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Ambiguity and Investment Decisions:

An Empirical Analysis on Mutual Fund Investor Behaviour

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Abstract *The paper empirically studies the relationship between ambiguity and mutual fund investor behaviour. Theoretical models for investment decisions incorporating ambiguity motivate our analyses. While the models indicate that investors would less likely to invest in financial markets when ambiguity increases, there is rare empirical evidence in natural occurring financial data to examine this hypothesis. In this paper, we test the hypothesis with equity fund flow data as for investment decisions and ambiguity with the degree of disagreement in equity analysts' prediction about asset returns. Our results support the hypothesis that increases in ambiguity could lead to less fund flows and this result remains consistently when adding various control variables affecting fund flows. Besides, we find that heterogeneous impacts of ambiguity: equity funds with high yield targets and active management style are affected more than funds investing in stable stocks; funds with larger proportion of institutional investors are more sensitive and affected by the ambiguity.*

Key words Ambiguity, fund flows, investor behaviour, financial market

JEL Codes: D81, E22, G11

1. Introduction

In financial markets with increasing complexity, investors nowadays are required to acquire and process large amounts of information when making investment decisions. Investors face ambiguity when not knowing the exact states of nature, i.e., the exact distribution of financial assets' return (Ellsberg, 1961; Epstein and Schneider, 2008). A considerable theoretical literature has incorporated ambiguity into investment decisions, and finds consistent evidence that investors are less willing to participate in financial market when ambiguity increases (Cao *et al*., 2005; Dow and da Costa Werlang, 1992; Epstein and Schneider, 2010). However, empirical evidence to test this predication from natural occurring financial data is relatively rare. In this paper, we provide empirical evidence by studying the relationship between ambiguity and mutual fund investor behaviour.

Mutual funds are appealing setting to explore the impacts of ambiguity on investment decisions. Mutual funds constitute a vital part of the financial market in China and the size of open mutual funds reaches 8.75 trillion RMB in 2016. Flows into and out of mutual funds are appropriate reflection of investors' portfolio allocation choices, which offer direct measurement of investor behaviour. Following Antoniou et al. (2015) and Li *et al.* (2016), the paper uses net fund flows as a proxy of investment decisions and mainly focuses on equity funds. Besides, mutual fund data provides considerable heterogeneity information for our study, i.e., different investment styles and owner structure, which allows us to get a comprehensive understanding on the impacts of ambiguity in financial markets.

To empirically analyze the impacts of ambiguity, we need an appropriate measurement of mutual funds' ambiguity. Following Anderson *et al.* (2009), the paper constructs the measurement of ambiguity by the degree of disagreement in equity analysts' prediction. When the degree of disagreement for future performance of an asset is high, ambiguity tends to be high due to conflicting views about the true state of the asset return. Therefore, investors need to consider multiple possible states of future return when making investment decisions, which implies high ambiguity. This measurement could originally attributed to Ellsberg (1961), who implies that the ambiguity is higher when agents have conflict expectations or views. There are also other financial studies employing this kind of measurement, such as Antoniou *et al*. (2015) and Ulrich (2013), which support our use of this measurement.

2. Literature review

When making investment decisions, investors confront ambiguity if they do not know the exact distribution of future return of financial assets (Chen and Epstein, 2002; Epstein and Schneider, 2008). A substantial literature finds that subjects are ambiguity averse, where subjects prefer lottery with known, rather than unknown probabilities, from experimental evidence (Ahn *et al*., 2014; Bossaerts *et al*., 2010) and in large representative samples (Dimmock *et al*., 2016). Incorporating ambiguity aversion when facing ambiguity, many theoretical models robustly predict lower financial market participation than classical Expected Utility (EU) model, and ambiguity could decrease investors' willingness to invest in financial markets (Cao *et al*., 2005; Dow and da Costa Werlang, 1992; Epstein and Schneider, 2010; Easley and O'Hara, 2009;

Maenhout, 2004). However, empirical evidence from natural occurring financial data is relatively rare. Antoniou *et al*. (2015) study the impacts of systematic ambiguity on fund flows by using the dispersion of analysts' prediction on economic growth. While in our paper, we measure idiosyncratic ambiguity for each mutual fund, which is supplement to the current literature.

Ambiguity could have heterogeneous impacts on investment decisions due to differences in characteristics of assets and investors. Due to differences in investment irreversibility, the degree of sensitivity to ambiguity is different across companies (Gulen and Ion, 2016). For mutual funds, with different investment styles and portfolio positions, funds could be affected heterogeneously by the ambiguity. As for heterogeneous types of investors, there are investors with different degree of ambiguity aversion in the financial markets (Potamites and Zhang, 2012). Specially, there are two types of investors in financial markets: retail investors and institutional investors. Due to differences in capability of information acquisition, these two types of investors behave quite differently (Barber and Odean, 2007). Unlike other developed countries, there is larger proportion of retail investors than institutional investors in China and it is important to explore behaviour differences between two types of inventors.

Our paper also contributes to the literature on exploring determinant factors of fund flows. Froot *et al*. (2001), Kacperczyk and Seru (2007), and Sirri and Tufano (1998) find that management ability of fund manager and funds' historical performances significantly affect fund flows. Ivković and Weisbenner (2009), Jain and Wu (2000) and Nanda *et al*. (2004) find that advertising costs and loading fees of mutual funds are important determinants in fund flows. Del Guercio and Tkac (2008) find that star funds attract fund flows and rating of funds also matters due to decrease in fund search costs. Our paper supplements this literature by studying the impacts of idiosyncratic ambiguity on fund flows and finds that ambiguity could negatively influence fund flows.

3. Methodology of research

3.1. Theoretical model and hypothesis

To explore the relationship between ambiguity and investment decisions, the paper develops a theoretical model following Cao et al. (2005). Suppose in a one-period endowment economy, a representative agent invests in two assets: one is risky free and the other is risky. Rate of return for risky free asset is set as 0 for simplification. The price of risky asset is p and the rate of return is r, where $r \sim N(\bar{r}, \sigma^2)$. Under ambiguity, the agent does not know the exact distribution of the risky asset. For simplicity, the paper assumes that the agent knows σ^2 but is not sure about $\bar{r}$: $\bar{r}=\mu+v$, μ is known and $v \in [-\delta, \delta]$, $\delta \geq 0$. The δ measures ambiguity in the economy: when $\delta > 0$, the agent does not know the exact $\bar{r}$. The agent has Constant Absolute Risk Aversion (CARA) utility function with absolute risk aversion coefficient $\alpha > 0$. Given v, the agent maximizes her expected utility $E[u(W_1)]$ in the end of the period as:

$$E[u(W_1)] = -\exp\{-\alpha[W_0 + (\bar{r} - p)d - \frac{1}{2}\alpha\sigma^2 d^2]\} \tag{1}$$

Where: W_0 is initial wealth and d is demand for risky asset.

Since being ambiguous about the $\bar{r}$, following Gilboa and Schmeider (1989), the agent maximizes her minimum expected utility:

$$\underset{d}{Max}\,\underset{v}{Min}\{(\mu + v - p)d - \frac{1}{2}\alpha\sigma^2 d^2\} \tag{2}$$

And we can solve the optimal demand for risky asset as:

$$d = \begin{cases} (\mu - p - \delta)/\alpha\sigma^2, & (\mu - p) > \delta \\ 0, & -\delta \leq (\mu - p) \leq \delta \\ (\mu - p + \delta)/\alpha\sigma^2, & (\mu - p) < -\delta \end{cases} \tag{3}$$

From (3), we can find that ambiguity affects the agent's investment decisions. When $\mu > p + \delta$ ($\mu < p - \delta$), the agent in long (short) in the risky asset and δ decreases her amount of investment. Specifically, the agent would even drop out from the financial market if the ambiguity is large enough: $\delta \leq (\mu - p) \leq \delta$. The theoretical model forms the hypothesis we test as follows:

Hypothesis: An increase in ambiguity will decrease investors' investment in financial market when all else is equal.

3.2. Sample selection and sources of data

The paper measures investor's decision with equity fund flows. Following Li *et al*. (2016) and Sirri and Tufano (1998), we exclude QDII funds. Data of Mutual fund data and stock market is all from the China Stock Market and Accounting Research (CSMAR) database (http://www.gtafe.com/). Before 2014, the number of equity funds is less than 20 so the paper selects unbalanced panel data including 604 equity funds from the second quarter in 2014 (2014Q1) to the fourth quarter in 2016 (2016Q4). To avoid outliers, we winsorize in 1% level based on quarterly fund flows.

3.3. Empirical methodology

Following Antoniou *et al*. (2015) and Ben-Rephael *et al*. (2012), the paper tests the relationship between ambiguity and fund flows with regression model as follows:

$$flow_{it} = \beta_0 + \beta_1 \Delta amb_t + \beta_2 flow_{it-1} + Z_{it}\gamma + \alpha_j + u_{it} \tag{4}$$

Where: $flow_{it}$ is fund flows of equity fund *i* in quarter t. We control lagged fund flows in case of autocorrelation;
amb_{it} is fund *i*'s ambiguity in quarter *t* and
Δamb_{it} is its change between quarter *t* and *t-1*.

In the theoretical model, the amount of investment to financial market is determined by the ambiguity. Since fund flows are changes of amount of investment, we also use changes of ambiguity in the regression model. Z_{it} includes other control variables other than ambiguity. α_j represents fund fixed effect (FE) and u_{it} is random error term. We will introduce variable constructions in the following subsections.

3.3.1. Fund flows

Following Li *et al*. (2016), we measure fund flows as relative total net asset value changes:

$$flow_{it} = \frac{TNA_{it} - (1 + rf_{it})TNA_{it-1}}{TNA_{it-1}} \tag{5}$$

TNA_{it} is fund *i*'s total net asset value and rf_{it} is its return rate in quarter *t*.

We use relative size change because of increasing fund size within the quarter. The calculation does not count net value increases or dividends, and assumes all flows coming in the end of the quarter, which is relatively conservative.
Figure 1 shows quarterly fund flows from 2004Q1 to 2016Q4. Before 2010, fund flows vary quite volatile, with a large flow into the equity funds in 2007 stock market boom and a flow out afterwards in 2008 crash. After 2010, fund flows are less volatile. As showed in Table 1, the average fund flows is -0.727%, which indicates a declining trend in equity fund market in China.

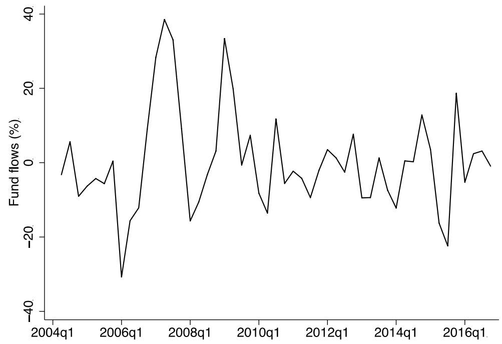

Figure 1. Fund flows for equity funds.

3.3.2. Fund ambiguity

When not knowing the exact state of risky asset, investors confront ambiguity. Various empirical and experimental studies find that subjects are in general ambiguity averse (Ahn *et al*., 2014; Bossaerts *et al*., 2010), and ambiguity aversion has been used to explain many portfolio choice problems (Epstein and Schneider, 2010). However, empirical works about ambiguity is relatively rare due to its difficulty of measurement in financial data. According to Ellsberg (1961), one measurement for ambiguity is the richness of the information or the disagreement among users of the information set. Following Anderson et al. (2009), the paper measures ambiguity with the degree of disagreement from equity analysts. Equity analysts publish prediction for earnings per share of stock (EPS) regularly and we measure the ambiguity for each stock based on the disagreement of EPS predication and then aggregate the ambiguity for each equity fund based on its position. In quarter *t*, f_{it} represents the number of ranks from equity analysts on EPS, x_{ijt} is analyst *i*'s rank for stock *j*. After sorting stock *i*'s ranks from high to low, the weight for k_{th} rank is:

$$W_{ijt}(v)=\frac{k^{v-1}(f_{it}+1-k)^{v-1}}{\sum_{m=1}^{f_{it}}k^{v-1}(f_{it}+1-m)^{v-1}} \tag{6}$$

Where: *v* indicates the shape of the weight function. Less weight is on extreme ranks if *v* increases and the ranks are equally weighted when *v*=1. In our calculation, we choose v=15.346 according to Anderson *et al.* (2009). Ambiguity for stock *i* in quarter *t* is:

$$samb_{it}=\sum_{j=1}^{f_{it}}W_{ijt}[x_{ijt+1lt}-\sum_{m=1}^{f_{it}}W_{imt}(v)x_{imt+1lt}]^2 \tag{7}$$

For equity funds, we get their stock positions in each quarter. For simplicity, we aggregate fund ambiguity amb_{it} for the top ten stocks weighted by their position shares. Figure 2 shows quarterly fund ambiguity from 2004Q1 to 2016Q4. We can find several obvious spikes in our sample: huge increases around 2008Q1 crash and 2016Q1 crash. This indicates that degree of disagreement increases in recession period.

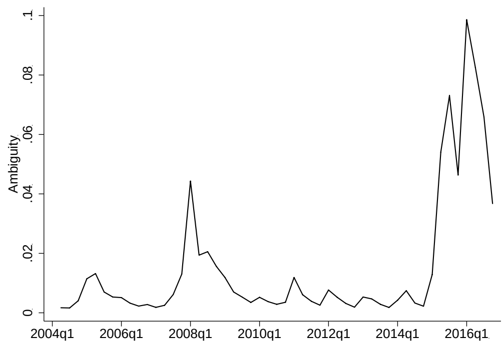

Figure 2. Ambiguity

3.3.3. Control variables

The paper adds various control variables to control other determinants of fund flows. Following Froot *et al.* (2001) and Nanda *et al.* (2004), the paper controls size of fund (*fsize*) and the age of fund (*fage*). We use natural logarithm of total net value in the end of *t* to measure *fsize*, and number of years since the fund is initiated to measure *fage*. Fund performance is an important determinant of fund flows (Ippolito, 1992; Sirri and Tufano, 1998) and the paper uses quarterly average return rate (*rf*) to measure fund performance. According to Li *et al.* (2016), investors are sensitive to mutual fund's worst performance due to ambiguity aversion, we also control minimum rate of return in the last four quarters ($rfmin_{t-4,t-1}$). In case our ambiguity measure is only capture risk, the regression also controls variance of fund return rate in the last four quarters ($rfvol_{t-4,t-1}$). Relative rank of funds is also determinant (Del Guercio and Tkac, 2008) so we control percentile of funds' rank (*frk*). To avoid reverse causality, the regression model controls lagged fund size $fsize_{t-1}$, fund's age $fage_{t-1}$, rate of return rf_{t-1} and relative rank frk_{t-1}. Table 1 reports summary statistics for fund flows, ambiguity and other control variables. The average ambiguity is 0.030 and its change is 0.001, which indicates the ambiguity increases during the sample period. The average and median of fund flows are -0.727%, showing a declining trend in equity fund market. The average rate of return is 0.5% and -0.1%, and this rate of return is relatively low. The average fund age is 3.588 years, which implies many new funds are initiated in recent years.

Table 1. Summary statistics

	Mean	Std	Median	75th Percentile	Minimum	Maximum
amb	0.030	0.179	0.003	0.006	0.000	3.818
Δamb	0.001	0.149	0.000	0.001	-2.985	3.817
flow (%)	-0.727	37.158	-4.316	5.378	-72.583	343.197
rf	0.005	0.124	-0.001	0.037	-1.994	0.634
rfmin	-0.094	0.242	-0.035	-0.004	-4.127	2.093
rfvol	0.030	0.177	0.003	0.015	0.000	8.265
frkp	0.505	0.206	0.508	0.662	0.010	0.997
fsize	20.237	1.747	20.277	21.517	14.431	24.749
fage	3.588	2.932	2.750	5.000	0.000	15.250

4. Data analyses and results

To explore the relationship between ambiguity and investment decisions, the paper quantifies the average impact of ambiguity on fund flows in 4.1. Subsection 4.2 and 4.3 further explore heterogeneous impacts of ambiguity on different investment styles and owner structure. The paper tests robustness of the results in subsection 4.4.

4.1. Ambiguity and fund flows

Table 2 reports regression results for ambiguity on fund flows based on model (4). The dependent variable is fund flows and main explanatory variable is changes of ambiguity. From Columns (1) to (4), we add various control variables step by step to get conservative estimation. From the Table 2, we can find that ambiguity could significantly decrease fund flows. The coefficient estimations of Δamb_t is -8.346, -8.486, -6.431 and -5.422 respectively across Columns (1) to (4). The former two coefficient estimations are significant at the 1% level and latter two estimations are significant at the 5% level. Take Column (4) as an example, every 0.1 unit changes of ambiguity changes will lead to -0.542%, which is quite large relative to average fund flows. The results support our hypothesis that the ambiguity could significantly decrease fund flows, and the relationship is quite robust under various settings.

As for the other control variables, we find consistent results with the literature. The coefficient estimation of lagged fund flows flowt-1 is positive, indicating inertia in fund investment as showed in Antoniou *et al.* (2015). Interestingly, the coefficient estimation of lagged rate of return rf_{t-1} is negative. This is consistent with "reverse selection" phenomenon that investors sell funds with higher performance in China (Lu *et al.,* 2007). The worst performance significantly decreases fund flows, and that coincides with findings in Li *et al.* (2016). In case of our ambiguity measurement only capturing risk, we control volatility of fund return $rfvol_{t-4,t-1}$ in the regression. The coefficient estimation of $rfvol_{t-4,t-1}$ is not significant and our results still hold. Consistent with Sirri and Tufano (1998), relative performance is significant in fund flows: the coefficient estimation of frk_{t-1} is negative and significant, which means that the higher the rank (the lower *frk*), the higher the fund flows. The size of fund is negative correlated with fund flows since we use relative fund changes.

4.2. Ambiguity and equity funds with different investment styles

Considering different sensitivity of assets, ambiguity could have heterogeneous impacts on equity funds with different investment styles. There are sixteen types of investment styles for equity fund, such as "aggressive growth" and "growth" in China. We categorize equity funds into four categories following Anderson *et al.* (2009) and Antoniou *et al.* (2012): "aggressive growth", "growth", "growth and income" and "income". According to the CSMAR, "aggressive growth" and "growth" equity funds pursue high capital gains and mainly invest in high-yield stocks, while "growth and income" and "income" equity funds are more conservative and mainly invest in stocks with stable market values and dividends. High-yield stocks are usually unstable and hard to predict future returns so they may be sensitive to ambiguity. Stocks with stable market values and dividends are relatively predictable so they should suffer fewer impacts from the ambiguity. Therefore, ambiguity should affect "aggressive growth" and "growth" funds more than "growth and income" and "income" funds.

Table 2. Regression of ambiguity on equity fund flows

	(1)	(2)	(3)	(4)
Δamb_t	-8.346***	-8.486***	-6.431**	-5.422**
	(2.585)	(2.605)	(2.560)	(2.604)
$flow_{t-1}$		0.081***	0.062***	0.014
		(0.022)	(0.021)	(0.021)
rf_{t-1}			-26.350***	-27.464***
			(5.235)	(4.955)
$rfmin_{t-4,t-1}$			-7.193*	-9.894**
			(3.789)	(4.451)
$rfvol_{t-4,t-1}$			2.719	-3.743
			(5.277)	(3.729)
frk_{t-1}			-22.196***	-20.491***
			(2.494)	(2.588)
$fsize_{t-1}$			-0.874***	-11.726***
			(0.237)	(1.077)
$fage_{t-1}$			-0.135	-1.510***
			(0.114)	(0.289)
Fund FE	NO	NO	NO	YES
Constant	-0.864**	-0.803**	27.977***	242.178***
	(0.417)	(0.389)	(5.275)	(22.303)
Observations	7,992	7,992	7,924	7,924
R^2	0.001	0.009	0.046	0.187

Note. Robust standard errors clustered in fund level in parentheses. ***p<0.01, **p<0.05, and *p<0.1, respectively.

Table 3 reports regression of ambiguity on equity fund flows with different investment styles. We can find that ambiguity significantly decreases fund flows for “aggressive growth” and “growth” equity funds but does not significantly affect “growth and income” and “income” funds. The coefficient estimations for Δamb_t is -38.346, -8.028, 2.486 and 0.597 for four types of equity funds, respectively. The coefficient estimations are marginally significant for “aggressive growth” and significant at the 5% for “growth” funds, while the latter two estimations for “growth and income” and “income” funds are not significant. These results support our guess that fund flows with active and risky investment styles are more affected by ambiguity. More interestingly, though the coefficient estimates are not significant for “growth and income” and “income” funds, they are positive, which is different with our theoretical prediction. Possible explanation is that when ambiguity increases, investors might shift their investment from “aggressive growth” and “growth” funds into less risky and more stable funds, i.e., “growth and income” and “income” funds. Since we only have aggregate data instead of individual investment data, this question deserves further study with more detailed data.

4.3. Ambiguity and equity funds with different owner structures

Due to differences in information acquisition, ambiguity may have heterogeneous effects on retail and institutional investors. Unlike financial markets in developed countries, the proportion of retail investors is higher than institutional investors in China so behavioural differences between retail and institutional investors are important to study. The mean and median of proportion of retail (institutional) investors are 70% (30%) and 79% (21%). We vary the proportion of retail or institutional investors’ cut-off to explore how ambiguity affects retail and institutional investors differently.

Table 4 reports regression of ambiguity on equity funds with different owner structures. From Columns (1) to (3), we analyse equity funds with more than 10%, 20% and 30% institutional investors and from Columns (4) to (6), we analyse equity funds with more than 90%, 80% and 70% institutional investors. From the regression results in Table 4, we can find that ambiguity decreases mutual funds and the higher the proportion of institutional investors, the larger the impact. Specifically, the coefficient estimates for Δamb_t are -7.998, -13.148 and -14.211 from Columns (1) to (3) and are significant at the 10%, 1% and 5% level respectively; the coefficient estimates for Δamb_t are -1.751, -1.315 and -2.621 from Columns (4) to (6) and none of them is significant. From the results, we find that ambiguity could significant decrease fund flows for funds with high proportion of institutional investors, and this effect is stronger when the proportion of institutional investors increases. While for funds with high proportion of retail investors, the impact of ambiguity on fund flows is not significant and is weaker when the proportion of retail investors increases. Since institutional investors are better in information acquisition and collection, our conjecture is that institutional investor’s face higher richness of information and ambiguity sensitivity than retail investors. These results are meaningful for retail investors, especially. Since ambiguity could decrease fund flows and affect fund net values further, retail investors should pay more attention to risky assets’ ambiguity and to avoid value loss caused by negative fund flows. And for fund managers, they should reduce fund ambiguity such as investing in more stable stocks, and remind their investors for potential risk to improve investors’ welfare.

Table 3. Regression of ambiguity on equity funds with different investment styles

	“Aggressive growth”	“Growth”	“Growth and income”	“Income”
	(1)	(2)	(3)	(4)
Δamb_t	-38.346*	-8.028**	2.486	0.597
	(21.617)	(3.516)	(3.300)	(6.906)
$flow_{t-1}$	0.084	-0.010	0.081**	-0.072
	(0.071)	(0.028)	(0.039)	(0.065)
rf_{t-1}	13.355	-30.221***	-27.117**	-7.703
	(27.074)	(5.531)	(12.894)	(14.968)
$rfmin_{t-4,t-1}$	-17.791	-9.119*	-9.901	26.656***
	(27.103)	(5.008)	(12.631)	(9.668)
$rfvol_{t-4,t-1}$	2.997	-5.523	73.530*	62.643**
	(54.322)	(3.376)	(42.178)	(29.825)
frk_{t-1}	-19.794**	-17.581***	-29.855***	-28.498
	(8.476)	(2.807)	(6.888)	(20.981)
$fsize_{t-1}$	-10.880**	-12.212***	-9.478***	-23.124**
	(4.582)	(1.352)	(1.985)	(10.363)
$fage_{t-1}$	-1.277	-2.094***	-0.517	-2.468
	(0.838)	(0.387)	(0.509)	(1.728)
Fund FE	YES	YES	YES	YES
Constant	255.684**	252.376***	191.828***	453.343**

	"Aggressive growth"	"Growth"	"Growth and income"	"Income"
	(104.481)	(27.989)	(39.324)	(205.919)
Observations	534	5,543	1,527	320
R^2	0.079	0.214	0.166	0.282

Note. Robust standard errors clustered in fund level in parentheses. ***p<0.01, **p<0.05, and *p<0.1, respectively.

4.4. Robustness check

To test robustness of our results, the paper firstly re-estimates regression model with System GMM (GMM-SYS) to overcome influences of endogeneity and error term autocorrelation. We also adjust the measurement of ambiguity by measuring the degree of disagreement in net profit predictions.

Column (1) in Table 5 reports GMM-SYS regression results. P-values of AR test show that at the 5% level, the model is of first-order autocorrelation but not second-order correlation so we need to control lagged fund flows. Sargen test shows that our moment condition holds. The coefficient estimation for Δamb_t is -7.683, and significant at the 5% level, which again indicates that the increase of ambiguity changes can decrease fund flows. Therefore, our results still hold if we change the estimation method.

From Columns (2) to (5), we use new measurement for ambiguity. Instead of using equity analysts' prediction on EPS, we use their predictions on net profits (NETPRO). From the coefficient estimations for $\Delta ambNETPRO_t$, we find that in general, ambiguity decreases fund flows but the significance levels decrease. Specifically, the coefficient estimations for $\Delta ambNETPRO_t$ are -0.054, -0.061, -0.048 and -0.040. Since NETPRO and EPS are different in unit, the coefficients cannot be compared directly but they have the same direction. While the former three is significant at least at 10% level, the last one is insignificant. These results also confirm our main conclusions and verify the robustness.

Table 4. Regression of ambiguity on equity funds with different owner structures

	Proportion of institutional investors			Proportion of retail investors		
	≥10%	≥20%	≥30%	≥90%	≥80%	≥70%
	(1)	(2)	(3)	(4)	(5)	(6)
Δamb_t	-7.998*	-13.148**	-14.211**	-1.751	-1.315	-2.621
	(4.140)	(5.191)	(7.051)	(2.510)	(2.212)	(2.159)
$flow_{t-1}$	0.028	0.019	0.015	-0.032	0.008	0.013
	(0.024)	(0.031)	(0.040)	(0.043)	(0.027)	(0.024)
rf_{t-1}	-27.787***	-31.235***	-31.683***	-23.636**	-21.934***	-23.036***
	(5.810)	(7.101)	(7.959)	(9.461)	(6.394)	(6.035)
$rfmin_{t-4,t-1}$	-9.637*	-5.388	-4.705	-11.242	-12.343**	-12.768***
	(5.453)	(6.205)	(8.579)	(8.324)	(5.470)	(4.614)
$rfvol_{t-4,t-1}$	-0.745	11.212	12.962	-9.749*	-8.250**	-8.189***
	(5.608)	(13.034)	(13.281)	(5.865)	(3.249)	(2.980)
frk_{t-1}	-20.428***	-21.468***	-14.744***	-20.779***	-19.731***	-23.684***
	(3.020)	(3.347)	(4.104)	(4.893)	(4.028)	(3.267)
$fsize_{t-1}$	-10.724***	-10.052***	-10.889***	-18.213***	-13.665***	-12.043***
	(1.087)	(1.335)	(1.650)	(4.801)	(1.817)	(1.387)
$fage_{t-1}$	-1.280***	-1.364***	-2.025***	-3.176**	-1.735***	-1.337***
	(0.278)	(0.397)	(0.491)	(1.315)	(0.435)	(0.350)
Fund FE	YES	YES	YES	YES	YES	YES
Constant	221.476***	208.901***	224.484***	362.069***	270.228***	240.249***
	(22.477)	(27.653)	(34.103)	(95.070)	(35.743)	(27.363)
Observations	5,964	4,171	2,759	1,960	3,753	5,165
R^2	0.185	0.183	0.207	0.210	0.195	0.177

Note. Robust standard errors clustered in fund level in parentheses. ***p<0.01, **p<0.05, and *p<0.1, respectively.

5. Conclusions

Our paper empirically studies the impacts of ambiguity on investment decisions with equity fund data. Our results show that ambiguity could significantly decrease equity fund flows and the results are robust after adding various control variables, changing estimation method and adjusting measurement for ambiguity. Furthermore, ambiguity has heterogeneous impacts on fund flows: equity funds with high yield targets and active management style such as "aggressive growth" and "growth" funds are affected more than funds investing in stable stocks such as "growth and income" and "income" funds; funds with larger proportion of institutional investors are more sensitive and affected by the ambiguity. Overall, our paper provides supportive evidence for predications in various theoretical models with ambiguity. Moreover, our findings have possible implications for both fund managers and investors. For fund managers, ambiguity would negatively affect fund flows and further affect fund net values, and hence fund managers could reveal more information about the invested stocks to reduce ambiguity among fund investors. For investors, they could use ambiguity as a fund selection fund and be more sensitive for this index, especially for retail inventors.

Table 5. Robustness check

	GMM-SYS	OLS			
	(1)	(2)	(3)	(4)	(5)
Δamb_t	-7.683**				
	(3.124)				
$\Delta ambNETPRO_t$		-0.054*	-0.061**	-0.048*	-0.040
		(0.029)	(0.029)	(0.028)	(0.027)
$flow_{t-1}$	0.043**		0.081***	0.063***	0.014
	(0.018)		(0.011)	(0.011)	(0.011)
rf_{t-1}	-38.561***			-26.717***	-27.783***
	(4.599)			(3.302)	(3.314)
$rfmin_{t-4,t-1}$	-17.229***			-7.158***	-9.884***
	(3.436)			(2.759)	(3.533)
$rfvol_{t-4,t-1}$	-10.060			2.720	-3.747
	(7.606)			(3.285)	(4.596)
frk_{t-1}	-7.506**			-22.198***	-20.484***
	(3.205)			(1.875)	(1.920)
$fsize_{t-1}$	0.238			-0.884***	-11.748***
	(0.314)			(0.231)	(0.607)
$fage_{t-1}$	-0.015			-0.131	-1.507***
	(0.173)			(0.136)	(0.178)
Fund FE	NO	NO	NO	NO	YES
Constant	-3.070	-0.876**	-0.815**	28.161***	242.634***
	(6.976)	(0.386)	(0.384)	(4.686)	(14.227)
Observations	7,924	7,992	7,992	7,924	7,924
R^2	NA	0.000	0.008	0.045	0.186
Sargen test	466.483				
	(1.000)				
AR(1) test	-8.951				
	(0.000)				
AR(2) test	0.562				
	(0.574)				

Note. P-values in parenthesis for Sargen test and AR test. Robust standard errors clustered in funds level in parenthesis. ***p<0.01, **p<0.05, and *p<0.1, respectively.

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