Ambiguity Aversion and Market Participation:

Evidence from Fund Flows

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Abstract

Stock market participation is very low, with approximately two thirds of all U.S. households not owning any public equity. This is a puzzle in the context of the basic Expected Utility model. One explanation put forward in the literature is that stock market participation is low because, in addition to risk, stocks also entail ambiguity and investors are ambiguity averse. We empirically test this hypothesis, measuring stock market participation using equity fund flows and ambiguity with dispersion in analyst forecasts about aggregate market returns. In a multivariate framework our results show that increases in ambiguity are significantly and negatively related to equity fund flows, and thus support the notion that limited market participation is related to ambiguity aversion.

Keywords: Stock market participation; ambiguity aversion; fund flows.

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Stock market participation is very low, with approximately two thirds of all U.S. households not owning any public equity. This is a puzzle in the context of the basic Expected Utility model. One explanation put forward in the literature is that stock market participation is low because, in addition to risk, stocks also entail ambiguity and investors are ambiguity averse. We empirically test this hypothesis, measuring stock market participation using equity fund flows and ambiguity with dispersion in analyst forecasts about aggregate market returns. In a multivariate framework our results show that increases in ambiguity are significantly and negatively related to equity fund flows, and thus support the notion that limited market participation is related to ambiguity aversion.

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1. Introduction

During the last century the U.S. stock market has yielded an average annual return of approximately 10% over treasury bills, with a standard deviation of 20%. Given this risk-return trade-off, the canonical expected-utility model (EU) predicts that risk-averse agents should be very willing to participate in the stock market. However, stock market participation is very low. For the period 1982-1995 the U.S. Consumer Expenditure Survey found that two thirds of all U.S. households do not invest in stocks. Even at the eightieth percentile of wealth, almost 20% of households have no public equity (Campbell, 2006). It is difficult to explain these results with the EU model, so this phenomenon is widely known as the limited-participation puzzle.[1]

Various explanations have been put forward for the limited-participation puzzle. Williamson (1994) and Allen and Gale (1994) suggest that liquidity needs and transaction costs deter stock market participation. Hong, Kubik and Stein (2004) suggest that the fixed cost of entering the stock market for the first time is too high, which also limits participation (see also Vissing-Jorgenson, 2002; Guiso, Haliassos and Jappelli, 2003). Hsu (2012) argues that households with low human capital have less need for diversification and therefore invest less in stocks. Haliassos and Bertatut (1996) suggest that borrowing constraints and minimum investment requirements also reduce market participation. However, these explanationscannot completely explain the non-participation puzzle, so some researchers have resorted to 'behavioural' explanations.

One prominent behavioural explanation is that limited-participation is driven by ambiguity aversion (Dow and Werlang, 1992; Mukerji and Tallon, 2001; Easley and O'Hara, 2009; Epstein and Schneider 2010; Werner, 2011; Takashi, 2011). The notion of ambiguity was initially developed by Knight (1921) and Keynes (1921), and describes a situation where the probabilities associated with future states of nature are unknown. Ellsberg (1961) was the first to conjecture that people are particularly averse to ambiguity, a result subsequently confirmed by many studies in experimental

[1] For a theoretical exposition of the puzzle see Haliassos and Bertaut (1995).

economics and psychology.[2] According to the ambiguity-based explanation of the non-participation puzzle, stocks involve both risk *and* ambiguity. Owing to the fact that the majority of people are averse to ambiguity, their propensity to invest in stocks is lower than that implied by the EU model.[3]

In this paper we empirically examine whether ambiguity is negatively related to stock market participation. The starting point for our analysis is the notion that for non-professional investors, the principal avenue for broad-based stock market participation is through mutual funds. The Investment Company Institute estimates that in 2011, households owned 89 percent of the mutual fund industry (ICI, 2012). This implies that flows in and out of mutual funds reflect the active reallocation decisions of individual investors, and thus provide a direct measure of market participation.

To test the hypothesis we require an empirical measure of ambiguity. To this end we rely on the measure proposed in a recent study by Anderson, Ghysels and Juergens (2009), which reflects dispersion in analysts' forecasts using data from the Survey of Professional Forecasters (SPF), issued by the Federal Reserve. The SPF contains forecasted quarterly data such as GDP growth and inflation from different analysts, and following Anderson, Ghysels and Juergens (2009) we use the Gordon Growth Model to derive a forecast for aggregate stock market return for each analyst. When dispersion among analysts regarding the future performance of stock markets is high, ambiguity is also likely to be high since experts have arrived at conflicting views regarding the fundamentals of the economy. In these conditions it is possible that different distributions of expected returns are plausible, and that investors cannot confidently narrow down the set to the 'correct' one. This measure of ambiguity proposed by Anderson, Ghysels and Juergens (2009) corresponds closely to the general definition of ambiguity provided by Ellsberg (1961):

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[2] A large literature, starting with Knight (1921) and Keynes (1921), and continuing through Ellsberg (1961) and up to the present day (Ahnet al., 2009), shows that situations that involve ambiguity are treated differently from those that involve risk. Hsu et al. (2005**)** and Levy et al. (2010) present evidence that ambiguous situations produce a unique neurological fingerprint, suggesting that ambiguity aversion is rooted in the fundamentals of human cognition. See Camerer and Weber (1992) and Keren and Gerritsen (1999) for reviews on the evidence on ambiguity aversion.

[3] Hong, Kubik and Stein (2004) put forward an alternative behavioural explanation, based on social interaction.

> "*Ambiguity is a subjective variable, but it should be possible to identify "objectively" some situations likely to present high ambiguity, by noting situations where available information is scanty or obviously unreliable or highly conflicting; or where expressed expectations of different individuals differ widely*;" Ellsberg (1961, p. 660).

Using data on U.S. fund flows from the Investment Company Institute, we examine in a multivariable framework whether ambiguity is related to capital flows into equity mutual funds, controlling for other factors that have been shown to be important in explaining fund flows, including risk. We use two empirical proxies for market participation: mutual fund flows, i.e. the net cash flow into equity funds, and mutual fund exchanges, i.e. the switch of capital between funds of different asset classes that are managed by the same investment house. Our results indicate that ambiguity is negatively and significantly related to both of these measures, suggesting that non-participation is related to ambiguity.

In our model, we control for factors that have been previously documented to affect flows, including past fund returns (Ippolito,1992; Sirri and Tufano, 1998), capital gains (Kamstra et al., 2011), past flows (Ben-Rephael, Kandel, and Wohl, 2011b), seasonal effects (Kamstra et al., 2011), advertising expenses (Gallaher, Kaniel, and Starks, 2006), past market returns (Ben-Rephael, Kandel, and Wohl, 2011a) and savings (Kamstra et al., 2011). To ensure that the ambiguity measure we use is not simply capturing risk, we include a measure of market risk in our regressions. Our results show that controlling for other factors that affect changes in flows, positive changes in ambiguity are associated with reductions in capital moving into equity mutual funds, using the categorization of Kamstra et al. (2011). We show that an increase of one standard deviation in stock market ambiguity results in a capital withdrawal of $280 million in mutual fund flows and $198 million in mutual fund exchanges. In addition, when we dissect equity flows into different categories, we find that the effect of ambiguity is concentrated in funds classed as 'aggressive growth' and 'growth', which are the those that invest in more ambiguous firms, and hence more likely to be eschewed by investors in periods of high ambiguity. Although our primary hypothesis is about equities we also examine whether ambiguity has an effect on funds that invest in other asset classes. We find that that it does not affect mutual fund flows into hybrid, government fixed income, corporate fixed income or money market funds. However, there is some evidence that ambiguity is positively related to mutual fund exchanges into money market funds. Since money market funds can only hold short-term fixed income securities that mature within 397 days and hence have better liquidity, a plausible explanation for this is that investors are seeking a more liquid asset class to circumvent long-term ambiguity.

Our study contributes to the literature by examining empirically the prediction made by several theoretical studies, that ambiguity aversion deters investors from entering the stock market (Dow and Werlang, 1992; Mukerji and Tallon, 2001; Easley and O'Hara, 2009; Epstein and Schneider, 2010; Werner, 2011; Takashi, 2011). Our evidence supports these theories, highlighting that limited-participation is related to ambiguity and ambiguity aversion. More broadly, our results support the notion that the equity premium puzzle, first documented by Mehra and Prescott (1985), is related to ambiguity as suggested by several authors (Epstein and Wang, 1994; Chen and Epstein, 2002; Collard et al., 2012; Anderson, Ghysels and Juergens, 2009).

The literature on ambiguity in financial markets has thus far mainly concentrated on the theoretical tools of analysis (for reviews of this literature, see Epstein and Schneider, 2010, and Mukerji and Tallon, 2003). It is important, however, to empirically test the predictions of these theories, and thus far the literature has relied mainly on the experimental tools of analysis (Camerer and Kunreuther, 1989; Sarin and Weber, 1993; Ahn et al., 2009; Bossaerts et al., 2010). More recently, however, several studies bring the predictions of the theoretical literature to financial data. Anderson, Ghysels and Juergens (2009) show that market returns exhibit a significant ambiguity premium, which is stronger than the risk premium. Antoniou, Galariotis and Read (2012) examine the response of investors to ambiguous information, as discussed theoretically in Epstein and Schneider (2008), and Kelsey, Ford and Pang (2010) analyze the link between violations of weak form market efficiency and ambiguity (see also the theoretical discussion by Caskey, 2009). Our study shows that ambiguity affects market participation. These studies highlight that ambiguity has important effects on financial markets that cannot be captured by the EU model.

The next section reviews the relevant literature in more detail and develops the hypothesis. The third section describes the data, the fourth presents and discusses the empirical analysis and the final section concludes the paper.

2. Hypotheses Development

In this section we use a simple model to develop our hypothesis. We begin with the basic EU model and then extend it to show how ambiguity can affect market participation. Our exposition follows Banerjee and Green (2012).

The economy has a representative agent and two assets: a risk free asset and a risky asset. The gross risk-free rate is normalized to $R \equiv 1 + r > 1$. The risky asset pays a stream of *i.i.d.* dividends $d_t \sim N(\mu, \sigma^2)$. The aggregate supply of the risky asset is constant and equal to *Z*. The price of the risky asset at time *t* is P_t and the dollar return is denoted:

$$Q_{t+1} = P_{t+1} + d_{t+1} - RP_t \tag{1}$$

The representative investor has standard mean-variance preferences over next period's wealth and submits a limit order x_t for the risky asset such that:

$$x_t = \arg\max \mathbb{E}_t\, [W_t R + xQ_{t+1}] - \frac{a}{2} var_t[W_t R + xQ_{t+1}] \tag{2}$$

where $\mathbb{E}_t[.]$ and $var_t[.]$ denote the conditional expectation and conditional variance of next period's wealth, respectively, given date *t* information, W_t is the wealth invested in the risk free asset, and α is the coefficient of risk aversion. The optimal demand for the risky asset is:

$$x_t = \frac{\mathbb{E}_t[Q_{t+1}]}{avar_t[Q_{t+1}]} \tag{3}$$

where x_t reflects the investor's market participation at time *t*. x_t increases in expected returns and decreases in variance (proportionately to risk aversion).

In this model it is implicitly assumed that the decision maker faces no ambiguity about the probability distribution that describes the risky asset's future payoffs. Even if these probabilities are not objectively known, as is usually the case, the Ramsey-Savage axioms imply that the decision maker is able to arrive at some subjective conditional probability distribution for the asset payoffs, so the usual pricing formula continues to hold. Ambiguity, however, is a situation in which the decision maker does not have enough information to arrive at a single probability distribution and faces a situation where multiple likelihoods can arise.

To illustrate the concept of ambiguity and itsimpact on choices we provide the following example, adapted from Ellsberg's (1961) seminal work. After we discuss this simple example we extend the above model to illustrate the effect of ambiguity onmarket participation. Assume we have two urns with 100 balls in each. The first urn contains 50 red and 50 black balls, whereas the second contains red and black balls in unknown proportions. Thus the first urn is 'risky' in the sense that there is no ambiguity about the probability distribution that describes its contents. However, the second is ambiguous since many different distributions are possible (i.e., 0 red and 100 black, 1 red and 99 black, etc). Note that there is no way for the agent to resolve this ambiguity and determine with certainty the distribution that describes the contents of the second urn.

Suppose that a decision maker is paid an amount *c* if he bets on an event that actually occurs (i.e., a draw of a ball from either urn). This decision maker is presented with the following options:

Bet A: bet on red from the first urn **Bet B:** bet on red from second urn

After a choice is made between Bets A and B the decision maker is faced with two more choices:

Bet C: bet on black from the first urn **Bet D:** bet on black from second urn

Experimental evidence shows that the majority of people prefer bet A over bet B (A>B), which suggests a belief that *pr*(black ball from second urn) >*pr*(black from first urn). However, when presented with the second choices the majority of people choose bet C over bet D, suggesting the opposite. This pattern of choices violates the Ramsey-Savage axioms.

The evidence indicates that agents always view the payoffs from ambiguous gambles *pessimistically*, behaving as if the probability distribution that describes their payoffs is the one under the worst case scenario. To illustrate, the expected utility of bet B is *pr*(red from second urn) x U(c), where $pr(\text{red from second urn}) \in [0,1]$. The choice made above (i.e., A>B) can be rationalized if bet B is viewed as having an expected utility consistent with *pr*(red from second urn) equal to 0 (and similarly for bet D).

Returning to the model above, we assume that the agent faces ambiguity about the expected return of the risky asset, so that $\mathbb{E}_t\left[Q_{t+1}^j\right] \in [Q_{t+1}^{MIN}, Q_{t+1}^{MAX}]$ with $j = MIN, .., MAX$. For simplicity we model beliefs only[4] and assume that the agent faces ambiguity only about the mean return of the asset and not its variance.[5] We also assume that $\mathbb{E}_t\left[Q_{t+1}^j\right]$ is always positive. The level of ambiguity faced by the agent is captured by the distance $[Q_{t+1}^{MIN}, Q_{t+1}^{MAX}]$. When the distance increases, the agent faces more ambiguity and therefore becomes more pessimistic as Q_{t+1}^{MIN} becomes lower.

The actual risk premium, $\mathbb{E}_t[Q_{t+1}^{ACTUAL}]$, lies in between $\mathbb{E}_t[Q_{t+1}^{MIN}]$ and $\mathbb{E}_t[Q_{t+1}^{MAX}]$. If, as postulated by Savage, the agent could determine its actual value[6] market participation would equal:

$$x_t^{NA} = \frac{\mathbb{E}_t[Q_{t+1}^{ACTUAL}]}{avar_t[Q_{t+1}]} \tag{4}$$

However, if the agent cannot resolve the ambiguity (as explained in the above thought experiment) market participation for the ambiguity averse investor will be determined according to the worst case risk premium:

[4]Various axiomatic models have been proposed that capture ambiguity aversion. Such models are the multiple priors model (Gilboa and Schmeidler 1989), the smooth ambiguity model (Klibanoff, Marinacci and Mukerji. 2005) and variational preferences (Maccheroni, Marinacci and Rustichini, 2006). All these models embed the simple idea of pessimism discussed in Ellsberg (1961).
[5]This is the assumption made by Anderson, Ghysels and Juergens (2009) when they construct their empirical measure of ambiguity.
[6] Savage did not assume that agents are Bayesian and use the objectively correct probabilities when making decisions. He only demonstrated that if their utility function obeys certain axioms, then their choices are consistent with some subjective probability about future events. He did not impose any structure on the algorithm that generates these subjective probabilities. To ease exposition in our model we assume that the agent is Bayesian.

$$x_t^A = \frac{\mathbb{E}_t[Q_{t+1}^{MIN}]}{avar_t[Q_{t+1}]} \tag{5}$$

It follows that market participation in the face of ambiguity is lower, i.e., $x_t^A < x_t^{NA}$, since the agent is pessimistic about the market's expected return. This analysis indicates that we should observe a negative relationship between market participation and ambiguity about the risk premium.

3. Data

3.1 Mutual Fund Flows and Exchanges

Our main source of fund data, the Investment Company Institute (ICI) provides detailed information about the monthly flows to thirty mutual funds investment categories. Our sample covers the period January 1984 to December 2010. For each fund category, ICI reports monthly data on sales, redemptions, exchanges, reinvested distributions and total net assets. We divide the thirty ICI investment objective categories into five groups by asset class using the categorization proposed by Kamstra et al. (2011), namely equity, hybrid, corporate fixed income, government fixed income and money market. Our main focus is the equity asset class; since the ambiguity measure that we construct below is based on the U.S. stock market, we omit the equity investment objective categories that represent investments that are mainly outside of the U.S., i.e. 'global equity', 'international equity', 'regional equity' and 'emerging markets'. Our equity asset class therefore comprises funds within the 'aggressive growth', 'growth', 'sector', 'growth and income', and 'income equity' investment objective categories. We also omit the non-U.S. investment objective categories for the corporate fixed income asset class, i.e. 'global bond – general', 'global bond – short term' and 'other world bond'. In Table 1 we report the classification of funds by investment objective category.

(Table 1 here)

We compute the net cash inflow into asset class *i* in month *t* as

$$Net\ Flow_{i,t} = \frac{Sales_{i,t} - Redmptions_{i,t} + Exchanges\ In_{i,t} - Exchanges\ Out_{i,t}}{TotalNetAssets_{i,t-1}} \tag{6}$$

Similarly we compute the net exchange into asset class *i* in month *t* as

$$Net\ Exchange_{i,t} = \frac{ExchangesIn_{i,t} - ExchangesOut_{i,t}}{TotalNetAssets_{i,t-1}} \tag{7}$$

Figure 1 plots the net flows and exchanges for the equity group of funds. Net flows and exchanges into equity were very much more volatile before 1993, with a large flow out of the equity asset class following the October 1987 crash. Since 1994, net flows and net exchanges have been less volatile, but also declining. Panel A of Table 2 reports summary statistics for the net flows and exchanges for the equity asset class. The average net flow is 0.51%, representing a substantial increase in total net assets over the sample, while the average net exchange is close to zero. Net exchanges are negatively skewed and strongly leptokurtic, while net flows have much lower skewness and kurtosis.

(Figure 1 here)

(Table 2 here)

3.2 Ambiguity

We construct the same measure of ambiguity used by Anderson, Ghysels and Juergens (2009), which is the beta-weighted dispersion of analysts' implied forecasts of the real market return. The raw data are taken from the Federal Reserve's Survey of Professional Forecasters (SPF), which reports the individual forecasts made by large financial institutions of a number of U.S. economic and financial variables, for a range of forecast horizons including the last quarter (the actual value of which may not have been published at the time the forecast is made) and the following four quarters, as well as for annual and longer horizons. The forecast data is available on a quarterly basis from 1968, and represents the views of between a minimum of nine and a maximum of 74 participants. Following Anderson, Ghysels and Juergens (2009), we use forecasts of aggregate output, the output deflator, and corporate profits after taxes.[7] We first calculate an approximation of the forecast at time *t* of real aggregate corporate profit at time *t*+1 for forecaster *i* as:

$$E_{it}(\pi_{t+1}) = \frac{E_{it}(\tau_{t+1})E_{it}(P_t)}{E_{it}(P_{t+1})} \tag{8}$$

where π_t is the real aggregate corporate profit level at time *t*, P_t is the GDP deflator at time *t*, τ_t is the nominal corporate profit level at time *t*. We then use the Gordon growth model to obtain the implied forecast at time *t* of the market return at time *t*+1:

$$E_{it}(r_{t+1}) = E_{it}\left(\frac{\pi_{t+1}}{q_t}\right) + \xi_{it} \tag{9}$$

where q_t is the aggregate market value in the U.S., obtained from the *Flow of Funds Accounts of the United States*, published by the Federal Reserve, ξ_{it} is the forecast at time *t* for forecaster *i* of the gross real growth rate of corporate profits, which is calculated as the approximate forecast gross growth rate from last quarter to three quarters ahead:

$$\xi_{it} = \left(\frac{E_{it}(\tau_{t+3})E_{it}(P_{t-1})}{E_{it}(\tau_{t-1})E_{it}(P_{t+3})}\right)^{1/4} \tag{10}$$

The forecast market return is computed every quarter from 1985Q1 to 2010Q4, for all available forecasters. We then calculate the beta-weighted dispersion of the forecast market return each quarter across individual forecasters. Define f_t as the number of forecasts available in quarter *t*. In each quarter *t*, we rank the f_t forecasts from high to low, and assign a weight to the i^{th} lowest forecast of:

$$W_{it}(v) = \frac{i^{v-1}(f_t+1-i)^{v-1}}{\sum_{j=1}^{f_t} j^{v-1}(f_t+1-i)^{v-1}} \tag{11}$$

[7]Output is defined as Gross National Product (GNP) before 1992Q1 and Gross Domestic Product (GDP) thereafter. Similarly, the output deflator is the GNP deflator before 1992Q1 and the GDP deflator thereafter.

where the parameter v determines the shape of the weight function: if v =1 the forecasts are equally weighted, while higher values of v gives less weight to extreme forecasts. Our quarterly ambiguity measure is given by:

$$amb_t(v) = \sum_{i=1}^{f_t} W_{it}(v)[x_{it+1|t} - \sum_{i=1}^{f_t} W_{it}(v)x_{it+1|t}]^2 \quad (12)$$

In the empirical analysis, we use $v = 15.346$, which is the value used by Anderson, Ghysels and Juergens(2009).

The fund flow data is recorded monthly. To maximise the number of observations in our sample, we convert the quarterly ambiguity series into a monthly series using linear interpolation. We consider the change rather than the level of ambiguity in our models because our hypothesis is that the degree of equity market participation, as measured by total net assets held by mutual funds, is determined by the level of ambiguity, and so fund flows, which represent changes in total net assets, are determined by changes in ambiguity. In equilibrium, for a given level of ambiguity, fund flows will be zero, and so positive (negative) fund flows arise from decreases (increases) in ambiguity. Figure 2 plots the quarterly ambiguity measure and the changes in the monthly interpolated series. There are large increases in ambiguity 1993 and 2004, corresponding to the recent troughs in the business cycle. Panel B of Table 2 reports summary statistics for the constructed ambiguity series and for changes in the monthly, interpolated series. Both series are moderately positively skewed and leptokurtic.

(Figure 2 here)

3.4 Control Variables

Conditional Volatility

To ensure that the ambiguity measure is not just capturing risk, we include a measure of conditional volatility in the model, following Andersen, Ghysels and Juergens (2009). In particular, we compute the weighted variance of past squared excess market returns. The weight for i^{th} lag is given by:

$$l_i(\omega) = \frac{(s+1-i)^{\omega}}{\sum_{j=1}^{s}(s+1-j)^{\omega}} \tag{13}$$

where *s* is the minimum number of available trading days for the previous 12 months over the entire sample, and the parameter ω determines the speed at which the weights decline as the lag length increases. In the empirical analysis, we follow Anderson, Ghysels and Juergens (2009) and use $\omega = 14.939$. The conditional variance is then given by:

$$cvar_t(\omega) = s\sum_{i=1}^{s} l_i(\omega)\left(r_{et,i} - \frac{1}{s}\sum_{j=1}^{s} r_{et,j}\right)^2 + 2s * \sum_{i=1}^{s-1}\sqrt{l_i(\omega)l_{i+1}(\omega)} * \left(r_{et,i} - \frac{1}{s}\sum_{j=1}^{s} r_{et,j}\right)\left(r_{et,i+1} - \frac{1}{s}\sum_{j=1}^{s} r_{et,j}\right) \tag{14}$$

where $r_{et,i}$ is the market excess return at *i*th lag, which is computed as the daily CRSP value-weighted index (series VWRETD) return minus the daily return of the three month T-bill. Figure 3 plots the monthly conditional variance together with the monthly ambiguity, for the period January 1985 to December 2010. It is clear that the two series capture very different dimensions of the market, with periods when ambiguity is high but conditional variance is low, and vice versa. The first row of Panel C of Table 2 reports summary statistics for conditional variance. As expected, the conditional variance is highly positively skewed and leptokurtic. Similar to ambiguity, we use the changes in monthly conditional variance in our regression, and the second row of Panel C of Table 2 reports the descriptive statistics for this series. It can be seen that changes in conditional variance are also positively skewed and leptokurtic.

(Figure 3 here)

Other Control Variables

There are a number of other factors that have been shown to be important in explaining mutual fund flows, including past fund returns (Ippolito,1992;Sirri and Tufano, 1998), capital gains (Kamstra et al., 2011), past flows (Ben-Rephael, Kandel and Wohl, 2011b), seasonal effects (Kamstra et al., 2011), advertising expenses (Gallaher, Kaniel and Starks, 2006), past market returns (Ben-

Rephael, Kandel and Wohl, 2011a) and savings (Kamstra et al., 2011). We capture serial correlation in fund flows by including lagged monthly net flows and net exchanges for the past one, three, six and 12 months. We include the personal savings rate from the Bureau of Economic Analysis (series PSAVERT). The data on capital gains and advertising cost is from Kamstra et al. (2011).[8] We include the aggregate return of the equity fund group over the previous 12 months to capture return-chasing behaviour and, following Ben-Rephael, Kandel and Wohl (2011b) and Oh and Parwada (2007), we also include the aggregate market return over the last three months. Finally, we include dummy variables for the months of November, December, January and February to capture the year-end effect. Panel C of Table 2 reports summary statistics for the control variables over the period January 1985 to December 2010. Table 3 reports the correlations between the variables, and we can see that the changes in ambiguity series is negatively correlated withboth net fund flow and net fund exchanges.

(Table 3 here)

4. Results

In this section, we report the results of the empirical analysis. We first focus on the equity asset class, and then consider the effects of ambiguity on non-equity fund flows and exchanges. Finally we evaluate the economic significance of our results.

4.1 Ambiguity and Equity Fund Flows

We estimate the relationship between net flows and changes in ambiguity, controlling for risk, advertising costs, capital gains, lagged fund returns, current and lagged market returns, lagged net flows, savings, and the end-of-year dummy variables. The regression for net flows is given by:

$$\begin{aligned} netflow_t = {} & a_0 + a_1 \Delta amb_t + a_2 \Delta cvar_t + a_3 adv_t + a_4 cap_t + a_5 ret_{t-12,t}^{fund} + a_6 ret_{t-3,t}^{mkt} \\ & + a_7 netflow_{t-1} + a_8 netflow_{t-3} + a_9 netflow_{t-6} \\ & + a_{10} netflow_{t-12} + a_{11} sav_t + a_{12} Jan_t + a_{13} Feb_t + a_{14} Nov_t + a_{15} Dec_t + \varepsilon_t \quad (15) \end{aligned}$$

[8] The data on capital gains is from Table 1 of Kamstra et al. (2011), and we would like to thank the authors for kindly providing us with the data on advertising costs.

where adv_t is the aggregate cost of print advertising across all funds divided by the previous year's total advertising cost, cap_t is the capital gains, sav_t is the personal savings rate, $ret_{t-12,t}^{fund}$ is the aggregate fund return of the previous year, $ret_{t-3,t}^{mkt}$ is the return on the value-weighted CRSP index over the last 3 months, and $\mathrm{Jan_t}$, $\mathrm{Feb_t}$, $\mathrm{Nov_t}$, and $\mathrm{Dec_t}$ are dummy variables that are equal to one in the respective month and zero otherwise. Following Kamstra et al. (2011), we estimate (15) simultaneously as a system for all five asset classes by Hansen's (1982) GMM, with Newey and West (1994) heteroscedasticity and autocorrelation consistent standard errors.

For net exchanges, we estimate a similar model, but exclude the liquidity variables (savings and the dummy variables for January, February, November and December) since, in contrast with flows, which represent the transfer of wealth between cash and the fund investment, exchanges represents investors' preferences for different asset classes, and are hence not a reflection of liquidity demands. The model for net exchanges is therefore given by

$$\begin{aligned} netexchange_t = {} & a_0 + a_1 \Delta amb_t + a_2 \Delta cvar_t + a_3 adv_t + a_4 cap_t + a_5 ret_{t-12,t}^{fund} + a_6 ret_{t-3,t}^{mkt} \\ & + a_7 netexchange_{t-1} + a_8 netexchange_{t-3} + a_9 netexchange_{t-6} \\ & + a_{10} netexchange_{t-12} + \varepsilon_t, \qquad (16) \end{aligned}$$

Again, (16) is estimated as a system for all five asset classes by GMM with heteroscedasticity and autocorrelation consistent standard errors.

Panel A of Table 4 reports the results of estimating model (15) for net flows, for the equity asset class. The coefficient on the change in ambiguity is negative and significant at conventional levels. Therefore, in support of our hypothesis, an increase in ambiguity is associated with a net outflow of capital from equity mutual funds. In contrast, changes in conditional variance do not have a statistically significant impact on net flows. The savings variable and the dummy variables for January and December all have significantly positive coefficient estimates, which is consistent with a liquidity explanation for fund flows. The coefficients for the February and November dummy variables are positive but not significant. The coefficients on advertising is also consistent with previous findings (Kamstra et al., 2011), with net fund flows into equity positively associated with advertising costs. The first two lags of net fund flows are positive and significant, consistent with the strong autocorrelation in flows. Overall, the model has a strong explanatory power, and is able to explain as much as 55 percent of the variation in net fund flows.

(Table 4 here)

Panel B of Table 4 reports the estimation results from (16) for net exchanges for the equity asset class. As with net flows, changes in ambiguity are negatively associated with net exchanges, and this relationship is statistically significant. Again, changes in risk have a negative but insignificant impact.[9] The second lag of net exchanges is positive and statistically significant, reflecting the strong autocorrelation in the series. Consistent with previous findings, advertising is significantly positive (Gallaher, Kaniel, and Starks, 2006), but the coefficient on capital gains is not significantly different from zero.

The results for the equity asset class therefore suggest that an increase in ambiguity has a negative and statistically significant impact on net flows and net exchanges into U.S. equity mutual funds, supporting our hypothesis that increases in ambiguity lead to a reduction in equity market participation. Moreover, while there is a clear link between ambiguity and net fund flows and exchanges, the impact of risk is not statistically significant. These results are consistent with Anderson, Ghysels and Juergens (2009), who show that excess market returns have a strong positive association with ambiguity, but a much weaker association with conditional variance, implying that investors' risk aversion is dominated by their ambiguity aversion.

4.2 Ambiguity, Equity Fund Flows and Investment Objective

We now investigate the relationship between ambiguity and fund flows by investment objective. The equity asset class comprises five investment objective categories: 'aggressive growth',

[9] We have experimented with alternative measures of risk, including realized variance and realized excess variance. The results show that risk remains insignificant but our conclusion about ambiguity holds regardless the risk measure.

‘growth’, ‘sector’, ‘growth and income’ and ‘income equity’. According to the ICI definition, ‘aggressive growth’ funds invest primarily in common stocks of small growth companies, while ‘growth’ funds invest primarily in the stocks of companies with above-average risk for potentially above-average gains. ‘Aggressive growth’ and ‘growth’ funds invest in companies that typically pay small or no dividends, and whose stock prices tend to be more volatile. ‘Sector’ funds invest primarily in companies in related fields while ‘growth and income’ funds invest primarily in common stocks of established companies with the potential for growth and a consistent record of dividend payments. ‘Income equity’ funds invest primarily in equity securities of companies with a consistent record of dividend payments, and seek income rather than capital appreciation.

As has been argued in the literature, growth firms entail more ambiguity (Bossaerts et al 2010). We expect, therefore, that increases in ambiguity will result in greater capital outflows and exchanges out from ‘aggressive growth’ and ‘growth’ mutual funds that invest in more ambiguous assets. To test this hypothesis we estimate models (15) and (16) for the individual equity investment objective categories.

The results are shown in Panel A of Table 5. For brevity, the table reports only the estimated coefficient on the change in ambiguity. For the ‘aggressive growth’ and ‘growth’ categories, the coefficient on the change in ambiguity is negative and statistically significant. For the ‘growth and income’ and ‘income equity’ categories, the coefficient is negative but not significant, while for the ‘sector’ category, the coefficient is insignificantly positive. Panel B of Table 5 reports the corresponding results for net exchanges by investment object category, and the results are broadly similar, with significantly negative coefficients on the ‘aggressive growth’ and ‘growth’ categories and a positive (although not quite significant) coefficient on the ‘sector’ category. Therefore, while our earlier results show that an increase in ambiguity leads to flows and exchanges out of the equity asset class as a whole, we can see that within the equity asset class, the effect is concentrated in the funds that invest in the most ambiguous assets, supporting our hypothesis.

(Table 5 here)

4.3 Ambiguity and Non-Equity Fund Flows

Although our main hypothesis is related to stock market participation, we also examine the relationship between changes in ambiguity and non-equity asset classes. It is reasonable to assume that in response to an increase in ambiguity in the stock market, investors will transfer funds into less ambiguous, non-equity investments. Panel A of Table 6 reports the estimated coefficient on the change in ambiguity from the net flows model (15) for all five asset classes, while Panel B reports the estimated coefficient for the net exchanges model (16). For net flows the coefficients on ambiguity for non-equity asset classes are not significantly different from zero. For net exchanges, however, the coefficient for the money market asset class is positive and significant. Thus, as ambiguity increases, investors withdraw capital from equity funds and reinvest, at least partially, in money market funds. According to the ICI definition, money market funds have assets that will receive full principal and interest within 397 days, with the weighted average of all assets' repayment time not exceeding 120 days. Since our ambiguity measure is based on the market's forecast of long-term growth, one possible explanation for this is that investors are seeking assets with higher liquidity in order to reduce their exposure to long-term ambiguity.

(Table 6 here)

4.4 Economic Significance

The empirical analysis above shows that the relationship between fund flows and exchanges, and changes in ambiguity is statistically significant. In this section, we establish the economic significance of our findings. From Table 4, the estimated coefficient onthe change in ambiguity is -1.59 for net flows and -0.98 for net exchanges. We take the product of each of these coefficients with the monthly change in ambiguity and the lagged monthly total net asset value of the equity fund group, to yield the monthly dollar flows and exchanges that can be accounted for by changes in ambiguity, after controlling for the other factors that affect fund flows. These monthly dollar flows and exchanges over the sample January 1985 to December 2010 are plotted in Figure 4. It can be seen that after 2000, variations in ambiguity have generated significant volume for both mutual fund flow and exchanges. At its peak in 2004, more than ten billion U.S. dollars flowed out of equity funds as a result of a large increase in ambiguity. An alternative way to view the economic significance of our results is to note that the standard deviation of the ambiguity measure is 0.0013, and the average total net assetsfor equity funds is $1.9trillion; consequently, a one standard deviation change in ambiguity will on average yield a net flow of $4.0 billion and a net exchange of $2.5 billion.

(Figure 4 here)

5. Conclusion

Limited stock market participation is a longstanding puzzle in finance and many explanations have been put forward, including frictions-based and behavioural explanations. In this paper we empirically test one prominent behavioural explanation, namely that non-participation is due to ambiguity aversion (Dow and Werlang, 1992; Mukerji and Tallon, 2001; Easley and O'Hara, 2009; Epstein and Schneider 2010; Werner, 2011; Takashi, 2011).

We measure market participation with flows of capital in and out of U.S. equity mutual funds. Our measure of ambiguity is based on a recent study by Anderson, Ghysels and Juergens (2009) and reflects the dispersion in analysts' implied forecasts about market returns. Our results show that, controlling for other factors that affect fund flows, increases in ambiguity are significantly negatively related to equity fund flows and exchanges, and thus support the notion that stock market participation appears too low in the context of the basic Expected Utility model because the stock market entails ambiguity, which is disliked by investors. More broadly, our findings are consistent with the notion that the equity premium compensates investors for exposures to both risk and ambiguity (Chen and Epstein, 2002).

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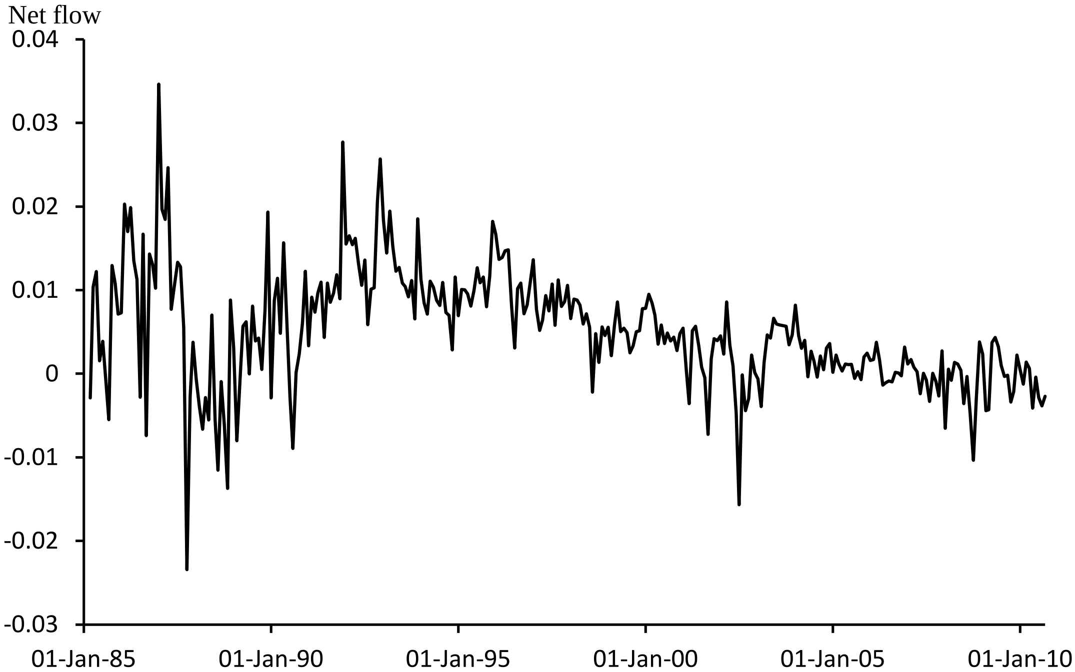
FIGURE 1. NET FLOWS AND NET EXCHANGES FOR THE EQUITY ASSET CLASS

The figure reports the monthly net flows and net exchanges for the equity asset class, which comprises funds within the 'aggressive growth', 'growth', 'sector', 'growth and income', and 'income equity' investment objective categories. The data is from ICI and covers the period January 1985 to December 2010. Net flows (reported in Panel A) and net exchanges (reported in Panel B) are calculated according to Equations (6) and (7).

Panel A. Net Flows



Panel B. Net Exchanges

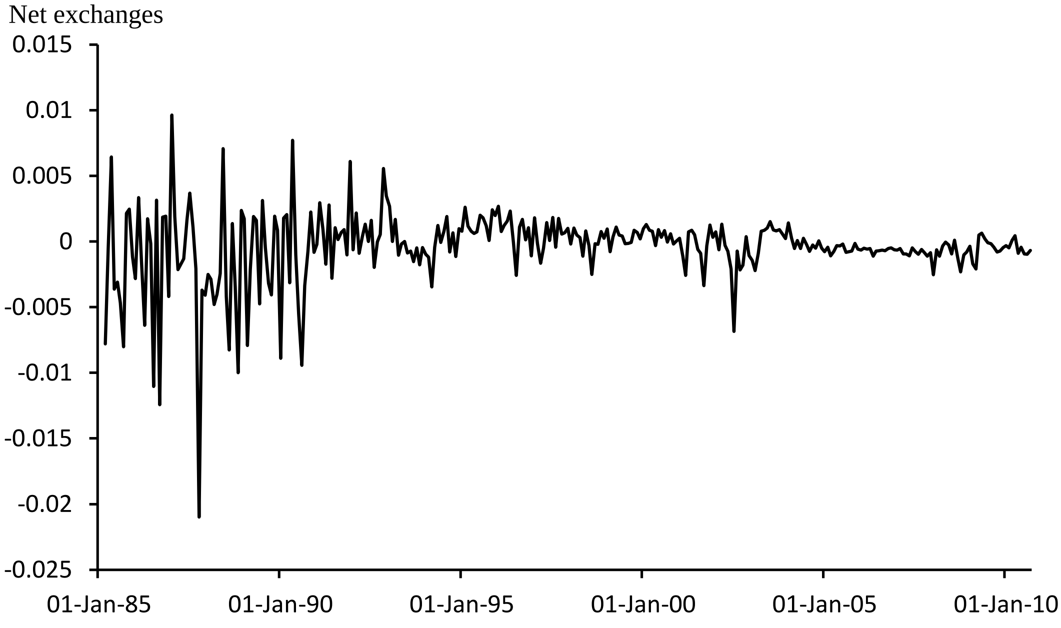
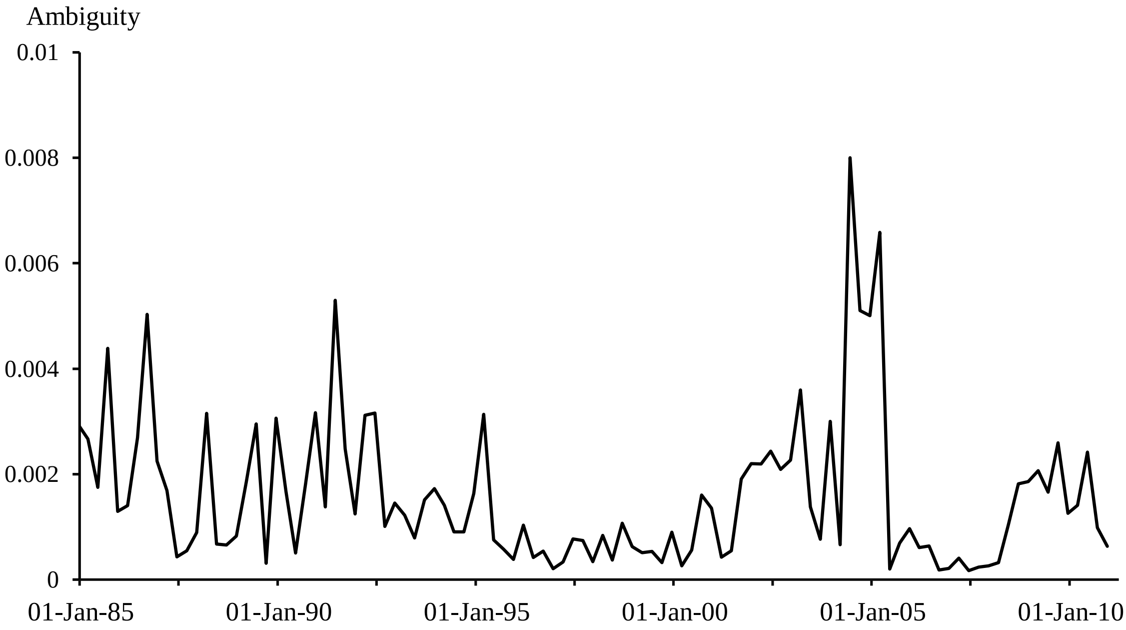


FIGURE 2. AMBIGUITY

The figure reports quarterly ambiguity and the change in monthly ambiguity, from 1985 to 2010. Quarterly ambiguity is calculated using Equation (12) with *v*=15.346. Monthly ambiguity is computed from the quarterly measure by linear interpolation. Both series are scaled by 100. Panel A reports quarterly ambiguity, and Panel B reports the change in monthly ambiguity. The forecast data is from http://www.phil.frb.org/econ/spf/index.html.

Panel A. Quarterly Ambiguity



Panel B. Changes in Monthly Interpolated Ambiguity

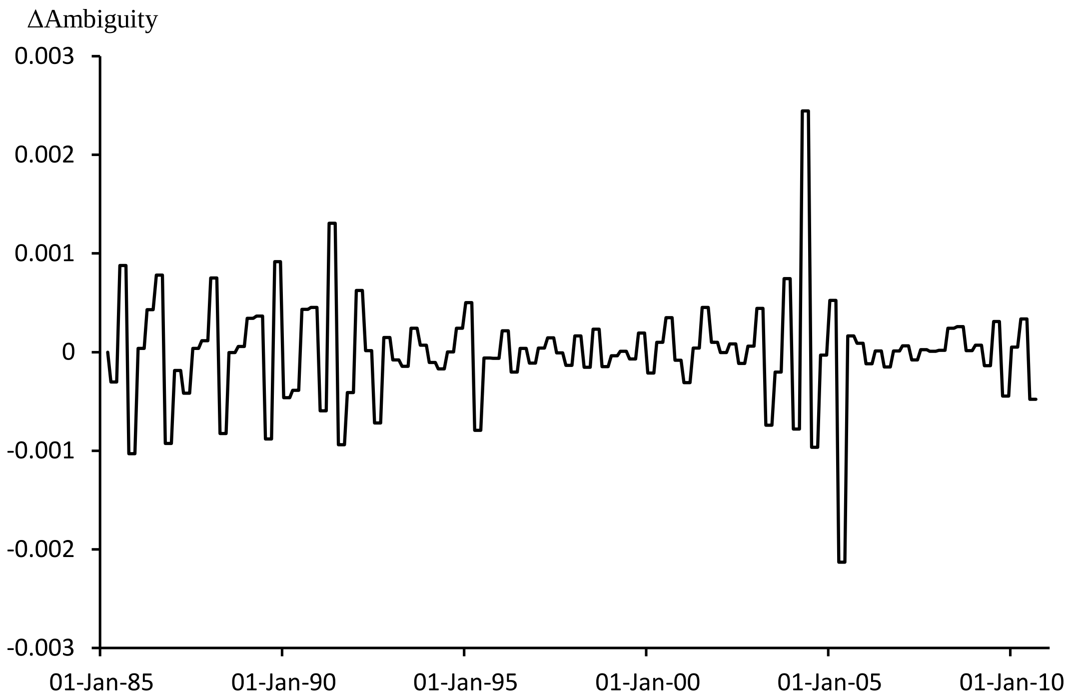


FIGURE 3. AMBIGUITY VS. RISK

The figure reports monthly ambiguity (unbroken line) and conditional variance (broken line) from January 1985 to December 2010. Conditional variance is calculated using Equation (14). The raw data is from CRSP. For comparison, ambiguity has been scaled by 5000.

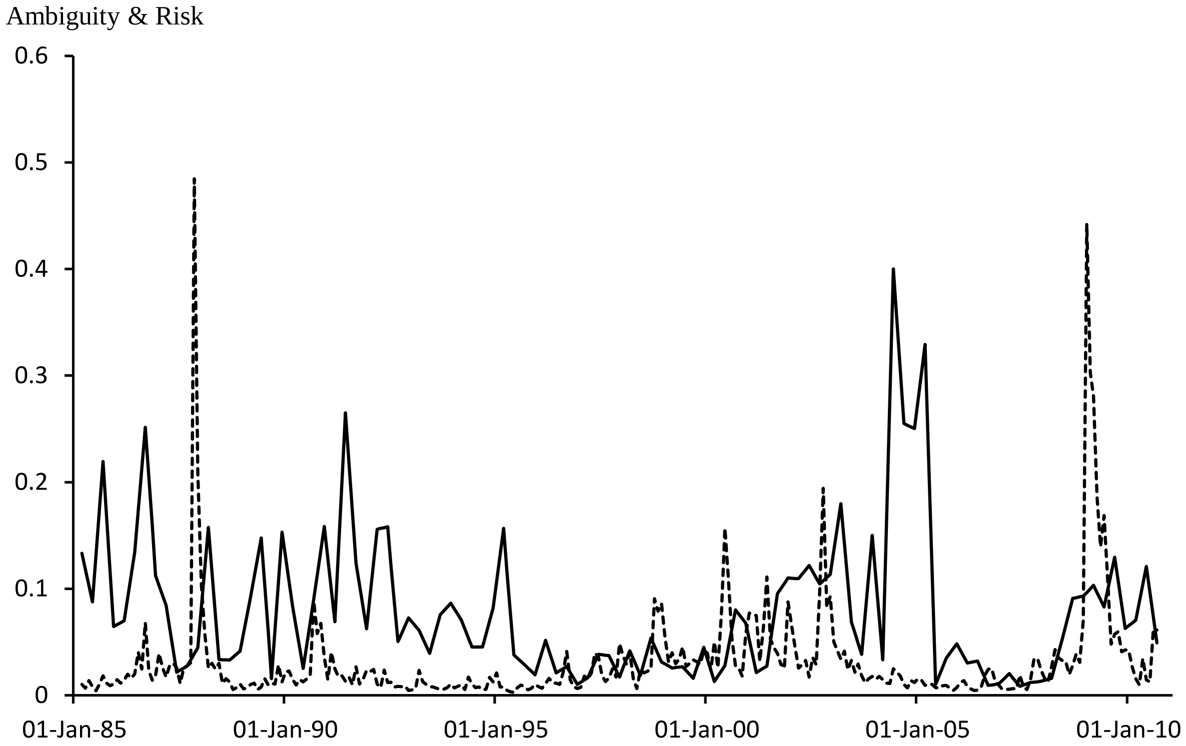


FIGURE 4. ECONOMIC MAGNITUDE

The figure reports the monthly net dollar flows and exchanges for equity funds (in millions of U.S. dollars) that are attributable to changes in ambiguity. The dollar flows and exchanges are calculated as the product of the monthly change in ambiguity, the estimated coefficient on the change in ambiguity in the net flows model (15) and the net exchanges model (16), respectively, and the lagged monthly total net assets. The solid line represents net flows and the broken line represents net exchanges.

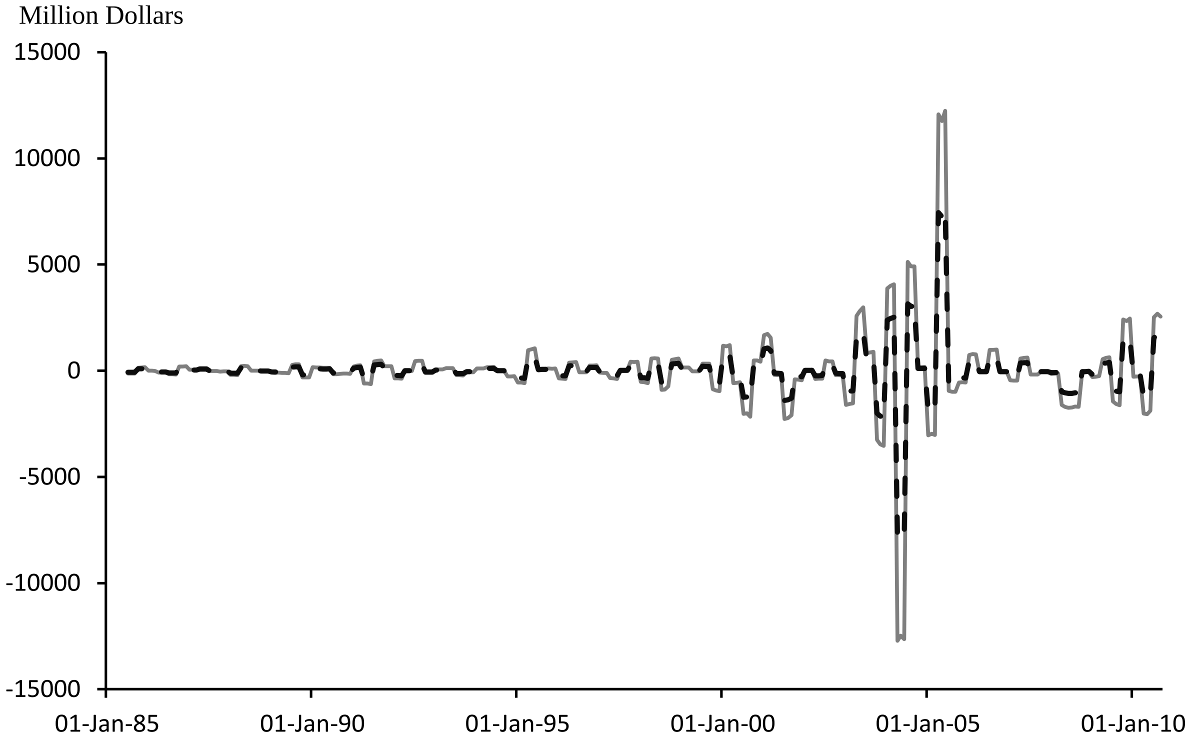


TABLE 1. CLASSIFICATION OF U.S. MUTUAL FUNDS

The table reports the categorisation of the ICI fund investment objective categories by asset class, based on Kamstra et al. (2011).

Fund Investment Objective	Fund Asset Class
Aggressive Growth	Equity
Growth	Equity
Sector	Equity
Growth and Income	Equity
Income Equity	Equity
Asset Allocation	Hybrid
Balanced	Hybrid
Flexible Portfolio	Hybrid
Income Mixed	Hybrid
Corporate - General	Corporate Fixed Income
Corporate - Intermediate	Corporate Fixed Income
Corporate - Short Term	Corporate Fixed Income
High Yield	Corporate Fixed Income
Strategic Income	Corporate Fixed Income
Government Bond - General	Government Fixed Income
Government Bond - Intermediate	Government Fixed Income
Government Bond - Short Term	Government Fixed Income
Mortgage Backed	Government Fixed Income
State Municipal Bond - General	Government Fixed Income
State Municipal Bond - Short Term	Government Fixed Income
National Municipal Bond - General	Government Fixed Income
National Municipal Bond - Short Term	Government Fixed Income
Taxable Money Market - Government	Money Market

TABLE 2. SUMMARY STATISTICS

The table reports summary statistics for the monthly net flows and net exchanges for the domestic equity funds group (Panel A), ambiguity and changes in ambiguity (Panel B) and the control variables (Panel C), for the period January 1985 to December 2010. amb_t is ambiguity and $cvar_t$ is conditional variance, and are calculated according to equations (12) and (14), respectively. Ambiguity is scaled by 100. $\Delta cvar_t = cvar_t - cvar_{t-1}$ and $\Delta amb_t = amb_t - amb_{t-1}$. adv_t is the aggregate cost of print advertising across all funds, divided by the previous year's total advertising cost, $cap_t$is the capital gains in month *t*, from Kamstra et al. (2011) Table 1. sav_t is the personal savings rate taken from the Bureau of Economic Analysis (series PSAVERT). $ret_{t-12,t}^{fund}$ is the aggregate return of equity funds over the previous 12 months. $ret_{t-3,t}^{mkt}$ is the return on the CRSP value-weighted index (series VWRETD) over the last 3 months.

Panel A. Net Exchanges and Net Flows

	Mean	Std	Skew	Kurt	Max	Min
Net exchanges	-0.0004	0.0030	-2.1020	13.1690	0.0100	-0.0210
Net flow	0.0051	0.0070	0.2310	1.6820	0.0350	-0.0240

Panel B. Ambiguity

	Mean	Std	Skew	Kurt	Max	Min
amb_t	0.00158	0.00130	1.78600	4.14900	0.00008	0.00017
Δamb_t	-0.00001	0.00053	0.28900	5.91200	0.00245	-0.00213

Panel C. Control Variables

	Mean	Std	Skew	Kurt	Max	Min
$cvar_t$	0.032	0.050	5.521	39.024	0.485	0.003
$\Delta cvar_t$	0.000	0.043	4.844	62.224	0.454	-0.276
$ret_{t-12,t}^{fund}$	0.168	0.219	-0.973	0.856	0.583	-0.580
adv_t	0.086	0.012	0.809	5.950	0.144	0.038
cap_t	8.196	19.166	3.001	7.214	72.000	0.900
sav_t	0.049	0.019	0.006	-0.830	0.103	0.009
$ret_{t-3,t}^{mkt}$	0.028	0.085	-1.081	2.865	0.264	-0.367

TABLE 3. CORRELATIONS

The table reports the correlation matrix of the variables used in net flows model (15) and the net exchanges model (16) for the period January 1985 to December 2010. Net flows and net exchanges are for equity funds.

	Net flows	*Net exchanges*	ΔAmb_t	$\Delta CVar_t$	adv_t	cap_t	sav_t	$ret_{t-12,t}^{fund}$	$ret_{t-3,t}^{mkt}$
Net flows	1.000	0.658	-0.036	-0.035	-0.034	0.117	0.318	0.482	0.219
Net exchanges	0.658	1.000	-0.039	-0.033	0.057	0.039	-0.049	0.060	0.030
Δamb_t	-0.036	-0.039	1.000	0.014	0.009	0.024	-0.106	0.077	0.050
$\Delta cvar_t$	-0.035	-0.033	0.014	1.000	-0.028	0.012	0.003	0.001	-0.137
adv_t	-0.034	0.057	0.009	-0.028	1.000	-0.008	0.064	-0.112	0.021
cap_t	0.117	0.039	0.024	0.012	-0.008	1.000	0.001	0.004	-0.025
sav_t	0.318	-0.049	-0.106	0.003	0.064	0.001	1.000	0.207	0.074
$ret_{t-12,t}^{fund}$	0.482	0.060	0.077	0.001	-0.112	0.004	0.207	1.000	0.447
$ret_{t-3,t}^{mkt}$	0.219	0.030	0.050	-0.137	0.021	-0.025	0.074	0.447	1.000

TABLE 4. AMBIGUITY AND EQUITY FUND FLOWS AND EXCHANGES

The table reports the results of estimating the net flows model (15) and the net exchanges model (16) for the equity asset class, for the period January 1985 to December 2010

Panel A. Net Flows

	Estimate	Std Err	t statistic	prob>t
Intercept	-0.00678	0.00	-2.68	0.01
Δamb_t	-1.58544	0.61	-2.61	0.01
$\Delta cvar_t$	0.01663	0.04	-0.10	0.92
adv_t	0.05943	0.03	2.13	0.03
cap_t	-0.00004	0.00	-0.96	0.34
$ret_{t-12,t}^{fund}$	0.00290	0.00	1.54	0.13
$ret_{t-3,t}^{mkt}$	-0.00554	0.00	-1.46	0.14
$net\ flow_{t-1}$	0.38129	0.11	3.60	<0.001
$net\ flow_{t-3}$	0.34766	0.07	5.17	<0.001
$net\ flow_{t-6}$	-0.00593	0.08	-0.08	0.94
$net\ flow_{t-12}$	0.03612	0.05	0.75	0.45
sav_t	0.03553	0.02	1.93	0.05
Jan_t	0.00243	0.00	2.29	0.02
Feb_t	0.00120	0.00	1.39	0.17
Nov_t	0.00149	0.00	1.68	0.09
Dec_t	0.00753	0.00	3.22	<0.001

TABLE 4 (Continued). AMBIGUITY AND EQUITY FUND FLOWS AND EXCHANGES

Panel B. Net Exchanges

	Estimate	Std Err	t statistic	prob>t
Intercept	-0.00307	0.00	-2.30	0.02
Δamb_t	-0.97689	0.41	-2.38	0.02
$\Delta cvar_t$	-0.00499	0.03	-0.61	0.54
adv_t	0.03148	0.02	2.03	0.04
cap_t	0.00001	0.00	0.97	0.33
$ret_{t-12,t}^{fund}$	0.00050	0.00	0.56	0.57
$ret_{t-3,t}^{mkt}$	-0.00188	0.00	-0.87	0.39
$net\ exc\hbar ange_{t-1}$	0.08147	0.10	0.78	0.43
$net\ exc\hbar ange_{t-3}$	0.20566	0.09	2.33	0.02
$net\ exc\hbar ange_{t-6}$	0.10355	0.08	1.20	0.23
$net\ exc\hbar ange_{t-12}$	-0.01656	0.06	-0.27	0.79

TABLE 5. AMBIGUITY AND FUND OBJECTIVES

The table reports the estimated parameter on the change in ambiguity in the net flows model (15) and the net exchanges model (16) for individual ICI investment objective categories. Panel A reports the results for net flows and Panel B reports the results for net exchanges.

Panel A. Net Flows

Fund type	Parameter	Estimate	Std Err	t statistic	prob>t
Aggressive growth	$\Delta ambiguty_t$	-5.12	2.04	-2.51	0.01
Growth	$\Delta ambiguty_t$	-1.82	0.69	-2.63	0.01
Growth and income	$\Delta ambiguty_t$	-0.48	0.45	-1.06	0.29
Income equity	$\Delta ambiguty_t$	-0.70	0.65	-1.08	0.28
Sector	$\Delta ambiguty_t$	0.38	1.97	0.19	0.85

Panel B. Net Exchanges

Fund type	Parameter	Estimate	Std Err	t statistic	prob>t
Aggressive growth	$\Delta ambiguty_t$	-3.51	1.56	-2.25	0.03
Growth	$\Delta ambiguty_t$	-1.30	0.53	-2.47	0.01
Growth and income	$\Delta ambiguty_t$	-0.05	0.12	-0.38	0.71
Income equity	$\Delta ambiguty_t$	-0.56	0.27	-2.06	0.04
Sector	$\Delta ambiguty_t$	0.97	1.31	0.74	0.46

TABLE 6. AMBIGUITY AND NON-EQUITY FUNDS

The table reports the estimated coefficient on the change in ambiguity for each of the five asset classes in the net flows model (15) and the net exchanges model (16) estimated over the period January 1985 to December 2010.

Panel A. Net Flows

	Estimate	Std Err	t statistic	prob>t
Equity	-1.59	0.61	-2.61	0.01
Hybrid	-0.65	0.56	-1.16	0.25
Government Fixed Income	-0.72	0.60	-1.20	0.23
Corporate Fixed Income	-0.96	0.61	-1.56	0.12
Money Market	1.05	1.17	0.91	0.37

Panel B. Net Exchanges

Fund family	Estimate	Std Err	t statistic	prob>t
Equity	-0.98	0.41	-2.38	0.02
Hybrid	-0.03	0.07	-0.46	0.64
Government Fixed Income	-0.34	0.19	-1.77	0.08
Corporate Fixed Income	-0.36	0.29	-1.23	0.22
Money Market	0.38	0.14	2.83	<0.001