How Will Brexit Impact Deposit Balances in the UK? A Forecast of Sight Deposits on UK Monetary Financial Institutions' using Structural Break in the Holt Method

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Abstract

Over the last few years an hypothesis of referendum about the presence in European Union (EU) was emerging in the United Kingdom (UK) based on several political and economic problems around Europe. Nowadays, the EU is the UK's largest trade partner. For this reason, '*Brexit*' would lower trade between both parties. The present research will quantify the impacts of '*Brexit*' in the Monetary Financial Institutions' (MFI's) deposits with an asymmetric volatility verified in the currency market. Asymmetric GARCH-family models, such as the TARCH, will be used to modeling markets' returns that are heavily affected by political events, like the '*Brexit*'. The analysis is subsequently extended to a Holt method for forecasting the Sight Deposits in UK MFI with fan chart. This research considers the amounts outstanding of sterling liabilities in the MFI's balance sheet (excluding central bank). To determine the uncertainty in the fan charts we will consider the extreme asymmetric volatility in the currency market.

Keywords: Asymmetric Volatility, Brexit, Deposit Balances, Fan Charts, Sight Deposits, UK Referendum, Volatility Modeling.

1. Introduction

Over the last month, the outcome of the UK's referendum on membership of the european project (EU) have been relevant impacts on the financial markets, especially in the currency market immediately after the '*Brexit*'. Beyond the impacts in the financial markets, the '*Brexit*' will shape the future of the political and economics' relationship with its largest trade partner, the EU. The membership of the EU has been several advantages in the trade activities with large european partners, such as (i) the reduction of trade costs between UK and the main european countries and (ii) other tariff barriers removed in the EU space. Both advantages in the membership of the EU allowed free trade in term of goods and services between both parties. On the other hand, economists should considers the effects of non-tariff barriers. These non-tariff barriers are the result of the EU policy to create a european single-market that results from the integrated european economy through removing economic barriers between EU economies. In these non-tariff barriers we can find regulation over the standards of quality, safety, border controls and other themes related to antitrust policy, for example. Note these non-tariff barriers increase the costs of trade and all members of EU benefits with the single-market created by the EU.

In 1973, when UK joined the European Economic Community (EEC), the trade with EEC represented one third approximately. Based on the Office for National Statistics report (2015), in 2014 the sum of EU members represented 45% of the UK's exports and 53% of imports respectively. It represents a relevant growth in the trade between UK and EU members. Furthermore, some economic agents (consumers, for example) benefits additionally with the single-market through (i) lower prices in other european markets and (ii) access to higher quality markets in terms of goods and services. In the specific case of firms, they benefits with several new export opportunities to other countries resulting in higher net profits.

Despite the effects of '*Brexit*' in the trade with EU members, the present research focus on the impact of '*Brexit*' in the banking system. In this article we will discuss the consequences of outcome of the UK's referendum in the sight deposits in the MFI's balance sheet (excluding the central bank), as shows the historical evolution since June 2014 (Figure 1). In terms of MFI's deposits from UK residents, based on *Bank of England* (BoE) Monetary & Financial Statistics, as shows Figure 2 and Figure 3, between January 2016 and May 2016 the cumulative average contribute of all industries and individuals for the sum of MFI's deposits was 42% and 58% respectively. An industrial and detailed approach is presented in appendix 1.The central questions of the research are: (i) How would '*Brexit*' affect the UK's sight deposits on MFI balance sheet and (ii) what impact would this have on the forecast of MFI' sight deposits?.

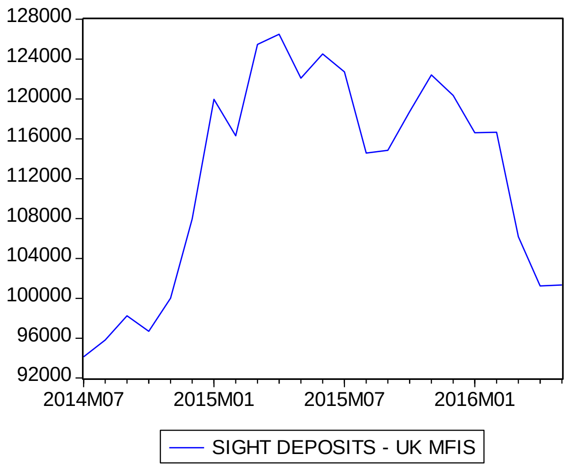

Figure 1: Evolution of Sight Deposits on UK Monetary financial institutions' (excluding central bank) balance sheet between Jun 2014- May 2016, in £ millions.

Source: Bank of England, *Bankstats*, Monetary & Financial Statistics (2016)

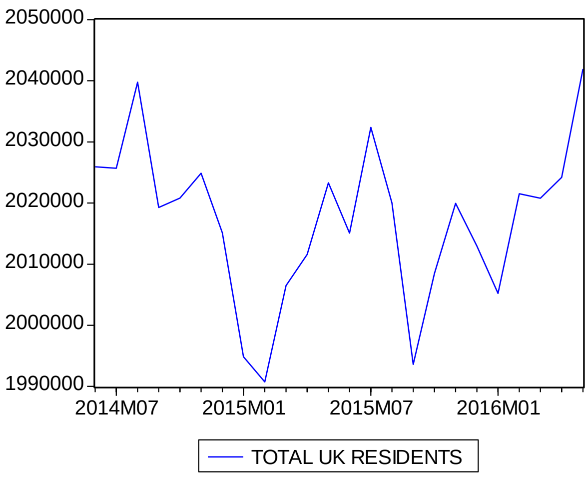

Figure 2: Evolution of Monetary Financial Institutions' deposits from UK residents between Jun 2014- May 2016, in £ millions.

Source: Bank of England, *Bankstats*, Monetary & Financial Statistics (2016)

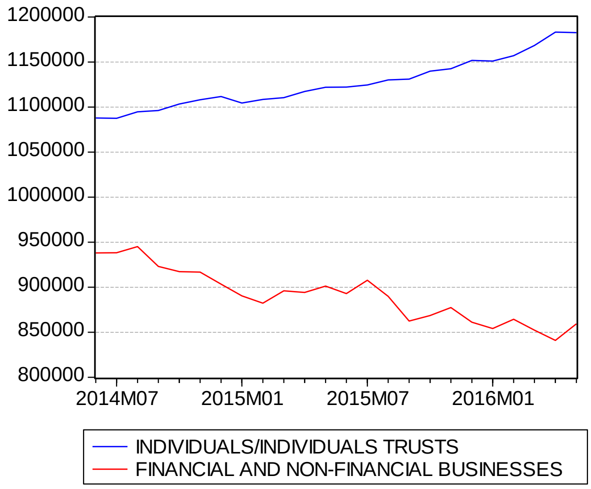

Figure 3: Evolution of Monetary Financial Institutions' deposits from UK industries and individuals between Jun 2014 - May 2016, in £ millions.

Source: Bank of England, *Bankstats*, Monetary & Financial Statistics (2016)

The remainder of this research is organized as follows. Section 2 describes the main economic impacts of '*Brexit*' in the UK economy. In this section our research focus the main conclusions of recent brief survey of literature about the consequences of UK leaving the EU, particularly about the trade and the financial system impact. Section 3 presents the main transmission mechanisms of the '*Brexit*' in the banking system. The goal of the section is presents the main channels of run on deposits, especially in sterling, such as the run to deposits in other currencies (U.S. dollars or euros), virtual coins, deposits in other countries or alternative investments in other economies. Section 4 describe and presents our quantitative model to quantify and forecast the impact of '*Brexit*' in deposits balances in sterling. The model includes the analysis of asymmetric volatility in the currency spot market and consider this extreme volatility in a Holt-Winters method. This research involves an analysis of MFI's sight deposits from UK residents. The fan charts – a technic used by the (BoE) to presents the uncertainty around the main macroeconomic variables – will be used with the extreme conditional and asymmetric volatility in the currency spot market after the '*Brexit*'. Finally, section 5 presents some concluding remarks about '*Brexit*' impacts on deposit balances in the UK and proposals for future research on these themes.

2. Economic Impacts of '*Brexit*' in the UK

To understand the risks of '*Brexit*' for financial system and particularly for MFI's sight deposits it is important list the main economic consequences of leaving the EU project. OECD (2016) studied the economic consequences of '*Brexit*' based on: (i) short-run impacts and (ii) long-run impacts. In a near-term, OECD (2016) suggests a formal exit in late-2018 and new trade negotiations with EU partners over 2019-2023. The longer term involves all economic and trade policies and consequences over 2024-2030. The main predict in the short-run is related to high current account deficit of 7% of Gross Domestic Product (GDP). It results by the possible significant capital outflows and decrease in the inflows to UK. In terms of non-quantified expectations, OECD presents the impact of economic uncertainty on the confidence levels of economic agents and the holding back in several decisions (including spending and other investment decisions). The economic uncertainty also impacts the risk premia and increase the cost of funding for few economic agents. In the currency spot market, an appreciation of other currencies against sterling is expected. In the long-run, the cut in Foreign Direct Investment (FDI) inflows has negative shocks in UK, especially in investment and capital stock. On the other hand, the fiscal savings with the net contributions to the EU budget will have a small impact on the UK economy per year: 0,3% or 0,4% of GDP. The central scenario of OECD presents a fall in 5% of the GDP in 2030 against a remain in the EU. It represent a cost of £3.200 per household in the central scenario. In a worst scenario, the cost of '*Brexit*' would be even higher, at £5.000 per household.

Dhingra et all (2016a) focus their research in the estimating the effects of *'Brexit'* for UK trade and living standards. The authors used two scenarios, one optimistic and another pessimistic. Based on their evaluating model, in the short-run *'Brexit'* has a negative impact in the UK trade (in both scenarios): -1,37% and -2,92% respectively. Dhingra et all (2016a) also evaluated the fiscal benefits and they determined a potential gain of 0,09% and 0.31% for the optimistic and pessimistic scenario. The authors concluded the change in the net income per capita is -1.28% -2.61% respectively (equivalent to -£850 -£1,700 per household). In terms of fiscal benefits, Dhingra et all (2016a) refers *'Brexit'* would not necessarily mean that the UK would no contributions to the EU budget and the authors indicates the Norway example. With a dynamic approach, including the effects of trade on productivity (for example), the authors concluded *'Brexit'* could be about three times larger than the results previously presented.

The same authors (Dhingra et all, 2016b) in another research also concluded that leaving the EU is a dangerous and uncertain move for the UK economy. They used the Costinot and Rodriguez-Clare (2013) approach and achieved identical conclusions in terms of impact on the cost to GDP.

In an economic modeling exercise, pwc (2016) assessed the potential economic impacts of *'Brexit'* under different scenarios: (i) the first scenario where UK negotiates a Free Trade Agreement (FTA) with the EU members over five years and (ii) other scenario where UK negotiates under World Trade Organization (WTO) rules. These scenarios would compares with the remaining in the EU where the potential economic growth is 2,3% per annum, based on historical trend. Pwc (2016) estimates a decrease in the UK GDP in 2020 (around 3% to 5,5%), comparing with a scenario of remaining in the EU membership. The large uncertainty, additional barriers to trade and behavior of labour market after the leaving the EU are the main reasons to the short-term impact in the pwc exercise in both scenarios.

3. The Possible Transmission Mechanisms of *'Brexit'* to MFI's Deposits from UK Residents

When the outcome of the UK's referendum on membership of EU was known, one of biggest concerns was about the banking system, especially bank runs. In this section we will present a possible framework of transmission mechanisms that impacts MFI's deposits in the case of exogenous events (political and economic events, such as *'Brexit'*). This possible framework includes the analysis of several conventional markets – the main financial markets - and other unconventional markets, like the virtual money. Note this possible framework would to be balanced with other safety mechanisms of UK MFI's sight deposits, like the Financial Services Compensation Scheme (FSCS), the own risk characteristics of deposits that partially discourages the deposits withdrawal and the extreme volatility in financial markets.

Based on a brief survey of literature about bank runs, there are two main classes models to explain the potential causes of bank runs (Iyer and Puri, 2007). In accordance with the first class of models, bank runs results from coordination problems among depositors. This class of models believe that bank run occurs due to self-fulfillment of depositors' expectations related the actions of other depositors. The researches of Bryant (1980), Diamond and Dybvig (1983), Postlewaite and Vives (1987), Goldstein and Pauzner (2005) and Rochet and Vives (2005) support this models. On the other hand, there is another class of models that believe bank runs results by asymmetric information among depositors. The asymmetric information includes bank fundamentals and solvency concerns. This class of models has support on the researches of Chari and Jagannathan, (1988), Jacklin and Bhattacharya (1988), Calomiris and Kahn, (1991) and finally Chen (1999).

Despite uncertainty of *'Brexit'* in MFI's deposits and solvency in the banking system, leaving the EU membership would impact self-fulfillment of depositors' expectations. In high uncertain time, MFI's deposits competing with other low risky assets. The present framework to explain possible deposits runs involves: (i) low risky assets from conventional markets and (ii) investments in unconventional markets. In the first class of markets – conventional markets – investors can find (i) other currency spot markets, (ii) MFI's deposits in other currencies and (iii) investments in metal markets. The second class of markets considers unconventional markets, where investors can protect their savings/investments in virtual money. The success of *'bitcoins'* provides a relevant example of virtual money and a very liquidity market.

The transmission mechanism presented incorporates the uncertainty about the future of UK in the Europe and suggest an analysis of conventional and unconventional markets to explain possible deposit runs in the banking system. Indeed, Figures 4, 5, 6, 7 and 8 provides these possibilities of deposit runs in UK. Usually, investments in U.S. dollars are considered low risky. Stability in the monetary policy provides one of the most important reasons, especially for U.S. treasury-bonds investors. Inflows in U.S. currency involves a nominal depreciation of the sterling against the U.S. dollar. Immediately after the announcement of outcome of the UK's referendum, a depreciation of sterling against dollar occurred (Figure 4).

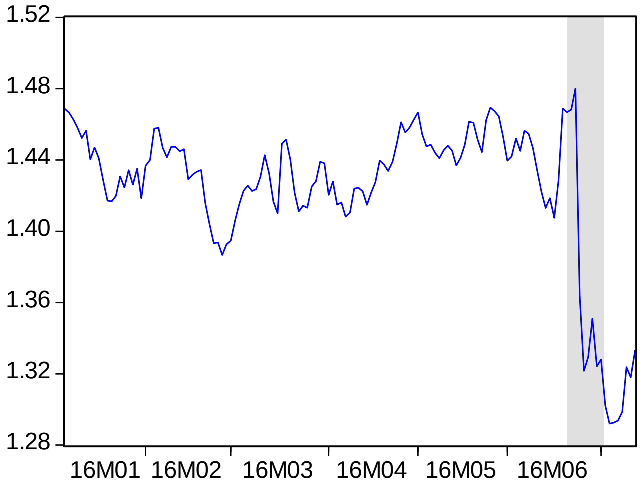

Figure 4: GBP/USD exchange rate in 2016 and the *'Brexit'*.
Source: Federal Reserve Bank of St. Louis (2016).

In parallel, German treasury bonds are also considered to be one of the least risky assets in the financial markets, as well as MFI's deposits in commercial banks in UK with investment grade ratings. Such as the U.S. treasury bonds, German government bonds are a benchmark against which most other investments are compared and there are also stability in the monetary policy of the European Central Bank (ECB). These facts allows an appreciation of the european currency against the sterling and the Figure 5 provides the depreciation in the sterling immediately after the *'Brexit'*.

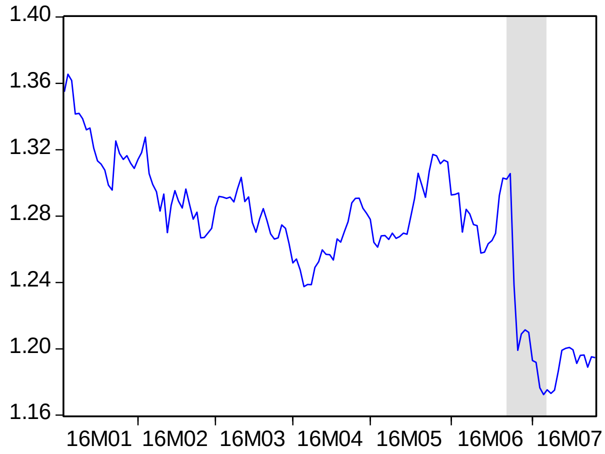

Figure 5: Evolution of GBP/EUR exchange rate in 2016 and the *'Brexit'*.
Source: European Central Bank (2016).

On the other hand, the stock market in UK – the FTSE 100 – registered the opposite movement. Despite the devaluation on the stock market in the days after the *'Brexit', the* FTSE 100 appreciated on the next days. The hedging against the *'Brexit'*(like the short selling in the stock market, for example) and the impossibility of active strategies by some institutional investors provides relevant arguments in favor of no devaluation of the FTSE 100 (Figure 6).

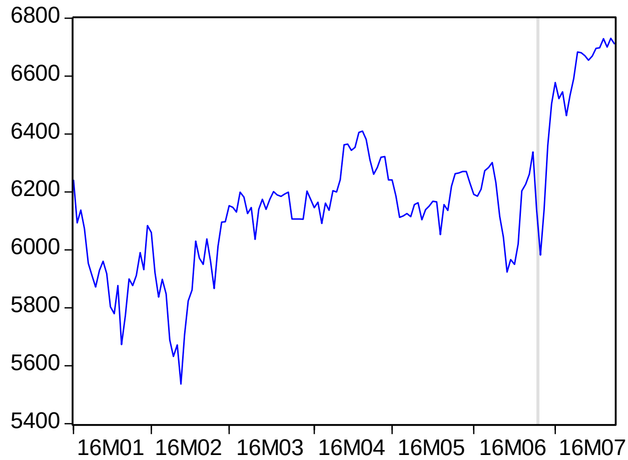

Figure 6: FTSE 100 in 2016 and the *'Brexit'*.
Source: London Stock Exchange (2016).

One month before the *'Brexit'*, virtual coins registered a demand rise in the on-line markets. It was not the first time that virtual coins appreciated with uncertainty times, where the crisis in the Cyprus financial system provides another relevant example. The same rationale is applicable for some metals, such as the appreciation of Gold Ounce to GBP (Figure 7 and 8).

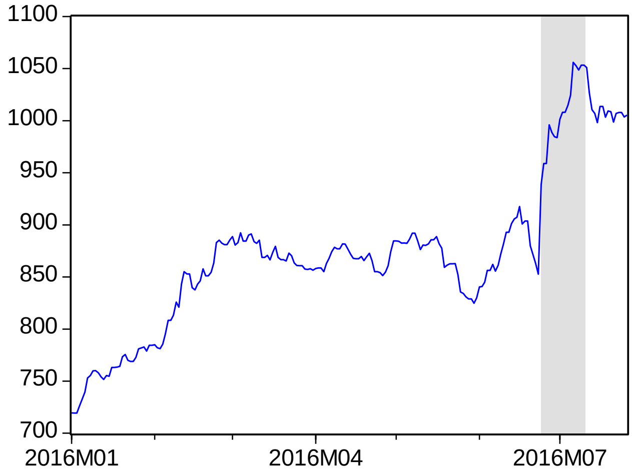

Figure 7: Gold Ounce to GBP in 2016 and the *'Brexit'*.
Source: Bloomberg (2016).

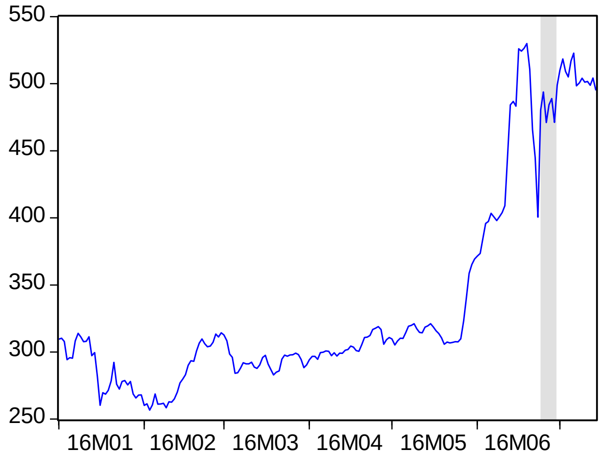

Figure 8: Bitcoin to GBP in 2016 and the *'Brexit'*.
Source: Over the Counter Market (2016).

All this transmission channels previously presented affects the benefits of deposits withdrawal. When the uncertain rise (in some events like *'Brexit'*, for exemple) investors would reduce the risk exposure and seek another investments in assets with risk free remuneration or low returns. In this scenario, investors has marginal benefits to deposits withdrawal.

However, as previously mentioned, there are safety mechanisms in the financial system. In the specific case of the UK, depositors has the Deposit Protection Scheme (DPS) by the FSCS, where their deposits are safe up to the limit of £75,000 per person, per authorized bank or building society. In extreme cases, where the banking system brings out no liquidity to satisfy their responsibilities to depositors, the FSCS would pay compensation to them. This scheme reveals an important mechanism to hold the MFI' sight deposits because the risk exposure is complete or partially hedged or mitigated. In the presented framework, this scheme impacts the cost of deposits withdrawal' curve, particularly when the uncertain is huge (Figure 10).

Secondly, there is another feature that contributes to hold deposits in UK MFI's. To understand it, an analysis to risk characteristics of deposits would to be considered. Deposits are investments with high liquidity (usually depositors can withdrawal long-term deposits to immediately cash positions) and low default risk – depending on the rating risk of the MFI where the deposit was done. However, sight deposits has market risk and generally deposits anticipations implies penalties in accrued interest. Thus, market risk on deposits would (i) minimize the deposits withdrawal or (ii) create a lag in the run to deposits. Typically, the market risk previously mentioned would be balanced with the default risk. In a hypothetical scenario of banking crisis, systematic risk or run to banks, the default risk prevails over the risk loose the accrued interests. Therefore, the market risk also would to be considered in the cost of deposits withdrawal' curve.

Finally, the high and extreme volatility in financial markets would suggest investors to hold sight deposits or increase them to minimize the risk exposure of their own investment portfolios or savings. For this topic, we suggest an analysis on the volatility of stock market and currency market, as shows Figure 9. Indeed, *'Brexit'* seems impacts on the volatility in these markets and probably it affects the increase in MFI's deposits. The main reason for this possibility is the usual risk free characteristic of the most deposits, especially with the deposit protection scheme.

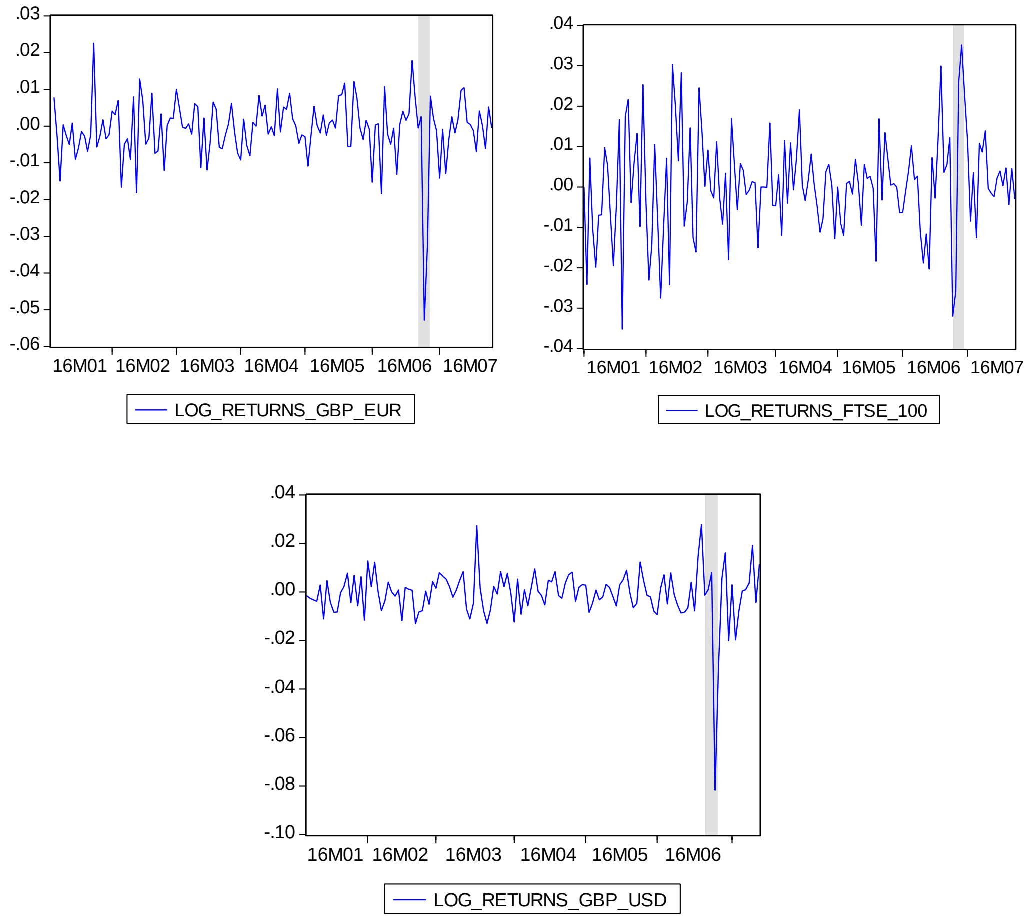

Figure 9: Volatility in the stock (FTSE100) and currency spot market (GBP/USD and GBP/EUR) and the *'Brexit'*.

The Marshallian scheme presented describes a synthetic approach where listed which factors affects the cost and benefits for deposits withdrawal. In the case of benefits, the transmission mechanisms incorporates the deposits outflows to conventional and unconventional markets. In opposite, the framework suggests a comparison with the scheme to protect depositors, the market risk on them and especially the uncertainty in the financial markets. On the next section we present a forecast model to MFI's sight deposits in UK based on auto-regressive methods with the implied volatility in the financial markets to include in the fan chart.

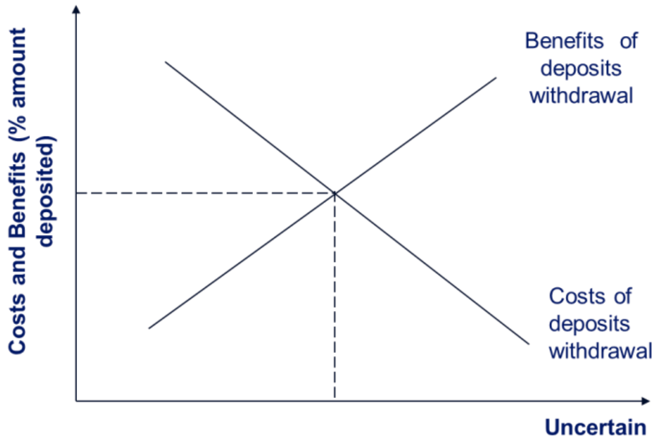

Figure 10: Decision of withdrawal or hold MFI's deposits.

4. The Deposit Balances based on Holt Method with Structural Break using Implied Asymmetric Volatility

In this section we will use a Holt method with structural break to forecast the sight deposits in UK MFI's. The Holt method incorporates the structural break in the currency spot market, especially in the GBP/USD and GBP/EUR market. In the final of the section the mentioned model is extended to a forecast with a fan chart of sight deposits in UK based on implied volatility in the currency market.

4.1. Asymmetric Conditional Volatility Models in Currency Markets

To modeling the volatility in financial time series, Bollerslev (1986) suggested a GARCH model. These models are a generalized from Autoregressive conditional heteroskedastic (ARCH) class of models and defines conditional variance as a linear function of squared past returns and lagged conditional variances. Let ε_t be a series of innovations and r_t a series of returns (or log-returns). If we assumed that series are to be independent identically distributed (i.i.d.), the GARCH (p,q) model for the financial time series' returns, r_t is defined as follows:

$$r_t = \sigma_t \varepsilon_t \quad (4.1)$$

$$\sigma_t^2 = \omega + \alpha_j (L) \varepsilon_t^2 + \beta i (L) \sigma_t^2 \quad (4.2)$$

where σ_t^2 is the variance of r_t given information at time t, $\alpha_j (L) = \alpha_1 L + \ldots + \alpha_q L^q$, $\alpha_j (L) = \beta_1 L + \ldots + \beta_p L^p$ and p,q = 0, 1... are integers, $\omega > 0$, $\alpha_j \geq 0$, $\beta_i \geq 0$, i = 1, ...p, j = 1, ...q, are model parameters.

Despite these models have been proved to be successful for describes the dependence structure in conditional variances, they presents few limitations. One of the main disadvantages of GARCH models is the symmetric response of volatility to negative and positive shocks and there are a large survey of literature that support negative shocks increase the volatility in financial time series and asymmetric volatility.

In order to attend the stylized facts of asymmetric volatility in financial time series, several alternative models have been proposed. Nelson (1991) provides an example of alternative models with the exponential GARCH (EGARCH). The author specifies the conditional variance in logarithmic form and takes the asymmetry into account while keeping the linear function form of conditional variance. In 1993, Rabemananjara and Zakoian developed the threshold ARCH class of model (TARCH). Using the TARCH (p,q) with p,q = 1, the TARCH (1,1) is defined as follows:

$$\sigma_t^2 = \omega + \alpha\, \varepsilon^2_{t-1} + \beta\, \sigma^2_{t-1} + \delta\, \varepsilon^2_{t-1} d_{t-1} \quad (4.3)$$

where d_t=1if ε_t is negative and 0 otherwise. The TARCH (p,q) model, where the TARCH (1,1) is included, allows analyze the asymmetric effect and the leverage effect. In this GARCH-family model, volatility tends to rise with the "bad news" ($\varepsilon_{t-1} < 0$) and to fall with the "good news" ($\varepsilon_{t-1} > 0$). To test the asymmetric effect in a financial time series model, TARCH provides an individual test hypothesis to δ, under the null hypothesis of no significance asymmetric effect. The hypothesis test to the asymmetric effect can be defined as follows:

$$H_0: \delta = 0 \quad (4.4)$$
$$H_1: \delta \neq 0$$

and a rejection of the null hypothesis describes the significance of the asymmetric effect. Thus, TARCH models specifies the variance in different responses according to negative innovations (bad news) or positive innovations (good news).

This GARCH-family model – TARCH - will be used in our article to modeling the asymmetric conditional variance using the currency spot market for *sterling*, particularly the GBP/USD spot market and the GBP/EUR spot market. To test the conditional asymmetric volatility we consider the *'Brexit'* as a negative new.

In terms of data, we used the historical GPB/USD spot market and the historical GBP/EUR spot data from Federal Reserve Bank of St. Louis and ECB, respectively (see Figure 4 and Figure 5). The variability in these currencies spot markets is captured by measuring variability in terms of returns rather than absolute price movements. The mentioned returns are determined as the natural logarithm of the ratio of the current currency spot quote over last the last currency spot quote and can be defined as follows:

$$\mathrm{r}t = \log\left(\frac{price\ t}{price\ t-1}\right) \quad (4.5)$$

To estimate the volatilities models to the GBP/USD currency spot market we used a simple ARCH (1), a GARCH (1,1) and a TARCH (1,1), as shows Figure 11. Other ARCH(q) class models was tested but the results do not shows statistical significant parameters. To evaluate the best fit solution to modeling the volatility in this market two information criterions was used: (i) the Akaike Information Criterion (AIC) and the (ii) Schwarz Bayesian Criterion (SBC). Bayesian methodology often require computationally intensive methods and techniques (such as Markov chain Monte Carlo, for example) to calculate model likelihoods. However, Bayes factor calculations requires some complex techniques and the Schwarz Bayesian Criterion (or Bayesian Information Criterion) offers more simplest approach (Schwarz, 1978) and can be defined as follows:

$$BIC = -2l + k \log n \quad (4.6)$$

where n is the sample size, k is the number of estimable parameter. Schwarz (1978) developed the SBC as an approximation to the log marginal likelihood of a model. On the other hand, Akaike (1973) have been proposed other information criterion. The model-selection proposed takes in account with a penalty term, as defined as follows:

$$AIC = -2 \log L(\theta) + 2k \quad (4.7)$$

where L(θ) is the maximized likelihood function, and k is the number of free parameters in the model. The main difference between these information criterion is BIC tends to select models that are less complex (more parsimonious) than Bayes factors. The survey of literature shows if $n > 8$ the SBC selects simpler models than the AIC. For both information criterion the model with minimum AIC and minimum SBC value is chosen as the best model to fit the time series data.

For the GBP/USD currency spot market, both models are statistical significant with 95% of confidence and the individual estimated coefficients are also significant (excluding the estimation to ω in the TARCH model). To test the asymmetric conditional volatility the test hypothesis in (4.4) shows TARCH (1,1) captures the asymmetric effect. The result of this test is aligned with the initial expectation of asymmetric volatility in the currency spot market. *'Brexit'* provides an relevant example to include in the "bad news" that affects financial markets. Using both information criterion, AIC and SBC are consistent and the model to be choosen is the TARCH (1,1).

GBP/USD Returns

		Coefficient	Std. Error	z-Statistic	p-value	AIC	SBC
TARCH(1,1)	ω	9.66E-06	7.42E-06	1.301.837	0.1930	-5.904.302	-5.817.374
	α	0.537552	0.177053	3.036.101	0.0024		
	δ	-0.517723	0.158517	-3.266.048	0.0011		
	β	0.773793	0.090599	8.540.864	0.0000		
GARCH(1,1)	ω	3.07E-06	5.23E-06	0.586923	0.5573	-5.813.099	-5.747.903
	α	0.381981	0.123512	3.092.656	0.0020		
	β	0.746422	0.079452	9.394.643	0.0000		
ARCH(1)	ω	8.94E-05	2.16E-05	4.133.295	0.0000	-5.624.403	-5.580.939
	α	1.599.969	0.193995	8.247.468	0.0000		

Figure 11: GARCH-family estimation to modeling GBP/USD log returns.

The results for the GBP/EUR currency spot market are similar. In this market, we only compares a TARCH (1,1) with a GARCH (1,1) due to statistical insignificant parameters under the ARCH(q). In the GARCH (1,1) the *z*-statistic seems lower value what could indicate statistical significant with a decreased confidence levels. The asymmetric test, under the null hypothesis of no asymmetric effects in the volatility, reveals there are asymmetric effects (*p-value* permits the rejection of the null hypothesis).

This conclusion is also consistent with the previous model. Once again, the AIC and the SBC reveals similar information criterion with a reduce advantage to TARCH (1,1), as well as the GBP/USD currency market. The results are synthetized in the Figure below.

GBP/EUR Returns

		Coefficient	Std. Error	z-Statistic	p-value	AIC	SBC
TARCH(1,1)	ω	4.71E-07	6.05E-06	0.077937	0.9379	-6.247.908	-6.165.413
	α	0.213363	0.052742	4.045.399	0.0001		
	δ	-0.212955	0.051599	-4.127.077	0.0000		
	β	0.925449	0.072367	1.278.828	0.0000		
GARCH(1,1)	ω	3.13E-05	4.61E-05	0.679515	0.4968	-6.200.917	-6.139.046
	α	0.049263	0.037821	1.302.529	0.1927		
	β	0.679981	0.404914	1.679.321	0.0931		

Figure 12: GARCH-family estimation to modeling GBP/EUR log returns.

The conditional standard deviation (where conditional variance can be derived) obtained from the selected model based on AIC and SBC – the TARCH (1,1) – from GBP/USD and GBP/EUR log-returns is represented in Figure 13 and shows the rise in the conditional standard deviation during the outcome of the UK's referendum on EU.

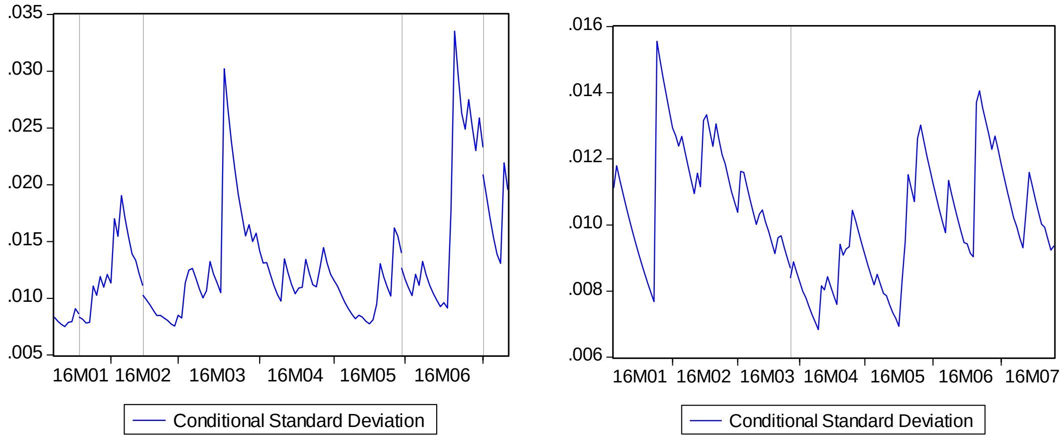

Figure 13: Conditional Standard Deviation from TARCH(1,1) model using GBP/USD (left) and GBP/EUR (right)

On the Appendix 2 the correlograms of standardized residuals squared for the TARCH (1,1) shows the correlograms represents a white noise process. These behaviors on the correlograms reveals the selected model– TARCH (1,1) – has fitted the volatility in the mentioned markets. The analysis to correlograms of standardized residuals squared could to be complemented with the ARCH-LM test. The results from the analysis of asymmetric conditional variance will be used in the Holt method with Structural Break, suggested in the next sub-section.

4.2. The Holt Method with Structural Break applied to Sight Deposits in UK and Forecasting with Fan Charts

In this section we will present the Holt forecasting method with structural break to sight deposits. The Figure 14 shows the historical evolution of sight deposits in UK MFI's (amounts outstanding of sterling liabilities) since 2010. In accordance with *Bankstats* of BoE, due to improvements in reporting at one institution, the amounts outstanding decreased by £85bn. This effect has been adjusted out of the flows for January 2014. On May 2016 – the month immediately before the outcome of the UK's referendum on membership of the UE – the sight deposits in the MFI's balance sheet (excluding the central bank) was £95,23bn. The present research will use the short-term nature of sight deposits in UK MFI's and apply the probability of the currency spot market returns reaches the thresholds of the negative returns during the next two days after the *'Brexit'*.

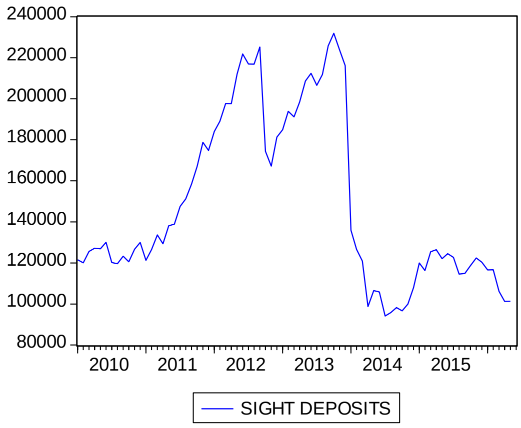

Figure 14: Sight Deposits from UK MFI's Balance Sheet (excluding central bank).

To achieve the goal of forecasting the sight deposits, we considered the traditional Holt method. Firstly, suppose we have a time series, y_t, which is observed at t=1,2,3,…,T. The exponential smoothing methodology will compute the smoothed series from y_t, $\tilde{y}_t$ in accordance with a recursive expression as defined as follows:

$$\tilde{y}_t = \alpha\, yt + (1 - \alpha)\, \tilde{y}_{t-1} \qquad (5.1)$$

where α is a smoothing parameter that take values between 0 and 1. Note this smoothing parameter also regulates the degree of smoothing. For trended time series (such as sight deposits if we consider the exclusion of improvements in reporting on the BoE *Bankstats*), Holt (1959) developed another model that includes a local trend variable, B_t:

$$\tilde{y}_t = \alpha_1\, yt + (1 - \alpha)\, (\tilde{y}_{t-1} + B_{t-1}) \qquad (5.2)$$

$$\tilde{B}_t = \beta_1\, (\tilde{y}_t - \tilde{y}_{t-1}) + (1 - \beta_1)\, B_{t-1} \qquad (5.3)$$

For Holt's method ((5.2) and (5.3)), an h-step-ahead forecast of y_t is obtained as defined as follows:

$$\tilde{y}_{t+h|t} = \tilde{y}_t + h\, B_t \qquad (5.4)$$

Based on the estimation of the Holt method, the estimation output is represented in the Figure 15. The end of period levels to the mean represent the last value of sight deposits in UK MFI's balance sheet (Appendix 3). The Sum of Squared Residuals (SSR) is the deviations predicted from actual empirical values of data and the Root Mean Squared Error (RMSE) is another metric to quantify the forecasting error, based on the differences between values (sample and population values) predicted by a model (the Holt method) or an estimator and the values observed (in this case, sight deposits in UK). The estimations for the parameters α and β are 1 and 0,02 respectively. The α estimation represents no smoothing while the β estimation represents a very high smoot. This estimation is consistent with de nature of the modeled time serie.

Parameters:	
Alfa	1
Beta	0,02
Sum of Squared Residuals	1.30E+10
Root Mean Squared Error	13.003,84
End of Period Levels:	
Mean	101.341
Trend	-346,9959

Figure 15: Estimation of traditional Holt-method.

However, the Holt method estimated and previously mentioned do not include the structural break in the currency market. As represented in Figure 16 and Figure 17, a parametric function (although there is no evidence to support the normal distribution of returns as shows the *Jarque-Bera* test and their *p-value*) is not suitable to properly model the currency quotes behavior in the tails, underestimating the extreme events, where we can consider the 'Brexit'. Therefore, Rosenblatt (1956) developed non-parametric data fitting with kernel functions. To support the application kernel distributions for several risks (such as the market risk), Dimakos and Aas (2003) applied this non-parametric technique to modeling the total economic capital required in the banking system. In our research we follow the kernel approach, based on a Gaussian kernel to fit the returns of each sterling currency spot market: the GBP/EUR and the GBP/USD .The kernel fitting result obtained from both series are shown in Figure 16 and 17.

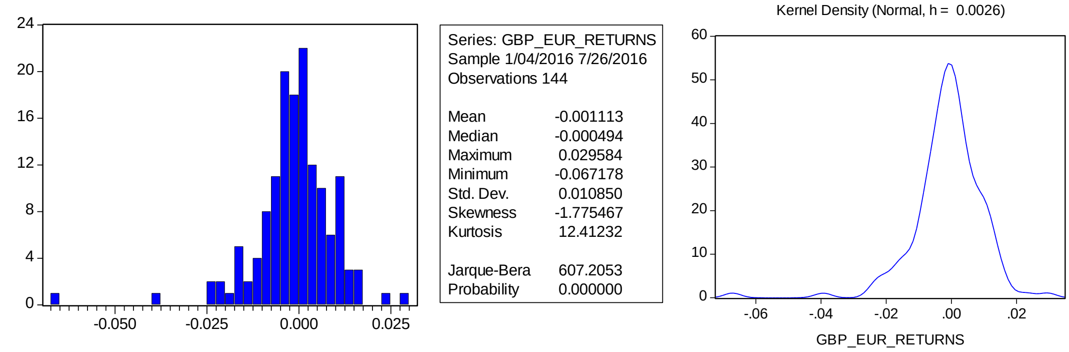

Figure 16: Histogram of GBP/EUR returns' and Gaussian Kernel fitting .

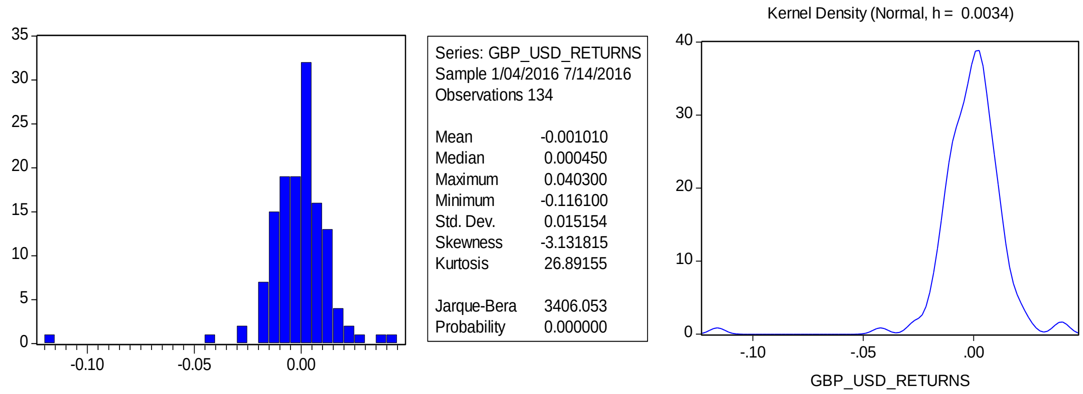

Figure 17: Histogram of GBP/USD returns' and Gaussian Kernel fitting .

Based on the histogram of returns for the GBP/EUR and GBP/USD, the implied probability of both returns reaches the thresholds of the negative returns during the next two days after the *'Brexit'* is around 5% with a confidence level of 95% (or 5% of significance level). These probability will be considered in the Holt forecasting method to give the structural break in the UK MFI's sight deposits. With the previously presented expressions in this section, we can compute the Holt method with structural break. The technique we recommend in this paper is the introduction of a "cleaned" version of y^*_t.

This methodology was firstly used by Gelper et all (2010). Introducing the "cleaned" version in the previously expressions, we obtain:

$$\tilde{y}_t = \alpha\, y^*_t + (1 - \alpha)\ \tilde{y}_{t-1} \qquad (5.5)$$

$$\tilde{y}_t = \alpha_1\, y^*_t + (1 - \alpha)\ (\ \tilde{y}_{t-1} + B_{t-1}) \qquad (5.6)$$

$$\tilde{B}_t = \beta_1\ (\ \tilde{y}_t - \tilde{y}_{t-1}) + (1 - \beta_1)\ B_{t-1} \qquad (5.7)$$

In the proposed "cleaned" version to y_t, y^*_t ,it can be expressed by:

$$y* = \begin{cases} y\,(1 - P),\ i(time > May\ 2016) \\ y\,, otherwise \end{cases} \qquad (5.8)$$

where i(time > May 2016) is a dummy variable to obtain the effect of *'Brexit' and P* is the probability of currency spot market of sterling decrease to unusual historical quotes (the average of GBP/EUR and GBP/USD between 2015 and 2016). Parallely, we also used the information of the histogram of returns into a fan chart. The fan chart includes the forecast for sight deposits between June 2016 and December 2016 and it is represented in the Figure 18. The obtained results shows a immediately decrease of sight deposits in 5% comparing with the data of the last month from *Bankstats*/BoE (May 2016).

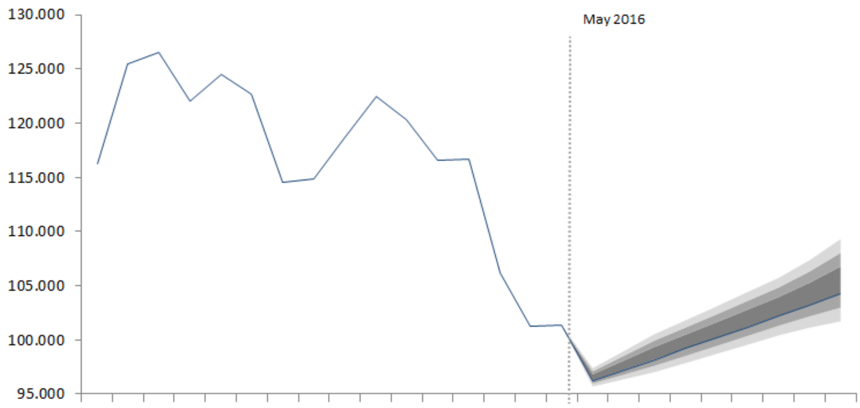

Figure 18: Forecast of Sight Deposits in UK with Fan Chart between June 2016 and December 2016, in £ millions.

5. Concluding Remarks

The present research concludes that *'Brexit'* will impact immediately a decrease in sight deposits (on the MFI's balance sheet, excluding the central bank) around 5%. The forecast model previously present in this research contains a structural break in sight deposits based on the probability of currency spot market of sterling decrease to unusual historical quotes.

In fact, over the last few days, the *Bankstats*[1] of *Bank of England* (BoE) published an update to June 2016, including the Monetary & Financial Statistics and the MFI' (excluding central bank) balance sheet (amounts outstanding of *sterling* liabilities). The data published by the BoE shows a decrease of sight deposits around 6,02% in the UK MFIs, which is consistent with the forecast model (Appendix 3). However, the impact of '*Brexit*' in deposits includes other deposits classes, such as sight deposits of intragroup banks, the sight deposits from UK public sector and other time deposits inclusive. The sight deposits includes the intragroup banks deposits, which also register a decrease against the last month (May 2016) around 7,72% (Appendix 3). On the other hand, the sight deposits from UK public sector seems no relevant effects of '*Brexit*' in terms of balance sheet. Comparing with the other classes of deposits (both from liabilities on the MFI's balance sheet), time deposits register a significant increase of 16,95% against May 2016. For this record on the MFI's balance sheet in June 2016, the main contribution is assigned to time deposits among intragroup banks (which register a rise around 17,61% against May 2016).

The assumptions in this paper assumes that UK MFI's sight deposits was affected by the nominal depreciation on the *sterling* spot market. Furthermore, the specific

[1] http://www.bankofengland.co.uk/statistics/Pages/bankstats/2016/jun.aspx

transmission proposed in the research from the currency spot market to sight deposits is related to the short-run nature of this class of deposits in the balance sheet of MFIs. However, the liabilities on the MFI's balance sheet increased what is also consistent with the framework previously mentioned in section 3. Probably, the main transmission mechanism to avoid deposits withdrawal was the DPS/FSCS. The high confidence level of UK residents and non-residents in the UK banking system would provide an additional reason to the stability in the UK financial system.

Future research, given these promising results, would to be compared with a Vector Autoregressive (VAR) model. We suggest for future researches a VAR model to analyze the impulse response functions of sight deposits (or other class of deposits in the MFI's balance sheets) to extreme changes in the fundamentals of the currency spot market of sterling comparing with other currencies (or other unconventional markets, described in section 3). In the specific theme of *'Brexit'*, a dummy variable would to be used in the VAR mentioned that represents the days immediately after the referendum in UK.

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Appendices:

Appendix 1: Industrial analysis of MFI deposits from UK residents between Jun14-May16, in £ millions.

	Agriculture, hunting and forestry	Fishing	Mining and quarrying	Manufacturing	Electricity, gas and water supply	Construction	Wholesale and retail trade	Accommodation and food service activities	Transport, storage and communication	Real State	Public administration and defence	Education	Human health and social work	community service	Financial intermediation	Insurance companies & pension funds	Activities auxiliary to financial intermediation	**financial and non-financial businesses**	**individuals trusts**	**UK residents**
2014 jun	5.673	289	5.222	30.725	8.010	28.570	32.095	7.612	32.472	124.101	31.450	19.062	16.845	27.537	353.395	50.311	164.707	**938.077**	**1.087.856**	**2.025.932**
jul	5.542	259	4.500	30.965	7.908	27.471	31.949	8.408	33.607	125.013	34.991	18.048	16.920	27.538	348.090	48.466	168.584	**938.261**	**1.087.435**	**2.025.696**
ago	5.518	227	4.914	30.335	8.238	27.540	33.580	8.145	32.159	122.014	37.323	17.742	17.480	27.793	344.440	48.834	178.813	**945.094**	**1.094.664**	**2.039.757**
set	5.552	229	4.674	31.592	8.167	27.680	33.348	8.338	33.261	124.774	29.811	18.812	18.074	28.020	342.958	51.532	156.311	**923.134**	**1.096.138**	**2.019.272**
out	5.585	232	4.607	31.873	8.200	28.220	34.133	7.534	33.944	123.758	33.767	19.161	18.590	27.903	320.791	48.374	170.675	**917.346**	**1.103.466**	**2.020.812**
nov	5.589	269	5.468	32.294	8.318	28.632	35.161	7.380	33.810	124.974	33.571	18.457	18.611	27.657	316.636	48.914	171.014	**916.756**	**1.108.105**	**2.024.860**
dez	6.485	258	5.803	33.626	9.036	30.086	40.393	7.443	35.175	123.116	28.673	17.851	18.666	27.541	317.671	48.626	152.947	**903.396**	**1.111.740**	**2.015.136**
2015 jan	6.266	252	4.832	31.785	8.523	28.392	38.213	7.066	35.679	122.308	31.007	18.731	18.579	27.979	294.151	53.802	162.906	**890.470**	**1.104.399**	**1.994.868**
fev	6.183	260	5.025	31.587	8.563	28.487	37.363	6.877	35.260	123.251	30.979	18.844	18.456	27.891	284.682	51.776	166.841	**882.322**	**1.108.421**	**1.990.744**
mar	6.070	258	5.820	32.393	9.575	29.985	38.405	7.013	35.843	131.593	29.261	17.925	18.694	28.170	291.171	54.466	159.379	**896.023**	**1.110.467**	**2.006.490**
abr	5.931	240	5.790	32.693	9.200	29.448	33.863	7.513	36.545	128.689	34.892	18.829	18.699	28.250	285.209	55.133	163.304	**894.228**	**1.117.355**	**2.011.582**
mai	5.873	238	6.300	32.391	9.859	29.371	33.834	7.641	36.936	129.118	34.007	20.617	18.938	28.460	287.452	51.751	168.610	**901.395**	**1.121.912**	**2.023.307**
jun	5.791	251	6.176	34.247	10.286	30.692	34.598	7.531	35.063	134.168	34.344	19.923	19.222	28.633	285.976	50.816	155.251	**892.968**	**1.122.093**	**2.015.062**
jul	5.782	238	6.793	34.177	9.650	30.385	34.590	7.866	35.214	135.962	37.486	19.096	19.138	28.970	283.172	48.367	170.923	**907.809**	**1.124.569**	**2.032.378**
ago	5.815	236	6.872	34.250	9.842	30.850	34.321	7.968	34.633	133.932	38.481	18.835	19.008	28.945	266.390	46.681	172.917	**889.976**	**1.130.038**	**2.020.013**
set	5.862	243	8.991	35.569	9.781	30.789	34.928	8.431	35.211	138.272	29.504	19.677	18.981	28.884	260.523	46.942	149.997	**862.584**	**1.131.035**	**1.993.619**
out	5.795	234	9.642	36.296	9.159	31.490	36.908	8.408	36.594	136.763	30.092	20.533	19.270	28.723	257.447	45.501	155.745	**868.599**	**1.139.888**	**2.008.487**
nov	5.840	245	11.127	36.518	9.641	32.159	37.237	8.409	36.782	140.383	31.109	19.388	19.521	28.478	254.777	45.714	160.159	**877.488**	**1.142.458**	**2.019.946**
dez	6.083	250	9.573	38.756	10.207	33.671	40.186	8.416	36.257	137.628	31.112	18.507	19.538	28.493	256.066	44.960	141.464	**861.167**	**1.151.799**	**2.012.966**
2016 jan	6.225	239	10.389	37.392	8.836	31.590	35.892	7.881	36.563	136.526	30.361	19.768	19.216	29.179	247.348	46.835	149.974	**854.213**	**1.151.007**	**2.005.221**
fev	6.201	260	3.508	37.068	9.450	31.580	37.288	7.945	39.478	137.273	28.983	20.180	19.466	29.426	248.455	46.757	161.202	**864.521**	**1.156.985**	**2.021.506**
mar	6.160	267	3.208	37.290	10.455	32.705	36.786	8.325	39.868	148.016	25.512	18.926	19.470	29.246	245.557	43.948	146.687	**852.426**	**1.168.353**	**2.020.779**
abr	6.160	259	2.918	36.244	9.809	32.422	36.363	7.914	37.837	137.682	33.478	20.075	19.623	29.236	238.839	42.635	149.481	**840.973**	**1.183.216**	**2.024.189**
mai	6.178	263	2.803	36.657	10.475	32.503	38.205	8.396	37.978	138.993	32.956	21.997	19.870	29.189	239.979	42.233	160.699	**859.372**	**1.182.546**	**2.041.918**

Source: Bank of England, *Bankstats*, Monetary & Financial Statistics (2016)

Appendix 2: Correlogram of Standardized Residuals Squared of GBP/EUR (left) and GBP/USD (right).

Sample: 1/06/2016 7/14/2016
Included observations: 133

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.020	0.020	0.0545	0.815
		2	-0.055	-0.056	0.4750	0.789
		3	-0.052	-0.050	0.8465	0.838
		4	0.145	0.145	3.7856	0.436
		5	0.097	0.088	5.1121	0.402
		6	0.006	0.015	5.1165	0.529
		7	-0.040	-0.017	5.3407	0.618
		8	-0.030	-0.041	5.4674	0.707
		9	0.004	-0.025	5.4693	0.792
		10	-0.005	-0.023	5.4733	0.857
		11	0.021	0.025	5.5391	0.902
		12	-0.036	-0.024	5.7333	0.929
		13	0.017	0.030	5.7790	0.954
		14	0.003	0.008	5.7803	0.972
		15	-0.010	-0.018	5.7970	0.983
		16	0.017	0.023	5.8398	0.990
		17	0.049	0.047	6.2170	0.992
		18	0.056	0.053	6.7111	0.992
		19	-0.020	-0.013	6.7751	0.995
		20	0.003	0.009	6.7765	0.997
		21	-0.010	-0.025	6.7937	0.999
		22	0.028	0.000	6.9199	0.999
		23	0.007	0.003	6.9283	0.999
		24	-0.017	-0.016	6.9784	1.000
		25	-0.017	-0.003	7.0240	1.000
		26	-0.025	-0.023	7.1263	1.000
		27	0.016	0.011	7.1681	1.000
		28	0.007	0.008	7.1771	1.000
		29	-0.012	-0.008	7.2005	1.000
		30	-0.003	0.013	7.2016	1.000
		31	-0.010	-0.014	7.2182	1.000
		32	0.016	0.014	7.2636	1.000
		33	0.034	0.030	7.4691	1.000
		34	-0.003	-0.009	7.4708	1.000
		35	-0.010	-0.007	7.4894	1.000

Sample: 1/05/2016 7/26/2016
Included observations: 144

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.161	0.161	3.8175	0.051
		2	-0.063	-0.092	4.4119	0.110
		3	-0.065	-0.040	5.0416	0.169
		4	0.088	0.105	6.2170	0.184
		5	0.057	0.017	6.7083	0.243
		6	-0.040	-0.045	6.9527	0.325
		7	-0.057	-0.027	7.4491	0.384
		8	-0.078	-0.077	8.3913	0.396
		9	0.042	0.053	8.6638	0.469
		10	-0.028	-0.054	8.7848	0.553
		11	-0.026	-0.006	8.8892	0.632
		12	-0.038	-0.017	9.1164	0.693
		13	0.028	0.026	9.2440	0.754
		14	0.176	0.167	14.242	0.432
		15	0.023	-0.034	14.329	0.501
		16	-0.045	-0.022	14.656	0.550
		17	0.019	0.058	14.718	0.616
		18	-0.023	-0.095	14.807	0.675
		19	-0.018	-0.006	14.859	0.732
		20	-0.027	-0.009	14.987	0.777
		21	-0.031	-0.030	15.153	0.815
		22	-0.006	0.033	15.159	0.855
		23	0.023	0.005	15.254	0.885
		24	0.002	0.009	15.255	0.913
		25	0.007	0.029	15.264	0.935
		26	-0.010	-0.029	15.283	0.952
		27	0.019	0.027	15.349	0.964
		28	-0.002	-0.055	15.350	0.975
		29	-0.006	-0.002	15.357	0.982
		30	-0.011	0.009	15.378	0.987
		31	0.003	-0.024	15.380	0.991
		32	-0.010	0.017	15.397	0.994
		33	0.007	0.025	15.406	0.996
		34	0.013	0.001	15.439	0.997
		35	0.021	0.047	15.523	0.998

Appendix 3: Sight Deposits in Monetary financial institutions' (excluding central bank) balance sheet, including the '*Brexit'* (June 2016)

	Sight deposits				
	UK MFIs	of which intragroup banks	UK public sector	Other UK residents	Non-residents
2014 jul	94.126	79.727	15.164	1.105.619	145.022
ago	95.817	81.188	14.227	1.112.259	140.505
set	98.245	83.644	13.938	1.126.047	146.254
out	96.691	82.111	14.560	1.123.571	144.177
nov	100.007	85.192	13.940	1.135.457	145.187
dez	107.959	93.751	14.227	1.147.349	150.731
2015 jan	119.954	102.936	15.486	1.145.124	146.519
fev	116.303	100.489	14.678	1.144.217	142.548
mar	125.471	108.555	13.851	1.174.246	158.621
abr	126.482	110.219	15.305	1.163.124	143.921
mai	122.076	106.802	14.627	1.168.681	144.400
jun	124.515	110.150	14.111	1.187.258	149.164
jul	122.708	105.865	15.519	1.189.927	146.148
ago	114.575	96.536	15.292	1.180.716	150.071
set	114.839	97.975	15.160	1.198.656	158.909
out	118.714	102.816	15.570	1.204.978	143.841
nov	122.413	105.979	15.351	1.215.760	150.548
dez	120.345	106.354	15.880	1.219.920	158.148
2016 jan	116.615	101.441	16.617	1.218.570	158.484
fev	116.650	100.824	16.012	1.237.202	158.086
mar	106.174	89.056	15.189	1.264.267	166.282
abr	101.243	85.379	16.398	1.249.182	161.550
mai	101.341	85.893	15.747	1.266.291	152.548
jun	95.237	79.259	15.764	1.294.533	166.716

Source: Bank of England, *Bankstats*, Monetary & Financial Statistics (2016)