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Political uncertainty and sentiment: Evidence from the impact of Brexit on financial markets

Abstract

This paper investigates whether the impact of Brexit on financial markets is consistent with rational asset pricing models using 34 financial indices. Our results indicate that, whilst Brexit events affect both the risk and returns of stocks, the returns on event days are largely justified by the risk and the risk premium on those days. Our results support the appropriateness of rational asset pricing models even in a period of such high political uncertainty and potentially raised sentiment.

Keywords: Event Study, EU Referendum, Risk, Investor Sentiment, Market Efficiency
***JEL* Classification**: G10, G11, G12, G14

1. Introduction

Financial markets have been heavily influenced by recent political events *e.g.* the US-China trade war and the withdrawal of the United Kingdom (UK) from the European Union (EU) (Brexit). As well as being extremely important these events are potentially difficult to analyse because of the political uncertainty involved and the fact that they are also extremely emotive issues which might well give rise to unduly positive or negative sentiment. Both political uncertainty and sentiment have been found to have significant, but not necessarily rational, influences on financial markets (Pástor and Veronesi, 2013; Kaplanski and Levy, 2010). Given this, the main contribution of our research is to study whether the impact of important Brexit events on financial markets is consistent with rational asset pricing models which broadly propose that the market prices of securities will rationally discount future events taking advantage of the best information available at the time. Our aim is to systematically evaluate this proposition by breaking it down into a number of empirically testable hypotheses. Our first hypothesis is that the price of an asset is the sum of its discounted future cashflows allowing for an appropriate risk model. We test this by looking at various models of the inter-temporal relationship between risk and return to see whether returns can be explained by risk and risk premium. Our second hypothesis is that market prices of securities will rapidly incorporate new information. We test this by looking for significant Cumulative Average Abnormal Returns (CAAR) before and after Brexit events using the mean-adjusted-return based event study approach. Prior research indicates that different market sectors are likely to respond to Brexit differently (Davies and Studnicka, 2018) so our investigations cover all different market sectors.

The rest of this investigation proceeds as follows. Section 2 describes our data and empirical methodology. Section 3 presents the empirical findings and discussion. Section 4 concludes the paper.

2. Data and Methodology

We use daily closing prices of 34 indices, covering the stock, bond and commodity markets, from 1st January 2012 to 26th April 2017 from *Datastream*. In line with the literature (Kaplanski and Levy, 2010; Davies and Studnicka, 2018), the selected Brexit events must satisfy three criteria. First, there must be widespread media coverage of the event. Second, the coverage is sufficiently compelling to impact the emotions of a large proportion of the population. Third, the impact should be correlated across the majority of the population, so the increased levels of emotions are likely to affect market sentiment and asset prices[1]. Table 1 presents the 17 pre-selected events,[2] along with the rationale for choosing them, and the movement of the FTSE All Share index on the event day.

To quantify the impact of Brexit events on assets returns and risks, we apply a GJR-GARCH modelling framework:

$$r_{M,t} = \alpha_0 + \sum_{k=1}^{3} \alpha_{1,k} r_{M,t-k} + \alpha_2 D_{Jan} + \alpha_3 D_{Mon} + \alpha_4 D_T + \alpha_5 D_{TOTM} + \sum_{k=-5}^{5} \alpha_{6,k}\, E_{t+k} + \varepsilon_{M,t}$$

$$h_{M,t} = \beta_0 + \beta_1 h_{M,t-1} + \beta_2 \varepsilon_{M,t-1}^2 + \sum_{k=-5}^{5} \beta_{3,k}\, E_{t+k} + \beta_4 \varepsilon_{M,t-1}^2 \times I_{t-1}$$

Where, $r_{M,t}$ is the logarithmic daily percentage return for the index. $r_{M,t-k}$ filters out any autocorrelation in the return series; D_{Jan} is a dummy variable for the January effect where $D_{Jan} = 1$ for the first two weeks in January, and 0 otherwise; D_{Mon} is a dummy variable for the Monday effect where $D_{Mon} = 1$ on Monday, and 0 otherwise; D_T is a dummy variable for the first five trading days of the tax year, and 0 otherwise. D_{TOTM} is a dummy variable for the turn-of-the-month where $D_{TOTM} = 1$ for the last trading day of the month and the first three trading days of the next month, and 0 otherwise. E_{t+k} are dummy variables around the event day, where $E_t = 1$ on the event day, and 0 otherwise. $\varepsilon_{M,t}$ is the residual. $h_{M,t}$ is the conditional variance of $\varepsilon_{M,t}$. If event day return effect exists, $\alpha_{6,0}$ should be statistically significant.

[1] For robustness an alternative method of selecting event days using structural breaks in the data is also used in an extended working paper version of this paper on SSRN (https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3638967).

[2] Table A1 in the SSRN working paper (https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3638967) reports the descriptive statistics for the indices.

To test whether risk is a possible reason for the event day return drift, in order to test our first hypothesis, we apply a GJR-GARCH-M model by adding $h_{M,t}$ with coefficient α_7 into the mean equation of GARCH model. If risk is the cause of the event day return effect, α_7 should be significant; and $\alpha_{6,0}$ would become statistically insignificant or its magnitude would be smaller. To examine whether the event day return is due to changes in the risk premium, we add the interaction term $h_{M,t} \times E_t$ with coefficient α_8 to the GJR-GARCH-M model. If the risk premium is a driver of the event day return effect, α_8 will be statistically significant and $\alpha_{6,0}$ will be smaller in magnitude or insignificant when compared with its counterparts in the GJR-GARCH and GJR-GARCH-M equations (Sun and Tong, 2010).

To test our second hypothesis, we calculate Cumulative Average Abnormal Returns (CAAR) around the Brexit events using the mean-adjusted-return approach to investigate how fast these indices reacted to the arrival of new information, where our mean return period is -262 to -11 days and we study a host of event windows.[3]

3. Empirical Findings

Table 2 reports the GJR-GARCH(1,1) results where we find that Brexit events have a clear impact on the financial market returns. There are a substantially greater proportion of significantly negative returns in the period from 2 days before to 1 day after the event day. In particular, 2 (10) out of 34 financial indices report statistically significant positive (negative) event day returns. The value of event day returns range from -1.88% to 0.29% with a mean value of -0.11%. In contrast, in the days further away from the event days, there tends to be a preponderance of significantly positive returns. The results from the GJR-GARCH(1,1)-M and the GJR-GARCH(1,1)-M-Interaction are very similar and show that the event day returns are substantially explained by the risk and risk premium on that day and the levels of significant returns on other days around the events are substantially reduced by allowing for risk and risk premiums. Thus these findings substantially support our first hypothesis. In Panel B of Table 2, we report our event study results and see that the CAARs are quite small, with the values ranging between -1.86% and 0.76% and a mean value of the CAARs on the event day of -0.08%. Only 3 out of 34 indices report statistically significant CAARs on the event window [0,0], although there are a few more statistically significant CAARs in other event windows. Therefore these findings support our second hypothesis that financial indices' prices quickly adjusted for new information, which is in line with the arguments of the semi-strong form EMH.

[3] More specific information about our methodology can be found in the online working paper (LINK).

4. Conclusion

This paper examines whether the impact of Brexit events on financial markets is consistent with rational asset pricing models using 34 indices. The GARCH analysis shows that a substantial proportion of industry indices reacts negatively around Brexit event days when there is no allowance for risk or risk premiums in the modelling. However, when risk premiums are incorporated this proportion falls considerably. This indicates that returns are largely explained by rational asset pricing models. The event study analysis shows little evidence of significant pre and post event drift with the exception of some very short-lived drops after Anti-Brexit events. These findings suggest that Brexit related news is generally quickly incorporated into market prices.

In summary, our results indicate that event day returns are largely justified by the risk and/or the risk premium on that day and that new information is quickly incorporated into prices. These findings suggest that, whilst both fundamental factors and market sentiment may play important roles, rational asset pricing models are very useful for explaining market behaviour around Brexit events.

References

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Tables

Table 1. Brexit events.

Date	Event and Rationale	Daily Market Return (%)
22/01/2013	David Cameron promises referendum if the Conservative Party wins next general election.	0.26
08/05/2015	The Conservative Party wins the UK 2015 general election	2.34
27/05/2015	The EU Referendum Bill was unveiled	1.10
05/01/2016	Conservative ministers are allowed to campaign to leave the EU.	0.65
02/02/2016	European Council publishes a draft blueprint for the proposed changes to the UK's membership of the EU.	-2.06
03/02/2016	David Cameron set out plans to Parliament.	-1.50
19/02/2016	David Cameron gets a "disappointing" deal with the EU.	-0.31
20/02/2016	Brexit referendum date announced.	1.34
16/06/2016	Labour Party MP Jo Cox, a supporter of remaining in the EU, was murdered.	-0.52
23/06/2016	Brexit referendum polling day.	1.33
24/06/2016	The UK votes to leave EU.	-3.90
11/07/2016	Theresa May will become Prime Minister on 13/07/2016.	1.70
02/10/2016	Theresa May confirms that she will trigger Article 50 notice of Lisbon Treaty in March 2017.	1.30
23/11/2016	The UK's Chancellor of the Exchequer, outlines his financial plans.	-0.07
20/03/2017	European Council was officially informed that the UK will trigger Article 50 on 29/03/2017.	0.10
29/03/2017	Two-year period for exit negotiations begins.	0.36
18/04/2017	Theresa May calls snap general election in bid to strengthen hand in Brexit talks.	-2.20

Table 2. Summary statistics for GJR-GARCH model, the GJR-GARCH(1,1)-M-Interaction model and event study where we report the mean, minimum and maximum returns as well as the number of positive and negative *t*-statistics.

Panel A: GJR-GARCH(1,1) Results						
Event Day	Obs.	Mean(%)	Min(%)	Max(%)	Sig.pos.	Sig.neg
$\alpha_{6,-5}$	34	0.26	-4.27	1.55	22	3
$\alpha_{6,-4}$	34	0.12	-0.54	0.79	8	1
$\alpha_{6,-3}$	34	0.00	-0.4	0.74	4	2
$\alpha_{6,-2}$	34	-0.22	-1.39	4.06	1	20
$\alpha_{6,-1}$	34	-0.33	-1.55	0.67	2	20
$\alpha_{6,0}$	34	**-0.11**	**-1.88**	**0.29**	**2**	**10**
$\alpha_{6,1}$	34	0.03	-0.75	5.58	1	9
$\alpha_{6,2}$	34	0.22	-1.26	0.66	17	1
$\alpha_{6,3}$	34	0.27	-0.24	1.07	17	2
$\alpha_{6,4}$	34	0.25	-0.48	0.77	18	0
$\alpha_{6,5}$	34	0.18	-0.49	2.85	12	2
Panel B: GJR-GARCH(1,1)-M-Interaction						
$\alpha_{6,-5}$	34	0.20	-3.37	1.78	15	2
$\alpha_{6,-4}$	34	0.10	-0.44	0.85	10	0
$\alpha_{6,-3}$	34	-0.01	-0.83	0.47	2	2
$\alpha_{6,-2}$	34	-0.12	-1.18	5.75	1	17
$\alpha_{6,-1}$	34	-0.30	-1.25	0.9	2	17
$\alpha_{6,0}$	34	**-0.03**	**-1.98**	**0.46**	**4**	**4**
$\alpha_{6,1}$	34	-0.08	-0.76	4.94	1	10
$\alpha_{6,2}$	34	0.14	-1.14	0.68	10	0
$\alpha_{6,3}$	34	0.21	-0.3	1.34	9	0
$\alpha_{6,4}$	34	0.22	-0.44	0.9	16	1
$\alpha_{6,5}$	34	0.16	-0.3	1.66	9	2
Panel C: Event Study Results						
Window						
[-2, -1]	34	0.12	-0.46	1.39	2	0
[-1, -1]	34	0.01	-1	3.42	0	3
[-5, 0]	34	0.16	-0.01	0.5	8	0
[-2, 0]	34	0.05	-0.4	0.4	1	2
[-1, 0]	34	-0.03	-0.63	0.78	0	3
[0, 0]	34	**-0.08**	**-1.86**	**0.76**	**0**	**0**
[0, 1]	34	-0.22	-1.59	0.86	0	0
[0, 2]	34	-0.19	-0.95	0.52	0	1
[0, 5]	34	-0.00	-0.81	0.4	0	0
[0, 10]	34	0.02	-1.23	0.58	3	1
[1, 1]	34	-0.34	-1.82	0.95	0	3
[1, 2]	34	-0.24	-1.17	1.62	0	3