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"Ambiguity Preferences and Portfolio Choices: Evidence from the Field"

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Abstract

We match administrative panel data on portfolio choices with survey data on preferences over ambiguity. We show that ambiguity averse investors bear more risk, due to a lack of diversification. In particular, they exhibit a form of home bias that leads to higher exposure to the domestic relative to the international stock market. While more sensitive to market factors, their returns are on average higher, suggesting that ambiguity averse investors need not be driven out of the market for risky assets. We also show that these investors rebalance their portfolio more actively and in a contrarian direction relative to past market trends, which allows them to keep their risk exposure relatively constant over time. We discuss these findings in relation to the theoretical literature on portfolio choice under ambiguity.

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1 Introduction

Ambiguity has been widely studied both theoretically and experimentally in the past decades. Its implications have been investigated in a variety of settings, including financial behaviors.[1] It is now commonly understood, at least at an intuitive level, that ambiguity is an important element that households face in their financial decisions (Ryan, Trumbull and Tufano (2011), Guiso and Sodini (2013)). It may also be a key ingredient to explain the functioning of financial markets.[2] Field evidence of how ambiguity affects households is however still very scarce:

> Interestingly, the empirical literature has so far provided little evidence linking individual attitudes toward ambiguity to behavior outside the lab. Are those agents who show the strongest degree of ambiguity aversion in some decision task also the ones who are most likely to avoid ambiguous investments? (Trautmann and Van De Kuilen (2015))

This paper attempts to partially fill this gap. We explore the relation between ambiguity aversion and portfolio choices using a unique data set that matches administrative panel data on portfolio choices with survey data on preferences over ambiguity.

We have obtained portfolio data from a large financial institution in France. We focus on a popular investment product among French households dubbed *assurance vie*. In this product, households decide their portfolio weight on relatively safe assets (essentially bundles of bonds, called *euro funds*) vs. relatively risky assets (essentially mutual funds, called *uc funds*) as well as some features of risky assets (such as their exposure to the domestic vs. international stock markets). Households can freely change their portfolios over time. Our data record the clients' portfolio of these contracts at a monthly frequency for about nine years. Moreover, for each portfolio, we can construct the corresponding returns.

Clients were also asked to answer a survey that we have designed and that serves two main purposes. First, while portfolio data only concern households' activities within the company, in the survey we gather a more com-

[1] See, e.g., Etner, Jeleva and Tallon (2012), Machina and Siniscalchi (2014), Gilboa and Marinacci (2013) for surveys of the various models, and Hey (2014) or Trautmann and Van De Kuilen (2015) for surveys of the experimental literature. Closely related experimental evidence is provided in Ahn, Choi, Gale and Kariv (2014), who study how ambiguity aversion affects portfolio choices, and in Bossaerts, Ghirardato, Guarnaschelli and Zame (2010), who focus on its effects on asset prices.

[2] Epstein and Schneider (2010) and Guidolin and Rinaldi (2013) provide recent insightful reviews on ambiguity and financial choices. Macro-finance applications include Uppal and Wang (2003), Ju and Miao (2012), Collard, Mukerji, Sheppard and Tallon (2012). On the role of ambiguity in financial crises, see e.g. Caballero and Krishnamurthy (2008) and Caballero and Simsek (2013).

plete picture of households' portfolios as well as various socio-demographic data. Second, we elicit a number of behavioral traits, and in particular households' attitudes towards ambiguity. Following standard procedures, we build our main measure of ambiguity aversion by asking subjects to choose between lotteries with known vs. unknown probability distributions over the final payoffs.

Guided by some fundamental insights developed in the theoretical literature of portfolio choices under ambiguity, we focus on three dimensions of household portfolios. We first look at how the composition of portfolios varies with ambiguity aversion. Is it the case that ambiguity aversion leads to a form of under-diversification, as predicted for example in Uppal and Wang (2003) and Hara and Honda (2016)? In particular, do ambiguity averse investors display a preference for home stocks, as in Boyle, Garlappi, Uppal and Wang (2012)?

Second, we ask whether ambiguity averse households display distinct portfolio returns. Are their returns systematically lower, so that in the long run these investors are bound to be wiped out of the market, as in Condie (2008)? At the same time, in relation to under-diversification, are their returns more volatile?

Third, we analyze the relation between ambiguity aversion and portfolio dynamics. In particular, as suggested by recent models on portfolio inertia (Garlappi, Uppal and Wang (2007), Illeditsch (2011)), is it the case that ambiguity averse households keep their portfolio weights more stable over time?

In terms of portfolio composition, we find that ambiguity averse investors are *more* exposed to risk, as defined both in terms of the volatility of returns and in terms of beta relative to the French stock market. This extra exposure to risk could come, as suggested for instance by Klibanoff, Marinacci and Mukerji (2005), from a desire to shy away from ambiguity. To pursue this line, we distinguish portfolios according to their relative exposure to the French and the world markets. We build a measure of differential exposure based on the difference between a "domestic" beta -which employs as benchmark the French stock market index CAC40- and an "international" beta -which instead uses as benchmark the MSCI World Index. We show that ambiguity averse investors are relatively more exposed to the French than to the international stock market. Ambiguity aversion is thus a good candidate to explain home bias in equity markets.

We also study the extent to which portfolio returns are explained by simple asset pricing models, and in particular by a domestic CAPM and by the Fama-French five-factor model. In both specifications, we find that the higher ambiguity aversion, the lower is the explanatory power of market factors. Ambiguity averse investors appear to bear more idiosyncratic volatility, suggesting a possible under-diversification in their portfolios.

We then look at portfolio returns. We find that, in our sample, ambiguity averse investors experience higher returns, even controlling for standard measures of risk. At the same time, however, their returns are more sensitive to market trends. Our estimates show that the larger ambiguity aversion, the *higher* are returns in good times and the *lower* are returns in bad times.

A similar picture emerges as we explore the differential exposure of ambiguity averse investors to Fama-French factors. These investors experience relatively higher returns when returns of the market portfolio are high, even more so when we construct market returns based only on the French stock market. Moreover, we show that ambiguity averse investors are more exposed to the Fama-French investment factor; that is, their portfolios load more on firms with "conservative" as opposed to "aggressive" investment strategies.

Finally, we investigate the dynamics of household portfolios. In particular, we focus on how households' risky share, as measured by the share of *uc funds* in their portfolios, evolves over time. Following the methodology developed in Calvet, Campbell and Sodini (2009), we distinguish changes in risk exposure which are driven by differential returns of risky vs. riskless assets from those which result from an active choice of the household. We show that ambiguity averse investors tend to rebalance their portfolio more actively; that is, their risky share tends to remain closer to the target share. Furthermore, we show that ambiguity averse investors adopt a contrarian strategy, moving wealth from funds which have experienced relatively higher returns to those who had relatively lower returns. This rebalancing strategy aims at keeping the risky share relatively constant over time, which is in line with the above mentioned models of ambiguity aversion and portfolio inertia.

In the next sections we discuss each of these findings and we highlight in more details their relation with the existing theoretical literature. From a somewhat broader perspective, we believe these insights contribute to a better understanding of the empirical content of ambiguity preferences. While from a conceptual viewpoint the importance of ambiguity has been recognized at least since Knight (1921), its empirical content is still unclear. In his Nobel lecture, Hansen (2014) calls for further research aimed at assessing whether ambiguity, in addition to risk, is empirically relevant for the study of asset pricing. Our results are strongly suggestive that ambiguity aversion is an important determinant of observed financial outcomes. We believe they should serve as motivation for further work aimed at distinguishing more clearly risk from ambiguity both in investors' perceptions and in their financial behavior.

Related Literature

To our knowledge, this study is the first to provide evidence on the effect of ambiguity aversion on financial outcomes observed in administrative data. As such, it relates, from an empirical angle, to the mostly theoretical literature that has studied the implications of ambiguity aversion for portfolio choices and financial markets.[3]

We also contribute to the household finance literature by looking at the determinants of households' financial decisions. The literature is growing rapidly and we refer to Campbell (2006) and Guiso and Sodini (2013) for recent surveys. Compared to this literature, our main novelty is in matching survey and administrative data. While as pointed out our data do not provide a detailed picture of the entire households' portfolios (as for example in Calvet, Campbell and Sodini (2007) and Calvet et al. (2009)), they offer the opportunity to study the relation between behavioral traits and the choices taken within the company. The latter allows us to address quantitative issues that purely survey data usually cannot address.

We know of only a few studies combining survey and administrative data. Dorn and Huberman (2005) focus on the relation between risk aversion, (perceived) financial sophistication and portfolio choices; Alvarez, Guiso and Lippi (2012) analyze the frequency with which investors observe and trade their portfolio; Guiso, Sapienza and Zingales (2017) and Hoffmann, Post and Pennings (2013) study how risk aversion has changed following the financial crisis; Bauer and Smeets (2015) and Riedl and Smeets (2014) investigate how social preferences affect socially responsible investments. None of these studies focuses on ambiguity preferences as we do.

Most closely related to our study, Dimmock, Kouwenberg and Wakker (2016) and Dimmock, Kouwenberg, Mitchell and Peijnenburg (2016) exploit large representative surveys in which subjects are asked about their preferences over ambiguity as well as about their portfolio holdings. We share with these authors a similar methodology to elicit ambiguity aversion (although our subjects receive no monetary reward in relation to their choices) but the nature of our data, and so the questions we address, are quite different. Their data are based on surveys, and they are larger in size and in scope. This allows them to investigate issues of stock market participation which we cannot address. Our data provide more details on the investment product at hand as well as a panel structure, and this allows us to investigate questions on portfolio dynamics and returns which cannot be addressed with their data.

Dimmock, Kouwenberg, Mitchell and Peijnenburg (2016) also point at

[3] Recent developments include Gollier (2011) on the comparative statics of ambiguity aversion in portfolio choices; Maccheroni, Marinacci and Ruffino (2013) on mean-variance preferences; Hara and Honda (2016) on CARA smooth ambiguity preferences; Epstein and Ji (2013) and Lin and Riedel (2014) on dynamic portfolio choices.

a positive relation between ambiguity aversion and lack of portfolio diversification. We complement their findings by documenting forms of under-diversification starting from information about realized portfolio returns as opposed to stock holding. This allows to highlight how under-diversification affects the riskiness of household portfolios, and to provide support for the idea that ambiguity averse investors tend to bear more risk so as to avoid ambiguity, consistently with different models in the literature (see Section 4 for details).

2 Data

We exploit three sources of data. First, we have obtained data on portfolio choices from a large French financial institution. These data describe clients' holdings of *assurance vie* contracts. These are investment products widely used in France; they are the most common way through which households invest in the stock market.[4] A typical *assurance vie* contract establishes the types of funds in which the household wishes to invest and the amount of wealth allocated to each fund.

A first key distinction is between *euro funds* and *uc funds*. The first type of assets, which are called *euro funds*, are basically bundles of bonds. The capital invested in these funds is guaranteed by the company. The second type of funds are called *uc funds,* and they are essentially bundles of stocks. It is made clear to investors that *uc funds* tend to provide larger expected returns and larger risk. Investors do not observe the exact composition of these funds (neither do we), but they receive some information about the intended risk profile of these funds (e.g. conservative vs. aggressive) as well as an indication of their exposure to different markets. A particularly salient feature is whether funds invest in domestic, emerging, or world markets.

Over time, clients are free to change the composition of their portfolios, make new investment and withdraw money as they wish.[5] Investors may opt for automatic rebalancing of their portfolio according to some pre-specified rule. In our sample, less than 10% of investors have chosen this option (see the Online Appendix for further details).

Our portfolio data records at a monthly frequency the value and composition of these contracts for 511 clients from September 2002 to April 2011. These data are combined with the responses to a survey we have designed

[4]According to the French National Institute for Statistics, 41% of French households held at least one of these contracts in 2010. This makes it the most widespread financial product after *Livret A*, a saving account whose returns are set by the state. See INSEE Premiere n. 1361 - July 2011 (http://www.insee.fr/fr/ffc/ipweb/ip1361/ip1361.pdf).

[5]A specific feature of the product is that there is some incentive not to liquidate the contract before some time (8 years in our sample period) so as to take advantage of reduced taxes on capital gains. We show in the Online Appendix that this feature is immaterial for our results.

and which was administered by a professional survey company at the end of 2010.[6]

The financial institution has provided to the survey company a sample of clients who had an account open at the end of 2010. The survey was then implemented in order to obtain a representative sample of French households in terms of family status, employment status, sector of employment, revenues (these characteristics follow official classifications of the National Institute for Statistics).[7] All clients in our sample held some *assurance vie* contract in the financial company at the time when the survey was conducted, but not necessarily throughout the entire sample period.[8]

These contracts can represent a sizeable fraction of households' financial wealth. In our sample, the average value of a portfolio is $32,700$ euros, the maximum is $590,000$ euros. The median total wealth in our sample is between 225 and 300 thousand euros and the median financial wealth is between 16 and 50 thousands euros. These figures are in line with those obtained for the general French population (see Arrondel, Borgy and Savignac (2012)).[9]

The survey serves two main purposes: first, we have gathered information about demographic characteristics, wealth and portfolio holdings outside the company. In this way we can control for a richer set of clients' characteristics than those recorded by the company. Moreover, this allows to gauge whether the behaviors we observe within the company are informative for clients' behaviors in their overall portfolio (see the Online Appendix for details).

A second purpose of the survey is to get an idea of clients' behavioral characteristics, and in particular of their preferences over ambiguity. In the next section, we describe how we have elicited these preferences.[10]

Finally, we collected data on portfolio returns. We have obtained from *Thomson Reuters Datastream* the returns experienced in a given month by

[6]It was made clear to the subjects that they were contacted as part of a scientific project on risk, while the insurance company was never mentioned during the interview. Clients completed the survey over the internet while on line with the surveyor.

[7]The insurance company gave to the survey company a sample of approximately 30,000 clients. This sample was stratified according to geographic regions (Ile De France, North-East, West, South-East, South-West) and the survey was conducted so as to meet pre-specified quotas of respondents in terms of the above-mentioned socio-demographic characteristics.

[8]We did not impose any minimal holding period to be included in the sample. We discuss in the Online Appendix a series of robustness checks to address the possibility of survivorship bias in this sample.

[9]For official and comprehensive data, see the 2010 Household Wealth Survey from the French National Institute for Statistics (http://www.insee.fr/en/methodes/default.asp?page=sources/ope-enquete-patrimoine.htm).

[10]Our measure of ambiguity aversion is taken just at one point in time, towards the end of the sample period. In the Online Appendix, we show that the effects of ambiguity aversion would be similar if we were to restrict our analysis to the beginning of the sample period. This suggests that our measure of ambiguity aversion has a persistent component.

each fund and, based on those, we can build the corresponding returns of each contract.

3 Ambiguity Preferences

We elicit preferences over ambiguity in a classical way. We ask respondents to choose between a risky lottery and an ambiguous lottery. For the former lottery, we provide an exact probability distribution over the final payoffs; for the latter, we provide no information about the probabilities associated to the final payoffs. Depending on their answer, we sequentially provide alternative lotteries in which the risky lottery is made relatively more or less attractive. We describe these lotteries in details in the Appendix.

This approach is in line with the results in Dimmock, Kouwenberg and Wakker (2016), who formally show that ambiguity attitudes can be entirely described by matching probabilities. Differently from Dimmock, Kouwenberg and Wakker (2016), we only had space for a few questions and thus we could only construct a coarser measure of ambiguity attitudes. Moreover, our lotteries were hypothetical, and this comes with the usual pros and cons.[11] As we detail below, however, we have found a remarkable consistency across various measures and elicitation methods, which suggests we are capturing a systematic component of investors' preferences.

We build the index *Ambig Aversion* which takes value 1 to 4 from the least to the most ambiguity averse client. This variable will serve as our main measure of ambiguity preferences.[12] In the Appendix, we also provide a description of the other variables used in the subsequent analysis. In Table 1, we report some descriptive statistics.

We first explore the correlation between *Ambig Aversion* and a set of demographic characteristics: age, gender, education, marital status, income, wealth (we refer to Table 1 in the Online Appendix for the corresponding results). *Ambig Aversion* appears negatively related to age and positively related to income. Other variables are not significantly correlated.[13] We also observe that our index is positively related to a qualitative measure of ambiguity aversion, which is based on how much the subject declares disliking uncertainty.

We then analyze the relation between ambiguity aversion and other behavioral traits. We start with risk aversion. Existing results on the rela-

[11] See Dimmock, Kouwenberg and Wakker (2016) and Gneezy, Imas and List (2015) for a discussion.

[12] In the Online Appendix, we consider several alternative measures such as dummy variables coding subjects as ambiguity averse as well as accounting for preferences in the loss domain.

[13] Butler, Guiso and Jappelli (2014) find a strong positive relation between ambiguity aversion and wealth. In our data, the relation is positive but not precise (t-stat 1.63). It would be interesting for future studies to explore this relation more systematically.

tion between risk and ambiguity preferences are not conclusive: Dimmock, Kouwenberg and Wakker (2016) report a negative relation while Butler et al. (2014) a positive relation between the two (see Wakker (2016) for an exhaustive list of references). We build a 1 to 4 index *Risk Aversion* (1 being the least and 4 the most risk averse client) by asking respondents to compare a sure outcome to a series of risky lottery. We observe no significant relation between risk and ambiguity aversion in our sample.

The literature suggests that ambiguity preferences may also relate to other characteristics such as sophistication (Halevy (2007); Chew, Ratchford and Sagi (2017)), lack of confidence about the context (Heath and Tversky (1991); Fox and Tversky (1995)), or present biased preferences (Halevy (2008); Cohen, Tallon and Vergnaud (2011)). Our survey allows to build some measures related to these traits, as we detail in the Appendix. We observe no significant relation between *Ambig Aversion* and our measures of sophistication, confidence, and time preference. This suggests that, in our subsequent analysis, these behavioral traits are unlikely to interfere with the estimated effects of ambiguity aversion.[14]

4 Portfolio Composition

In this section, we investigate how ambiguity aversion affects the composition of household portfolios. We first revisit some theoretical insights on this relation. We then provide evidence that ambiguity averse decision makers are more exposed to domestic risk, in line with the theory that sees ambiguity aversion as a possible explanation for the home bias puzzle, and that this extra exposure is associated to more volatile portfolios.

4.1 Theoretical Background

A general idea from the theoretical literature is that ambiguity aversion leads to under-diversified portfolio and, in particular, could be an ingredient helping understand the home bias puzzle. This is a fairly robust prediction which has been established in various settings and with different modeling of ambiguity preferences. In Uppal and Wang (2003), investors consider the possibility that their model of asset returns is misspecified, in line with the approach to robustness developed in Hansen and Sargent (2001). This concern leads to portfolios which are significantly under-diversified relative to the standard mean-variance portfolio. The reason is that robustness considerations induce investors to put less weight on expected returns and to focus on stocks (or benchmarks) which are perceived as less risky.

[14] We refer to the Online Appendix for a series of robustness checks on the interaction between ambiguity aversion and other behavioral traits and to Bianchi (2017) for a study of the effects of financial literacy in this setting.

Building on models with maxmin preferences à la Gilboa and Schmeidler (1989), Garlappi et al. (2007) and Boyle et al. (2012) compare the optimal portfolio of an ambiguity averse decision maker to that of a more traditional Markowitz investor. They show that ambiguity aversion leads to portfolios that are overly exposed to more familiar stocks, which are perceived as less ambiguous. In Boyle et al. (2012), domestic stocks are perceived as more familiar, which suggests that ambiguity aversion can provide an explanation to the home bias puzzle. In a general equilibrium framework, Epstein and Miao (2003) show that introducing maxmin investors helps to resolve the puzzles concerning home bias in consumption and equity.

Finally, forms of under-diversification occur in the smooth approach to ambiguity aversion proposed by Klibanoff et al. (2005). In this class of models too, the desire to avoid ambiguity may induce investors to take more risk. Klibanoff et al. (2005) provide an example in which the ratio of the holding of the ambiguous asset on the risky asset decreases with ambiguity aversion. Hara and Honda (2016) extend a classic CARA-Normal setting so as to accommodate ambiguity and ambiguity aversion. They show that in general the two funds theorem does not hold with ambiguity aversion: the optimal portfolio of an ambiguity averse investor cannot be simply expressed in terms of a safe asset and a mutual fund, and different investors are likely to hold ambiguous assets in different proportions. The reason is that, in the smooth ambiguity model, ambiguity aversion works as if the investor was distorting the information about the distribution of returns. This implies that investors with different levels of ambiguity aversion tend to hold different mutual funds in their portfolios.

Despite the different formalizations of ambiguity preferences, these models share similar predictions in terms of under-diversification. In particular, they predict that ambiguity averse investors tend to hold portfolios which are overly exposed to assets perceived as less ambiguous.

4.2 Results

In this section, we first provide some suggestive evidence on the relation between ambiguity aversion and exposure to risk. This serves as a motivation to study in more details the composition of household portfolio so as to shed light on the relation between ambiguity aversion and under-diversification. First, we consider households' exposure to the domestic relative to the international market. Then, we estimate the level of idiosyncratic volatility borne by each client through standard market factors models.

In order to have a first pass on the relation between ambiguity aversion and exposure to risk, we start with regressions of the following form:

$$y_{i,t} = \alpha + \beta AmbigAvers_i + X_i^{'}\gamma + \mu_t + \varepsilon_{i,t}, \tag{1}$$

where $y_{i,t}$ is a given measure of risk of individual i's portfolio at time t, $X_i^{'}$ is a set of controls and μ_t are month-year fixed-effects. Unless otherwise noted, our set of controls includes age, gender, education, marital status, income and wealth.[15] We also include *Risk Aversion* as control so as to make sure that the estimated effects of ambiguity aversion are not contaminated by risk aversion. (Results are however unaffected by this inclusion.)

Our coefficient of interest is β, which describes the impact of ambiguity preferences, as elicited in our survey, on individual i's portfolio. As the effects may be correlated over time, we cluster standard errors at the individual level.[16]

In column 1 of Table 2, the dependent variable is the value of *uc funds* over the total value of the portfolio at time t. Ambiguity averse investors do not display significantly different portfolios in terms of composition between *euro funds* and *uc funds.* A similar result is obtained by using as dependent variable an indicator of whether the investor holds some *uc funds* in his portfolio. Hence, we do not find evidence that ambiguity aversion leads to non-participation in the stock market through lower investment in *uc funds.*[17] Actually, our findings suggest that investors do not view all *uc funds* as ambiguous.

In columns 2-3, the dependent variable in (1) is the standard deviation of the returns in the previous 12 months (in percentage points). We see that ambiguity averse investors hold more volatile portfolios. A unit increase in *Ambiguity Aversion* is associated to about 0.04 larger volatility of returns, relative to an average volatility of 0.48. In columns 4-5, the dependent variable is *Beta(F)*, constructed by regressing portfolio returns in the previous 12 months on the French stock market index CAC40. A unit increase in *Ambiguity Aversion* is associated to about 0.01 larger beta, relative to an average of 0.09.[18]

The previous results show that more ambiguity averse investors tend to hold portfolios whose returns are more risky, although they do not significantly hold a larger share of *uc funds.* Following the theoretical insights presented above, we explore whether the extra exposure to risk could be

[15]We asked subjects to report their level of education, age, income and wealth within pre-specified intervals. In our regressions we include the corresponding ordinal variables. Results would be unchanged if instead we used a series of dummies (see the Online Appendix).

[16]This makes it harder for us to find statistically significant results. As shown in the Online Appendix, standard errors would be much smaller with alternative clustering.

[17]The non-participation hypothesis rests on the prediction of the maxmin expected utility model that an ambiguity averse investor will not hold an ambiguous asset for a range of prices. Note though that our data set is not ideal to study non-participation as it only captures participation in the stock market through mutual funds.

[18]In the Online Appendix, we show that one gets similar results by constructing these variables in a forward-looking way based on the standard deviation and beta of the returns in the *next* 12 months.

driven by a desire to avoid ambiguity.

Taking the theoretical insights to the data is challenging. Ideally, it would require to classify assets in terms of (perceived) ambiguity, for which no general method is available. Some indirect ways have been proposed to estimate ambiguity at the market level.[19] At the micro level, the perception may be subjective and hence difficult to assess. Moreover, as mentioned, in our data we have no direct information on which individual stocks are included in a given *uc fund*.

We address the issue in two ways, taking advantage of the fact that we observe realized returns in our data. First, we distinguish portfolios according to their exposure to the French relative to the international market. Second, similarly to Calvet et al. (2007), we employ standard market factors models in order to estimate the level of idiosyncratic volatility borne by each client. In both cases, the premise is that, while reducing exposure to stocks perceived as more ambiguous, ambiguity aversion may lead to portfolio under-diversification.

We start by considering the exposure to foreign stock markets. We compute *Beta(W)* by regressing portfolio returns in the previous 12 months on the MSCI World Index. In column 1 of Table 3, we observe no significant relation between *Beta(W)* and *Ambig Aversion*. Given the earlier evidence of higher exposure to the French stock market, we are lead to investigate whether ambiguity aversion is associated to a *differential* exposure to the domestic vs. foreign markets. If we follow conventional wisdom and the above mentioned literature, a higher exposure to international markets is tantamount to bearing higher ambiguity.

The measure we take is simply the *difference* between *Beta(F)* and *Beta(W)*. In column 2, we indeed observe that the larger ambiguity aversion the larger is the difference *Beta(F)-Beta(W)*. In column 3, we include the sum of the two betas in order to control for scale effects. The effect of ambiguity aversion is positive and significant, suggesting that ambiguity averse investors are more exposed to the French rather than to the international stock market. The estimated coefficient implies that a standard deviation increase in ambiguity aversion increases the difference *Beta(F)-Beta(W)* by 0.7%, relative to the average difference of 2.3%.

This is direct evidence that ambiguity aversion is a plausible explanation of the observed home bias in the stock market: portfolios of more ambiguity averse investors are more exposed to domestic stocks than to foreign stocks compared with less ambiguity averse investors.

In a similar vein, Dimmock, Kouwenberg, Mitchell and Peijnenburg (2016) employ a survey question on whether the respondent holds foreign

[19] Antoniou, Harris and Zhang (2015) identify ambiguity with more widespread experts' forecasts. Jurado, Ludvigson and Ng (2015) assimilate ambiguity with the unpredictable part of the times series studied.

stocks and document a negative relation between foreign stock holding and ambiguity aversion. Our results complement their findings. First, we document home bias starting from information about portfolio returns, as opposed to self-reported measures of stock holding, which allows to show the consistency between the two approaches. Moreover, our results point at a form of home bias in mutual fund (as opposed to direct stock) holdings, which we find particularly remarkable given that mutual funds are commonly perceived as instruments to obtain well diversified portfolios. Third, as we show in Section 5, we can explore in further details the implications of home bias for realized returns.

We further address the relation between portfolio composition and ambiguity preferences by investigating to what extent the returns of the portfolios held by our investors are explained by standard market factors. We run the following time-series regressions separately for each client:

$$r_{i,t} = \alpha_i + \beta_i CAC_t + \varepsilon_{i,t}, \tag{2}$$

in which $r_{i,t}$ are the returns experienced by client i at time t, CAC_t are the returns of the CAC40 index in percentage points. We then repeat a similar exercise using instead the Fama-French 5 factors model. For each client, we consider the following model:

$$r_{i,t} = \alpha_i + \beta_i mktrf_t + s_i smb_t + h_i hml_t + r_i rmw_t + c_i cma_t + \upsilon_{i,t}, \tag{3}$$

in which the returns experienced by client i at time t are regressed on the standard 5 Fama-French Global factors.[20]

For each regression in (2) and in (3), we use the sum of squared residuals (rss_i) as a measure of how much the returns of a given portfolio are explained by its exposure to the market factors and so of how much idiosyncratic risk the agent bears. We also consider the R-squared from these regressions, which indicates the level of idiosyncratic risk relative to total risk. The latter is measured by the variance of the returns, which as showed earlier, tends to increase with ambiguity aversion.

We investigate the relation between idiosyncratic risk and ambiguity preferences in the following regression:

$$rss_i = a + bAmbigAvers_i + X_i^{'} c + \varepsilon_i,$$

[20] The factors are taken from Kenneth French's webpage and are explained in Fama and French (2015). Mktrf denotes the excess return of the market portfolio; smb denotes Small Minus Big; hml denotes High Minus Low; rmw denotes Robust Minus Weak and cma denotes Conservative Minus Aggressive. Our result are qualitatively unchanged when including only some of these factors as well as when including other factors (such as momentum). Similarly, results do not change by considering factors at the European level (whenever available).

in which rss_i is the above constructed sum of squared residuals and X_i' includes our usual set of controls. In alternative specifications, we use the R-squared as dependent variable.

We report our results in Table 3. In column 4, we report a positive relation between ambiguity aversion and rss_i as derived in regressions (2). The same relation is obtained when estimating the sum of squared residuals from the richer model (3), as reported in column 5. Similarly, we observe a negative relation between ambiguity aversion and the R-squared obtained in regressions (3). These estimates show a robust pattern: the higher ambiguity aversion the lower is the ability of standard market factors to explain portfolio returns. These results suggest that ambiguity averse investors bear more idiosyncratic volatility, also pointing to under-diversification.

5 Portfolio Returns

We now turn to the relation between ambiguity preferences and the returns which investors experience in their portfolio. The following regressions should not be viewed as a test of a particular asset pricing model nor as an assessment of the performance of our investors. This would require a well-defined normative benchmark about which portfolio our investors should hold, as a function of their characteristics and, in particular the ambiguity they perceive. The theoretical literature however does not provide a synthetic benchmark against which one should assess how ambiguity averse investors perform.[21] Moreover, as discussed above, we have no direct measure of the ambiguity perceived by investors.

Yet, we do observe the returns of their portfolio and can assess whether, in our sample, more ambiguity averse agents earn higher or lower returns. This type of analysis is new in the literature and it complements the results presented in the previous section by showing their implications in terms of portfolio returns. Furthermore, this analysis points out that it is not necessarily the case that ambiguity averse investors experience lower returns, an observation which is relevant for the theoretical literature on the long-run impact of ambiguity aversion on asset prices. This literature typically builds on the idea that ambiguity averse investors earn lower returns (as expected utility agents with biased beliefs would) and then studies their long-run survival based on market selection arguments (see e.g. Condie (2008) and Guerdijkova and Sciubba (2015)). While different models may have different predictions on how much investors would affect asset prices depending on their relative wealth in the economy, or on the speed of decline of lower performing investors, our results question the view that ambiguity averse investors must earn lower returns. Irrespective of the specific selection

[21] Hara and Honda (2016) show that any given portfolio can be optimal for certain levels of ambiguity aversion and perceived ambiguity.

model at hand, these results suggest that the influence of ambiguity averse investors need not disappear, and this can be seen as a further motivation to incorporate them in asset pricing models.

5.1 Results

We employ the same specification as in equation (1) and use as dependent variable the monthly returns (in percentage points) experienced by investor i at time t. As benchmark, the average monthly return in the overall sample is 0.38%.

In columns 1 and 2 of Table 4, it appears that in our sample ambiguity averse individuals experience higher raw returns. We then add various measures of portfolio risk as controls. In column 3, we include the value of *uc funds* over the total value of the portfolio; in column 4, the standard deviation of the returns; in column 5, we control for the beta of the returns relative to the French stock market. In column 6, we account for higher moments in the return distribution by including the skewness of the return and the coskewness relative to the French stock market.[22] The estimated impact of ambiguity aversion, however, does not change much. Overall, investors with an extra unit of ambiguity aversion experience about 0.012% higher returns per month (that is, about 0.2% per year).

Given the results on portfolio composition documented in the previous section, we then investigate whether these differences in returns are heterogeneous with respect to market conditions. In Table 5, *AvgRet* is the average returns (in %) across all portfolios at time t. Our interest is in the interaction with ambiguity preferences. It appears that the higher ambiguity aversion, the higher are returns in good times and the lower are returns in bad times. In particular, when average market returns increase by 1%, investors experience 0.14% *higher* returns for each extra unit of ambiguity aversion. Conversely, ambiguity averse investors experience lower returns when market returns are low.[23] These results are consistent with the above evidence that ambiguity averse investors take more risk, in particular in terms of exposure to the French market. Overall, their returns are higher, but at the same time they are more sensitive to market trends. As in the model by Boyle et al. (2012), under-diversification leads to more volatile returns.

We explore these patterns further by replacing *AvgRet* with the five Fama-French factors introduced in equation (3). We are interested in inves-

[22] We measure the skewness as $E[(R-\mu_R)^3/\sigma_R^3]$, where μ_R and σ_R are respectively the mean and the standard deviation of the returns R in the previous 12 months. We measure the coskewness as $E[(R-\mu_R)^2(C-\mu_C)/\sigma_R^2\sigma_C]$, where μ_C and σ_C are respectively the mean and the standard deviation of the French stock market index CAC40 C in the previous 12 months.

[23] These interactions are not affected when controlling for measures of riskiness of the portfolio.

tigating whether the returns experienced by investor i at time t depend on the interaction between investor i's attitude towards ambiguity and a given factor f_t. These interactions terms indicate whether more ambiguity averse investors hold a different exposure to factor f_t.

In columns 3-4, we observe that the larger ambiguity aversion, the larger is the exposure to factor *Mktrf*, that is the excess return of the market portfolio. Consistently with the previous evidence, a larger exposure to *Mktrf* would predict higher returns in good times and lower returns in bad times.

As we have shown that ambiguity averse investors tend to be more exposed to the French stock market, we then replace *Mktrf* with CAC, which measures the returns of the French CAC40 Index. In column 5, we observe that ambiguity averse investors have a larger exposure to CAC. When we include both *Mktrf* and CAC (column 6), we observe that the interaction between ambiguity aversion and *Mktrf* is no longer significant once the exposure to CAC is accounted for. These results are in line with our previous evidence that ambiguity averse investors are overly exposed to the domestic vs. the international stock market.[24]

Columns 3-6 also show that ambiguity averse investors hold portfolios which are more exposed to "conservative" relative to "aggressive" firms. This may indicate that aggressive firms, which display higher rates of investment and growth, are perceived as more ambiguous than conservative firms (see Fama and French (2015)). Under this assumption, our result is in line with the experimental literature (such as Bossaerts et al. (2010) and Kocher and Trautmann (2013)) showing that ambiguity averse investors are less likely to invest in ambiguous assets. While these authors focus on the implications for the value premium (which would correspond to the HML factor in our regressions), we highlight the interaction with the CMA factor. To our knowledge, this result is new in the literature and we view it as a suggestive line for future research.

6 Portfolio Dynamics

We now turn to investigating whether, depending on their attitudes towards ambiguity, investors display different portfolio dynamics. A distinctive feature of our database is its panel dimension: we observe clients' behavior at a monthly frequency for about 9 years. This allows us to explore how investors adjust their portfolio over time, and so to relate to a recent literature on portfolio dynamics under ambiguity aversion.

[24]Notice however that a larger exposure to CAC40 relative to MSCI does not automatically lead to higher returns in our sample period. In this period, the average monthly returns of CAC40 are equal to 0.5% while for MSCI they are equal to 0.7%. We further discuss this point in the Online Appendix, where we show that ambiguity averse investors had higher information ratios in our sample.

6.1 Theoretical Background

Several recent models have shown that ambiguity aversion may lead to forms of portfolio inertia in that households may wish to keep their risk exposure constant over time even upon observing shocks, say, to the distribution of expected returns. Portfolio inertia can have important consequences also for the functioning of asset markets, as it impacts the amount of information revealed in prices and ultimately their level and volatility (Condie and Ganguli (2012)).

The simplest intuition behind portfolio inertia can be found in a model by Epstein and Schneider (2010) in which any realization of an ambiguous variable entails good news (say about the returns of an asset) and at the same time bad news (say about the variance of these returns). As they show, there exist some portfolio position at which such news offset each other and so the agent is completely hedged against ambiguity. This leads to a form of portfolio inertia since it takes a large shock to prices to induce ambiguity averse investors to move away from that position.

The intuition has proven robust in various settings. Illeditsch (2011) considers a more general portfolio choice problem in which agents receive signals of ambiguous precision. He shows that ambiguity averse investors would stick to some intermediate portfolio weights for a range of prices since at these positions agents' utility becomes independent of the signal precision. Similar results appear in Garlappi et al. (2007) and Ganguli, Condie and Illeditsch (2012), who show that ambiguity averse investors tend to keep their portfolio weights constant as they tend not to respond to news about future returns.

Based on these models, we expect that ambiguity averse investors will be more likely to hold to a given position and therefore rebalance their portfolio to maintain this position over time (i.e. after observing the various returns, that affect the value of the different funds they hold in their portfolio). Two important observations should be mentioned in relation to our next analysis. First, in the above mentioned models, portfolio inertia occurs even *conditional on participation*, at positions containing a positive share of ambiguous assets. Second, portfolio inertia does *not* mean that ambiguity averse investors rebalance their portfolio less frequently. On the contrary, that may require continuous rebalancing so as to compensate the fluctuations induced by the market. If, say, realized returns of *uc funds* exceed those of *euro funds*, the relative value of *uc funds* in the portfolio would mechanically increase. If the investor wishes to keep her exposure to *uc funds* constant, she needs to reallocate wealth from *uc funds* to *euro funds*.

6.2 Results

For each investor, we analyze how the value of *uc funds* over the total value of the portfolio evolves over time. The share of *uc funds* is only a rough measure of exposure to uncertainty (indeed, we have argued that the composition of *uc funds* may also matter). At the same time, this measure has the advantage of being simple (it is arguably the most salient characteristic of the portfolio) and of being the closest to the literature. The above mentioned models focus mostly on the fraction of wealth invested in uncertain assets, not on their composition. Our empirical analysis follows closely Calvet et al. (2009), who look at the fraction of wealth invested in uncertain assets, which they call risky share. We adopt the same terminology and, in the next analysis, we refer to the share of *uc funds* simply as the risky share.

We start by analyzing the intensity of portfolio rebalancing; that is, how much of the observed change in the risky share is driven by active rebalancing as opposed to passive changes induced by past market trends. Denote with $X_{i,t-1}$ the risky share for individual i at time $t-1$. If $r_{i,t} - r_f$ is the realized excess return of *uc funds* for individual i between $t-1$ and t, the passive share is defined as

$$X_{i,t}^P = \frac{(1 + r_{i,t})X_{i,t-1}}{1 + r_f + (r_{i,t} - r_f)X_{i,t-1}}. \tag{4}$$

The change of the risky share from $X_{i,t-1}$ to $X_{i,t}$, can be decomposed as follows:

$$\Delta X_{i,t} = \Delta X_{i,t}^P + \Delta X_{i,t}^A \equiv \left(X_{i,t}^P - X_{i,t-1}\right) + \left(X_{i,t} - X_{i,t}^P\right) \tag{5}$$

i.e., it is the sum of the passive change and the active change. We then employ the structural model developed by Calvet et al. (2009) so as to study the intensity of rebalancing by observing the evolution of $\Delta X_{i,t}^P$ and $\Delta X_{i,t}^A$. Calvet et al. (2009) assume that households differ in their speed of adjustment between the passive risky share and an (unobservable) target share, and show that the speed of adjustment can be conveniently estimated under the following conditions. First, the log of the risky share $x_{i,t}$ is a weighted average between the log of the passive share $x_{i,t}^P$ and the log of the (unobservable) target $x_{i,t}^*$. Denoting as ϕ_i the speed of adjustment towards the target share, we have

$$x_{i,t} = \phi_i x_{i,t}^* + (1 - \phi_i)x_{i,t}^P + u_{i,t}. \tag{6}$$

Second, the speed of adjustment is a linear function of a set of observable household characteristics $w_{i,t}$; that is,

$$\phi_i = \gamma_0 + \gamma' w_{i,t}. \tag{7}$$

Third, the change in the log target share is a linear function of these characteristics,

$$\Delta x_{i,t}^* = \delta_{0,t} + \delta_t^{'} w_{i,t}. \tag{8}$$

An advantage of the log specification is that $\Delta x_{i,t}^*$ can be defined independently of individual-specific time-invariant characteristics. Taking the first difference of (6), and using ϕ_i and $\Delta x_{i,t}^*$ from (7) and (8), we obtain

$$\Delta x_{i,t} = a_t + b_0 \Delta x_{i,t}^P + b^{'} w_{i,t} \Delta x_{i,t}^P + c_t^{'} w_{i,t} + w_{i,t}^{'} D_t w_{i,t} + \Delta u_{i,t}, \tag{9}$$

in which $a_t = \gamma_0 \delta_{0,t}$; $b_0 = 1 - \gamma_0$; $b = -\gamma$; $c_t = \gamma_0 \delta_t + \gamma \delta_{0,t}$ and $D_t = \gamma \delta_t^{'}$. In (9), $\Delta x_{i,t}$ is the change in the log risky share and $\Delta x_{i,t}^P$ is the change in the log passive share where all the changes are expressed in yearly terms (that is, relative to 12 months before). The vector $w_{i,t}$ may include demographic characteristics as well as portfolio characteristics (returns, standard deviation). The coefficient b_0 measures the fraction of total change in the risky share which is driven by the passive change. The lower the speed of adjustment, the closer b_0 should be to 1. Our main interest is in exploring whether the speed of adjustment varies systematically with ambiguity preferences, which we include in the set of characteristics $w_{i,t}$.

An important observation in Calvet et al. (2009) is that OLS estimates of b_0 and b in equation (9) may be negatively biased since $\Delta x_{i,t}^P$ and $\Delta u_{i,t}$ may be negatively correlated. From (6) and (9), we can observe that a positive shock to $u_{i,t-1}$, for example, would reduce $\Delta u_{i,t}$ and at the same time increase $x_{i,t-1}$, which in turn would increase $x_{i,t}^P$ and so increase $\Delta x_{i,t}^P$. An instrument for $\Delta x_{i,t}^P$ is $\Delta x_{i,t}^{IV}$ defined as the (log) passive change that would be observed in case the household did not rebalance in period $t-1$.[25] As expected, given partial rebalancing, $\Delta x_{i,t}^{IV}$ is indeed highly correlated with $\Delta x_{i,t}^P$. The key assumption for the validity of the instrument is that the returns $r_{i,t}$ are uncorrelated with the error term.

We collect our results in Table 6. In column 1, the OLS estimate of β equals 0.37; in column 2, the IV estimate is 0.43. The latter implies that on average our investors rebalance about 57% of their passive change over 12 months. The magnitude is comparable to Calvet et al. (2009), who report estimates around 50% for Swedish households.

In columns 3-5, we investigate whether these effects vary with ambiguity preferences. In column 3, we include no control; in column 4, we include our standard set of controls and time dummies; in column 5, we replicate the full model in (9) by adding portfolio characteristics (returns and standard deviation in the past 12 months), interacting all terms with the passive change (that corresponds to $b^{'} w_{i,t} \Delta x_{i,t}^P$) and including the squared terms of all controls (that corresponds to $w_{i,t}^{'} D_t w_{i,t}$). These estimates reveal that the

[25] Formally, $\Delta x_{i,t}^{IV} = \hat{x}^P - x_{t-1}^P$ where $\hat{x}^P = \ln(\frac{(1+r_{i,t})X_{t-1}^P}{1+r_f+(r_{i,t}-r_f)X_{t-1}^P})$.

higher ambiguity aversion the lower is the impact of the passive change on the total change.

In terms of magnitude, each extra unit of ambiguity aversion decreases the effect of the passive change by approximately 26%. According to the estimates in column 4, with *Ambiguity Aversion* equal to 1, the passive change contributes to the entire change in risk exposure over 12 months. If *Ambiguity Aversion* is equal to 4, the passive change instead contributes to about 20% of the total change.

These results indicate that ambiguity averse investors display a higher speed of adjustment of their portfolios. As noticed, this may be driven by the desire to keep their risk exposure constant over time, which would be in line with the above mentioned theoretical predictions.

We then look at the direction of rebalancing, described by the sign of the active change relative to the passive change. If active change and passive change have the same sign, for example, the investor is rebalancing his portfolio in the same direction as past market trends: he is increasing his exposure to assets which have performed relatively well in the past. We estimate the following equation:

$$\Delta X_{i,t}^{A} = \alpha + \beta AmbigAvers_i * \Delta X_{i,t}^{P} + \gamma \Delta X_{i,t}^{P} + Z_i^{'}\delta + \mu_t + \varepsilon_{i,t}. \tag{10}$$

In equation (10), the coefficient γ estimates the impact of the passive change $\Delta X_{i,t}^{P}$ on the active change $\Delta X_{i,t}^{A}$.[26] If investor i wishes to keep its risk exposure constant over time, he needs to compensate any passive change with an active change of the same magnitude and opposite sign. The coefficient γ should then be close to -1. Our coefficients of interest is β, which measures the differential impact of investors' preferences over ambiguity. The vector $Z_i^{'}$ includes the variables *Ambiguity Aversion* as well our standard set of controls; μ_t are month-year fixed-effects; standard errors are clustered at the individual level.

Results appear in Table 7. In column 1, the coefficient γ is -0.63, which implies that on average households compensate about 63% of the passive change in their risky share. This is consistent with the estimates of Table 4 (column 1), and with Calvet et al. (2009), who show that on average households act as rebalancer. Further evidence along those lines is reported in Guiso and Sodini (2013).

In columns 2-5, we observe that the coefficient β is negative. Estimates are rather stable as we add various controls (column 3), lagged risky share as in Calvet et al. (2009) (column 4) and if we exclude portfolios with zero passive change (column 5). According to these estimates, the larger ambiguity aversion the closer the estimated impact is to -1. Specifically, for the least ambiguity averse investors, a unit increase in the passive change leads

[26] We estimate the equation in levels. Estimates in logs give qualitatively similar results.

to active change of -0.53. For the most ambiguity averse investors, a unit increase in the passive change leads to an active change of -0.67. Put differently, for the most ambiguity averse investors, the distance between the risky share and the constant share is on average 1/3 of the passive change. As in our sample the average passive change is -3.8%, that leads to a risky share which is on average 1.3% lower than the constant share.

This evidence is consistent with the theoretical models mentioned above in which ambiguity averse investors may be reluctant to change their exposure to uncertainty over time. For this purpose, they need to rebalance their portfolio actively and in a contrarian direction relative to market trends, which is indeed what we observe.

7 Concluding Remarks

Our analysis has provided novel results relating ambiguity preferences to the composition, the returns and the dynamics of household portfolios. We have performed several robustness checks on these results, which we report in details in the Online Appendix. First, we have showed that the effects we observe within the company do not vary systematically with the fraction of wealth invested in the company, suggesting that they are representative of clients' behaviors in their overall portfolios. We have also checked that some specific features of assurance vie contracts, like the possibility of delegated portfolio management and fiscal advantages, do not affect our results. On ambiguity aversion, we have considered alternative measures (including preferences in the loss domain) as well as their interaction with other behavioral traits (such as sophistication, confidence, and time preference). Finally, we have discussed our treatment of standard errors and the possibility of survivorship bias in our sample. These tests have shown the robustness of our main findings along all these dimensions.

We view this study only as a first step towards an understanding of the empirical content of ambiguity preferences in relation to financial choices. Further research is needed to assess whether one particular decision model is most relevant to describe investors' preferences over ambiguity. Our study has identified channels through which ambiguity aversion (measured independently of a specific decision model) affects portfolio behaviors. While this gives some insights on which models are consistent with these effects, it does not provide a direct test of these models.[27] Getting richer investment data and finer measures of ambiguity aversion is an obvious direction of improvement, for which a close collaboration with financial institutions is required.

Our results can also be helpful to guide recommendations regarding the

[27] In fact, using a much more structured approach, Ahn et al. (2014) find that not one single model can explain their experimental portfolio data.

way individuals' tolerance for uncertainty should be assessed by financial institutions. At the European level for instance, regulation requires financial institutions to gather information about their clients' objectives and preferences before selling them financial products. What our results suggest is that ambiguity aversion should be carefully taken into account when advising individual investors.

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8 Appendix

8.1 Description of variables

Ambig Aversion

The variable is based on the following questions: *"You have two options: (a) win* 1000 *euros with a completely unknown probability vs. (b) win* 1000 *euros with* 50% *chance and zero otherwise. Which one would you choose?"* If (a) is chosen, we propose (c) win 1000 euros with a completely unknown probability vs. (d) win 1000 euros with 60% chance and zero otherwise. If (b) is chosen, we propose (e) win 1000 euros with a completely unknown probability vs. (f) win 1000 euros with 40% chance and zero otherwise. We build the variable *Ambig Aversion* which takes values 1 if (a) and (c) are chosen, 2 if (a) and (d) are chosen, 3 if (b) and (e) are chosen, and 4 if (b) and (f) are chosen.

Education

The variable takes value 1 if no formal education is reported, 2 refers to vocational training, 3 refers to baccalaureat, 4 refers to a 2-years post bac diploma, 5 refers to a 3-years post bac diploma, 6 refers to a 4-years post bac diploma, 7 refers to a 5-years post bac diploma or above.

Age

The variable takes value 1 if the respondent is less than 30 years old, 2 refers to between 30 and 44 years old, 3 refers to between 45 and 64 years old, 4 refers to 65 years or older.

Income

Monthly net revenues of the household (in euros). A value of 1 corresponds to less than 1000, 2 indicates between 1000 and 1499, 3 indicates between 1500 and 1999, 4 indicates between 2000 and 2999, 5 indicates between 3000 and 4999, 6 indicates 5000 and 6999, 7 indicates between 7000 and 9999, 8 indicates over 10000.

Wealth

Total wealth of the household (in euros). A value of 1 corresponds to less than 8000, 2 indicates between 8000 and 14999, 3 indicates between 15000 and 39999, 4 indicates between 40000 and 79999, 5 indicates between 80000 and 149999, 6 indicates 150000 and 224999, 7 indicates between 225000 and 299999, 8 indicates between 300000 and 449999, 9 indicates between 450000 and 749999, 10 indicates between 750000 and 999999, 11 indicates over 1 million.

Dislike Uncertainty

The variable is based on the following question: "*I don't mind facing uncertainty*". 1 corresponds to "*I completely agree.*" 2 corresponds to "*I partly agree.*" 3 corresponds to "*I do not agree nor disagree.*" 4 corresponds to "*I quite disagree.*" 5 corresponds to "*I fully disagree.*"

Risk Aversion

The variable is based on the following questions: *"You have two options: (a) win* 400 *euros for sure vs. (b) win* 1000 *euros with* 50% *chance and zero otherwise. Which one would you choose?"* In case (a) is chosen, we then offer the choice between (c) win 300 euros for sure vs. (d) win 1000 euros with 50% chance and zero otherwise. In case (b) is chosen, we instead offer the choice between (e) win 500 euros for sure vs. (f) win 1000 euros with 50% chance and zero otherwise. We build the variable *Risk Aversion* which takes values 4 if (a) and (c) are chosen, 3 if (a) and (d) are chosen, 2 if (b) and (e) are chosen, and 1 if (b) and (f) are chosen.

Compute Interest

"*Suppose that you have 1000 € in a saving account which offers a return of 2% per year. After five years, assuming that you have not touched your initial deposit, how much would you own? a) Less than 1100€; b) Exactly 1100€; c) More than 1100€; d) I don't know."* The variable *Compute Interest* is a dummy equal to 1 if the subject answered *More than 1100 €*, and equal to zero otherwise.

Confident

The variable is a 1-7 index based on "*Do you think you can master financial risk?*" 1 corresponds to "not at all" and 7 corresponds to "completely."

Hyperbolic

"You can choose between 1) 1000 euros now; 2) 1020 euros in a month. Which one would you choose?" and *"You can choose between 1) 1000 euros in 12 months; 2) 1020 euros in 13 months. Which one would you choose?"* The variable *Hyperbolic* is a dummy equal to 1 if 1) was chosen in the first question and 2) was chosen in the second question, and to zero otherwise.

8.2 Tables

Table 1: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Ambig Aversion	511	3.086	1.134	1	4
Education	501	4.421	1.886	1	7
Married	511	0.763	0.426	0	1
Age	511	2.613	0.753	1	4
Female	511	0.472	0.500	0	1
Income	494	4.532	1.553	1	8
Wealth	469	6.885	2.467	1	11
Dislike Uncertainty	510	3.318	1.081	1	5
Risk Aversion	511	3.090	1.198	1	4
Compute Interest	511	0.534	0.499	0	1
Confidence	511	3.603	1.438	1	7
Hyperbolic	511	0.196	0.397	0	1
UC Share	39892	0.231	0.286	0	1
Std Dev (in %)	38894	0.478	0.697	0	8.240
Beta (F)	40083	0.097	0.174	-0.126	1.180
Beta (W)	39892	0.074	0.127	-0.268	1.091
Beta(F)-Beta(W)	39892	0.023	0.153	-0.996	1.057
Monthly Returns (in %)	40083	0.385	0.940	-8.616	7.391
Skewness	37937	-0.079	1.230	-3.606	3.606
Coskewness	37435	-0.073	0.473	-4.096	3.916
Change Risky Share	16455	-0.011	0.547	-7.752	6.709
Change Pass Share	13957	-0.104	0.521	-7.357	6.762
Change Pass Share (IV)	13927	-0.106	0.486	-6.051	5.225
Active Change	33217	0.052	0.171	-1	0.999
Passive Change	30847	-0.038	0.142	-0.999	1
Residuals(1)	511	0.005	0.008	0	0.059
Residuals(5)	511	0.005	0.009	0	0.077
R-squared	511	0.204	0.152	0.006	0.805
AvgRet	104	0.385	0.367	-0.587	1.24
Mktrf	104	0.579	4.599	-17.23	10.19
SMB	104	0.483	2.481	-4.76	6.73
HML	104	0.164	2.562	-9.87	7.57
RMW	104	0.078	2.082	-8.86	5.69
CMA	104	0.155	1.510	-3.16	5.02
CAC	104	0.337	5.365	-17.49	13.41

NOTE: The table reports summary statistics for all variables used in the regressions. A definition of these variables can be found in the text and in Section 8.1.

Table 2: Risk Exposure

Dep Variable	UC Share	Std Dev		Beta(F)	
	(1)	(2)	(3)	(4)	(5)
Ambig Aversion	0.007	0.048	0.043	0.013	0.010
	(0.011)	(0.020)**	(0.019)**	(0.005)**	(0.005)**
Controls	Yes	No	Yes	No	Yes
Time Dummies	Yes	No	Yes	No	Yes
Number of Obs	35578	38894	34672	40083	35759
Number of Clusters	457	510	457	510	457
R-squared	0.074	0.006	0.122	0.008	0.128

NOTE: This table reports the results of OLS regressions. In column 1, the dependent variable is the value of uc funds over the total value of the portfolio. In columns 3-4, the dependent variable is the standard deviation of the returns in the previous 12 months. In columns 5-6, the dependent variable Beta(F) is obtained by regressing the returns in the previous 12 months on the French stock market index CAC40. Controls include risk aversion, age, gender, education, marital status, income and wealth. Robust standard errors, clustered at the individual level, are in brackets. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 3: Under-Diversification

Dep Variable	Beta(W)	Beta(F)-Beta(W)		Residuals(1)	Residuals(5)	R-squared
	(1)	(2)	(3)	(4)	(5)	(6)
Ambig Aversion	0.001	0.009	0.007	0.001	0.001	-0.013
	(0.003)	(0.003)***	(0.002)***	(0.0001)***	(0.0003)***	(0.006)**
Beta(F)+Beta(W)			0.202			
			(0.024)***			
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	No	No	No
Number of Obs	35578	35578	35578	452	452	451
Number of Clusters	457	457	457	452	452	451
R-squared	0.106	0.061	0.165	0.081	0.073	0.088

NOTE: This table reports the results of OLS regressions. In column 1, the dependent variable Beta(W) is obtained by regressing the returns in the previous 12 months on the world stock market index MSCI. In columns 2-3, the dependent is the difference between Beta(F) and Beta(W). In column 3, Beta(F)+Beta(W) is the sum of Beta(F) and Beta(W). In column 4, the dependent variable is the sum of squared residuals in the regression of each client's returns on the returns in the domestic stock market CAC40 (see equation (2)). In column 5, the dependent variable is the sum of squared residuals in the regression of each client's returns on Fama-French market factors (see equation (3)). In column 6, the dependent variable is the R-squared of the same regression. Controls include risk aversion, age, gender, education, marital status, income and wealth. Robust standard errors, clustered at the individual level, are in brackets. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

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Table 4: Portfolio Returns

Dep Variable	Monthly Returns (in %)					
	(1)	(2)	(3)	(4)	(5)	(6)
Ambig Aversion	0.016	0.014	0.014	0.013	0.012	0.012
	(0.006)***	(0.006)**	(0.006)**	(0.006)**	(0.006)**	(0.006)**
UC Share			0.056			
			(0.031)*			
Std Dev				0.035		0.08
				(0.014)**		(0.039)**
Beta(France)					0.056	-0.189
					(0.042)	(0.148)
Skewness						0.037
						(0.014)***
Coskewness						0.038
						(0.021)*
Controls	No	Yes	Yes	Yes	Yes	Yes
Time Dummies	No	Yes	Yes	Yes	Yes	Yes
Number of Obs	37642	33561	33391	32549	33561	31265
Number of Clusters	510	457	456	456	457	456
R-squared	0.001	0.218	0.220	0.220	0.218	0.232

NOTE: This table reports the results of OLS regressions. The dependent variable is the monthly returns of the portfolio in percentage points. UC Share is the value of the uc funds over the total value of the portfolio. Std Dev and Skewness are respectively the standard deviation and the skewness of the returns in the previous 12 months. Beta(F) is obtained by regressing the returns in the previous 12 months on the French stock market index CAC40. Coskewness measures the coskewness between the returns and the French stock market index CAC40 in the previous 12 months. Controls include risk aversion, age, gender, education, marital status, income and wealth. Robust standard errors, clustered at the individual level, are in brackets. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 5: Market Factors

Dep Variable	Monthly Returns (in %)					
	(1)	(2)	(3)	(4)	(5)	(6)
Ambig Aversion	-0.037	-0.041	0.011	0.009	0.01	0.01
	(0.022)*	(0.023)*	(0.006)*	(0.006)	(0.006)*	(0.006)
AvgRet*Ambig	0.137	0.144				
	(0.058)**	(0.058)**				
Mktrf*Ambig			0.007	0.007		0.001
			(0.004)*	(0.004)*		(0.002)
SMB*Ambig			-0.001	-0.001	0.001	0.001
			(0.002)	(0.002)	(0.001)	(0.002)
HML*Ambig			0.001	-0.001	-0.002	-0.002
			(0.002)	(0.002)	(0.002)	(0.002)
RMW*Ambig			0.003	0.003	0.004	0.005
			(0.003)	(0.002)	(0.002)*	(0.003)*
CMA*Ambig			0.005	0.006	0.006	0.006
			(0.003)*	(0.003)**	(0.002)**	(0.003)**
CAC*Ambig					0.007	0.006
					(0.347)**	(0.299)**
Controls	No	Yes	No	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs	37642	33561	37642	33561	33561	33561
Number of Clusters	510	457	510	457	457	457
R-squared	0.213	0.223	0.21	0.22	0.22	0.22

Note: This table reports the results of OLS regressions. The dependent variable is the monthly returns of the portfolio in percentage points. AvgRet is the average returns across all portfolios at time t; Mktrf, SMB, HML, RMW and CMA are the Fama-French factors; CAC is the average returns of the CAC40. *Ambig denotes the interaction with Ambig Aversion. Controls include risk aversion, age, gender, education, marital status, income and wealth. Robust standard errors, clustered at the individual level, are in brackets. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 6: Portfolio Dynamics

Dep Variable	Total Change log Risky Share				
	OLS	IV			
	(1)	(2)	(3)	(4)	(5)
Ambig Av * Change Pass Share			-0.296 (0.106)***	-0.261 (0.061)***	-0.266 (0.085)***
Change Pass Share	0.365 (0.062)***	0.429 (0.065)***	1.388 (0.380)***	1.300 (0.244)***	2.644 (0.896)***
Ambig Av			-0.021 (0.012)*	-0.017 (0.011)	-0.006 (0.118)
Controls	No	No	No	Yes	Yes
Controls Interacted and Squared	No	No	No	No	Yes
Time Dummies	No	No	No	Yes	Yes
Number of Obs	13888	13853	13853	12477	12477
Number of Clusters	314	314	314	284	284
R-squared	0.133	0.123	0.096	0.166	0.116

NOTE: This table reports the results of OLS regressions (column 1) and IV regressions (columns 2-5). The dependent variable is the total change in the log risky share $\Delta x_{i,t}$. Change Pass Share in the passive change in the log risky share $\Delta x^P_{i,t}$. In columns 2-6, the instrument is the zero-rebalancing (log) passive change $\Delta x^{IV}_{i,t}$. Ambig Av* Change Pass Share is the interaction between Ambiguity Aversion and $\Delta x^P_{i,t}$. In column 5, for each control variable, we include its interaction with $\Delta x^P_{i,t}$ as well its squared value. Controls include risk aversion, age, gender, education, marital status, income and wealth. In column 5, controls include also the returns and the standard deviation of the returns in percentage points. Robust standard errors, clustered at the individual level, are in brackets. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 7: Portfolio Rebalancing

Dep Variable	Active Change				
	(1)	(2)	(3)	(4)	(5)
Ambig Av * Pass Change		-0.050	-0.048	-0.046	-0.044
		(0.028)*	(0.022)**	(0.020)**	(0.021)**
Passive Change	-0.635	-0.472	-0.498	-0.49	-0.518
	(0.025)***	(0.103)***	(0.081)***	(0.077)***	(0.079)***
Ambig Av		0.001	0.001	0.001	0.001
		(0.002)	(0.002)	(0.002)	(0.003)
Lagged Risky Share				0.043	0.064
				(0.009)***	(0.014)***
Controls	No	No	Yes	Yes	Yes
Time Dummies	No	No	Yes	Yes	Yes
Number of Obs	30790	30790	27395	27394	14904
Number of Clusters	502	502	449	449	298
R-squared	0.414	0.417	0.457	0.464	0.540

Note: This table reports the results of OLS regressions. The dependent variable is the active change in the risky share and Passive Change is the passive change in the risky share, as defined in equation (5). Ambig Av * Pass Change is the interaction between Ambiguity Aversion and Passive Change. Lagged risky share is the risky share in the previous month. Controls include risk aversion, age, gender, education, marital status, income and wealth. Robust standard errors, clustered at the individual level, are in brackets. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Online Appendix

Ambiguity Preferences and Portfolio Choices: Evidence from the Field

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1 Ambiguity Aversion and Other Traits

Table 1: Ambiguity Aversion

Dep Variable	Ambig Aversion					
	(1)	(2)	(3)	(4)	(5)	(6)
Dislike Uncertainty		0.096				
		(0.048)**				
Risk Aversion			-0.048			
			(0.043)			
Compute Interest				0.104		
				(0.106)		
Confident					-0.009	
					(0.036)	
Hyperbolic						-0.144
						(0.129)
Education	0.003	0.001	0.008	-0.002	0.002	0.005
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
Married	-0.039	-0.037	-0.027	-0.038	-0.039	-0.033
	(0.132)	(0.132)	(0.131)	(0.132)	(0.132)	(0.132)
Age	-0.159	-0.158	-0.157	-0.164	-0.162	-0.162
	(0.076)**	(0.076)**	(0.076)**	(0.076)**	(0.077)**	(0.076)**
Female	-0.150	-0.144	-0.200	-0.133	-0.15	-0.138
	(0.105)	(0.105)	(0.106)*	(0.105)	(0.105)	(0.105)
Income	0.141	0.139	0.133	0.142	0.141	0.137
	(0.046)***	(0.046)***	(0.046)***	(0.046)***	(0.046)***	(0.046)***
Wealth	0.043	0.040	0.042	0.041	0.043	0.044
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)*
Observations	457	458	457	458	458	458
R-squared	0.069	0.072	0.076	0.071	0.069	0.072

NOTE: This table reports the results of OLS regressions. A detailed description of all the variables appears in Section 8.1 in the main text. Robust standard errors are in brackets. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

2 Robustness Checks

In Table 2, we collect our main results so as to facilitate the comparison; in the subsequent tables we report the results of our tests.

Representativeness

As we only observe clients' behaviors within the company, one may question whether our effects are informative about households' behaviors in their overall portfolios. As a way to address this question, we exploit the information collected in our survey on households' financial assets and total wealth, and check whether the effects of ambiguity and risk preferences are different for those who have invested a lot vs. little of their wealth in the company. We build the variable *Fraction* as the value of the portfolio held in the company as of August 2010 (around the time when the survey was conducted) and the client's total wealth, which we estimate as the midpoint in the reported interval.[1] *Fraction* takes values between 0.01% and 67.8%, with average equal to 10.3%. We first observe that this fraction is not related to ambiguity preferences. In Table 3, we observe that our estimates do not vary systematically with the fraction of wealth invested in the company.

Delegated Portfolio Management and Fiscal Gains

The management of *assurance vie* contracts can be delegated. Clients could mandate the company to automatically rebalance their contracts in order to keep the fraction of *uc funds* relative to *euro funds* constant over time (so as to fully compensate passive changes in the risky share); alternatively, they could mandate the company to automatically increase the share of *euro funds* in the portfolio (so as to turn to safer portfolios as the age of retirement approaches). In both cases, automatic rebalancing is done once per year and clients can freely opt in or out. In our sample, about 10% of the clients have subscribed one such option in at least one of their contracts. We first observe that the propensity to opt in one these options is not related to ambiguity preferences. We then replicate our main results omitting clients who have opted for delegated management in at least one contract. Results appear in Table 4, and show no significant difference with the results in the main analysis.

Another distinct feature of *assurance vie* contracts is that clients benefit from reduced taxes on capital gains if they keep their contract for at least 8 years. While there should be no mechanical relation between tax advantages and the patterns analyzed in our main analysis, we report here results for the subsamples of clients who have no contract younger than 8 years. While

[1] For the highest interval, where clients report wealth of 1 million euros or above, we consider the minimum of the interval. Results are insensitive to choosing other point estimates within the range, the value of portfolios in nearby months, as well as the value of the portfolio relative to the client's financial assets.

the sample size drops significantly (to about half of the original sample), we observe in Table 5 that our main results are not substantially affected.

Other measures of ambiguity aversion and behavioral traits

We have constructed a dummy *Ambig Averse* which is equal to 1 if *Ambig Aversion* is 4 (that is, if the subject prefers 1000 euros with 40% chance than with unknown probability) and zero otherwise. Accordingly, 70% of our subjects are coded as ambiguity averse. In Table 6, we revise our main results by employing this alternative variable and observe that *Ambig Averse* has very similar effects to our main variable *Ambig Aversion.*

Our survey also contains questions with lotteries involving losses, and based on these questions we can define the 1-4 index *Ambig Aversion(Loss).*[2] In Table 7, we observe that preferences over losses have a different impact, but often not statistically significant. The effects of our main measures are however unchanged.

The literature suggests that ambiguity preferences may be related to behavioral traits such as sophistication, confidence, and time preference. While investigating the effects of all these traits on portfolio choices remains beyond the scope of the present analysis, we here take a more limited task and show that our coefficients of interest are not affected by the inclusion of these extra variables (see Table 8).

Standard Errors

Since we expect some persistence over time in household behaviors and since our variable of interest *Ambig Aversion* varies by individuals and not over time, we have clustered standard errors at the individual level in our main analysis. The error structure we have in mind is one in which observations are independent in any given cross section but not necessarily so for a given individual over time. To confirm the validity of this assumption, we repeat our regressions on returns in Table 4 in the main text (column 1) without using the time dimension. We run a cross-sectional regression in which the dependent variable is the average returns experienced by each client over our sample period. We observe that our estimates are remarkably in line with those reported in the main text (see column 3 of Table 10).

We also notice that this choice of clustering is rather conservative, it would be easier to find statistically significant effects by adopting different specifications. To see this, in Table 9, we report two alternative clustering

[2] *Ambig Aversion(Loss)* is based on: *"You have two options: (a) lose* 1000 *euros with a completely unknown probability vs. (b) lose* 1000 *euros with* 50% *chance and zero otherwise."* If (a) is chosen, (c) lose 1000 euros with unknown probability vs. (d) lose 1000 euros with 40% chance and zero otherwise. If (b) is chosen, (e) lose 1000 euros with unknown probability vs. (f) lose 1000 euros with 60% chance and zero otherwise. The variable takes values 1 if (a) and (c) are chosen, 2 if (a) and (d) are chosen, 3 if (b) and (e) are chosen, and 4 if (b) and (f) are chosen.

of standard errors. In columns 1-3, we cluster by time in order to account for cross-sectional correlation of returns and show that standard errors are considerably lower in this case. The effect is even more dramatic when one considers rather persistent behaviors such as risk taking. In columns 4-6, we employ a double clustering by client and by time following the method developed by Petersen (2009). We observe that our results are basically unchanged.

Sample Selection

As mentioned in the main text, our analysis is based on a sample of clients who had an *assurance vie* contract in the company at the end of 2010. These contracts were opened at possibly different points in time, and this creates a variation across clients in the number of periods in which they appear in our sample.[3] This variation is not random. For example, older clients are more likely to have opened their account earlier and so to appear in our sample for a longer period.

We do not believe however that survivorship bias is driving our results. First, we are mostly exploiting the cross-sectional variation and not the time series dimension in our data. Our estimates would in fact be very similar (though sometimes less precise) if, instead of estimating equation (1), we would run simple cross-sectional regressions using as dependent variable $\bar{y}_i$, the sample average of $y_{i,t}$. We report these estimates in Table 10 (columns 1-4).

Second, we can restrict our sample to those clients who appear for more than 100 periods (the median duration in our sample). Of course, this is an even more selected sample, but our coefficients of interest are consistent (though sometimes noisier) with those reported in the main analysis (see Table 11).

Third, we can apply inverse probability weighting. Let s_i denote the number of periods in which client i appears in our sample, X_i^0 a set of explanatory variables, Z_i a set of auxiliary variables and let $X_i \equiv X_i^0 \cup Z_i$. We define the inverse probability weight as $p_i = \hat{s}_i^0/\hat{s}_i$, where $\hat{s}_i$ is the predicted value of s_i given X_i and $\hat{s}_i^0$ is the predicted value of s_i given X_i^0. In our simplest specification, Z_i includes the client's age, which is the main determinant of s_i, and X_i^0 includes all other demographic variables (gender, education, marital status, income and wealth) as well as ambiguity and risk aversion. In this way, p_i applies larger weights to younger clients, whose predicted probability to be included in the full sample is lower. Results of weighted regressions are reported in Table 12, and they are very much in line with those observed in the main analysis.

While this method only accounts for selection along observables, and

[3]The number of months for which our clients appear in the sample varies between 11 and 104, with mean equal to 78 and median equal to 100.

one may question which variables should be included in X_i^0 and Z_i, our estimates have proven robust across various specifications. If anything, our effects become stronger as we consider additional auxiliary variables. We believe that our baseline specifications provide conservative estimates of our coefficients of interest.

Other specification tests

We have asked our subjects if their education, age, income and wealth fall within pre-specified intervals. For simplicity, in our main analysis, we have included the corresponding categorical variables as controls. There are no strong reasons to impose that any change in these variables would have the same effect. As we show in Table 13, however, our results would be unchanged if we were to add these controls as a series of dummy variables instead.

We measure ambiguity attitudes at one point in time, towards the end of our sample period. In order to explore whether the effects we identify are rather stable over time, we estimate our regressions by restricting to the first half of our sample period, from September 2002 to December 2006. As shown in Table 14, estimates are noisier but comparable in magnitude to our baseline specification.

Finally, while in Tables 2 and 3 in the main text we consider measures of risk exposure based on past returns, investors may be forward-looking. Accordingly, we build the standard deviation of their returns and their betas using returns in the *next* 12 months (as opposed to returns in the past 12 months). As shown in Table 15, results are very similar to the ones reported in our main analysis.

Table 2: Main Results

Dep Variable	Std Dev	$\beta(F)-\beta(W)$	Returns		Tot Change	Act Change
	(1)	(2)	(3)	(4)	(5)	(6)
Ambig Aversion	0.043	0.007	0.012	-0.042	-0.017	0.001
	(0.019)**	(0.002)***	(0.006)**	(0.023)*	(0.011)	(0.002)
AvgRet*Ambig				0.142		
				(0.059)**		
Ambig * Change Pass Share					-0.241	
					(0.059)***	
Change Pass Share					1.300	
					(0.244)***	
Ambig * Pass Change						-0.048
						(0.022)**
Pass Change						-0.498
						(0.081)***
Number of Obs	34672	35578	31265	31265	12477	27395
Number of Clusters	457	457	456	456	284	449
R-squared	0.11	0.165	0.232	0.236	0.166	0.457

NOTE: This table reports the results of OLS regressions (columns 1-4 and 6) and IV regressions (column 5). In column 1, the dependent variable is the standard deviation of the returns in the previous 12 months. In column 2, the dependent variable is the difference between Beta(F) and Beta(W). Controls include the sum of Beta(F) and Beta(W). In columns 3-4, the dependent variable is the monthly returns of the portfolio in percentage points. Controls include the standard deviation, Beta(F), the skewness and the coskewness of the returns. AvgRet is the average returns across all portfolios at time t. In column 5, the dependent variable is the total change in the log risky share. Change Pass Share is the passive change in the log risky share. The instrument is the zero-rebalancing (log) passive change. In column 6, the dependent variable is the active change in the risky share. Passive Change is the passive change in the risky share. All regressions also include time fixed effects and standard controls (risk aversion, age, gender, education, marital status, income and wealth). Robust standard errors, clustered at the individual level, are in brackets. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 3: Representativeness

Dep Variable	Std Dev	$\beta(F)-\beta(W)$	Returns		Tot Change	Act Change
	(1)	(2)	(3)	(4)	(5)	(6)
Ambig Aversion	0.06	0.005	0.014	-0.051	0.001	0.003
	(0.032)*	(0.003)*	(0.006)**	(0.034)	(0.017)	(0.002)
Ambig*Fraction	-0.191	0.021	-0.006	0.105	-0.106	-0.014
	(0.17)	(0.019)	(0.004)	(0.177)	(0.075)	(0.013)
Fraction	0.124	-0.101	0.021	0.134	0.347	0.06
	(0.535)	(0.058)*	(0.015)	(0.534)	(0.265)	(0.042)
AvgRet*Ambig				0.191		
				(0.085)**		
AvgRet*Ambig*Fraction				-0.457		
				(0.456)		
Ambig *Change Pass Share					-0.308	
					(0.070)***	
Ambig*Change Pass*Fraction					0.077	
					(0.102)	
Change Pass Share					1.452	
					(0.275)***	
Ambig*Pass Change*Fraction						0.192
						(0.118)
Ambig*Pass Change						-0.065
						(0.031)**
Passive Change						-0.418
						(0.164)**
Number of Obs	32700	33571	31003	29532	11502	25768
Number of Clusters	429	429	447	428	267	424
R-squared	0.123	0.175	0.233	0.245	0.167	0.466

NOTE: This table reports the results of OLS regressions (columns 1-4 and 6) and IV regressions (column 5). Fraction is the value of the portfolio within the company over the total value of reported wealth. In column 1, the dependent variable is the standard deviation of the returns in the previous 12 months. In column 2, the dependent variable is the difference between Beta(F) and Beta(W). Controls include the sum of Beta(F) and Beta(W). In columns 3-4, the dependent variable is the monthly returns of the portfolio in percentage points. Controls include the standard deviation, Beta(F), the skewness and the coskewness of the returns. AvgRet is the average returns across all portfolios at time t. In column 4, AvgRet*Fraction is included. In column 5, the dependent variable is the total change in the log risky share. Change Pass Share is the passive change in the log risky share. The instrument is the zero-rebalancing (log) passive change. Change Pass Share*Fraction is also included. In column 6, the dependent variable is the active change in the risky share. Passive Change is the passive change in the risky share. Passive Change*Fraction is also included. All regressions also include time fixed effects and standard controls (risk aversion, age, gender, education, marital status, income and wealth). Robust standard errors, clustered at the individual level, are in brackets. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 4: Delegated Portfolio

Dep Variable	Std Dev	$\beta(F) - \beta(W)$	Returns		Tot Change	Act Change
	(1)	(2)	(3)	(4)	(5)	(6)
Ambig Aversion	0.033	0.006	0.014	-0.024	-0.015	0.001
	(0.019)*	(0.002)***	(0.006)**	(0.024)	(0.012)	(0.002)
AvgRet*Ambig				0.099		
				(0.059)*		
Ambig * Change Pass Share					-0.288	
					(0.062)***	
Change Pass Share					1.455	
					(0.246)***	
Ambig * Pass Change						-0.058
						(0.029)**
Pass Change						-0.424
						(0.104)***
Number of Obs	31215	31971	27927	27927	11477	24921
Number of Clusters	433	433	432	432	251	418
R-squared	0.069	0.12	0.203	0.205	0.185	0.369

NOTE: This table reports the results of OLS regressions (columns 1-4 and 6) and IV regressions (column 5). The sample is restricted to clients who have no contract with delegated management. In column 1, the dependent variable is the standard deviation of the returns in the previous 12 months. In column 2, the dependent variable is the difference between Beta(F) and Beta(W). Controls include the sum of Beta(F) and Beta(W). In columns 3-4, the dependent variable is the monthly returns of the portfolio in percentage points. Controls include the standard deviation, Beta(F), the skewness and the coskewness of the returns. AvgRet is the average returns across all portfolios at time t. In column 5, the dependent variable is the total change in the log risky share. Change Pass Share is the passive change in the log risky share. The instrument is the zero-rebalancing (log) passive change. In column 6, the dependent variable is the active change in the risky share. Passive Change is the passive change in the risky share. All regressions also include time fixed effects and standard controls (risk aversion, age, gender, education, marital status, income and wealth). Robust standard errors, clustered at the individual level, are in brackets. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 5: Tax Advantage

Dep Variable	Std Dev	$\beta(F) - \beta(W)$	Returns		Tot Change	Act Change
	(1)	(2)	(3)	(4)	(5)	(6)
Ambig Aversion	0.045	0.011	0.008	-0.035	-0.026	-0.001
	(0.021)**	(0.006)*	(0.007)	(0.026)	(0.014)*	(0.002)
AvgRet*Ambig				0.099		
				(0.059)*		
Ambig * Change Pass Share					-0.32	
					(0.047)***	
Change Pass Share					1.494	
					(0.176)***	
Ambig * Pass Change						-0.127
						(0.042)***
Pass Change						-0.172
						(0.154)
Number of Obs	16797	17058	15648	15648	6523	14813
Number of Clusters	262	263	258	258	153	259
R-squared	0.109	0.097	0.215	0.221	0.29	0.379

NOTE: This table reports the results of OLS regressions (columns 1-4 and 6) and IV regressions (column 5). The sample is restricted to clients who have no contract younger than 8 years. In column 1, the dependent variable is the standard deviation of the returns in the previous 12 months. In column 2, the dependent variable is the difference between Beta(F) and Beta(W). Controls include the sum of Beta(F) and Beta(W). In columns 3-4, the dependent variable is the monthly returns of the portfolio in percentage points. Controls include the standard deviation, Beta(F), the skewness and the coskewness of the returns. AvgRet is the average returns across all portfolios at time t. In column 5, the dependent variable is the total change in the log risky share. Change Pass Share is the passive change in the log risky share. The instrument is the zero-rebalancing (log) passive change. In column 6, the dependent variable is the active change in the risky share. Passive Change is the passive change in the risky share. All regressions also include time fixed effects and standard controls (risk aversion, age, gender, education, marital status, income and wealth). Robust standard errors, clustered at the individual level, are in brackets. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 6: Ambiguity Averse Dummy

Dep Variable	Std Dev	$\beta(F) - \beta(W)$	Returns		Tot Change	Act Change
	(1)	(2)	(3)	(4)	(5)	(6)
Ambig Averse	0.119	0.016	0.02	-0.142	0.002	-0.05
	(0.052)**	(0.005)***	(0.014)	(0.055)***	(0.004)	(0.030)*
AvgRet*Ambig				0.423		
				(0.137)***		
Ambig * Change Pass Share					-0.502	
					(0.100)***	
Change Pass Share					0.81	
					(0.109)***	
Ambig * Pass Change						-0.14
						(0.062)**
Pass Change						-0.543
						(0.057)***
Number of Obs	34672	35578	31265	31265	27395	12477
Number of Clusters	457	457	456	456	449	284
R-squared	0.112	0.165	0.231	0.237	0.458	0.191

NOTE: This table reports the results of OLS regressions (columns 1-4 and 6) and IV regressions (column 5). Ambig Averse is a dummy equal to 1 if Ambig Aversion is 4 and zero otherwise. In column 1, the dependent variable is the standard deviation of the returns in the previous 12 months. In column 2, the dependent variable is the difference between Beta(F) and Beta(W). Controls include the sum of Beta(F) and Beta(W). In columns 3-4, the dependent variable is the monthly returns of the portfolio in percentage points. Controls include the standard deviation, Beta(F), the skewness and the coskewness of the returns. AvgRet is the average returns across all portfolios at time t. In column 5, the dependent variable is the total change in the log risky share. Change Pass Share is the passive change in the log risky share. The instrument is the zero-rebalancing (log) passive change. In column 6, the dependent variable is the active change in the risky share. Passive Change is the passive change in the risky share. All regressions also include time fixed effects and standard controls (risk aversion, age, gender, education, marital status, income and wealth). Robust standard errors, clustered at the individual level, are in brackets. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 7: Preferences over Losses

Dep Variable	Std Dev	$\beta(F)-\beta(W)$	Returns		Tot Change	Act Change
	(1)	(2)	(3)	(4)	(5)	(6)
Ambig Aversion	0.044	0.007	0.011	-0.043	-0.015	0.001
	(0.021)**	(0.002)***	(0.006)**	(0.023)*	(0.012)	(0.002)
Ambig(loss)	-0.012	0.001	0.011	0.03	0.001	-0.001
	(0.023)	(0.002)	(0.006)*	(0.025)	(0.011)	(0.002)
AvgRet*Ambig				0.142		
				(0.058)**		
AvgRet*Ambig(loss)				-0.05		
				(0.064)		
Ambig *Change Pass Share					-0.218	
					(0.068)***	
Ambig(loss)*Ch Pass Share					0.055	
					(0.030)*	
Change Pass Share					0.999	
					(0.300)***	
Ambig*Pass Change						-0.05
						(0.021)**
Ambig(loss)*Pass Change						0.017
						(0.017)
Passive Change						-0.537
						(0.091)***
Number of Obs	34672	35578	31265	31265	12477	27395
Number of Clusters	457	457	456	456	284	449
R-squared	0.111	0.165	0.232	0.236	0.193	0.458

NOTE: This table reports the results of OLS regressions (columns 1-4 and 6) and IV regressions (column 5). Ambig(loss) is a measure of ambiguity aversion elicited with lotteries involving losses. In column 1, the dependent variable is the standard deviation of the returns in the previous 12 months. In column 2, the dependent variable is the difference between Beta(F) and Beta(W). Controls include the sum of Beta(F) and Beta(W). In columns 3-4, the dependent variable is the monthly returns of the portfolio in percentage points. Controls include the standard deviation, Beta(F), the skewness and the coskewness of the returns. AvgRet is the average returns across all portfolios at time t. In column 5, the dependent variable is the total change in the log risky share. Change Pass Share is the passive change in the log risky share. The instrument is the zero-rebalancing (log) passive change. In column 6, the dependent variable is the active change in the risky share. Passive Change is the passive change in the risky share. All regressions also include time fixed effects and standard controls (risk aversion, age, gender, education, marital status, income and wealth). Robust standard errors, clustered at the individual level, are in brackets. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 8: Other Traits

Dep Variable	Std Dev	$\beta(F) - \beta(W)$	Returns		Tot Change	Act Change
	(1)	(2)	(3)	(4)	(5)	(6)
Ambig Aversion	0.041	0.01	0.012	-0.042	-0.016	0.001
	(0.021)*	(0.005)*	(0.006)**	(0.023)*	(0.012)	(0.002)
AvgRet*Ambig				0.141		
				(0.059)**		
Ambig * Change Pass Share					-0.261	
					(0.061)***	
Change Pass Share					1.3	
					(0.244)***	
Ambig * Pass Change						-0.048
						(0.022)**
Pass Change						-0.498
						(0.081)***
Compute Interest	0.068	0.015	0.013	0.013	-0.013	0.001
	(0.051)	(0.012)	(0.017)	(0.017)	(0.025)	(0.004)
Confident	0.014	0.002	0.002	0.002	0.001	0.001
	(0.02)	(0.005)	(0.004)	(0.004)	(0.009)	(0.001)
Hyperbolic	0.013	0.001	-0.015	-0.014	0.002	-0.002
	(0.057)	(0.014)	(0.016)	(0.016)	(0.03)	(0.005)
Number of Obs	34672	35759	31265	31265	12477	27395
Number of Clusters	457	458	456	456	284	449
R-squared	0.113	0.13	0.232	0.236	0.166	0.457

NOTE: This table reports the results of OLS regressions (columns 1-4 and 6) and IV regressions (column 5). Compute Interest is a dummy equal to one if the subject could correctly compute compound interests. Confident is a 1-7 index based the perception of whether financial risk can be mastered. Hyperbolic is a dummy equal to one if the subject reported hyperbolic time preferences. In column 1, the dependent variable is the standard deviation of the returns in the previous 12 months. In column 2, the dependent variable is the difference between Beta(F) and Beta(W). Controls include the sum of Beta(F) and Beta(W). In columns 3-4, the dependent variable is the monthly returns of the portfolio in percentage points. Controls include the standard deviation, Beta(F), the skewness and the coskewness of the returns. AvgRet is the average returns across all portfolios at time t. In column 5, the dependent variable is the total change in the log risky share. Change Pass Share is the passive change in the log risky share. The instrument is the zero-rebalancing (log) passive change. In column 6, the dependent variable is the active change in the risky share. Passive Change is the passive change in the risky share. All regressions also include time fixed effects and standard controls (risk aversion, age, gender, education, marital status, income and wealth). Robust standard errors, clustered at the individual level, are in brackets. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 9: Clustering of Standard Errors

Dep Variable	UC Share	Monthly Returns		UC Share	Monthly Returns	
	(1)	(2)	(3)	(4)	(5)	(6)
Ambig Aversion	0.007	0.012	-0.042	0.007	0.012	-0.042
	(0.001)***	(0.004)***	(0.009)***	(0.011)	(0.006)**	(0.024)*
Risk Aversion	-0.006	-0.002	-0.002	-0.006	-0.002	-0.002
	(0.001)***	(0.003)	(0.003)	(0.011)	(0.006)	(0.006)
AvgRet*Ambig			0.141			0.141
			(0.013)***			(0.059)**
Number of Obs	35578	31265	31265	35578	31265	31265
Number of Clusters	104	103	103	104/457	103/456	103/456
R-squared	0.074	0.232	0.236	0.074	0.232	0.236

Note: This table reports the results of OLS regressions. In columns 1-3, standard errors are clustered by time (month*year). In columns 4-6, standard errors are clustered by client and time (double clustering). In columns 1 and 4, the dependent variable is the value of uc funds over the total value of the portfolio. In columns 2,3,5 and 6, the dependent variable is the monthly returns of the portfolio in percentage points. Controls include the standard deviation, Beta(F), the skewness and the coskewness of the returns. AvgRet is the average returns across all portfolios at time t. All regressions also include time fixed effects and standard controls (risk aversion, age, gender, education, marital status, income and wealth). Robust standard errors are in brackets. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 10: Sample Averages and Information Ratios

Dep Variable	Avg Std Dev	Avg $\beta(F) - \beta(W)$	Avg Monthly Returns		IR (CAC40)	IR (MSCI)
	(1)	(2)	(3)	(4)	(5)	(6)
Ambig Aversion	0.032	0.004	0.017	-0.325	0.003	0.003
	(0.022)	(0.002)*	(0.007)**	(0.179)*	(0.001)**	(0.001)**
AvgRet*Ambig				0.939		
				(0.447)**		
Controls	Yes	Yes	No	Yes	Yes	Yes
Time Dummies	Yes	Yes	No	Yes	Yes	Yes
Number of Obs	457	457	486	434	33561	33561
Number of Clusters					457	457
R-squared	0.121	0.623	0.013	0.043	0.967	0.96

NOTE: This table reports the results of OLS regressions. In column 1, the dependent variable is the average standard deviation of the returns of the client over the sample period. In column 2, the dependent variable is the difference between the average Beta(F) and the average Beta(W) of the client over the sample period. Controls include the sum of the average Beta(F) and the average Beta(W). In columns 3-4, the dependent variable is the average monthly returns of the client portfolio over the sample period. Controls include the average standard deviation, average Beta(F), the average skewness and the average coskewness of the returns. AvgRet is the average returns across all portfolios at time t. In column 5, the dependent variable is the information ratio relative to the CAC40 index, defined as the ratio of the difference between the monthly returns of the client and that of CAC40 over the standard deviation of this difference. In columns 6, the dependent variable is the information ratio relative to the MSCI index, defined as the ratio of the difference between the monthly returns of the client and that of MSCI over the standard deviation of this difference. Controls include risk aversion, age, gender, education, marital status, income and wealth. Robust standard errors, clustered at the individual level in columns 5-6, are in brackets. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 11: Balanced Sample

Dep Variable	Std Dev	$\beta(F) - \beta(W)$	Returns		Tot Change	Act Change
	(1)	(2)	(3)	(4)	(5)	(6)
Ambig Aversion	0.034	0.008	0.01	-0.029	-0.016	0.001
	(0.023)	(0.002)***	(0.007)	(0.027)	(0.013)	(0.002)
AvgRet*Ambig				0.101		
				(0.066)		
Ambig * Change Pass Share					-0.302	
					(0.056)***	
Change Pass Share					1.494	
					(0.228)***	
Ambig * Pass Change						-0.087
						(0.039)**
Pass Change						-0.305
						(0.142)**
Number of Obs	23070	23495	21145	21145	9192	19649
Number of Clusters	232	232	232	232	155	232
R-squared	0.077	0.112	0.211	0.214	0.227	0.374

NOTE: This table reports the results of OLS regressions (columns 1-4 and 6) and IV regressions (column 5). The sample is restricted to clients who appear in the sample for more than 100 periods. In column 1, the dependent variable is the standard deviation of the returns in the previous 12 months. In column 2, the dependent variable is the difference between Beta(F) and Beta(W). Controls include the sum of Beta(F) and Beta(W). In columns 3-4, the dependent variable is the monthly returns of the portfolio in percentage points. Controls include the standard deviation, Beta(F), the skewness and the coskewness of the returns. AvgRet is the average returns across all portfolios at time t. In column 5, the dependent variable is the total change in the log risky share. Change Pass Share is the passive change in the log risky share. The instrument is the zero-rebalancing (log) passive change. In column 6, the dependent variable is the active change in the risky share. Passive Change is the passive change in the risky share. All regressions also include time fixed effects and standard controls (risk aversion, age, gender, education, marital status, income and wealth). Robust standard errors, clustered at the individual level, are in brackets. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 12: Weighted Regressions

Dep Variable	Std Dev	$\beta(F) - \beta(W)$	Returns		Tot Change	Act Change
	(1)	(2)	(3)	(4)	(5)	(6)
Ambig Aversion	0.043	0.007	0.013	-0.041	-0.018	0.001
	(0.022)**	(0.002)***	(0.006)**	(0.024)*	(0.011)	(0.002)
AvgRet*Ambig				0.142		
				(0.061)**		
Ambig * Change Pass Share					-0.256	
					(0.061)***	
Change Pass Share					1.276	
					(0.242)***	
Ambig * Pass Change						-0.046
						(0.021)**
Pass Change						-0.506
						(0.080)***
Number of Obs	34672	35578	31265	31265	12477	27395
Number of Clusters	457	457	456	456	284	449
R-squared	0.114	0.171	0.235	0.239	0.163	0.462

NOTE: This table reports the results of Least Squares regressions (columns 1-4 and 6) and 2SLS regressions (column 5) in which observations are weighted by inverse probability weights. In column 1, the dependent variable is the standard deviation of the returns in the previous 12 months. In column 2, the dependent variable is the difference between Beta(F) and Beta(W). Controls include the sum of Beta(F) and Beta(W). In columns 3-4, the dependent variable is the monthly returns of the portfolio in percentage points. Controls include the standard deviation, Beta(F), the skewness and the coskewness of the returns. AvgRet is the average returns across all portfolios at time t. In column 5, the dependent variable is the total change in the log risky share. Change Pass Share is the passive change in the log risky share. The instrument is the zero-rebalancing (log) passive change. In column 6, the dependent variable is the active change in the risky share. Passive Change is the passive change in the risky share. All regressions also include time fixed effects and standard controls (risk aversion, age, gender, education, marital status, income and wealth). Robust standard errors, clustered at the individual level, are in brackets. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 13: Controls as Dummies

Dep Variable	Std Dev	$\beta(F) - \beta(W)$	Returns		Tot Change	Act Change
	(1)	(2)	(3)	(4)	(5)	(6)
Ambig Aversion	0.042	0.008	0.014	-0.04	-0.02	0.001
	(0.022)*	(0.002)***	(0.006)**	(0.024)*	(0.012)	(0.002)
AvgRet*Ambig				0.141		
				(0.059)**		
Ambig * Change Pass Share					-0.266	
					(0.060)***	
Change Pass Share					1.317	
					(0.239)***	
Ambig * Pass Change						-0.047
						(0.021)**
Pass Change						-0.493
						(0.080)***
Number of Obs	34672	35578	31265	31265	12477	27395
Number of Clusters	457	457	456	456	284	449
R-squared	0.144	0.171	0.233	0.237	0.176	0.462

NOTE: This table reports the results of OLS regressions (columns 1-4 and 6) and IV regressions (column 5). In column 1, the dependent variable is the standard deviation of the returns in the previous 12 months. In column 2, the dependent variable is the difference between Beta(F) and Beta(W). Controls include the sum of Beta(F) and Beta(W). In columns 3-4, the dependent variable is the monthly returns of the portfolio in percentage points. Controls include the standard deviation, Beta(F), the skewness and the coskewness of the returns. AvgRet is the average returns across all portfolios at time t. In column 5, the dependent variable is the total change in the log risky share. Change Pass Share is the passive change in the log risky share. The instrument is the zero-rebalancing (log) passive change. In column 6, the dependent variable is the active change in the risky share. Passive Change is the passive change in the risky share. All regressions also include time fixed effects and standard controls (risk aversion, age, gender, education, marital status, income and wealth). For age, education, income and wealth, we include a series of dummies variables instead of categorical variables as in the baseline regressions. Robust standard errors, clustered at the individual level, are in brackets. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 14: Initial Sample Period

Dep Variable	Std Dev	$\beta(F) - \beta(W)$	Returns		Tot Change	Act Change
	(1)	(2)	(3)	(4)	(5)	(6)
Ambig Aversion	0.046	0.004	0.015	-0.08	0.033	0.003
	(0.024)*	(0.002)*	(0.009)*	(0.039)**	(0.015)**	(0.002)*
AvgRet*Ambig				0.201		
				(0.079)**		
Ambig * Change Pass Share					-0.526	
					(0.200)***	
Change Pass Share					2.301	
					(0.707)***	
Ambig * Pass Change						-0.071
						(0.036)*
Pass Change						-0.464
						(0.135)***
Number of Obs	14137	14577	12812	12812	4370	9975
Number of Clusters	346	352	344	344	179	323
R-squared	0.084	0.196	0.212	0.217	0.176	0.449

NOTE: This table reports the results of OLS regressions (columns 1-4 and 6) and IV regressions (column 5). The sample is restricted to the first half of our sample period, from September 2002 to December 2006. In column 1, the dependent variable is the standard deviation of the returns in the previous 12 months. In column 2, the dependent variable is the difference between Beta(F) and Beta(W). Controls include the sum of Beta(F) and Beta(W). In columns 3-4, the dependent variable is the monthly returns of the portfolio in percentage points. Controls include the standard deviation, Beta(F), the skewness and the coskewness of the returns. AvgRet is the average returns across all portfolios at time t. In column 5, the dependent variable is the total change in the log risky share. Change Pass Share is the passive change in the log risky share. The instrument is the zero-rebalancing (log) passive change. In column 6, the dependent variable is the active change in the risky share. Passive Change is the passive change in the risky share. All regressions also include time fixed effects and standard controls (risk aversion, age, gender, education, marital status, income and wealth). Robust standard errors, clustered at the individual level, are in brackets. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

Table 15: Future Variables

Dep Variable	Std Dev		Beta(F)		Beta(F)-Beta(W)	
	(1)	(2)	(3)	(4)	(5)	(6)
Ambig Aversion	0.056	0.049	0.013	0.01	0.009	0.007
	(0.024)**	(0.023)**	(0.005)***	(0.005)**	(0.003)***	(0.002)***
Beta(F)+Beta(W)						0.235
						(0.014)***
Controls	No	Yes	No	Yes	Yes	Yes
Time Dummies	No	Yes	No	Yes	Yes	Yes
Number of Obs	39541	35272	40083	35759	35578	29842
Number of Clusters	511	458	511	458	457	450
R-squared	0.008	0.123	0.007	0.142	0.061	0.215

NOTE: This table reports the results of OLS regressions. In columns 1-2, the dependent variable is the standard deviation of the returns in the next 12 months. In columns 3-4, the dependent variable Beta(F) is obtained by regressing the returns in the next 12 months on the French stock market index CAC40. In columns 5-6, the dependent is the difference between Beta(F) and Beta(W), which is obtained by regressing the returns in the next 12 months on the world stock market index MSCI. In column 6, Beta(F)+Beta(W) is the sum of Beta(F) and Beta(W). Controls include risk aversion, age, gender, education, marital status, income and wealth. Robust standard errors, clustered at the individual level, are in brackets. *, ** and *** denotes significance at 10%, 5% and 1% level, respectively.

References

Petersen, M. A. (2009), 'Estimating standard errors in finance panel data sets: Comparing approaches', *Review of Financial Studies* **22**(1), 435–480.