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Behavioral determinants of home bias - theory and experiment*

Dennis Dlugosch[†], Kristian Horn[‡], Mei Wang[§]

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Abstract

We study portfolio diversification in an experimental decision task, where asset returns depend on a draw from an ambiguous urn. Holding other information identical and controlling for the level of ambiguity, we find that labeling assets as being familiar or from the homeland of subjects increases portfolio weights by around 25%, respectively; although the return-generating process remains unaffected. Importantly, we only find these effects when the returns of assets are highly ambiguous. Our ambiguity robust mean-variance model accurately predicts benchmark portfolio weights of the experimental control group, where assets are not labeled: subjects allocate more wealth to assets with low ambiguity. For treatment group portfolios, which show a bias towards assets with a familiar or homeland label, the model does not hold. This misdiversification against the benchmark portfolio can be rationalized via the concept of source dependence of uncertainty attitudes.

Keywords: Home bias, ambiguity aversion, familiarity, experiment
JEL-Classification: C91, D14, D81, G11

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1 Introduction

Today, financial markets are highly integrated and costs of information acquisition are comparatively low. Many investors, however, still primarily buy domestic equities. This well-known phenomenon is usually referred to as home bias: Investors hold disproportionately more domestic than foreign securities. As a consequence, investors forego benefits from international diversification, which proves to be widely profitable (Santis and Gerard 1997). Home bias, nevertheless, is of remarkably high magnitude and persistent over developed and emerging countries (Coeurdacier and Rey 2013). Although institutional factors are apparent contributors, they do not satisfactorily explain the high degree of observed home bias. For example, transaction costs are unlikely to be a main driver of home bias, because turnover of foreign assets is higher than turnover of domestic assets in well developed capital markets such as USA, UK, Germany, Canada, and Japan(Tesar and Werner (1995)). Hence, already French and Poterba (1991), who were among the first to identify home bias, note that it is likely to be a behavioral phenomenon.

In this paper we shed light on prominent behavioral explanations of home bias, in particular ambiguity aversion (Boyle et al. 2012; Maccheroni et al. 2013), familiarity heuristics (Huberman 2001) and homeland sympathy, or patriotism (Morse and Shive 2011). In non-experimental empirical studies, it is hard to distinguish these factors because they are naturally confounded. Ambiguity typically refers to the second-order uncertainty on the return distribution of a given asset, whereas familiarity refers to the extent to which the person is familiar with the name of the asset. A more familiar security, for example, then is likely to be also perceived as less ambiguous.[1] Therefore, with an orthogonal experimental design, we systematically disentangle these factors in the lab, using the idea of source dependence of uncertainty aversion (Abdellaoui et al. 2011). We let sub-

[1] In the same vein, every asset an investor holds out of patriotic reasons obviously is from the homeland. Hence, it is likely to be also viewed as more familiar as well as less ambiguous than a foreign asset from a comparable company.

jects allocate an endowment on assets whose returns depend on a draw from an ambiguous urn. The information on the composition of the urn for each asset is the same in all treatments. However, over treatments we change the source of uncertainty for the asset specific urn to be associated either with pure chance, or a certain homeland, or a more or less familiar company. Thus, we can disentangle the effects of ambiguity, homeland loyalty and familiarity as potential determinants of home bias. To this end we derive predictions for our experimental groups from the ambiguity augmented mean-variance model of Maccheroni et al. (2013). The portfolio weights of our experimental control group serve as our benchmark portfolio.

In line with the model ambiguity has a profound effect: Higher ambiguity as well as higher ambiguity aversion reduce investment in all treatments. In particular the model, thus, nicely predicts all variation in the benchmark portfolio of our experimental control group. Comparing treatments we find that investment is indeed source dependent: Labeling the source of the security's ambiguity as the subjects' homeland or a familiar company generates a deviation from the benchmark portfolio, which can explain home bias. This misdiversification, however, the model does not predict. Importantly, we show that the bias is driven by investment in securities with particularly high ambiguity; consistent with the finding that uncertainty exaggerates investor biases (Kumar 2009). The bias can be roughly attributed half to familiarity and half to homeland loyalty. Note that this misdiversification regarding the benchmark group portfolio is indeed a bias. It can neither be rationalized with an informational advantage, as argued by advocates of the institutional explanation for home bias (e.g. Van Nieuwerburgh and Veldkamp (2009)), nor with a lower level of ambiguity (e.g. Epstein (2003); Maccheroni et al. (2013)). Both aspects have been held constant in our experiment.

Ambiguity, indeed, is well-known to play a major role in explaining investor behavior and biases (Guidolin and Rinaldi 2013). Hence, controlling for ambiguity in the analysis of home bias determinants seems crucial. Interestingly, a number of studies (e.g. Cao et al. (2011) and Boyle et al. (2012)) interpret ambiguity to be negatively related to familiarity, the next frequently proposed behavioral determinant of home bias (Huberman 2001): It is often assumed that the higher the familiarity the lower the ambiguity of an asset. This interpretation indeed can be a fine approximation for empirical work. It implies, however, that the concepts of familiarity and ambiguity are two sides of the same coin. On the contrary, we distinguish these two concepts in a more precise way. Following the standard definition of ambiguity, we refer to actual ambiguity as the uncertainty on a probability distribution a decision maker assigns to a prospect based on all relevant information he has. Whereas we refer to familiarity as the ease to recall in the memory, which stems from the availability heuristic proposed by Tversky and Kahneman (1973). Familiarity may well explain lower perceived ambiguity. The objective or actual ambiguity of a prospect itself, however, can be different from the degree of familiarity. The return distribution of a highly familiar asset, for example, may still be ambiguous due to some intrinsic properties of the asset or lack of information. Therefore, in our experiment ambiguity is associated with the underlying distribution, a statistical concept, whereas familiarity captures the psychological distance to a given asset.[2]

In light of this argument, controlling for ambiguity seems particularly important, since empirical studies employ numerous variables like distance, common language, common border etc. to proxy familiarity (e.g. Coval and Moskowitz 1999; Huberman 2001; Grinblatt and Keloharju 2001; Chan et al. 2005). While being significant predictors, these variables obviously are confounded with ambiguity. For example, if the effect of distance on the holdings of a specific share is positive, this may be due to either fact: that assets closer to the investor are more familiar, or that closer assets are perceived as less ambiguous; or even both. The very same is true for patriotism, or homeland sympathy, which is another

[2]This argument is in line with Huberman (2001) and relies on the distinction between perceived familiarity and real informational advantages with respect to a certain prospect.

frequently mentioned behavioral factor for home bias (Morse and Shive (2011)). Every asset an investor potentially buys out of patriotic reasons, almost naturally will also be more familiar; and its return, thus, correspondingly perceived as less ambiguous.

In our investigation, we view the role of ambiguity, familiarity, and homeland sympathy as distinct determinants of home bias. On the one hand, we control the source and size of the confounding factor for ambiguity. While the source is different over treatments, the return of each asset always depends upon a draw from the same ambiguous distribution. On the other hand, institutional factors, such as informational frictions or transaction costs, are absent in our experimental setting. Our paper draws upon the findings of Ackert et al. (2005), who probably are closest to our work. Using a comparable experimental setting they do identify a substantial bias towards more familiar assets. There are several notable differences to our paper. First, they do not identify effects of homeland loyalty. Second, they employ the U.S. and Canada as in- and outgroup, respectively, which may represent a very different relationship compared to Germany and Japan, which we use in our experiment. The third and most important difference is that they do not control for ambiguity. Thus, they do not determine whether the difference in portfolio weights is due to the effect of familiarity or due to ambiguity of the underlying distribution, both of which we find to be major determinants of home bias.

2 Experimental Design

2.1 Task

We ask subjects to play the role of an investor and to allocate an endowment of 100 Taler on a portfolio of 8 assets. Returns of these assets depend on a draw from an asset specific urn, which always contains red and green balls. If a green ball is drawn, the asset pays a dividend of 2 Taler for each Taler invested. If a red ball is drawn, the asset pays no dividend. By giving the minimum number of balls for each color and urn, we control the assets' ambiguity level to be low or high: Half of the assets are assigned an expected return interval of $[0.45, 0.55]$ (at least 9 of 20 balls are green and red, respectively); the other half of $[0.15, 0.85]$ (at least 3 of 20 balls are green and red, respectively).

2.2 Treatments

While the level of ambiguity for each asset stays constant over treatments, we vary its source. That is, across treatments we change the source associated with each asset specific urn from pure chance, to a certain homeland, to a familiar or unfamiliar company. Hence, our treatments differ with respect to the potential determinants of home bias: the ambiguity, the homeland, and the familiarity of each asset. To this end, across our treatments we vary one, two, or all of these three factors within-subject. In our CONTROL treatment, the source of uncertainty is pure chance, as we only vary the baseline factor ambiguity to be low or high, as described above. In treatment NATION we additionally vary the homeland of assets by assigning half of the assets headquarters in Germany (ingroup) and the other half in Japan (outgroup).[3] In treatment FULL, finally, in addition to the homeland we change the familiarity of assets by giving half of the assets names of familiar and half of the assets names of unfamiliar firms.

Add Table 1 about here

To sum up we use a mixed design with four between-subject treatments (see Table 1). This design includes two robustness checks: First, in treatment NAME we only vary the familiarity of assets, assigning Japan as the homeland for all assets. Thus, we can check whether a potential effect of familiarity also holds

[3]We choose Japan as the outgroup country for several criteria. First, a priori we could make sure that for all of our subjects Japan is indeed not their homeland. Second, Japan neither evokes particularly positive nor negative feelings for most of our subjects, probably because of being a less well-known culture among ordinary German and Austrian citizens; see experimentally elicited sympathy for Japan in section 4.3. Therefore, we avoid confounding fan effects. Third, Japan still is economically powerful enough to provide us with a number of familiar as well as unfamiliar firms to contrast with their ingroup counterparts within both industries that we utilize in this experiment.

for outgroup countries alone. Second, we also look at Austrian subjects as the ingroup in treatment NATION. This allows us to examine whether a potential influence of homeland loyalty may depend on the specific nation analyzed.

Recall that the asset-specific ambiguity level, which usually confounds both homeland and familiarity, stays constant over all treatments. This allows us to distinguish the behavioral determinants of home bias along their interpretation as different sources of uncertainty.

2.3 Subjective indicators

As indicated in the introduction, behavioral determinants of home bias, such as uncertainty, familiarity and homeland loyalty, are difficult to analyze in non-experimental settings. One important reason is that these factors are at least partly subjective and hence difficult to measure from market data. Data on these variables is hardly available at the individual investor level. In our study we are able to assess subjective indicators regarding these factors, and relate them to the investment decisions.

2.3.1. Uncertainty indices. For each individual after the portfolio choice task we elicit standardized certainty equivalents of a risky (CE_r) and an ambiguous lottery (CE_a) via switching points in choice lists (Holt and Laury 2002; Dohmen et al. 2011).[4] The respective standardized CE we define as the first safe choice divided by the total number of choices in 10 decision pairs between a safe payment ranging from 0 to 5 EUR and an (ambiguous) risky prospect paying zero or 5 EUR with (un)known probability. Following Trautmann et al. (2011) and Sutter et al. (2013) these measures serve as a basis for our risk and ambiguity tolerance indices. The individual risk tolerance r is defined as

$$r = 1 - CE_r, \tag{1}$$

[4] Comparing different elicitation methods for ambiguity attitudes, Trautmann et al. (2011) find that choice lists avoid shortcomings such as overestimation and preference reversal, which are commonly found for other measurement methods, such as directly eliciting willingness-to-pay for risky and ambiguous prospects.

ranging from zero to 1. Increasing values imply less risk tolerance. The focus variable regarding the results of our experiment is the individual ambiguity tolerance a. This parameter is defined as

$$a = CE_r - CE_a, \tag{2}$$

ranging from -1 (highly ambiguity tolerant) to 1 (highly ambiguity averse). This ambiguity tolerance measure for each subject relates the CE_a of the ambiguous to the CE_r of the risky lottery in the choice list task. It computes a CE difference, i.e. an *ambiguity premium*, which indicates whether subjects require compensation for accepting an ambiguous lottery. Note that a classification of individual uncertainty attitudes, i.e. of whether a subject is risk and ambiguity averse, neutral, or loving, respectively, would usually rely on an assumption regarding his utility function. As we do not aim at calibrating a specific utility model, we refrain from applying such an assumption. For our purpose measuring model-free indices of risk and ambiguity tolerance suffices.

2.3.2. Familiarity and sympathy scores. At the end of the experiment we assess perceived familiarity with all firms utilized in this experiment (familiarity score) as well as sympathy with a list of countries (sympathy score). That is, on the one hand, based on a question of the World Value Survey, all participants were asked to state their sympathy on a scale from 1 (little) to 4 (strong) towards several nations, including those we choose to represent the ingroup (Germany or Austria) and the outgroup (Japan).[5] On the other hand, all participants were supposed to judge their general familiarity on a scale from 1 (unfamiliar) to 6 (very familiar) with a complete list of all firms made use of in the experiment. Indeed, checking our manipulation we find that those firms we a priori chose to be familiar in treatments NAME and FULL were on average assigned substan-

[5]The World Values Survey (WVS) covers about 250 questions ranging from demographic information to feelings and opinion about politics, religion, family, and a wide variety of additional subjects. It is administered by the University of Michigan and carried out in about 50 countries. See http://www.worldvaluessurvey.org/.

tially higher familiarity scores from all subjects than the unfamiliar firms (see the full list of firms and familiarity scores in Table 2). All firms compared were matched by industry to avoid confounding effects.[6]

2.4 Procedure

The portfolio choice task is replicated for five rounds in all treatments. After each round subjects learn about the assets' dividend payments as well as their return on investment. In all our experimental sessions subjects were told that the first round is a trial, which does not affect payoffs. This is to make sure that subjects truly understand and consider the consequences of their decisions. At the end of the experiment we asked the subjects to fill in a questionnaire, which includes questions on the familiarity and sympathy scores as well as experience in financial markets, socio-demographic factors and several control questions.

2.5 Subject pool and sample

Sessions were conducted at the Innsbruck-EconLab for experimental economic research. Recruitment was done with ORSEE (Greiner 2004) from a standard pool of roughly 4200 undergraduate and graduate students from all faculties. In total 215 students of various backgrounds participated in our four treatments, yielding a total of 1075 portfolio decision rounds.

Add Table 3 about here

None of the students had any prior experience in experiments with an investment decision context. Table 3 gives an overview on our sample. Almost 80 percent of the subjects were either Austrian or German. Due to our focus on these ingroups in treatments NATION and FULL, 14.4 percent of our observations from outgroup nationalities (31 subjects in total) were omitted. The

[6] We choose firms from the automobile sector for practical reasons: For both the ingroup as well as the outgroup country this industry is large and important enough to account for unfamiliar and familiar firms with respect to a non-expert subject pool. Changing the industry and additionally introducing firms from the information technology industry as a robustness check in treatment NAME did not change results.

experiment was computerized with zTree (Fischbacher 2007). The average experimental session lasted for approximately 75 minutes. Average earnings were 13.17 EUR per subject.

3 Theory and hypotheses

3.1 Theoretical framework

In the mean-variance model by Markowitz (1952), investors hold a risky portfolio, which is a function of means, variances and covariances of the given assets. The input factors are derived from the distribution functions of the assets' returns. Uncertainty about the return distribution can be reduced to a single estimate for the first two moments and for the first co-moment. This is because subjects are either neutral to ambiguity and include subjective prior knowledge by correctly applying the Bayesian rule or because ambiguity is absent and probabilities are objectively known.

Both cases seem unrealistic. First, return distributions on financial markets are usually not known precisely. Second, by now a large body of evidence - beginning with Ellsberg (1961) - suggests that most people are averse to situations of ambiguity (see Halevy (2007) for a recent experimental study). Our setup shares the feature of return distributions that are not objectively given. To derive quantitative implications without assuming neutrality to ambiguity, we make use of the robust mean-variance model of Maccheroni et al. (2013), which is based on the axiomatized preference model of Klibanoff et al. (2005). This theory has two main advantages. First, this ambiguity model distinguishes between ambiguity (beliefs) and attitudes towards ambiguity (tastes). Opposite to the popular max-min expected utility model (Gilboa and Schmeidler (1989)), where all agents react similarly to a given level of ambiguity, different levels of ambiguity tolerance can be analyzed. Second and more importantly, all available tools developed for the analysis of different risk attitudes can also be applied to the smooth ambiguity model. This second feature allows Maccheroni et al.

(2013) to apply the Arrow-Pratt approximation to obtain the following generalized mean-variance model which accounts for uncertainty about the true return distribution:

$$C(W) = E_P(W) - \frac{\lambda}{2}\sigma_P^2(W) - \frac{\theta}{2}\sigma_\mu^2(E(W)) \tag{3}$$

This mean-variance evaluation of the prospect W depends on three parameters: λ, θ and μ. λ and θ are strictly positive coefficients denoting attitudes towards risk and ambiguity, where higher values imply less tolerance. $E_P(W)$ is the expected value under the reference probabilistic model P and $\sigma_P^2(W)$ is its variance, which measures perceived risk - or state uncertainty - of prospect W. However, in addition to the classical mean-variance model, the agent also regards other probabilistic models possible. These alternatives have a different underlying probability distribution over payoffs. The agent weighs all possible models with a belief about their occurrence. This belief is captured by μ in the term $\sigma_\mu^2(E(W))$, which accounts for ambiguity or model uncertainty in this mean-variance framework.[7] Intuitively, $\sigma_\mu^2(E(W))$ is the variance of the average payoff in all probabilistic models considered, weighted with the probability distribution μ.

It is easy to see that the generalized mean-variance model in equation 3 reduces to the classic mean-variance functional when the variance of averages $\sigma_\mu^2(E_P(W))$ is zero. Consequently, when there is no model uncertainty regarding the true return distribution, the optimal portfolio weights depend only on the reference model. However, if the true return distribution is not known, model uncertainty $\sigma_\mu^2(E_P(W))$ will be nonzero, and thus affecting the optimal vector of portfolio weights. Hence, in this augmented mean-variance framework an ambiguous asset would always receive a smaller weight than an asset whose payoff is only driven by risk, or state uncertainty.

[7] To avoid confusion we stick with the wording of Maccheroni et al. (2013) and term risk and ambiguity to be different forms of uncertainty, namely state and model uncertainty, respectively. This intuitively fits the theory as well as the idea of source dependence of uncertainty aversion; see section 5.

3.2 A robust mean-variance model

We now apply the generalized mean-variance framework to our setup. The state space in our experiment consists of two states: Paying dividend (green ball), or paying no dividend (red ball). The probabilities of drawing green or red from each asset specific urn are not objectively given and depend on a probabilistic model. Subjects only have the following information: For the asset with low ambiguity at least 9 of 20 balls are green; for the one with high ambiguity at least 3 of 20 balls are green. Hence, the probability of drawing green, that is the expected return for the low ambiguity asset, is between 45% and 55%; for the high ambiguity asset it is between 15% and 85%. This is a case of uncertainty, since the probabilistic model, which determines the probabilities of the two states, is not known. Therefore, we may assume subjects in our experiment compute the vector of optimal portfolio weights using the preference functional in equation 3, which is robust to model uncertainty. Each subject maximizes wealth m by choosing the optimal vector of portfolio weights w. If there is no risk-free asset and short-selling is not allowed the maximization problem takes the following form:

$$\max_{\mathbf{w}\in\mathbb{R}^n}\{\mathbf{w^T}\cdot\mathbf{m}-\frac{1}{2}\mathbf{w^T}\mathbf{E}\mathbf{w}\} \tag{4}$$

subject to

$$\mathbf{1}^T\mathbf{w}=1$$

$$w_i \geq 0, i\in\{1,...,8\},$$

where $\mathbf{w}=[w_1,\ldots,w_n]^T$ is a $n\times 1$ vector of portfolio weights invested in the i-th asset, $i\in\{1,\ldots,n\}$.

$\mathbf{m}=[E_p(r_1),\ldots,E_p(r_n)]^T$ is a $n\times 1$ vector of expected returns of the i-th asset.

$\mathbf{1}$ is a $n \times 1$ vector of ones.

$\mathbf{E} = \lambda\mathbf{\Sigma_P} + \theta\mathbf{\Sigma}_\mu$, where $\mathbf{\Sigma_P}$ is the variance-covariance matrix of expected returns in the reference model and $\mathbf{\Sigma}_\mu$ is the variance-covariance matrix of expected returns under model uncertainty. As before λ and θ denote the coefficients for attitudes towards risk and ambiguity.

To solve the maximization problem, we set up the Lagrangian:

$$L = \mathbf{w} \cdot \mathbf{m} - \frac{1}{2}\mathbf{w^T E w} - \gamma_0(\mathbf{1}^T\mathbf{w} - 1) - \gamma_1\mathbf{w} \tag{5}$$

where γ_0 and γ_1 are Lagrange multipliers. Taking derivatives with respect to the vector of optimal weights and with respect to the Lagrange multipliers yields the following first-order conditions:

$$\frac{\partial L}{\partial \mathbf{w}} = \mathbf{m} - \mathbf{Ew} - \gamma_0\mathbf{1} - \gamma_1 = 0 \tag{6a}$$

$$\frac{\partial L}{\partial \gamma_\mathbf{0}} = \mathbf{1}^T\mathbf{w} - 1 = 0 \tag{6b}$$

$$\mathbf{w} \geq 0, \gamma_1 \geq 0 \text{ and } \mathbf{w} \cdot \gamma_1 = 0 \tag{6c}$$

To solve for the vector of optimal portfolio weights, we consider $N = 8$ assets and assume returns are always zero and equal across assets; just as in our experiment. Thus, $\mathbf{m} = [E_p(r_1), \ldots, E_p(r_8)]^T$ simplifies to $\mathbf{m} = [E_p(r), \ldots, E_p(r)]^T = E_p(r) \cdot \mathbf{1^T}$. Since also covariances between asset returns are always 0, $\mathbf{\Sigma}_\mu$ and $\mathbf{\Sigma_P}$ are diagonal matrices. Furthermore, zero covariances and equal asset returns imply that investors should allocate to every asset a weight $w_i > 0$, $i \in \{1, \ldots, 8\}$. Hence, the constraint $w_i \geq 0, i \in \{1, ..., 8\}$, is non-binding and $\gamma_1 = 0$.

The vector of optimal portfolio weights $\mathbf{w}^*$ can be found by rearranging 6a s.t.

$$\mathbf{w}^* = \mathbf{E^{-1}m} - \gamma_0\mathbf{E^{-1}1}. \tag{7}$$

We insert $\mathbf{w}^*$ in 6b to substitute for the Lagrange multiplier γ_0 and finally obtain:

$$\mathbf{w}^* = \mathbf{E}^{-1}\mathbf{m} - \frac{\mathbf{1}^{\mathbf{T}}\mathbf{E}^{-1}\mathbf{m} - 1}{\mathbf{1}^{\mathbf{T}}\mathbf{E}^{-1}\mathbf{1}}\mathbf{E}^{-1}\mathbf{1}. \tag{8}$$

We can further simplify our solution, since covariances of risk and ambiguity are all zero. In addition, all variances under the reference model and under model uncertainty are nonzero. Thus, both variance-covariance matrices are diagonal. The optimal portfolio weight of asset i, w_i, under the robust mean-variance model in our experimental setup then reduces to:

$$w_i^* = \frac{(\lambda\sigma_P^2(r_i) + \theta\sigma_\mu^2(E(r_i)))^{-1}}{\sum_{j=1}^{8}(\lambda\sigma_P^2(r_j) + \theta\sigma_\mu^2(E(r_j)))^{-1}}. \tag{9}$$

In contrast to the classical mean-variance model, the portfolio weight of asset i now depends on four variables instead of two: risk and ambiguity attitudes λ and θ, state uncertainty $\sigma_P^2(r)$, and model uncertainty $\sigma_\mu^2(E(r))$ over all possible models. When there is no model uncertainty, i.e. when the variance of averages is zero, the robust mean-variance model collapses to its classical counterpart. As for equation 3, it is easy to see that increasing ambiguity or the ambiguity attitude parameter θ in 9 has a negative effect on the portfolio weight of the asset in question, which is absent in the classic model. As a consequence, we state the following proposition.

Proposition 1. *When the ambiguity of asset i increases, the portfolio weight of asset i of an ambiguity-averse subject decreases with the coefficient of ambiguity-aversion θ.*

Proof. See the appendix. □

3.3 Hypotheses

We now derive hypotheses related to the potential behavioral determinants of home bias we investigate in our experiment. Hypothesis 1 is concerned with the factor ambiguity and mirrors proposition 1. To solve for the vector of optimal portfolio weights in our experiment, we have to make an assumption about the distribution of μ. Given the fact, that we do not convey any information about which probabilistic model is the true, we figure it is reasonable to assume that each possible model is weighted the same, i.e. the distribution μ is following is uniform. Then, indeed the variance of averages - or model uncertainty - of the asset specific urn with high ambiguity generally is greater than the variance of averages of the one with low ambiguity. This holds in all treatments.

Hypothesis 1. *Subjects in our experiment allocate more weight to assets with low ambiguity and less to assets with high ambiguity. This effect is stronger for subjects that are more averse to ambiguity, i.e. for subjects with a higher θ.*

Our second hypothesis is concerned with the factors homeland and familiarity, i.e. the labeling of assets in treatments other than CONTROL. From a normative point of view, merely giving such a label should have no impact on portfolio weights. Recall that over treatments the expected returns of each asset, depending on the draws from the urns, stay exactly the same. That is, we neither vary state (risk) nor model uncertainty (ambiguity) over treatments. The robust mean variance model only distinguishes these two sources of uncertainty. Hence, our model predicts no treatment effect.

Hypothesis 2. *Subjects' portfolio weights for assets comprising high and low ambiguity, respectively, do not depend on the homeland and familiarity of the assets.*

4 Results

We now present experimental results that test our hypotheses. At the end of this section we report on the sympathy and familiarity scores and show that the preference for assets indeed depends on whether they are associated with the homeland and a familiar company, respectively. Hypothesis 1 relates to the first potential determinant of home bias, the baseline factor ambiguity, which is varied across assets, as well as the effect of the ambiguity attitude parameter θ. We start by reporting the results for the risk and ambiguity tolerance indices r and a, which will serve as proxies for the individual risk and ambiguity parameters λ and θ introduced in section 3. We find a mean risk tolerance of $r = 0.475$ and a mean ambiguity tolerance of $a = 0.023$. According to Trautmann et al. (2011), with our definition of a, ambiguity aversion refers to a positive ambiguity premium, i.e. a compensation for ambiguity. Applying this logic, in the aggregate we find significant ambiguity aversion for our subject sample ($p < 0.05$, t-test as well as Wilcoxon signed-ranks test, checking whether a is different from zero).

Add Table 4 about here

Table 4 presents regressions (1) and (2) for both our tolerance indices r and a, respectively, on demographic indicators and treatment dummies. Well in line with the literature for r we find a gender effect: women are more risk-averse then men (Croson and Gneezy 2009). All other predictors have no significant effect on neither r nor a. In particular the treatment dummies as well as the nation of subjects do not systematically influence our uncertainty indices.[8]

4.1 Hypothesis 1. Impacts of ambiguity and ambiguity aversion

First, we analyze average portfolio weights for assets with high and low ambiguity, respectively. Over all treatments subjects clearly show ambiguity aversion in their investment. On average they invest roughly 60% in low ambiguity assets vs. 40% in high ambiguity assets ($p < 0.001$). See figure 1.

Add figure 1 about here

Second, we look at mixed model (1) in Table 5. In this model we regress the investment in all eight assets on a dummy for the ambiguity level as well as the ambiguity attitude parameter a as fixed effects and include a random effect on the individual level to control for the fact that we have repeated measures of the subjects over trials. Indeed the high ambiguity level itself decreases investment

[8] All results qualitatively hold if we regress on CE_r and CE_a instead.

from about 15.3 to just below 10 Taler. This effect is exaggerated with stronger aversion represented by a positive a, which, consequently, increases investment in low ambiguity assets by the same amount.

All together the results so far support hypothesis 1: Investment decreases with ambiguity as well as the ambiguity attitude parameter θ, proxied with a, which indeed indicates aversion to ambiguity for our subject sample. Thus, concerning ambiguity as a potential factor for home bias, we find that if one generally associates foreign assets with more ambiguity, our results clearly indicate pure ambiguity as a strong determinant of home bias. Finally, we figure that underlying our smooth robust mean-variance model, which accounts for model uncertainty and varying ambiguity attitudes, seems to be a qualified approach for our data to start with.

4.2 Hypothesis 2. Factors homeland and familiarity

Judging from figure 1 one is tempted to infer that our data also supports hypothesis 2, namely that the asset allocation does not depend on the country and familiarity of the assets. Note, however, that for all treatments these numbers are averaged over the four assets comprising high and low ambiguity, respectively. That is, in this figure we do not distinguish between assets which have been associated with different sources of uncertainty in treatments other than CONTROL.

Figure 2 conveys a more detailed picture. For each ambiguity level, we compare the weights of the assets labeled with the homeland and a familiar company in NATION and FULL, respectively, to the weights of all assets in CONTROL. That is, distinguishing the ambiguity level, the average investment in CONTROL is contrasted with the average investment in homeland assets in NATION, and with the average investment in familiar homeland assets in FULL. For high ambiguity assets, in fact, we find home bias: For those assets whose source of uncertainty is associated with the homeland firm in NATION there is an increase in average investment of more than 25 percent (from 8.66 to 10.84 Taler); for those associated with a familiar homeland firm in FULL we find an increase of around 40 percent (from 8.66 to 12.15 Taler). Interestingly, we do not find comparable effects for low ambiguity assets. For these average investment stays approximately constant over treatments.

Add figure 2 about here

Thus, home bias in our experiment is driven by investment in assets with a high ambiguity level. For these assets the marginal effect of each factor, homeland and familiarity, amounts to around 20 to 25 percent. The same is true for the familiarity effect in NAME, where homeland is held constant; see figure 3. These results exactly correspond to the results of the mixed models (2) and (3) in table 5, where the dependent variable is the investment in assets comprising low and high ambiguity, respectively. Regressors are our between (TREATMENTS) and within subject variables (factors homeland and familiarity) as well as their interactions as fixed effects. Again, we also control for a random effect on the subject level.

Add table 5 about here

In model (3) for the investment in assets with high ambiguity we find significant treatment effects, just as depicted in figure 2: Being labeled with the homeland in NATION increases investment by approximately 2.2 Taler; being labeled with the homeland and being familiar at the same time in FULL increases investment by approximately 3.5 Taler.[9] The same interactions are not significant in model (2), regressing on the investment in assets comprising low ambiguity. Taken together these results contradict hypothesis 2. In other words, investment in high ambiguity assets is indeed source dependent and exhibits

[9]Note that precisely these interaction variables, NATION*homeland and FULL*homeland*familiarity, are most interesting, since others also include either the outgroup (Japan) or unfamiliar firms, or both.

home bias. Thus, our model can only explain investment in our benchmark portfolio in CONTROL, but not in our treatment groups.

Add figure 4 about here

Consider Figure 4 as a robustness test regarding the effects of homeland and familiarity for high ambiguity assets. We compare the benchmark investment in CONTROL to investments in NAME and NATION, where assets have a familiar or homeland label. These labels largely increase the percentage investment in all rounds. We conclude, first, time effects over rounds are unlikely to have any significant influence on our findings. Second, the familiarity effect also is present in NAME, where subjects cannot be attracted by homeland considerations. Finally, varying the ingroup in NATION we can replicate our finding for Germans also with subjects of other descent, namely Austrians. Hence, our results do not seem to depend on the country of origin (homeland), but to hold more generally.

4.3 Familiarity and sympathy scores

If homeland sympathy and familiarity drive portfolio weights in our experiment, higher sympathy and familiarity scores elicited in the questionnaire should correspond to higher investment in the portfolio choice task.

Add Table 6 about here

Panel A in table 6 shows the familiarity scores assigned in the NAME treatment, averaged over the four assets we categorized as familiar and unfamiliar, respectively. Recall that in NAME we hold the homeland constant. Hence, we here examine the mere effect of familiarity. The familiarity scores of the familiar assets are greater than those assigned to the unfamiliar assets ($p < 0.001$, Wilcoxon rank sum test, panel A). This pattern holds if we split assets in high and low ambiguous assets, as panel B shows. Regarding investment weights, we confirm our previous findings: For high ambiguity assets the weight to familiar assets is significantly higher than that to unfamiliar assets. This does not hold if ambiguity is low. Hence, for the effect of familiarity ambiguity is a major determinant.

Add table 7 and 8 about here

Table 7 depicts the perceived sympathy scores of German subjects from the NATION treatment with investment opportunities in Germany and Japan. Indeed, individuals assign significantly higher sympathy scores to their home country. We also find that weights to the ingroup country are significantly higher, yet again only in case of high ambiguity. Analyzing Austrian subjects from the NATION treatment as a robustness test gives very similar results (see table 8).

Add table 9 about here

Looking at high ambiguity only, panel A of table 9 shows that in treatment FULL familiar assets are assigned a higher familiarity score, no matter if the assets are from the ingroup or the outgroup country. As a result, we also find higher investment for both groups, suggesting that there indeed is an effect of the factor familiarity alone. Still, familiarity scores with familiar investment opportunities from the home country are significantly greater than that of the foreign country, as panel B shows. This does not hold for unfamiliar assets. Nevertheless, also here weights are higher for ingroup assets. This supports the notion that there also is an additional effect of the homeland alone, as shown previously. In panel C, finally, we draw the most severe comparison: between familiar ingroup and unfamiliar outgroup assets. Hence, we look at the simultaneous effect of the factors familiarity and homeland. We find that misdiversification here also holds with low ambiguity. That is, taken together the factors homeland and familiarity result in a bias towards familiar ingroup assets, regardless of whether they comprise low or high ambiguity.

We conclude from the analysis of familiarity and sympathy scores, that portfolio weights are an increasing function of perceived familiarity and homeland sympathy. Importantly, our results suggest: i) The effect of homeland sympathy is likely to hold independent of the nation analyzed. ii) The effect of familiarity also holds for outgroup countries (NAME), even if the ingroup country is available (FULL).

5 Discussion

In our experiment, subjects prefer to allocate their endowment to assets with low rather than high ambiguity in their return distributions. However, they are less averse to the ambiguous assets when the uncertainty is associated with a familiar or national label, rather than pure chance; although the actual ambiguity of the prospects stays the same. A well established idea in the literature on uncertainty attitudes, which explains this behavior, is that people's preferences over prospects are dependent upon the source of uncertainty.[10] For a decision maker a source of uncertainty concerns a group of events sharing certain characteristics which determine the common nature of their uncertainty. For example, in a toss of a fair coin, the events heads and tails have the same source of uncertainty (the toss of the coin). Thus, one would expect people to agree on trading a bet on heads for a bet on tails. Similarly, in the Ellsberg (1961) urn experiment people are willing to exchange a bet on black for a bet on red, drawing from a risky urn containing 50 black and 50 red balls. However, they are not willing to swap a bet on the risky urn for a bet on the ambiguous urn containing 100 black and red balls in unknown proportion; presumably because they treat the urns as different sources of uncertainty.

In more complex situations, such as investment decisions, further characteristics regarding the events may play a role: e.g. (perceived) competence or ability, subjective affectation or loyalty, familiarity, conformity, etc. (Fox and Tversky 1995; Chew and Sagi 2008; Chew et al. 2011). Allowing for all kinds of uncertainty preferences, the strength of the concept of source dependence of

[10]The concept is also known as issue preference (Halevy 2007; Tversky and Wakker 1995).

uncertainty attitudes is its capability of giving these phenomena a unifying descriptive framework, which may also explain the home bias in equities. This is what we find in our experiment: Depending on the variation of the three factors ambiguity, familiarity and homeland, the asset specific urns seem to be treated as distinct sources of uncertainty: with 2 sources in CONTROL, 4 in NATION and NAME, and 8 in FULL. The different sources, hence, we can interpret as the decisive factors that determine home bias we establish in the lab.

Therefore, the decomposition of the variance in the augmented mean-variance model along the lines of the two most fundamental sources of uncertainty, namely risk (or state uncertainty) and ambiguity (or model uncertainty), into the variance under the reference probabilistic model $\sigma_P^2(W)$ and the variance of averages $\sigma_\mu^2(E_P(W))$ is a crucial one.[11] While the model of Maccheroni et al. (2013), which is based on the preference model of Klibanoff et al. (2005), does distinguish risk and ambiguity as the most fundamental sources of uncertainty, it is not intended to incorporate a distinction between different ambiguous sources. Consequently, it does not predict a difference in behavior over treatments, which we do find in our experiment. We consider this an important insight with an obvious implication: using the ambiguity augmented mean-variance functional of Maccheroni et al. (2013) as a basis for an asset pricing model, one has to be aware that it may not capture important phenomena of investor behavior, such as home bias, which in our setup we find to be driven by the source dependence of uncertainty aversion.

6 Conclusion

Obstfeld and Rogoff (2000) call home bias one of the "six major international macroeconomics puzzles". We show that behavioral determinants are indeed crucial to distinctively establish home bias and highlight the importance of source dependence of uncertainty attitudes as an explanatory framework. Clearly, am-

[11]See appendix A.3 in Maccheroni et al. (2013) for a proof of this statement in their general framework.

biguity produces a shift towards the less ambiguous assets, absence from other behavioral factors. This can be rationalized via the model of Maccheroni et al. (2013). In contrast to the model predictions, the aversion to ambiguous assets is mitigated with familiar and homeland assets. As a result, we observe that the preference for familiar and homeland assets is especially strong for highly ambiguous assets. For assets with low ambiguity home bias is basically non-existent in our laboratory. Our findings are in line with former empirical research. Barber and Odean (2007) show that investment is attention-driven and responds to pure labeling. More importantly, heuristics and biases, in particular home bias, are fostered in the face of uncertainty (Hirshleifer 2001; Kumar 2009). Our results imply that it is possible to mitigate home bias by reducing the ambiguity and providing better information on asset returns. This not only is an interesting insight for researchers and regulators. As home bias is such a persistent phenomenon on financial markets understanding the drivers of home bias may help investors to realize the same return on their portfolios with reduced uncertainty.

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7 Tables and figures

Table 1 – Treatment matrix

Factors		*homeland*	
		(const.)	*(var.)*
familiarity	*(const.)*	CONTROL	NATION
	(var.)	NAME	FULL

Table 2 – Firms and familiarity scores

Firm	Industry	Treatments	Manipulation	Fam.-score
BMW	Automotive	FULL	familiar	4.10
Volkswagen	Automotive	FULL	familiar	4.12
Delticom	Automotive	FULL	unfamiliar	1.21
Renk AG	Automotive	FULL	unfamiliar	1.20
Honda Motor	Automotive	FULL, NAME	familiar	2.64
Toyota Motor	Automotive	FULL, NAME	familiar	2.80
Fuji Heavy Industries	Automotive	FULL, NAME	unfamiliar	1.41
GS Yuasa	Automotive	FULL, NAME	unfamiliar	1.25
Fujifilm	Information Technology	FULL, NAME	familiar	2.94
Canon	Information Technology	FULL, NAME	familiar	3.55
Ricoh	Information Technology	FULL, NAME	unfamiliar	1.50
Tokyo Electron	Information Technology	FULL, NAME	unfamiliar	1.30

Table 3 – Subject sample

	N	CE_r	CE_a	Age	% Female	% Inv.Exp.	Pat-sc.
CONTROL	46	0.53	0.52	23.50	41.30	30.40	3.07
NAME	56	0.53	0.50	24.40	51.80	23.20	2.46
NATION	75	0.51	0.50	23.90	62.70	22.70	3.20
German	35	0.50	0.48	23.10	54.30	20.00	2.97
Austrian	40	0.52	0.51	24.70	70.00	25.00	3.40
FULL	38	0.55	0.51	23.60	63.20	26.30	2.87
Total	215	0.53	0.50	23.90	55.30	25.10	2.92

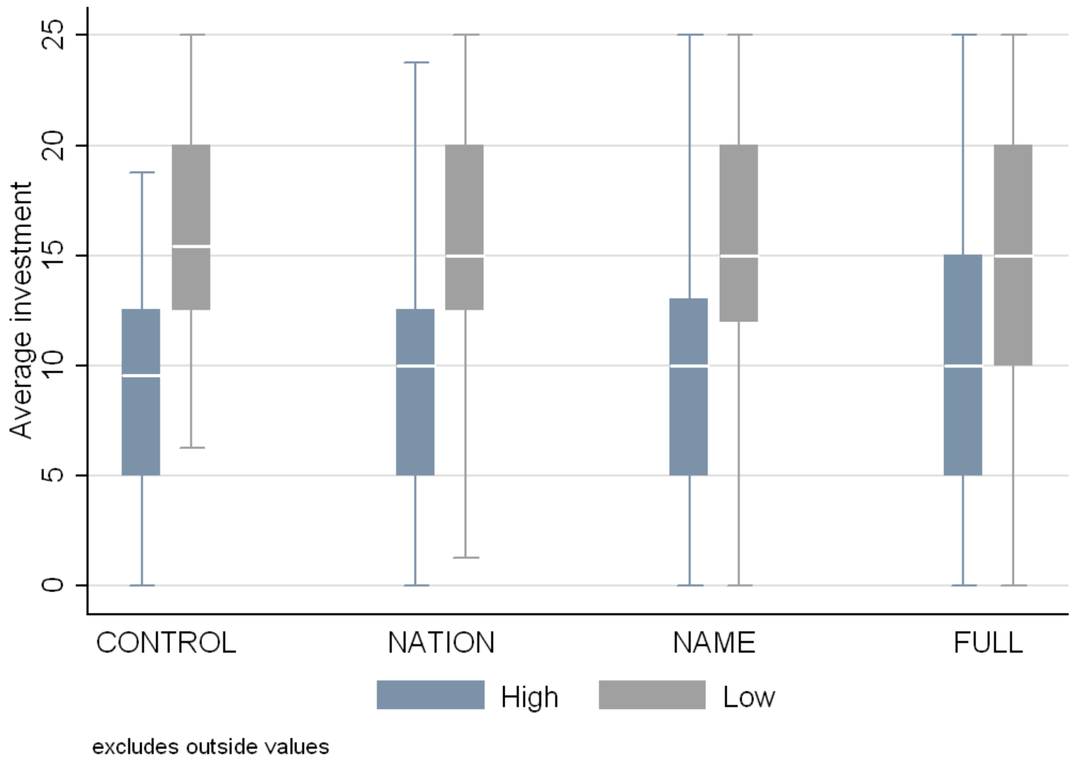
Notes. We show a standardized certainty equivalent of a risky (CE_r) and an ambiguous lottery (CE_a). This is the number of the first safe choice divided by the total number of choices in 10 decision pairs involving one safe and one risky (ambiguous) prospect. Investment experience (*Inv-Exp.*) is a binary variable indicating knowledge on financial markets. Patriotism (*Pat-sc.*) is the sympathy score subjects assign to the home country and scaled from 1-4.

Table 4 – OLS analysis for risk and ambiguity tolerance indices

Dependent variable	r risk tolerance	a ambiguity tolerance
Intercept	0.43***	-0.01
	(0.10)	(0.04)
Female	0.04**	-0.01
	(0.02)	(0.01)
Age	0.000	0.00
	(0.00)	(0.00)
German	0.02	-0.01
	(0.03)	(0.02)
Foreign	-0.00	0.01
	(0.04)	(0.02)
NAME	0.01	0.01
	(0.03)	(0.02)
NATION	0.01	0.00
	(0.03)	(0.0,)
FULL	-0.04	0.04
	(0.04)	(0.03)
N	199	199
R^2	0.03	0.03

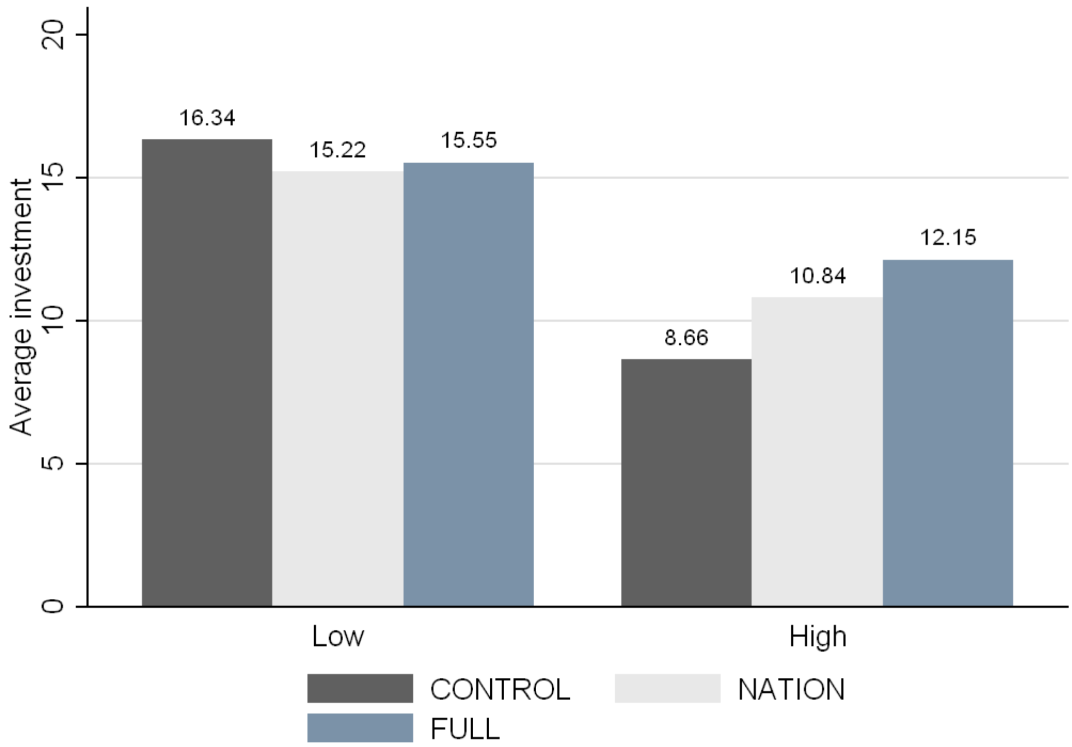
Notes. Positive coefficients of r and a imply increasing risk/ambiguity tolerance respectievly. In terms of the nation (treatment) Austrian (CONTROL) is the reference group. Robust standard errors in parentheses.

Figure 1 – Investment over ambiguity level



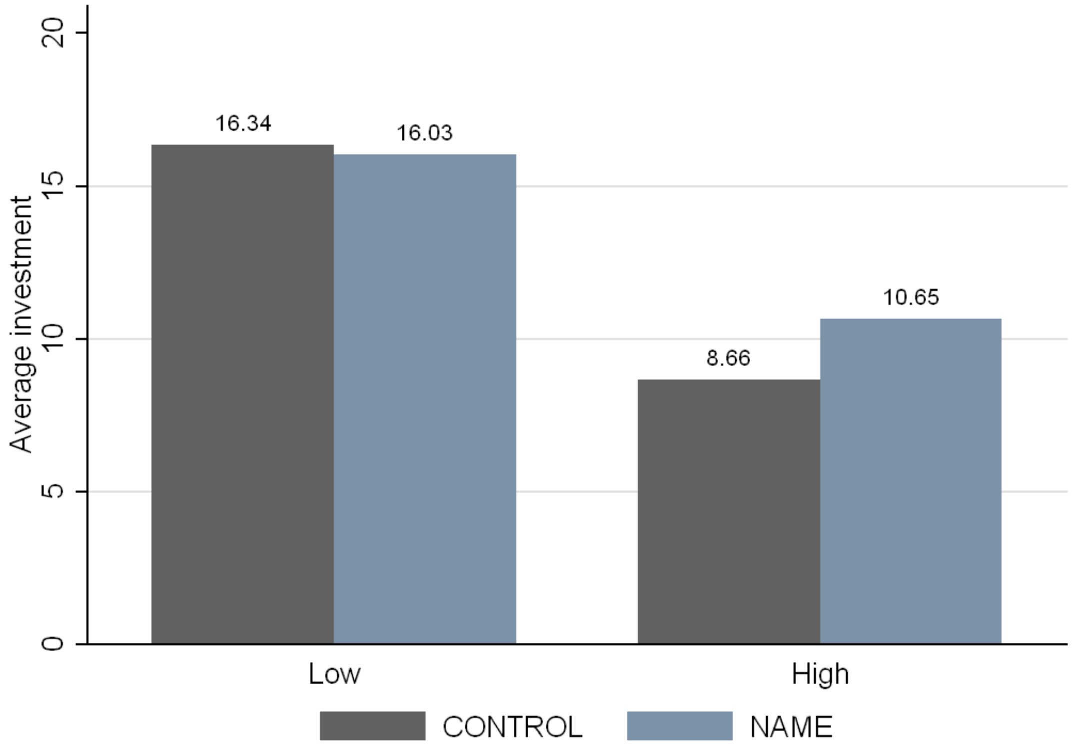
Notes. For each treatment this graphs shows box plots of the average investment in all assets comprising high and low ambiguity, respectively.

Figure 2 – Investment over treatments and ambiguity level



Notes. For each ambiguity level this figure contrasts the average investment in CONTROL with the average investment in homeland assets in NATION, and with the average investment in familiar homeland assets in FULL.

Figure 3 – Investment in NAME and CONTROL over ambiguity level



Notes. For each ambiguity level this figure contrasts the average investment in CONTROL with the average investment in familiar assets in NAME.

Table 5 – Mixed models

	(1) all assets	(2) low ambiguity assets	(3) high ambiguity assets
Fixed effects			
Intercept	15.28***	16.34***	8.66***
	(0.27)	(0.72)	(0.72)
ambiguity	-5.57***		
	(0.25)		
a (ambiguity tolerance)	8.51***		
	(1.90)		
a*ambiguity	-8.51***		
	(1.90)		
NATION		-1.03	-0.03
		(0.95)	(0.94)
NATION*homeland		-1.12	2.18**
		(0.95)	(0.94)
FULL		-2.57**	0.05
		(1.25)	(1.19)
FULL*familiarity		0.42	1.22
		(1.25)	(1.19)
FULL*homeland		-3.92***	2.09*
		(1.25)	(1.19)
FULL*homeland*familiarity		-0.79	3.49***
		(1.25)	(1.19)
Random effects			
Subject	0.00	4.27	4.48
	(0.00)	(0.31)	(0.30)
Residual	9.66	9.36	7.60
	(0.09)	(0.14)	(0.110)
N	6368	2544	2544
Wald χ^2	630.99	21.87	44.74
$P > \chi^2$	0.000	0.001	0.000
Log likelihood	-9416.62	-9416.62	-8916.93
LR test: $\bar{\chi}^2$	0.000	464.85	798.23
$P \geq \bar{\chi}^2$	1.00	0.00	0.00

Notes. In three models we regress investment ω over periods 1 to 4 and all eight assets on various regressors as fixed effects, controlling for a random effect on the subject level. Note that the LR test indeed supports including the random effect in models (2) and (3). In model (1) this is not true; using panel or OLS regression, however, does not change results. Generally, fixed effects are shown as simple effects. That is, interacted variables are parametrized as simple effects of the first at each level of the interacted variables. We leave out observations of treatment NAME in (2) and (3), since with a constant homeland it is not fully comparable to NATION and FULL. Standard errors in parentheses. Time fixed effects are not significant.

Figure 4 – Investment in high ambiguous assets

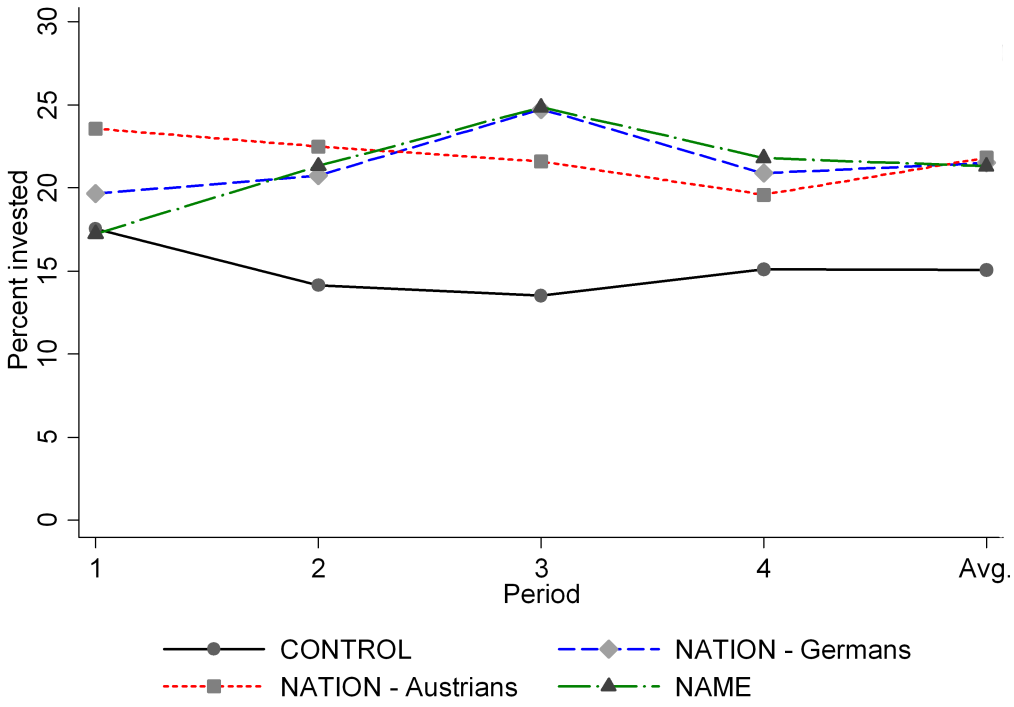


Table 6 – NAME treatment: familiarity scores and investment weights

Panel A: All assets

Familiarity score	Familiar	3.30	z-Statistic	11.04
		(1.15)	p-value	0.00
	Unfamiliar	1.59		
		(0.90)		

Panel B: High and low ambiguity assets

Ambiguity	High		Low	
	Familiar	Unfamiliar	Familiar	Unfamiliar
Weight	10.65	8.31	15.61	15.43
p-values	0.00		0.81	
Familiarity score	3.21	1.54	3.38	1.64
p-values	0.00		0.00	

Notes. Panel A shows the mean and standard deviation (in parentheses) of perceived familiarity scores of investment into assets that we labelled as familiar and unfamiliar. We test the statistical significance using the Wilcoxon rank-sum test. The resulting z-Statistic is reported with its p-value. Panel B shows the mean weight and mean perceived familiarity scores of investment into assets divided by their level of ambiguity. The p-values are based on the Wilcoxon rank-sum test and show whether differences in investments and familiarity scores in familiar and unfamiliar assets grouped by ambiguity are statistically different from zero.

Table 7 – NATION treatment: sympathy scores and investment weights - German subjects

Panel A: All assets				
Sympathy score	Ingroup	3.57	z-Statistic	9.35
		(0.69)	p-value	0.00
	Outgroup	2.27		
		(0.78)		

Panel B: High and low ambiguity assets				
Ambiguity	High		Low	
	Ingroup	Outgroup	Ingroup	Outgroup
Weight	10.75	8.31	15.29	15.65
p-values	0.00		0.53	

Notes. Panel A shows the mean and standard deviation (in parentheses) of perceived sympathy scores of the home and foreign country. We test the statistical significance using the Wilcoxon rank-sum test. The resulting z-Statistic is reported with its p-value in parentheses. Panel B shows the mean weight of investment into home and foreign assets divided by their level of ambiguity. The p-values are based on the Wilcoxon rank-sum test and show whether differences in investments in home and foreign assets grouped by ambiguity are statistically different from zero.

Table 8 – NATION treatment: sympathy scores and investment weights - Austrian subjects

Panel A: All assets

Sympathy score	Ingroup	3.80	z-Statistic	10.58
		(0.46)	p-value	0.00
	Outgroup	2.38		
		(0.83)		

Panel B: High and low ambiguity assets

Ambiguity	High		Low	
	Ingroup	Outgroup	Ingroup	Outgroup
Weight	10.91	8.90	15.17	15.02
p-values	0.00		0.51	

Notes. Panel A shows the mean and standard deviation (in parentheses) of perceived sympathy scores of the home and foreign country. We test the statistical significance using the Wilcoxon rank-sum test. The resulting z-Statistic is reported with its p-value. Panel B shows the mean weight of investment into home and foreign assets divided by their level of ambiguity. The p-values are based on the Wilcoxon rank-sum test and show whether differences in investments in home and foreign assets grouped by ambiguity are statistically different from zero.

Table 9 – FULL treatment: Familiarity scores and investment weights

Panel A: Comparisons of familiarity over groups for high ambiguity assets

Homeland	Ingroup		Outgroup	
	Familiar	Unfamiliar	Familiar	Unfamiliar
Weight	12.15	10.75	9.88	8.71
p-values	0.016		0.02	
Familiarity score	3.58	1.07	2.34	1.13
p-values	0.000		0.00	

Panel B: Comparisons of groups over familiarity for high ambiguity assets

	Familiar		Unfamiliar	
Familiarity	Ingroup	Outgroup	Ingroup	Outgroup
Weight	12.15	9.88	10.75	8.71
p-values	0.00		0.00	
Familiarity score	3.58	2.34	1.07	1.13
p-values	0.00		0.69	

Panel C: Comparisons of groups and familiarity for high and low ambiguity assets

	High		Low	
Familiarity	Familiar	Unfamiliar	Familiar	Unfamiliar
Homeland	Ingroup	Outgroup	Ingroup	Outgroup
Weight	12.15	8.71	15.55	13.77
p-values	0.00		0.05	
Familiarity score	3.58	1.13	3.68	1.34
p-values	0.00		0.00	

Notes. Panel A shows the mean investment weight and corresponding familiarity scores for high ambiguity assets that we labeled as familiar and unfamiliar, respectively, grouped by homeland. Panel B compares the mean investment weight and corresponding familiarity scores for high ambiguity in- and outgroup assets, respectively, grouped by familiarity. Finally, panel C contrasts the simultaneous effect of familiarity and homeland on portfolio weights for assets grouped by ambiguity level and shows corresponding familiarity scores. All p-values are based on the Wilcoxon rank-sum test and show whether differences are statistically different from zero.

A Proof of Proposition 1

The partial derivative

$$\frac{\partial w_i}{\partial \sigma_\mu^2(E(r_i))} = \frac{\frac{-\theta(\sum_{j=1}^{8}(\lambda\sigma_P^2(r_j)+\theta\sigma_\mu^2(E(r_j)))^{-1}-(\lambda\sigma_P^2(r_i)+\theta\sigma_\mu^2(E(r_i)))^{-1})}{(\lambda\sigma_P^2(r_i)+\theta\sigma_\mu^2(E(r_i)))^2}}{(\sum_{j=1}^{8}(\lambda\sigma_P^2(r_j)+\theta\sigma_\mu^2(E(r_j)))^{-1})^2} \tag{10}$$

is negative, since $\sum_{j=1}^{8}(\lambda\sigma_P^2(r_j)+\theta\sigma_\mu^2(E(r_j)))^{-1}$ is larger than $(\lambda\sigma_P^2(r_i)+\theta\sigma_\mu^2(E(r_i)))^{-1}$. The same holds for the partial derivative $\frac{\partial w_i}{\partial \theta}$ w.r.t. θ. This completes the proof.

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Behavioral determinants of home bias - theory and experiment

Abstract
We study portfolio diversification in an experimental decision task, where asset returns depend on a draw from an ambiguous urn. Holding other information identical and controlling for the level of ambiguity, we find that labeling assets as being familiar or from the homeland of subjects increases portfolio weights by around 25%, respectively; although the return-generating process remains unaffected. Importantly, we only find these effects when the returns of assets are highly ambiguous. Our ambiguity robust mean-variance model accurately predicts benchmark portfolio weights of the experimental control group, where assets are not labeled: subjects allocate more wealth to assets with low ambiguity. For treatment group portfolios, which show a bias towards assets with a familiar or homeland label, the model does not hold. This misdiversification against the benchmark portfolio can be rationalized via the concept of source dependence of uncertainty attitudes.

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