Economic Policy Uncertainty, Learning and Incentives: Theory and Evidence on Mutual Funds

LAURA T. STARKS and SOPHIA YUE SUN*

March 19, 2016

Abstract

Using the mutual fund industry as a laboratory, we demonstrate theoretically and empirically that economic policy uncertainty affects investment decisions through an information rather than real options channel. Specifically, we find that fund flow-performance sensitivity decreases in uncertainty and does so more strongly for funds with shorter track records. The evidence supports the implication of our model that investor learning about manager ability weakens when uncertainty increases. Further, the effect of uncertainty on learning impacts managerial incentives. Consequently, managers are less likely to engage in active management during periods of greater uncertainty, an effect increasing in career concerns.

JEL Classification: D82, D83, D84, G11, G23, G28.

Keywords: uncertainty, policy, learning, managerial incentives, flow-performance sensitivity, active share.

*The authors are from the University of Texas at Austin. We thank Aydogan Alti, Audra Boone, Stefan Lewellen, Shuo Liu, Clemens Sialm, Michael Sockin, Sheridan Titman, Miao (Ben) Zhang, Qifei Zhu, and seminar participants at Baylor University, Texas State University and the University of Texas at Austin for their comments and suggestions. We also thank Martijn Cremers for sharing the active share data with us.

Uncertainty affects economic outcomes through various channels. A well-researched mechanism among them is that uncertainty affects the values of real options, which delays corporate investment and hinders economic growth.[1] In this paper, we provide evidence of another key mechanism through which uncertainty impacts the economy in that it weakens decision makers' abilities to process information. To isolate the informational effect of uncertainty from other competing channels, we examine investor learning about managerial ability in the mutual fund industry. This industry is particularly valuable for our analysis because the decision to invest in mutual funds can be reversed at a minimal cost, rendering the real options channel inapplicable. A further advantage of our empirical design is that the type of uncertainty we examine - economic policy uncertainty - is largely exogenous to the activities of mutual fund investors and managers, allowing us to draw causal inferences from the results.

To understand how uncertainty affects information processing, we develop a simple model in which policy uncertainty influences investor learning. Investors infer mutual fund manager ability from signals of fund performance. Such learning in turn affects fund flow-performance sensitivity. The unique feature of our model is that the manager's ability consists of two components, a time-invariant component and a component that changes with the prevailing economic policy. The latter component reflects the intuition that managers may perform very well in some policy regimes, but their ability may not adapt quickly when the regime changes.[2] Thus, although investors can increasingly gain knowledge of the manager's time-invariant ability, similar to the mechanism in Berk and Green (2004), they nevertheless have difficulty ascertaining the time-varying component of the manager's ability and how the manager will perform under a new policy regime. Following Pastor and Veronesi (2012), we define policy uncertainty as the probability that the economic policy will differ in the next period. With this structure, if uncertainty increases, past returns become less informative

[1] See Bloom (2014) for a comprehensive review of the uncertainty literature. Studies related to the real options effects of uncertainty on corporate investment include Bernanke (1983), Leahy and Whited (1996), Guiso and Parigi (1999), Bloom, Bond, and Van Reenen (2007), Bloom (2009), Julio and Yook (2012), Gulen and Ion (2016), Kim and Kung (2014), etc.

[2] An example would be Bill Miller whose Value Trust Fund was a top performing fund for decades, but during the financial crisis lost large amounts of money. After departing from that fund, Mr. Miller later lead another fund to stellar performance. We also present empirical evidence in Section II.G in support of this assumption.

about the manager's future ability and fund performance. As a result, Bayesian investors rationally choose to put less weight on realized returns when making their capital allocation decisions among funds.

Our model provides insights into how uncertainty affects investment decisions through an information channel rather than a real options channel. Further, the model provides a guide for empirically testing the importance of the former mechanism. We do so by assessing the expected relation between economic policy uncertainty and mutual fund flow-performance sensitivity. To capture the type of uncertainty described in the model, we need a measure that represents the likelihood of future policy changes as perceived by the decision maker, in our case, the mutual fund investor. The most intuitive choice is the Economic Policy Uncertainty (EPU) Index of Baker, Bloom, and Davis (2015). The index incorporates three components of economic uncertainty: newspaper coverage of policy-related economic uncertainty, the number of federal tax code provisions set to expire in future years, and disagreement among economic forecasters. The news-based component, which has the highest weight in the index, closely reflects the level of policy uncertainty observed by an investor. Furthermore, reverse causality should not be a problem because investor learning about mutual funds is unlikely to have a major impact on the policy uncertainty in the overall U.S. economy.

Using the EPU index, along with data on mutual fund characteristics, returns and holdings over the 1985-2014 sample period, we test hypotheses derived from the times-series and cross-sectional implications of our model. We first evaluate the hypothesis that investor learning slows down in the face of higher policy uncertainty by determining whether fund flow-performance sensitivity decreases with the EPU index. Figure 1 provides a simple illustration of the general differences in flow-performance sensitivity during periods of high and low economic policy uncertainty. Consistent with our hypothesis, the sensitivity clearly dampens when uncertainty is relatively high. Our regression analysis shows that when the EPU index increases by one standard deviation, mutual fund flows become 20% - 27% less responsive to past performance, an effect that is both economically and statistically significant. The result is robust to controlling for fund and time fixed effects, or using alternative measures of fund flow, performance and uncertainty. Furthermore, the effects of uncertainty we document are not subsumed by effects from recessions, market returns, extreme market

conditions or individual fund volatilities. Lastly, consistent with our learning-based explanation, the uncertainty effects are only present in actively managed mutual funds, not in index funds for which learning about managerial ability is irrelevant.

[Insert Figure 1 Here.]

To distinguish our proposed learning mechanism from alternative interpretations, we consider cross-sectional differences in the uncertainty effects.[3] Previous studies document that a fund's flow-performance sensitivity decreases with fund age, a result commonly taken as evidence in support of investor learning (e.g. Berk and Green (2004)). Our empirical tests confirm this finding. In addition, we demonstrate that the effect of uncertainty on flow-performance sensitivity is also weaker for older funds. In the context of our model, as the track record of the fund becomes longer, investors' estimates of the manager's time-invariant ability become more precise, and each additional return signal reveals less incremental information. Since policy uncertainty reduces signal informativeness, we expect younger funds for which the most recent performance signal is more important to investors to experience more reduction in flow-performance sensitivity during uncertain times. Our empirical results support this hypothesis.

Although not explicitly examined in the model, the informational effect of uncertainty we discover also has implications on managerial incentives and actions. The dampened flow-performance sensitivity during periods of higher uncertainty translates into weaker implicit incentives faced by fund managers. Specifically, weakened investor learning implies that signals about managerial ability will have lower marginal effect on capital flows. In response to the changing incentives, managers become less willing to engage in activities that signal their ability as the level of uncertainty rises. Consistent with this corollary hypothesis, we

[3] A potential alternative explanation is that investors' risk aversion increases with policy uncertainty. Consequently, their capital allocation decisions become less sensitive to past performance. Since investor's risk aversion is difficult to measure, we cannot directly control for it in our regression analysis. However, this issue does not appear to be a major concern as we show that the effect of uncertainty varies in the cross section in a way that is consistent with our learning mechanism, but difficult to reconcile with alternative explanations, such as increased investor risk aversion.

document that, on average, managers are less likely to deviate from the fund's benchmark during more uncertain times, i.e., the active shares of the funds (Cremers and Petajisto (2009)) decrease with the economic policy uncertainty. When we use alternative measures to proxy for managers' attempts to signal their skills, such as return gap (Kacperczyk, Sialm, and Zheng (2008)) or the deviation of the fund's beta from the market, the conclusion remains unchanged.

Rather than the incentive channel, our finding that managers' portfolio choices change with policy uncertainty may also be explained by optimal investment strategy shifts based on macroeconomic conditions (Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014)). Although we cannot completely rule out such possibilities, our cross-sectional tests suggest that incentives are a critical factor in explaining the covariation of active shares with policy uncertainty. In particular, we find the effects of uncertainty on active share to be more pronounced when the fund manager is younger, consistent with models on career concerns (e.g. Holmstrom (1999)).

Our paper is related to several areas of research. First, it contributes to the literature that examines whether and how uncertainty influences economic outcomes (e.g. Bernanke (1983), Bloom (2009) and Julio and Yook (2012)). Many studies in this literature focus on the idea that uncertainty increases the delay value of real options (see footnote 1). As a result, investment, hiring and consumption decline as the level of uncertainty rises. In this paper, we use the mutual fund industry as a laboratory to isolate the informational effect of uncertainty. Specifically, we show that uncertainty slows down investor learning and hinders their capital allocation among mutual funds. Similar mechanisms are likely to be present in other types of firms, as well.[4] However, it is difficult to separate the information channel from the real options channel in the corporate investment setting because uncertainty can also affect sensitivity through its effect on real options (e.g. Bloom (2014) and Bertola, Guiso, and Pistaferri (2005)). In contrast, the real options channel is negligible if not completely absent in the mutual fund industry. The reason is that unlike real investments, investments

[4]For example, Durnev (2010) documents that corporate investments are less sensitive to past stock prices during election years when policy uncertainty is relatively high, implying that managers are less likely to learn from the stock prices when higher uncertainty reduces price informativeness.

in mutual funds can be easily reversed, in large part due to the legal liquidity requirements imposed on them. In other words, the decision to invest in mutual funds cannot be viewed as a decision to exercise a real option. Thus, our results more unequivocally identify the information channel.

This paper also belongs to the rich literature that utilizes mutual fund flow-performance sensitivity to examine investor decision-making processes (e.g. Sirri and Tufano (1998), Lynch and Musto (2003), Huang, Wei, and Yan (2007)). Although one branch of this literature argues that mutual fund investors are naive and subject to various behavioral biases (e.g. Elton, Gruber, and Busse (2004), Barber, Odean, and Zheng (2006), Li, Tiwari, and Tong (2015)), our theoretical and empirical evidence suggests that in a fashion consistent with Bayesian learning investors infer managerial ability from past performance and adjust weights on performance signals based on the prevailing policy uncertainty. Thus, our paper adds another piece of evidence to the literature that uses the rational expectations framework to analyze investor capital allocation across mutual funds, such as Berk and Green (2004), Pastor and Stambaugh (2012), Berk and Van Binsbergen (2015, 2016), and Barber, Huang, and Odean (2016). Among these studies, the ones that are the closest to ours are Huang, Wei, and Yan (2012) and Franzoni and Schmalz (2014), which show that flow-performance sensitivity decreases with individual fund volatility and extreme market periods, respectively. We show conceptually and empirically that the new mechanism proposed in our paper is complementary to but distinct from theirs.[5] Another literature related to this study considers macroeconomic conditions and mutual funds, including Glode (2011) and Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014, 2016). These papers focus more on whether and how business cycles affect mutual fund performance, while we examine how policy uncertainty influences investor learning about managerial ability.

Our results on the relation between economic policy uncertainty and fund managers' active share choices are linked to studies on mutual fund manager incentives and actions, such

[5] Although both papers present theories related to investor learning, their mechanisms are different from ours. Huang, Wei, and Yan (2012) considers uncertainty about the idiosyncratic shock to fund performance. Franzoni and Schmalz (2014)'s result is derived from uncertainty about the parameters in risk adjustment models. Empirically, we also show that the effect of policy uncertainty remains strong after controlling for fund volatility and indicators on extreme market periods.

as Brown, Harlow, and Starks (1996), Chevalier and Ellison (1997, 1999), Kempf, Ruenzi, and Thiele (2009), Huang, Sialm, and Zhang (2011), Chen et al. (2013), Del Guercio and Reuter (2014), Lee, Trzcinka, and Venkatesan (2015), among many others. Most papers in this literature examine how manager incentives and actions vary in the cross-section.[6] We instead illustrate how exogenous macroeconomic conditions can affect managers' willingness to signal their abilities. Furthermore, in contrast to the literature on managerial risk taking, our conclusions do not rely on the convexity of the flow-performance relationship or managerial compensation contracts.[7]

More broadly, our findings provide further evidence in support of corporate theories on managerial incentives and market learning (e.g. Holmstrom (1999) and Scharfstein and Stein (1990)). Although policy uncertainty is not explicitly analyzed in those models, the general theme that reduction in signal informativeness lowers incentives and changes managerial behaviors is aligned with our results. The corporate finance study that echoes a similar message to ours is Panousi and Papanikolaou (2012). They show that when managerial ownership is high, increased idiosyncratic uncertainty combined with risk aversion can lead to suboptimal corporate investment decisions. We complement their findings by showing that when incentives are connected to market learning, higher uncertainty weakens learning and thus reduces incentive power.

The rest of the paper is organized as follows. Section I presents the theoretical model. Section II reports tests on the flow-performance sensitivity of mutual funds. Section III analyzes managerial portfolio decisions. Section IV concludes.

[6] One exception is Kempf, Ruenzi, and Thiele (2009), which studies how aggregate employment risk interacts with compensation incentives to affect managerial risk taking.

[7] Our hypothesis that the managers are less willing to signal their ability during high uncertainty periods only relies on the fact that the slope (not convexity) of the flow-performance relationship is lower when uncertainty increases. We also use Spiegel and Zhang (2013)'s market share specification to ensure that the effect of uncertainty on the flow-performance sensitivity is not affected by different empirical specifications.

I Economic Setting

A Setup

We consider a setting in which capital markets are perfectly competitive and investors receive returns through their mutual fund investments, the performance of which is influenced by the manager's portfolio selection ability as well as a random noise component. Specifically, the investors receive the net returns on the portfolio (gross returns less the manager's compensation, defined as a fixed fraction f of the assets under management q_t.) All participants in the model, including investors and the manager, learn about the manager's ability through the fund's performance over time.[8] The novelty of our approach lies in how we model fund manager ability. Existing models (e.g. Berk and Green (2004), Huang, Wei, and Yan (2012) and Franzoni and Schmalz (2014)) usually assume manager ability to be time-invariant. However, since managers differ in their abilities to handle certain economic conditions, we diverge from those models by allowing the fund manager's ability to vary with aggregate economic policies. In particular, we model the manager's ability as the sum of a time-invariant parameter μ and a policy-dependent parameter g_t. Within the same policy regime, g_t is a constant, but when the economic policy shifts, g_t, changes value.[9] At the beginning of every period, the government announces its economic policy, which can continue unchanged from the previous period or be revised. At the same time, the market participants also observe π_t, the probability that the policy will change in the following period. When π_t is large, the *policy uncertainty* in our economy is high. We model policy uncertainty in a similar fashion to that in Pastor and Veronesi (2012, 2013). However, unlike their analysis, we do not consider the government's choice of optimal policy, but rather take the policy uncertainty as an exogenous factor. This assumption arises from our belief that activities in the mutual fund industry are unlikely to have a major influence on the government's

[8] We abstract away from investor participation costs (e.g., Huang, Wei, and Yan (2007)) and from any non-pecuniary costs to the manager in investing. We follow Holmstrom (1999) and Berk and Green (2004) in assuming that managers and investors have symmetric information. In reality, managers are likely to have better information about their own ability than investors. However, adding asymmetric information only complicates the model without delivering additional insights.

[9] In Section II.G, we provide empirical evidence supporting this assumption.

economic policy decisions.

Following Berk and Green (2004), we assume that the return generating technology exhibits diseconomies of scale. Formally, the return of the fund received by the investors is

$$r_t = \mu + g_t - cq_{t-1} - f + \epsilon_t. \tag{1}$$

where c is a positive constant governing the efficiency of the fund, and ϵ_t is a random shock idiosyncratic to the manager, which is normally distributed with mean zero and variance v_ϵ. The investors and the manager learn about the time-invariant ability, μ, and the policy-dependent ability, g_t, through observing past returns. The prior distributions of μ and g_t at $t = 0$ are $N(\mu_0, v_\mu)$ and $N(0, v_g)$, respectively. We do not specify how investors compute r_t since the intuition of our model does not depend on any specific risk-adjustment model. Furthermore, the decreasing returns to scale assumption is only used to keep the assets under management bounded. Alternatively, we can use investors' risk aversion to limit their demand for mutual funds and obtain similar implications. We choose to use the current setup to facilitate comparisons with most existing models.

B *Equilibrium Belief*

Let m_t be the expectation of the manager's ability $(\mu + g_{t+1})$ conditional on $I_t = \{r_1, r_2, ..., r_t\}$, and $z_t = \mu + g_t + \epsilon_t = r_t + cq_{t-1} + f$ be the effective signal derived from r_t. Since the capital market is perfectly competitive, $E(r_{t+1}|I_t) = 0$. This condition implies that the assets under management in period t can be described by

$$q_t = \frac{m_t - f}{c}. \tag{2}$$

Intuitively, when the economic policy changes, past learning about the policy-dependent component of the manager's ability becomes useless, but past learning about the time-invariant component still remains important to discerning the manager's ability. In other

words, returns realized within the same policy regime are informative about $(\mu + g_t)$, while returns realized in a different policy regime are only informative about μ. When participants use returns realized in the previous regime to update on μ in the current regime, they take the noise correlation into account. For example, if the policy-dependent ability at $t = \tau + 1$ is g^{new} and at $t = \tau', \tau' + 1, ..., \tau$ is g^{old}, then $z_{\tau'}, z_{\tau'+1}, ..., z_\tau$ can be used as signals on μ to form beliefs on $(\mu + g^{new})$. Given that the noise terms $(g^{old} + \epsilon_{\tau'}), (g^{old} + \epsilon_{\tau'+1}), ..., (g^{old} + \epsilon_\tau)$ are correlated, we introduce a compound signal $x_{\tau',\tau}$. Observing signals $z_{\tau'}, z_{\tau'+1}, ..., z_\tau$ is then equivalent to observing

$$x_{\tau',\tau} = \frac{1}{\tau - \tau' + 1} \sum_{t=\tau'}^{\tau} z_t = \mu + g^{old} + \frac{1}{\tau - \tau' + 1} \sum_{t=\tau'}^{\tau} \epsilon_t. \tag{3}$$

When using $x_{\tau',\tau}$ as a signal on μ, the variance of the signal noise is $(v_g + \frac{v_\epsilon}{\tau - \tau' + 1})$. Following this logic, we can compute the posterior belief about the manager's ability in the next period.

PROPOSITION 1. *Let π_τ denote the probability that the policy will change in period $\tau + 1$, and τ' denote the starting period of the current policy regime. The expectation of the manager's ability $(\mu + g_{\tau+1})$ conditional on observing r_1, r_2, ..., r_τ is*

$$m_\tau = \pi_\tau \tilde{m}_\tau + (1 - \pi_\tau)\hat{m}_\tau, \tag{4}$$

where

$$\tilde{m}_\tau = \frac{\tilde{h}_{\tau'-1}\tilde{m}_{\tau'-1} + (v_\epsilon + (\tau - \tau' + 1)v_g)^{-1} \sum_{t=\tau'}^{\tau} z_t}{\tilde{h}_{\tau'-1} + (\tau - \tau' + 1)(v_\epsilon + (\tau - \tau' + 1)v_g)^{-1}}, \tag{5}$$

$$\hat{m}_\tau = \frac{\tilde{h}_{\tau'-1}(1 + v_g\tilde{h}_{\tau'-1})^{-1}\tilde{m}_{\tau'-1} + v_\epsilon^{-1} \sum_{t=\tau'}^{\tau} z_t}{\tilde{h}_{\tau'-1}(1 + v_g\tilde{h}_{\tau'-1})^{-1} + (\tau - \tau' + 1)v_\epsilon^{-1}}. \tag{6}$$

We specify $\tilde{h}_\tau$ and $\hat{h}_\tau$ in the appendix.

Equation (4) in Proposition 1 implies that investors' expectation of the manager's ability (m_τ) is the probability weighted average of the expected ability if the policy changes in the following period $(\tilde{m}_\tau)$, and the expected ability if the policy remains the same $(\hat{m}_\tau)$. More weight is given to the most recent return signal when the probability of a policy change (π_τ) is low. In particular, the weight on z_τ is higher in $\hat{m}_\tau$ than in $\tilde{m}_\tau$. The intuition is that if

the policy changes, past returns become noisier signals on the manager's ability, and thus play a less important role in the formation of the posterior belief.

C Testable Predictions

Although participants' beliefs cannot be observed by an econometrician, the investors' actions are observable. That is, investors buy or redeem shares in the fund after learning about the manager's ability and these actions can be captured by the change in the fund's assets under management, i.e., the net capital flow of the fund $F_\tau = q_\tau - q_{\tau-1}$. In Proposition 2, we show that mutual fund flows reflect the effect of policy uncertainty on investors' learning and thus can be employed for testing this effect. The proof is shown in the appendix.

PROPOSITION 2. *Define the flow-performance sensitivity of the mutual fund at $t = \tau$ as*

$$S_\tau = \frac{\partial F_\tau}{\partial r_\tau}. \tag{7}$$

S_τ decreases with policy uncertainty π_τ.

Proposition 2 shows that on average investor learning slows down in the face of policy uncertainty. We next consider cross-sectional variations in investor learning. Previous literature has shown that investors learn more about a fund's management the longer the fund operates, so fund flow-performance sensitivity is decreasing in the age of the fund (Berk and Green (2004)). In our context, as the track record of the fund gets longer, investors obtain a more precise estimate of the time-invariant component of the manager's ability, μ. They then rationally put more weight on their prior distribution and less weight on the most recent return realization. When an increase in policy uncertainty reduces the flow-performance sensitivity of the fund, a younger fund is affected more than an older fund because the incremental information revealed by an additional signal is higher for the former. In Proposition 3, we summarize how the effect of uncertainty on flow-performance sensitivity varies across fund age. The proof is given in the appendix.

PROPOSITION 3. *The effect of policy uncertainty on the flow-performance sensitivity decreases with the age of the fund.*

D Discussion

The most distinctive feature of our model is the policy-dependent component of manager ability, a choice we have made to reflect the intuition that managers have differential skills in handling an ever-changing political environment. Imagine an extreme situation in which a star U.S. mutual fund manager is forced to relocate to China. Because of the drastically different political environment, her future performance will be highly uncertain and investors will be less confident in extrapolating her past superior record to the future. In Section II.G, we provide more empirical evidence to support this assumption. Furthermore, an important modeling advantage of assuming the manager has time-varying ability is that the uncertainty about the manager's ability never disappears. In a model with fixed ability absent of entry and exit, as time passes investors will eventually know the manager's ability.

The source of uncertainty in our model differs from a model in which the fund performance is affected by an aggregate shock, and the variance of that shock increases in uncertainty. In such a model, the true aggregate state is essentially known to the investors because the average of a large cross section of funds reveals the realized aggregate state. In our model, uncertainty is the probability of entering a new policy regime. When the regime changes, past learning about the manager's ability is partially lost, making uncertainty unfavorable to investors.

In Propositions 2 and 3, the fund's idiosyncratic volatility v_ϵ is held constant. Thus, the variations in flow-performance sensitivity are entirely driven by changes in policy uncertainty, distinguishing our model from that of Huang, Wei, and Yan (2012). In reality, it is plausible to come up with situations where policy uncertainty directly impacts v_ϵ. We do not explicitly model these cases as it makes the model unnecessarily complex. Nevertheless, in our empirical tests we control for the effects of idiosyncratic volatility in order to show

that policy uncertainty affects learning beyond its effect on idiosyncratic volatility. Our model can also be distinguished from that of Franzoni and Schmalz (2014), as our results are not driven by uncertainty about the parameters in risk adjustment models. A further conceptual difference is that they consider periods of extreme market conditions, while we consider periods with high economic policy uncertainty. Empirically, we show that these two types of market conditions do not entirely overlap.

II Flow-Performance Sensitivity and Economic Policy Uncertainty

The theoretical model presented in the previous section implies that when the likelihood of a policy change increases, investors have more difficulties inferring mutual fund managers' ability using realized returns as signals. Their capital allocation decisions thus become less sensitive to past fund performance, reflecting the sluggish learning process. The intuition that increased uncertainty reduces signal informativeness and hinders learning also applies to settings outside the mutual fund industry. For example, Durnev (2010) shows that corporate investments become less sensitive to stock prices during election years, which the author interprets as evidence that managerial learning from the stock price slows down when increased political uncertainty reduces price informativeness. Although this story is intuitive, alternative mechanisms related to real options can also explain the result. Specifically, investments in physical capital cannot be easily reversed and are associated with substantial adjustment costs. Thus, they can be viewed as real options. When uncertainty increases, the option value of delay increases. Firm managers are therefore more likely to postpone investments till later dates when the uncertainty resolves (Dixit and Pindyck (1994)). Furthermore, driven by this wait-and-see mentality, the managers' investment decisions become less sensitive to changes in the cost of capital, which is correlated with the firm's stock market valuation (Bloom (2014)). As a result, the real options argument can also justify the finding that firms' investments are less responsive to stock prices when political uncertainty is high.

In contrast to these previous studies focused on corporations, the empirical design of our

paper is not inflicted with confounding mechanisms related to real options because investors' decisions to invest in mutual funds can be reversed at a minimal cost. Mutual funds are required to maintain liquidity in order to allow for daily redemptions by their investors. Thus, the irreversibility assumption that is essential to the real options argument is not present in the mutual fund setting. Therefore, our tests using flow-performance sensitivity can more clearly identify the learning effect of uncertainty, compared with studies in the corporate setting. In the rest of this section, we detail the data and empirical tests that support the main predictions of our model.

A Data

We obtain data on mutual fund returns and characteristics from the CRSP Survivor-Bias-Free US Mutual Fund Database, and data on mutual fund holdings from Thomson Reuters Mutual Fund Common Stock Holdings Database.[10] Our sample only includes actively managed domestic equity funds for two reasons.[11] First, our hypothesis on investor learning about fund manager's ability does not apply to index funds since the goal of index funds is to passively track certain indexes. Second, measures of uncertainty, as discussed later in the paper, are better developed for the U.S. economy than others. Datasets on mutual fund returns and holdings are also more reliable for domestic equity funds. CRSP and Thomson Reuters datasets are merged using MFLINKS constructed in Wermers (2000).[12]

[10]For funds with multiple share classes, we combine the share classes into one observation by taking the value-weighted averages of returns and fund characteristics, with three exceptions. We use the sum of the total net assets, the age of the oldest share class, and the style of the largest share class. The results on flow-performance sensitivity also hold when conducting analyses on each share class separately.

[11]We use the CRSP style code to select domestic equity funds. When the style code is unavailable, the fund is included if it on average holds more than 80% of common stocks. We exclude index funds by searching for "index" or similar words in fund names and using the index fund flag in CRSP. To improve accuracy, we also use the investment objective codes (IOC) in Thomson Reuters. Specifically, we exclude funds with the following IOC: international, municipal bonds, bond and preferred, and balanced.

[12]Starting in 2003, all funds have been required to disclose their holdings every quarter. Prior to that, mutual funds were only required to disclose their holdings semi-annually, but about half of funds voluntarily disclosed their holdings quarterly. We assume that holdings disclosed at the end of quarter t are held until the end of quarter $t+1$. If new holdings data are not available at the end of quarter $t+1$, holdings from quarter t are carried forward for a maximum of two quarters. The results are not sensitive to carrying the holdings backward rather than forward.

To construct holdings-based measures for each fund, we obtain data on returns of individual stocks from the CRSP Monthly Stock File and merge these stock returns with the mutual fund holdings data using historical CUSIP of the stocks. We also download the risk factors from Kenneth French's Website.

Our primary uncertainty measure is the Economic Policy Uncertainty (EPU) US Monthly Index proposed and constructed by Baker, Bloom, and Davis (2015). This index consists of three components: (i) news on policy-related economic uncertainty, (ii) federal tax code provisions set to expire in the near future, and (iii) forecaster disagreement on macro variables. To guarantee the quality of the index, the authors conducted an extensive audit to show that the indexes generated by computer algorithms are highly correlated with those generated by human auditors. Furthermore, the EPU index has been used in several recent finance studies to measure economic uncertainty and it is carried by major commercial data providers to meet customers' demands.[13] In some analyses we also use an alternative measure of uncertainty, the Chicago Board Options Exchange Market Volatility Index (VIX).[14] Since our analyses are conducted at the quarterly frequency, we calculate the quarterly average of each index. For ease of interpretation, we standardize each index by subtracting its sample mean and dividing by its standard deviation. In Figure 2, we plot the standardized quarterly indices. The EPU and the VIX indices seem to measure somewhat different aspects of uncertainty as shown by their correlation coefficient of 0.46.

The EPU index is particularly attractive for testing our learning hypothesis because it measures uncertainty using sources that are readily accessible to an average mutual fund investor. Even an unsophisticated investor who does not pay particular attention to financial markets can form a general idea about the uncertainty in the U.S. economy by reading major newspapers. The news component, which is given the highest weight in the index, is able to proxy for the level of uncertainty as perceived by such an investor. Furthermore, the EPU

[13] Academic studies using the EPU index to consider questions in the finance literature include Pastor and Veronesi (2013), Brogaard and Detzel (2015), Akey and Lewellen (2015), Gulen and Ion (2016) among others. The EPU index is downloaded from the Economic Policy Uncertainty website. For more details regarding the EPU index, please refer to http://www.policyuncertainty.com/. In addition, commercial providers carrying the EPU index include Bloomberg, FRED, Haver and Reuters, etc.

[14] The VIX is downloaded from the Federal Reserve Economic Data (FRED) website.

index captures both financial and policy uncertainty and is more exogenous to the activities of mutual fund investors and managers. In comparison, the underlying data for the VIX index is less visible to mutual fund investors, reflects mostly financial uncertainty, and could be influenced by mutual fund trading activities.

[Insert Figure 2 Here]

Since the EPU index starts in 1985, we focus on the 1985-2014 sample period. As shown in Table I the final sample consists of 3,620 distinct funds (138,399 fund-quarters), with the number of funds in a given quarter ranging from 221 (in the second quarter of 1985) to 1,979 (in the fourth quarter of 2008). We define mutual fund net flows as

$$FLOW_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + R_{it})}{TNA_{i,t-1}(1 + R_{it})}, \tag{8}$$

where $TNA_{i,t}$ is fund i's total net assets at the end of quarter t, and R_{it} is the investor return of fund i in quarter t.[15] The average quarterly flow is 0.37%, as in aggregate the mutual fund industry grows over the sample period. We postpone the discussion of the various measures of fund returns to the next few sections. Fund return volatility is estimated at the end of each quarter using monthly returns over the past 36 months, and then rescaled to the quarterly level. The age of the fund is defined as the number of years since the fund was first offered. The average fund in our sample returns 2.38% per quarter to its investors, has $1.37 billion of asset under management, and is 16 years old. The average return volatility is 8.85% per quarter. We Winsorize fund flows and turnover ratios at the 1st and 99th percentiles to mitigate the influence of outliers.

[Insert Table I Here]

[15] This measure of fund flow has the benefit of never going below -1. Our results are also robust to using $TNA_{i,t-1}$ as the denominator.

B Effects of Economic Policy Uncertainty on Flow-Performance Sensitivity

In this section we consider empirical tests of the relation between fund flow-performance sensitivity and economic policy uncertainty. Although fund flows are relatively straightforward to measure, the literature has not reached a consensus regarding the appropriate model to evaluate fund performance. Thus, for our primary performance measure, we use an essentially model-free measure, quarterly investor return in excess of the market return. The implication is that when considering relative fund performance for their decisions, investors simply need to subtract the market return from the fund return, an exercise that requires little financial expertise. Furthermore, the simplest strategy investors can take as an alternative to investing in an actively managed mutual fund is to invest in an index fund that follows the market, making the market return a natural benchmark to consider. To ensure that our results are not driven by the model used to calculate abnormal returns, we repeat our analyses using several other performance measures, the CAPM alpha, the four-factor model alpha, and a gross return percentile ranking. We estimate the CAPM alpha by $R_{it}^{mon} - R_t^f - \beta_{it-1}(R_t^{mkt} - R_t^f)$, where R_{it}^{mon} is the investor return of fund i in month t, R_t^f and R_t^{mkt} are the risk-free rate and the market return in month t, and β_{it-1} is the fund beta estimated at the end of month $t-1$. We then calculate the average alpha in a given quarter and rescale so that the resulting measure is a quarterly return. Second, we consider the four-factor risk-adjustment model proposed in Fama and French (1993) and Carhart (1997). The four-factor alpha is calculated in a similar way to the CAPM alpha. The average fund in our sample has a market adjusted return of -0.10%, a CAPM alpha of -0.12% per quarter, and a four-factor alpha of -0.31% per quarter. Lastly, we consider a rank-based measure such as that used in Sirri and Tufano (1998). In each quarter, we rank funds into percentiles based on their quarterly returns within each investment objective class.[16] For example, a fund ranked in the 16th percentile in its objective class is given a return rank of 16.

We first test the empirical implication of Proposition 2 that funds' flow-performance

[16] We use the Investment Objective Code (IOC) reported in the Thomson Reuters Holdings Database. Funds with IOC's equal to 2, 3 and 4 are classified as Aggressive Growth, Growth, and Growth & Income, respectively. The remaining funds are combined into the same class. For robustness, we also categorize funds based on their CRSP style codes. The results are unchanged.

sensitivities decrease during periods of higher economic policy uncertainty. Specifically, we employ the following regression specification for the determinants of fund flow:

$$FLOW_{i,t} = b_1 PERF_{i,t-1} + b_2 log(EPU_{t-1}) + b_3 PERF_{i,t-1} \times log(EPU_{t-1}) + CONTROLS_{i,t-1} + e_{i,t}, \quad (9)$$

where $FLOW_{i,t}$ is the quarterly percentage flow to the fund as defined in Equation (8), $PERF_{i,t-1}$ in the baseline regressions is the market adjusted return of fund i in quarter $t-1$, and $log(EPU_{t-1})$ is the logarithm of the EPU index in quarter $t-1$.[17] For ease of interpretation, we standardize $log(EPU)$ by subtracting its time-series mean and dividing by its time-series standard deviation so that the resulting measure reflects the number of standard deviations away from the average level of uncertainty. The control variables include the logarithm of the assets under management, the total load fees, the expense ratio, the turnover ratio, the logarithm of the fund age, the volatility of the fund return, and the average flow of the investment objective class. In addition, we include the square term of $PERF_{i,t-1}$ to control for a potential non-linear relationship between flow and performance.[18] All control variables are lagged by one quarter, except for the average flow of the investment objective class, which is measured concurrent to the dependent variable. Standard errors are double clustered by fund and time.

Table II reports the regression results. In column (1), the positive coefficient on *Market Adjusted Return* is consistent with the previously well documented finding that mutual fund flows respond positively to past performance. Consistent with Proposition 2 we find that the interaction between past return and the $log(EPU)$ has a negative effect on flow that is both statistically and economically significant. When the level of economic uncertainty is average ($log(EPU)$ is equal to zero), a one percentage point increase in quarterly fund returns increases mutual fund flows by 0.29 percentage points in the next quarter. On the other hand, when the level of uncertainty is one standard deviation above the average ($log(EPU)$

[17] We use the logarithm of the EPU index to follow the specification in Baker, Bloom, and Davis (2015). The results are very similar when the level of the EPU index is used.

[18] As mentioned earlier, our hypothesis that the flow-performance sensitivity of mutual funds is lower during uncertain periods does not depend on the convexity of the flow-performance relationship. When the square of $PERF_{i,t-1}$ are dropped from the regressions, the results are stronger.

is equal to one), a one percentage point increase in quarterly returns only increases flows by 0.23 percentage point. Thus, the flow-performance relationship weakens by 20% when uncertainty increases by one standard deviation. In column (2), we add fund fixed effects to absorb unobserved time-invariant fund characteristics. The economic magnitude of the uncertainty effect slightly increases. A one-standard-deviation increase in $log(EPU)$ from the average level leads to a 26% reduction in flow-performance sensitivity. Lastly, we include the time fixed effects in the regression.[19] The effect remains strong, suggesting that our result is not driven by time trends.

[Insert Table II Here]

To provide a vivid visualization of our main result, we plot the Fama-MacBeth estimates of flow-performance sensitivity and the logarithm of the lagged EPU index (both standardized) in Figure 3. Specifically, we estimate the flow-performance sensitivity every quarter by running a cross-sectional regression of the fund flow on the lagged market adjusted return while controlling for the fund characteristics mentioned earlier. As shown in Figure 3, the flow-performance sensitivity and the lagged $log(EPU)$ are highly negatively correlated. The time-series regression shown in the table suggests that when the economic uncertainty increases by one standard deviation, the flow-performance sensitivity decreases by 0.32 standard deviation. The Newey-West t-statistic of 2.76 suggests that the effect is statistically significant at the 1% level after accounting for the potential serial correlation in the error term. The results in Table II and Figure 3 provide strong evidence supporting our hypothesis that increased economic policy uncertainty hampers investor learning in financial markets.

[Insert Figure 3 Here]

[19] To avoid colinearity, $log(EPU)$ is dropped from the regression.

C Heterogeneity across Fund Age

As discussed earlier, investors learn about fund manager ability through the fund's time series of returns. Thus, a fund with a longer track record will have a better established reputation and the fund's recent performance provides less incremental information to the investors, resulting in the fund's flow being less sensitive to the most recent performance. Given that there is less to learn from a new signal, the effects of uncertainty should then be less of a hindrance to an older fund. In other words, the gap in flow-performance sensitivity between older and younger funds shrinks during high uncertainty periods. We examine whether this hypothesis holds in our data by interacting the EPU index, fund performance and fund age in the regression:

$$\begin{aligned} FLOW_{i,t} = {} & b_1 PERF_{i,t-1} + b_2 log(EPU_{t-1}) + b_3 PERF_{i,t-1} \times log(EPU_{t-1}) + \\ & b_4 PERF_{i,t-1} \times log(EPU_{t-1}) \times log(FAGE_{i,t-1}) + b_5 PERF_{i,t-1} \times log(FAGE_{i,t-1}) + \\ & b_6 log(FAGE_{i,t-1}) \times log(EPU_{t-1}) + b_7 log(FAGE_{i,t-1}) + CONTROLS_{i,t-1} + e_{i,t}, \quad (10) \end{aligned}$$

where $FAGE_{i,t-1}$ is the age of fund i at the end of quarter $t-1$. Based on Proposition 3, the negative effect of uncertainty on the flow-performance sensitivity should be weaker for older funds, i.e., $b_4 > 0$.

The results in Table III confirm our hypothesis. As the track record of the fund lengthens, investors' estimates of the manager's ability become increasingly precise. Consequently, fund flows respond less to the most recent return realization. Similarly, since for older funds the most recent return is less important to the investors, the reduction in flow-performance sensitivity during uncertain times is lower for older funds than for newer funds. This result is also economically significant: based on the result in column (1), if during a period with average uncertainty we compare a fund with the average $log(FAGE)$ with a fund whose age is one standard deviation above the average, the flow-performance sensitivity is 0.275 for the former, and 0.217 for the latter.[20] The older fund's flow performance sensitivity is 21% lower on average. Furthermore, if the economic uncertainty increases to one standard

[20] The mean and standard deviation of $log(FAGE)$ are 2.56 and 0.68, respectively.

deviation above the average, the flow-performance sensitivity of the younger fund becomes 0.226, and that of the older fund becomes 0.197. Thus, although higher uncertainty slows down investor learning for both types of funds, its effects on flow-performance sensitivity is 59% lower for the older fund. The results are similar when fund and time fixed effects are added in columns (2) and (3). The heterogeneous effects of uncertainty across fund age are consistent with the explanation that mutual fund investors Bayesian-update their beliefs about manager ability using realized returns as signals. Such results are difficult to reconcile absent investor learning.

[Insert Table III Here]

D Robustness Tests

The evidence shown thus far supports our hypothesis on the relationship between economic policy uncertainty and investor learning. When the level of uncertainty is high, mutual fund investors find return realizations to be less informative about the managers' ability and consequently, investor learning from past performance is significantly weakened. In this section, we conduct several robustness checks of this relationship. We first consider an alternative measure of uncertainty. In Table IV, column (1), we show the results are very similar if we use the VIX instead of the EPU index as a proxy for uncertainty. We also consider alternative performance specifications. First, we use a rank-based performance measure and allow for a nonlinear relationship through a piece-wise linear specification as in Sirri and Tufano (1998). That is, rather than including return rank in the regression, we include *LOW = min(return rank, 20), MID = min(return rank - LOW, 60)*, and *HIGH = return rank - LOW - MID*, instead. The coefficients reported in column (2) indicate that our results are robust to this change. In column (3), we employ another specification, the CAPM alpha as the performance measure, and find that the flow-performance sensitivity is weakened by 21% when $log(EPU)$ increases by one standard deviation from the average level. Alternatively, in column (4) we employ a four-factor alpha as the measure of performance. In this case again the weakening effect is similar at 16%. Overall, the regressions in columns (2)-(4) pro-

vide strong evidence that our primary result is unaffected by alternative measures of fund performance.

In the last two robustness checks, we consider different measures of fund flows. Earlier studies, such as Brown, Harlow, and Starks (1996), Chevalier and Ellison (1997) and Sirri and Tufano (1998), all suggest that the flow-performance relationship is convex. However, Spiegel and Zhang (2013) argues that the convexity could be due to misspecification in the empirical model. They recommend using the change in market share as an alternative to the conventional fractional specification that is adopted in our earlier tests, and show that the flow-performance relationship is in fact linear under this alternative. In column (5), we examine whether our hypothesis that the flow-performance sensitivity is lower during periods of higher uncertainty holds under the market share specification. Following the definition in Spiegel and Zhang (2013), we compute the change in percentage market share as $dMktShr = (\frac{TNA_{i,t}}{\sum_{j\in\Omega_{t-1}} TNA_{j,t}} - \frac{TNA_{i,t-1}}{\sum_{j\in\Omega_{t-1}} TNA_{j,t-1}}) \times 100$, where Ω_{t-1} is the set of all funds that exist in our sample in quarter $t-1$. The regression result suggests that when $log(EPU)$ moves from the average to one standard deviation above the average, the effect of past performance on the change in market share is reduced by 52%, supporting our hypothesis. In the last column, we use the dollar change in assets under management, $dTNA_{i,t} = TNA_{i,t} - TNA_{i,t-1}$, as the dependent variable. This definition is more consistent with the measure of flow in our theoretical model.[21] The regression estimates imply that the flow-performance sensitivity is lowered by 51% when the EPU index increases by one standard deviation from the average level. In summary, we find that the weakening effect of uncertainty on flow-performance sensitivity remains strong when alternative measures of uncertainty, fund performance or fund flow are employed in the regressions.

[Insert Table IV Here]

[21] The choice of dollar flows in the model is made to keep the algebra simpler. To be consistent, we also replace the logarithm of total net assets with the dollar amount of total net assets, and the average flow in the investment objective class with the average change in total net assets in the investment objective class in the regression.

E Alternative Explanations

In this section we consider potential alternative explanations for our results. First, the macroeconomic literature documents a strong negative correlation between uncertainty and business cycles (e.g. Bloom (2014)). Conceptually our results could be explained by business cycles if the mutual fund investors take actions consistent with the disposition effect. For example, when aggregate output is low, mutual fund investors suffer an income loss and may be forced to liquidate their shares to maintain consumption in the current period. If they own shares in several funds, the fund that has performed the best in the most recent period will experience the largest outflows assuming that naive investors are reluctant to realize losses (i.e., the disposition effect). We control for possible alternatives related to business cycles by including an interaction term between an indicator variable for NBER recessions and the fund return in excess of the market in the past quarter. Since the recession variable is binary, in order to allow better comparison with the coefficient on the policy uncertainty variable, we construct a binary policy uncertainty variable that takes the value of one when the EPU index is above its time-series median, and zero otherwise. In column (1) of Table V, we find that the coefficient on *Market Adjusted Return* $\times$ *Recession* is negative and significant. However, the coefficient on *Market Adjusted Return* $\times$ *High Uncertainty* remains statistically and economically strong. An alternative method for measuring poor economic conditions is to use the market return. In column (2), we interact the fund's past performance with the market return and the $log(EPU)$ (both standardized), respectively. The interaction term between the market return and the past performance has a positive coefficient, but is not statistically significant. On the other hand, our main variable of interest, the interaction term between the $log(EPU)$ and the past performance, still has a strong negative effect that is statistically significant at 1% level. The economic magnitude is only slightly lower than that in column (3) of Table II when the effect of market return is not controlled. This test provides strong evidence that the uncertainty captured in the EPU index has a distinct effect on investor learning that can be separately identified from the effect of market return or aggregate output.

In a recent study, Huang, Wei, and Yan (2012) (HWY hereafter) examine how mutual

fund flow-performance sensitivity varies across funds with different volatilities. They find that funds with more volatile past returns have lower flow-performance sensitivity. In their theoretical model, which examines the effects of idiosyncratic volatility on investor learning, the manager's ability is assumed to be constant over time. Their primary implication derives from a cross-sectional comparison of funds with different volatilities. In our model, the manager's ability changes as policy changes. Thus, when uncertainty is high about future policy variations, the probability that the manager's ability changes in the next period is high as well. Investors then rationally put less weight on previous returns in their learning process about manager ability. Given the HWY hypotheses and empirical results, we assess how our empirical implications relate to theirs. To do so, we add an interaction term between fund return volatility and past return to our specification. The results, shown in column (3) of Table V, are consistent with those of HWY in that we find the flow-performance sensitivity is lower for funds with higher return volatility. More importantly, the results also show that our mechanism is independent of the HWY mechanism as the interaction between the $log(EPU)$ and past performance remains significant both economically and statistically.

Another paper that is closely related to ours is Franzoni and Schmalz (2014) (FS hereafter). The authors argue that when the factor loadings of mutual fund returns are unknown to investors, learning about the loadings leads to weaker flow-performance sensitivity during periods with extreme market returns. Their implication is derived from basic properties of Bayesian updating. To distinguish empirically between our hypotheses and theirs, we alter our regression specification to be similar to theirs. Specifically, we interact the CAPM alpha with an indicator for extreme market conditions that takes the value of one when the market return in excess of the risk-free rate is below -5% or above 5%, and zero otherwise. The results, reported in the last column of Table V, show that when *CAPM Alpha* $\times$ *High Uncertainty* is included in the same regression as *CAPM Alpha* $\times$ *Extreme Market*, only the former is statistically significant[22], distinguishing the effects of economic policy uncertainty on investor learning from the effects of extreme market conditions.

[Insert Table V Here.]

[22]There are 64 extreme market periods and 60 high uncertainty periods. The numbers are comparable.

Besides the three alternative stories discussed above, our result that policy uncertainty reduces flow-performance sensitivity is also consistent with several behavioral explanations. First, if investors become more risk averse during uncertain periods, their investment decisions will be less sensitive to performance signals. Second, if mutual fund investors have limited attention, they may be too distracted by news about policy changes during uncertain periods to adjust their mutual fund investments, a mechanism similar to that documented in Barber and Odean (2008). Unfortunately, investor risk aversion and attention are both difficult to measure, so we cannot directly control for them in the regressions. Instead, we rely on the finding that the effect of uncertainty on flow-performance sensitivity varies with the age of the fund to show that at least some type of learning occurs during investors' decision making process. For example, if investors are boundedly rational, i.e., they have limited attention but rationally allocate their attention and process signals, then it is possible to show that the reduction in flow-performance sensitivity is lower for older funds during periods of greater uncertainty. However, the reason that such a model can deliver the same prediction as ours is because the investors are rational and follow Bayesian rules. Although we cannot definitively rule out these behavioral explanations, the rational theory we present seems to be more intuitive and parsimonious.

F Falsification Test Using Index Funds

Our hypothesis that investor learning slows down during times of higher policy uncertainty should be relevant only for actively managed funds. Investors have little to learn about manager ability in index funds, which suggests that index funds should have no significant differences in flow-performance sensitivity across varying levels of policy uncertainty. To examine this implication, we conduct a falsification test by repeating the analyses reported in Tables II and III using index funds rather than the actively managed funds employed in those tables. We identify index funds by searching for "index" or similar words in fund names as well as by using the index fund flag in CRSP. The results are shown in Table VI. In contrast to our results for actively managed funds, we find no differences in flow-performance sensitivity across various levels of policy uncertainty for the index funds.

That is, the coefficients on the interaction terms *Market Adjusted Return* $\times$ $log(EPU)$ and *Market Adjusted Return* $\times$ *Fund Age* $\times$ $log(EPU)$ are both insignificant.[23]

[Insert Table VI Here.]

G Is Managerial Ability More Likely to Change When EPU is High?

In our theoretical model, the weakened investor learning during high uncertainty periods is due to the assumption that the fund manager's ability is more likely to change when uncertainty is higher. As pointed out in the introduction and the theory section, fund manager skill is unlikely to be constant over different policy environments. In this section, we test whether the data provides support for this assumption.

In the model, the manager's ability $(\mu + g_t)$ corresponds to the return before fees and expenses. We compute two empirical measures to proxy for this definition of ability. The first is the fund's gross return, defined as the sum of the expense ratio and the net return. To adjust for risk, we also use the before-expense four-factor alpha, which is the sum of the expense ratio and the abnormal fund return estimated using the Fama-French-Carhart four-factor model. Intuitively, these measures capture whether the fund's investment strategies are profitable before considering their costs. To estimate a change in the manager's ability, we first rank funds into percentiles based on their gross return and before-expense four-factor alpha within their investment objective class every quarter. We then take the absolute change in this "ability" rank over the previous quarter's rank and examine the relationship of the absolute rank change to the level of economic policy uncertainty. That is, we regress the absolute change in ability rank on the lagged $log(EPU)$, while controlling for fund characteristics (i.e., the logarithm of the assets under management, the total load fees, the expense ratio, the turnover ratio and the logarithm of the fund age). If our assumption

[23] A potential concern that could be raised about this falsification test is that the sample size of index funds is much smaller than that of the active funds, so the lack of statistical significance could be attributed to the limited power of the regression. However, the signs of the coefficients are also the opposite to those in Tables II and III.

about managerial ability changing with the level of economic policy uncertainty is supported by the data, the lagged $log(EPU)$ should have a positive effect.

In column (1) of Table VII, the absolute change in gross return rank is the dependent variable and we find that $log(EPU)$ has a positive coefficient statistically significant at the 10% level. For a one-standard-deviation increase in economic policy uncertainty, the gross return rank in the following quarter changes by 0.99 percentile, on average. When fund fixed effects are included in column (2), the estimated effect is almost unchanged in either magnitude or statistical significance. In columns (3) and (4), the before-expense four-factor alpha rank is used as the dependent variable. When the $log(EPU)$ increases by one standard deviation, the alpha rank in the next quarter changes by 0.77 percentile (with no fund fixed effects) or 0.85 percentile (with fund fixed effects). The estimates are statistically significant at the 5% and 1% levels, respectively. The results in Table VII are consistent with our assumption that when economic policy uncertainty is high, a manager's ability is more likely to change in the future. Consequently, past returns become less informative about future managerial ability.

[Insert Table VII Here.]

Overall, our analysis in Section II shows that funds' flow-performance sensitivities are significantly weaker when the EPU index is relatively high, implying that economic policy uncertainty hinders investor learning and consequently capital allocation in the mutual fund industry.

III Economic Policy Uncertainty and Manager Portfolio Decisions

Our results to this point have supported the hypothesis that economic policy uncertainty affects investor learning about managerial ability. Specifically, during periods of higher uncertainty it becomes more difficult for investors to infer manager ability from return realizations. As a consequence, fund flows become less responsive to past performance. Such a

change in investor learning and fund flow-performance sensitivity implies a change in managers' incentives given that managers are compensated based on the amount of assets under management. Although we do not explicitly model the fund manager's incentive problem, existing theoretical studies such as Holmstrom (1999), Scharfstein and Stein (1990) and Huberman and Kandel (1993) provide guidelines for us to formulate empirical hypotheses on manager behaviors. In particular, these theories imply that market learning about managerial ability provides incentives for the managers to engage in activities that attempt to influence the market's perception about their ability. Thus, when market learning weakens during periods of higher uncertainty, we hypothesize that managers would be less inclined to signal their ability because of the lower marginal effect their actions have on future compensation. This hypothesis is also motivated by existing studies that suggest mutual fund manager portfolio choices are dependent on the incentives they are provided (e.g. Starks (1987), Brown, Harlow, and Starks (1996), Chevalier and Ellison (1997, 1999) and Del Guercio and Reuter (2014)).

A prime way in which managers can differentiate themselves is in their choice of the fund's activeness, i.e., their active share, a measure first proposed in Cremers and Petajisto (2009) and further refined in Cremers and Pareek (2015). Active share is defined as the deviation of a fund's portfolio weights from its benchmark index's portfolio weights:

$$AS = \frac{1}{2}\sum_{j=1}^{N} |w_{fund,j} - w_{index,j}|, \tag{11}$$

where $w_{fund,j}$ is the weight in stock j held by the fund, $w_{index,j}$ is the weight in stock j held by the benchmark index, and N is the total number of equity positions held by the fund or the benchmark. The fund's active share reflects the manager's portfolio weight choice, specifically, the choice to deviate from the fund's benchmark. The data on active share are available from 1985-2013 for a subset of the funds in our initial sample.[24] To check the robustness of our tests, we also employ two alternative measures of manager portfolio decisions. The first measure is the return gap, as proposed in Kacperczyk, Sialm, and Zheng (2008). Return gap is defined as the difference between the fund's gross return and the

[24]The construction of the dataset is described in Cremers and Pareek (2015).

return on a portfolio that invests in the previously disclosed fund holdings, i.e., holdings return. This measure reflects the unobserved actions of mutual funds, which are associated with better fund performance as shown in the paper. The authors interpret the return gap as value-added actions by the managers. The second alternative measure is the absolute deviation of the fund's holdings beta from one. We use the beta deviation measure to capture the difference of the fund manager's systematic risk choice from the market. To compute this measure, we first estimate the CAPM beta for each common stock in the CRSP database using the same method as for the fund returns discussed previously. The beta of each fund is then calculated as the value-weighted average of the holdings betas. Using a beta estimated from fund holdings is more appropriate for testing our hypothesis than using a beta estimated from 36 months of fund returns because the holdings beta reflects the strategies taken in the current period. In contrast, the returns beta reflects the fund manager's strategies during the entire 36-month estimation period. Consequently, the holdings beta better captures changes in fund strategies associated with changes in policy uncertainty.

To show that changes in managerial portfolio decisions during high uncertainty periods can be attributed to time-varying incentives, we rely on heterogeneous effects across managers of different ages, similar to our flow-performance test using fund age. We obtain manager-level data from Morningstar, and merge it with the active share sample using fund CUSIP.[25] Because the year of birth is missing for many managers, we compute manager age using primarily the college graduation year, assuming that managers graduate at the age of twenty-two. When the college graduation year is unavailable, we use the year of birth if available. To be included in the sample, the observation must have non-missing values on fund CUSIP, active share, manager starting date at the fund and manager age.[26] The summary statistics of this sample are shown in Table VIII.

[Insert Table VIII Here.]

[25]This is a multiple-to-multiple merge. One manager could be matched with multiple funds, and one fund could be matched to multiple managers.

[26]Since we examine how incentives affect managerial actions in this section, we use the biological age of the managers, rather than the age of the fund. The manager data also allows us to control for organizational structures, such as whether the manager works in a team, which could potentially affect their incentives. Our findings generally hold if we only use fund-level data.

A Effects of Economic Policy Uncertainty on Manager Portfolio Decisions

To test the hypothesis that mutual fund managers become less active when the economic policy uncertainty increases, we regress funds' active shares on the standardized lagged $log(EPU)$, controlling for fund and manager characteristics:

$$AS_{i,m,t} = c_1 log(EPU_{t-1}) + CONTROLS_{i,m,t-1} + \nu_{i,m,t}. \tag{12}$$

The control variables are the logarithm of the assets under management, the total load fees, the expense ratio, the turnover ratio, the fund flow, the logarithm of manager age, and two dummy variables indicating whether the fund is managed by a team of managers and whether the manager manages multiple funds. We double cluster the standard errors by fund-manager and time.

The results, as reported in column (1) of Table IX, support our hypothesis. For a one-standard-deviation increase in uncertainty, the average active share drops by 1.05 percentage points. Cremers and Petajisto (2009) show that a fund's active share is persistent across time. Our hypothesis that managers choose different levels of activeness based on the amount of uncertainty should be reflected in the component of active share that is time-varying. Thus, in the regression reported in column (2) we include fund-manager fixed effects. The results suggest that a fund's active share decreases by 0.529 percentage point when the $log(EPU)$ increases by one standard deviation. In the third column, when we substitute the VIX index for the measure of uncertainty, the implications are very similar.

In Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014) (KVV hereafter), the authors present evidence that mutual fund managers switch between market timing and stock picking strategies based on the aggregate economic state. Such changes in strategies are actually beneficial to investors, that is, they generate abnormal returns. Although active share is not the same as the market timing or stock picking measures presented in KVV, it is likely that these measures are correlated. Thus, one might argue that our result of active share decreasing with economic policy uncertainty could be attributable to these optimal strategy changes around business cycles, rather than time-varying flow incentives. To check this

possibility, in column (4), we include the market return in the regression as a control for the business cycle effect discussed in KVV. The coefficient on market return is statistically insignificant, but the coefficient on $log(EPU)$ remains approximately the same magnitude and significance as the one in column (2). Therefore, the effect of economic policy uncertainty on active share that we have identified is different from the strategy shifts around business cycles shown in KVV. As further robustness checks, we use return gap and beta deviation instead of active share to proxy for manager activeness in the last two columns, and find that an increase in uncertainty leads to reductions in both variables.

[Insert Table IX Here.]

B Heterogeneity across Manager Age

If our results are due to managerial incentives as we argue, the effects of uncertainty on active share should be more pronounced in managers who have stronger incentives. The cross-sectional characteristic we consider is the age of the manager. As suggested in Holmstrom (1999), managers with longer track records, and thus well-established reputations would be less concerned about signaling their ability to the investors than managers with shorter track records. Therefore, as managers become older and relatively less concerned about their careers, their incentives to influence the market's perception about their abilities decline. Although the model in Section I does not directly examine the effect of uncertainty on managerial actions, it can be shown in a setup similar to that of Holmstrom (1999) that the manager's effort level decreases in the level of uncertainty, and this effect is stronger for younger managers than older ones. The intuition of this hypothesis is similar to the previous finding that the effect of economic policy uncertainty on the flow-performance sensitivity, and consequently investor learning, is weaker for older funds than for younger funds. Since investors have more precise estimates on the ability of older managers, high effort in the most recent period has a lower marginal effect on the managers' future careers. Furthermore, the level of uncertainty and its effect on investor learning in the most recent period is less important to older managers' decisions.

To examine the hypothesis related to manager career concerns, we estimate the following regression:

$$AS_{i,m,t} = c_1 log(EPU_{t-1}) + c_2 log(MAGE_{i,m,t-1}) \times log(EPU_{t-1}) + c_3 log(MAGE_{i,m,t-1}) + CONTROLS_{i,m,t-1} + \nu_{i,m,t}, \quad (13)$$

where $AS_{i,m,t}$ is the active share, and $MAGE_{i,m,t-1}$ is the age of manager m in fund i at the end of quarter $t-1$. We expect that $c_2 > 0$ and $c_3 < 0$. The regression results are shown in Table X. Overall, we find that during periods of higher uncertainty, the reduction in active share varies across managers of different ages as predicted. In column (1), the active share decreases by 1.05 percentage points for a manager with the average $log(MAGE)$ when the $log(EPU)$ increases by one standard deviation. If $log(MAGE)$ is one standard deviation above the average, the active share decreases by 0.98 percentage points for a one-standard-deviation increase in the level of uncertainty.[27] The effect of policy uncertainty on active share is dampened by 7%. In column (2), we add in the fund-manager fixed effects to isolate the time-varying component of the active share. The interaction term between $log(MAGE)$ and $log(EPU)$ become more statistically significant. In column (3), we further include the time dummies instead of the $log(EPU)$ term. The conclusion remains unchanged.

[Insert Table X Here.]

In addition to the optimal strategy shift around business cycles discussed earlier, time-varying managerial risk aversion, a concept difficult to directly control for, can also explain our finding on active management and policy uncertainty. The tests using manager age help us distinguish these competing explanations from ours. If mutual fund managers' risk aversion increases with aggregate uncertainty, they may prefer strategies that hug the benchmark, leading to lower active share during uncertain periods. However, it is unclear a priori whether older or younger managers will experience more reduction in risk aversion when uncertainty increases. Thus, our results on the differences in the effects of policy uncertainty across manager age support the incentive rather than risk aversion hypothesis.

[27] The mean and standard deviation of $log(MAGE)$ are 3.86 and 0.21 respectively.

Our findings in this section suggest that increased economic policy uncertainty affects mutual fund managers' portfolio decisions through weakening investor learning and consequently managerial incentives. Furthermore, this effect is stronger among younger managers, consistent with the explanation that younger managers have more career concerns and are thus more responsive to changing incentives.

IV Conclusions

This paper examines the effects of economic policy uncertainty on market learning and managerial incentives. We find evidence in the mutual fund industry that investors have more difficulties differentiating investment skills from luck when policy uncertainty increases. The dampened investor learning further leads to weaker incentives provided by flows. Consequently, mutual fund managers are less inclined to engage in active management to signal their ability.

Our empirical findings are consistent with a theoretical model in which Bayesian investors learn about mutual fund manager ability through realized performance signals. In the model, the manager's ability changes with the prevailing policy in the economy, an assumption proven by the data. When the likelihood of a policy change increases, i.e., the policy uncertainty is relatively high, investors become less assured that returns generated in the past by the manager are indicative of her future performance. As a result, investor capital allocation decisions are less dependent on realized fund returns. Since investors' knowledge about the time-invariant component of the managerial ability accumulates over time, each additional performance signal provides more incremental information to investors when the fund is relatively young. Therefore, the level of flow-performance sensitivity and the effect of policy uncertainty on flow-performance sensitivity are both weaker as the track record of the fund increases. We test the implications of this model using the Economic Policy Uncertainty Index proposed in Baker, Bloom, and Davis (2015). Our empirical results support the main predictions of the model. We also provide evidence that distinguishes our learning-based explanation from alternative stories.

The weakening effect of uncertainty on investor learning and thus flow-performance sensitivity should affect managerial incentives since fund managers' compensation is highly dependent on the assets under management. Thus, we consider how managers change their portfolio choices in response to changes in economic policy uncertainty. We find, consistent with the incentives derived from the weakened investor learning process, that managers reduce active shares during periods of greater uncertainty, and this effect is more pronounced among younger managers whose career concerns are stronger.

Our results are important for at least two reasons. First, we provide further support to the literature that argues the positive correlation between mutual fund flows and past returns is caused by investors inferring manager ability from realized performance signals (e.g. Berk and Green (2004), Huang, Wei, and Yan (2012)), rather than naive investors blindly chasing after returns. Our results that the flow-performance sensitivity changes with uncertainty and the effect varies with fund age are difficult to reconcile absent investor learning. More generally, we provide theoretical and empirical support that variations in uncertainty, in particular, economic policy uncertainty, affect learning in financial markets. Due to the resultant sluggish learning process, capital allocation decisions are less efficient during periods of higher uncertainty in the sense that investors have more difficulty moving their investments to the mutual fund manager with superior return generating ability. The lower efficiency in the capital market also feeds back to the managers' portfolio decisions, potentially aggravating managerial incentive problems. Our results complement the findings in macroeconomics and corporate finance that highlight the impact of uncertainty on the efficiency of real investments (e.g. Bloom (2009), Julio and Yook (2012) and Durnev (2010)). Using mutual funds for empirical tests allow us to clearly separate the information effect of uncertainty from the real options effect. The intuition that uncertainty reduces economic agents' ability to process information could be applied more broadly to settings outside the mutual fund industry.

References

Akey, Pat, and Stefan Lewellen, 2015, Policy uncertainty, political capital, and firm risk-taking, Working paper, London Business School.

Baker, Scott R, Nicholas Bloom, and Steven J Davis, 2015, Measuring economic policy uncertainty, NBER Working paper 21633, Stanford University.

Barber, Brad M, Xing Huang, and Terrance Odean, 2016, Which risk factors matter to investors? Evidence from mutual fund flows, Working paper, UC Davis.

Barber, Brad M, and Terrance Odean, 2008, All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors, *Review of Financial Studies* 21, 785–818.

Barber, Brad M, Terrance Odean, and Lu Zheng, 2006, Out of sight, out of mind: The effects of expenses on mutual fund flows, *Journal of Business* 78, 2095–2119.

Berk, Jonathan, and Richard Green, 2004, Mutual fund flows and performance in rational markets, *Journal of Political Economy* 112, 1269–1295.

Berk, Jonathan B, and Jules H Van Binsbergen, 2015, Measuring skill in the mutual fund industry, *Journal of Financial Economics* 118, 1–20.

Berk, Jonathan B, and Jules H Van Binsbergen, 2016, Assessing asset pricing models using revealed preference, *Journal of Financial Economics* 119, 1–23.

Bernanke, Ben S, 1983, Irreversibility, uncertainty, and cyclical investment, *Quarterly Journal of Economics* 98, 85–106.

Bertola, Giuseppe, Luigi Guiso, and Luigi Pistaferri, 2005, Uncertainty and consumer durables adjustment, *Review of Economic Studies* 72, 973–1007.

Bloom, Nicholas, 2009, The impact of uncertainty shocks, *Econometrica* 77, 623–685.

Bloom, Nicholas, 2014, Fluctuations in uncertainty, *Journal of Economic Perspectives* 28, 153–176.

Bloom, Nick, Stephen Bond, and John Van Reenen, 2007, Uncertainty and investment dynamics, *Review of Economic Studies* 74, 391–415.

Brogaard, Jonathan, and Andrew Detzel, 2015, The asset-pricing implications of government economic policy uncertainty, *Management Science* 61, 3–18.

Brown, Keith C, W Van Harlow, and Laura T Starks, 1996, Of tournaments and temptations: An analysis of managerial incentives in the mutual fund industry, *Journal of Finance* 51, 85–110.

Carhart, Mark M, 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Chen, Joseph, Harrison Hong, Wenxi Jiang, and Jeffrey D Kubik, 2013, Outsourcing mutual fund management: Firm boundaries, incentives, and performance, *Journal of Finance* 68, 523–558.

Chevalier, Judith, and Glenn Ellison, 1997, Risk taking by mutual funds as a response to incentives, *Journal of Political Economy* 105, 1167–1200.

Chevalier, Judith, and Glenn Ellison, 1999, Career concerns of mutual fund managers, *Quarterly Journal of Economics* 114, 389–432.

Cremers, Martijn, and Ankur Pareek, 2015, Patient capital outperformance: The investment skill of high active share managers who trade infrequently, *Journal of Financial Economics,* forthcoming.

Cremers, Martijn, and Antti Petajisto, 2009, How active is your fund manager? A new measure that predicts performance, *Review of Financial Studies* 22, 3329–3365.

Del Guercio, Diane, and Jonathan Reuter, 2014, Mutual fund performance and the incentive to generate alpha, *Journal of Finance* 69, 1673–1704.

Dixit, Avinash K, and Robert S Pindyck, 1994, *Investment under Uncertainty* (Princeton University Press).

Durnev, Art, 2010, The real effects of political uncertainty: Elections and investment sensitivity to stock prices, Working paper, University of Iowa.

Elton, Edwin J, Martin J Gruber, and Jeffrey A Busse, 2004, Are investors rational? Choices among index funds, *Journal of Finance* 59, 261–288.

Fama, Eugene F, and Kenneth R French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Franzoni, Francesco A, and Martin C Schmalz, 2014, Performance measurement with uncertain risk loadings, Working paper, Swiss Finance Institute.

Glode, Vincent, 2011, Why mutual funds "underperform", *Journal of Financial Economics* 99, 546–559.

Guiso, Luigi, and Giuseppe Parigi, 1999, Investment and demand uncertainty, *Quarterly Journal of Economics* 185–227.

Gulen, Huseyin, and Mihai Ion, 2016, Policy uncertainty and corporate investment, *Review of Financial Studies* 29, 523–564.

Holmstrom, Bengt, 1999, Managerial incentive problems: A dynamic perspective, *Review of Economic Studies* 66, 169–182.

Huang, Jennifer, Clemens Sialm, and Hanjiang Zhang, 2011, Risk shifting and mutual fund performance, *Review of Financial Studies* 24, 2575–2616.

Huang, Jennifer, Kelsey Wei, and Hong Yan, 2012, Investor learning and mutual fund flows, Working paper, UT Austin.

Huang, Jennifer, Kelsey D Wei, and Hong Yan, 2007, Participation costs and the sensitivity of fund flows to past performance, *Journal of Finance* 62, 1273–1311.

Huberman, Gur, and Shmuel Kandel, 1993, On the incentives for money managers: A signalling approach, *European Economic Review* 37, 1065–1081.

Julio, Brandon, and Youngsuk Yook, 2012, Political uncertainty and corporate investment cycles, *Journal of Finance* 67, 45–83.

Kacperczyk, Marcin, Clemens Sialm, and Lu Zheng, 2008, Unobserved actions of mutual funds, *Review of Financial Studies* 21, 2379–2416.

Kacperczyk, Marcin, Stijn Van Nieuwerburgh, and Laura Veldkamp, 2014, Time-varying fund manager skill, *Journal of Finance* 69, 1455–1484.

Kacperczyk, Marcin, Stijn Van Nieuwerburgh, and Laura Veldkamp, 2016, A rational theory of mutual funds' attention allocation, *Econometrica,* forthcoming.

Kempf, Alexander, Stefan Ruenzi, and Tanja Thiele, 2009, Employment risk, compensation incentives, and managerial risk taking: Evidence from the mutual fund industry, *Journal of Financial Economics* 92, 92–108.

Kim, Hyunseob, and Howard Kung, 2014, The asset redeployability channel: How uncertainty affects corporate investment, Working paper, Cornell University.

Leahy, John V, and Toni M Whited, 1996, The effect of uncertainty on investment: Some stylized facts, *Journal of Money, Credit and Banking* 28, 64–83.

Lee, Jung Hoon, Charles Trzcinka, and Shyam Venkatesan, 2015, Mutual fund risk-shifting and management contracts, Working paper, Tulane University and Indiana University.

Li, C Wei, Ashish Tiwari, and Lin Tong, 2015, Investment decisions under ambiguity: Evidence from mutual fund investor behavior, *Management Science,* forthcoming.

Lynch, Anthony W, and David K Musto, 2003, How investors interpret past fund returns, *Journal of Finance* 58, 2033–2058.

Panousi, Vasia, and Dimitris Papanikolaou, 2012, Investment, idiosyncratic risk, and ownership, *Journal of Finance* 67, 1113–1148.

Pastor, Lubos, and Robert F Stambaugh, 2012, On the size of the active management industry, *Journal of Political Economy* 120, 740–781.

Pastor, Lubos, and Pietro Veronesi, 2012, Uncertainty about government policy and stock prices, *Journal of Finance* 67, 1219–1264.

Pastor, Lubos, and Pietro Veronesi, 2013, Political uncertainty and risk premia, *Journal of Financial Economics* 110, 520–545.

Scharfstein, David S, and Jeremy C Stein, 1990, Herd behavior and investment, *American Economic Review* 80, 465–479.

Sirri, Erik R, and Peter Tufano, 1998, Costly search and mutual fund flows, *Journal of Finance* 53, 1589–1622.

Spiegel, Matthew, and Hong Zhang, 2013, Mutual fund risk and market share-adjusted fund flows, *Journal of Financial Economics* 108, 506–528.

Starks, Laura T, 1987, Performance incentive fees: An agency theoretic approach, *Journal of Financial and Quantitative Analysis* 22, 17–32.

Wermers, Russ, 2000, Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses, *Journal of Finance* 55, 1655–1703.

Figure 1: Flow-Performance Relationship and Economic Policy Uncertainty

This figure contrasts the flow-performance relationship in high and low uncertainty regimes. We first rank all sample periods based on the Economic Policy Uncertainty Index (EPU) of Baker, Bloom, and Davis (2015). The high (low) uncertainty subsample includes periods in the highest (lowest) EPU quintile. Second, for each quarter, we divide funds into 20 equal groups based on their returns in the previous period. Lastly, we calculate the average percentage fund flow for each of the 20 groups and for high and low uncertainty subsamples separately.

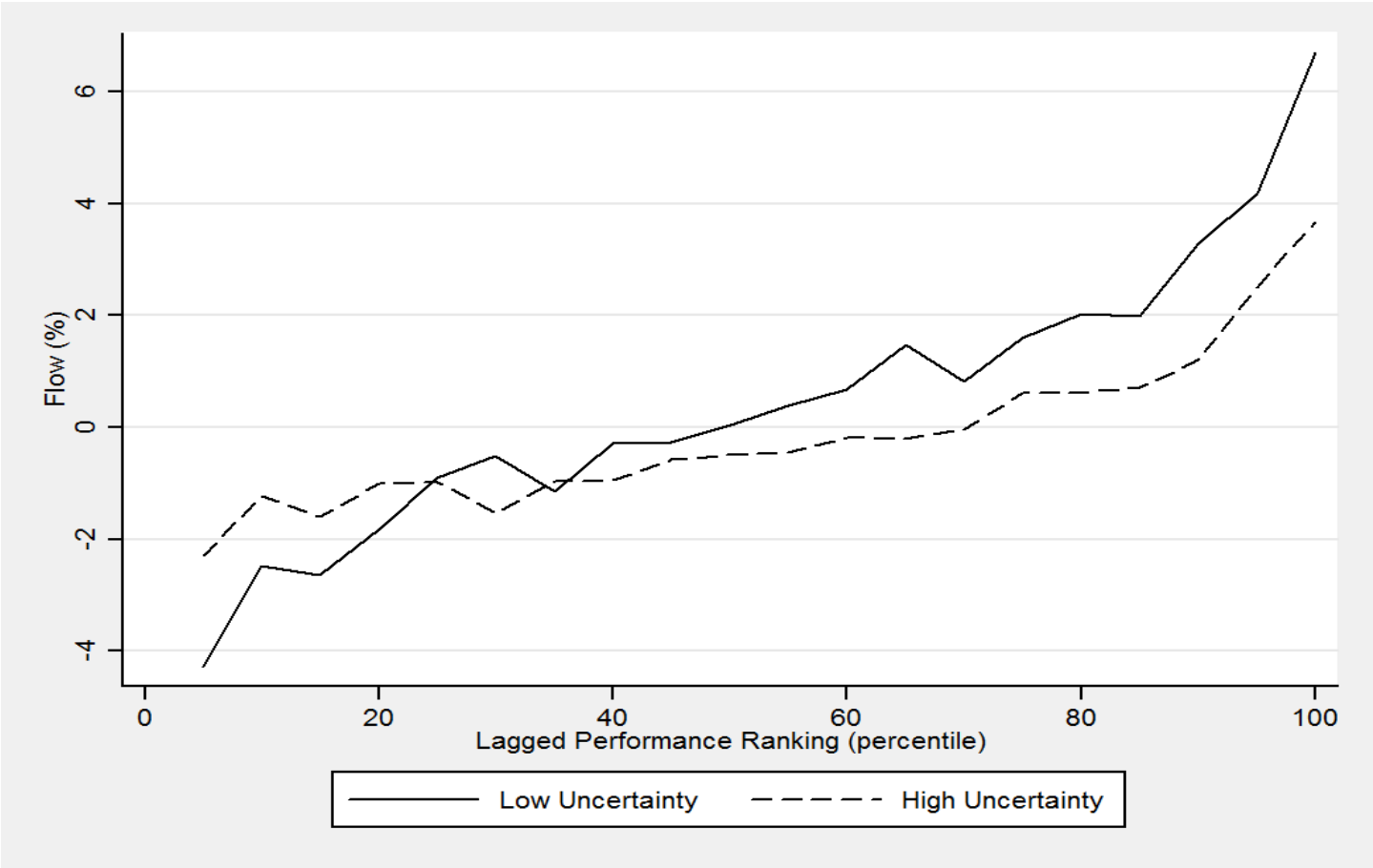


Figure 2: Uncertainty Indexes

This figure plots the Economic Policy Uncertainty Index (EPU) of Baker, Bloom, and Davis (2015) and the Chicago Board Options Exchange Market Volatility Index (VIX). The EPU index starts in 1985. The VIX index starts in 1990. Each index is standardized by subtracting the mean and then dividing by the standard deviation so that 1 on the y-axis means one standard deviation above the mean. Several major events are marked. LTCM refers to the Long-Term Capital Management fund.

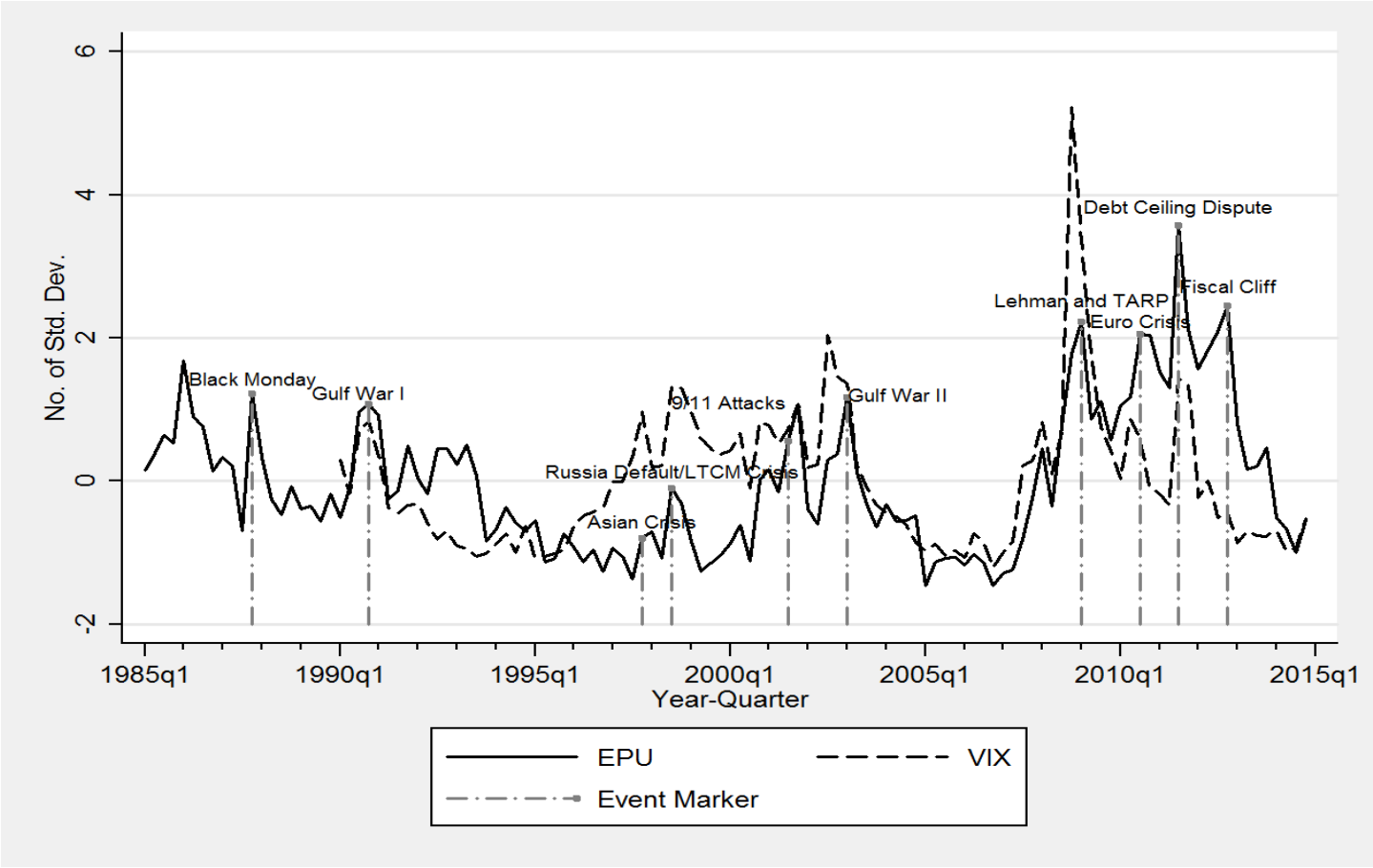
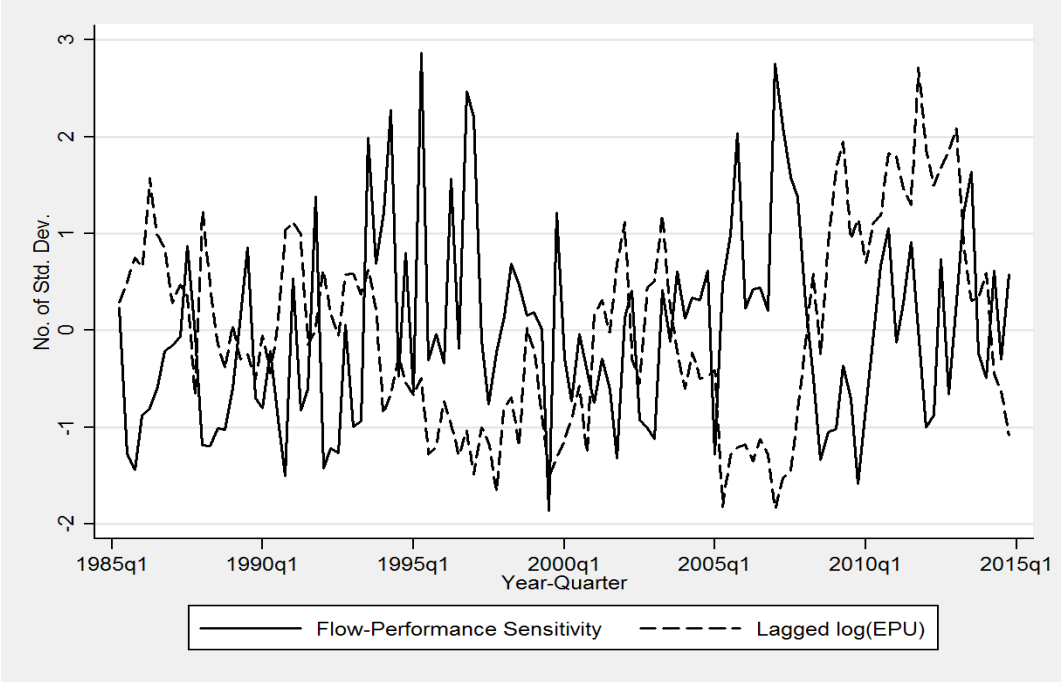


Figure 3: Flow-Performance Sensitivity and Economic Policy Uncertainty - Fama-MacBeth Regressions

This figure plots the Fama-MacBeth estimates of flow-performance sensitivity and the logarithm of the Economic Policy Uncertainty Index (EPU) of Baker, Bloom, and Davis (2015). We estimate the flow-performance sensitivity every quarter by regressing the percentage fund flow on the fund's market adjusted return while controlling for other fund characteristics: the square of the market adjusted return, the logarithm of the total net assets, the total loads, the expense ratio, the turnover ratio, the logarithm of the age of the fund and the average flow of the investment objective class (IOC). All control variables are lagged by one quarter, except for the average flow of the IOC, which is concurrent to the dependent variable. For ease of interpretation, we standardize the time-series of the flow-performance sensitivity estimates and the logarithm of the EPU index by subtracting the mean and then dividing by the standard deviation. The results in the table are obtained by regressing the flow-performance sensitivity on the lagged $log(EPU)$ (both standardized). We report the Newey-West t-statistic. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.



Dependent Variable	Flow-Performance Sensitivity	
	coef.	t-stat.
log(EPU)	-0.3234***	(-2.7573)
No. of Periods	119	

Table I: Summary Statistics for Flow-Performance Sensitivity Analysis

This table reports the summary statistics of the sample of actively managed domestic equity funds from 1985 to 2014. $Flow_{it} = \frac{TNA_{i,t} - TNA_{i,t-1}(1+R_{it})}{TNA_{i,t-1}(1+R_{it})}$, where $TNA_{i,t}$ is the fund's total net assets at the end of quarter t, and R_{it} is the fund's return in quarter t net of expenses, that is, the *Investor return*. *Gross return* is the sum of the investor return and the expenses. *Holdings return* is the value-weighted average return of all stocks held by the fund. *Market adjusted return* is the investor return in excess of the market. *CAPM alpha* is computed using $R_{it}^{mon} - R_t^f - \beta_{it-1}(R_t^{mkt} - R_t^f)$, where R_{it}^{mon} is the investor return of fund i in month t, R_t^f and R_t^{mkt} are the risk-free rate and the market return in month t, and β_{it-1} is the *fund beta* estimated at the end of month $t-1$. *Four-factor alpha* is computed in a similar way using the factors proposed in Fama and French (1993) and Carhart (1997). *Fund volatility* is the time-series standard deviation of monthly returns. The estimation period for all time-series regressions is the past 36 months. Monthly alphas and volatilities are rescaled to the quarterly level. *Fund age* is the number of years since the fund was first offered. Flow and turnover ratio are Winsorized at the 1st and 99th percentiles.

	(1) Mean	(2) Standard Deviation	(3) Median
Flow (% per quarter)	0.37	11.87	-1.29
Investor Return (% per quarter)	2.38	10.25	3.21
Gross Return (% per quarter)	2.70	10.27	3.53
Holdings Return (% per quarter)	2.84	10.74	3.71
Market Adjusted Return (% per quarter)	-0.10	5.41	-0.23
CAPM Alpha (% per quarter)	-0.12	5.02	-0.19
Four-Factor Alpha (% per quarter)	-0.31	4.33	-0.29
Fund Beta	1.02	0.31	1.01
Fund Volatility (% per quarter)	8.85	3.66	8.34
Total Net Assets (Millions $)	1,367	5,061	264
Fund Age (Years)	15.66	13.64	11.00
Expense Ratio (%)	1.27	0.45	1.21
Turn Ratio (%)	87.36	105.15	63.00
Total Loads (%)	3.73	3.55	3.00
No. of Funds	3,620		
No. of Obs.	138,399		

Table II: Flow-Performance Sensitivity and Economic Policy Uncertainty

This table reports results of a regression of fund flows on determinants, including the market adjusted return, the logarithm of the EPU index, and the interaction of these variables. The dependent variable is the quarterly percentage fund flow. We standardize $log(EPU)$ by subtracting the time-series mean and dividing by the time-series standard deviation. All explanatory variables are lagged by one quarter, except for the average flow of the investment objective class (IOC), which is concurrent to the dependent variable. Standard errors are double clustered by fund and time. We present the t-statistics in the parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Variable definitions are shown in the legend of Table I.

	(1) No FE	(2) Fund FE	(3) F & T FE
Market Adjusted Return × log(EPU)	-0.0572***	-0.0669***	-0.0732***
	(-2.702)	(-3.133)	(-3.187)
log(EPU)	0.257***	-0.0575	
	(3.767)	(-0.708)	
Market Adjusted Return	0.288***	0.261***	0.273***
	(13.16)	(11.25)	(11.16)
log(Fund Age)	-1.159***	-1.863***	-4.501***
	(-10.99)	(-7.492)	(-11.70)
Market Adjusted Return Squared	0.00248***	0.00181**	0.00181**
	(2.619)	(2.448)	(2.146)
log(Assets)	0.0423	-1.398***	-1.660***
	(0.925)	(-9.593)	(-10.18)
Expense Ratio	-0.307	-0.0290	-0.507
	(-1.630)	(-0.0800)	(-1.353)
Turn Ratio	0.000858	0.000848	0.000683
	(0.982)	(0.718)	(0.569)
Total Loads	-0.0603***	-0.0750**	-0.109***
	(-3.113)	(-1.994)	(-2.738)
Volatility	-0.170***	-0.0882***	-0.128**
	(-5.395)	(-2.653)	(-1.964)
Average Flow of IOC	0.893***	0.902***	0.880***
	(33.25)	(28.17)	(14.53)
Observations	138,399	138,399	138,399
R-squared	0.063	0.162	0.166
Fund FE	NO	YES	YES
Time FE	NO	NO	YES

Table III: Flow-Performance Sensitivity and Economic Policy Uncertainty
- Heterogeneity across Fund Age

This table examines whether the effect of uncertainty on the flow-performance sensitivity varies with the age of the fund. The dependent variable is the quarterly percentage fund flow. We standardize $log(EPU)$ by subtracting the time-series mean and dividing by the time-series standard deviation. All explanatory variables are lagged by one quarter, except for the average flow of the investment objective class (IOC), which is concurrent to the dependent variable. Standard errors are double clustered by fund and time. We present the t-statistics in the parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Variable definitions are shown in the legend of Table I.

	(1) No FE	(2) Fund FE	(3) F & T FE
Market Adjusted Return × log(Fund Age) × log(EPU)	0.0432**	0.0508***	0.0540***
	(2.475)	(3.103)	(3.264)
Market Adjusted Return × log(Fund Age)	-0.0862***	-0.0627***	-0.0564***
	(-5.159)	(-3.809)	(-3.387)
Market Adjusted Return × log(EPU)	-0.160***	-0.190***	-0.205***
	(-2.643)	(-3.344)	(-3.510)
log(Fund Age) × log(EPU)	0.0971	0.216**	0.105
	(1.190)	(2.245)	(1.195)
log(EPU)	0.00702	-0.633**	
	(0.0291)	(-2.241)	
Market Adjusted Return	0.496***	0.412***	0.409***
	(9.021)	(7.480)	(7.219)
log(Fund Age)	-1.170***	-1.838***	-4.403***
	(-11.07)	(-7.451)	(-11.48)
Market Adjusted Return Squared	0.00208*	0.00144*	0.00142
	(1.881)	(1.695)	(1.472)
log(Assets)	0.0445	-1.393***	-1.655***
	(0.972)	(-9.571)	(-10.15)
Expense Ratio	-0.311*	-0.0248	-0.514
	(-1.645)	(-0.0685)	(-1.374)
Turn Ratio	0.000874	0.000880	0.000669
	(1.004)	(0.752)	(0.562)
Total Loads	-0.0600***	-0.0745**	-0.110***
	(-3.093)	(-1.989)	(-2.768)
Volatility	-0.167***	-0.0842**	-0.124*
	(-5.169)	(-2.532)	(-1.893)
Average Flow of IOC	0.893***	0.901***	0.879***
	(34.42)	(28.62)	(15.41)
Observations	138,399	138,399	138,399
R-squared	0.064	0.163	0.167
Fund FE	NO	YES	YES
Time FE	NO	NO	YES

Table IV: Flow-Performance Sensitivity and Economic Policy Uncertainty - Robustness Tests

This table reports several robustness tests. The dependent variable is the quarterly percentage fund flow in columns (1)-(4), the quarterly change in percentage market share in column (5), and the quarterly dollar change in total net assets in column (6). We standardize $log(EPU)$ and $log(VIX)$ by subtracting their respective time-series mean and dividing by their respective time-series standard deviation. *Return rank* is the percentile rank of the investor returns within each investment objective class (IOC). *LOW = min(return rank, 20), MID = min(return rank - LOW, 60) and HIGH = return rank - LOW - MID.* Other control variables include the logarithm of the total net assets (total net assets in column (6)), the total loads, the expense ratio, the turnover ratio, the logarithm of the age of the fund, the volatility of the fund return and the average flow (average dollar change in total net assets in column (6)) of the IOC. All explanatory variables are lagged by one quarter, except for the average flow of the IOC, which is concurrent to the dependent variable. VIX starts in 1990, so the number of observations is smaller in column (1). Standard errors are double clustered by fund and time. We present the t-statistics in the parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Variable definitions are shown in the legend of Table I.

	(1) VIX	(2) Return Rank	(3) CAPM	(4) Four-Factor	(5) dMktShr	(6) dTNA
Market Adjusted Return × log(VIX)	-0.077***					
	(-3.99)					
Market Adjusted Return	0.32***				0.00021***	4.10***
	(11.3)				(3.97)	(4.71)
Market Adjusted Return Squared	0.0026***					0.023
	(3.35)					(0.84)
Return Rank × log(EPU)		-0.011***				
		(-3.21)				
LOW		0.073***				
		(5.80)				
MID		0.034***				
		(9.44)				
HIGH		0.18***				
		(11.9)				
CAPM Alpha × log(EPU)			-0.066***			
			(-2.60)			
CAPM Alpha			0.32***			
			(11.6)			
CAPM Alpha Squared			0.0044***			
			(4.61)			
Four-Factor Alpha × log(EPU)				-0.044**		
				(-2.34)		
Four-Factor Alpha				0.28***		
				(12.2)		
Four-Factor Alpha Squared				0.0028**		
				(2.20)		
Market Adjusted Return × log(EPU)					-0.00011***	-2.08***
					(-2.71)	(-3.10)
Observations	132,908	138,399	138,399	138,399	138,399	138,399
R-squared	0.168	0.169	0.168	0.160	0.040	0.194
Fund FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES

Table V: Flow-Performance Sensitivity and Economic Policy Uncertainty
- Alternative Explanations

This table addresses several alternative explanations. The dependent variable in all regressions is the quarterly percentage fund flow. We standardize $log(EPU)$ and market return by subtracting their respective time-series means and dividing by their respective time-series standard deviations. *High uncertainty* is a binary variable that takes the value of one when the EPU index is above its time series median, and zero otherwise. *Recession* is a binary variable indicating NBER recessions and zero otherwise. *Extreme market* is a binary variable that takes the value of one when the market return in excess of the risk-free rate is below -5% or above 5%, and zero otherwise. Other control variables include the logarithm of the total net assets, the total loads, the expense ratio, the turnover ratio, the logarithm of the age of the fund and the average flow of the investment objective class (IOC). All explanatory variables are lagged by one quarter, except for the average flow of the IOC, which is concurrent to the dependent variable. Standard errors are double clustered by fund and time. We present the t-statistics in the parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Variable definitions are shown in the legend of Table I.

VARIABLES	(1) Recession	(2) Market Return	(3) HWY	(4) FS
Market Adjusted Return × High Uncertainty	-0.147***			
	(-3.008)			
Market Adjusted Return × Recession	-0.118**			
	(-2.417)			
Market Adjusted Return × log(EPU)		-0.0636***	-0.0594***	
		(-2.629)	(-2.697)	
Market Adjusted Return × Market Return		0.0254		
		(1.555)		
Market Adjusted Return × Volatility			-0.0178***	
			(-6.562)	
CAPM Alpha × High Uncertainty				-0.162**
				(-2.546)
CAPM Alpha × Extreme Market				-0.0325
				(-0.516)
Market Adjusted Return	0.381***	0.277***	0.494***	
	(12.13)	(12.22)	(10.74)	
Volatility	-0.131**	-0.154**	-0.139**	-0.133**
	(-2.185)	(-2.377)	(-2.402)	(-2.425)
CAPM Alpha				0.421***
				(11.28)
Market Adjusted Return Squared	0.00157*	0.00151	0.00256***	
	(1.882)	(1.634)	(3.709)	
CAPM Alpha Squared				0.00416***
				(4.151)
Observations	138,399	138,399	138,399	138,399
R-squared	0.168	0.167	0.168	0.169
Fund FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES

Table VI: Flow-Performance Sensitivity and Economic Policy Uncertainty
- Falsification Tests Using Index Funds

This table repeats the regressions in Tables II and III using a sample of index funds. The dependent variable is the quarterly percentage fund flow. We standardize $log(EPU)$ by subtracting the time-series mean and dividing by the time-series standard deviation. Other control variables include the square of market adjusted return, the logarithm of the total net assets, the total loads, the expense ratio, the turnover ratio, the volatility of the fund return and the average flow of all index funds. All explanatory variables are lagged by one quarter, except for the average flow of all index funds, which is concurrent to the dependent variable. Standard errors are double clustered by fund and time. We present the t-statistics in the parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Variable definitions are shown in the legend of Table I.

	Effect of Uncertainty			Heterogeneity across Fund Age		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	No FE	Fund FE	F & T FE	No FE	Fund FE	F & T FE
Market Adjusted Return × log(EPU)	0.0722	0.115	0.0867	2.493	2.576	2.940
	(0.920)	(1.007)	(0.897)	(1.163)	(1.166)	(1.199)
log(EPU)	0.455	-0.357		-5.842	-7.283	
	(1.627)	(-0.260)		(-0.804)	(-0.943)	
Market Adjusted Return	0.0546	-0.0131	0.0121	-3.695	-3.860	-4.789
	(0.392)	(-0.0590)	(0.0560)	(-0.862)	(-0.885)	(-0.947)
log(Fund Age)	-8.498	-1.870	-110.8	-9.874	-2.728	-112.1
	(-1.397)	(-0.246)	(-1.023)	(-1.288)	(-0.313)	(-1.025)
Market Adjusted Return × log(Fund Age) × log(EPU)				-1.170	-1.190	-1.379
				(-1.163)	(-1.163)	(-1.198)
Market Adjusted Return × log(Fund Age)				1.794	1.841	2.307
				(0.897)	(0.920)	(0.985)
log(Fund Age) × log(EPU)				2.843	3.010	0.107
				(0.839)	(0.781)	(0.0444)
Observations	17,582	17,582	17,582	17,582	17,582	17,582
R-squared	0.061	0.093	0.111	0.062	0.095	0.112
Fund FE	NO	YES	YES	NO	YES	YES
Time FE	NO	NO	YES	NO	NO	YES

Table VII: Change of Manager Ability and Economic Policy Uncertainty

This table examines whether uncertainty predicts future change in the fund manager's ability. The fund manager's ability is proxied by the percentile rank of the gross return within each investment objective class (IOC) in the first two columns, and that of the before-expense four-factor alpha in the last two columns. The dependent variable is the absolute change in the ability proxy since the previous quarter. We standardize $log(EPU)$ by subtracting the time-series mean and dividing by the time-series standard deviation. All explanatory variables are lagged by one quarter. Standard errors are double clustered by fund and time. We present the t-statistics in the parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Variable definitions are shown in the legend of Table I.

	|ΔGross Return Rank|		|ΔBefore-Expense Four-Factor Alpha Rank|	
	(1)	(2)	(3)	(4)
	No FE	Fund FE	No FE	Fund FE
log(EPU)	0.994*	1.066*	0.766**	0.852***
	(1.768)	(1.763)	(2.404)	(2.595)
log(Assets)	-0.128	-0.241	-0.236***	0.0850
	(-1.134)	(-0.753)	(-2.884)	(0.525)
Expense Ratio	3.396***	-0.652	3.638***	0.00700
	(7.838)	(-0.871)	(9.749)	(0.0120)
Turn Ratio	0.00504***	-0.000587	0.00485***	0.00373**
	(3.330)	(-0.300)	(3.855)	(2.108)
Total Loads	-0.153***	-0.0628	-0.138***	-0.00644
	(-3.572)	(-0.585)	(-3.334)	(-0.0956)
log(Fund Age)	0.0113	-0.902	0.129	-0.782
	(0.0369)	(-0.696)	(0.513)	(-1.039)
Observations	138,399	138,399	138,399	138,399
R-squared	0.007	0.078	0.007	0.081
Fund FE	NO	YES	NO	YES

Table VIII: Summary Statistics for Manager Portfolio Decision Analysis

This table reports the summary statistics of the sample used in the manager decision analysis. The sample period is from 1985 to 2013. *Active share*, as defined in Cremers and Petajisto (2009) and Cremers and Pareek (2015), is equal to $\frac{1}{2}\sum_{j=1}^{N}|w_{fund,j} - w_{index,j}|$, where $w_{fund,j}$ is the weight in stock j held by the fund, $w_{index,j}$ is the weight in stock j held by the benchmark index, and N is the total number of stocks held by the fund or the benchmark. *Return gap*, as defined in Kacperczyk, Sialm, and Zheng (2008), is the difference between the gross return and the holdings return. *Beta deviation* is equal to $|\sum_{j=1}^{N} w_{fund,j}\beta_j - 1|$, where β_j is the CAPM beta of stock j, estimated using the returns in the past 36 months. To calculate the manager's age, we first use the manager's college graduation year. We assume that managers graduate from college at the age of twenty-two, so the age of the manager is the difference between the current year and the college graduation year plus twenty-two. When the college graduation year is unavailable, we use the year of birth, instead. *Manage multiple funds* is a dummy variable that takes the value of one if the manager manages more than one fund, and zero otherwise. *Team managed* is a dummy variable that takes the value of one if the fund is managed by more than one manager, and zero otherwise. The definitions of other variables are shown in the legend of Table I.

	(1) Mean	(2) Standard Deviation	(3) Median
Active Share (%)	76.16	15.73	79.18
Return Gap (% per quarter)	-0.12	2.33	-0.07
Beta Deviation	0.23	0.22	0.17
Manager Age (Years)	47.52	10.31	46.00
Manage Multiple Funds	0.63	0.48	1.00
Team Managed	0.64	0.48	1.00
Total Net Assets (Millions)	1,702.21	6,412.34	349.20
Expense Ratio (%)	1.24	0.42	1.19
Turn Ratio (%)	80.05	96.52	59.00
Total Loads (%)	3.53	3.56	2.00
Flow (% per quarter)	0.19	11.20	-1.30
Investor Return (% per quarter)	2.35	10.07	3.33
Gross Return (% per quarter)	2.67	10.09	3.64
Holdings Return (% per quarter)	2.79	10.56	3.82
No. of Funds	2,141		
No. of Managers	2,579		
No. of Obs.	92,816		

Table IX: Economic Policy Uncertainty and Manager Portfolio Decisions

This table shows how mutual fund managers' decisions are related to changes in uncertainty. The dependent variable is the active share in columns (1)-(4), the return gap in column (5), and the beta deviation in column (6). We standardize $log(EPU)$ and $log(VIX)$ by subtracting their respective time-series means and dividing by their respective time-series standard deviations. All explanatory variables are lagged by one quarter, except for flow, which is concurrent. VIX starts in 1990, so the number of observations is smaller in column (3). Standard errors are double clustered by fund-manager and time. We present the t-statistics in the parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Variable definitions are shown in the legend of Table VIII.

	Active Share				Alternative Measures	
	(1)	(2)	(3)	(4)	(5)	(6)
	No FE	F-M FE	VIX	MktRet	Return Gap	Beta Deviation
log(EPU)	-1.048***	-0.529***		-0.496***	-0.137**	-0.0157**
	(-6.156)	(-4.753)		(-4.538)	(-2.261)	(-2.250)
log(VIX)			-0.778***			
			(-11.24)			
Market Return				0.173		
				(1.328)		
log(Manager Age)	-0.287	-15.99***	-18.69***	-16.23***	0.862*	-0.0798
	(-0.253)	(-7.589)	(-9.846)	(-7.717)	(1.652)	(-1.292)
Team Managed	-2.178***	-0.312	-0.271	-0.304	-0.0747	-0.00342
	(-4.593)	(-1.017)	(-0.904)	(-0.992)	(-1.299)	(-0.417)
Manage Multiple Funds	-2.387***	-0.329	-0.189	-0.313	0.0182	0.0150***
	(-5.259)	(-1.276)	(-0.756)	(-1.216)	(0.382)	(2.673)
log(Assets)	-1.126***	-1.019***	-1.013***	-1.026***	-0.152***	0.0190***
	(-7.489)	(-6.370)	(-6.530)	(-6.397)	(-4.334)	(4.535)
Expense Ratio	8.217***	0.711	0.909	0.698	-0.0790	0.0353**
	(10.79)	(1.076)	(1.322)	(1.058)	(-0.575)	(2.462)
Turn Ratio	-0.00351*	-0.00111	-0.000385	-0.00107	0.000201	0.000100
	(-1.782)	(-0.940)	(-0.327)	(-0.903)	(0.507)	(1.570)
Total Loads	-0.637***	-0.370***	-0.375***	-0.362***	0.0170	0.00303*
	(-8.530)	(-5.028)	(-4.949)	(-4.966)	(1.246)	(1.873)
Flow	0.0580***	0.00173	-0.000141	0.000991	-0.00535***	0.000192
	(3.932)	(0.437)	(-0.0350)	(0.254)	(-3.202)	(1.288)
Observations	92,816	92,816	90,753	92,816	92,816	92,816
R-squared	0.112	0.903	0.906	0.903	0.092	0.593
Fund-Manager FE	NO	YES	YES	YES	YES	YES

Table X: Economic Policy Uncertainty and Manager Portfolio Decisions
- Heterogeneity across Manager Age

This table examines variations in the effects of economic policy uncertainty on active share across managers of different ages. The dependent variable is the active share. We standardize $log(EPU)$ by subtracting the time-series mean and dividing by the time-series standard deviation. All explanatory variables are lagged by one quarter, except for flow, which is concurrent. Standard errors are double clustered by fund-manager and time. We present the t-statistics in the parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Variable definitions are shown in the legend of Table VIII.

	(1) No FE	(2) F-M FE	(3) F-M & T FE
log(Manager Age) × log(EPU)	0.334*	0.393***	0.355***
	(1.700)	(3.336)	(3.723)
log(EPU)	-2.342***	-2.057***	
	(-3.074)	(-3.908)	
log(Manager Age)	-0.321	-15.96***	-1.291
	(-1.361)	(-12.43)	(-0.611)
Team Managed	-2.179***	-0.319***	-0.271***
	(-20.99)	(-3.537)	(-3.095)
Manage Multiple Funds	-2.388***	-0.324**	-0.124
	(-23.22)	(-2.504)	(-1.064)
log(Assets)	-1.127***	-1.025***	-0.949***
	(-35.42)	(-13.25)	(-13.81)
Expense Ratio	8.214***	0.715**	1.106***
	(59.50)	(2.541)	(4.004)
Turn Ratio	-0.00351***	-0.00113*	0.000979*
	(-6.762)	(-1.891)	(1.868)
Total Loads	-0.637***	-0.369***	-0.218***
	(-42.58)	(-8.857)	(-7.209)
Flow	0.0580***	0.00168	-0.00227
	(13.30)	(0.548)	(-0.696)
Observations	92,816	92,816	92,816
R-squared	0.112	0.903	0.908
Fund-Manager FE	NO	YES	YES
Time FE	NO	NO	YES

Appendix: Proofs of Propositions

A Proof of Proposition 1

The posterior mean of $(\mu + g_{\tau+1})$ at $t = \tau$ is

$$m_\tau = \pi_\tau \tilde{m}_\tau + (1 - \pi_\tau)\hat{m}_\tau, \tag{A1}$$

where π_τ is the probability that the policy changes at $t = \tau + 1$, $\tilde{m}_\tau$ is the expectation of the manager's ability given that the policy changes in the next period, and $\hat{m}_\tau$ is the expectation of the manager's ability given that the policy stays the same in the next period. Note that before forming their expectations the agents observe π_τ and whether the policy in the current period is the same as the previous period.

First, we compute $\tilde{m}_\tau$ as the sum of the conditional expectation of μ plus the prior mean of $g_{\tau+1}$, which is zero. This is because when the policy changes at $t = \tau + 1$, realized returns are only informative about μ, but not $g_{\tau+1}$. Let τ' denote the starting period of the current policy regime. We can form the compound signal $x_{\tau',\tau}$ using Equation (3). Note that $x_{\tau',\tau}$ is a signal on μ with precision $(\frac{v_\epsilon}{\tau-\tau'+1} + v_g)^{-1}$. Therefore, we have

$$\begin{aligned}
\tilde{m}_\tau &= \frac{\tilde{h}_{\tau'-1}\tilde{m}_{\tau'-1} + (\frac{v_\epsilon}{\tau-\tau'+1} + v_g)^{-1} x_{\tau',\tau}}{\tilde{h}_{\tau'-1} + (\frac{v_\epsilon}{\tau-\tau'+1} + v_g)^{-1}} + 0 \\
&= \frac{\tilde{h}_{\tau'-1}\tilde{m}_{\tau'-1} + (v_\epsilon + (\tau - \tau' + 1)v_g)^{-1} \sum_{t=\tau'}^{\tau} z_t}{\tilde{h}_{\tau'-1} + (\tau - \tau' + 1)(v_\epsilon + (\tau - \tau' + 1)v_g)^{-1}};
\end{aligned} \tag{A2}$$

and

$$\tilde{h}_\tau = \tilde{h}_{\tau'-1} + (\tau - \tau' + 1)(v_\epsilon + (\tau - \tau' + 1)v_g)^{-1}. \tag{A3}$$

Next, we compute the expectation of the manager's ability given that the policy does not change in the next period, $\hat{m}_\tau$. In this case, returns realized between periods τ' and τ are informative about $\mu + g_{\tau+1}$, but returns realized before period τ' are informative about only

μ. Hence,

$$\begin{aligned}\hat{m}_\tau &= \frac{(\tilde{h}_{\tau'-1}^{-1} + v_g)^{-1}\tilde{m}_{\tau'-1} + v_\epsilon^{-1}\sum_{t=\tau'}^{\tau} z_t}{(\tilde{h}_{\tau'-1}^{-1} + v_g)^{-1} + (\tau - \tau' + 1)v_\epsilon^{-1}} \\ &= \frac{\tilde{h}_{\tau'-1}(1 + v_g\tilde{h}_{\tau'-1})^{-1}\tilde{m}_{\tau'-1} + v_\epsilon^{-1}\sum_{t=\tau'}^{\tau} z_t}{\tilde{h}_{\tau'-1}(1 + v_g\tilde{h}_{\tau'-1})^{-1} + (\tau - \tau' + 1)v_\epsilon^{-1}},\end{aligned} \tag{A4}$$

where $\tilde{m}_{\tau'-1}$ and $\tilde{h}_{\tau'-1}$ can be specified using Equations (A2) and (A3), and

$$\hat{h}_\tau = \tilde{h}_{\tau'-1}(1 + v_g\tilde{h}_{\tau'-1})^{-1} + (\tau - \tau' + 1)v_\epsilon^{-1}. \tag{A5}$$

B Proof of Proposition 2 and 3

The flow of the fund is

$$F_\tau = q_\tau - q_{\tau-1} = \frac{m_\tau - m_{\tau-1}}{c}. \tag{A6}$$

The flow-performance sensitivity of the fund is thus

$$\begin{aligned}S_\tau = \frac{\partial F_\tau}{\partial r_\tau} &= \frac{1}{c}\frac{\partial m_\tau}{\partial r_\tau} \\ &= \frac{\pi_\tau}{c}\frac{(v_\epsilon + (\tau - \tau' + 1)v_g)^{-1}}{\tilde{h}_{\tau'-1} + (\tau - \tau' + 1)(v_\epsilon + (\tau - \tau' + 1)v_g)^{-1}} \\ &\quad + \frac{1 - \pi_\tau}{c}\frac{v_\epsilon^{-1}}{\tilde{h}_{\tau'-1}(1 + v_g\tilde{h}_{\tau'-1})^{-1} + (\tau - \tau' + 1)v_\epsilon^{-1}}\end{aligned} \tag{A7}$$

Furthermore,

$$\begin{aligned}\frac{\partial S_\tau}{\partial \pi_\tau} &= \frac{1}{c}\Big(\frac{(v_\epsilon + (\tau - \tau' + 1)v_g)^{-1}}{\tilde{h}_{\tau'-1} + (\tau - \tau' + 1)(v_\epsilon + (\tau - \tau' + 1)v_g)^{-1}} - \frac{v_\epsilon^{-1}}{\tilde{h}_{\tau'-1}(1 + v_g\tilde{h}_{\tau'-1})^{-1} + (\tau - \tau' + 1)v_\epsilon^{-1}}\Big) \\ &= \frac{-v_g\tilde{h}_{\tau'-1}}{c(\tilde{h}_{\tau'-1}(v_\epsilon + v_g(\tau - \tau' + 1)) + \tau - \tau' + 1)} < 0\end{aligned} \tag{A8}$$

Therefore, fund flow-performance sensitivity is decreasing in policy uncertainty. Furthermore, Equation (A8) suggests that $|\frac{\partial S_\tau}{\partial \pi_\tau}|$ is decreasing in the τ, i.e., the effect of policy uncertainty on flow-performance sensitivity in decreasing in the age of the fund.