0.257***	**−0.650*****
	(0.40)	(1.26)	(0.44)	**(1.78)**	(1.44)	**(1.89)**	**(−3.46)**	(−0.76)	**(−1.83)**	**(−2.90)**
PERF-Squared$_{(t-1)}$	0.001	0.006	0.001	0.000	0.001	0.001	0.002	0.000	0.000	0.001
	(0.54)	(1.39)	(0.64)	(0.38)	(0.58)	(0.71)	(0.85)	(0.00)	(0.25)	(0.59)
Volatility$_{(t-1)}$	−0.124	−0.125	−0.418	0.190	−0.649*	0.041	0.133	−0.042	0.116**	−0.001
	(−0.50)	(−0.25)	(−1.17)	(0.99)	(−1.87)	(0.23)	(1.35)	(−0.79)	(2.03)	(−0.01)
log (Assets)$_{(t-1)}$	−0.639**	−1.334***	−2.372***	−0.709***	−2.589***	−0.402*	−2.816***	0.190	−0.573***	−2.042***
	(−2.12)	(−3.72)	(−7.61)	(−3.79)	(−8.34)	(−1.72)	(−8.98)	(1.16)	(−3.17)	(−6.68)
log (Fund Age)$_{(t-1)}$	0.010	−2.483***	−1.207*	−1.107***	−1.387**	−1.387**	−0.595	−1.496***	−0.840***	−1.156***
	(0.01)	(−3.26)	(−1.82)	(−2.70)	(−2.35)	(−2.33)	(−1.34)	(−6.18)	(−3.17)	(−2.59)
Momentum$_{(t-1)}$	0.013	−0.011			0.019	0.010	0.017**	−0.000	−0.003	0.018**
	(0.95)	(−0.56)			(1.37)	(1.34)	(1.99)	(−0.06)	(−0.66)	(2.26)
Tracking error$_{(t-1)}$	0.055	0.028	0.225	−0.143	0.414	−0.144	−0.252*	−0.010	−0.194**	−0.028
	(0.20)	(0.05)	(0.58)	(−0.70)	(1.11)	(−0.74)	(−1.75)	(−0.14)	(−2.51)	(−0.19)
Intercept	−2.371	−13.167	6.359	−9.642	−9.038	−5.703	13.140***	7.381***	6.374***	13.312***
	(−0.29)	(−0.56)	(0.41)	(−1.06)	(−0.47)	(−0.76)	(6.08)	(6.24)	(4.90)	(6.30)
Observations	3578	6755	8645	8808	8862	8584	8330	8592	8347	8582
Adj. R^2	0.035	0.037	0.026	0.039	0.024	0.091	0.023	0.056	0.045	0.023

(Continues)

TABLE 3 (Continued)

	Panel A: Geo. Focus		Panel B: Momentum		Panel C: Size		Panel D: Idiosync. Volatility		Panel E: Downside risk	
	Local	**Global**	**High**	**Low**	**Large**	**Small**	**High**	**Low**	**High**	**Low**
Fixed Effects	Fund and Time	Fund and Time	Fund and Time	Fund and Time	Fund and Time	Fund and Time	Fund and Time	Fund and Time	Fund and Time	Fund and Time

Note: This table reports the results for Equation (2) for various fund partitions based on geographical focus, momentum, fund size, idiosyncratic volatility and downside risk. Panel A reports the sub-sample results for the sample of funds partitioned into Local and Global based on the fund's geographical focus. Panel B partitions the full sample into high (low) momentum funds if the return in month t is above (below) the median trailing year ($t-1$ to $t-11$ month) return. Panels C, D and E report the results for funds partitioned based on size, idiosyncratic volatility and downside risk, respectively. Fund performance is measured by the Fama–French-Carhart alpha. All explanatory variables are lagged by 1 month and all models include fund and time fixed effects. Standard errors are double clustered by fund and time. The t-statistics are reported in the parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Statistical significance at the 1%, 5% and 10% levels are indicated in bold values.

TABLE 4 Accounting for macroeconomic factors.

	Dependent: Flow (t)							
	Conventional monetary policy		Unconventional monetary policy		Central bank balance sheet		Fiscal/budget policy	
	Macro: Shadow rate		Macro: QE dummy		Macro: RBNZ and fed balance sheet		Macro: Current account and fiscal budget	
	US	Euro	March QE	All QE	RBNZ	Fed	Current deficit/ surplus as % of GDP	Fiscal deficit/ surplus as % of GDP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PERF × log (EPU)$_{(t-1)}$	**−0.037***	**−0.061*****	**−0.048*****	**−0.050*****	**−0.279****	**−0.247****	**−0.059*****	**−0.062*****
	(−1.85)	**(−2.78)**	**(−2.63)**	**(−2.61)**	**(−2.51)**	**(−2.08)**	**(−2.90)**	**(−3.18)**
PERF$_{(t-1)}$	**0.189****	**0.279*****	**0.236*****	**0.246*****	**0.331*****	**0.252*****	**0.281*****	**0.285*****
	(2.18)	**(3.14)**	**(2.93)**	**(2.93)**	**(3.66)**	**(3.12)**	**(3.19)**	**(3.40)**
log (EPU)$_{(t-1)}$	**−0.328****	**−0.538*****	**−0.432*****	**−0.486*****	**−9.025****	**3.229**	**−0.541*****	**−0.522*****
	(−2.25)	**(−2.87)**	**(−3.38)**	**(−3.67)**	**(−2.41)**	**(0.60)**	**(−3.92)**	**(−3.64)**
PERF-Squared$_{(t-1)}$	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.78)	(0.81)	(0.77)	(0.80)	(0.97)	(0.85)	(0.82)	(0.72)
Macro$_{(t)}$	−0.88***	0.31	−0.923	−4.380	−3.829**	1.052	0.129	−0.009
	(−2.97)	(1.61)	(−1.10)	(−1.26)	(−2.18)	(0.66)	(0.69)	(−0.04)
log (EPU)$_{(t-1)}$ × Macro$_{(t)}$	21.138***	−5.729	0.000	0.842	0.838**	−0.242	−0.040	−0.007
	(3.00)	(−1.37)	(0.00)	(1.29)	(2.28)	(−0.69)	(−1.02)	(−0.16)
PERF$_{(t-1)}$ × Macro$_{(t)}$	−13.085	−1.352	−0.037	−0.016	−0.025	−0.016	0.006	−0.009
	(−1.52)	(−0.31)	(−0.30)	(−0.03)	(−1.28)	(−1.20)	(0.13)	(−0.20)
PERF$_{(t-1)}$ × Macro$_{(t)}$ × log (EPU)$_{(t-1)}$	−0.263	−0.112	0.000	0.005	0.020**	0.013*	−0.001	−0.001
	(−1.38)	(−1.09)	(0.00)	(0.05)	(2.11)	(1.71)	(−1.12)	(−1.56)
Volatility$_{(t-1)}$	0.059	0.032	0.039	0.042	0.013	0.071	0.001	0.038
	(1.06)	(0.57)	(0.72)	(0.76)	(0.19)	(1.14)	(0.02)	(0.63)

(Continues)

TABLE 4 (Continued)

	Dependent: Flow (t)							
	Conventional monetary policy		Unconventional monetary policy		Central bank balance sheet		Fiscal/budget policy	
	Macro: Shadow rate		Macro: QE dummy		Macro: RBNZ and fed balance sheet		Macro: Current account and fiscal budget	
	US (1)	Euro (2)	March QE (3)	All QE (4)	RBNZ (5)	Fed (6)	Current deficit/ surplus as % of GDP (7)	Fiscal deficit/ surplus as % of GDP (8)
log (Assets)$_{(t-1)}$	−1.280***	−1.391***	−1.289***	−1.285***	−1.298***	−1.348***	−1.275***	−1.346***
	(−7.74)	(−8.04)	(−7.82)	(−7.78)	(−7.74)	(−7.95)	(−7.73)	(−7.98)
log (Fund Age)$_{(t-1)}$	−1.087***	−1.013***	−1.078***	−1.085***	−1.107***	−1.068***	−1.096***	−1.031***
	(−4.48)	(−2.87)	(−4.51)	(−4.52)	(−4.02)	(−3.41)	(−4.57)	(−4.16)
Momentum$_{(t-1)}$	0.005	0.002	0.005	0.005	0.003	0.004	0.005	0.005
	(1.29)	(0.57)	(1.19)	(1.13)	(0.82)	(0.84)	(1.19)	(1.09)
Tracking error$_{(t-1)}$	−0.127*	−0.173**	−0.139*	−0.138*	−0.108	−0.186**	−0.124	−0.155**
	(−1.74)	(−2.22)	(−1.90)	(−1.84)	(−1.30)	(−2.25)	(−1.64)	(−2.05)
N	17,501	17,225	17,501	17,501	17,356	17,304	17,501	17,241
Adj. R^2	0.029	0.028	0.028	0.028	0.028	0.028	0.028	0.029
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table the reports results for Equation (3), for monthly fund flows regressed on fund performance, PERF; log of EPU index, Macro$_{(t)}$ and the interaction of these variables, in addition to fund level controls. Fund performance is measured by Fama–French-Carhart alphas. Macro$_{(t)}$ proxies for important macro-economic factors such as (i) Conventional Monetary policy captured through Shadow rates for US and Eurozone by Wu and Xia (2016); (ii) Unconventional Monetary policy captured through the dummy variables for months that had Quantitative Easing (QE) by Reserve Bank of New Zealand (RBNZ), where March QE takes a value of 1 for March 2020 and 0 otherwise, similarly All QE takes a value of 1 for months intervened by RBNZ and 0 otherwise; (iii) Central Bank Balance sheet captured through log values of monthly RBNZ and US Federal Reserve (Fed) balance sheet size; (iv) Current account and Fiscal budget captured through the ratio of current deficit to GDP and fiscal deficit to GDP for New Zealand. Fund flows are based on Franzoni and Schmalz (2017), tracking error is computed as the standard deviation of abnormal fund returns where abnormal return is the difference between monthly fund returns and monthly NZX market index returns. All explanatory variables are lagged by 1 month. All the models include intercepts and fund fixed effects. Standard errors are double clustered by fund and time. The t-statistics are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Statistical significance at the 1%, 5% and 10% levels are indicated in bold values.

securities (Demirci et al., 2019) and banks' credit risk through the channels of government guarantees and borrowers' risk (Silva, 2021), we use the deficit (or surplus) of the New Zealand government as a proxy for its fiscal capacity.[7]

Therefore, to control for the various macroeconomic factors described above, we augment our main specification with the $Macro_t$ variables, which can potentially capture capital flows to managed funds, and overall uncertainty in the marketplace.[8] Our augmented model (Equation 3) takes the following form:

$$\begin{aligned} FLOW_{i,t} = {} & \beta_1 PERF_{i,t-1} + \beta_2 \log(EPU_{t-1}) + \beta_3 PERF_{i,t-1} \times \log(EPU_{t-1}) + \beta_4 Macro_t + \beta_5 \log(EPU_{t-1}) \times Macro_t \\ & + \beta_6 \log(EPU_{t-1}) \times Macro_t + \beta_7 PERF_{i,t-1} \times \log(EPU_{t-1}) \times Macro_t + \theta.CONTROLS_{i,t} + \sum_{i \in I} u_i x 1_i + \varepsilon_{i,t}, \end{aligned} \tag{3}$$

where, $Macro_t$ is used to capture one of the four macro factors, that is, unconventional monetary policy, conventional monetary policy, central bank balance sheet and fiscal policy. $PERF_{i,t-1}$ captures the fund performance through Carhart (1997) four-factor alpha.

Table 4 presents the estimates of the augmented model in Equation (3). Columns (1) and (2) control for the conventional monetary policy measures, captured through shadow rates for US and Eurozone by Wu and Xia (2016). Columns (3) and (4) control for unconventional Monetary policy captured through the dummy variables for months that had Quantitative Easing (QE) by Reserve Bank of New Zealand (RBNZ), where March QE takes a value of 1 for March 2020 and 0 otherwise, similarly All QE takes a value of 1 for months intervened by RBNZ and 0 otherwise. Similarly, columns (5) and (6) control for the central bank balance sheet captured through log values of monthly RBNZ and US Federal Reserve (Fed) balance sheet size. Finally, columns (7) and (8) control for Current account and Fiscal budget captured through the ratio of current deficit to GDP and fiscal deficit to GDP for New Zealand. In all models we find that the coefficients for our main variables [$PERF_{i,t-1} \times \log(EPU_{t-1})$, $PERF_{i,t-1}$ and $\log(EPU_{t-1})$] are negative and significant. More importantly, we find that the coefficient for $PERF_{i,t-1} \times \log(EPU_{t-1})$ continues to be negative and significant in Equation (3). Overall, these additional tests confirm our inferences regarding the role of policy uncertainty on fund flow performance sensitivity. The negative relationship between performance-EPU and flow remains robust even after controlling for various macroeconomic factors.

5 | CONCLUSION

This paper contributes to the emerging literature on the effect of policy uncertainty on investor learning of managerial ability in the managed fund industry in a unique setting. We empirically test our hypotheses by employing a comprehensive sample of actively managed equity funds in New Zealand. To do so, we utilize a recently developed EPU index for New Zealand, where we find a negative and significant relationship between flow and past performance under high uncertainty, supporting the argument that investor learning about fund managers' skills weakens under uncertainty. Interestingly, the role of policy uncertainty as a determinant of the fund flow performance sensitivity is found to be stronger, particularly for larger funds, funds with a global focus, high momentum funds and those that have high idiosyncratic volatility and low downside risk. These findings thus support the argument that high uncertainty dampens investors' ability to process information that will allow them to differentiate investment skill from luck. For future work, it will be interesting to explore whether behavioral anomalies like herd formation among fund managers facilitates the informational channel that links policy uncertainty to fund flow-performance sensitivity.

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ENDNOTES

[1] These recent works, thus, add a new perspective to the relationship between stock market dynamics and policy uncertainty that is shown to drive return and volatility dynamics in financial markets (see Ali, Badshah, & Demirer, 2022; Ali, Badshah, Demirer, & Hegde, 2022; Kelly et al., 2016; Liu & Zhang, 2015; Pástor & Veronesi, 2013; You et al., 2017; among others).

[2] We start our sample in 1997 as LIM's fund coverage for New Zealand is sparse prior to 1997.

[3] LGC guidelines assign each fund to a particular geographical focus if the fund maintains at least 50% of its exposure to that country/region.

[4] It is worth noting that in our Lipper dataset there are NZ domiciled equity funds that have majority investments in other specific regions or countries (other than New Zealand or Global). Thus, to have a cleaner sample for our tests we exclude these funds resulting in a total sample of 206 equity funds. However, our results remain qualitatively similar when we classify these funds as global or local focused (available upon request).

[5] The flow-performance and EPU relationship remains largely consistent for market-adjusted fund returns and CAPM-alpha (available upon request).

[6] In unreported tests, we standardize log (EPU) by subtracting its time-series mean and dividing by its time-series standard deviation to determine the relationship between flow-performance and EPU. Even with this alternative measure, the flow-performance and EPU relationship holds.

[7] For our macroeconomic factors we obtain the shadow rates from Jing Cynthia Wu's personal website: https://sites.google.com/view/jingcynthiawu/shadow-rates. We obtain the quantitative easing (QE) intervention dates from the Reserve Bank of New Zealand (RBNZ): Monetary policy/OCR decisions - Reserve Bank of New Zealand - Te Pūtea Matua (rbnz.govt.nz). We obtain the central bank's balance sheet size from the Federal Reserve Economic Data (FRED) for New Zealand and US. Finally, the fiscal policy data is obtained from Refinitive database.

[8] We thank an anonymous reviewer for suggesting the augmented specification.

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