Ambiguity Aversion and Stock Market Participation: Evidence from Fund Flows

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June 2013

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 eight percent over treasury bills (Mehra, 2003). Given this equity premium the canonical expected-utility model (EU) predicts that agents with reasonable risk-aversion 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 reconcile 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 explanations cannot 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; Cao, Wang and Zhang, 2005; 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

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

many studies in experimental 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 Factbook, 2012). Therefore, flows in and out of mutual funds reflect the active reallocation decisions of individual investors, and thus provide a direct measure of market participation.[4]

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 multiple distributions of expected returns are plausible,

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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 (Ahn et al., 2011), 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. Grinblatt, Keloharju and Linnainmaa (2011) show that cognitive ability also relates to market participation decisions.

[4] This measure does not capture total stock market participation decisions, however, as it omits households that invest in stocks directly.

and that investors cannot confidently narrow down the set to the 'correct' one.[5] We discuss this measure in more detail in section 3.2 of the paper.

Using data on U.S. fund flows from the Investment Company Institute, we examine in a multivariate 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. Whilst the first measure captures stock market participation in absolute terms, the second, proposed by Ben-Rephael, Kandel and Wohl (2012), provides a stock-market participation metric that is relative to other asset classes.

In our models, 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, 2011), seasonal effects (Kamstra et al., 2011), advertising expenses (Gallaher, Kaniel, and Starks, 2006), past market returns (Ben-Rephael, Kandel, and Wohl, 2012) 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, increases in ambiguity are associated with reductions in capital moving into equity mutual funds, using the categorization of Kamstra et al. (2011). This finding confirms the prediction of the theoretical ambiguity literature, that market participation is negatively related to ambiguity aversion.

Furthermore, 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. We also analyze flows in and out of non-equity mutual funds and find that ambiguity is positively related to mutual fund exchanges into money market funds. Since money market funds

[5] Drechsler (2012) uses a very similar dispersion-based measure of ambiguity, calculated from the SPF data.

invest in safer, short-term high-grade securities, a plausible explanation for this result is that investors are seeking a safer and more liquid asset class when faced with higher ambiguity in expected equity returns.

Our study contributes to the literature that analyzes stock market participation by empirically examining the prediction made by several theoretical studies, that ambiguity 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 stock market participation is negatively related to ambiguity.

Our study also contributes to the literature that analyzes the determinants of fund flows. Jain and Wu (2000) and Kacperczyk and Seru (2007) show that fund flows are related to funds' advertising expenses and the ability of the fund manager, respectively. Ivkovich and Weisbenner (2009) show that flows are affected by past fund performance, expense ratios and loads. Cooper, Gulen and Rau (2005) show that flows are affected by catering effects via name changes, and Kamstra, Kramer, Levi and Wermers (2011) show that flows are affected by seasonal variations in risk aversion. Our study shows that flows are negatively related to ambiguity about future stock market returns.

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, Kozhan 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. Ambiguity and market participation

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:

$$x_t = \arg\max_x \mathrm{E}_t[W_t R + xQ_{t+1}] - \frac{a}{2}\mathrm{var}_t[W_t R + xQ_{t+1}] \tag{2}$$

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:

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

where x_t reflects the investor's stock 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 is able to uniquely estimate a conditional probability distribution for the asset payoffs, and is thus making a decision in conditions of risk. 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 plausibly arise.

To illustrate the concept of ambiguity and its impact on choices we provide the following example, adapted from Ellsberg's (1961) seminal work. After we discuss this example we extend the above model to illustrate the effect of ambiguity on stock market 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. The first urn is risky because the probability distribution that describes its contents is known with certainty. 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 $c>0$ 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 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 for their utility. 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). More formally, the ambiguity averse agent chooses the action that yields the maximum minimum utility. With such max-min preferences ambiguous gambles like B and D are dominated by risky gambles like A and C. For further discussion on max-min preferences see Epstein and Schneider (2010).

Returning to the model above, the agent now faces multiple possible distributions, each with a different expected return for 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[6] and assume that the conditional variance is the same for each *j*.[7] We also assume that $\mathbb{E}_t\left[Q_{t+1}^j\right]$ is always positive (we discuss this assumption in section 4.4). The Savage axioms imply that the agent, through appropriate reduction of compound lotteries, will arrive at $\mathbb{E}_t[Q_{t+1}^{Average}]$, the probability weighted average for the expected risk premium, which lies somewhere in between $\mathbb{E}_t[Q_{t+1}^{MIN}]$ and $\mathbb{E}_t[Q_{t+1}^{MAX}]$.[8] In this risk-only situation market participation equals:

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

[6] 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).

[7] This is the assumption made by Anderson, Ghysels and Juergens (2009) when they construct their empirical measure of ambiguity.

[8] Savage did not assume that agents are Bayesian. He only demonstrated that if their utility function obeys certain axioms, then their choices are consistent with some subjective probability about future events, without imposing structure on the algorithm that generates these subjective probabilities. To ease exposition in our model we assume that the agent who is in a position to resolve ambiguity is Bayesian.

However, if the agent cannot assign probabilities to the possible distributions (as explained in the above thought experiment) he faces ambiguity. Being ambiguity averse he makes decisions pessimistically so stock market participation will be determined according to the worst case risk premium:

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

In conditions of ambiguity market participation is therefore lower, i.e., $x_t^{Ambiguity} < x_t^{Risk}$. The level of ambiguity faced by the agent is captured by the distance $[Q_{t+1}^{MIN}, Q_{t+1}^{MAX}]$. If this distance increases the agent faces more ambiguity and therefore becomes more pessimistic, as Q_{t+1}^{MIN} becomes lower. Therefore we should observe a negative relationship between market participation and ambiguity about expected stock returns.

3. Data

3.1 Mutual Fund Flows and Exchanges

Our main source of fund data is the Investment Company Institute (ICI), which 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, which comprises funds classified as 'aggressive growth', 'growth', 'sector', 'growth and income', and 'income equity'. Moreover, since the ambiguity measure that we construct is for the U.S. stock market, we omit the equity investment objective categories that represent investments outside of the U.S., i.e. 'global equity', 'international equity', 'regional equity' and 'emerging markets'. When we analyse flows into non-equity funds we eliminate 'global bond – general', 'global bond – short term' and 'other world bond' fund categories. 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, following Ben-Rephael, Kandel, and Wohl (2012), 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. 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 Measuring ambiguity

Ellsberg's (1961) definition of when ambiguity will arise remains the most perspicuous: "*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). Ellsberg thus views ambiguity as negatively related to what might be called the "richness" of the information that is available to compute the likelihood of interest,[9] and suggests two broad ways to empirically measure ambiguity: Either by quantifying the richness of the information directly; or by inferring this richness indirectly using as an index the disagreement between different users of the information set.

In our study we use the empirical measure of ambiguity proposed by Anderson, Ghysels and Juergens (2009) (AGJ) which is based on the latter approach. This measure reflects disagreement among experts regarding aggregate economic performance in the future. Experts analyze the available information related to the future prospects of the economy, form a subjective probability distribution and report the mean of this distribution as their forecast. High disagreement amongst these experts implies an incomplete information set and, therefore, ambiguity. [10]

The data to calculate this measure 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.[11] We first calculate an approximation of the forecast at time t of real aggregate corporate profit at time t+1 for forecaster i as:

[9] This view is common among decision theorists. Frisch and Baron (1988) proposed that "ambiguity is uncertainty about probability, created by missing information that is relevant and could be known" (P. 1988). Einhorn and Hogarth (1985) suggest that ambiguous situations arise when the available information is vague, and does not allow one to confidently rule out alternative possibilities, while Gärdenfors and Sahlin (1982, 1983) argue that feelings of ambiguity are produced when the relevance of the available information is low.

[10] Antoniou et al. (2012) use the first approach suggested by Ellsberg (1961) and measure ambiguity in the cross section of stocks by examining the extent to which analyst earnings forecast accuracy (the likelihood of interest to decision makers that price earnings forecasts) can be predicted from factors such as analyst ability, forecast timeliness, etc.

[11] 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.

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

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 (i.e., the period for which we have available fund flow data), for all available forecasters. We then follow Anderson et al (2009) and calculate a 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:

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

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:

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

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

As the SPF data are available on a quarterly basis, and the fund flow data are available only from 1985, we are left with a small sample of 102 data points, which does not allow a powerful test of our hypothesis, especially given the large number of control variables that must be included in the regressions. To circumvent this problem we convert the quarterly ambiguity series into a monthly series using linear interpolation, and conduct the analysis using monthly data.[12] To ensure, however, that this procedure has no implications for our conclusions, in our robustness checks, discussed in Section 4.3, we conduct the analysis using non-interpolated, quarterly data and obtain very similar results.

In our models we consider the change rather than the level of ambiguity 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. We estimate all our models using Newey and West (1987, 1994) heteroscedasticity and autocorrelation consistent standard errors.

Panel A in Figure 2 plots the quarterly ambiguity measure and Panel B the changes in the monthly interpolated series. Both measures produce spikes in the mid 1980s to mid 1990s and in the 2000s. 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]

[12] Specifically we calculate monthly ambiguity using quarter t and t+1 observations as follows: $amb_{t,i} = amb_t + \frac{i}{3} * (amb_{t+1} - amb_t), i = 1,2,3$, where i stands for the i^{th} month of quarter t.

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:

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

$$1sj=1sret,jret,i+1-1sj=1sret,j \tag{14}$$

where $r_{et,i}$ is the market excess return at ith 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 March 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. Table 2 reports summary statistics for conditional variance. As expected, the conditional variance is highly positively skewed and leptokurtic. As with ambiguity, we use the changes in monthly conditional variance in our regression, and 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, 2011), seasonal effects (Kamstra et al., 2011), advertising expenses (Gallaher, Kaniel and Starks, 2006), past market returns (Ben-Rephael, Kandel and Wohl, 2012) 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 costs is from Kamstra et al. (2011).[13] 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 (2011) and Oh and Parwada (2007), we also include the aggregate market return over the last three months. Since transaction costs and liquidity needs have been proposed as explanations for the limited participation puzzle, we include the measure of illiquidity proposed by Amihud (2002) in our regressions, which captures the responsiveness of prices to trading volume. Following Amihud (2002), for each individual stock i we define the illiquidity measure in month t as:

$$Iliquid_{i,t} = \sum_{d=1}^{j} \frac{|ret_{i,d}|}{vol_{i,d}}$$

where j is the number of the available trading days in month t, and $ret_{i,d}$ and $vol_{i,d}$ are the daily return and volume of stock i in month t, respectively. We again take the value weighted average as our measure of market level illiquidity, and use the rolling average over the previous three months' in the regressions.

Finally, we include dummy variables for the months of November, December, January and February to capture the year-end effect. Table 2 reports summary statistics for the control variables

[13] 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 expenses.

over the period March 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 with both net fund flow and net fund exchanges.

[Table 3 here]

The regression for net flows is given by:

$$netflow_t = a_0 + a_1\Delta amb_t + a_2\Delta cvar_t + a_3 adv_t + a_4 cap_t + a_5 ret_{t-12,t}^{fund} + a_6 ret_{t-3,t}^{mkt} + a_7 netflow_{t-1} + a_8 netflow_{t-3} + a_9 netflow_{t-6} + a_{10} netflow_{t-12} + a_{11} sav_t + a_{12} Ilq_{t-3,t} + a_{13} Jan_t + a_{14} Feb_t + a_{15} Nov_t + a_{16} Dec_t + \varepsilon_t \quad (15)$$

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. $Ilq_{t-3,t}$ is the average market illiquidity from the previous three months, and Jan_t, Feb_t, Nov_t, and Dec_t are dummy variables that are equal to one in the respective month and zero otherwise.

For net exchanges, we estimate a similar model, but exclude the savings variable and the seasonal dummy variables. The model for net exchanges is therefore given by:

$$netexchange_t = a_0 + a_1\Delta amb_t + a_2\Delta cvar_t + a_3 adv_t + a_4 cap_t + a_5 ret_{t-12,t}^{fund} + a_6 ret_{t-3,t}^{mkt} + a_7 netexchange_{t-1} + a_8 netexchange_{t-3} + a_9 netexchange_{t-6} + a_{10} netexchange_{t-12} + a_{11} Ilq_{t-3,t} + \varepsilon_t \quad (16)$$

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, in the last part of the section, we conduct some robustness checks.

4.1 Ambiguity and Equity Fund Flows

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 (-1.455, *p*= 0.02). 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 (-0.001, *p* =0.84). The savings variable has significantly positive coefficient (0.037, *p*=0.05), which is consistent with a "free cash flow" effect on fund flows. Consistent with previous literature (Kamstra et al, 2011) lagged net fund flows from the previous one and three months are positive and highly significant, showing strong autocorrelation in flows. The remaining variables are not significant.

[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 (-0.895, *p*=0.03). Again, changes in risk have a negative but insignificant impact (-0.002, *p*=0.52).[14] The three month lag of net exchanges is positive and statistically significant, reflecting strong autocorrelation in this series as well.

These results suggest that an increase in ambiguity has a negative and statistically significant impact on net flows and net exchanges, 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 negative but 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, and broadly imply that investors' risk aversion is dominated by their ambiguity aversion.

[14]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.

To gauge the economic significance of our results note that the standard deviation of the ambiguity measure is 0.0013 and the average total net assets for equity funds is $1.9trillion; consequently, a one standard deviation change in ambiguity will on average yield a net flow of $3.3 billion and a net exchange of $2.2 billion.

4.2 Ambiguity and Different Equity Styles

The results in the previous section show that ambiguity adversely affects overall stock market participation. However, since ambiguity varies across equities (see Kelsey et al, 2010; Brenner and Izhakian, 2011; Antoniou, Galariotis and Read, 2012), this effect will be more pronounced among funds that invest in more ambiguous stocks. In this section we test this hypothesis by investigating the relationship between ambiguity and fund flows for the five investment objective categories separately, namely ‘aggressive growth’, ‘growth’, ‘sector’, ‘growth and income’ and ‘income equity’. According to the ICI definition, aggressive growth and growth funds invest in riskier, non-dividend paying stocks with a focus on capital gains. Conversely, funds in the remaining three categories focus on less risky, dividend-paying stocks (ICI Factbook, 2012).

Dividend policy is a signal about the stability of the expected profitability of the firm. This is because firms, being concerned with the penalties associated with dividend omissions (e.g., Michaely, Thaler and Womack, 1995), tend to initiate and pay dividends when they reach a mature stage in their life cycle and thus expect to be able to consistently make these payouts in the future.[15] Conversely, firms that do not pay dividends are typically those with significant growth opportunities, and it is often quite challenging to foresee how these opportunities will develop. Therefore, on average, ambiguity is considerably higher for non-dividend payers, which in turn implies that the effect of ambiguity will be stronger among the aggressive growth and growth categories.[16]

[15] For example Denis and Osobov (2008) show that dividend payers tend to be larger and more profitable companies.

[16] Bossaerts et al (2010) also note that growth companies entail significant ambiguity.

The results for net flows 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 highly 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. The results for net exchanges are broadly similar, as shown by Panel B of Table 5. 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 more ambiguous, non-dividend paying assets.[17]

(Table 5 here)

4.3 Ambiguity and non-Equity Fund Flows

In this section we examine the relationship between changes in ambiguity and flows in funds that invest in non-equity asset classes, namely hybrid, government and corporate fixed income and money market. It is reasonable to expect that in response to an increase in ambiguity in the stock market, investors will transfer funds into less ambiguous, non-equity investments.

Panel A (B) of Table 6 reports the estimated coefficient on the change in ambiguity from the net flows (exchanges) model. For net flows the coefficients on ambiguity 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 invest in low risk, high-grade assets that will receive full principal and interest within 90 days on average. Since our ambiguity measure is based on the stock market's forecast of long-term growth, one possible explanation for this finding is that investors are seeking safer assets with higher liquidity when faced with higher ambiguity in expected stock returns.

[17] The variables that control for aggregate market characteristics (i.e., risk, returns and liquidity) are the same as those in the baseline model because ICI does not provide details on holdings.

[Table 6 here]

4.4 Ambiguity and Short Selling

In our theoretical exposition we have assumed that the ambiguity-averse agent always expects positive returns on the risky asset, and showed that in the presence of ambiguity he assumes a long position, which is smaller compared to the ambiguity-neutral case. This assumption is motivated by the fact that in our empirical analysis we measure participation via mutual funds, which most commonly do not take short positions.[18]

However, there is a caveat: it is possible that our previous analysis is only picking up a bias in beliefs, whereby pessimistic EU (not ambiguity averse) agents withdraw their long positions, and at the same time initiate short positions, so overall market participation does not change in response to ambiguity. Although this explanation is unlikely[19] we conduct some analysis in this section to formally rule it out. Thus, we correlate a measure for the level of short selling activity in the market with our ambiguity proxy. Using data from Compustat we calculate the aggregate value-weighted short ratio (numbers of shares held $short_t$ / number of shares outstanding at $time_t$), and then correlate the change in this variable with our measure of ambiguity. In unreported analysis we find that the correlation is -0.127 (p=0.02), which suggests that increases in ambiguity *reduce* short positions in the stock market. So overall, increases in ambiguity lead to reductions in both long and short positions in the stock market, as predicted by the theoretical literature (i.e., Dow and Werlang, 1992; Epstein and Schneider, 2010).

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[18] In more formal models of ambiguity like Dow and Werlang (1992) and Epstein and Schneider (2010), where expected returns for the risky asset can be either positive or negative, agents can be either long or short. Ambiguity aversion has opposite effects in these cases: when the agent is long his pessimism leads him to expect low returns, and when he is short to expect high returns. For certain parameters for ambiguity these models produce situations where the agent is *neither* long nor short.

[19] Firstly, as we have discussed, fund flows reflect the active reallocation decisions of individual investors, and it is well documented in the literature that these investors are reluctant to sell-short (Barber and Odean, 2008). Secondly, it would be difficult to explain why these investors delegate decisions to go long to mutual funds managers, but feel able to handle short positions on their own.

4.5 Robustness

As discussed in our methodology section we use linear interpolation for the ambiguity measure to obtain monthly estimates and hence increase the power of our tests. In this section we estimate the models shown in (15) and (16) using non-interpolated, quarterly data. We continue to use Newey and West (1987, 1994) heteroscedasticity and autocorrelation consistent standard errors.

Net flows and exchanges are calculated on a quarterly basis. The changes in ambiguity and conditional variance are equal to $\Delta Qcvar_t = cvar_t - cvar_{t-3}$ and $\Delta Qamb_t = amb_t - amb_{t-3}$, respectively. Quarterly capital gains, savings and advertising costs are equal to the sum of the monthly values over each quarter: $Qadv_t = \sum_{k=t-2}^{t} adv_k$, $Qcap_t = \sum_{k=t-2}^{t} cap_k$ and $Qsav_t = \sum_{k=t-2}^{t} sav_k$. Lagged market return, illiquidity premium and fund return are defined as previously. The quarterly regressions are of the form:

$$\begin{aligned} netflow_t = a_0 &+ a_1 \Delta Qamb_t + a_2 \Delta Qcvar_t + a_3 Qadv_t + a_4 Qcap_t + a_5 ret_{t-12,t}^{fund} + a_6 ret_{t-3,t}^{mkt} \\ &+ a_7 netflow_{t-3} + a_8 netflow_{t-6} \\ &+ a_9 netflow_{t-12} + a_{10} Qsav_t + a_{11} Ilq_{t-3,t} + a_{12} Dec_t + \varepsilon_t \end{aligned} \quad (18)$$

$$\begin{aligned} netexchange_t = a_0 &+ a_1 \Delta Qamb_t + a_2 \Delta Qcvar_t + a_3 Qadv_t + a_4 Qcap_t + a_5 ret_{t-12,t}^{fund} \\ &+ a_6 ret_{t-3,t}^{mkt} + a_7 netexchange_{t-3} + a_8 netexchange_{t-6} \\ &+ a_9 netexchange_{t-12} + a_{10} Ilq_{t-3,t} + \varepsilon_t \end{aligned} \quad (19)$$

The results for these quarterly regressions are shown in Table 7. Even though the number of observations in these models is reduced threefold, we still find that increases in ambiguity are negatively and significantly related to both fund flows (Panel A: -1.716, *p*=0.03) and fund exchanges (Panel B:-0.899, *p*=0.07).

[Table 7 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. According to the ambiguity-based explanation, stocks involve both risk *and* ambiguity, and since investors are ambiguity averse, their propensity to invest in stocks is lower than that predicted by neoclassical models.

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 limited stock market participation arises because the stock market entails ambiguity, which is disliked by investors.

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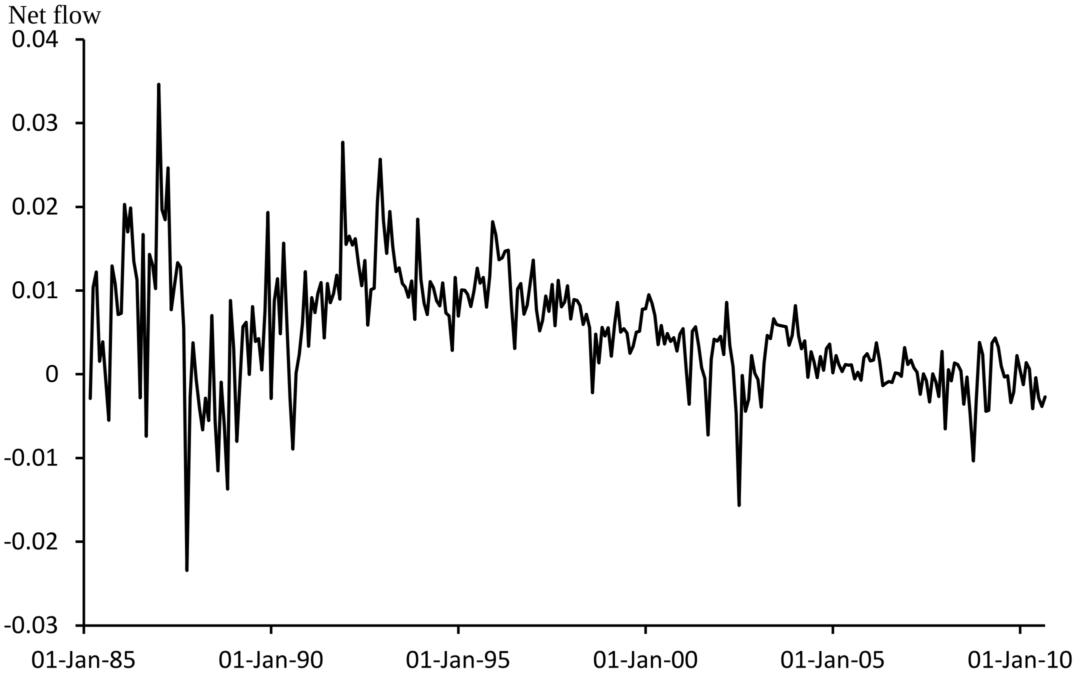
FIGURE 1. NET FLOWS AND NET EXCHANGES FOR THE EQUITY ASSET CLASS

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 March 1985to 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

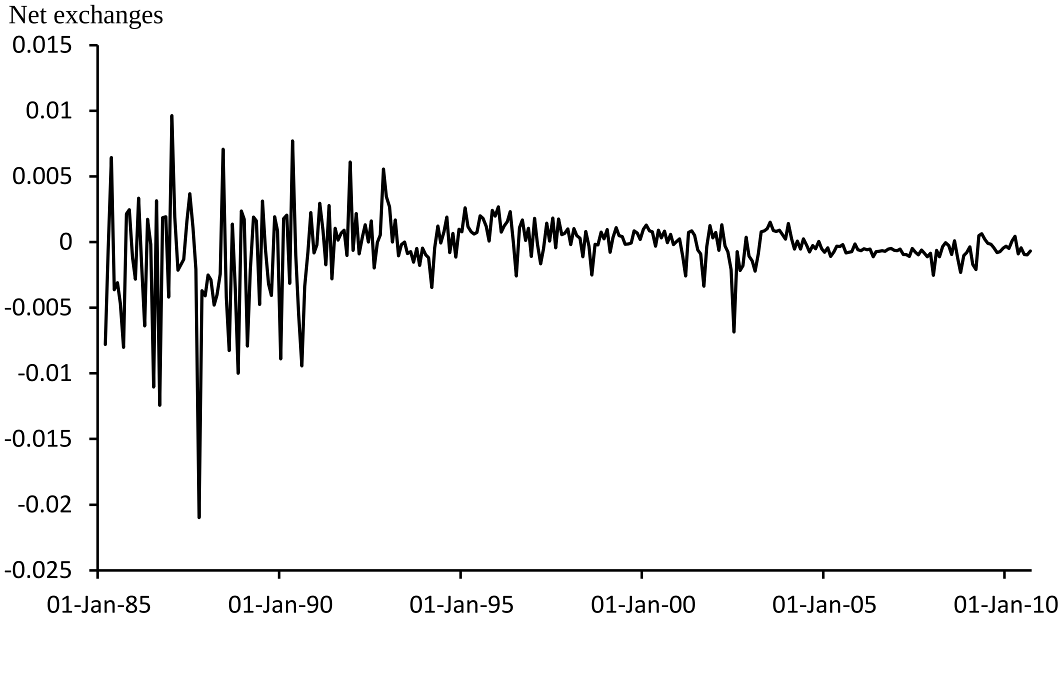
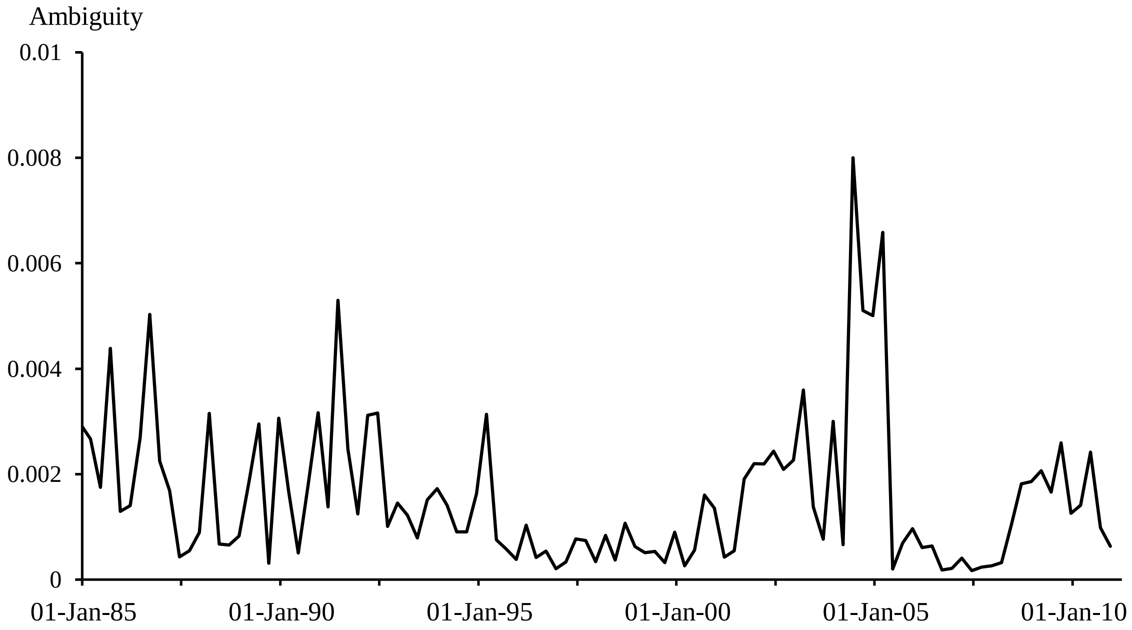


FIGURE 2. AMBIGUITY

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

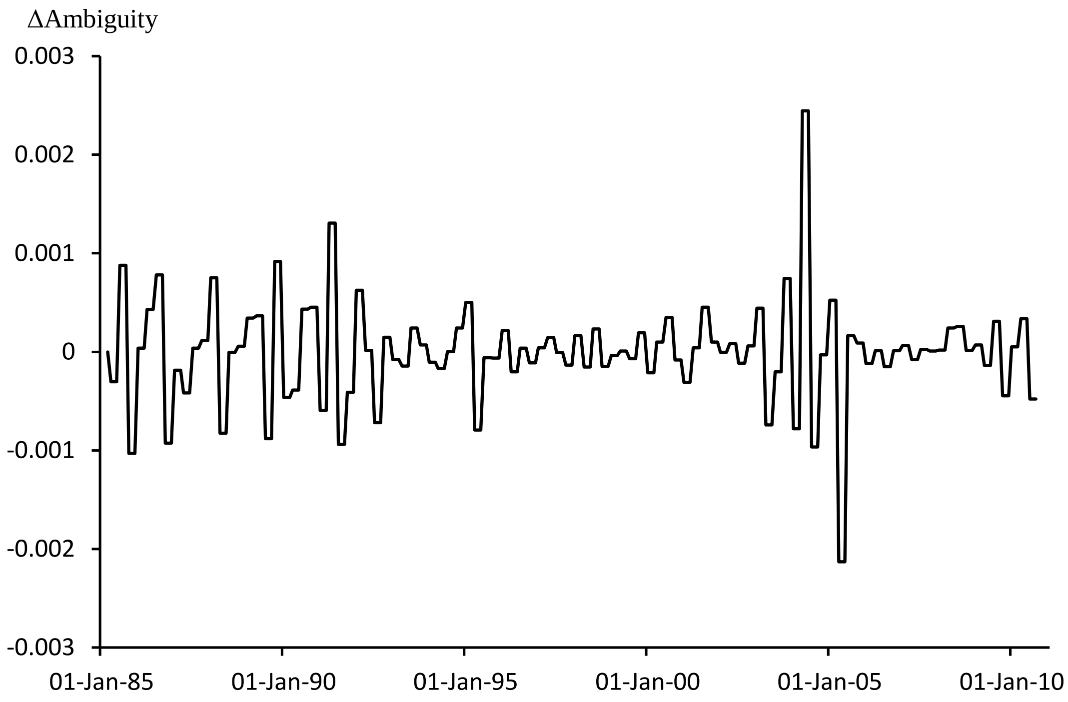


FIGURE 3. AMBIGUITY VS. RISK

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

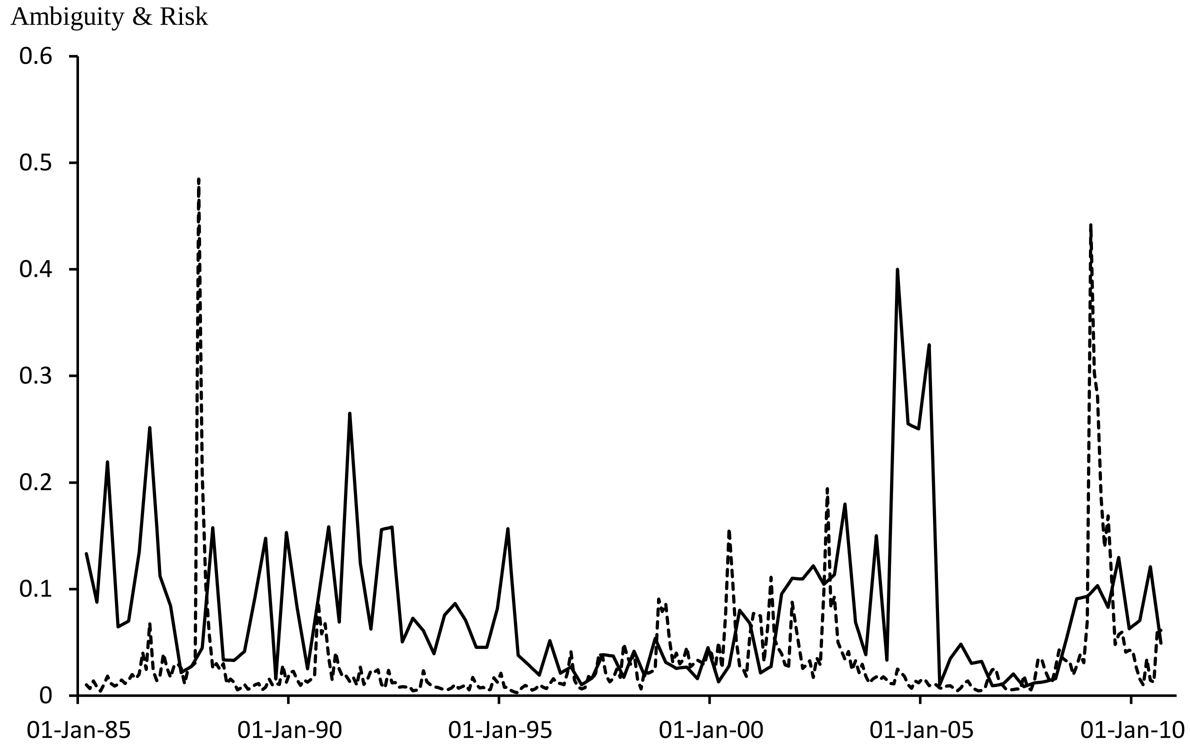


TABLE 1. CLASSIFICATION OF U.S. MUTUAL FUNDS

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, ambiguity and changes in ambiguity and the control variables for the period March 1985to 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. $\Delta cvar_t = cvart - cvart-1$ and $\Delta ambt = ambt - ambt-1$. $advt$ 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 and $Ilq_{t-3,t}$ is the Amihud liquidity measure of previous three months.

	Mean	Std	Skew	Kurt	Max	Min
Net exchanges	-0.00040	0.00271	-2.14912	13.95975	0.00963	-0.02098
Net flow	0.00505	0.00706	0.24226	1.69242	0.03465	-0.02345
amb_t	0.00158	0.00129	1.79998	4.20630	0.00800	0.00017
Δamb_t	-0.00001	0.00052	0.29638	5.99293	0.00245	-0.00213
$cvar_t$	0.03228	0.05060	5.49622	38.66370	0.48476	0.00259
$\Delta cvar_t$	0.00007	0.04326	4.82699	61.81308	0.45413	-0.27649
$ret_{t-12,t}^{fund}$	0.16747	0.21849	-0.96633	0.86778	0.58296	-0.58001
adv_t	0.08600	0.01240	0.81052	5.93306	0.14438	0.03810
cap_t	8.40841	19.44562	2.93770	6.82710	72.00000	0.90000
sav_t	0.04935	0.01889	0.00658	-0.80069	0.10300	0.00900
$ret_{t-3,t}^{mkt}$	0.02761	0.08464	-1.07597	2.85516	0.26384	-0.36722
$Ilq_{t-3,t}$	0.00002	0.00001	3.01512	14.23607	0.00009	0.00000

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 March 1985to 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	$ret_{t-12,t}^{fund}$	$ret_{t-3,t}^{mkt}$	$Ilq_{t-3,t}$
Net flows	1.000	0.681	-0.098	-0.033	0.158	0.316	0.431	0.210	0.471	1.000
Net exchanges	0.681	1.000	-0.159	-0.035	0.058	-0.049	0.045	0.031	0.013	0.681
Δamb_t	-0.098	-0.159	1.000	-0.017	-0.003	0.046	0.010	-0.017	-0.027	-0.098
$\Delta cvar_t$	-0.033	-0.035	-0.017	1.000	-0.026	0.003	0.001	-0.137	-0.018	-0.033
adv_t	0.158	0.058	-0.003	-0.026	1.000	0.006	0.001	-0.072	0.017	0.158
cap_t	0.316	-0.049	0.046	0.003	0.006	1.000	0.206	0.075	0.660	0.316
sav_t	0.431	0.045	0.010	0.001	0.001	0.206	1.000	0.442	0.331	0.431
$ret_{t-12,t}^{fund}$	0.210	0.031	-0.017	-0.137	-0.072	0.075	0.442	1.000	0.031	0.210
$ret_{t-3,t}^{mkt}$	0.471	0.013	-0.027	-0.018	0.017	0.660	0.331	0.031	1.000	0.471
$Ilq_{t-3,t}$	1.000	0.681	-0.098	-0.033	0.158	0.316	0.431	0.210	0.471	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 March 1985 to December 2010.

Panel A. Net Flows

	Estimate	Std Err	t statistic	prob>t
Intercept	0.000	0.002	-0.30	0.76
Δamb_t	-1.455	0.618	-2.35	0.02
$\Delta cvar_t$	-0.001	0.005	-0.21	0.84
adv_t	-0.011	0.016	-0.68	0.50
cap_t	0.000	0.000	-0.64	0.52
$ret_{t-12,t}^{fund}$	0.003	0.002	1.76	0.08
$ret_{t-3,t}^{mkt}$	-0.005	0.004	-1.35	0.18
$net\ flow_{t-1}$	0.371	0.102	3.65	<0.01
$net\ flow_{t-3}$	0.325	0.064	5.09	<0.01
$net\ flow_{t-6}$	-0.033	0.083	-0.40	0.69
$net\ flow_{t-12}$	0.043	0.048	0.89	0.38
sav_t	0.037	0.019	2.00	0.05
$Ilq_{t-3,t}$	15.582	19.237	0.81	0.42
Jan_t	0.001	0.001	0.96	0.34
Feb_t	0.001	0.001	1.06	0.29
Nov_t	0.004	0.003	1.16	0.25
Dec_t	0.024	0.028	0.84	0.40
N	309	Adj. R^2	0.52	

Panel B. Net Exchanges

	Estimate	Std Err	t statistic	prob>t
Intercept	0.000	0.001	0.09	0.93
Δamb_t	-0.895	0.401	-2.23	0.03
$\Delta cvar_t$	-0.002	0.004	-0.65	0.52
adv_t	-0.005	0.008	-0.60	0.55
cap_t	0.000	0.000	1.64	0.10
$ret_{t-12,t}^{fund}$	0.000	0.001	0.41	0.68
$ret_{t-3,t}^{mkt}$	-0.001	0.002	-0.55	0.59
$net\ exchange_{t-1}$	0.063	0.092	0.69	0.49
$net\ exchange_{t-3}$	0.184	0.094	1.95	0.05
$net\ exchange_{t-6}$	0.076	0.082	0.93	0.35
$net\ exchange_{t-12}$	-0.006	0.065	-0.10	0.92
$Ilq_{t-3,t}$	-1.761	11.103	-0.16	0.87
N	309	Adj. R^2	0.05	

TABLE 5. AMBIGUITY AND DIFFERENT STYLE EQUITY FUNDS

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

Panel A: Net Flow						
Fund Style	Estimate	Std Err	t statistic	prob>t	N	Adj. R^2
Aggressive Growth	-4.44	1.84	-2.41	0.02	309	0.33
Growth	-2.03	0.73	-2.8	0.01	309	0.46
Growth and Income	-0.63	0.48	-1.3	0.19	309	0.64
Income Equity	-0.54	0.67	-0.8	0.42	309	0.75
Sector	3.96	4.13	0.96	0.34	309	0.18
Panel B: Net exchanges						
Aggressive Growth	-3.30	1.45	-2.28	0.02	309	0.08
Growth	-1.41	0.53	-2.65	0.01	309	0.07
Growth and Income	-0.27	0.26	-1.05	0.30	309	0.13
Income Equity	-0.55	0.27	-2.01	0.05	309	0.30
Sector	2.00	1.63	1.22	0.22	309	0.04

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 March 1985 to December 2010.

Fund Family	Estimate	Std Err	t statistic	prob>t	N	Adj. R^2
Panel A: Net Flow						
Hybrid	-0.68	0.55	-1.24	0.22	309	0.73
Government Fixed Income	-0.72	0.62	-1.17	0.24	309	0.88
Corporate Fixed Income	-0.49	0.69	-0.72	0.47	309	0.62
Money Market	1.35	1.23	1.09	0.27	309	0.16
Panel B: Net exchanges						
Hybrid	-0.04	0.07	-0.50	0.62	309	0.61
Government Fixed Income	-0.33	0.22	-1.47	0.14	309	0.30
Corporate Fixed Income	-0.29	0.34	-0.85	0.39	309	0.09
Money Market	0.35	0.13	2.64	0.01	309	0.06

TABLE 7. QUARTERLY REGRESSIONS

The table reports the results of estimating the net flows model (18) and the net exchanges model (19) for the equity asset class, for the period March 1985 to December 2010 using quarterly data.

Panel A. Quarterly Net Flows

	Estimate	Std Err	t statistic	prob>t
Intercept	0.014	0.009	1.53	0.13
Δamb_t	-1.716	0.794	-2.16	0.03
$\Delta cvar_t$	-0.014	0.032	-0.43	0.67
$adv_{t-3,t}$	-0.028	0.024	-1.17	0.24
$cap_{t-3,t}$	-0.003	0.001	-2.13	0.04
$ret_{t-12,t}^{fund}$	0.010	0.007	1.34	0.18
$ret_{t-3,t}^{mkt}$	0.063	0.015	4.25	<.01
$net\ flow_{t-3}$	0.611	0.109	5.62	<.01
$net\ flow_{t-6}$	-0.022	0.087	-0.25	0.80
$net\ flow_{t-12}$	0.111	0.088	1.27	0.21
$sav_{t-3,t}$	0.144	0.074	1.96	0.05
$Ilq_{t-3,t}$	-45.454	83.222	-0.55	0.59
Dec_t	0.206	0.093	2.21	0.03
N	102	Adj. R^2	0.69	

Panel B. Quarterly Net Exchanges

	Estimate	Std Err	t statistic	prob>t
Intercept	0.000	0.002	0.11	0.91
Δamb_t	-0.899	0.499	-1.8	0.07
$\Delta cvar_t$	-0.018	0.014	-1.28	0.20
$adv_{t-3,t}$	-0.007	0.009	-0.77	0.44
$cap_{t-3,t}$	0.000	0.000	1.54	0.13
$ret_{t-12,t}^{fund}$	0.002	0.002	0.67	0.50
$ret_{t-3,t}^{mkt}$	0.021	0.007	3.02	0.00
$net\ exchange_{t-3}$	0.270	0.079	3.41	0.00
$net\ exchange_{t-6}$	0.017	0.065	0.27	0.79
$net\ exchange_{t-12}$	0.072	0.099	0.72	0.47
$Ilq_{t-3,t}$	-36.570	42.376	-0.86	0.39
N	102	Adj. R^2	0.27	