Crash-o-phobia in Currency Carry Trade Returns *

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December 4, 2017

ABSTRACT

The standard Euler equation of a representative agent with rational beliefs and CRRA utility cannot explain currency carry trade returns. We relax several assumptions to allow for crash-o-phobia, which is the combination of belief misestimation, belief distortion and loss aversion. Using non-linear least squares, we estimate this behavioral Euler equation to price a basket of 10 different currencies. The parameter estimates reveal crash-o-phobic beliefs and preferences: carry trade investors exhibit loss aversion and overweight states with low probabilities. These observations are robust across several model specifications and consistent with experimental evidence. Overall, our behavioural model performs significantly better at explaining currency returns than the standard model.

Keywords: currency carry trade returns, loss aversion, belief misestimation, probability distortion, crash-o-phobia
JEL Classification: G11; G12; G40

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*We are grateful to Thorsten Hens, Ferdinand Langnickel, Harald Lohre, Thomas Maurer, Luzius Meisser, Thomas Nitschka, Klaus Schenk-Hoppé and seminar participants at the University of Zurich for valuable feedback.
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I. Introduction

According to the uncovered interest parity (UIP) the expected return from investments in different currencies with different levels of local interest rates should be zero. However, the UIP does not hold empirically which is known as the forward premium puzzle and has led to the famous currency carry trade investment strategy.[1] That is, borrowing in low interest currencies and lending in high interest currencies consistently generates positive excess returns. These high average returns are usually negatively skewed and exhibit fat tails.[2] While traditional risk based factor models struggle to explain currency returns (Burnside 2012), recent studies have identified two types of risks for which carry trade investors are compensated for. Currency carry trade returns display high downside market risk (Dobrynskaya (2014), Atanasov and Nitschka (2014)) and high crash risk or the presence of rare disasters such as peso problems (Jurek (2014), Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011)).

To explain currency carry trade returns we depart from the standard rational expected utility framework (EUT) and incorporate elements from cumulative prospect theory (CPT), such as loss aversion and probability weighting. Using a basket of 10 currencies and a sample of over 10 years, we estimate a behavioral version of the Euler equation to fit risk-neutral state prices derived from currency options. We find that carry trade investors exhibit substantial loss aversion and overweight states with low probabilities—two characteristics which we refer to as *crash-o-phobia*. The estimated crash-o-phobia parameters are implied by market data to match risk-neutral probabilities and not inferred via experiments. Nevertheless, we find loss aversion and probability weighting similar to what is found in experimental data. Moreover, we document substantial time-series and cross-sectional variation in parameter estimates. Currencies of developed countries exhibit higher loss aversion but less overweighting of extreme events than emerging market currencies. At times of crisis, loss aversion spikes and probability weighting increases across all currencies.

To evaluate the relevance of our behavioral consumption asset pricing model for explaining currency carry trade returns, we compare its explanatory power to the fit of a standard expected

[1] The failure of the UIP is first documented by Tryon (1979), Hansen and Hodrick (1980) and Fama (1984). Comprehensive literature surveys about exchange rates and the forward premium puzzle can be found in Froot and Thaler (1990), Lewis (1995) and Engel (1996, 2014).

[2] See for example summary statistics of currency carry trade returns documented by Burnside, Eichenbaum, and Rebelo (2011), Dobrynskaya (2014) or Jurek (2014).

utility model with CRRA preferences as a benchmark. We find that including loss aversion, belief misestimation and probability weighting significantly improves the fit relative to the benchmark model. The results indicate that loss aversion captures the high downside market risk of currency returns documented in the literature and probability weighting accounts for crash risk or peso problems. This is consistent with two strands of the literature, which show that currency carry trade returns are exposed to, first, downside market risk and, second, crash risk.

The literature on downside market risk as an explanation for currency carry trade returns is consistent with the model of loss aversion by Tversky and Kahneman (1992). They postulate that investors are more averse to losses than they are enticed by gains. Based on the economic rationale of investors' loss aversion, Dobrynskaya (2014), Lettau, Maggiori, and Weber (2014) and Atanasov and Nitschka (2014) investigate whether downside market risk is priced in currency returns.[3] Dobrynskaya (2014) identifies a global downside risk market factor, which loads positively on high interest currencies, and finds that currency carry trades perform disproportionally worse in times of stock market crashes. Similarly, Lettau, Maggiori, and Weber (2014) propose a downside risk CAPM where both the market price of risk and the beta of currencies with the market are allowed to vary conditional on the aggregate stock market return. While these two studies investigate forward discount sorted currency portfolio returns, Atanasov and Nitschka (2014) find that global downside risk is also priced in bilateral currency excess returns. Overall, high interest currencies tend to depreciate during aggregate market downturns and hence, returns to currency carry trades seem to be a fair compensation for their high downside market risk.

Besides this positive exposure to equity market downside risk, currency carry trade returns are also exposed to systematic crash risk induced by rapid devaluations of high interest currencies. Brunnermeier, Nagel, and Pedersen (2008) argue that these sudden exchange rate moves, which are unrelated to fundamental news, are due to the unwinding of carry trades when speculators near funding constraints.[4] Alternatively, Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011) show that the high currency carry trade returns reflect a peso event risk which comes in the form

[3] Downside risk measures the covariance of an asset's return with the market in the worst states of the world, i.e. when the overall market performs poorly. It is also a relevant risk source for returns of other asset classes, see for example Ang, Chen, and Xing (2006), Botshekan, Kraeussl, and Lucas (2012) or Galsband (2012).

[4] Brunnermeier and Pedersen (2009) develop a formal model to explain liquidity spirals. They show that negative skewness of investment assets is partly due to the amplification of negative shocks when speculators hit their funding constraints and unwind their positions. On the other hand, Abreu and Brunnermeier (2003) argue that when investors hold on to their carry trade positions too long, because they do not know when others unwind their positions, then, a currency crash after a bubble can even be price correcting.

of a high value of the stochastic discount factor (SDF) rather than large carry trade losses.[5] Jurek (2014) uses out-of-the money foreign exchange options and computes returns to a crash-hedged carry trade strategy. He finds that the high returns to currency carry trades cannot fully be explained by a peso problem, since the crash risk premia only accounts for one third of carry trade returns. In a similar vein, Farhi, Fraiberger, Gabaix, Ranciere, and Verdelhan (2015), Farhi and Gabaix (2015) and Chernov, Graveline, and Zviadadze (2016) develop theoretical models to formally evaluate the crash risk of different currencies and find that approximately one third of carry trade returns is due to disaster risk. Moreover, Dupuy (2015) constructs an empirical global tail risk factor, where tail risk is understood as the interaction of different moments, and shows that it prices the cross-section of currency carry trade returns.

To summarize, the literature shows that investments in high interest currencies deliver large positive returns, which are negatively skewed, exhibit fat tails and crash occasionally due to some rare event or systematically along with the stock market. The aim of this paper is not to provide a risk-based explanation of currency carry trade returns,[6] but to rationalize these stylized properties using a behavioral approach. The behavioral approach includes loss aversion and probability distortions. In this vein, Dobrynskaya (2014) finds that her estimated downside risk premia for currency returns is in line with the downside risk premia implied by prospect theory.[7] Concerning belief distortions, Barberis and Huang (2008) and Brunnermeier, Gollier, and Parker (2007) show that belief distortions create a preference for positive skewness, which implies higher expected returns for assets with negatively skewed payoffs. Furthermore, Chabi-Yo and Song (2012) find that probability weighting of rare events can explain the time-series and cross-sectional variation of currency returns. They use a rank-dependent expected utility (RDEU) model and non-parametric methods to recover the probability weighting implied by currency options. Based on these implied weights, they construct a global weighting measure of left tail events which they use to conduct standard time-series predictability regressions as well as cross-sectional asset pricing tests. Similarly, Polkovnichenko and Zhao (2013) also use

[5] The peso problem was first mentioned by Rietz (1988) and refers to the effects on inference caused by low-probability events that do not occur in the sample.

[6] Besides downside risk and crash risk, the literature has proposed many other risk factors which try to explain the cross-section of currency carry trade returns. Examples are the HML carry factor (Lustig, Roussanov, and Verdelhan 2011), the Dollar factor (Verdelhan 2013), global currency volatility (Menkhoff, Sarno, Schmeling, and Schrimpf 2012), FX correlation risk factor (Mueller, Stathopoulos, and Vedolin 2016), variance risk premia (Della Corte, Sarno, and Tsiakas 2011) and inflation risk (Jylhä, Suominen, and Lyytinen 2008).

[7] Dobrynskaya (2014, p.22-23) provides a very nice numerical example to show how her estimated downside risk premia matches the risk premia implied by Kahneman and Tversky's (1979) prospect theory.

a RDEU model to estimate non-parametric probability weighting functions implied by S&P 500 index options. While the results of Chabi-Yo and Song (2012) are in line with ours, i.e. probability weighting matters for currency carry trade returns, their methodology differs substantially. First, we use a behavioral consumption asset pricing model including loss aversion instead of a RDEU model and instead of constructing a risk factor, we evaluate the monthly fit of our extended Euler equation. Second, we estimate a parametric probability weighting function proposed by Prelec (1998) and third, we apply the parametric Vanna-Volga method (Castagna and Mercurio 2007) to recover risk-neutral probabilities from currency options.

To conclude, we believe that the asymmetries in the return distribution of the carry trade, in particular negative skewness and tail risk, might well be captured by loss aversion and over-weighting of rare events with small probabilities.

To show this, we estimate a traditional Euler equation as well as a behavioral Euler equation and compare their performance to explain carry trade returns. In terms of methodology, our approach is related to Hens and Reichlin (2013) and Kliger and Levy (2009). In section 7 of Hens and Reichlin (2013), the authors estimate a similar form of the Euler equation with belief distortion and belief misestimation but without loss aversion. Moreover, they only price S&P 500 returns and we extend their model to price currency returns from the perspective of a US investor as well as a currency trader. While Kliger and Levy (2009) also price S&P 500 returns, their focus is on evaluating the performance of different models, such as EUT, RDEU and CPT, using information from option markets. They constrain their parameter estimates to be constant over the whole sample period, whereas we reestimate the Euler equation every month to analyse time-series variation. Hence, this paper is the first study to explain currency carry trade returns with a behavioral consumption asset pricing model, including belief distortion, belief misestimation and loss aversion. All parameter estimates are implied by financial market data, which allows for a unique angle on time-series and cross-sectional variation of investors' loss aversion and probability weighting with respect to different currencies. Overall, we find that crash-o-phobia matters for the pricing of currency carry trade returns.

The paper is structured as follows. Section II describes the traditional asset pricing model and the different behavioral aspects we use to derive the behavioral Euler equation. The data, derivation of risk-neutral probabilities and our estimation method is outlined in Section III. In

Section IV we describe our main empirical results and Section V discusses several robustness tests. Section VI concludes.

II. Asset Pricing Model

In this section, we describe the asset pricing model with which we test whether crash-o-phobia is a valid explanation for carry trade returns. By making certain assumptions on the investor's utility and belief formation process, we can use Euler equations to calculate model-implied state prices. We then compare these state prices with state prices calculated from empirical option data. If the model-implied and the option-implied state prices are the same or similar, then, the model is potentially a good explanation for the empirical data. Using this approach, we compare the performance of the traditional Euler equation, assuming CRRA utility and rational beliefs, with a version of the Euler equation which is extended by elements of CPT: misestimation of probabilities, distortion of probabilities and loss aversion, i.e. crash-o-phobia. In the following, we first describe the standard expected utility framework, which we use as benchmark model. Then, we explain the elements necessary to derive our behavioral crash-o-phobia model. Finally, we outline the concept behind our two pricing perspectives, i.e. the US investor and currency trader.

A. Traditional approach

The benchmark model of choice is the traditional Euler equation. We closely follow the standard two-period model with a representative investor outlined in Hens and Reichlin (2013). We assume that markets are complete and that there is a finite number of possible states, $s = 1, \ldots, S$, in the second period. Further, we assume CRRA utility and rational beliefs for our benchmark expected utility framework. Hence, the first-order condition is

$$\frac{p_s u'(x_s)}{\sum_s p_s u'(x_s)} = \pi_s^* \tag{1}$$

$$\text{where} \quad u(x) = \frac{x^{1-\eta}}{1-\eta} \tag{2}$$

where x_s represent gross returns in state s of the asset which we want to price, p_s are the beliefs on physical probabilities and π_s^* are risk-neutral probabilities, which are equivalent to normalized state prices. Further details on the setup of the standard asset pricing model and the derivation of the first-order condition are given in Appendix A.

To estimate this Euler equation, it is important to determine the state space, as p_s, π_s^*, and x_s are defined with respect to this state space. For now, we assume that the state space is determined by a US investor. As this investor is assumed to predominantly consume S&P 500 returns, his state space is defined by these equity returns. When calculating the physical probabilities or the state prices to test the model, we thus use data from the S&P 500.

To define the agent's beliefs about the physical probabilities, p_s, we assume that the agent forms his beliefs according to the historical distribution of the returns as in Ziegler (2006). As the state space is defined with respect to the S&P 500, we use historic kernel density estimates of S&P 500 returns to calculate the physical probabilities. The state prices, π_s^*, are as well calculated from S&P 500 data: we use option prices written on the S&P 500. Further details on the approach are described in Section III. The returns, x_s, which are priced in the model, are currency returns but they are defined with respect to the S&P 500 state space. In Section III, we explain how we match currency returns to the S&P 500 state space.

With the set-up described above, we can thus test if a model based on a US investor with rational beliefs and CRRA utility, can explain currency carry trade returns. A related approach has been used by Hens and Reichlin (2013) to show that the traditional asset pricing model performs poorly at pricing S&P 500 returns. They assume that a US investor consumes and prices S&P 500 returns. Therefore, they use S&P 500 data to determine risk-neutral probabilities, π_s^*, the beliefs p_s and the returns x_s. To improve the fit, the authors extend the model and show that including belief distortion and misestimation improves the explanatory power of the model. We take a similar approach and relax certain assumptions of the standard model to see how well a behavioral model performs at explaining currency carry trade returns compared to a traditional asset pricing model.

B. Behavioral approach

In standard economic theory, it is assumed that agents are risk-averse and hold correct beliefs about future states. We introduce three ways to relax these assumptions in order to capture the non-normal properties of currency carry trade returns: first, loss aversion, second, belief misestimation of probabilities, and, third, probability distortion.

B.1. Loss aversion

Loss aversion implies that investors are more averse to losses than they are enticed by gains. It is one of the key elements of Tversky and Kahneman's (1992) cumulative prospect theory. In terms of utility, loss aversion means that marginal utility is higher in the domain of losses than in the domain of gains. Moreover, according to prospect theory investors value gains and losses and not the overall wealth level. Hence, the utility function is applied to asset returns instead of wealth levels. The original loss averse utility function proposed by Kahneman and Tversky (1979) is convex over losses and concave over gains. Additionally, it has a kink at the reference point. To ensure a global maximum and differentiability at the reference point, we use the loss averse utility function proposed by Rosenblatt-Wisch (2008)

$$u(x) = (x-1)\left(1 + \frac{\delta}{1 + e^{\kappa(x-1)}}\right) \tag{3}$$

where κ is the speed of the switching and δ the degree of loss aversion. Note that we shifted the reference point from 0 to 1, since we work with gross returns. Figure 1 plots the loss averse utility function with a κ of 20 and a δ of 0.5. One can clearly see the increase in marginal utility left of the reference point.

[Figure 1 about here.]

B.2. Belief misestimation

Besides introducing loss aversion, we relax the assumption of rational belief formation. A standard assumption on belief formation is that agents base their beliefs on historical data (Ziegler 2006). To capture belief formation processes other than the forward projection of past realizations, we relax this assumption. Following Ziegler (2006) and Hens and Reichlin (2013) we assume that investors have lognormal beliefs about historical probabilities

$$p = \frac{1}{x\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln(x)-\mu)^2}{2\sigma^2}\right) \tag{4}$$

where x represents past gross returns. Thus, the beliefs are specified by μ and σ, i.e. $p_s \sim \mathcal{LN}(\mu, \sigma)$. We refer to this phenomenon as belief misestimation.

B.3. Probability distortion

The third extension which we introduce, is probability distortion: According to cumulative prospect theory (Tversky and Kahneman 1992) agents overweight extreme events that occur with small probability. To model these probability distortions we use the the two parameter probability weighting function proposed by Prelec (1998) applied separately to gains and losses[8]

$$T(p) = \begin{cases} \exp(-\beta^{+}(-\ln(p))^{\gamma}) & \text{if } x \geq 0 \\ \exp(-\beta^{-}(-\ln(p))^{\gamma}) & \text{if } x < 0 \end{cases} \tag{5}$$

with $0 < \gamma < 1$ and $\beta^{+}, \beta^{-} > 0$. The parameter γ captures subproportionality, and β^{+} and β^{-} capture convexity. The probability weighting function is typically applied to cumulative probabilities. Figure 2 plots this probability weighting function with a γ of 0.5 and a β of 0.8. These distortions imply that small probabilities are substantially overweighted while large probabilities are underweighted.

[Figure 2 about here.]

B.4. Behavioral asset pricing model

Including all three behavioral aspects—loss aversion, belief misestimation and probability distortion—in the standard expected utility first order condition given in equation (1), results in the following behavioral Euler equation

$$\frac{u'(x_s^{FX}) p_s T'\left(\sum_{i=1}^{s} p_i\right)}{\sum_{s=1}^{S} u'(x_s^{FX}) p_s T'\left(\sum_{i=1}^{s} p_i\right)} = \pi_s^{*} \tag{6}$$

[8] See Fehr-Duda and Epper (2012) for an overview and evaluation of different probability weighting functions. According to their study, the two parameter probability weighting function of Prelec (1998) has the most realistic as well as best mathematical properties.

$$\text{where } u(x) = (x-1)\left(1 + \frac{\delta}{1+e^{\kappa(x-1)}}\right)$$

$$\text{and } T(p) = \begin{cases} \exp(-\beta^{+}(-\ln(p))^{\gamma}) & \text{if } x \geq 0 \\ \exp(-\beta^{-}(-\ln(p))^{\gamma}) & \text{if } x < 0 \end{cases}$$

$$\text{and } p_s \sim \mathcal{LN}(\mu, \sigma)$$

where p_s are the beliefs on historical probabilities and π_s^* represent risk-neutral probabilities. Note that the probability weighting function is applied to the cumulative sum of individual probabilities, i.e. $T(\sum_{i=1}^{s} p_i)$.[9]

C. Investor perspective

When estimating a Euler equation, it is important to define the investor's state space. We consider two approaches to estimate the behavioral Euler equation: the US investor approach and the currency trader approach. These two approaches differ in their assumption on what determines the state space.

First, we take the view of a US investor who's portfolio consists of the S&P 500. The returns on the S&P 500 determine the state prices and we assume that the state space is fully spanned by S&P 500 options. In our model, this US investor now wants to price different currencies. There is just one investor with certain preferences and beliefs who prices several other assets (i.e. currencies). The state space is thus defined by one asset (the S&P 500) and used to price another asset (a currency). The question we investigate is whether the state prices implied by the S&P 500 can explain currency carry trade returns of various currencies.

Second, we take the view of a currency trader who's portfolio consists of a single currency. The returns to this currency investment determine the state prices. In this case, the state space is defined by foreign exchange options on the same currency the investor prices. Although the reference currency is the US dollar and all returns are denominated in US dollars, we do not model a trader's consumption portfolio nor the correlation with the US market. Instead, we are

[9] The decision weights in the original version of Tversky and Kahneman's (1992) cumulative prospect theory are defined as the difference between to probability weighted cumulative probabilities. The decision weight applied to the outcome in state s is $T\left(\sum_{i=1}^{s} p_i\right) - T\left(\sum_{i=1}^{s-1} p_i\right)$. Due to numerical instabilities we approximate this first difference by a first order Taylor approximation, similar to Hens and Reichlin (2013). Hence, our decision weight applied to the outcome in state s is $p_s T'\left(\sum_{i=1}^{s} p_i\right)$.

interested in currency specific behavioral phenomena. In particular, is a hedging currency priced differently compared to a risky high interest currency?

The difference between these two perspectives with respect to the behavioral Euler equation given in equation (6) is the following. In the first case—the US investor perspective—we use risk-neutral probabilities derived from S&P 500 options. Hence, they are denoted as $\pi_s^{*,SP}$ and they are the same for every currency being priced. In the second case—the currency trader perspective—the risk-neutral probabilities are currency specific and derived from foreign exchange options, denoted by $\pi_s^{*,FX}$.

Moreover, the first approach allows us to find a unified set of behavioral characteristics pricing all currencies from the perspective of a US investor. Because, in this setting, there is only one set of parameters pricing all currency returns, there is no cross-sectional variation. As we analyze US specific behavioral characteristics, the estimated parameters will most likely be determined by the performance of the US equity market. As this performance is time-varying, we expect some time-series variation in the characteristics we estimate.[10] Alternatively, the second approach allows as well for substantial cross-sectional variation since the state space and risk-neutral probabilities are different for each currency. Hence, we can investigate time-series and cross-sectional variation in parameter estimates.

III. Data and Estimation Method

Our data set consists of 10 different currencies which are CHF, EUR, GBP, YEN, NOK, BRL, ZAR, RUB, INR and MXN. All currencies are denoted vis-à-vis the USD. We choose 5 developed and 5 emerging market currencies to cover a broad spectrum of high- and low-interest rate currencies.[11] The focus of this paper is on pricing currency returns to identify different behavioral characteristics and not on developing currency trading strategies or analysing diversification potentials. Hence, the choice of currencies as well as the sample size should be representative and not exhaustive.

[10] We have also estimated the Euler equation separately for each currency and find that the parameter estimates are very similar across currencies at each point in time. Hence, this cross-sectional constraint does make sense and is not restrictive. Instead, we believe that it even improves the reliability of the proposed model since a single parameter set per time period can price returns of several different currencies.

[11] The classification between developed and emerging market countries closely follows the Morgan Stanley market classification which can be found at `https://www.msci.com/market-classification`.

A. Currency carry trade returns

We collect monthly data on spot and one-month forward exchange rates from Datastream over the time period from January 1990 to December 2015.[12] Let s_t be the log spot rate and f_t the log one-month forward exchange rate. Both rates are denoted as units of US dollars per foreign currency, i.e. an increase in the spot rate means an appreciation of the foreign currency. The currency return is what an investor earns from buying the foreign currency in the forward market and selling it in the spot market after one month or equivalently, you can borrow in the domestic currency and invest in the foreign currency. Hence, the log excess return on a currency is defined as

$$rx_{t+1} = s_{t+1} - f_t \tag{7}$$

This expression can be extended by adding and subtracting the current spot rate, $rx_{t+1} = \Delta s_{t+1} + s_t - f_t$, where $\Delta s_{t+1} = s_{t+1} - s_t$ and $s_t - f_t$ is called the forward discount or premium, respectively. Assuming that the covered interest parity (CIP) holds,[13] i.e. $s_t - f_t = i_t^* - i_t$ where i_t^* and i_t are the foreign and domestic one-month interest rates, results in

$$rx_{t+1} = \Delta s_{t+1} + (i_t^* - i_t) \tag{8}$$

The first part, Δs_{t+1}, represents the realized currency return which comprises the uncertainty about future appreciation or depreciation of the foreign currency vis-à-vis the US dollar. The second part, $i_t^* - i_t$, refers to the interest rate differential between the two currencies and it is also called the carry. Since the carry is known ex-ante, the uncertainty about the future exchange rate is the only source of risk driving currency returns.

This decomposition shows that the carry (representing the interest rate differential) is already included in currency excess returns. Thus, we refer to the currency returns defined in equation (7) as *currency carry trade returns*.[14] Note however that we always take a long position in the foreign

[12] There are a few currencies where spot and forward rates are only available from a later starting point. These are (starting dates are mentioned in brackets): EUR (1999/01), BRL (1994/06), RUB (1996/03), INR (1993/12), MXN (1993/12). However, these data limitations are not restrictive for our analysis, since the data on options across different strikes is only available since the beginning of the new millennium, i.e. 2000 and later.

[13] Akram, Rime, and Sarno (2008) show that the CIP is violated only at very high frequencies, but it holds at daily or lower horizons. Since we work with monthly returns, we can assume that CIP holds.

[14] We use the two terms currency returns and currency carry trade returns interchangeably and always refer to the log excess returns defined in equation (7).

currency and short the US dollar which implies that there is no sorting based on the forward discount or premium. Moreover, we investigate the carry trade returns of each currency separately and do not sort them cross-sectionally or aggregate individual currencies to a carry trade portfolio. All currency carry trade returns are denominated in US dollars.

Table I reports summary statistics for all 10 monthly currency return time-series. While the annualized mean return of most developed market currencies is on average negative, it is substantially higher and positive for all emerging market currencies, except the Russian ruble. During our sample period, the best risk-adjusted performance—measured by the highest Sharpe ratio—was achieved by an investment in the Brazilian real. Currency carry trade returns are clearly negatively skewed, except the Japanese yen, which is known as a safe haven currency, as well as the South African Rand, which appears to have positively skewed excess returns during our sample period. Moreover, the excess kurtosis is positive for all 10 currency returns indicating the presence of fat tails. Overall, these currency carry trade returns are obviously not normally distributed and there is substantial cross-sectional variation.

B. Risk-neutral probabilities

To estimate the Euler equation we further need to calculate risk-neutral probabilities. These probabilities can be calculated from option prices. For the two different approaches, the US investor and the currency trader approach, we use different sets of option prices.

First, for the US investor perspective we need risk-neutral probabilities derived from S&P 500 options. From the Wharton Research Data Service we retrieve end-of-month quotes on European S&P 500 index call options as well as the S&P 500 total return index level over the time period from January 2000 to December 2015. For each month, we have implied volatilities for a set of different strike prices. To be in line with the forward rates, we only select options with one month to maturity. Using the fast and stable method proposed by Jackwerth (2004), we inter- and extrapolate between the observed volatilities to fit an implied volatility curve across a fine grid of strike prices. The main advantage of this method is its simple computation as well as an external control of the trade-off between fit and smoothness. Then, we calculate the call option price for each implied volatility using the Black-Scholes option pricing formula and last, we use the result of Breeden and Litzenberger (1978) and approximate the state price density by the second derivative of the call price function with respect to the strike price. Moreover, we normalize these state prices to obtain risk-neutral probabilities which sum up to one. Note that this procedure is repeated every month such that we get a risk-neutral probability surface across strikes for every month.

Second, for the currency trader perspective, we derive risk-neutral probabilities from foreign exchange options for each currency. According to FX market conventions, we download for each currency the following end-of-month volatility quotes from Bloomberg (European style, one month to maturity): at-the-money volatility, 25-delta-call strangle and 25-delta-call risk reversal.[15] A long strangle consists of a long out-of-the money call and a long out-of-the money put option. A long risk reversal buys an out-of-the money call and shorts an out-of-the money put option. Again, all foreign exchange options are quoted vis-à-vis the US dollar and we use the same denomination as USD per one foreign currency unit. Furthermore, we assume that the CIP holds and hence, we only need the one month US interbank rate from Bloomberg since we can back out the foreign interest rate using forward and spot exchange rates. Depending on the currency, the sample period starts between 2003 and 2008 and ends in December 2015.

To calculate risk-neutral probabilities we use the Vanna-Volga method (Castagna and Mercurio 2007) which allows to infer an implied volatility smile from these three commonly traded quotes in foreign exchange option markets. The idea is to construct a locally replicating portfolio whose associate hedging costs are added to the corresponding Black-Scholes prices in order to produce smile-consistent values. Since these market quotes are a combination of different call and put options, the first step is to solve for the implied volatilities of a 25-delta-put options and a 25-delta-call option. Note that the at-the-money volatility is already given, which in total results in three volatility data points. Next, these implied volatilities are used to calculate strike prices corresponding to the deltas which is done via the Garman and Kohlhagen (1983) version of the Black-Scholes option pricing formula. We use the exact version of the Vanna-Volga scheme to inter- and extrapolate the implied volatility curve across a fine grid of strike prices and to infer the corresponding call option prices.[16] Last, we again calculate normalized risk-neutral probabilities

[15] Currency options are quoted for different deltas instead of strike prices and the current prices are given in terms of implied volatilities. The delta of a call option is the first derivative of the Black-Scholes price with respect to the spot price. Moreover, traded FX options are usually quoted as a combination of individual call and put options.

[16] Castagna and Mercurio (2007) also provide a first- and second-order approximation of there implied volatility surface which is computationally easier and faster. However, we find that it puts too much weight on the tails of the distribution and the fit is not very good.

using the results of Breeden and Litzenberger (1978) via the second derivative of call option prices. Overall, we estimate a separate risk-neutral distribution for each currency and every month.

C. State space matching

As described above, for the perspective of the US investor, the risk-neutral probabilities and the physical probabilities are calculated from data on the S&P 500. Thus, the state space is defined by the S&P 500. However, the agent prices currency carry trade returns, x_{FX}. To estimate the Euler equation, we need to know what currency return an agent expects in a state defined with respect to the S&P 500. For example, what currency return is expected when the S&P 500 has a return of 2%? To answer this question, we calculate expected returns of a currency conditional on returns of the S&P 500. To do this, we need to model the relation between S&P 500 returns and carry trade returns. Let X_{SP} be the variable describing S&P 500 returns and x_{SP} are realizations of this variable. Similarly, X_{FX} is the variable of currency returns and x_{FX} are realizations of this variable. We first estimate a bi-variate Kernel density for realizations of currency returns and S&P 500 returns, $f(x_{FX}, x_{SP})$. The optimal bandwidth is chosen according to Botev, Grotowski, Kroese, et al. (2010) applying their code.[17] Then, we calculate the expected currency return conditional on the realized S&P 500 return, $\mathbb{E}[X_{FX}|X_{SP}]$.

$$\mathbb{E}[X_{FX}|X_{SP} = x_{SP}] = \int x_{SP}\ f(x_{FX}|x_{SP})\partial x_{FX} \tag{9}$$

This approach allows us to estimate conditional expectations while taking into account dependencies between the S&P 500 and currency returns. A simpler approach is to calculate these expectations via linear regressions. This approach is included as a robustness check in Section V.

D. First-order condition estimation

The general form of the behavioral Euler condition is given in equation (6), which we estimate every month and for every currency via non-linear least squares. That is, we minimize the squared

[17]Using the rule-of-thumb which is optimal for normal distributions leads to a slightly lower bandwidth while the simple rule applied by Jackwerth (2000) leads to slightly higher values for the bandwidth. The results of our paper are not very sensitive to the choice of bandwidth.

distance between the actual risk-neutral probabilities observed in the market and the model-implied state prices. Let $\Theta_1 = \delta,\, \kappa$, be the parameters of the utility function, $\Theta_2 = \mu,\, \sigma$, the parameters of the lognormal distribution modelling the misestimated beliefs and $\Theta_3 = \gamma,\, \beta^+,\, \beta^-$, the parameters of the probability weighting function. For the US investor perspective, we constrain the parameters to be the same across all currencies per month while for the currency trader case we allow for cross-sectional variation, i.e. the parameter estimates can vary across currencies. Moreover, every month we take gross currency returns over a lookback period of 5 years, sort them in ascending order, $x_1^{FX}, \ldots, x_s^{FX}, \ldots, x_S^{FX}$, and fit them to the end-of-month normalized state prices. Formally, we can write the behavioral Euler equation as a non-linear regression model as follows.

US investor:

$$\pi_s^{*,SP} = \frac{u'(x_{s,j}^{FX};\Theta_1)\, p(x_{s,j}^{FX};\Theta_2)\, T'\left(\sum_{i=1}^{s} p(x_{i,j}^{FX};\Theta_2);\Theta_3\right)}{\sum_{s=1}^{S} u'(x_{s,j}^{FX};\Theta_1)\, p(x_{s,j}^{FX};\Theta_2)\, T'\left(\sum_{i=1}^{s} p(x_{i,j}^{FX};\Theta_2);\Theta_3\right)} + \varepsilon_{s,j} \tag{10}$$

$$\min_{\Theta_1,\Theta_2,\Theta_3} \quad \sum_{j=1}^{10}\sum_{s=1}^{S} \varepsilon_{s,j}^2 \tag{11}$$

Currency trader:

$$\pi_{s,j}^{*,FX} = \frac{u'(x_{s,j}^{FX};\Theta_{1,j})\, p(x_{s,j}^{FX};\Theta_{2,j})\, T'\left(\sum_{i=1}^{s} p(x_{i,j}^{FX};\Theta_{2,j});\Theta_{3,j}\right)}{\sum_{s=1}^{S} u'(x_{s,j}^{FX};\Theta_{1,j})\, p(x_{s,j}^{FX};\Theta_{2,j})\, T'\left(\sum_{i=1}^{s} p(x_{i,j}^{FX};\Theta_{2,j});\Theta_{3,j}\right)} + \varepsilon_{s,j} \tag{12}$$

$$\min_{\Theta_{1,j},\Theta_{2,j},\Theta_{3,j}} \quad \sum_{s=1}^{S} \varepsilon_{s,j}^2 \qquad \text{for } j = 1, \ldots, 10 \tag{13}$$

Note that we left out the subscript t, but of course we estimate the non-linear regressions models (10) and (12) every month. Furthermore, we calculate White heteroscedasticity-consistent standard errors.

IV. Empirical Results

In the following, we present the empirical results from estimating the parameters of the Euler equations by non-linear least squares as described in Section III. First, we describe the results of the traditional model and, then, the results of the behavioral model. The traditional model refers to equation (1), i.e. CRRA utility, rational beliefs and no probability distortions, while the behavioural model always includes loss aversion, belief misestimation and probability weighting. Furthermore, the analysis of the behavioural model is split up in two parts: first, we consider the US investor perspective and second, we take the view of a currency trader. All models are estimated by non-linear least squares, that is we minimize the sum of squared differences between the model-implied state prices and the option-implied risk-neutral probabilities. The analysis shows that the behavioral model with crash-o-phobia explains currency carry trade returns well and offers an improvement compared to the standard model even when correcting for the degrees of freedom.

A. Traditional model as a benchmark

First, we estimate the traditional model given in equation (1), which will later serve as a benchmark to assess the performance of the behavioral model with crash-o-phobia. We take the perspective of a US investor who consumes S&P 500 returns and prices currency carry trade returns. In this case, the only free parameter is η, i.e. the coefficient of risk aversion for CRRA utility. On average η is estimated to be 10.44. Figure 3 shows that the coefficient of risk aversion varies strongly over time and ranges between 0 and 60.

[Figure 3 about here.]

Assuming that the traditional model is correct, the time-series displayed in Figure 3 can be interpreted as the level of risk aversion. However, it is important to keep in mind that the traditional model makes strict assumptions on how agents form their beliefs about the future performance of an assets. If in reality the beliefs differ from the ones modelled in the traditional approach, then the interpretation of this time-series is less straight forward (Cohn, Engelmann, Fehr, and Maréchal 2015).

If we nevertheless interpret this parameter according to the traditional model as the coefficient of risk aversion, the level and the range of our results are in line with other studies (Mehra and Prescott (1985), Aït-Sahalia and Lo (2000), and Bliss and Panigirtzoglou (2004)). These authors show that the values of risk aversion needed to match empirical data are implausibly high when compared to experimental data: experimental studies find values between 0 and 2 (Aït-Sahalia and Lo (2000) and Haug, Hens, and Woehrmann (2013)). When correcting for the effect of narrow framing in experiments, reasonable values range between 10 and 20 (Haug, Hens, and Woehrmann 2013). While the average value we find, is consistent with narrow framing, the point estimates in many periods are above 20 and thus not plausible. The first weakness of the standard model is therefore that parameters needed to minimize the error of the model relative to the data are not plausible when compared to values found in experimental studies. This weakness makes the CRRA utility an unfavorable benchmark model. To correct for this, we set $\eta = 1$ in the benchmark model, i.e. we use logarithmic utility.

The second weakness of the benchmark model is that the fit of the model is not very good. In a first step we graphically evaluate the fit by comparing the option-implied risk-neutral density with the model-implied risk-neutral density. The model performs well, if these two densities are very similar. Figure 4 shows the option-implied density (black dashed line) and risk-neutral density implied by the model with logarithmic utility (red line) for October 2008 and October 2012 for all ten currencies. The option-implied risk-neutral density is estimated from S&P 500 options and is thus the same for all currencies. The model-implied densities are calculated according to the left-hand side of equation (1). It is thus based on the beliefs about future S&P 500 states and the marginal utility from the consumption of currency returns.[18] For both dates, October 2008 and October 2012, it is evident that the empirical model fit is not good. Comparing the plots for 2008 with the plots for 2012 reveals that the performance of the standard model is worse in times of crises (2008) than in relatively calm times (2012).

[Figure 4 about here.]

In brief, the standard model is not able to explain currency carry trade returns. The difficulties of the model to explain the data are more accentuated in times of crises.

B. Behavioural asset pricing model - US investor perspective

To test the behavioral asset pricing model, the standard approach is extended by allowing for misestimation of probabilities, distortion of probabilities and loss aversion. In the following, we discuss the results of the behavioral asset pricing model from a US investor perspective. Similar to the traditional approach, we use non-linear least squares to estimate the parameters that minimize

[18] We show the results for the case of the logarithmic utility function. The performance of the CRRA model is however very similar.

the squared difference between the data-implied and the model-implied risk-neutral density. As shown in equation (11), for the behavioral asset pricing model, seven parameters are estimated: the misestimation is modeled with μ and σ, the distortion with γ, β^+, and β^-, and the loss aversion is described by the parameters δ and κ. Figure 5 shows the resulting fit for October 2008 and October 2012 for the ten currencies.

[Figure 5 about here.]

Compared to Figure 4, the fit of the model has significantly improved. The black dashed line is the option-implied risk-neutral density calculated from S&P 500 options and the blue line represents the model-implied risk-neutral density calculated from the estimation of the Euler equation. The two lines overlap almost perfectly, which means that the explanatory power of the model is very good. Further, in comparison to the traditional approach, the performance of the model does not deteriorate in times of crises.

The behavioral Euler equation is estimated every month and hence, we get a time-series of parameter estimates. In the following, we will show the average of the estimated parameters over time as well as the time-series variation in the parameter estimates.

B.1. Average parameter estimates

Panel A of Table II shows the time-series average of each estimated parameter together with the corresponding standard error denoted in brackets.[19] The mean of the lognormal distribution characterizing the agent's beliefs, μ, is estimated to be 0.013 and the standard deviation is on average 0.0407. We find that all parameter estimates are highly significant at the 1 % confidence level, where we test the parameters of the utility function (δ, κ) and lognormal distribution (μ, σ) against the null hypothesis of 0 while the parameters of the probability weighting function (γ, β^-, β^+) are tested against 1.

To describe the probability distortion, we used Prelec (1998) two parameter specification given by equation (5). The value for γ is found to be 0.809, which is close to but slightly

[19]We calculate standard errors according to the Fama and MacBeth (1973) method. Since we estimate the Euler equation every month, we get a time-series of parameter estimates of which we can calculate sample averages and standard deviations. Let $\hat{\mu}_t$ be a time-series of estimated parameters. Then, our time-series average is given by $\hat{\mu} = \mathbb{E}[\hat{\mu}_t]$ and the standard error is $\sigma(\hat{\mu}) = \sqrt{\frac{Var(\hat{\mu}_t)}{T}}$.

higher than values from experiments, which range from 0.44 to 0.74 (Gonzalez and Wu (1999), Fehr-Duda and Epper (2012) and Wu and Gonzalez (1996)). Polkovnichenko and Zhao (2013), who use stock market data, find values between 0.563 and 1.64, which is consistent with our findings.[20] For β_+ and β_- our estimates are on average 0.830 and 0.834 respectively,[21] which is in line with experimental and empirical data: Gonzalez and Wu (1999) find 0.77, Fehr-Duda and Epper (2012) estimate values between 0.868 and 0.958 while Polkovnichenko and Zhao (2013) find values between 0.7 and 1.2. Overall, the values estimated for the probability distortion implied by carry trade returns are in line with experimental and other empirical data. Figure 6 shows the probability weighting function for a γ of 0.809 and a β of 0.830 and one can see that small probabilities are clearly overweighted. Further, the overweighting is stronger for low values of the CDF. This means that the probability distortion affects small probabilities in the loss domain more than small probabilities in the gain domain. This gives the notion of crash-o-phobia further support: Agents put a higher weight on the probabilities of very low returns (i.e. a crash) than on the probabilities of very high returns.

[Figure 6 about here.]

A further important aspect of crash-o-phobia is loss aversion. We estimate loss aversion to be on average 1.26. According to our utility function, the loss aversion is asymptotically equal to $1 + \delta$ while the exact value depends additionally on κ. Using a slightly different utility function and a different probability weighting function compared to our approach, Kahneman and Tversky (1979) find a value of 2.25 for loss aversion. Part of this difference might be explained by the different functions they use. In further experiments Abdellaoui, Bleichrodt, and Paraschiv (2007) find values ranging between 1.19 and 2.34, which is in line with our results. Using empirical data Kliger and Levy (2009) find parameters ranging between 1.163 and 1.406, which is again in line with our results. Thus, the loss aversion we estimate is comparable in range with other experimental and empirical analyses.

From the average parameter estimates, we can therefore conclude that there is clear evidence for misestimation and distortion of probabilities, as well as loss aversion, i.e. crash-o-phobia. The parameters are in line with values found in experiments and other empirical analyses.

[20] In contrast to many other approaches they allow for $\gamma > 1$.

[21] Our estimates for β_+ and β_- are very similar. This is in line with experimental results. In our case, the similarity can arise as well because we minimize the difference to a smooth function without kinks.

B.2. Time-series variation in parameter estimates

The use of market data enables us to not only find parameter estimates at a single point in time, like in experiments, but to as well analyze in which states of the world crash-o-phobia strongly influences market perception. We thus investigate the time-series variation of the estimated parameters.

These variations over time are illustrated in Figure 7 where the monthly estimates of each parameter are plotted in a separate graph. Overall, the plots show that crash-o-phobia is present in all time periods. It is however interesting to see that the extent to which the agent is crash-o-phobic increases in times of crises: for example, during the financial crisis of 2008 the distortion of probabilities (low γ, low β) is stronger and loss aversion is higher than during times without turmoil. Further, the parameter σ, indicating the beliefs about volatility, clearly increases during this period. Hence, the time series variation of the parameters does, at least partially, reflect times of market turmoil.

[Figure 7 about here.]

The increased crash-o-phobia during times of crises is reflected in Figures 4 and 5 as well: In contrast to the standard model, the behavioral model can explain both probability distributions very well. This is the case because varying degrees of crash-o-phobia can match the different risk-neutral probability distributions implied by the data. In Panel B of Table II we additionally report parameter estimates for two points in time to further highlight the difference in parameter estimates between crises and non-crises periods. For October 2008, the loss aversion is estimated to be 1.69 while in October 2012 the loss aversion is only 1.03. In October 2008, γ is estimated to be 0.501, β_+ and β_- 0.44 implying that the probability distortion was very strong during the financial crisis. Four years later, in calmer times, the probability distortion is quasi absent (γ is 0.96 , β_+ and β_- are 1.01). Thus, the estimated level of crash-o-phobia is substantially higher in 2008 than in 2012, which enables the model to match both option-implied distributions very well.

Crash-o-phobia is clearly of importance to explain currency carry trade returns—both on average and over time. In contrast to the standard model, the behavioral asset pricing model performs much better at explaining the form of the risk-neutral density, which we calculate from option prices. The empirical fit is greatly improved using the crash-o-phobia model. Time-series analysis further reveals that people are more crash-o-phobic in times of crises.

B.3. Model comparison

From the analysis so far, we conclude that the behavioral model fits the data substantially better than the standard asset pricing model. To get a better understanding about which behavioral characteristics contributes the most to the overall fit improvement as well as to see the relative performance of different models over time, we calculate the Akaike information criterion (AIC) (Akaike 1998) for each model. The AIC measures the error of a model while correcting for the degrees of freedom and it is calculated as follows:

$$AIC = n * \log\left(\frac{RSS}{n}\right) + 2k \tag{14}$$

where n is the number of observations, RSS is the sum of squared residuals from the estimation, and k are the degrees of freedom of the model, i.e. the number of parameters estimated.

Figure 8 plots the Akaike information ratio of the standard model and of different forms of the behavioral model. In general, the lower a model's information criterion, the better the model performs. Obviously, the explanatory power of the behavioral asset pricing model is substantially better than that of the standard model and this outcome is not due to an increased number of free parameters. The top line in Figure 8, i.e. the line with the lowest explanatory power, is the standard model based on a logarithmic utility function. The bottom line, and thus the model with the highest explanatory power correcting for degrees of freedom, is the crash-o-phobia model. The lines in between show the information ratios of models for which we only introduce certain aspects of crash-o-phobia: the green dashed line shows that adding misestimation to the model has a strong influence in increasing the performance of the model. Further adding distortion results in the blue dashed line. Using a two-sided t-test, we find that each extension of the model performs significantly better than the simpler models at the 1% confidence level correcting for the degrees of freedom.

[Figure 8 about here.]

To summarize, first, we show that our parameter values are consistent with experimental findings. Second, the behavioral asset pricing model with crash-o-phobia outperforms the standard model even when correcting for the degrees of freedom. Third, all three elements of crash-o-phobia—distortion, misestimation, and loss aversion—are needed to explain the returns from carry trades.

C. Currency trader perspective

In the following, we present the results of the behavioral Euler equation estimated from the perspective of a currency trader. Every month we fit equation (12) to price past currency carry trade returns by minimizing the sum of squared differences between foreign exchange option-implied risk-neutral probabilities and model-implied state prices, as given by equation (13). As a result, we obtain monthly parameter estimates of $\Theta_{1,j}, \Theta_{2,j}, \Theta_{3,j}$ for each currency which allows us to analyze currency specific behavioral phenomena.

First, we focus on cross-sectional differences across our sample of developed and emerging market currencies. Table III summarizes the time-series average of each parameter estimate together with the corresponding standard errors denoted in brackets.[22] Results for developed market currencies are given in Panel A and the estimates for emerging market currencies in Panel B. We find that all parameter estimates are highly significant at the 1 % confidence level, where we test the parameters of the utility function, $\Theta_{1,j}$, and lognormal distribution, $\Theta_{2,j}$ against the null hypothesis of 0 while the parameters of the probability weighting function, $\Theta_{3,j}$, are tested against 1. The currency specific means of the lognormal distribution characterizing the agent's beliefs, μ, are slightly negative and on average they are lower for emerging market currencies than for developed markets. On the contrary, the agent's estimates of the volatility parameter, σ, are fairly similar across the two subsamples of currencies.

Regarding the probability distortions implied by the different currency carry trade returns, we obtain substantial cross-sectional variation in parameter estimates. For example, the parameter γ which captures subproportionality varies between 0.4469 (NOK) and 0.7124 (YEN) for the developed market currencies while it ranges from 0.2518 (ZAR) to 0.4591 (INR) for the emerging market currencies. Hence, the average γ of developed market currencies is higher than those

[22]Note that we again estimate the standard errors according to the Fama-MacBeth methodology.

of emerging market currencies implying a much stronger overweighting of small probabilities for the latter. These differences might indicate that a currency trader prices the higher tail risk of emerging market currency returns with increased probability distortions. These findings are in line with the survey results on international risk sharing conducted by Rieger, Wang, and Hens (2017), who find that wealthier countries exhibit less probability weighting. Similar to the results for the US investor perspective, there is very little difference between the overweighting of gains or losses. Moreover, the cross-sectional differences in β_- and β_+ are in line with the variation described for γ.

To quantify the implied loss aversion, we evaluate the utility function at a loss of 30 % using the estimated parameter values of δ and κ and the results are reported in the last column of Table III. Again, we obtain substantial cross-sectional variation where the average loss aversion of developed market currencies is higher than the loss aversion implied by emerging market currency returns. Most strikingly, the highest values are found for the CHF (2.8301) and the YEN (3.5897)—two currencies which are commonly referred to as safe haven currencies. Regarding our behavioral explanation of currency returns, these high values of implied loss aversion indicate that investors holding the CHF or the YEN are really afraid of severe currency crashes, i.e. you fear losses, hence you invest in safe haven currencies. Taken together, developed market currencies exhibit less probability overweighting but higher loss aversion, while the reverse is true for emerging market currency returns. Moreover, we conclude that the crash-o-phobia component of carry trade returns is currency specific, at least from the viewpoint of a currency trader, and it varies across currencies.

Second, we investigate the time-series variation of these currency specific parameter estimates. Figure 9 shows the time-series of monthly parameter estimates for the implied loss aversion at 30 %, the probability weighting parameter γ and the volatility σ for each currency. The first row in each Panel always refers to the developed market currencies, while the second row includes estimates for emerging market currencies. Regarding the implied loss aversion (top Panel), we can observe that the average level is higher for developed market currencies than emerging market currencies across the whole sample period. Nevertheless, there are some distinct spikes during currency specific or other economic crises. The time-series plots of the probability weighting parameter γ reveal a similar picture (middle Panel). The average level is lower for emerging market currencies implying stronger overweighting of small probabilities compared to developed market currencies. Moreover, at times of crises or when currency traders fear a severe crash or a strong devaluation of the specific currency against the USD, we can observe a sudden drop in γ.

Besides some currency specific events, we observe a general increase in uncertainty and crash-o-phobic phenomena around the financial crisis of 2008. In particular, the bottom Panel of Figure 9 reveals a substantial spike in the volatility of currency carry trade returns across all currencies. Related to this observation, Farhi, Fraiberger, Gabaix, Ranciere, and Verdelhan (2015) find that the fall of 2008 appears as a turning point in currency option markets. Before the crises, foreign exchange option smiles were fairly symmetric, while after 2008 option smiles became clearly asymmetric. They argue that these asymmetries depend on the interest rate level, where high interest currencies reflect the risk of large depreciation during bad times and hence, the smile is skewed. In a similar vein, Brunnermeier, Nagel, and Pedersen (2008) find that after a currency crash, speculators are willing to pay more for crash insurance which increases its price. This crash risk insurance is reflected by currency risk reversal options. Thus, after a crisis the price of currency risk reversal options increase which translates into an increased negative skewness of the corresponding risk-neutral distribution. Our results are in line with these findings in the literature. In particular, we document that after a crash people become more loss averse and increase the overweighting of small probabilities, which can reconcile the rise in negative skewness and tail risk of currency carry trade returns.

[Figure 9 about here.]

Third, to evaluate the fit of the behavioral model from the currency trader perspective, we plot the model-implied and the option-implied risk-neutral probability distribution for each currency at two specific points in time. Consistent with the results for the US investor perspective, Figure 10 shows these plots for October 2008 and October 2012. Obviously, the fit of our model at times of crises, i.e. in October 2008, is less good than at normal times, such as in October 2012. The latter fit is very precise for the developed market currencies and fairly good for emerging market currencies. However, for these currencies the estimation of the currency option implied risk-neutral distribution is also less precise.

[Figure 10 about here.]

V. Robustness Analysis

In this section, we present several robustness checks for our main results. We analyze the effect of restricting the time-variation of parameters, adjusting the state space matching and changing the lookback period. Overall, the results are very robust to changes in these assumptions. Note that the whole robustness analysis refers to the behavioural asset pricing model from the US investor perspective.

A. Constrained estimation over time

In the main analysis in Section IV, we estimate a new set of parameters every month and all the parameters are allowed to change over time. In the following, we restrict the time-variation of the parameters and assume that the agent's belief distortion and loss aversion are constant over time. However, the beliefs are still time-varying. The underlying intuition is that while an agent's belief about the future might change over time, there could be reasons to assume that his preferences and distortions remain the same. Moreover, fixing the parameters over time reduces the degrees of freedom as the parameters for loss aversion and probability distortions are estimated only once and not every period. From a theoretical point of view, this can be highly relevant since a good model should explain the data sufficiently well without allowing for too many free parameters. Hence, this allows us to test if crash-o-phobia is a robust modelling feature persistent over time, or whether it just adds additional degrees of freedom to improve the monthly fit.

The estimated parameters are shown in Panel A of Table IV. The parameters depict crash-o-phobia: μ and σ are positive and reasonable. γ is estimated to be 0.91, which is somewhat higher than in the main analysis. The same is true for β^- and β^+. Thus, there is probability distortion but to a slightly lower degree than with time-varying parameters. Further, the loss aversion is estimated to be 2.97 which is higher than in the main analysis. Overall, even with time-fixed probability distortion and loss aversion the estimated parameters indicate crash-o-phobia and it seems that it is a robust feature describing the data well.

B. Linear state space matching

To estimate the parameters of the behavioral asset pricing model from the perspective of a US investor, we need to match the state spaces of the currency returns and the S&P 500: the state space, which we use to price currencies, is defined by the S&P 500. In the main analysis, we use a bivariate kernel density to estimate an expected value of the currency return conditional on the state defined by the S&P 500. This approach allows for non-normality of the data and a non-linear relation between currency returns and S&P 500 returns.

As a robustness test, we simplify this assumption and match the state spaces using a linear regression which implies that both the currency and the S&P 500 return follow a bivariate normal distribution. For every currency, we estimate $\hat{x}_{FX}$ according to the regression

$$x_{FX,t} = \alpha + \beta * x_{SP,t} + \varepsilon_t \tag{15}$$

where $\hat{x}_{FX}$ corresponds to $\mathbb{E}[X_{FX}|X_{SP} = x_{SP}]$. Hence, the currency returns are projected onto the state space of the S&P 500 and then, we use the matched currency returns to estimate the parameters of the behavioral Euler equation given in (10) and (11).

The corresponding results are shown in Panel B of Table IV. The parameters are very similar to the ones in Panel A of Table III which are based on the bivariate kernel density approach. Thus, we can conclude that our results on crash-o-phobia in currency carry trade returns are robust to the way we match the state space.

C. Lookback period

The lookback period determines over which horizon the agent forms his beliefs and expectations. That is, how far the investor looks into the past to estimate the expected currency return conditional on the state space. Further, it also sets the time frame over which we model the investor belief formation process about historical probabilities. Hence, the bivariate kernel density or linear regression respectively, as well as the lognormal probability density all depend on the lookback period.

In the main analysis we use a lookback period of 5 years. Now, we analyze the effect of shortening the lookback period to 3 years and prolonging it to 8 years. If the horizon is shorter, more extreme events will probably have a stronger influence on the agent's expectation formation while their influence will diminish when the lookback period is longer. Thus, if crash-o-phobia is important to explain carry trade returns, we would expect that it is more accentuated when the horizon is shortened to 3 years and is muted when the horizon is prolonged to 8 years.

Panel C of Table IV summarizes the results of the behavioural Euler equation estimated over a lookback period of 3 and 8 years instead of 5 years. As we expected, the effect of crash-o-phobia is strongest when we use a lookback period of 3 years (lower γ and β, higher λ) and it slightly diminishes with an increasing horizon. Nevertheless, we find evidence for belief misestimation, probability distortion and loss aversion across all lookback periods and we conclude that crash-o-phobia exists independent of the lookback period while its magnitude depends on the influence of extreme events.

VI. Conclusion

In this paper we propose a behavioral extension of the standard Euler equation to price currency carry trade returns. We show that the standard asset pricing model with rational beliefs and CRRA utility fails to explain currency returns. Departing from this standard model, we relax assumptions on the belief formation and the utility function by allowing for crash-o-phobia, which entails belief misestimation, belief distortion and loss aversion. We incorporate these crash-o-phobia elements into the Euler equation and use it to price a basket of 10 currency carry trade returns. Every month, we estimate a set of parameters by minimizing the difference between model-implied state prices and option-implied risk-neutral densities via non-linear least squares. Our results suggest that carry trade investors exhibit substantial loss aversion and overweight states with low probabilities. While all our parameter estimates are in line with values found by experimental studies, it is important to note that all estimates are implied financial market data which further validates the behavioural asset pricing model.

To estimate the behavioural Euler equation, we need to define the state space. First, we assume that all currencies are priced by a US investor whose state space is defined by the S&P 500. While his beliefs and preferences are time-varying, they are fixed across currencies since we model one investor pricing different assets. This allows us to do an extensive model comparison and we show that the behavioural model significantly outperforms the standard asset pricing model even after correcting for the degrees of freedom. Hence, crash-o-phobia matters to explain currency carry trade returns, both economically as well as statistically and even more so in times of crises.

Second, we take the perspective of a currency trader whose state prices are formed conditional on the currency return he prices and not on the states of the S&P 500. The currency trader prices each currency separately which allows us to analyze not only time-series but also cross-sectional variation in parameter estimates: we show that investors pricing developed market currencies are more crash-o-phobic than investors holding emerging market currencies. This is consistent with higher returns of these currencies, i.e. not so crash-o-phobic investors hold the currencies which other investors deem too risky due to their crash-o-phobia. Less crash-o-phobic investors then earn a higher return.

The results of our behavioral asset pricing model are robust to changes in the assumptions about the belief and expectation formation process. Moreover, even if we restrict the parameters to be constant over time, we can identify a significant loss averse behavior as well as probability distortions which implies that crash-o-phobia seems to be a persistent phenomena over time. The consistency with experimental studies as well as the statistical robustness of our results suggest that crash-o-phobia is a highly relevant factor for pricing currency carry trade returns. We believe that pursuing the approach of integrating behavioral aspects into asset pricing models improves our understanding of currency returns.

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A. Model Setup

The standard two-period asset pricing model with a representative investor follows closely the model outlined in Hens and Reichlin (2013) as well as the theory described in Hens and Rieger (2010). In our two-period model the representative investor trades a finite set of assets at time zero that deliver payoffs at period one in a finite set of states of the world. Markets are assumed to be complete.

- There are two time periods, $t = 0, 1$. In period $t = 0$, the state is denoted by $s = 0$. In period $t = 1$ a finite number of states $s = 1, \ldots, S$ can occur.
- There are K assets denoted by $k = 1, \ldots, K$. The payoff by asset k in state s is denoted by A_s^k and the asset price is denoted by $\mathbf{q} = (q^0, q^1, ..., q^K)$. Assuming no-arbitrage, asset prices can be expressed in terms of state price discounted asset payoffs, i.e. there exist state prices $(\pi_1, \pi_2, ...\pi_S) \in \mathbb{R}^S_{++}$ such that $q_k = \sum_{s=1}^S A_s^k \pi_s$ for $k = 0, \ldots, K$.
- The representative investor has exogenous wealth defined over all possible states $\mathbf{w} = (w_0, w_1, ..., w_S)'$ and a consumption stream $\mathbf{x} = (x_0, x_1, ..., x_S)$, where x_s are asset returns. He discounts future consumption at the rate β.

The agent maximizes expected utility over utility function u and expects state s to occur with probability p_s. The maximization problem can then be written as follows[23]

$$\max_{x_s} \quad u(x_0) + \beta \sum_{s=1}^S p_s u(x_s), \tag{16}$$

$$\text{such that} \quad x_0 + \sum_{s=1}^S \pi_s x_s = w_0 + \sum_{s=1}^S \pi_s w_s. \tag{17}$$

Formulating the Lagrangian

$$\mathbb{L} = u(x_0) + \beta \sum_{s=1}^S p_s u(x_s) - \lambda \left(x_0 + \sum_{s=1}^S \pi_s x_s - w_0 - \sum_{s=1}^S \pi_s w_s \right), \tag{18}$$

[23]Note that no-arbitrage implies that the maximization problem can be written in terms of returns and state prices.

which gives the following first order conditions

$$\beta p_s u'(x_s) = \lambda \pi_s, \tag{19}$$

$$u'(x_0) = \lambda. \tag{20}$$

Inserting (20) into (19) results in the first order condition in terms of state prices, π_s,

$$\frac{\beta p_s u'(x_s)}{u'(x_0)} = \pi_s \tag{21}$$

Because state prices are unobservable, we have to standardize to express the first order condition in terms of risk-neutral probabilities, π_s^*,[24]

$$\frac{\frac{\beta p_s u'(x_s)}{u'(x_0)}}{\sum_s \frac{\beta p_s u'(x_s)}{u'(x_0)}} = \frac{\pi_s}{\sum_s \pi_s} \tag{22}$$

Since β and $u'(x_0)$ are constants, we can simplify

$$\frac{\frac{\beta p_s u'(x_s)}{u'(x_0)}}{\frac{\beta}{u'(x_0)} \sum_s p_s u'(x_s)} = \pi_s^* \tag{23}$$

and hence, the first order condition is

$$\frac{p_s u'(x_s)}{\sum_s p_s u'(x_s)} = \pi_s^* \tag{24}$$

Thus, it is sufficient to know any utility function u and any consumption process x to determine the standardized state prices, also called the likelihood ratio process. Equally, knowing the risk-neutral probabilities and the physical probabilities is enough to back-out marginal utilities $u'(x_s)$.

[24] Using the result of Breeden and Litzenberger (1978), we can derive risk-neutral probabilities from call options data.

Table I
Summary statistics

The table gives summary statistics for all 10 currency carry trade returns. It reports the mean, standard deviation (vola) and Sharpe Ratio (SR), which are annualized and in percent, as well as the monthly skewness (skew), kurtosis (kurt), minimum (min) and maximum (max) return over the time period January 1990 to December 2015. The following currencies have a later starting date which is mentioned in brackets: EUR (1999/01), BRL (1994/06), RUB (1996/03), INR (1993/12), MXN (1993/12).

	CHF	EUR	GBP	JPY	NOK	BRL	ZAR	RUB	INR	MXN
mean	0.43	−0.43	−0.43	−1.02	0.48	8.53	6.84	−0.23	1.36	2.81
vola	11.09	10.26	8.66	10.86	10.88	15.91	16.81	15.24	7.38	10.17
SR	0.04	−0.04	−0.05	−0.09	0.04	0.54	0.41	−0.02	0.18	0.28
skew	−0.01	−0.15	−0.50	0.37	−0.34	−0.59	0.56	−0.66	−0.30	−0.99
kurt	3.96	3.84	4.59	5.08	3.86	4.42	5.43	6.62	5.66	6.23
min	−11.83	−10.39	−10.09	−10.72	−12.80	−15.87	−15.53	−17.86	−7.45	−13.90
max	12.60	9.38	8.46	15.55	7.36	12.64	17.65	14.28	7.81	7.40

Table II
US investor perspective time-average parameter estimates

The table reports estimation results of the behavioral model from the perspective of a US investor given by equations (10) and (11). Panel A gives monthly parameter estimates, which are averaged over time and standard errors are denoted in brackets. Panel B reports parameter estimates for October 2008 and October 2012. The non-linear least square standard errors are given in brackets for these two dates.

	μ	σ	γ	β^-	β^+	δ	κ	LA (30%)
Panel A: Average over time								
	0.0130	0.0407	0.8094	0.8290	0.8339	0.2704	57.0679	1.2579
	(0.0023)	(0.0015)	(0.0136)	(0.0298)	(0.0294)	(0.0340)	(7.2238)	(0.0341)
Panel B: Selected months								
October	0.0431	0.0199	0.5011	0.4442	0.4446	0.8433	4.8948	1.6855
2008	(0.0006)	(0.0001)	(0.0074)	(0.0055)	(0.0084)	(0.4869)	(0.0000)	(0.4869)
October	0.0035	0.0403	0.9598	1.0094	1.0077	0.0481	4.4200	1.0380
2012	(0.0002)	(0.0000)	(0.0012)	(0.0054)	(0.0053)	(0.0084)	(0.0000)	(0.0084)

Table III
Currency specific time-average parameter estimates

The table reports estimation results of the behavioral model from the perspective of a currency trader given by equations (12) and (13). Monthly parameter estimates are averaged over time and reported for each currency separately grouped by developed and emerging markets. Standard errors are denoted in brackets.

	μ	σ	γ	β^-	β^+	δ	κ	LA (30%)
Panel A: Developed market currencies								
CHF	−0.0282	0.0754	0.6039	1.7657	1.7636	1.8589	13.8325	2.8301
	(0.0044)	(0.0019)	(0.0137)	(0.0586)	(0.0567)	(0.0934)	(0.5480)	
EUR	−0.0381	0.0683	0.5447	1.9027	1.8875	1.6187	13.0306	2.5869
	(0.0045)	(0.0018)	(0.0110)	(0.0626)	(0.0612)	(0.0940)	(0.5317)	
GBP	−0.0391	0.0605	0.5205	1.9682	1.9008	1.5568	14.8498	2.5389
	(0.0041)	(0.0014)	(0.0098)	(0.0612)	(0.0580)	(0.0988)	(0.7364)	
YEN	−0.0425	0.0981	0.7124	2.0575	2.1055	2.6281	14.0351	3.5897
	(0.0079)	(0.0039)	(0.0151)	(0.0892)	(0.0887)	(0.0798)	(0.5432)	
NOK	−0.0581	0.0730	0.4469	1.8160	1.8210	0.9982	13.7762	1.9825
	(0.0050)	(0.0019)	(0.0098)	(0.0518)	(0.0504)	(0.0597)	(0.5828)	
Panel B: Emerging market currencies								
BRL	−0.0636	0.0725	0.3812	1.9162	1.7705	0.7009	14.5268	1.6920
	(0.0069)	(0.0026)	(0.0113)	(0.0756)	(0.0728)	(0.1492)	(0.7581)	
ZAR	−0.1464	0.0737	0.2518	2.1585	2.2061	0.2895	20.7925	1.2889
	(0.0054)	(0.0013)	(0.0069)	(0.0529)	(0.0567)	(0.0173)	(0.8113)	
RUB	−0.1072	0.0803	0.3945	2.6595	2.5668	0.4567	19.5174	1.4554
	(0.0086)	(0.0052)	(0.0149)	(0.1224)	(0.1204)	(0.0702)	(1.8989)	
INR	−0.0514	0.0527	0.4591	2.4444	2.1986	1.7263	13.1342	2.6934
	(0.0036)	(0.0016)	(0.0116)	(0.0812)	(0.0846)	(0.1427)	(0.9032)	
MXN	−0.0890	0.0612	0.3750	2.4094	2.2689	0.7653	17.4462	1.7612
	(0.0052)	(0.0021)	(0.0104)	(0.0746)	(0.0764)	(0.1022)	(1.1245)	

Table IV
Robustness tests concerning belief and expectation formation

The table reports results from robustness tests when the assumptions on the belief and expectation formation process are adjusted. Panel A shows the estimated parameters under the assumption that the belief distortion and loss aversion are fixed over time. Panel B reports parameter estimates when the conditional expectation of currency returns is modelled by a linear regression. Panel C summarizes the results if the lookback period is changed to 3 or 8 years. Given numbers are average values of the estimated monthly parameters. Where applicable, the standard errors are given in brackets.

	μ	σ	γ	β^-	β^+	δ	κ	LA (30%)
Panel A: Fixed parameters								
	0.0025	0.0511	0.9083	1.0002	0.9634	1.9659	64.3540	2.9659
Panel B: Linear regression approach								
	0.0104	0.0415	0.8077	0.8426	0.8324	0.2765	20.2932	1.2654
	(0.0022)	(0.0201)	(0.0134)	(0.0285)	(0.0284)	(0.0417)	(2.6570)	(0.0418)
Panel C: Lookback period								
three	0.0106	0.0412	0.8042	0.8302	0.8222	0.3802	39.6298	1.3676
years	(0.0034)	(0.0014)	(0.0131)	(0.0311)	(0.0311)	(0.0821)	(4.0876)	(0.0815)
eights	0.0026	0.0447	0.8062	0.9130	0.9055	0.2410	20.4458	1.2267
years	(0.0012)	(0.0015)	(0.0129)	(0.0202)	(0.0201)	(0.0279)	(2.7654)	(0.0279)

Figure 1. Utility function with loss aversion

The figure shows a linear utility function and loss averse utility function proposed by Rosenblatt-Wisch (2008) with a κ of 20 and a δ of 0.5.

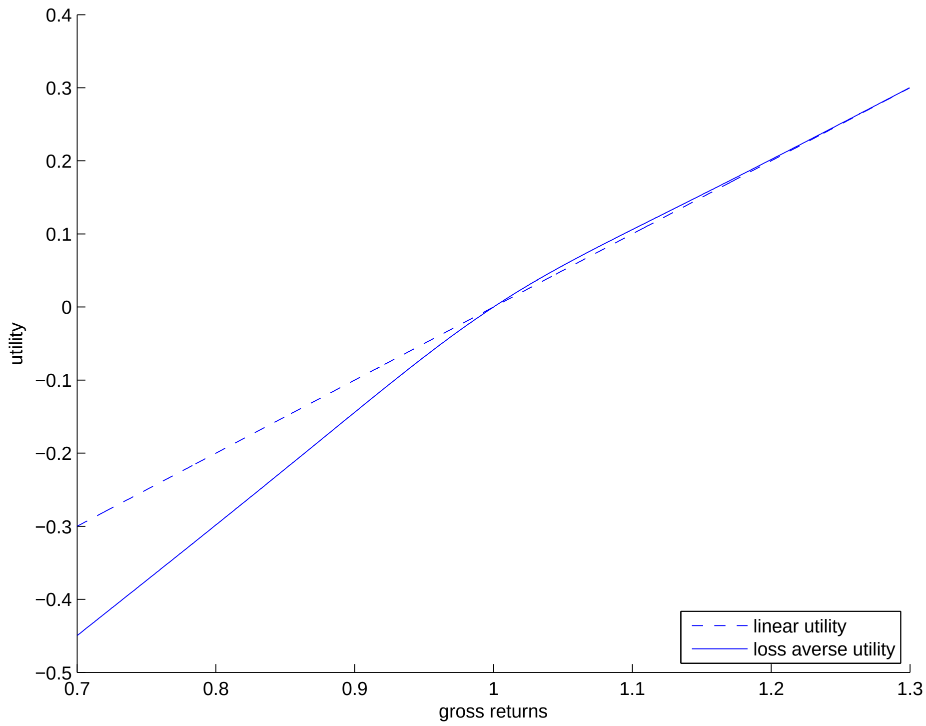


Figure 2. Probability weighting function

The figure shows the two parameter probability weighting function proposed by Prelec (1998) with a γ of 0.5 and a β of 0.8.

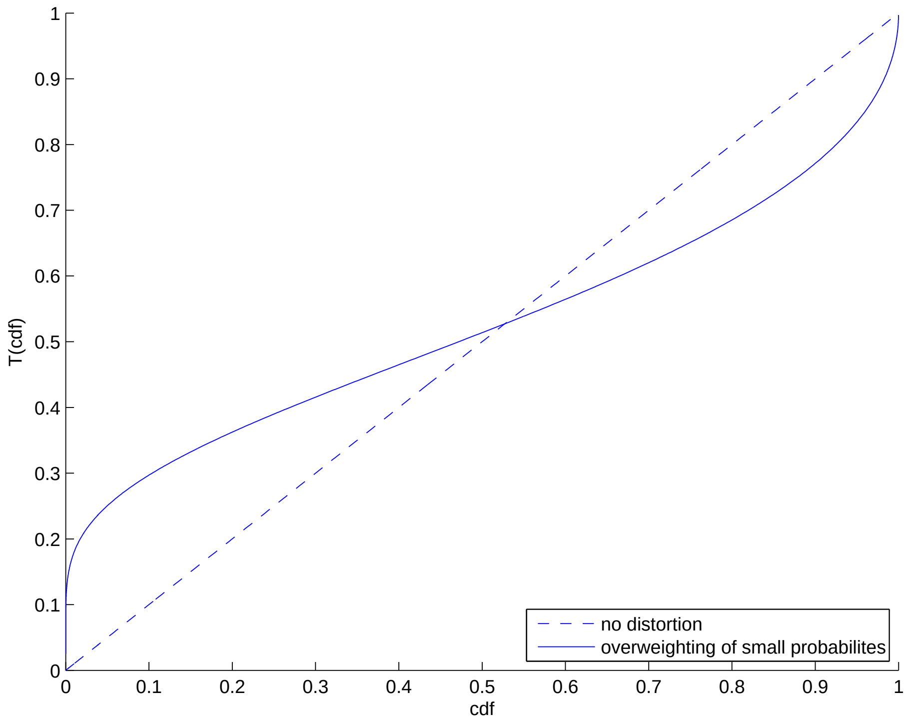


Figure 3. Implied CRRA coefficient of risk aversion

The figure shows the time-series of the estimated risk aversion parameter for a CRRA utility.

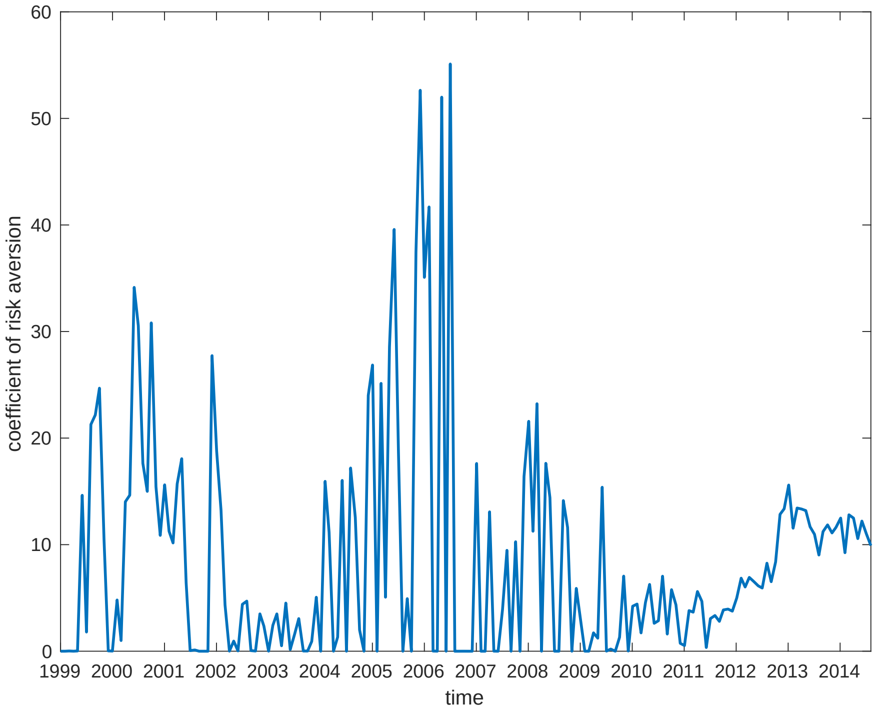
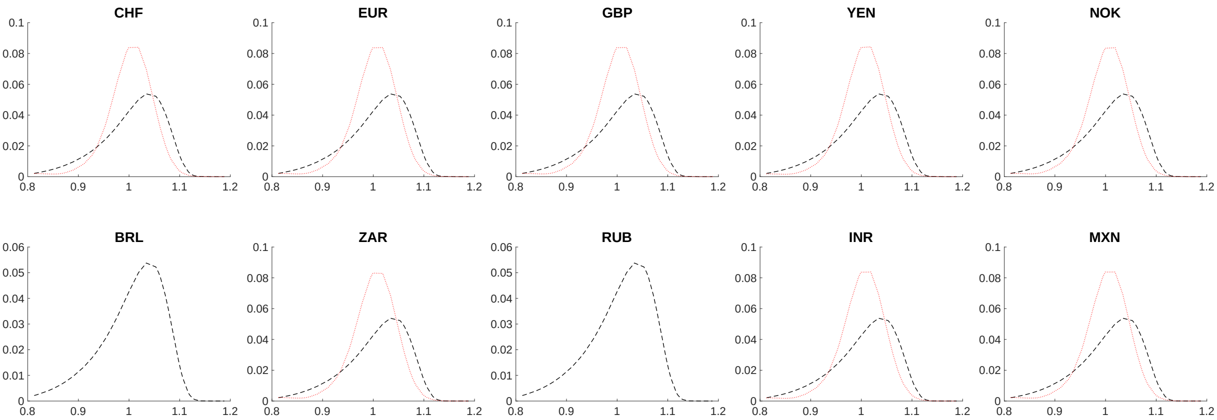


Figure 4. Risk-neutral densities: traditional model

The figure shows the S&P 500 option-implied risk-neutral densities (black dashed line) together with model-implied risk-neutral densities using a logarithmic utility (red line) for October 2008 and October 2012. The x-axis displays the state space while the y-axis indicates the risk-neutral probabilities.

October 2008



October 2012

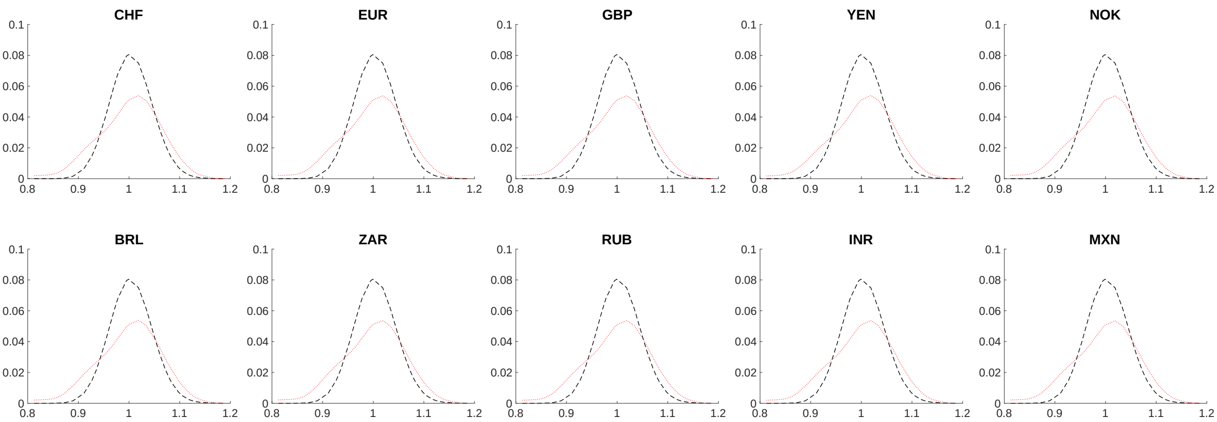
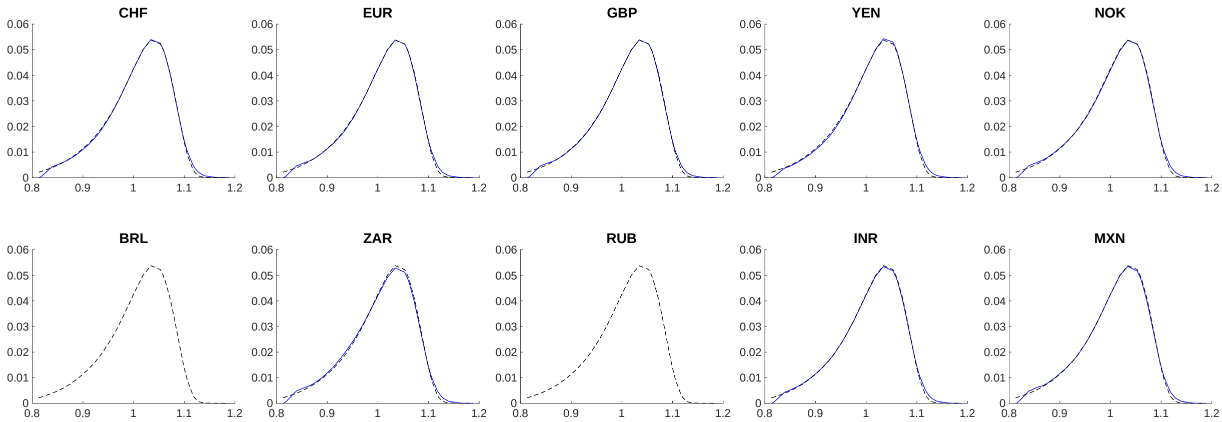


Figure 5. Risk-neutral densities: crash-o-phobia model

The figure shows the S&P 500 option-implied risk-neutral densities (black dashed line) together with model-implied risk-neutral densities using the behavioral crash-o-phobia Euler equation (blue line) for October 2008 and October 2012. The x-axis displays the state space while the y-axis indicates the risk-neutral probabilities.

October 2008



October 2012

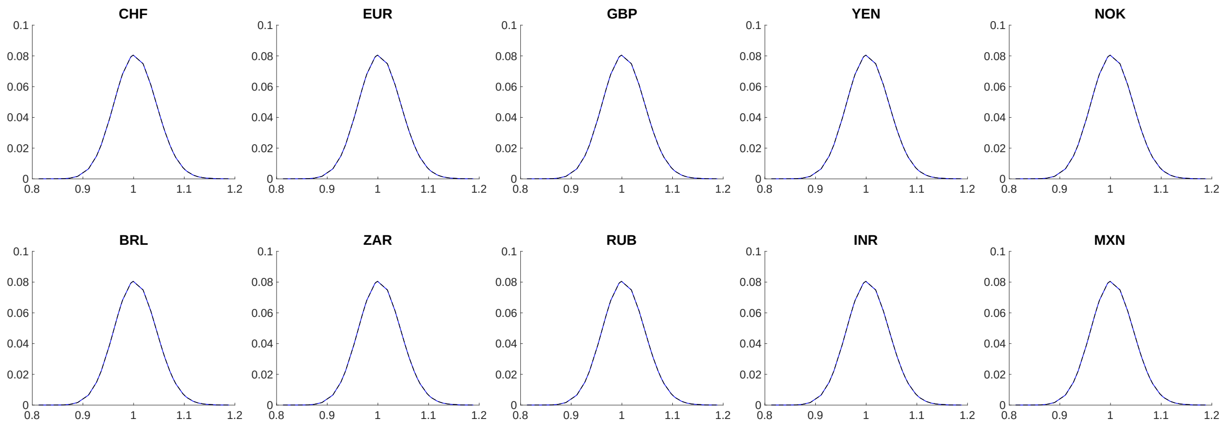


Figure 6. Estimated probability weighting function

The figure shows the two parameter probability weighting function proposed by Prelec (1998) with our parameter estimates for $\gamma = 0.809$ and $\beta = 0.830$.

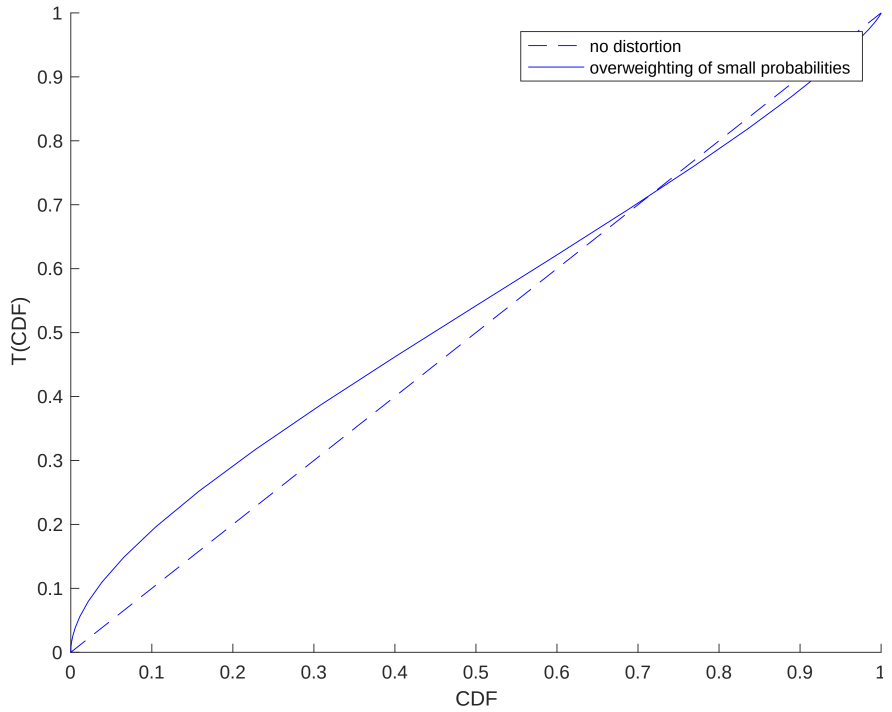


Figure 7. US investor perspective parameter estimates over time

The figure shows the monthly estimates of the crash-o-phobia model parameters.

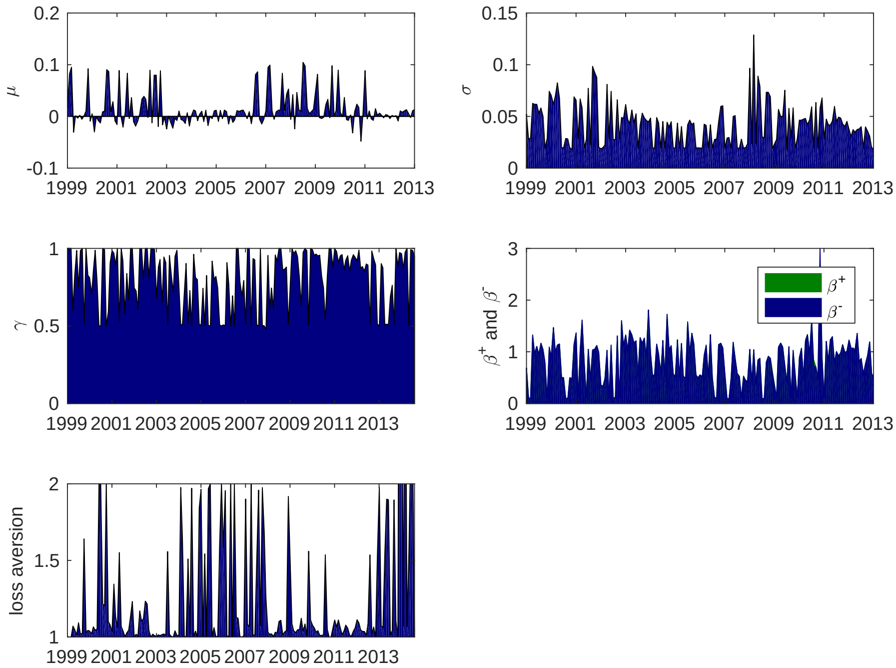


Figure 8. Information ratio

The figure shows the time series of the AIC for the standard approach with the log utility (red dashed line), the standard approach extended with misestimation (green dotted line), the standard approach with distortion and misestimation (blue dashed line) and the model with loss aversion, distortion and misestimation, i.e. crash-o-phobia (black line). The x-axis shows the year and the y-axis shows the information criterion.

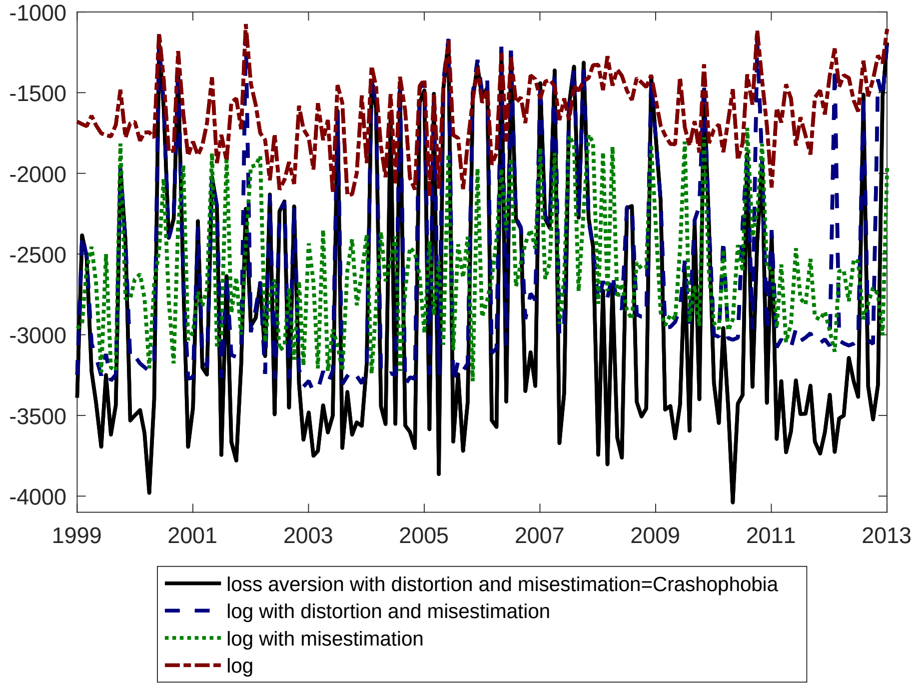
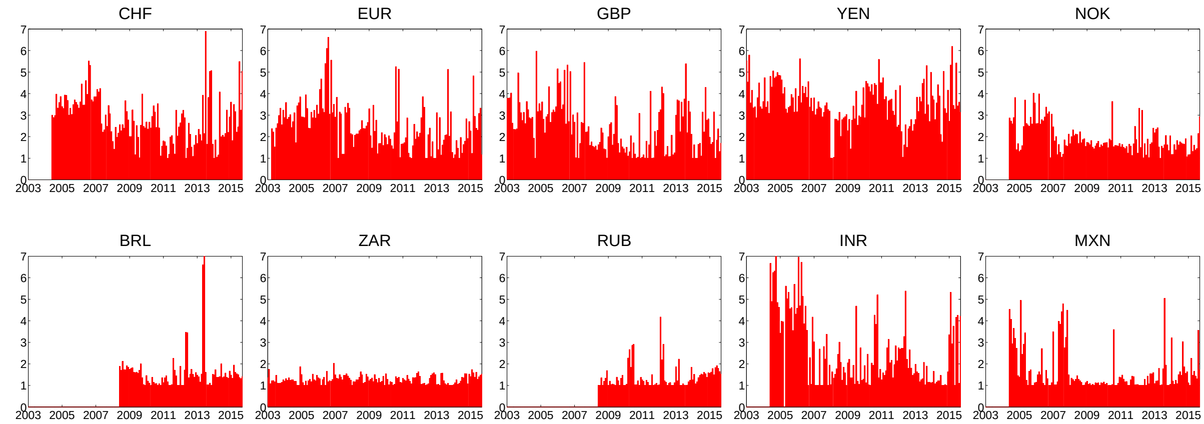


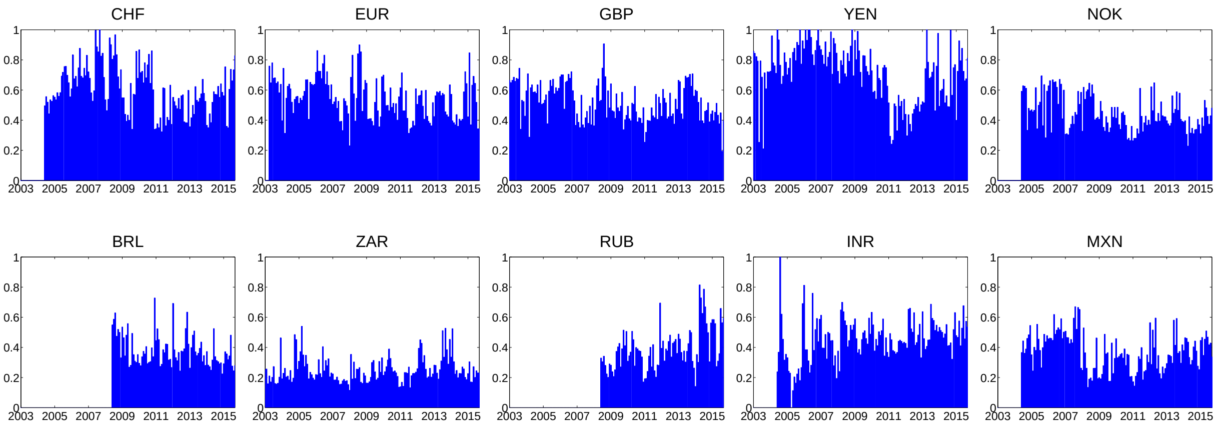
Figure 9. Currency specific parameter estimates

The figure shows the currency specific monthly parameter estimates for the loss aversion evaluated at 30 %, the probability weighting γ and the volatility σ.

Loss aversion (at 30%)



Probability weighting (gamma)



Volatility (sigma)

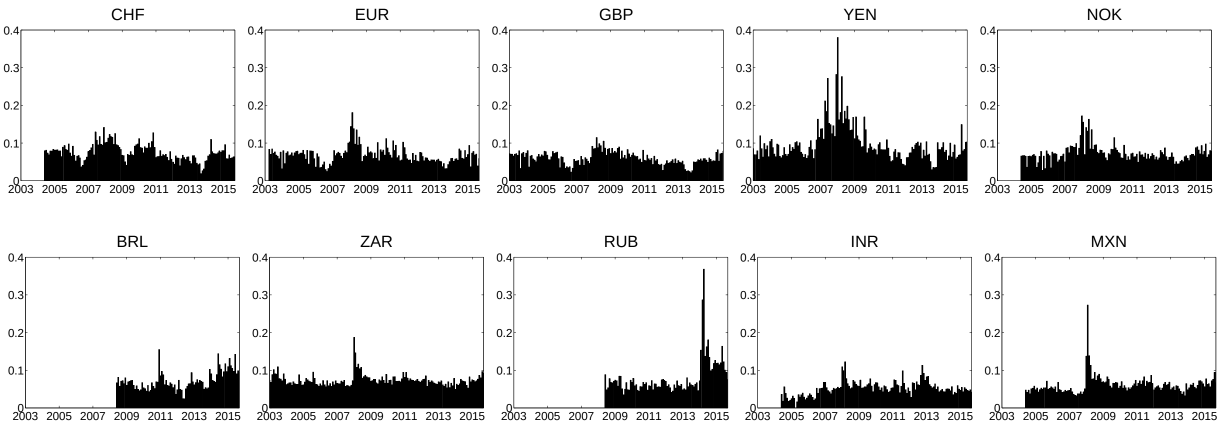
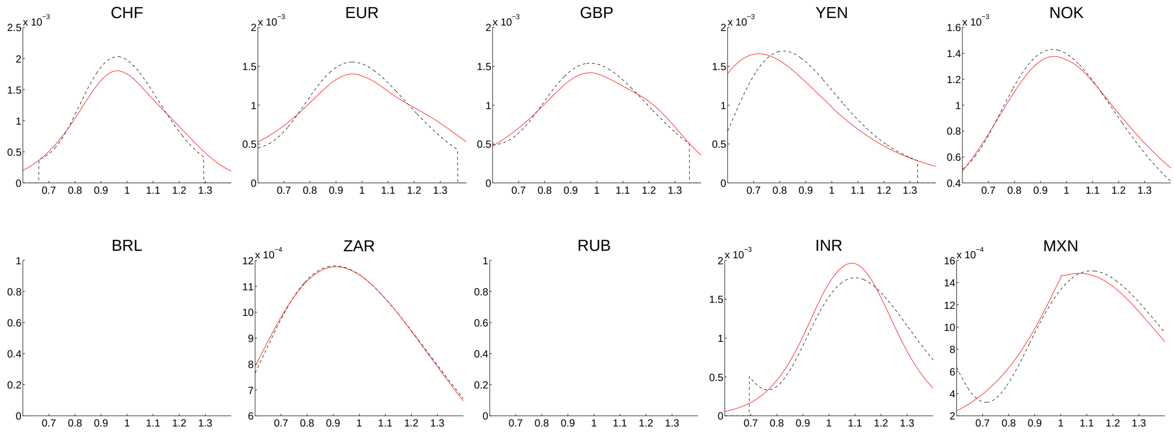


Figure 10. Currency specific risk-neutral densities

The figure shows the risk-neutral probability distribution implied by the behavioral model (12) (red line) for each currency together with the option-implied risk-neutral density (black dotted line) for October 2008 and October 2012.

October 2008



October 2012