The January Effect as Seasonal Equity Carry Trades

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Abstract

We examine the presence of the month effect in the foreign exchange market and its possible link with the well-documented similar seasonal anomaly in stock markets. Our main focus is on the key world currency pair, the US dollar-Deutsche mark (euro) from 1971 to 1998 (1999 to 2017). We consider it likely that seasonality in the German-US stock market returns differential is associated with seasonal capital flows to the stock market with higher returns and a similar seasonality in the foreign exchange market. Using a Markov-switching framework to account for nonlinear seasonal patterns, we detect recurrent January and December effects with similar timing in the US dollar-Deutsche mark (euro) returns, the German-US stock returns differential and the US-German net equity flows. A seasonal equity carry trade opportunity exists, as evidenced by the sign and significance of seasonal exchange rate returns, stocks returns differential and equity flows as well as their reversals.

Keywords: Seasonality, month effect, Foreign Currency Market, UEP, Markov-switching, carry trade.

JEL classification codes: F21, F31, G12, G15

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1 Introduction

Seasonal anomalies are a robust stylized fact in major stock markets, and in spite of being well-known they have not been arbitraged away, still representing a violation of the Efficient Market Hypothesis (EMH) (Fama, 1970). Higher (lower) returns in January (December) than in any other month have indeed been a recurring feature of many stock markets for more than a century. Given the scope and size of capital flows in globalized markets, could such seasonal anomalies be also present in other markets, especially the foreign exchange market, which is a mandatory conduit for links between different countries' stock markets? This issue has been neglected by research on calendar anomalies in the foreign exchange market which mostly focuses on high frequencies, principally the day-of-the-week effect (Baillie and Bollerslev, 2002; Berument et al., 2007; Breuer, 1999; Caporale et al., 2014; Cornett et al., 1995; Hsieh, 1988; Ke et al., 2007; McFarland et al., 1987, 1982; Yamori and Kurihara, 2004). Seasonal anomalies in foreign currency returns at low frequencies, such as the month effect, have received only little attention (Cellini, 2011; Cellini and Cuccia, 2014; Kumar and Pathak, 2016; Li et al., 2011). More importantly, the drivers of such a possible month effect (higher or lower returns in a specific month than in other months) in the foreign exchange market have been overlooked, even though the sign of the links between equity and exchange rate returns has generated a heated controversy (Curcuru et al., 2014; Hau and Rey, 2006). The literature on equity carry trades (Cenedese et al., 2016) has not considered the possibility that carry trade opportunities (the profit opportunities from selling the low-return domestic equities and buying the high-return foreign ones) may vary within a year, with seasonal features and reversals, and has sometimes even focused on yearly data (Doskov and Swinkels, 2015).

We propose to further our understanding of the monthly seasonality in the foreign exchange market and its similarities and links with other financial markets by setting four objectives. First, we re-examine the presence of the month effect in the foreign exchange market over a four-and-a-half-decade-long sample from the fall of the Bretton Woods system, in 1971, by focusing on the point of view of German and US investors and the most traded currency pairs in the foreign exchange market, i.e. the Deutsche mark-US dollar, up to late 1998, and the euro-USD subsequently. Our second objective is to detect whether the possible seasonal pattern in the foreign exchange market is dominant over such a long sample, i.e. whether it represents a recurring feature across regimes detected by a Markov-switching model (Hamilton's (1989)). Third, we propose for the first time to explore the possible link between the seasonality in two different financial markets, the foreign exchange and stock markets. We search whether the seasonal pattern of the stock returns differential matches the month effects in the corresponding exchange rate returns. Given our focus on the seasonal capital gain opportunities of US and German investors, we study the DAX and the S&P 500 indices. And fourth, we investigate whether this seasonal link is reflected in the seasonal pattern of the bilateral equity flows between Germany and the US, pointing to the possibility of seasonal carry trades and reversals.

Our choice of the Deutsche mark-US dollar (up to 1998) and the euro-USD dollar (from 1999) exchange rates is motivated by our focus on the profitable opportunities created for American and German investors associated with the month effect in the bilateral exchange rate. The DM, which had been for decades the second most important international currency after the US dollar and played a leadership role in the European Exchange Rate Mechanism (ERM) (Gros and Lane, 1989), bequeathed its status to the euro after the unification of European currencies in January 1999. Therefore, from the perspective of German and American investors the euro is a continuation of the Deutsche Mark, and should be stacked on the latter (the series which we call DM/EUR-USD hereafter), using the officially agreed conversion coefficient for the German mark into the euro, in order to examine, with a consistent series, the possible seasonal profits for German and US investors over a long sample. If instead we intended to focus on European investors' perspective, the ECU may seem a legitimate proxy for the euro prior to 1999. However, we refrain from doing so; not only because, in contrast to the DM, the ECU always remained only a unit of account and never became a major traded currency, but also since the ECU was dominated by the DM in the ERM. In addition the euro zone member countries are different from the members of the ECU.

Two main bodies of literature are related to the objectives of this study which we review in sequence. The first focuses on the seasonality in different financial markets, its persistence and instability; and the second examines the linkage between the foreign exchange market and the stock markets through capital flows.

The body of literature concerning monthly seasonality is composed of two streams of empirical literature which, to date, have fully remained isolated from each other. In contrast to the little attention paid to such seasonality in the foreign exchange market, there is a large body of literature on stock market returns. The report by the Harvard Committee on Economic Research (Persons, 1919), the first study to address seasonal anomalies in the US stock market, concludes that no systematic seasonal variation can be found in the Dow Jones Industrial Average over the two decades from 1897. However, subsequently, a considerable strand of literature documents the presence of monthly seasonal anomalies in the US stock market. A special attention has been devoted to the well-known January effect (with higher returns than in any other month), which is detected for a variety of samples, going back to before WWI (Choudhry (2001)), the interwar period (Wachtel (1942)), as well as covering the first three quarters of the 20th century (Rozeff and Kinney (1976) and Lakonishok and Smidt (1988)), though rejected by Mehdian and Mark (2002) for the decade after the 1987 crash. Besides, there is conflicting evidence on the more frequent presence of the January effect for low- rather than large-capitalization firms, with some studies supporting this size effect (Reinganum (1983), Keim (1983), Ritter (1988) and Roll (1983)), and others rejecting it (Koher and Kohli (Kohers and Kohli, 1991) and Agnani and Aray (2011))[1].

Similarly to the US stock market, the month effect has been detected by many studies of the European stock markets. The January effect is present for 11 (and month effect for 13) out of 17 European countries' stock markets for the 1960s and 1970s (Gultekin and Gultekin (1983)), and for 8 out of 10 European countries also in the 1980s (Agrawal and Tandon (1994)). The month effect is shown be present before WWI, for both German and UK stock markets (Choudhry (2001)), and during the decade after the 1987 crash, for the UK, but not for the decades after 1960 for these two countries (Silvapulle (2004)). However, over the latter sample, this seasonal anomaly is significant for France and Italy (Silvapulle (2004)), also, on a long sample going back to the 1930s, for Ireland (Lucey and Whelan (2004)), as well as for seven out of eight European transition economies in the closing decade of the 20th century (Asteriou and Kavetsos (2006)). In contrast to all these findings supporting it, the month effect is rejected for Greece (Floros (2008)) in the 1990s, as well as for the first decade of the new millennium in Romania (Tudor (2006)), Ukraine (Depenchuk, Compton, and Kunkel (2010)), and Slovakia and Slovenia, though not for the Czech Republic (Tonchev and Kim, 2004).

[1] A number of studies also focused on the higher volatility of returns during January than in other months (Agnani and Aray, 2011; Rogalski and Tinic, 1986; Rozeff and Kinney, 1976; Sun and Tong, 2010).

The instability of the seasonal pattern in European stock markets has been supported by a number of studies. Borges (2009), benefiting from a large cross-section of European countries, but a short time-series (1997 to 2007), claims that only country-specific month effects are present, and they are not stable over time. Similar findings were obtained by Heininen and Puttonen (2008) who suggest in addition that some countries' accession to EU can be a reason for the fading month effects. Along the same lines, Zhang and Jacobsen (2013), using over 300 years of UK stock returns data, show that monthly seasonal patterns enjoy periods of fame and disappear over time. For instance, the January effect appears around 1830 when Christmas was introduced as a public holiday and remained significant only until 1951. Therefore they underline the importance of using a long sample.

The existing literature on monthly seasonal anomalies in the foreign exchange market does not seem to reach a firm conclusion, which calls for more research. Li et al (2011) using a set of ordinary least squares (OLS) and seemingly unrelated regressions, which include monthly dummy variables, detect the month effects (especially January and December) which are significant from 1972 to 2010, for end-of the-month US Dollar-exchange rates of 6 major currencies (euro, British pound, Japanese yen, Canadian dollar, Swedish krona and Australian dollar) but not the Swiss franc or the New Zealand dollar. Cellini & Cuccia (2011) on a long sample (1974 to 2010) of monthly average data for 8 major currency pairs, with the X-12-ARIMA[2] method, only find monthly seasonality for the Deutsche mark vis-à-vis the USD from 1974 to 1989, without identifying the month which contributes to this anomaly. Cellini & Cuccia (2014) for euro-US dollar exchange rate returns, up to 2012, detect January and December effects in mean returns, and differences between variances of returns across months, without providing any explanation for such anomalies, but pointing to the importance of the changing the behavior of volatility over time.

The second related body of literature focuses on capital flows[3] which provide the transmission channel between the stock and currency markets, both according to portfolio balance models (Branson, 1983, 1981; Frankel, 1983) and the uncovered equity parity (UEP) condition (Cappiello and De Santis, 2005; Djeutem and Dunbar, 2018; Hau and Rey, 2008, 2006, 2004). However, despite the existing work on monthly seasonality in either the stock or foreign exchange markets, no attention has been granted to the associated seasonal pattern of capital flows. At a general level, portfolio balance models, under which a currency depreciates through capital outflows if domestic stock prices fall, have received only mixed empirical support[4].

Under UEP the currency of a country depreciates through portfolio rebalancing if its equity market outperforms foreign equity markets. Following such an outperformance, in the first leg of UEP, risk averse investors with restricted opportunities to hedge need either to rebalance their positions to avoid over-exposure to foreign exchange risk (Hau and Rey, 2006), or to shy away from recently high-performing stock markets subject to mean-reversion, employing carry trade or return-chasing strategies (Curcuru et al., 2014). Therefore, in the second leg of UEP, capital flows out of the high-performing equity market, causing the foreign currency to depreciate. This strand of the literature goes further than solely examining the

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[2] which is a standard method developed by the US Census Bureau for the seasonal adjustment of economic time series relying on moving-average smoothing (Shiskin et al., 1967). https://www.census.gov/srd/www/x13as/,

[3] Another body of literature has considered the relationships between stock returns or currency returns and order flow, but such research is concerned with high-frequency data (Dunne et al., 2010; Ferreira Filipe, 2012; Gyntelberg et al., 2018),

[4] See Frankel and Rose (1995) and Cushman (2007) for review of the empirical evidence on Portfolio Balance Models and Sarno and Taylor (2003) for thorough explanation of the model.

relationship between stock market and exchange rate returns. Taking advantage of the availability of monthly equity flow data, such research indeed studies the channel through which this relationship is maintained, with somewhat conflicting empirical evidence. For instance, Hau and Rey (2006) and Curcuru et al. (2014), provide evidence in favor of a correlation between foreign exchange returns and the stock market returns gap (higher stock market return in a domestic than in a foreign country) as defined by the UEP, do not find any support for the second leg of this parity condition for a number of countries including Germany. Cho et al. (2016) document that the correlation between foreign exchange returns and stock returns differentials is negative among developed economies (in accordance with UEP) but positive among emerging economies (confirmed for Asian countries by Fuertes et al. (2017)). Such differences may explain why Cenedese et al. (2016) do not find any support for UEP for a cross-section of 43 countries. Even though this literature closely looks at the out-performance of some equity markets, it ignores seasonal effects or the time-variability in the proposed transmission channel via the foreign currency market.

In contrast to the existing literature on monthly seasonality in foreign exchange market, which extensively uses parametric and non-parametric tests of the equality of monthly means and variances, smoothing (Census X-ARIMA method) and linear models, we rather rely on a non-linear framework. We employ an approach which allows the seasonal parameters to switch among recurring regimes, with a Markov-switching model (Hamilton, 1989), since such a recurrence would not be detected by the use of Bai and Peron's (2003) structural break tests (Hamilton, 2016). In addition this regime-switching model is able to identify different seasonal patterns during turmoil against calm periods or in high- against low-volatility periods, which previous literature has detected (Agnani and Aray, 2011; Floros and Salvador, 2014), making us able to provide some economic interpretation of each regime. Finally, such a framework will enable us to compare the regime classification of the seasonal patterns in foreign exchange returns, the stock market returns differential and the bilateral equity flows. The use of that frameworks presupposes to pass tests of non-linearity, based on Markov-switching parameters, as proposed by Carrasco, Hu, and Ploberger (2014).

We reach five main results. First, we provide evidence that a non-linear framework is needed to detect seasonal effects. Second, a Markov-switching model shows the presence of the month effect, with a weak December effect (depreciation of the USD), and a strong January effect (appreciation of the USD) in the DM/EUR-USD returns in more than 75% of the time from the early 1970s to 2017. Such month effects remain robust after taking transaction costs into account, implying a violation of the EMH. Third, using the same Markov-switching approach, we find similar December and January effects for the German-US stock returns differential over the same sample[5]. In most Januaries, German investors, who expect higher returns from the US stock market during that month, would sell a part of their German stock portfolio, short the euro (or the DM prior to 1999) and long the USD to invest in the US stock market, and implement the opposite strategy during Decembers. Fourth, during the Januaries (Decembers) in which the US stock market out-performs the German stock market, not only the USD does not depreciate but rather substantially appreciates (depreciates) vis-a-vis the German (euro) currency. These effects represent a seasonal violation of UEP, reinforce the findings of Cenedese et al. (2016), and are in line with the Portfolio Balance model under which a negative correlation should exist between exchange rate and stock returns differential. Fifth, the similar seasonality in the foreign exchange market and the German-US stock returns

[5] In an earlier version of this paper, using the same procedure we have estimated the monthly seasonal pattern of the returns differential of the Europe and the US using the STOXX 600 index and the S&P 500 as the representatives of each market respectively. We obtained very similar results on the January effect and the above conclusions remain valid.

differential creates a significant seasonal carry trade opportunity. This opportunity seems to have been seized by agents since our separate Markov-switching estimations show that the net bilateral equity flows from the US to Germany are also frequently characterized by December and January effects. These effects are recurrent for three-and-a-half decades, from the late 1970s until the beginning of the new millennium, though less so afterwards. The opposite signs of the equity capital flows in Decembers and Januaries are a further confirmation of carry trades and their reversal[6].

Our results imply that, accounting for the probabilities of regimes and average returns in each regime, an investor selling her US equities in December (February) to buy the German currency and equities would have made on average a 2.8% (1.1%) monthly gross return, and a 1.9 % return in January for the opposite investment, thus yielding 5.8% over three months. It is likely that the net gain would not fall much below 5% when accounting for bid-ask spreads and fees on the three markets.

This paper has four main contributions. The first and foremost contribution is to encompass different literatures on seasonality in the foreign exchange and stock markets, showing the necessity of examining their similar seasonal anomalies. Our second contribution points to the benefit of using non-linear tools for capturing recurring seasonality in financial markets. Third, we document that, similarly to the widely-supported on the recurrence of seasonality in stock markets, the month effect in the foreign exchange market has also not been arbitraged away. Fourth, we provide evidence supporting the conjecture that the end/beginning of year effect in stock markets would be transmitted to the foreign exchange market via equity flows which share the same seasonality, thus pointing to seasonal carry trades and reversals.

The paper is organized as follows: in section 2 we present a description of our data, and the modelling strategy used subsequently for the detection of seasonality. In Section 3, for the foreign exchange market, stock markets and net equity flows, we present the results of our parametric and non-parametric tests of seasonality and our findings on their regime-switching seasonal pattern, and search for matching seasonality. Section 5 concludes.

2 Data and Methodology

2.1 Data

To test the hypothesis that the month-effect is present in the DM/EUR-USD exchange rate returns, we stack the DM-USD returns from 1971 to 1998 (prior to the introduction of the euro in January 1999) using the officially agreed conversion coefficient (1.95583 DM per euro) and the euro-USD returns afterwards. We use end-of-month quotes of the DM-USD (number of DMs per USD) and the euro-USD (number of euros per USD) exchange rates from January 1971 to May 2017 obtained from International Financial Statistics of the International Monetary Fund. By using this long sample, which starts from the Nixon shock and the beginning of the fall of the Bretton Woods system in August 1971 on the way to floating rates (March 1973), we rule out the possibility of sample-selection bias. In addition, we take the advantage of using this 45-year long monthly series to capture the transformation of the seasonal pattern over time, which can be caused by many factors such as arbitrage activities which could have exploited a monthly anomaly in the

[6] Such equity carry trades would have been present from the late 1970s onwards.

market, government intervention in the currency market such as Plaza and Louvre accord periods, capital controls, etc.

Figure 1 shows the time series of the DM/EUR-USD exchange rate from January 1971 to May 2017. The period between September 1985 and February 1987 is characterized by extensive government invention in the currency market. In September 1985 G5 nations (the United States, the United Kingdom, West Germany, France, and Japan) agreed on in the Plaza Accord to depreciate the United States' currency against the other 4 nations' currency over a two-year period. After this agreement each country's central bank intervened heavily in the foreign exchange market to reach an agreed undisclosed target rate. This agreement caused around a 50% decline in the value of the United States' currency. Subsequently, the Louvre Accord in February 1987 agreed to stop the decline of the dollar and to stabilize G6 nations' (the G5 plus Canada) currencies. Stability was achieved for the first 8 months after the agreement, but it broke down, due to an interest rate increase by the German Bundesbank, triggering a rise of the discount rate by the Federal Reserve. Therefore, between these two accords we expect these policy events to generate an absence, or a disturbance, of monthly seasonal anomalies in the foreign currency market.

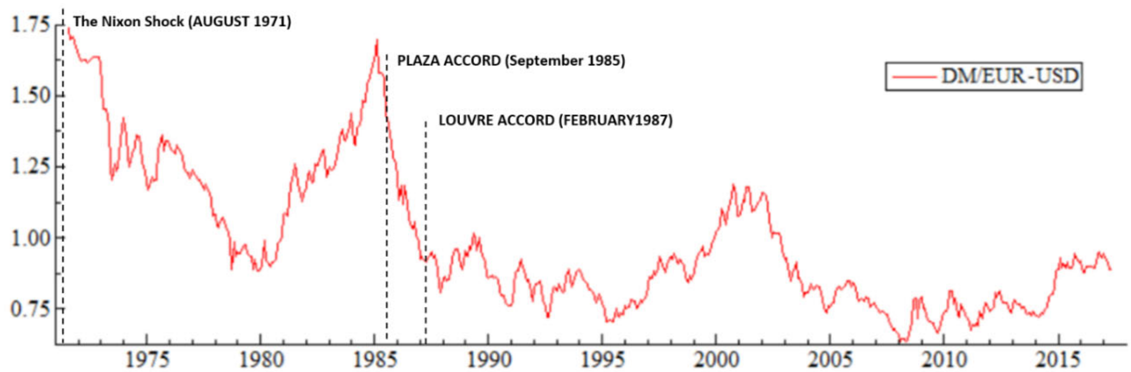

Figure 1- DM/euro-US dollar exchange rate from January 1971 to May 2017

For the purpose of testing the hypothesis about the presence of an overlap in the seasonal pattern of the foreign exchange and stock markets we use the differential between the returns on the German and the US stock markets. We employ monthly closing quotes of the DAX index[7] as representative of the former and the S&P500 index as the representative of the latter stock market from February 1971 to May 2017, both obtained from Global Financial Data. The differential is computed as the returns (exclusive of dividends) on the German DAX minus the (ex. dividends) returns on the S&P500.

To evaluate the channel through which the seasonality in the stock markets could have impacted the foreign exchange market we investigate the seasonal pattern of the equity flows between Germany and the US. Following Hau and Rey (2006) and Brennan and Cao (1997), we use net equity flows from the US into Germany, which are the net purchases of German stocks by US residents minus the net purchases of US stocks by German residents, normalized on the average of the absolute value of net equity flows from US to Germany during the previous 12 months. Capital flows between Germany and the US have been reported

[7] DAX index was first introduced by the association of the German Stock Exchanges, the Frankfurt Stock Exchange and the Börsen-Zeitung on July 1, 1988 but is a continuation of the stock market newspaper index which had been reported since 1959.

by the US Department of the Treasury in the Treasury International Capital system (TIC) since January 1977, which is thus the start of our sample the our study of net equity flows.

Table 1-Descrpitive statistics for foreign exchange returns, stock returns differential and normalized net equity flows

	Min	Mean	Max	Standard deviation	Skewness	Kurtosis	Jarque-Bera	Box-pierce test Q(5)
ΔL(DM/EUR-USD)	-0.118	-0.001	0.122	0.031	0.08	1.36**	43.23**	3.09
ΔLDAX-ΔLS&P	-0.222	0.001	0.184	0.054	-0.25**	1.21***	39.28***	10.74*
NEF	-4.01	-0.06	4.36	1.40	0.152	0.46**	6.30**	110.51***

	ADF (1979)	Zivot and Andrews (2002)	Phillips and Perron (1988)	KPSS (1992)	Ng and Perron (2001)	
					MZa	MZt
ΔL(DM/EUR-USD)	-12.46***	-11.61***	-22.53***	0.12	-49.29***	-4.96***
ΔLDAX-ΔLS&P	-13.12***	-10.87***	-29.96***	0.039	-20.64***	-3.19***
NEF	-9.01***	-9.19***	-18.38***	0.25	-70.98***	-5.94***

*** significant at 1% level, ** significant at 5% level, * significant at 10% level

ΔL(DM/EUR-USD) is the DM/euro-US dollar exchange rate return, ΔLDAX-ΔLS&P is the returns differential between the German and the US stock markets, NEF is the net equity flows.

Sample: February 1971 to May 2017 for the DM/EUR-USD exchange rate returns and March 1971 to May 2017 Stock Market Returns Differential, from January 1977 for the NEF.

Table 1 shows the descriptive statistics of the exchange rate returns, stock markets returns differentials and net equity flows form the US to Germany. The three variables have a non-normal distribution caused by excess kurtosis according to the Jarque-Bera test, and all three are stationary according to the Augmented Dickey-Fuller, the Phillips and Perron (1988) and the Kwiatkowski et al. (1992) (KPSS) tests. As these tests are said to be biased towards rejecting the null of unit root (or accepting the null of stationarity in the case of KPSS) in the presence of structural breaks, we also conduct Zivot and Andrews' (2002) test, which allows for structural breaks, and confirms the stationarity of all variables. A similar confirmation of stationarity is provided by Ng and Perron's (2001) MZa and MZt tests[8], which are modified versions of Phillips' (1987) and Phillips and Perron's (1988) unit root tests[9].

Table A1 in Appendix A reports for each month the descriptive statistics of the DM/EUR-USD returns, stock returns differential and normalized net equity flows. On average the USD has the lowest returns vis-à-vis the DM/euro in Novembers and the highest returns in Decembers. The average of the stock returns differential has the highest value in Februaries and lowest in Mays. The German net equity flows to the US have their lowest mean value in Januaries and highest mean value in Augusts. The monthly data distributions are shown to be non-normal.

2.2 Methodology

The usual parametric and non-parametric tests of equality of means and variances have been extensively used for the detection of seasonality in the literature (see for instance: Gultekin & Gultekin, 1983; Kumar & Pathak, 2016; Lucey & Whelan, 2004; McFarland et al., 1982; Rozeff & Kinney, 1976; Zhang &

[8] By applying GLS de-trending they enhance the power of the tests especially for small samples.

[9] Elliott, Rothenberg and Stocks' (1996) efficient test for autoregressive unit root which is a modified Dickey and Fullers' (1979) test could also be implemented. However, in contrast to the trendless nature of our variables, this test is rather proposed for the autoregressive series with trend component. Therefore, we rather rely on the results of previous tests' results.

Jacobsen, 2013 among others). Among these tests the Analysis of Variance (ANOVA) test (Fisher, 1920) and its non-parametric alternative, the Kruskall-Wallis test (Kruskal and Wallis, 1952), focus on the equality of the means of several independent groups, e.g. the average exchange rate return across months in our case. Levene's test (1960) and its non-parametric counterpart (Nordstokke and Zumbo, 2010) assess the equality of variances of several independent groups (equality of exchange rate variances across months in our case) [10].

Another parametric test for the detection of monthly anomalies is the usual linear framework which relies on an ordinary least squares (OLS) estimation of a model including 12 monthly dummies (Adrangi and Ghazanfari, 2011; Depenchuk et al., 2010; Floros, 2008; Franses and van Dijk, 2000; Gultekin and Gultekin, 1983; Kumar and Pathak, 2016; Li et al., 2011; Yamori and Kurihara, 2004; Zhang and Jacobsen, 2013) as follows:

$$M_{i,t} = \sum_{j=1}^{12} \beta_{i,j} D_{j,t} + \varepsilon_{i,t} \tag{1}$$

where $M_{i,t}$ is a monthly series integrated of order 0, with i being either exchange rate returns ($M_{FX,t}$ = $R_{DM/EUR\text{-}USD}$), the stock market returns differential ($M_{SDR,t}$) or the net equity flows form the US to Germany ($M_{NEF,t}$). $D_{j,t}$ is the monthly dummy variable taking value 1 in the j^{th} month (j= 1 to 12) and 0 in other months[11]. β_js are the seasonal coefficients which show the average value of the $M_{i,t}$ series during the corresponding month. Finally $\varepsilon_{i,t}$ is an iid error terms.

Returns on financial assets ($R_{l,t}$) are calculated as:

$$R_{l,t} = \ln(\frac{P_{l,t}}{P_{l,t-1}}) \tag{2}$$

with l being the financial asset (foreign currency and stocks) and $P_{l,t}$ its spot price. Therefore the stock market returns differential can be computed as ($M_{SRD,t} = R_{DAX,t} - R_{S\&p500,t}$).

An important concern when estimating such a linear model for a long sample is the stability of the parameters, since the seasonal pattern of the exchange rate series may change over time. Given the sophisticated trading technologies, no seasonal anomaly is expected to resist being arbitraged away over time in the globalized currency or stock market. In addition, government policy changes such as intervention in the market or even cultural changes, such as starting the celebration of holidays (Zhang and Jacobsen, 2013), may affect the seasonal pattern of financial series such as exchange rate or stock returns

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[10] ANOVA tests the null of equality of the average value of returns across groups (months) against the alternative of having at least one group (month) with a different mean (average return) and produces an F-test to conclude. The Kruskall-Wallis non-parametric test uses ranks of data instead of their original values and therefore tests the equality of mean ranks. In contrast to ANOVA, the Kruskall-Wallis non-parametric test does not assume normally distributed data. The test statistic obtained by applying this test is approximately Chi-squared distributed. Levene's test can be considered as an ANOVA test on the absolute value of each monthly return from the average return of its corresponding group (month) and its test statistic is approximately F-distributed. The non-parametric version of this test uses ranks instead of original values of the observations and consists of an ANOVA test on the absolute value of the difference between the rank of each observation with the average rank of it corresponding group (month).

[11] To avoid the dummy variable trap, this model should not include an intercept, otherwise one of the monthly dummy variables should be omitted from the model.

over time. Therefore, in this study in order to gauge the modification of the seasonal pattern we suggest the application of a non-linear specification.

In this context, the use of the Markov-switching model developed by Hamilton (1989) would serve our purpose of modeling the time series which are subject to regime shifts and allowing for the possibility of regime recurrence (in contrast with structural break tests (Hamilton, 2016)). The Markov-switching framework for the detection of seasonal effects of variable M is as follows:

$$M_{i,t} = \sum_{k=1}^{q} \alpha_{i,k}(s_{i,t})M_{i,t-k} + \sum_{j=1}^{12} \beta_{i,j}(s_{i,t})D_j + \sigma_i(s_{i,t})\varepsilon_{i,t} \quad (3)$$

In equation (1), k (=1 to q) autoregressive lags of $M_{i,t-k}$ are entered as explanatory variables and $\varepsilon_{i,t}$ is Gaussian white noise with covariance matrix Σ. $s_{i,t}$ is an unobservable state variable and all the parameters in this model are allowed to switch between states. Therefore, $\alpha_{i,k}(s_{i,t})$ are the state-dependent coefficients of the autoregressive lags, $\beta_{i,j}(s_{i,t})$ indicates the state-dependent seasonal coefficient of month j and $\sigma_i(s_{i,t})$ is the state-dependent variance.

In this model, the state variable follows a first-order Markov chain, meaning that its current value is affected only by its immediate previous value. Given an information set (data) and a model, we will be able to assign each observation to a specific state. Optimal inference on this unobservable state variable then can yield a matrix of smoothed transition probabilities whose elements show the probability of persistence of a given regime (when starting from that regime) and the probabilities of transition to other regimes. We do not decide a priori about the number of regimes, but test for it. We estimate these parameters using the sequential quadratic programming algorithm of Lawrence and Tits (2001) along with a pre-estimation with the Expected Maximization (EM) algorithm of Dempster, laid and Rubin (Dempster et al., 1977).

There are two challenges when specifying a Markov-switching model. The first is that the usual test-statistics of parameter constancy, such as the likelihood ratio test, do not follow standard distributions (Carrasco et al., 2014; Di Sanzo, 2009). This is both because under the null of linearity some of the hyper-parameters are not identified and the information matrix is singular (since the underlying regimes are unobservable). Therefore, in order to test whether a linear model outperforms a non-linear model, we apply the optimal test for Markov-switching proposed by Carrasco et al. (2014). Their test only requires the estimation of the Markov-switching model under the null hypothesis of constant parameters. Therefore, we need only to compute the critical values by parametric bootstrap simulations using our Markov-switching estimation under the null hypothesis (Carrasco et al., 2014). To implement this test for a model with switching intercept and variance, we compute the critical values from 500 iterations.

The second challenge is the choice of the optimal number of regimes. The Akaike (AIC), Bayesian or Schwarz's (SC) and Hannan and Quinn (1979) (HQ) information Criteria are the general metrics used in the literature for comparing the goodness of fit of several models. The three information criteria trade off the log-likelihood obtained from the Markov-switching model against the number of parameters estimated. However, they are all suspected of misleading the users to choose an inaccurate number of regimes, the SC and HQ by suggesting models with a low number of regimes (Psaradakis and Spagnolo, 2003) and the AIC by having the tendency to accept a model with a high number of regimes (Smith et al., 2006), leading to the reduction of estimation accuracy.

Therefore, we prefer to conduct our analysis with the Markov-switching Criterion (MSC), developed by Smith et al. (2006), and based on the Kullback–Leibler (KL) divergence, which allows us to choose simultaneously the optimal number of regimes and autoregressive lags. This criterion was shown to be efficient across different sample sizes and with noisy data (Smith et al., 2006). After the estimation of the model parameters, the MSC is computed by imposing a penalty based on full-sample smoothed probabilities, in order to trade off the fit of the model against its parsimony. The criterion is computed as:

$$MSC = -2\,L + \sum_{i=1}^{N} \frac{\hat{\tau}_i\,(\hat{\tau}_i + S\eta)}{\tau_i - SR - 2} \quad (4)$$

where L is the log-likelihood of the estimated model, S is the number of regimes and η is the number of regressors. $\hat{\tau}_i$ is computed using full-sample smoothed probabilities. The model which yields the minimum MSC is chosen with the optimal number of Markov-switching regimes and autoregressive lags.

In our empirical analysis, we consider various combinations of states (s) and autoregressive lags (q) for the estimation of equation (3). We let s= 2,…,4 and also k= 0,…5. We do not go further than 4 regimes because our model would be over-parametrized. Therefore, we estimate 24 different models and compute the three information criteria presented above (AIC, SC and MSC). However, the final decision about the best number of regimes and number of autoregressive lags depends on the MSC.

3 Empirical Results

To meet the four objectives of our study, we follow a sequential strategy. First, to be able to compare and decide upon the necessity of the application of a non-linear framework, we apply conventional parametric and non-parametric test. We then examine the monthly seasonality in the foreign exchange market using the non-linear Markov-switching framework. In the next steps, we examine the possible drivers of seasonality in foreign currency returns by comparing the timing of its occurrence with the seasonal pattern of the German-US stock returns. We then consider whether this similarity in seasonal pattern is matched by seasonal bilateral US-German net equity flows.

3.1 Parametric and Non-parametric Tests of Seasonality

The results of the widely-used parametric and non-parametric tests of equality of means and variances of the monthly foreign currency returns, stock returns differential and net equity flows are reported in table 2. None of the test show any significant differences between monthly means and variances of the stock returns differential. However, conducting the Analysis of Variance (ANOVA) test, a significant difference between means of the DM/EUR-USD exchange rate or between the means of net equity flows from the US to Germany are found, without indicating the month(s) which is(are) contributing to the unequal means (Table 2, second column). The Kruskal-Wallis non-parametric test shows very weak evidence (at the 10% level of confidence) that the mean ranks of monthly returns of the DM/EUR-USD can differ and a strong evidence of differences between monthly means of the net equity flows. Finally, while Levene's test of equality of variances of monthly returns does not indicate any significant difference in the monthly variances of each group, its non-parametric version shows a difference between the variances of monthly net equity flows.

Table 2- parametric and non-parametric tests of mean and variance equality

Variable	ANOVA test	Kruskal-Wallis test	Levene's test	Levene's non-parametric test
M_{FX}	1.871**	17.392*	0.768	1.084
	[0.041]	[0.097]	[0.673]	[0.371]
M_{SRD}	1.148	0.097	1.439	1.367
	[0.322]	[0.330]	[0.152]	[0.184]
M_{NEF}	2.1805**	25.485***	0.715	2.345***
	[0.014]	[0.007]	[0.725]	[0.008]

*** significant at 1% level, ** significant at 5% level, * significant at 10% level

Values is square brackets are p-values.

M_{FX}= ΔL(DM/EUR-USD): Deutsche mark/euro- USD exchange rate return,, $M_{SRD=}$ ΔLDAX-ΔLS&P: stock markets returns differential, M_{NEF}: net equity flow form the US to Germany.

Sample: February 1971 to May 2017 for the DM/EUR-USD exchange rate returns and March 1971 to May 2017 stock market returns differential, and from January 1977 to May 2015 for the net equity flows form the US to Germany.

A linear model with monthly dummies as in equation (1) was estimated as a starting point. The results reported in table 3 show that significant January, September and December effects exist in the DM/EUR-USD foreign exchange returns. However, the results of the linear model estimation for the stock returns differential only reveal the presence of a significant February effect. Hence, the hypothesis of the presence of a January effect in the stock markets returns differential is rejected and, based on this linear results, we cannot conclude that there is any similarity between the seasonality in the foreign exchange and stock markets. For the net equity flows, several months such as January, August, October and November have a significant coefficient. So according to the linear estimation, the January effect is common between the DM/EUR-USD returns and the net equity flows. However the reliability of such results depends on the validity of the linearity assumption.

Table 3- Linear Model Estimation for foreign exchange returns, stock returns differential and normalized net equity flows

Dependent variables	Jan	Feb	Mar	Apr	May	Jun
M_{FX}	0.011**	-0.004	0.001	-0.003	0.006	-0.003
	[0.02]	[0.31]	[0.82]	[0.40]	[0.16]	[0.49]
M_{SRD}	-0.008	0.014*	0.002	0.001	-0.012	0.003
	[0.29]	[0.07]	[0.79]	[0.85]	[0.12]	[0.66]
M_{NEF}	-0.501**	-0.152	-0.331	0.028	0.042	0.272
	[0.02]	[0.48]	[0.13]	[0.90]	[0.85]	[0.22]

Dependent variables	Jul	Aug	Sep	Oct	Nov	Dec
M_{FX}	-0.002	0.001	-0.010**	-0.003	0.003	-0.011**
	[0.66]	[0.86]	[0.02]	[0.59]	[0.60]	[0.01]
M_{SRD}	0.013	-0.010	-0.005	0.006	0.004	0.007
	[0.11]	[0.21]	[0.57]	[0.48]	[0.64]	[0.40]
M_{NEF}	0.128	0.524**	0.263	-0.389*	-0.476**	-0.028
	[0.56]	[0.02]	[0.23]	[0.08]	[0.03]	[0.90]

*** significant at 1% level, ** significant at 5% level, * significant at 10% level

Values is square brackets are p-values.

M_{FX}= ΔL(DM/EUR-USD): Deutsche mark/euro- USD exchange rate return, $M_{SRD=}$ ΔLDAX-ΔLS&P: stock markets returns differential, M_{NEF}: net equity flow form the US to Germany.

Sample: February 1971 to May 2017 for the DM/EUR-USD exchange rate returns and March 1971 to May 2017 stock market returns differential, and from January 1977 to May 2015 for the net equity flows form the US to Germany.

3.2 Markov-switching Estimation Results

3.2.1 Linear model vs. Markov-switching

To make sure that a regime-switching model is relevant for our data, we first implement the optimal test for the constancy of parameters. We implement Carrasco et al (2014)'s test of linearity vs. Markov Switching mean and variance separately for the DM/EUR-USD exchange rate returns, the German-US stock market returns differential, and the net equity flows from the US to Germany, using 500 iterations. The results obtained from these tests are provided in Table 4, where SupTS is the sup-type test statistic used by Davies (1987) and expTS is an exponential-type test statistic suggested by Andrews and Ploberger (1994).

The results (Table 4) show that the null of a linear model against switching mean and variance is strongly rejected for all three variables. Therefore, the results of the linear model with 12 monthly dummy variables and conventional parametric test are not acceptable and we should rather rely on a non-linear model such as Markov-switching model.

Table 4- Carrasco et al (2014)'s Test of Linearity vs. Markov-switching Model with Switching Mean and Variance

	supTS	expTS
M_{FX}	9.356 [0.00]	14.00 [0.00]
M_{SRD}	12.582 [0.00]	8.076 [0.00]
M_{NEF}	9.480 [0.00]	75.807 [0.00]

M_{FX}= ΔL(DM/EUR-USD): Deutsche mark/euro- USD exchange rate return,, $M_{SRD=}$ ΔLDAX-ΔLS&P: stock markets returns differential, M_{NEF}: net equity flow form the US to Germany.
Sample: February 1971 to May 2017 for the DM/EUR-USD exchange rate returns and March 1971 to May 2017 stock market returns differential, and from January 1977 to May 2015 for the net equity flows form the US to Germany.

3.2.2 Foreign Exchange Market

To choose the optimal number of regimes we estimated 18 models with *s*=2 to 4 regimes and *k*=0 to 5 autoregressive lags in which all the components of equation (3) were allowed to switch. The period of estimation is from July 1971 to May 2017 as we reserved the first observation for the computation of the returns from the spot prices and the next 5 observations for the inclusion of autoregressive lags. Columns 3 to 5 of table 5 report the obtained values for the three information criteria for the 18 models with DM/EUR-USD returns as the dependent variable. AIC suggests a model with 4 regimes and 5 autoregressive lags, while a model with 2 regimes and no autoregressive lag is suggested by SC. The lowest MSC is obtained by a 3-regime model with 4 autoregressive lags. So, as we expected, MSC favors fewer regimes in comparison with AIC and a larger number of regimes in comparison with SC.

The estimated coefficients for a 3-regime model with 4 autoregressive lags, suggested by MSC, are presented in table 6. Regime switches have taken place following the changes in the variance of the error terms, the seasonal pattern and the autoregressive terms. The first regime is the most persistent, or dominant (the probability of its persistence is 97%) and the second regime is the least persistent (figure 2). The third regime is the high-volatility regime, and the second one is the low-volatility regime (refer to table A2 in Appendix A for regime transition probabilities).

Table 5- Information Criteria Obtained from Estimated MS Models for DM/EUR-USD Exchange Rate Returns (July 1971-May 2017) and Stock Market Returns Differential (August 1971-May 2017)

	Info.	M_{FX}			M_{SRD}		
	Criterion	*s*=2	*s*=3	s=4	*s*=2	*s*=3	*s*=4
k=5	MSC	-1604.38	-1117.02	-1651.6	-1131.7119	-1019.4631	-887.0614
	SC	-3.78731	-3.64808	-3.59569	-2.7455	-2.5386	-2.3748
	AIC	-4.08467	-4.10195	-4.22954	-3.0433	-3.0009	-3.0017
k=4	MSC	-1608.96	-3314.62	-1749.49	-1123.39	-1044.23	-514.743
	SC	-3.78433	-3.70657	-3.69241	-2.7312	-2.5562	-2.5592
	AIC	-4.06604	-4.13696	-4.29496	-3.0133	-3.0028	-3.1626
k=3	MSC	-1618.83	-2389.48	-1716.54	-1129.68	No convergence	No convergence
	SC	-3.80682	-3.65835	-3.57184	-2.7494	No convergence	No convergence
	AIC	-4.07288	-4.08091	-4.12744	-3.0159	No convergence	No convergence
k=2	MSC	-1628.26	-903.649	-1846.32	-1136.62	-1098.69	-962.557
	SC	-3.82741	-3.7576	-3.61177	-2.7688	-2.6008	-2.6153
	AIC	-4.07782	-4.14104	-4.14389	-3.0196	-2.9926	-3.1403
k=1	MSC	-1638.13	-1045.91	-1671.2	-1145.92	-1151.08	-1099.67
	SC	-3.84977	-3.71007	-3.6833	-2.7930	-2.7037	-2.4980
	AIC	-4.08453	-4.07786	-4.16847	-3.0281	-3.0641	-2.9997
k=0	MSC	-1633.86	-1361.24	-2200.4	-1141.76	No convergence	-1188.4154
	SC	-3.88504	-3.74982	-3.62212	-2.7921	No convergence	-2.6672
	AIC	-4.10415	-4.08631	-4.10729	-3.0114	No convergence	-3.1373

M_{FX}= ΔL(DM/EUR-USD): Deutsche mark/euro- USD exchange rate return,, $M_{SRD=}$ ΔLDAX-ΔLS&P: stock markets returns differential.
k: number of Autoregressive lags, *s*=number of regimes.

During the first regime, the only significant coefficients are the ones corresponding to January (significant at the 1% level) with average return of 1.6 percentage points (0.016) and December (significant at the 10% level) with average return of -0.8 percentage points (0.008). Therefore, we cannot reject the hypothesis that the January and December effects are present for the DM/EUR-USD exchange rate during the most persistent regime. As shown in Figure 2, as well as table A3 of the Appendix A for the regime classifications, the first regime still has many occurrences in the most recent period. Accordingly the end/beginning of the year seasonal anomaly of the US dollar-euro exchange rate returns does not pertain to the past, and market participants have not been able to gradually smooth it out (or arbitrage it away). The January (December) effect here corresponds to an appreciation (depreciation) of the US dollar vis-à-vis the DM/EUR.

During the second regime, which is the least persistent one, we have 10 significant monthly coefficients. This regime is in place in only less than 10% of the whole sample. Similarly, the third regime is only in place in 67 out of 552 months (12% of the whole sample) and only coefficients corresponding to March, April and July are significant. Having few observations in a regime (like here the second and third ones) can generate the statistical significance of many coefficients, which cannot be interpreted as the presence of the month effect in those regimes. Interestingly, the period between the Plaza and the Louvre accords plus the first three months after the Louvre accord (September 1985 to April 1987) fall in the second and third regimes (total of 20 months). This is in accordance with our expectation of no monthly seasonal pattern when governments intervene in the market.

Table 6- Markov-switching Estimated Coefficients of DM/EUR-USD Exchange Rate Returns (July 1971-May 2017)

Regime	January	February	March	April	May	June
1	0.016***	-0.005	0.001	0.001	0.006	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
2	-0.058***	-0.028***	-0.042***	-0.034***	-0.002	-0.010***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)
3	-0.002	-0.027	0.099***	-0.017	0.008	-0.009
	(0.018)	(0.017)	(0.028)	(0.017)	(0.019)	(0.016)

Regime	July	August	September	October	November	December
1	0.004	-0.005	-0.006	-0.001	0.004	-0.008*
	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)
2	0.003	-0.007***	-0.044***	-0.011***	-0.042***	-0.048***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.003)
3	-0.060***	0.020	-0.015	0.002	0.049	-0.011
	(0.021)	(0.017)	(0.018)	(0.020)	(0.030)	(0.023)

Regime	$M_{FX}(-1)$	$M_{FX}(-2)$	$M_{FX}(-3)$	$M_{FX}(-4)$	variance	prob. of persistence
1	0.170***	-0.005	0.013	-0.051	0.025***	0.976
	(0.051)	(0.049)	(0.047)	(0.045)	(0.001)	(0.008)
2	-0.390***	-0.269***	-0.261***	-0.150***	0.004***	0.503
	(0.020)	(0.017)	(0.020)	(0.018)	(0.001)	(0.093)
3	-0.079	0.310*	0.218	0.473***	0.039***	0.668
	(0.118)	(0.144)	(0.145)	(0.161)	(0.003)	(0.071)
	Portmanteau (36)	18.986	Normality test	2.5956	ARCH test	0.19560

*** significant at 1% level, ** significant at 5% level, * significant at 10% level

Numbers in parentheses are standard errors.

MFX= ΔL(DM/EUR-USD): USD-Deutsche mark/euro exchange rate returns

Coefficients in this table should be read as follows : for example: 0.016 in January means a 1.6% exchange rate return

With the application of the Markov-switching framework, we are thus able to document the presence of the January and December effects in the DM/EUR-USD exchange rate returns. These effects either were not identified in previous papers (Cellini, 2011) or were only modeled in a linear framework and with a much shorter sample (Li et al., 2011). As opposed to the results using a linear OLS framework, we do not find any significant evidence of a monthly anomaly in September.

To show that this finding of a month effects in the foreign exchange market is not simply a statistical anomaly but is also exploitable for trading, we must make sure that the transaction costs do not exceed the profit from the arbitrage transactions. The most common form of transaction costs in the foreign exchange market is the bid-ask spread. Since October 1989, the variable bid-ask spreads of the DM/EUR-USD exchange rate have usually been so small (on average 1 pip) that all the transactions involved in arbitraging the January effect in the foreign currency market remain profitable after the subtraction of the spread (table A4 in Appendix A). It is also shown in Appendix A that the profit after the spread is high enough to be larger than any fixed or variable transaction fees[12].

[12] Transaction fees (bid-ask spreads) are omitted from the return made from the appreciation of the US dollar (German Mark-Euro) in January (December). Bid-ask spreads are the major transaction costs in the foreign exchange market.

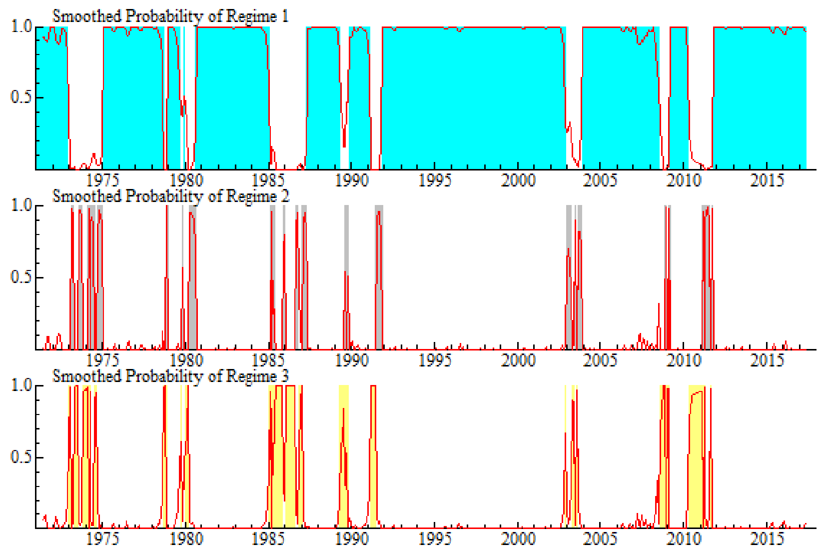

Figure 2-Smoothed Regime Probabilities of the DM/EUR-USD Exchange Rate Returns

3.2.3 Stock Market

With respect to the returns differential between the German and US stock market indices (DAX and S&P500 respectively), we use the same procedure as for exchange rate returns, and estimate 18 models with s=2 to 4 and k=0 to 4, and reserve the first 6 observations for autoregressive lags and differencing. Therefore our estimation sample is from August 1971 to May 2017. As shown in table 5, the model suggested by MSC has 4 regime with no autoregressive lags. Estimated coefficients are reported in table 7. Similar to the case of the DM/EUR-USD exchange rate returns, the first regime is dominant and the three other regimes have short durations and are very seldom in place (9.45% of the whole sample for the second and third regimes 4.18% for the fourth regime). With the same reasoning as for (in)significant coefficients in the second and the third regimes of the model for exchange rate returns, we reject the presence of a monthly seasonal pattern in the last three regimes of the model for the stock market returns differential.

In the first regime, which is dominant and highly-volatile, we find significant coefficients for January, February, May, July, August and December (refer to tables A5 and A6 of the Appendix A for regime transition probabilities and the dating of regimes). In that regime, the January dummy variable is almost equal but of opposite sign to the coefficient of the December and February dummies. In Januaries (December and February respectively) US stock returns are 1.5 (1.4 and 1.7 respectively) percentage points higher (lower) than German stock returns. This double reversal can give an equity carry trade opportunity to investors who can not only benefit from the stock market returns differential returns in the stock market, but also take advantage of currency movements during December and January. An investor who moves her capital to the German stock market in December can benefit from an overall gross return (adding the stock returns differential and the exchange rate appreciation) larger than 2.0 percentage points and the movement of capital during the following month in the opposite direction can generate an overall gross return of 3.0 percentage points.

Table 7- Markov-switching Estimated Coefficients of the German-US Stock Market Returns Differential (August 1971- May 2017)

Regime	Jan	Feb	Mar	Apr	May	Jun
1	-0.015*	0.017*	0.005	0.002	-0.014**	-0.005
	(0.008)	(0.009)	(0.008)	(0.008)	(0.007)	(0.008)
2	0.015	0.000	-0.011	-0.087***	0.038*	0.073***
	(0.020)	(0.027)	(0.017)	(0.021)	(0.019)	(0.016)
3	0.080***	-0.032	0.051*	0.121***	-0.021	0.019
	(0.022)	(0.020)	(0.031)	(0.018)	(0.018)	(0.033)
4	-0.161***	0.113***	-0.149***	-0.061***	-0.193***	-0.041***
	(0.012)	(0.011)	(0.019)	(0.014)	(0.016)	(0.015)

Regime	Jul	Aug	Sep	Oct	Nov	Dec
1	0.015**	-0.017**	0.003	0.000	0.003	0.014*
	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)
2	-0.077***	-0.019	-0.124***	0.048**	0.057***	-0.038**
	(0.017)	(0.020)	(0.018)	(0.024)	(0.016)	(0.016)
3	0.046***	0.059***	0.082***	0.126***	-0.081***	0.117***
	(0.017)	(0.014)	(0.021)	(0.022)	(0.018)	(0.043)
4	0.045*	-0.222***	-0.045***	-0.117***	0.136***	-0.068***
	(0.026)	(0.016)	(0.015)	(0.014)	(0.016)	(0.013)

Regime	Variance	prob. of persistence				
1	0.040***	0.945				
	(0.002)	(0.015)				
2	0.031***	0.748				
	(0.004)	(0.070)				
3	0.034***	0.640				
	(0.005)	(0.156)				
4	0.016***	0.176				
	(0.003)	(0.106)				
	Portmanteau (36)	28.695	Normality test	2.0299	Arch test	2.0462

*** significant at 1% level, ** significant at 5% level, * significant at 10% level

Numbers in square brackets: standard errors.

Coefficients in this table should be read as follows : for example: -0.015 in January means that during that month US stock returns are 1.5 percentage points higher than the German stock returns

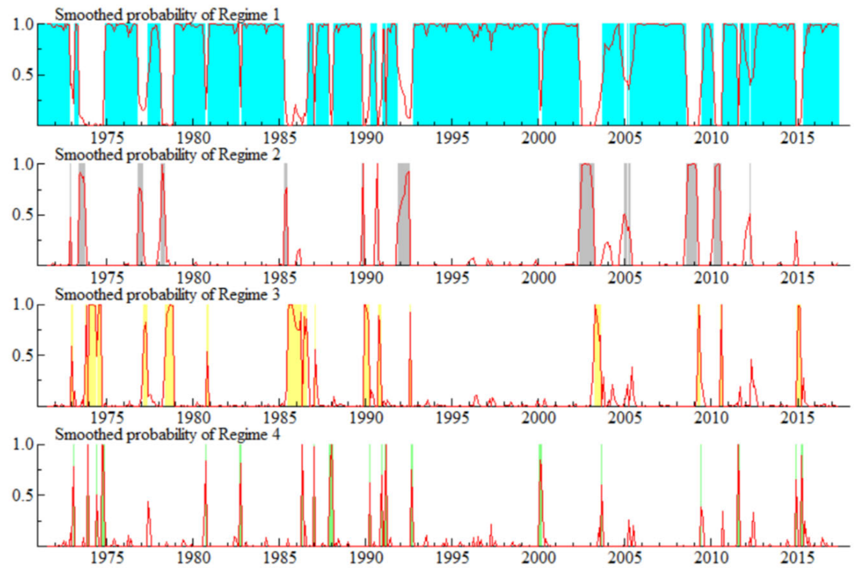

Figure 3- Smoothed Regime Probabilities of the (German-US) stock market returns differential

3.2.4 Joint January effect in the foreign exchange market and the stock market returns differential

The first regime of the model for the DM/EUR-USD exchange rate returns and the first regime of the stock market returns differential have similar timings, as shown respectively in the lower and upper panels of Figure 4. More specifically, since August 1971, the DM/EUR-USD exchange rate returns fall in the first regime for a total of 431 months. As shown in table 8, 368 out of these 431 months correspond also to the first regime of the stock market returns differential. In other words, there are only 62 months which are classified in the first regime of the DM/EUR-USD exchange rate return model but not in the first regime of the stock markets returns differential one. Conversely there are 54 month that are classified in the first regime of the model for the stock markets returns differential but not in the model for DM/EUR-USD exchange rate returns.

This considerable overlap of the January and December effects is a presumption of the presence of a joint seasonality in the two markets. The negative (positive) sign of the coefficient of January (December and February) in the first regime of the model for the stock returns differential, which indicates the presence of an incentive for investors to switch a part of their portfolio from the German to the US stock market, is accompanied by an appreciation (depreciation) of the dollar in Januaries (Decembers but not Februaries). Therefore, it is likely that the January and December effects in the DM/EUR-USD exchange rate returns derive from the significant differential between the returns of the US and the German stock market in Januaries and Decembers. In other words, in Januaries investors tend to sell German stocks quoted in euros (or DM prior to formation of the euro), and use the proceeds to buy the USD in order to invest in the American stock market (and vice versa in Decembers). This marks a violation UEP (Hau and Rey, 2006) during the joint-seasonality period, meaning that the stock returns differential is not compensated by the depreciation of the USD. The induced cross-border capital flows transiting via the foreign currency market are likely to be the source of the similar seasonality in the stock market returns differential and the foreign exchange returns.

There are still a few years when the January effect is jointly absent from both the DM/EUR-USD returns and the stock returns differential. We can explore the common causes of the elimination of this seasonal anomaly during three episodes. Firstly, in 1973 and 1974, the first oil shock, in the early autumn 1973, seems to have caused the returns differential of the two stock markets to temporarily switch from its high-volatility dominant state to another state, for a period of one year. But this would not be correct as we do not see such an effect following the second oil shock, in December 1979. We may rather interpret the 1973-74 specificity as the effect of temporary capital controls, such as the prohibition of interest payments to non-resident deposits until 1975 in Germany (refer to IMF Annual Report on Exchange Arrangement and Exchange Restrictions). Secondly, the effect of the controls on capital inflows in Germany can be also observed during the years 1977 and 1979, when both the DM/EUR-USD exchange rate returns and the stock market returns differential are out of their dominant regimes. Finally, the period between 1985 and 1987 does not lie in the first regime of the foreign currency returns, thus showing no January and December effects. This was the period between the Plaza and Louvre accords (see above), characterized by heavy interventions in the foreign exchange market managing an orderly depreciation of the US dollar vis-à-vis the G5 nations' currencies. Therefore, not only we do not observe any January and December effects in the DM/EUR-USD during this period, but also a reinforced January effect in the German-US stock returns differential could have been prevented due to expectations of the depreciation of the USD.

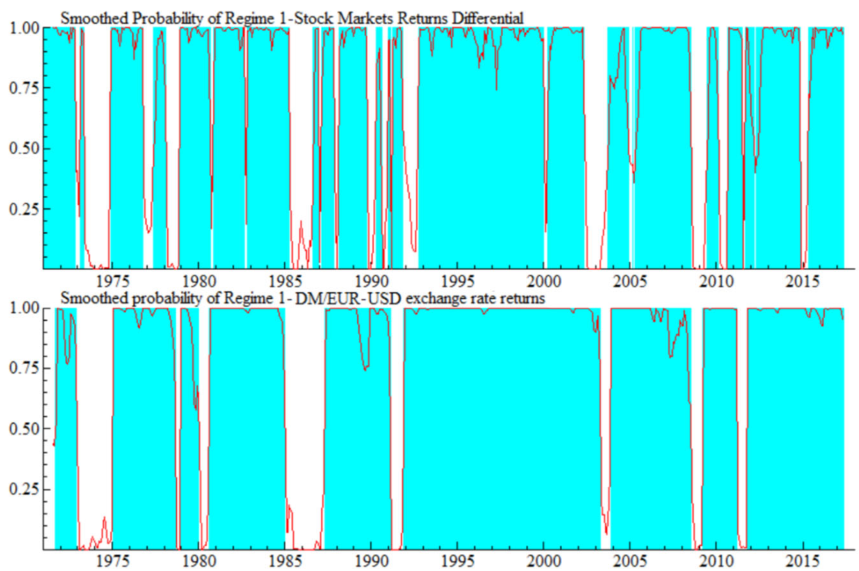

Figure 4-Smoothed Regime probabilities of the first regimes of the (German-US) stock market returns differential (upper panel) and the DM/EUR-USD exchange rate returns (lower panel)

The period from mid-2002 to mid-2003 marks the downturn in the US and European stock markets known as the burst of the internet bubble. As it is expected for turmoil periods, our estimations show that the DM/EUR-USD returns and the stock returns differentials do not stand in their dominant regimes. The stock returns differential lies in its second regime, with relatively-low volatility, and the EUR-USD bounces between the most- and least-volatile regimes. The Global Financial Crisis caused a similar elimination of the January and December effects from mid-2008 to mid-2009.

Table 8- Timing of Joint Seasonality between DM/EUR-USD exchange Rate Returns and the (German-US) Stock Market Returns Differential (June 1987-May 2017)

Joint seasonality	Months	Classified only the 1st regime of in ΔL(DM/EUR-USD)	Months	Classified only the 1st regime of ΔLDAX-ΔLS&P	Months
1971(08)- 1971(11)	4	1971(12)	1	1973 (03)- 1973(05)	2
1972(01)- 1972(11)	11	1972(12)	1	1974(12)	1
1975(02)- 1976(10)	21	1976(11)- 1977(05)	7	1978(10)	1
1977(06)- 1978(02)	9	1978(03)- 1978(09)	7	1979(10)- 1979(11)	2
1979(01)- 1979(09)	9	1980(11)- 1980(12)	2	1980(01)- 1980(08)	8
1979(12)	1	1982(10)	1	1985(02)- 1985(04)	3
1980(9)	1	1987(12)- 1988(02)	3	1986(09)- 1986(12)	4
1980(12)- 1982(09)	10	1989(12)- 1990(04)	5	1987(03)- 1987(04)	2
1982(11)- 1985(01)	27	1990(09)- 1990(12)	4	1989(05)- 1989(10)	6
1987(05)- 1987(11)	7	1991(12)- 1992(09)	10	1991(04)- 1991(11)	8
1988(03)- 1989(04)	14	2002(06)- 2002(11)	6	2003(10)- 2003(11)	2
1990(05)- 1990(08)	4	2003(10)- 2003(11)	2	2010 (09)- 2010(12)	4
1991(01)- 1991(02)	2	2005(01)- 2005(02)		2011(01)- 2011(07)	7
1992(10)- 2000(01)	88	2005(04)	1	2011(09)- 2011(10)	2
2000(04)- 2002(05)	26	2009(04)- 2009(06)	3		
2003(12)- 2004(12)	13	2010(03)- 2010(04)	2		
2005(03)	1	2012(04)	1		
2005(05)- 2008(07)	39	2014(12)- 2015(04)	5		
2009(07)- 2010(02)	8				
2011(01)- 2011(02)	2				
2011(11)- 2012(03)	5				
2012(05)- 2014(11)	31				
2015(05)- 2017(05)	25				
Total	368		62		54

Overall, combining the probabilities of regimes and average returns in each regime for both foreign currency returns and the stock returns differential, we can infer that an investor selling her US equities in December in order to purchase the German currency and equities, would have made on average a 2.8% total gross monthly return. The opposite transactions would generate a 1.9% gross total monthly return in January, and similar transactions in February than in December would generate a 1.1% gross gain. The overall gross gain over three months would thus be 5.8%, and the net gain would likely fall between 4.5% and 5%, when accounting for bid-ask spreads and fees on the three markets. As a point of comparison, it is instructive to note that an investor who would have conducted the same investment strategies every year (from December 1971 to February 2017) would have made on average a gross capital gain of 1.82 % in December, 1.93% in January, and 1.82 percent in February, computed using the actual average returns by month as reported in Table A1. The overall gross gain (5.63%) would thus be close to that implied by our model estimates.

3.2.5 Seasonal Carry Trade

A valid concern about the seasonality we found in the foreign exchange market returns and its linkage with the seasonality in the stock market returns differential is the effect of regulatory barriers to the mobility of capital. Capital controls, which were at the heart of the Bretton Woods system, were gradually abolished in the 1970s and 1980s in European countries. As mentioned earlier, in the case of Germany, which was the most liberal European country in this sense, controls on capital outflows were relaxed very early on, in 1957. However, some inflow restrictions were still in place during the 1960s and early 1970s. Subsequently, during the years 1968 to 1973, and 1977 to 1978, different types of controls with varying degrees of severity were imposed again on capital inflows into Germany. In addition, interest payments to non-residents were prohibited until 1975[13]. Subsequently European countries, pioneered by Germany, started to relax their capital controls. The Single Market program imposed the total lifting of such controls by July 1st 1990.

In order to assess the impact of capital controls of varying intensity on currency returns' seasonal anomalies one may be tempted to look at reports on the regulations of capital movements as compiled by the International Monetary Fund. However this would not in any way inform us on the actual effectiveness of such controls, which are likely to have been sidestepped in a country with a very open trade account (see Aizenman (2009)), such as Germany. The acid test of such effectiveness is the magnitude of bilateral capital flows, in our case between Germany and the United States. Therefore, we use US-German net equity flows as described in section 2. We were not able to use the capital flow data between the Euro area and the US as the time span for such data is very short. Further, studying aggregate euro-area equity flows would introduce some nuisance into our analysis, as Germany is the main financial actor in the area.

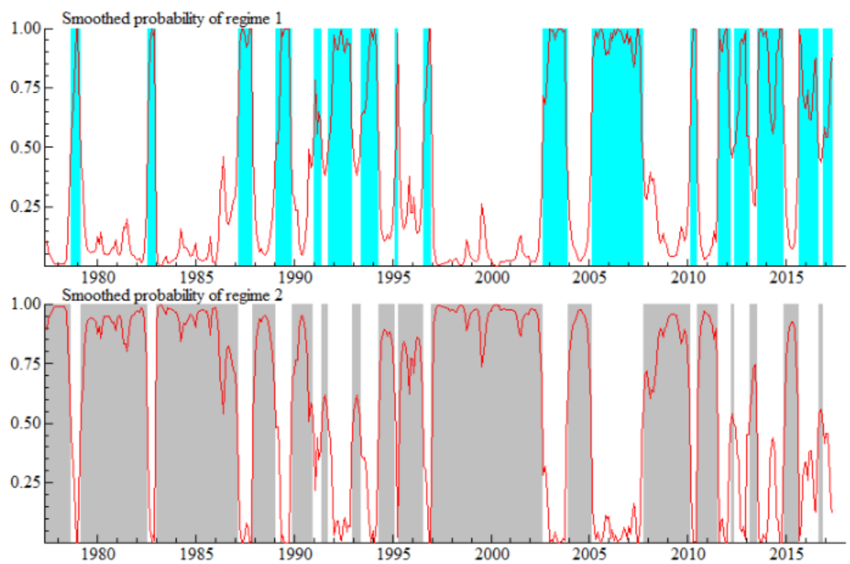

Figure 5- Smoothed Regime Probabilities of the Net Equity Flows- whole Sample (June 1977-May 2017)

Accordingly, we estimate the MS equation (3) for the bilateral net equity flows from the US into Germany using 12 monthly dummy variables for the sample from June 1977 to May 2017 (for the sake of comparison between models with different number of autoregressive lags, the first 5 observations were omitted). We did not allow more than 3 regimes to preserve degrees of freedom and avoid over-parameterization. By applying the same procedure as in the previous sections, we find that a model with 2 regimes and one autoregressive lag is supported by MSC (refer to Appendix B for the comparison of the information criteria

[13] Refer to Ghosh and Qureshi (2016) for a brief presentation of the capital controls in Germany and the IMF Annual Report on Exchange Arrangement and Exchange Restrictions for more extensive information

obtained by the estimation of the 10 models, and the regime classification of the selected model). Figure 5 shows the smoothed regime probabilities of this model.

Table 9- Markov-switching Estimated Coefficient of the US Net Equity Flows into Germany (June 1977- May 2017)

Regime	Jan	Feb	Mar	Apr	May	Jun
1	-0.047	0.297	-0.108	0.839*	0.716	1.184**
	(0.507)	(0.531)	(0.495)	(0.432)	(0.477)	(0.506)
2	-0.695***	0.039	-0.212	-0.061	-0.073	-0.027
	(0.187)	(0.248)	(0.185)	(0.194)	(0.193)	(0.183)

Regime	Jul	Aug	Sep	Oct	Nov	Dec
1	0.471	1.217***	0.524	-0.146	-0.019	-0.262
	(0.484)	(0.445)	(0.416)	(0.397)	(0.417)	(0.473)
2	0.058	0.031	0.053	-0.658***	-0.494**	0.645***
	(0.192)	(0.196)	(0.207)	(0.224)	(0.201)	(0.203)

Regime	M_{NEF} (-1)	Variance	prob. of persistence			
1	-0.076	1.586***	0.873			
	(0.096)	(0.102)	(0.0532)			
2	0.633***	0.815***	0.918			
	(0.051)	(0.049)	(0.027)			
	Portmanteau (36)	40.671 [0.272]	Normality test	1.907 [0.385]	Arch test	0.0005 [0.982]

*** significant at 1% level, ** significant at 5% level, * significant at 10% level
Numbers parentheses: standard errors
M_{NEF}: the net equity flows form the US to Germany.

As shown in table 9, the net US equity flows into Germany exhibit seasonal movements. We observe strong January, October, November and December effects in the second regime which is dominant (in place in more than 64% of the total time) and the least-volatile. During the first regime strong June and August effects and a weak April effect are present. The negative sign of the seasonal dummy in January, October and November (in regime 2) implies that during these months capital was flowing from Germany to the US and in the opposite way during December. The timing of the second regime of the net equity flows has major overlaps with the timings of the first regime of the two models for the exchange rate returns and the stock market returns differential. The discrepancies are prominent in the mid-1980s, between the Plaza and Louvre accords, when we do not observe any January effect either in foreign exchange returns or in the stock market return differentials, while this effect is significant in the US net equity flows into Germany. The discrepancies during more recent years may be explained by the influence of other types of bilateral capital flows (government or corporate bonds, as well as bank flows, etc.) on the foreign exchange returns. In total, the stock market returns are significantly higher in the US than in Germany in 31 out of the 40 Januaries of our sample (from 1977 to 2017) and the net equity flow also exhibit seasonality in 20 Januaries. Finally an overlapping seasonality is found in stock market returns differential, exchange rate returns and the net equity flows during 18 Januaries.

A very important feature of the seasonal pattern in all three (stock market, foreign currency market and equity flow) models is the significant December and January coefficients which have opposite signs. This common pattern can be regarded as an evidence of carry trade reversal. The capital which generally flows from the US to Germany in December for return-chasing purposes subsequently flows back to the US, in order to gain from the larger January effect in the US than in the German stock Market. Such inverse flows cause significant and consistent movements in foreign exchange returns both in January and December. These patterns match the argument of Curcuru et al (2014) who suggest that the rationale behind the link between the stock market returns differential and foreign exchange returns may not be due to risk balancing and repatriation of investments (suggested by UEP of Hau and Rey (2006)) but to carry trades and the return-chasing behavior of investors. Our findings also suggest that carry trades can be regarded as a seasonal phenomenon which can regularly be present for decades. There is no evidence of a carry trade reversal in February. It is not possible to judge with the net equity flow data whether the equity capital which flows from Germany to the US during January is invested there for a relatively longer horizon (a few months) or if investors rebalance their portfolio later in the year to chase returns in third markets. However we did document earlier the presence of an incentive for an equity capital flow reversal in February, with a substantial capital gain.

4 Conclusion

We have provided some new evidence on the presence of the month effect in the DM/EUR-USD exchange rate returns over a four-and-a-half decade long sample starting in the early 1970s, representing a persistent violation of the efficient market hypothesis in the foreign exchange market. Using a regime-switching framework we have shown that the January and December effects in the foreign exchange market have not been arbitraged away.

We attempted to explain the recurrent seasonal anomaly in the foreign exchange market by the equally recurrent seasonality in stock markets, and found a significant overlap of the month effect in both markets. This led us to put forward the conjecture that the monthly seasonal pattern of the German-US stock market returns differential could trigger capital flows between the two markets and consequently generate the observed seasonal pattern in the foreign exchange market returns. We documented that, since 1971, stock returns have been higher (lower) in the US than in Germany in most Januaries (Decembers), and were associated with dollar appreciation (depreciation) during these same months. Such findings led us to infer the profitability of seasonal carry trade positions. We thus suggested that Hau and Rey's (2006) evidence, in support of a depreciation of the German mark subsequent to the outperformance of the German stock over the US stock market, may not be due to risk aversion of investors but rather to carry trades, as suggested by Curcuru et al. (2014).

It was the choice of a non-linear model which allowed us to detect this persistent seasonal carry trade opportunity while conventional tools of detecting seasonality rejected that. Therefore, it may be wise to avoid using linear models for detecting the seasonal pattern of financial data, which is affected by many policy changes and events and is regime-dependent. This study opens up other avenues to explore the links between the seasonality in other stock market returns differentials and the corresponding currency returns. Application of a trading robot approach by developing trading strategies exploiting the seasonal pattern in both stock markets returns differential and foreign exchange market returns may be worth pursuing.

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Appendix A: Descriptive statistics, regime classifications and profitability of arbitrage.

Table A1- Monthly Descriptive Statistics of the DM/EUR-USD Exchange Rate returns, German-US Stock Market Returns Differential and net equity flows

Variable	January				February			
	Mean	Std dev.	Skewness	kurtosis	Mean	Std dev.	Skewness	kurtosis
ΔL(DM/EUR-USD)	0.0109	0.0326	0.1510	0.1510	-0.0044	0.0295	-1.2132	2.5759
ΔLDAX-ΔLS&P	-0.0084	0.0613	-0.4691	0.3077	0.0144	0.0451	0.3201	0.2313
NEF	-0.5469	1.3723	0.1462	-0.5947	-0.1295	1.3186	0.4310	0.3220

	March				April			
	Mean	Std dev.	Skewness	kurtosis	Mean	Std dev.	Skewness	kurtosis
ΔL(DM/EUR-USD)	0.0011	0.0345	0.9489	3.0392	-0.0033	0.0266	-0.2203	0.4830
ΔLDAX-ΔLS&P	0.0021	0.0560	-0.6076	1.1175	0.0015	0.0633	0.4310	0.5170
NEF	-0.2545	1.3602	0.2774	0.0778	0.0086	1.3448	-0.5774	0.3893

	May				June			
	Mean	Std dev.	Skewness	kurtosis	Mean	Std dev.	Skewness	kurtosis
ΔL(DM/EUR-USD)	0.0063	0.0308	0.0813	0.0081	-0.0031	0.0308	-0.9708	3.6768
ΔLDAX-ΔLS&P	-0.0124	0.0498	-0.8413	2.7875	0.0035	0.0421	0.6254	0.0488
NEF	0.0249	1.4401	0.6721	0.0135	0.2377	1.6363	0.2441	0.5133

	July				August			
	Mean	Std dev.	Skewness	kurtosis	Mean	Std dev.	Skewness	kurtosis
ΔL(DM/EUR-USD)	-0.0021	0.0325	-0.0904	1.0868	0.0007	0.0251	0.5361	0.2573
ΔLDAX-ΔLS&P	0.0127	0.0457	-0.9569	0.3812	-0.0101	0.0602	-0.8619	2.5415
NEF	0.1058	1.2407	1.0467	2.5537	0.5044	1.1857	0.6882	0.1397

	September				October			
	Mean	Std dev.	Skewness	kurtosis	Mean	Std dev.	Skewness	kurtosis
ΔL(DM/EUR-USD)	-0.0104	0.0301	0.2971	0.0775	-0.0028	0.0359	0.4884	3.3184
ΔLDAX-ΔLS&P	-0.0045	0.0585	-0.7842	1.2532	0.0057	0.0634	0.1935	0.6825
NEF	0.2374	1.2456	-0.1065	0.4592	-0.3999	1.3200	-0.0771	0.6145

	November				December			
	Mean	Std dev.	Skewness	kurtosis	Mean	Std dev.	Skewness	kurtosis
ΔL(DM/EUR-USD)	0.0027	0.0344	0.4801	0.2438	-0.0114	0.0307	-0.5774	-0.1610
ΔLDAX-ΔLS&P	0.0037	0.0504	0.0412	0.7871	0.0068	0.0517	0.7033	0.6281
NEF	-0.4875	1.3402	0.4169	2.1055	-0.0084	1.7235	-0.4204	0.5847

ΔL(DM/EUR-USD): US dollar-DM/EUR exchange rate return, ΔLDAX-ΔLS&P is the return differential between the German and the US stock markets, NEF is normalized net equity flows form the US to Germany.

Sample: February 1971 to May 2017 for the DM/EUR-USD exchange rate returns and March 1971 to May 2017 German-US Stock Market Returns Differential, June 1977 to May 2017 for normalized net equity flows

Table A2- Regime Transition Probabilities- DM/EUR-USD Exchange Rate Returns (July 1971- May 2017)

	Regime 1,t	Regime 2,t	Regime 3,t
Regime 1,t+1	0.976	0.221	0.000
Regime 2,t+1	0.000	0.503	0.333
Regime 3,t+1	0.024	0.275	0.668

Table A3-Regime Classifications Based on Smoothed Probabilities for MS model of DM/EUR-USD Exchange Rate Returns (July 1971- May 2017)

Regime 1	Months	Ave. Prob.	Regime 2	Months	Ave. Prob.	Regime 3	Months	Ave. Prob.
1971(7) - 1972(12)	19	0.937	1973(3) - 1973(4)	2	0.959	1973(1) - 1973(2)	2	0.786
1975(2) - 1978(9)	44	0.97	1973(8) - 1973(10)	3	0.96	1973(5) - 1973(7)	3	0.995
1979(1) - 1979(9)	9	0.918	1974(3) - 1974(3)	1	0.988	1973(11) - 1974(2)	4	0.972
1979(12) - 1979(12)	1	0.512	1974(5) - 1974(7)	3	0.891	1974(4) - 1974(4)	1	0.963
1980(9) - 1985(1)	53	0.985	1974(10) - 1975(1)	4	0.892	1974(8) - 1974(9)	2	0.921
1987(5) - 1989(4)	24	0.969	1978(12) - 1978(12)	1	1	1978(10) - 1978(11)	2	0.998
1989(12) - 1991(2)	15	0.946	1979(11) - 1979(11)	1	0.567	1979(10) - 1979(10)	1	0.611
1991(12) - 2002(11)	132	0.995	1980(4) - 1980(8)	5	0.89	1980(1) - 1980(3)	3	0.74
2003(12) - 2008(7)	56	0.964	1985(3) - 1985(3)	1	0.961	1985(2) - 1985(2)	1	0.961
2009(4) - 2010(4)	13	0.979	1985(5) - 1985(5)	1	0.48	1985(4) - 1985(4)	1	0.842
2011(11) - 2017(5)	67	0.993	1985(12) - 1986(1)	2	0.751	1985(6) - 1985(11)	6	0.966
			1986(9) - 1986(10)	2	0.905	1986(2) - 1986(8)	7	1
			1987(2) - 1987(4)	3	0.896	1986(11) - 1987(1)	3	0.798
			1989(9) - 1989(9)	1	0.537	1989(5) - 1989(8)	4	0.703
			1989(11) - 1989(11)	1	0.514	1989(10) - 1989(10)	1	0.529
			1991(7) - 1991(11)	5	0.915	1991(3) - 1991(6)	4	0.999
			2003(1) - 2003(4)	4	0.581	2002(12) - 2002(12)	1	0.67
			2003(7) - 2003(7)	1	0.906	2003(5) - 2003(6)	2	0.892
			2003(9) - 2003(11)	3	0.785	2003(8) - 2003(8)	1	0.972
			2008(12) - 2008(12)	1	0.998	2008(8) - 2008(11)	4	0.884
			2009(3) - 2009(3)	1	0.986	2009(1) - 2009(2)	2	0.986
			2011(3) - 2011(3)	1	0.965	2010(5) - 2011(2)	10	0.92
			2011(5) - 2011(8)	4	0.93	2011(4) - 2011(4)	1	0.996
			2011(10) - 2011(10)	1	0.982	2011(9) - 2011(9)	1	0.982
433 months (78.44%) with average duration of 39.36 months			Total: 52 months (9.42%) with average duration of 2.17 months.			Total: 67 months (12.14%) with average duration of 2.79 months.		

Table A4- Net Profit after Transaction Costs- DM/EUR-USD Exchange Rate (July 1971 to May 2017)

	Profit after transaction costs- January effect					Profit after transaction costs- December effect				
	Date	EUR-USD return	Bid-Ask spread/2	Return after spreads	Net profit per standard lot	Date	EUR-USD return	Bid-Ask spread/2	Return after spreads	Net profit per standard lot
Fixed spread (5 pips)						1971(12)	-0.012	0.0005	-0.012	(1187.5)
	1972(1)	-0.018	0.0005	-0.018	(1790.0)	1972(12)	0.002	0.0005	0.001	134.5
	1976(1)	-0.011	0.0005	-0.010	(1020.0)	1976(12)	-0.018	0.0005	-0.017	(1724.6)
	1978(1)	0.003	0.0005	0.003	272.5	1978(12)	-0.051	0.0005	-0.050	(5037.2)
	1979(1)	0.018	0.0005	0.018	1771.4	1979(12)	0.001	0.0005	0.000	36.7
	1981(1)	0.077	0.0005	0.077	7692.4	1981(12)	0.023	0.0005	0.023	2251.4
	1982(1)	0.024	0.0005	0.023	2303.7	1982(12)	-0.046	0.0005	-0.045	(4502.9)
	1983(1)	0.029	0.0005	0.029	2893.8	1983(12)	0.010	0.0005	0.009	938.8
	1984(1)	0.033	0.0005	0.032	3204.3	1984(12)	0.017	0.0005	0.016	1605.9
	1985(1)	0.006	0.0005	0.006	573.8	1985(12)	-0.020	0.0005	-0.020	(1989.0)
	1988(1)	0.058	0.0005	0.058	5747.7	1988(12)	0.026	0.0005	0.025	2504.4
	1989(1)	0.046	0.0005	0.046	4576.5	1989(12)	-0.053	0.0005	-0.052	(5210.3)
Variable spread	1990(1)	-0.009	0.0005	-0.009	(850.0)	1990(12)	-0.007	0.0005	-0.007	(683.6)
	1991(1)	-0.003	0.0005	-0.002	(220.0)	1991(12)	-0.074	0.0003	-0.073	(7330.8)
	1992(1)	0.063	0.0004	0.062	6207.1	1992(12)	0.008	0.0010	0.007	677.5
	1993(1)	-0.013	0.0007	-0.012	(1210.0)	1993(12)	0.009	0.0008	0.008	810.2
	1994(1)	0.009	0.0008	0.008	832.6	1994(12)	-0.014	0.0007	-0.013	(1340.5)
	1995(1)	-0.026	0.0007	-0.026	(2550.0)	1995(12)	-0.002	0.0009	-0.001	(133.0)
	1996(1)	0.040	0.0007	0.040	3948.1	1996(12)	0.013	0.0006	0.013	1260.7
	1997(1)	0.049	0.0007	0.049	4905.6	1997(12)	0.016	0.0007	0.015	1527.4
	1998(1)	0.019	0.0026	0.019	1875.8	1998(12)	-0.017	0.0003	-0.017	(1688.6)
	1999(1)	0.027	0.0002	0.026	2625.1	1999(12)	0.005	0.0010	0.004	406.4
	2000(1)	0.026	0.0002	0.025	2500.6	2000(12)	-0.069	0.0005	-0.069	(6857.0)
	2001(1)	0.001	0.0003	0.001	78.0	2001(12)	0.010	0.0014	0.008	819.9
	2002(1)	0.020	0.0005	0.019	1900.5	2002(12)	-0.055	0.0008	-0.054	(5407.8)
	2004(1)	0.020	0.0002	0.019	1938.3	2004(12)	-0.024	0.0001	-0.024	(2412.50)
	2005(1)	0.036	0.0001	0.036	3560.8	2005(12)	-0.002	0.0004	-0.002	(197.6)
	2006(1)	-0.027	0.0001	-0.027	(2670.0)	2006(12)	0.002	0.0003	0.002	197.5
	2007(1)	0.017	0.0001	0.016	1627.6	2007(12)	0.003	0.0001	0.003	261.4
	2008(1)	-0.010	0.0001	-0.010	(1000.0)	2008(12)	-0.089	0.0002	-0.089	(8918.5)
	2010(1)	0.031	0.0001	0.031	3086.8	2010(12)	-0.028	0.0003	-0.027	(2731.9)
	2012(1)	-0.018	0.0001	-0.018	(1810.0)	2012(12)	-0.016	0.0003	-0.016	(1559.0)
	2013(1)	-0.027	0.0001	-0.027	(2650.0)	2013(12)	-0.014	0.0001	-0.014	(1414.1)
	2014(1)	0.020	0.0001	0.020	1997.9	2014(12)	0.028	0.0002	0.028	2758.0
	2015(1)	0.071	0.0002	0.071	7104.4	2015(12)	-0.029	0.0001	-0.029	(2859.9)
	2016(1)	-0.003	0.0002	-0.003	(280.0)	2016(12)	0.009	0.0005	0.008	837.8
	2017(1)	-0.020	0.0003	-0.020	(1980.0)					

- The bid-ask spread quotes are only available since October 1989. The bid and ask quotes provided by Datastream generates fixed spreads up to 1990. Therefore to test whether the transaction profits prior to October 1989 were exploitable, we used the same fixed spread (5 pips).
- Only the Januaries and Decembers which fall into the first regime are included in our calculations (their corresponding dates are provided in column 2).
- The left panel corresponds to the calculation of the net profit from buying the USD in Januaries and the right panel corresponds to the net profit from buying German mark/euro in Decembers.
- Negative (positive) returns correspond to the depreciation (appreciation) of the dollar vis-à-vis the German mark/euro and accordingly profits in parentheses can be made from buying German mark.

Table A5-Regime Transition Probabilities- German-US Stock Markets Returns Differential (August 1971- May 2017)

	Regime 1,t	Regime 2,t	Regime 3,t	Regime 4,t
Regime 1,t+1	0.945	0.000	0.165	0.558
Regime 2,t+1	0.031	0.748	0.000	0.000
Regime 3,t+1	0.000	0.252	0.640	0.267
Regime 4,t+1	0.024	0.000	0.195	0.176

Table A6- Regime Classifications Based on Smoothed Probabilities for MS model of German-US Stock Markets Returns Differential (August 1971- May 2017)

Regime 1	months	avg.prob.	Regime 2	months	avg.prob.
1971(8)- 1971(8)	16	0.98	1972(12)- 1972(12)	1	0.47
1973(3)- 1973(5)	3	0.94	1973(06)- 1973(10)	5	0.86
1974(12)- 1976(10)	23	0.98	1976(11)- 1977(02)	4	0.67
1977(6)- 1978(2)	9	0.83	1978(03)- 1978(05)	3	0.77
1978(12)- 1980(9)	22	0.97	1985(05)- 1985(06)	2	0.73
1980(12)- 1982(9)	22	0.99	1989(11)- 1989(11)	1	1.00
1982(11)- 1985(4)	30	0.99	1990(09)- 1990(09)	1	1.00
1986(9)- 1986(12)	4	0.91	1991(12)- 1992(07)	8	0.73
1987(3)- 1987(11)	9	0.96	2002(06)- 2003(03)	10	0.92
1988(3)- 1989(10)	20	0.98	2005(01)- 2005(02)	2	0.47
1990(5)- 1990(8)	4	0.80	2005(04)- 2005(04)	1	0.38
1991(1)- 1991(2)	2	0.95	2008(08)- 2009(03)	8	0.94
1991(4)- 1991(11)	8	0.92	2010(03)- 2010(07)	5	0.91
1992(10)- 2000(1)	88	0.97	2012(04)- 2012(04)	1	0.51
2000(4)- 2002(5)	26	0.96			
2003(10)- 2004(12)	15	0.80			
2005(3)- 2005(3)	1	0.44			
2005(5)- 2008(7)	39	0.96			
2009(7)- 2010(2)	8	0.89			
2010(9)- 2011(7)	11	0.95			
2011(9)- 2012(3)	7	0.77			
2012(5)- 2014(11)	31	0.94			
2015(5)- 2017(5)	25	0.95			
423 months (76.91%) with average duration of 18.50 months.			52 months (9.45%) with average duration of 2.19 months.		

Regime 3	months	avg.prob.	Regime 4	months	avg.prob.
1973(01)- 1973(01)	1	0.591	1973(02)- 1973(02)	1	0.781
1973(11)- 1973(11)	1	0.984	1973(12)- 1973(12)	1	0.994
1974(01)- 1974(05)	5	0.994	1974(06)- 1974(06)	1	0.502
1974(07)- 1974(09)	3	0.929	1974(10)- 1974(11)	2	0.993
1977(03)- 1977(05)	3	0.724	1980(10)- 1980(10)	1	0.832
1978(06)- 1978(11)	6	0.911	1982(10)- 1982(10)	1	0.812
1980(11)- 1980(11)	1	0.533	1986(05)- 1986(05)	1	1
1985(07)- 1986(04)	10	0.882	1987(01)- 1987(01)	1	0.972
1986(06)- 1986(08)	3	0.814	1987(12)- 1988(02)	3	0.765
1987(02)- 1987(02)	1	0.557	1990(04)- 1990(04)	1	0.618
1989(12)- 1990(03)	4	0.928	1990(12)- 1990(12)	1	0.701
1990(10)- 1990(11)	2	0.854	1991(03)- 1991(03)	1	0.996
1992(08)- 1992(08)	1	0.924	1992(09)- 1992(09)	1	0.753
2003(04)- 2003(08)	5	0.826	2000(02)- 2000(03)	2	0.813
2009(04)- 2009(05)	2	0.897	2003(09)- 2003(09)	1	0.605

2010(08)- 2010(08)	1	0.999	2009(06)- 2009(06)	1	0.387
2015(01)- 2015(03)	3	0.977	2011(08)- 2011(08)	1	1
			2014(12)- 2014(12)	1	0.659
			2015(04)- 2015(04)	1	0.885
Total: 52 months (9.45%) with average duration of 3.06 months.			Total: 23 months (4.18%) with average duration of 1.21 months.		

Appendix B:

Table B1- Information Criteria Obtained from Estimated MS Model for US Net Equity Flows into Germany (June 1977 to May 2017)

	S=2	S=3
K=5	2158.641	2478.355
K=4	2148.387	2426.162
K=3	2137.354	2379.772
K=2	2127.777	2341.9
K=1	1995.593	2311.427
K=0	2169.252	2281.744

*The model for the Net equity flow into the Euro zone starts from June 2001 since the 5 first observation were reserved for the autoregressive lags.

Table B3- Regime Classifications Based on Smoothed Probabilities for the MS model of the US Net Equity Flows into Germany (June 1977- May 2017)

Regime 1	months	avg.prob.	Regime 2	months	avg.prob.
1978(09)- 1979(02)	6	0.773	1977(06)- 1978(08)	15	0.939
1982(08)- 1982(12)	5	0.904	1979(03)- 1982(07)	41	0.904
1987(03)- 1987(11)	9	0.942	1983(01)- 1987(02)	50	0.899
1989(02)- 1989(11)	10	0.812	1987(12)- 1989(01)	14	0.845
1991(01)- 1991(05)	5	0.637	1989(12)- 1990(12)	13	0.766
1991(10)- 1992(12)	15	0.85	1991(06)- 1991(09)	4	0.581
1993(06)- 1994(04)	11	0.813	1993(01)- 1993(05)	5	0.57
1995(03)- 1995(04)	2	0.765	1994(05)- 1995(02)	10	0.829
1996(08)- 1996(12)	5	0.833	1995(05)- 1996(07)	15	0.759
2002(09)- 2003(11)	15	0.898	1997(01)- 2002(08)	68	0.947
2005(03)- 2007(09)	31	0.936	2003(12)- 2005(02)	15	0.872
2010(03)- 2010(06)	4	0.942	2007(10)- 2010(02)	29	0.816
2011(08)- 2012(03)	8	0.869	2010(07)- 2011(07)	13	0.879
2012(06)- 2013(02)	9	0.745	2012(04)- 2012(05)	2	0.521
2013(08)- 2014(11)	16	0.861	2013(03)- 2013(07)	5	0.656
2015(09)- 2016(08)	12	0.746	2014(12)- 2015(08)	9	0.802
2016(12)- 2017(05)	6	0.669	2016(09)-2016(11)	3	0.543
169 months (35.21%) with average duration of 9.94 months.			311 months (64.79%) with average duration of 18.29 months.		