Still crazy after all these years: the returns on carry trade

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January 2016

Abstract

This paper proposes a novel approach to provide directional forecasts for carry trade strategies; this approach is based on Support Vector Machines (SVM), a learning algorithm which delivers extremely promising results. Building on recent findings of the literature on carry trade we condition the SVM on indicators of uncertainty and risk; we show that this provides a dramatic improvement of the performance of the strategy, in particular during periods of financial distress such as the recent financial crises. Disentangling between measures of risk we show that the best performances are obtained by conditioning the SVM on measures of liquidity risk rather than on market volatility.

Keywords: Carry trade, Support Vector Machines, liquidity, volatility

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[†]We thank participants to the 2015 Infiniti conference and to the 2015 Money, Macro and Finance conference for helpful comments.

1 Introduction

The uncovered interest parity (UIP) is probably one of the simplest and most intuitive no-arbitrage conditions in financial markets. For risk neutral investors with rational expectations the expected exchange rate change has to compensate the interest differential that may arise between two currencies. Such no arbitrage condition is most likely to hold in the FX market as it is the closest approximation to the notion of market efficiency. Yet the empirical evidence fails to provide support for the UIP, on the contrary it supports the opposite: high yielding currencies tend to appreciate instead of depreciating as predicted by the theory. This is known as the "forward bias puzzle"[1] and has a natural implication: the possibility of realising excess returns from carry trade, i.e. the practice of investing in high yield currency by going short on low yield ones.

Simple carry trade strategies delivered positive average excess returns for substantially long periods, coupled with Sharpe ratios significantly higher than those measured in other financial markets (such as the US stock market), spurring a considerable attention by economists and practitioners alike. During the last decades a large literature has developed investigating the reasons underlying the UIP puzzle and the explanations for the excess of returns from carry trade.[2]

Being based on a simple arbitrage condition, the carry trade does not require any model. As such it is a rather naïve strategy and we know that more sophisticated investors would make use of any information that they may find useful, particularly if deriving from some established model. Unfortunately the literature is of little help in this respect. In fact in a carry trade strategy the only unknown is the exchange rate and the improvement of the strategy necessarily implies making a correct guess about the future change in the exchange rate. However, since the seminal work by Meese and Rogoff (1983) the literature struggled in finding a model able to display sufficient predictive power for the exchange rate, to the point that over the last 30 years "to beat the random walk" has been the most relevant challenge for international economists involved in exchange rate forecasting (see Rossi (2013) for a recent survey). In explaining excess returns from carry trade, two main approaches have been followed by the litera-

[1]The name derives from the fact that the failure of the UIP results in the forward rate being a biased predictor of future spot rates.

[2]See Engel (2014) for a recent survey.

ture. On the one hand the "traditional view" emphasises the importance of fundamentals in providing useful information for exchange rate forecasting; in particular Jordà and Taylor (2012) show that conditioning the carry trade strategy on the predictions of a simple fundamental equilibrium exchange rate model yields an increase in performance with a significant improvement in Sharpe ratios. On the other hand, building on the fact that carry trade returns are negatively skewed, the "risk view" posits they are essentially a compensation for currency crashes reflecting a sort of "Peso problem". Indeed Brunnermeier, Nagel, and Pedersen (2009), Burnside et al. (2011) and Farhi et al. (2015) show that crash risk accounts for a high fraction of the carry trade risk premium in advanced countries over the last 20 years.[3] Menkhoff et al. (2012) find that excess returns to carry trades are a compensation for time-varying risk and in particular to for global foreign exchange volatility risk. More recently Cenedese, Sarno, and Tsiakas (2014) provide some theoretical underpinnings of the relationship between volatility and carry trade returns using an intertemporal capital asset pricing model and show that conditioning the carry trade strategy on FX risk measures results in a clear improvement in the performance, even accounting for transaction costs.

Our paper fits in this line of research by providing innovative contributions on several domains: first we propose a novel approach to directional forecasts for carry trade strategies; this approach is based on Support Vector Machines, a learning algorithm which provides extremely promising results and a wide range of possible applications in finance. To our knowledge this is the first time these tools been applied exchange rate modelling and carry trade. Second we condition the SVM model on indicators of uncertainty and risk; we show that this provides a dramatic improvement of the performance of the strategy, in particular during periods of financial distress such as the recent financial crises. This provides a clear support for the view that considers excess returns from carry trade a compensation for risk. Third we disentangle among different measures of risk showing that the best performances derive from measures of liquidity risk rather than from measures of market volatility.

The remainder of the paper is structured as follows: section 2 illustrates the methods applied and the data used; section 3 presents the results; section 4 concludes.

[3] Using different techniques Jurek (2014) downsizes the importance of crash risk.

2 Methdods and data

There are two general approaches in constructing the carry trade. The traditional approach defines the carry strategy in terms of interest rate differentials; this is the approach followed by, among others, Brunnermeier, Nagel, and Pedersen (2009) and Jordà and Taylor (2012). An alternative approach casts the carry trade in terms of forward currency contracts, see for example Burnside et al. (2011), Cenedese, Sarno, and Tsiakas (2014) and Bakshi and Panayotov (2013). Clearly the two approaches are equivalent so long as the Covered Interest Parity holds which is one assumption well supported by the empirical evidence.

We chose to follow the latter approach which has the major advantage of allowing a simple incorporation of transaction costs which are crucial in determining the real return on carry trade strategies.[4]

The return from the carry trade strategy can be briefly illustrated as follows:

$$z_{t+1} = \begin{cases} \left(\frac{F^{ask}_{t,t+1}}{S^{bid}_{t+1}}\right)^{\gamma_t} - 1 & \text{if } \gamma_t > 0 \\ \left(\frac{F^{bid}_{t,t+1}}{S^{ask}_{t+1}}\right)^{\gamma_t} - 1 & \text{if } \gamma_t < 0 \end{cases}$$

where:

$$\gamma_t = \begin{cases} +1 & \text{if } \log\left(\frac{F_{t,t+1}}{S_{t+1}}\right) > 0 \\ -1 & \text{if } \log\left(\frac{F_{t,t+1}}{S_{t+1}}\right) < 0 \end{cases}$$

Considering the return i on deposits, the return from carry trade becomes:

$$r_t = (1 + z_t)(1 + i) - 1$$

Clearly, given that there are several currency pairs to be considered among the countries considered there is an issue of the identification of the “best” strategy. In order to avoid the problem of data snooping we concentrate only on two portfolios: one equal-weight portfolio which consists in placing a uniform bet of size $1/N$ where N is the number of currency pairs. The second is a dynamically rebalanced portfolio where in

[4]As shown by Lyons (2001) bid ask spreads quoted by standard data providers are approximately twice the size of inter-dealer spreads. Therefore our estimates on transaction costs are very conservative.

each period currencies are ranked by their interest rate differential and the investment is conducted in only the first three currencies.

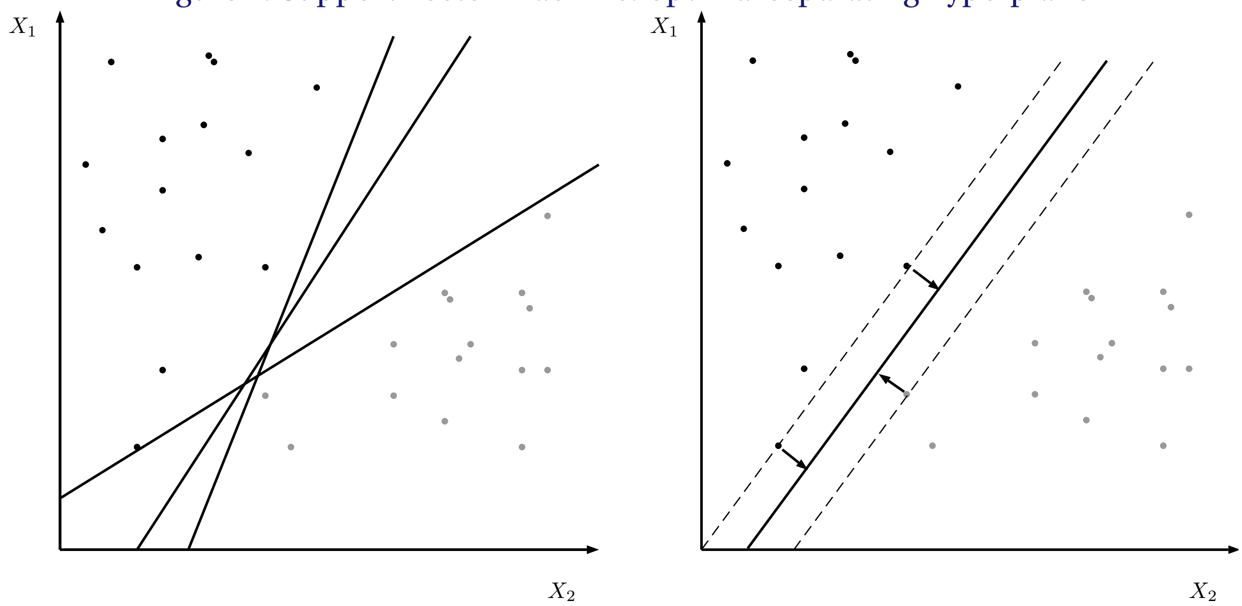
2.1 Carry trade and Support Vector Machines

As stated in the introduction the standard carry trade strategy is rather simple and naïve and could be ideally improved by adding information that help predicting future exchange rate changes. We do so by conditioning the long-short trade choices of a carry trade strategy on the prediction of a model. Instead of using the direction of the forecast of a standard regression model, we use a Support Vector Machine where the input variables are indicators of market uncertainty. Thus conditional upon observing indicators of market uncertainty at time t the SVM yields a prediction about the direction of the carry trade return at time *t+1*. SVM is currently one of the most popular machine learning algorithms and has successfully been applied to numerous fields, and recently also to financial market forecasts.[5] The SVM is a binary classification algorithm that classifies observations with certain features in two classes. This is particularly interesting for the purpose of the carry trade since what really matters for the investor or the trader is the ability to predict the direction of the trade, not its magnitude. In order to gain excess returns from the carry trade one in fact has to correctly guess the direction of change of exchange rates not to accurately forecast the exchange rate itself. In this respect binary classification systems may work better than standard econometric tools such as Probit or Logit regressions.

Intuitively the Support Vector is an algorithm which constructs the hyperplane that maximises the distance between two classes of observations (long and short positions in our case). When the two classes are clearly separable the SVM is analogous to a linear optimization problem that can be solved with standard tools (i.e. lagrange multiplier). Figure 1 helps refining the intuition. In the figure we have represented two classes of observations (black and grey dots) each of which is defined by two variables (X_1, X_2); there are infinite possible linear separating hyperplanes that can be used as classifiers (the figure on the left panel shows three of them). SVMs identify the optimal separating hyperplane in the following way: first the perpendicular distance between

[5] See for example Huerta, Corbacho, and Elkan (2013) and Papadimitriou, Gogas, and Stathakis (2014).

Figure 1: Support Vector Machine: optimal separating hyperplane

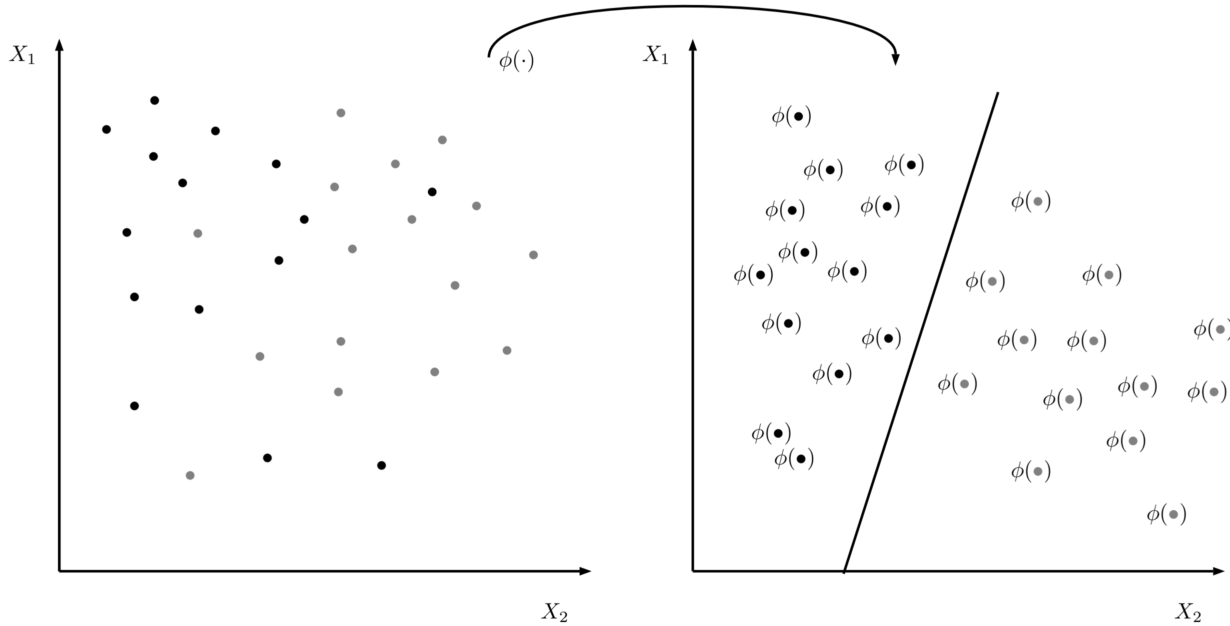


any observation and the given hyperplane is computed, subsequently it is identified the smallest distance from the observation to the hyperplane; this defines the margin, that is the maximal width of the slab parallel to the hyperplane that has no interior data points. The optimal separating hyperplane is such that maximises the margin. In the right panel of Figure 1 there are three observations (two black and one grey) that have the minimum distance from the hyperplane. These observations are called the support vectors and they identify the margin (the distance between the two dashed lines). The intuition underlying the margin maximisation is that a large margin on the training data is expected to deliver a good classification on the test data.

A classification based on the optimal separating hyperplane could be extremely efficient but has a drawback: it could be too sensitive to individual observations; as clear from Figure 1 a change in the support vectors would imply a potentially large change in the position of the maximal margin hyperplane. SVMs are flexible instruments that solve this problem by introducing a form of soft margin classification; in other words they allow the misclassification of few training observations in order to reach a better classification for most of the training observations.

The example provided in Figure 1 is rather simple, however there are several cases where a linear separation is not possible, for instance when the relationship between the predictors and the outcome is non-linear. This is indeed the case with exchange

Figure 2: Support Vector Machines: the kernel principle



rates where there is a growing literature stressing the presence of non-linearities in their dynamic adjustment (Sarno, Valente, and Leon, 2006). The left panel of Figure 2 show one such example, where a linear classificator would perform rather poorly.

In principle it would be possible to enlarge the feature space with non linear functions of the predictors, but this would result in a huge number of features and the computational cost would be unmanageable.

Fortunately a useful result by Cortes and Vapnik (1995) shows that it is possible to project the dataset through a kernel function into a higher dimensional space (i.e. feature space) where the dataset is linearly separable (see the right panel of the figure).

More formally let x be a M element vector of variables (in our case the returns from carry trade and the conditioning factors such as uncertainty) and let N be the number of training periods. The SVM is a classification function:

$$f(\mathbf{x}) = \beta + \sum_{i=1}^{N} \alpha_i y_i \phi(\mathbf{x}, \mathbf{x}_i)$$

where $\mathbf{x}_i$ defines the vector of variables in the training set, y_i is a classifier that takes values of $+1$ or -1 formally assigning each observation in one of the two groups, β is a constant that shifts the SVM output, α_i are parameters which are non zero only for the support vectors and depend on the tuning parameter for the soft margin classification. Both β and α_i are chosen optimally within the training period. Finally we chose the kernel function ϕ following the literature, selecting the Radial Kernel:

$$\phi(\mathbf{x}, \mathbf{x}_i) = e^{-\delta||\mathbf{x}-\mathbf{x}_i||^2}$$

where δ is a parameter chosen to optimise the in sample fit of the model.

SVMs have several interesting features which make them potentially extremely useful for providing directional forecast of the exchange rate. The two main advantages are the following.

- By construction the SVM is optimised to discriminate around the decision margin while it attaches no weight to data which are easily classifiable. This is the main difference with a regression based approach: the latter in fact weights all the observations and not just those close to the decision margin resulting less effective in binary classification problems. In principle also logistic regression is efficient as a classifier, it is limited by the fact that it estimates a *linear* decision boundary
- SVM deals with non-linearity quite naturally through the kernel function without imposing a particular functional form which could be valuable in cases such as the one we are dealing with where there is not a well established theory that provides clearly testable implications.[6] This could help overcome a general problem with non-linear models which are known to perform well in sample but fail in out of sample forecasting (Teräsvirta, 2006).

As any machine learning algorithms the SVM needs a training period; we select the training period as the previous 5 years, the algorithm is subsequently applied with a rolling window of 5 years. The use of rolling window approach is widespread in exchange rate modelling since the seminal work of Meese and Rogoff (1983), and has the benefit of reducing the problem of parameter instability over time (a known issue in this field), at the cost of not considering possible efficiency gains from a sample size increasing with time.

[6] Indeed Jordà and Taylor (2012) show that their augmented carry trade strategy improves the most when they use a non linear model.

2.2 Measuring performance

In comparing the results of a SVM strategy with the standard carry trade we use a number of measures. In a mean-variance setting we provide, alongside with the average return, standard deviation, skewness, and Sharpe ratio. It is well known that standard tests comparing Sharpe ratios of different investment strategies fail when tails are heavier than the normal distribution or display time series correlation. We therefore use the Ledoit and Wolf (2008) test, which is robust to non-normality and serial correlation in returns. Given the skewness in carry trade returns we compute additional measures widely used in finance which are particularly suitable with non normal returns: the Omega ratio, the Sortino Index and the Upside potential. The Omega ratio measures the probability weighted ratio of gains versus losses for some threshold return target, and it employs all the information contained within the distribution of returns, not assuming normality of returns' distribution.

$$\Omega = \frac{\frac{1}{T}\sum_{t=1}^{T} i^{+}(r_t - R_{min})}{\frac{1}{T}\sum_{t=1}^{T} i^{-}(r_t - R_{min})}$$

Where R_{min} is the minimum acceptable return (0 in our case), T is the total number of periods, i^{+} and i^{-} are two indicator functions constructed as follows: $i^{+} = 1$ if $r_t >= R_{min}$ and $i^{+} = 0$ if $r_t < R_{min}$; $i^{-} = 1$ if $r_t <= R_{min}$ and $i^{-} = 0$ if $r_t > R_{min}$

The Sortino Index is analogous to the Sharpe ratio with the difference that in computing the standard deviation of excess returns it considers only negative returns.

$$SI = \frac{R - T}{DR}$$

where R is the average return and $DR = \left(\frac{1}{T}\sum_{t=1}^{T} i^{-}(r_t - R_{min})^2\right)^{1/2}$ is the downsize risk.

When return distributions are symmetrical and the target return is close to the median of the distribution, the Sortino and the Sharpe ratio provide similar results. However in the presence of skewness of returns there can be substantial differences. Generally speaking the larger the Sortino index the lower is the risk of large losses.

We include also the upside potential which measures the upside potential relative to the downside risk

$$UP = \frac{\frac{1}{T}\sum_{t=1}^{T} i^{+}(r_t - R_{min})}{\sqrt{\frac{1}{T}\sum_{t=1}^{T} i^{-}(r_t - R_{min})^2}}$$

Finally, following Della Corte and Tsiakas (2012) Fleming, Kirby, and Ostdiek (2001) and Thornton and Valente (2012), we compute a utility based measure of performance. In particular we calculate the performance fee, that is the maximum fee that an investor is willing to pay to switch from the standard carry trade strategy to the improved SVM strategy. The fee (F) is derived by equating the average utility of the portfolios based on the two investment strategies. Formally F solves the following equation:[7]

$$\sum_{t=0}^{T-1}\left\{\left(R_{t+1}^{CTSVM} - F\right) - \frac{\lambda}{2(1+\lambda)}\left(R_{t+1}^{CTSVM} - F\right)^2\right\} = \sum_{t=0}^{T-1}\left\{R_{t+1}^{CT} - \frac{\lambda}{2(1+\lambda)}\left(R_{t+1}^{CT}\right)^2\right\}$$

Clearly the measure above depends on the shape of the utility function and in particular on the relative risk aversion parameter λ.[8]

2.3 Data

Exchange rate data are extracted from Factset which provides bid, ask, and mid quotes for spot and forward contracts on a daily basis. We conducted our analysis using both monthly and weekly forward rates and our sample starts in October 1997 and ends in August 2015.[9] In terms of currency selection, in order to compare our results with the major part of the literature we have considered only the most liquid currencies, i.e. the so called G10 currencies. Specifically the selected currency are: Australian Dol-

[7] The equation below can be derived considering quadratic utility as good second-order approximation to the investors true utility function. Thus $U(W_{t+1}) = W_t R_{t+1}^p - \frac{1}{2}\alpha W_t^2 (R_{t+1}^p)^2$ where W is the investor's wealth, α is his absolute risk aversion and R^p is the return on his portfolio. Assuming constant αW_t, defining the coefficient of relative risk aversion $\lambda = \alpha W_t/(1-\alpha W_t)$ and defining W_0 as initial wealth, we can derive the average utility as a consistent estimate of expected utility:

$$\bar{U}(\cdot) = W_0\left(\sum_{t=0}^{T-1} R_{t+1}^p - \frac{\lambda}{2(1+\lambda)}(R_{t+1}^p)^2\right)$$

From which the equation in the text follows.

[8] In our calculations we assumed a value of $\lambda = 6$.

[9] More specifically the sample for the monthly forward contracts ranges from 10-1997 to 08-2015 while the sample for the weekly forward contract ranges from 10-1999 to 08-2015.

lar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Euro (EUR), UK Pound (GBP), Japanese Yen (JPY), Norwegian Krona (NOK), New Zealand Dollar (NZD), Swedish Krona (SEK), US Dollar (USD). In computing the returns to carry trade it is necessary to define a reference currency in terms of which they are calculated; we select the Dollar as the majority of the studies do, therefore the perspective is that one of an American investor who selects different investment strategies.

Regarding the measures of uncertainty that are employed in the SVM we use different variables. First we consider the well known VIX index, i.e. the measure of the implicit volatility of the S&P 500 index options. The VIX is probably the most popular measure of the expected volatility of the stock market. Second we consider the TED spread, the difference between the LIBOR and the US short-term government bonds rate (T-bills); it is the most popular measure of credit risk. Third we consider the Chicago Fed National Financial Conditions Index (NFCI) which measures U.S. financial conditions in money markets, debt and equity markets, and the traditional and shadow banking systems. Fourth, following Christiansen, Ranaldo, and Söderlind (2011) we construct a measure of the FX Implied Volatility by using the implicit volatility of the at the money 1-month options on CAD, CHF, EUR, JPY and GBP all against the USD.[10] The VIX, TED and NFCI indexes are obtained from the Federal Reserve Bank of St.Louis database, the option data used for the FX implicit volatility measure are obtained from Bloomberg. The frequency and the time availability is the same as the corresponding carry trade strategy (weekly and monthly).

3 Results

In presenting the results we proceed as follows. First we document the failure of the UIP in the sample of exchange rate considered, subsequently we show the importance of measures of risk and uncertainty in explaining carry trade returns, finally we use measures of uncertainty with the SVM in order to improve the carry trade strategy.

The excess returns from carry trade are a direct consequence of the failure of the uncovered interest parity. Table 1 reports the results of the standard equation used to

[10] We use the simple average across these measures; using the 1st principal component instead of the simple average would not change our results.

test the UIP: $s_{t+1}-s_t = \alpha+\beta(f_t-s_t)+\epsilon_{t+1}$, using monthly rates. The table reveals the well known issues associated with the uncovered interest parity. First there is generally very little support for the UIP: estimates of β are largely different from 1.[11] Second although several coefficients are negative suggesting the profitability of carry trade, there is a large heterogeneity of results across currencies hinting that the selection of currencies with which the carry trade is conducted can make a big difference.

3.1 Carry trade and uncertainty

We have stressed before that one possible explanation for the excess returns of carry trade is that they are a compensation for a "crash risk" where traders are exposed to larger losses the more the exchange rate deviates from fundamentals. In fact Brunnermeier, Nagel, and Pedersen (2009) and Clarida, Davis, and Pedersen (2009) document that carry trades are characterised by negative skewness. By linking funding and market liquidity, Brunnermeier and Pedersen (2009) provide a theoretical rationalisation for this. On the one hand the ability of traders to provide market liquidity depends on their availability of funding; on the other hand traders' funding, depends on assets' market liquidity. In such context in period of high volatility liquidity can dry up generating liquidity spirals which can cause large losses on the carry trade. More importantly the relationship between volatility and market return is asymmetric, determining a negatively skewed distribution of asset returns: in periods of high volatility and market uncertainty large negative shocks generate losses and make traders' funding constraints binding, forcing them to sell assets which in turn worsen volatility and the funding problem. On the contrary funding constraints are not binding in case of positive shocks, and the amplification mechanism would not unfold.

In this setting the relationship between carry trades returns and market uncertainty is different from what traditionally posited by the standard intertemporal capital asset pricing model - ICAPM - (Merton, 1973): $E_t[r_{t+1}] = \alpha + \beta Var_t[r_{t+1}]$

According to the ICAPM the condition above should hold for the full conditional distribution of asset returns. On the contrary with a skewed distribution of returns, the coefficient β varies along the distribution of expected returns possibly assuming

[11] In the table the level of significance refers to the test that the coefficient is different from 1 as predicted by the UIP.

different signs at its extremes.

Following Cenedese, Sarno, and Tsiakas (2014) we document this by estimating predictive regressions where the expected return of carry trade at different quantiles are regressed on measures of volatility. Our approach differs from Cenedese, Sarno, and Tsiakas (2014) in one important aspect: they use a measure of ex post realised volatility of the exchange rate, while we use forward looking measures of market uncertainty. We believe that this is the most correct approach to frame the intertemporal capital asset relationship which holds ex ante in expected terms.

In detail we estimate the following regression:

$$Q_{r_{t+1}}(k|Unc_t) = \alpha(k) + \beta(k)Unc_t + \epsilon_{t+1} \tag{1}$$

Where $Q_{r_{t+1}}(k|\cdot)$ is the k-th quantile of the distribution of returns from carry trade and Unc are the following measures of uncertainty/risk: Ted spread, VIX, NFCI, FX implied volatility, as described in section 2.3.

Table 4 reports the results. Following the Brunnermeier and Pedersen (2009) argument we expect the relationship between market uncertainty and returns from carry trade to be negative al lower quantiles and positive at higher quantiles of the return distribution. The table fully confirms our prior for all the measures of uncertainty used, for both monthly and weekly data. In addition Table 3 reports R2 of the regressions at the different quantiles revealing that at lower quantiles not only market uncertainty has a negative effect on carry trade returns but its explanatory power is particularly high. Finally Figures 3 and 4 report the standardised coefficients that allow comparison across uncertainty measures.

3.2 SVM strategies

If market uncertainty is so important in predicting large negative returns, this information could be used to improve carry trade strategies. We do so by implementing the SVM tool described in section 2.1: we therefore augment the carry trade strategies on the prediction of a SVM algorithm conditioned on the set of variables capturing market uncertainty. Our strategy is extremely simple: for any pair of currency, given a direction of trade pointed out by the standard carry trade, we confirm it if this is suggested by the prediction of the SVM, otherwise we invert it. We therefore use the SVM for what it is more efficient: directional forecast.

In order to compare our results with the literature, we implement the investment strategy on both monthly and weekly forward rates and compute two different portfolios. The first is an equally weighted portfolio that places a uniform bet on every currency pair in the sample (Jordà and Taylor, 2012); the second is a dynamic portfolio that invest in each period in the 3 currency pairs that display the largest forward-spot differential.[12] In every case the results are compared with the standard classic carry trade strategy.

Table 4 present the results. A classic carry trade strategy conducted over the entire period 2002-2015[13] yields an average yearly return of 2.74% (considering transaction costs) in line with the results of the literature. Generally carry trade strategies deliver Sharpe ratios that are well above the value of 0.4 which is the average of the SP500 over the same period; in our case the Sharpe ratio is close to 0.7. Finally we confirm the fact that carry trade returns are also characterised by negative skewness stressing the importance of considering measures that account for more than just the first two moments.

The presence of transaction costs can make a big difference in terms of average return; in fact they explain a large part of the difference between the strategies conducted on 1 week and 1 month forward contract (the average return drops from 2.7 to -0.4). This is due to the fact that with forward contracts the frequency of transaction is higher hence the amount of costs. This effect is mitigated in the dynamic rebalanced portfolio by the lower frequency of portfolio adjustment and therefore by the reduced number of transactions.

Dynamic rebalancing improves consistently the carry trade strategy: the average return increases from 2.7% to 5.3% with monthly data and from -0.4% to 2.2% with weekly data. This is in line with the results of Bakshi and Panayotov (2013) and with Table 1 that shows a great deal of heterogeneity in UIP failures across currency pairs.

Turning to the main innovation of the paper, the use of the SVM conditioned on uncertainty and risk improves spectacularly the returns from carry trade. Considering

[12] Both strategies involve a weekly rebalancing. In case of the monthly strategy every week we rebalance 1/4 of the portfolio.

[13] As stressed in section 2 the period before 2002 is used in sample for training the SVM algorithm.

the equally weighted portfolio the average return jumps from 2.7 to 10.6% with monthly data and from -0.4 to 9.9 with weekly data. Also the Sharpe ratio improves significantly and the negative skeweness is strongly reduced (it actually disappears in the monthly data); Omega, Sortino and Upside potential all increase significantly. In particular the strong increase of the Sortino index suggests that the strategy based on the SVM model minimizes the risk of heavy losses.

Finally turning to utility based performance measures, an investor would be willing to pay a fee of up to 11% for switching from the standard carry trade strategy to the SVM based one for the equally weighted portfolio with monthly forward rates. The fact that the fee is higher than the return of the SVM model itself is an indicator of the attractiveness of this strategy: the investor is willing to pay a lot not only for capturing the higher return but also as a reward for the lower risk and a lesser exposure to negative outcomes.

In order to better understand the origin of this improvement in performances Table 5 splits the results between cases where the SVM and the standard carry trade model agree and where they disagree. It is evident that accounting for market uncertainty allow to gain precisely in periods where the standard carry trade would yield negative returns.

This is clearly shown in Figure 5 where the distribution of returns from the SVM model and the standard carry trade are plotted for periods where the latter are positive and are negative. The use of the SVM model allows to gain in negative periods rather than improve performance in positive ones.

Figures 7 - 8 show the cumulative returns from carry trade strategies over the period considered: while the risk based SVM does not improve dramatically the performance prior to the financial crisis (where the standard carry trade is highly profitable), it makes a huge difference during and after the crisis.

3.3 Inspecting the mechanism

The results of the previous section show that the use of the SVM algorithm conditioned on measures of market uncertainty allows to improve significantly the returns from carry trade and in particular to hedge against large negative drawdowns. The extremely positive result of the SVM model however comes at a price. As any other machine learning algorithm the SVM is a bit of a black box since it does not provide the information economists are used to, such as the standard output from a regression (i.e. coefficients, degree of significance, goodness of fit etc.). In this section we provide additional analysis that shed more light on the factors that drive the results.

3.3.1 Splitting time periods

With a dynamic perspective Figure 6 plots the returns from the standard carry trade and from the SVM model during the period considered. It is striking that during periods of financial turbulence such as the global financial crisis the SVM model has been able to hedge considerably against large drawdowns of carry trade.

Table 6 splits the sample in three periods and shows that indeed the major gains from the SVM model are obtained during and after the financial crisis when, in the presence of low or negative returns from carry trade, correcting the strategy for uncertainty yields consistently higher returns coupled with substantially higher Sharpe and Omega ratios. This is the period where the information on market uncertainty is used more efficiently by the learning algorithm.

3.3.2 Disentangling between uncertainty measures

As stated above the SVM model uses information from four indicators of market uncertainty to improve the carry trade strategy. As a matter of fact the SVM is more efficient in using disaggregated information rather than aggregated one, thus its performances worsen slightly if we collapse the four indicators by, for example, a principal component or factor analysis.

However the measures we have considered for market uncertainty capture somewhat different aspects and it would be interesting to understand what effect the SVM model is really capturing. In order to shed light on this issue we have split the measures of market uncertainty in two groups: one comprising the VIX and the FX volatility index, another comprising the TED and the NFCI index. While the former capture market volatility the latter capture uncertainty linked to liquidity issues and as such are more in line with the Brunnermeier, Nagel, and Pedersen (2009) argument. Table 7 shows that both groups of measures provide useful information to the SVM model: using only one group of indicators instead of both in fact reduces the average returns significantly. However it seems that conditioning the SVM on liquidity measures yields better performances than conditioning on volatility measures only, particularly during the financial crises where the difference in Sharpe ratios and in the Sortino index is extremely relevant.

Finally we have performed predictive regressions where the realised returns of SVM carry trade have been regressed on lagged uncertainty measures. This analysis is very stylised as the coefficients cannot be interpreted as proper factor loadings since the SVM can by construction use a nonlinear approach whereas here we are using a linear regression model; nevertheless despite its limitations this approach can be fruitful in shedding light on the relative role of the different indicators of market uncertainty. Table 8 shows that overall, with the exception of the Forex volatility, all the indicators are significant; comparing indicators of volatility and of liquidity the former seem to be less relevant of the latter both in terms of significance and of the explained variance of the returns. The analysis by time periods reveals that before the global financial crisis indicators of market uncertainty are not predictive of carry trade returns, while during the crisis they become highly significant, particularly those of market liquidity. Interestingly in the period following the financial crisis, when it is well known that global carry trade resumed, indicators of market liquidity are still significant, but with the opposite sign, denoting a different relationship between carry trade and market liquidity which is captured by the flexibility of the SVM algorithm.

4 Conclusions

In this paper we have contribute to the literature on carry trade by proposing a novel approach to provide directional forecasts for carry trade strategies. This approach is based on Support Vector Machines, a binary classification mechanism which can potentially be applied to several fields in economic forecasting with extremely promising results. This is particularly interesting for the purpose of the carry trade since what really matters for the investor or the trader is the ability to predict the direction of the trade not its magnitude. We condition the SVM model on indicators of uncertainty and risk; we show that this provides a dramatic improvement of the performance of the strategy in particular during periods of financial distress such as the recent financial crises. Finally we show that the relative contribution of liquidity variables is more relevant than that one of volatility variables.

Albeit at its infancy the use of machine learning algorithms can help researchers to understand several aspects of international finance where standard tools perform rather poorly. Further research on these issues is certainly needed.

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Table 1: Results from UIP test

	AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK	USD
AUD	-									
CAD	0.230***	-								
CHF	0.101***	0.034***	-							
EUR	0.040***	0.073***	-0.001***	-						
GBP	0.009***	0.009***	0.003***	0.016***	-					
JPY	0.000***	0.000***	0.000***	0.000***	0.000***	-				
NOK	-0.003***	-0.005***	0.000***	-0.003***	-0.001***	0.015***	-			
NZD	-0.079***	-0.049***	-0.077***	-0.014***	-0.003***	0.009***	0.013***	-		
SEK	-0.003***	-0.004***	-0.001***	-0.002***	-0.001***	0.014***	-0.134***	-0.004***	-	
USD	0.014***	0.011***	0.009***	-0.027***	-0.012***	0.008***	0.006***	0.010***	0.008***	-

Values of β from the regression $s_{t+1} - s_t = \alpha + \beta(f_t - s_t) + \epsilon_t$. OLS estimates, monthly data. Significance refers to the test H0: $\beta = 1$.

Table 2: Quantile regressions

Quantile		0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Monthly											
TED	con	-0.005	-0.003	-0.002	0.000	0.000	0.001	0.001	0.002	0.003	0.004
		-15.794	-14.404	-9.484	-2.943	2.467	6.784	12.069	17.208	23.179	27.981
	beta	-0.001	-0.001	-0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000
		-2.467	-3.961	-3.955	-3.313	-2.411	-2.762	-1.928	-0.585	2.541	1.216
VIX	con	-0.005	-0.003	-0.001	0.000	0.000	0.001	0.001	0.002	0.003	0.004
		-15.771	-15.098	-9.014	-2.930	2.232	7.555	12.487	17.626	22.570	27.118
	beta	0.000	-0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
		-1.492	-2.545	-1.480	-0.030	1.192	1.957	3.123	2.867	3.556	4.889
NFCI	con	-0.005	-0.003	-0.002	0.000	0.000	0.001	0.001	0.002	0.003	0.004
		-18.351	-17.140	-9.715	-3.155	1.760	7.007	12.040	17.932	22.874	27.537
	beta	-0.001	-0.002	-0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000
		-6.152	-8.212	-4.340	-2.944	-0.990	-0.672	0.651	2.678	2.579	3.949
FXV	con	-0.005	-0.003	-0.002	0.000	0.000	0.001	0.001	0.002	0.003	0.004
		-17.284	-15.470	-9.388	-2.935	2.138	6.947	11.554	17.465	22.473	28.329
	beta	-0.001	-0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
		-3.162	-3.065	-1.870	-0.042	0.208	1.026	0.957	1.863	2.535	5.571
Weekly											
TED	con	-0.014	-0.009	-0.005	-0.003	-0.001	0.000	0.002	0.004	0.006	0.008
		-21.263	-21.046	-15.101	-9.297	-3.609	1.519	7.611	12.709	18.656	23.663
	beta	-0.007	-0.005	-0.002	-0.001	-0.001	0.000	0.000	0.000	0.001	0.002
		-6.936	-8.770	-5.692	-4.585	-2.097	-1.376	-0.140	0.227	2.365	3.733
VIX	con	-0.013	-0.010	-0.005	-0.003	-0.001	0.001	0.002	0.004	0.006	0.009
		-21.351	-19.136	-14.184	-8.645	-3.257	2.274	8.001	12.874	18.899	26.490
	beta	-0.004	-0.004	-0.001	0.000	0.000	0.001	0.001	0.001	0.001	0.003
		-5.459	-5.272	-2.111	-0.968	-0.652	1.885	3.023	3.171	4.323	7.211
NFCI	con	-0.013	-0.009	-0.005	-0.003	-0.001	0.001	0.002	0.004	0.006	0.009
		-18.964	-19.096	-14.798	-9.352	-3.646	1.803	7.982	13.019	18.864	25.341
	beta	-0.005	-0.003	-0.002	-0.001	-0.001	0.000	0.001	0.001	0.001	0.003
		-6.069	-5.875	-4.426	-3.614	-2.560	-0.369	1.777	1.797	3.480	7.312
FXV	con	-0.013	-0.009	-0.005	-0.003	-0.001	0.001	0.002	0.004	0.006	0.008
		-21.827	-20.766	-14.824	-9.674	-3.261	1.924	8.157	13.389	20.032	28.386
	beta	-0.004	-0.003	-0.001	-0.001	0.000	0.000	0.001	0.001	0.002	0.003
		-6.733	-6.563	-4.157	-2.146	-0.416	1.194	3.080	3.774	6.603	9.461

Coefficients from predictive regressions of the carry trade returns on various measures of uncertainty. TED: difference between the LIBOR and US T-bills. VIX index: measure of the implicit volatility of the S&P 500 index options. NFCI: Chicago Fed National Financial Conditions Index, measures U.S. financial conditions in money, debt and equity markets, plus the traditional and "shadow" banking systems. FXV: implicit volatility of at the money 1-month options on CAD, CHF, EUR, JPY and GBP against the USD.
Carry trade returns are computed for an equally weighted portfolio. T stats are reported below coefficients.

Table 3: R2 from quantile regression

Quantile	0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Monthly										
TED	4.39	3.10	1.57	0.89	0.68	0.69	0.14	0.02	0.37	0.32
VIX	2.37	1.59	0.22	0.00	0.16	0.47	0.71	0.82	0.90	1.43
NFCI	9.59	5.87	1.75	0.67	0.20	0.03	0.04	0.36	0.64	1.06
FX VOL	3.86	2.94	0.49	0.00	0.00	0.10	0.12	0.35	0.50	1.09
Weekly										
TED	13.44	5.90	2.57	1.03	0.42	0.14	0.01	0.01	0.27	2.14
VIX	10.72	3.33	0.55	0.11	0.01	0.14	0.69	0.74	1.82	7.34
NFCI	12.04	5.44	2.05	0.87	0.43	0.01	0.10	0.21	0.92	5.21
FX VOL	12.22	5.86	1.69	0.50	0.01	0.16	0.60	0.79	2.98	9.22

R2 from predictive regressions of the carry trade returns on various measures of uncertainty. TED: difference between the LIBOR and US T-bills. VIX index: measure of the implicit volatility of the S&P 500 index options. NFCI: Chicago Fed National Financial Conditions Index, measures U.S. financial conditions in money, debt and equity markets, plus the traditional and “shadow” banking systems. FXV: implicit volatility of at the money 1-month options on CAD, CHF, EUR, JPY and GBP against the USD.
Carry trade returns are computed for an equally weighted portfolio.

Table 4: Alternative carry trade strategies

	Mean	StDev	Skew	Max	Min	Sharpe	Fees	Omega	Sortino	Upside
Monthly										
Equal weights										
Carry Trade	2.74	2.69	-0.36	1.90	-2.03	0.69		1.46	0.21	0.68
Carry Trade SVM	10.56	2.78	0.51	2.09	-1.23	3.49***	11.1	4.42	1.29	1.66
Dynamic										
Carry Trade	5.26	5.17	-0.41	3.38	-3.37	0.84		1.46	0.21	0.67
Carry Trade SVM	12.95	4.49	-0.26	3.38	-3.37	2.68***	7.28	2.97	0.73	1.11
Weekly										
Equal weights										
Carry Trade	-0.41	5.78	-1.46	3.15	-6.77	-0.22		0.97	-0.01	0.44
Carry Trade SVM	9.95	5.45	-0.58	3.15	-4.38	1.67***	14.4	2.00	0.40	0.80
Dynamic										
Carry Trade	2.18	10.45	-1.02	6.30	-11.24	0.13		1.08	0.04	0.49
Carry Trade SVM	8.93	8.96	-0.96	4.63	-7.22	0.90***	8.17	1.47	0.20	0.61

Equal weights = equally weighted portfolio
Dynamic = carry trade on first 3 currencies rebalanced every period
All values are computed on annual basis and include transaction costs. High/Low ret. report the highest (lowest) return of the period.
Significance levels for the Sharpe ratio refer to the Ledoit and Wolf (2008) test.

Table 5: Agreement and disagreement between SVM and standard carry trade strategy

	Mean	StDev	Skew	Sharpe	Min	Max	Median
Monthly							
Equal weights							
Model Agree	0.18	0.76	-0.31	0.22	-4.94	4.45	0.19
Model Disagree							
Carry Trade	-0.24	0.79	0.15	-0.33	-5.09	5.13	-0.24
Carry Trade SVM	0.24	0.81	0.37	0.28	-4.28	6.34	0.22
Dynamic							
Model Agree	0.24	0.86	-0.67	0.25	-4.94	4.45	0.31
Model Disagree							
Carry Trade	-0.28	0.81	-0.18	-0.37	-3.53	2.36	-0.23
Carry Trade SVM	0.28	0.83	0.46	0.32	-2.23	4.07	0.21
Weekly							
Equal weights							
Model Agree	0.15	1.55	-1.21	0.09	-19.00	11.34	0.27
Model Disagree							
Carry Trade	-0.37	1.56	0.05	-0.25	-8.84	6.67	-0.45
Carry Trade SVM	0.28	1.55	-0.08	0.17	-6.85	8.72	0.37
Dynamic							
Model Agree	0.15	1.78	-1.34	0.08	-16.33	7.26	0.33
Model Disagree							
Carry Trade	-0.37	1.67	0.11	-0.23	-6.52	5.41	-0.42
Carry Trade SVM	0.25	1.67	-0.16	0.14	-5.64	6.33	0.31

Equal weights = equally weighted portfolio
Dynamic = carry trade on first 3 currencies rebalanced every period
All values are computed on annual basis and include transaction costs. High/Low ret. report the highest (lowest) return of the period

Table 6: Carry trade strategies, splitting by time periods, monthly rates

	Mean	StDev	Skew	Max	Min	Sharpe	Omega	Sortino	Upside
2003-2006									
Equal weights									
Carry Trade	5.98	2.48	-0.09	0.98	-0.97	2.06	2.30	0.62	1.10
Carry trade SVM	14.88	2.65	0.58	1.46	-0.54	5.28***	9.38	3.18	3.56
Dynamic									
Carry Trade	9.67	4.45	-0.17	1.66	-1.60	1.97	2.14	0.54	1.01
Carry trade SVM	18.37	3.95	-0.02	1.69	-1.59	4.43***	5.24	1.66	2.06
2007-2011									
Equal weights									
Carry Trade	-1.35	3.42	-0.33	1.90	-2.03	-0.66	0.86	-0.07	0.44
Carry trade SVM	15.20	3.45	0.51	2.09	-1.23	4.15***	5.75	1.66	2.01
Dynamic									
Carry Trade	3.23	7.06	-0.37	3.38	-3.37	0.33	1.19	0.09	0.57
Carry trade SVM	15.59	5.88	-0.41	3.38	-3.37	2.50***	2.85	0.64	0.98
2012-2015									
Equal weights									
Carry Trade	-0.04	1.81	-0.14	0.64	-0.71	-0.52	0.99	0.00	0.54
Carry trade SVM	7.44	1.82	-0.19	0.81	-0.86	3.60***	4.41	1.27	1.64
Dynamic									
Carry Trade	-4.52	4.30	-0.12	1.33	-1.54	-1.26	0.69	-0.18	0.40
Carry trade SVM	8.86	3.51	-0.05	1.43	-1.48	2.28***	2.55	0.66	1.09

Equal weights = equally weighted portfolio
Dynamic = carry trade on first 3 currencies rebalanced every period
All values are computed on annual basis and include transaction costs. High/Low ret. report the highest (lowest) return of the period.
Significance levels for the Sharpe ratio refer to the Ledoit and Wolf (2008) test.

Table 7: Carry trade strategies, disentangling between uncertainty measures

	Mean	StDev	Skew	Max	Min	Sharpe	Omega	Sortino	Upside
All sample									
Carry Trade	2.74	2.69	-0.36	1.90	-2.03	0.69	1.46	0.21	0.68
SVM liquidity	8.75	2.70	0.29	1.46	-1.37	2.91***	3.50	0.98	1.38
SVM volatility	6.63	2.59	0.22	1.73	-1.32	2.21***	2.65	0.69	1.11
2003-2006									
Carry Trade	5.98	2.48	-0.09	0.98	-0.97	2.06	2.30	0.62	1.10
SVM liquidity	11.49	2.91	0.79	1.46	-0.76	3.66***	4.95	1.77	2.21
SVM volatility	10.10	2.69	0.64	1.33	-0.64	3.43***	4.31	1.48	1.93
2007-2011									
Carry Trade	-1.35	3.42	-0.33	1.90	-2.03	-0.66	0.86	-0.07	0.44
SVM liquidity	12.81	3.10	-0.05	1.44	-1.37	3.85***	5.00	1.29	1.62
SVM volatility	6.36	3.08	0.14	1.73	-1.32	1.78***	2.21	0.52	0.95
2011-2015									
Carry Trade	-0.04	1.81	-0.14	0.64	-0.71	-0.52	0.99	0.00	0.54
SVM liquidity	5.39	1.97	-0.04	0.84	-0.65	2.28***	2.71	0.74	1.17
SVM volatility	4.61	1.80	0.09	0.84	-0.80	2.07***	2.58	0.69	1.12

Values refer to monthly returns on equally weighted portfolios
SVM liquidity= carry trade with SVM conditioned on measures of liquidity (TED and NFCI)
SVM volatility= carry trade with SVM conditioned on measures of liquidity (VIX and FX Vol.)
All values are computed on annual basis and include transaction costs. High/Low ret. report the highest (lowest) return of the period.
Significance levels for the Sharpe ratio refer to the Ledoit and Wolf (2008) test.

Table 8: Determinants of SVM carry trade returns

	All sample	All sample	All sample	2003-2006	2007-2011	2012-2015
Forex vol	-0.000	0.000		-0.000	-0.000	0.000
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
VIX	-0.000**	-0.000*		0.000	-0.000	-0.000
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
TED	-0.002***		-0.002**	-0.003	-0.002**	0.017**
	(0.001)		(0.001)	(0.003)	(0.001)	(0.008)
NFCI	0.003***		0.002**	-0.004	0.003**	-0.006**
	(0.001)		(0.001)	(0.004)	(0.001)	(0.003)
Cons.	0.006***	0.001	0.004***	0.002	0.006***	-0.008*
	(0.002)	(0.001)	(0.001)	(0.005)	(0.002)	(0.005)
r2	0.055	0.008	0.039	0.015	0.050	0.067
N	858	864	864	235	228	171

The table reports the coefficients of regressing returns of the SVM carry trade strategy on lagged indicators of market uncertainty.
SVM carry trade returns refer to monthly rates on equally weighted portfolios. Weekly data
The reported standard errors are based on NeweyWest approach with optimal lag selection.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Figure 3: Standardised beta coefficients from quantile regressions on carry trade returns, Forward 1M

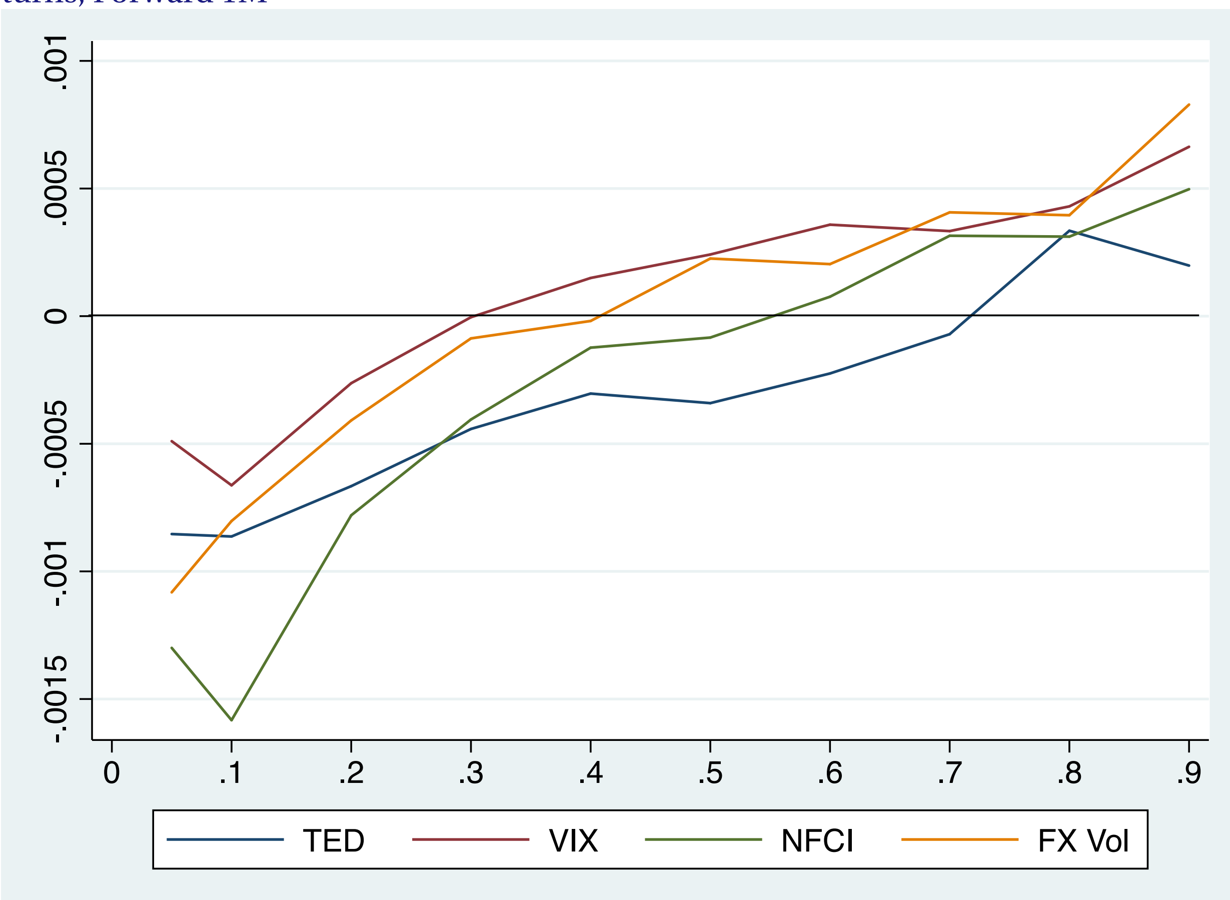

Figure 4: Standardised beta coefficients from quantile regressions on carry trade returns, Forward 1W

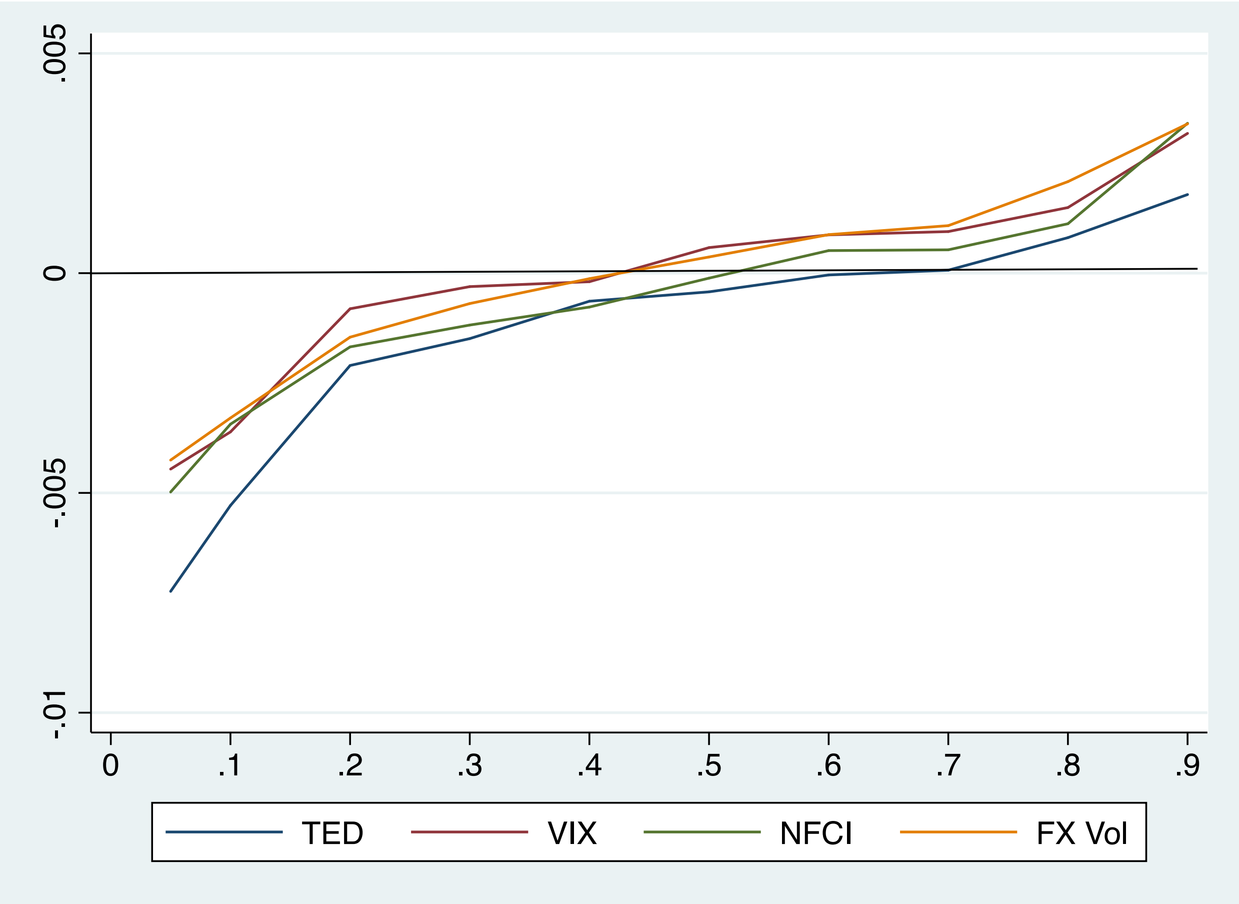

Figure 5: Distribution of returns of the carry trade and SVM model; equally weighted portfolio, monthly forward rates.

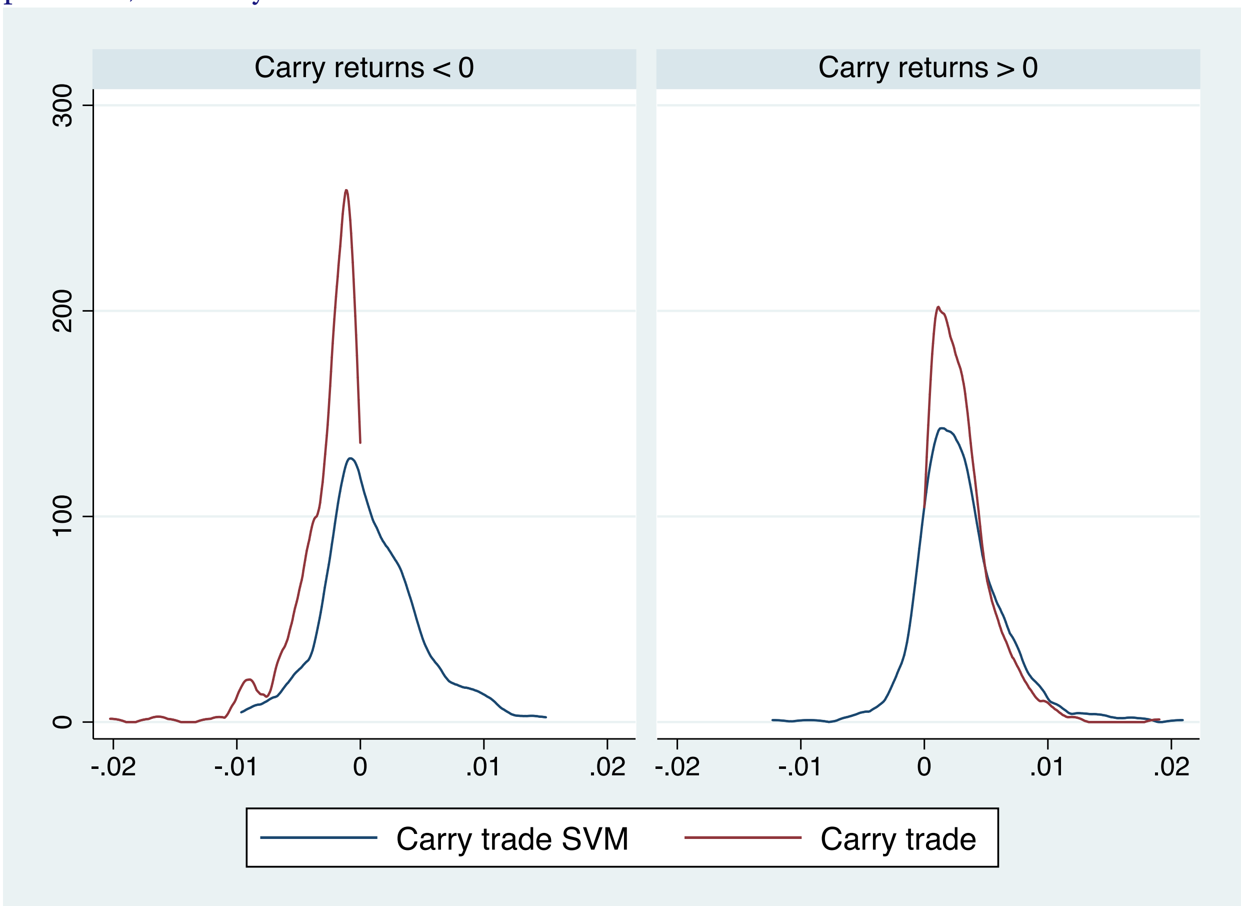

Figure 6: Returns from carry trade strategies; equally weighted portfolio, monthly forward rates.

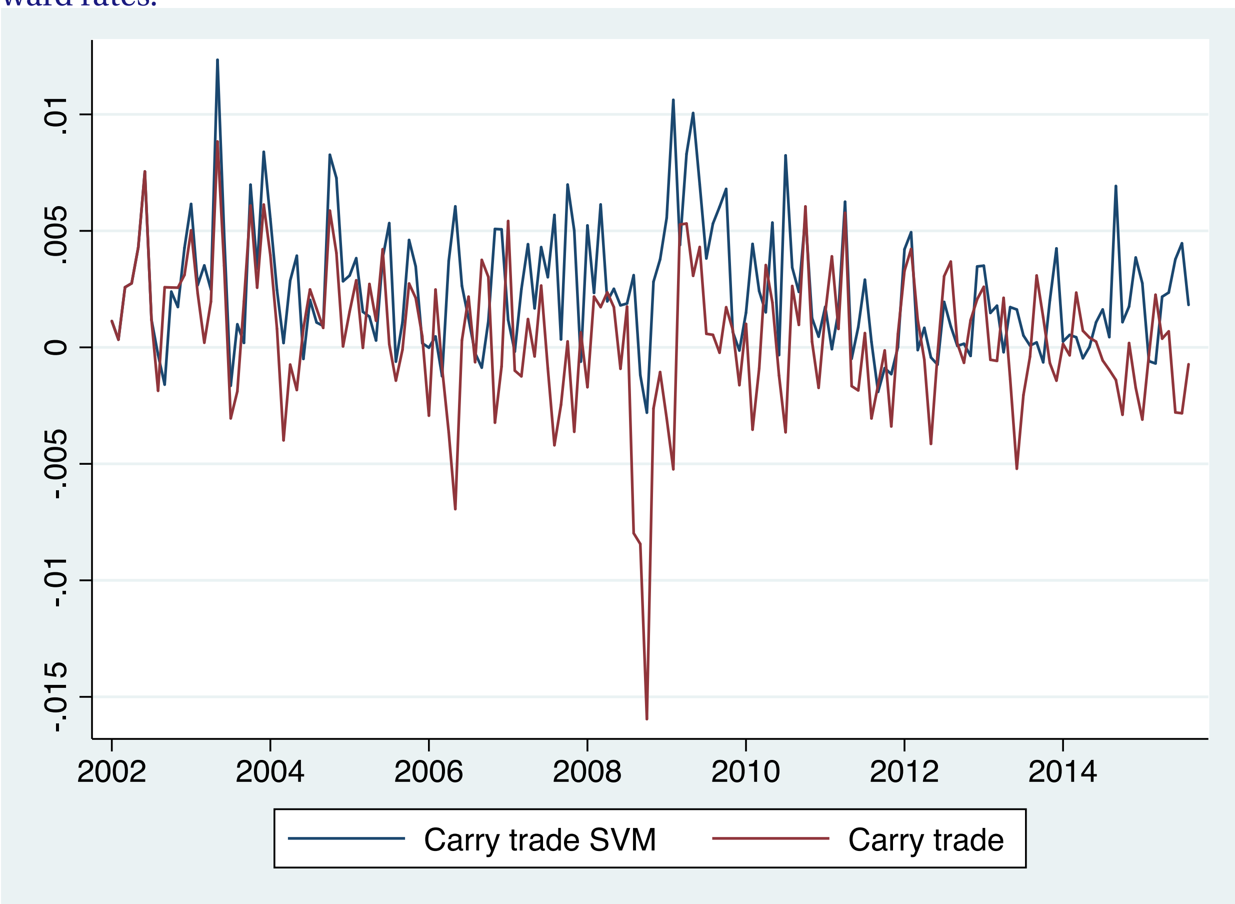

Figure 7: Cumulative returns from carry trade strategies, monthly rates

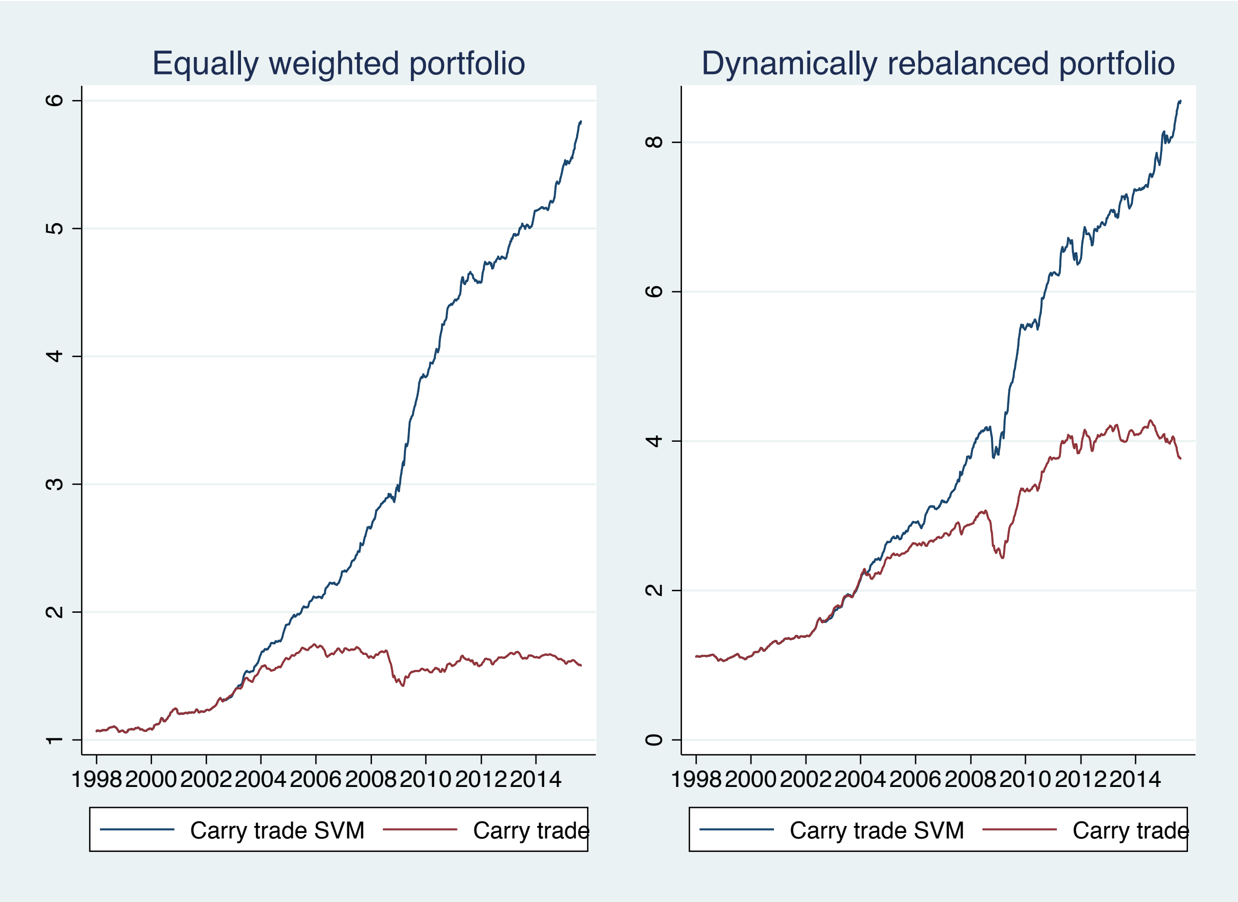

Figure 8: Cumulative returns from carry trade strategies, weekly rates