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Political markets as equity price factors*

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1 Introduction

This paper is concerned with the interaction and behaviour of prediction and financial markets around political events. That political risk affects asset prices is an established concept. Similarly, the information content and superior forecasting ability of political prediction markets is a settled matter in the literature. Surely the 'wisdom of the crowds' from both these markets concerning political risk can be used to derive pricing relationships between these two very different markets? There are very large bodies of literature concerning both the financial market implication of political risk and separately, prediction and election markets. However there is virtually no overlap between these fields, despite the very obvious, at least to this author, links between them. There are certainly no general pricing theories or models linking the two markets. This paper is an attempt to bridge that gap.

There are many studies in the literature that study single elections or other political events. However, studies that consider both political and financial markets, or multiple events, are few and far between. The papers that do exist typically only consider empirical and not economically derived relationships. There is a major gap in the literature for economically derived pricing model of prediction and financial markets that apply in a general setting. One working paper, which shares some methodological aspects with this one, Auld (2022), attempts to fill the void in the very particular situation of the hours directly after an election. But, the question remains, how do markets behave on a longer term, during the weeks and months preceding an election? This is the topic of this study.

The successful election night model of Auld (2022) used a key assumption. This was that asset prices are uniquely determined by the probability of a binary political outcome. Combined with conditions consistent with market efficiency and risk neutrality, this led to the there being only a single stochastic trend driving prices in all markets and the presence of cointegration. However, it is difficult to argue that, outside of the unique hours directly following election, financial prices do not respond to the ebb and flow of other non-political information. One implication of the key assumption in Auld (2022) is that the conditional expectations of asset prices given binary political outcomes is fixed in time. This does not apply on a longer term basis. Conditional expectations of prices will change with the arrival of non-political information. Instead, the key assumption in this paper is that the *difference,* (or ratio), of the two conditional expectations is fixed. This is equivalent to assuming that the outcome of the elections has a fixed effect on the prospects of a company or financial asset. The resulting model yields a relationship between asset price returns and first differences in betting markets. This is no great surprise. A small number of studies have studied this relationship, albeit only for single events and only empirically. However, our model is based on an assumption combined with common pricing restrictions from the asset pricing literature and applies in a general setting. The residue of returns beyond that driven by the political factor is allowed to vary. This is due to the existence of other economic and commercial information beyond that related to the political event. The distribution of returns is effectively partitioned into a political factor and a non-political component. The theory is quite naturally extended to equities, by modelling the non-political part of the returns with the ubiquitous 5 Fama–French factors, Fama and French (2015). The result is a 6-factor augmented Fama–French characteristic factor model, with an additional factor being described by the betting markets and related to political risk. We test the model on six elections. Strong support is found for four, mixed results for one, and no evidence for a single election (the 2017 UK general election). The conclusion for the latter event is that this election was not meaningful for stock prices. We also find evidence that betting markets become more informative as the event approaches. This idea already has some support in the literature. An exponential weighting scheme, where observations closer to the election are weighted more heavily, improves and sharpens our results. Finally an inspection of the political factor loadings reveals some pleasing relationships between firm characteristics and political sensitivity. Internationalisation of revenue was a key explanatory factor. This is consistent with the hypothesis that firms that have a greater share of off-shore sales are more able to diversify domestic political risks. We also find geographical location and nationalisation risk, under an opposition win, also explain differences in political sensitivity.

The question of whether or not the identified political factor is a risk factor, and the ultimate purpose of this study, requires comment. What this study is most definitely not is an attempt to add yet another questionable risk factor to the 'factor zoo' of Cochrane (2011). We will make no claims about the existence or otherwise of a political return premia. There is an economic argument that a premium should be earned by holding stocks with exposure to an upcoming election. The result is effectively a coin toss and investors should be rewarded for taking such a risk. However, we would need data from a far larger sample of events than the six studied here to generate significance (and boosting portfolio returns by taking such coin flip type risks every couple of years when there is an election is probably not a very sensible investment approach). The risk factor literature is concerned with explaining the cross section of returns whereas we are concerned with explaining the *variance* of returns, during the campaign period. The implications of our work for portfolio choice are not related to increasing expected returns, but to reducing volatility (elections are very volatile times). This can be achieved through the hedging of the new, albeit temporary, political factor that is unrelated to the other common risk factors in the literature. Of course it also provides a way for investment managers to express a view about an election, by increasing exposure to the said political factor, if they so wish.

The main contribution of this paper is the presentation of a general pricing model linking prediction markets with financial asset prices. It applies both for political events as well as any prediction market whereby the underlying event has an effect (through the conditional expectation) on asset prices. Secondly we discover firm characteristics that drive political sensitivity which both confirms and extends the existing literature on this topic. Finally, the discovery of a significant, albeit temporary, political equity factor contributes to the literature on equity factor modelling and portfolio choice.

The remainder of the paper proceeds as follows: Section 2 builds the pricing model using the assumption of a fixed difference in conditional expectations of financial prices given the outcome of a binary political event. The empirical and testing framework is outlined in section 3. Section 4 tests the model on several recent elections and section 5 concludes our study. The paper includes several appendices including appendix D which presents all tables of results.

2 Literature review

The financial market implications of elections and political risk are well documented. Changes in the composition of government naturally brings about changes in policy. There are many studies that demonstrate either the effects on financial markets of election campaign periods or results. Three large multi-country studies demonstrate changes of asset price volatility around elections. Białkowski et al. (2008) studies 134 elections in 27 OECD countries from 1980 to 2004. They find that the relevant national stock exchange index volatility can easily double during the week after the election. Apparently 'investors are surprised by the election outcome'. Kelly et al. (2016) find that this uncertainty is priced in the options market. They analyse data from 1990-2012 for options prices on national indices for a sample of 20 countries finding that prices and implied volatility are higher for options that span elections. They also document spillover effects from the election country to other international markets. Pantzalis et al. (2000) is another large multi country study. This paper finds significantly positive returns two weeks prior to election dates for elections in 33 countries between 1974 and 1995. The conclusion is that as election uncertainty is resolved, prices respond positively. Two later papers come to the opposite conclusion for US presidential elections. Goodell and Bodey (2012) consider how the Graham price to earnings (P/E) of the S&P500 index stocks, as well as a measure of consumer sentiment, changes during the campaign periods of US presidential elections. They find the measure *worsens* as the winner becomes clearer, according to the probability seen on the Iowa market (that is, as uncertainty reduces). They conclude that for the US, 'during presidential election seasons, the market discovers its distaste for the economic policies of the likely winner'. The analysis is extended in Goodell and Vähämaa (2013). They find the VIX is positively associated with positive changes in the probability of the winner. This 'indicates that the presidential election process engenders market anxiety as investors form and revise their expectations regarding future macroeconomic policy.'

There are also studies in the literature that demonstrate association between election polls and asset prices. Gemmill (1992) considers the campaign period of the 1987 UK general election. In the paper the author derives the probability of a Conservative party win from polling data. They find that the 'FTSE100 index was very closely related to the probability of a Conservative win'. Further, in the final two weeks before the voteshare options prices showed large increases in implied volatility. This was particularly the case for nationalisation targets (of the opposition Labour party). Brander (1991) and Bernhard and Leblang (2006) study the 1988 Canadian election. This was shortly after the implementation of the Canada-US FTA which was opposed by the opposition Liberal party.[1] Prices on the Toronto Stock Exchange were found to be significantly positively related to polling numbers for the Conservative party during the campaign period.

There is a plethora of research on the accuracy of prediction, and election markets. For a recent review of prediction markets see Horn et al. (2014) and for political markets see Graefe (2016). Studies, many of which are based on the Iowa and UBC markets[2], have demonstrated the remarkable accuracy of forecasts from election markets. There is a consensus in the literature that political markets outperform other methods including polling and expert predictions. Two early papers by Forsythe et al. demonstrate the outperformance of prediction markets when comparing final prices with final polling numbers (despite the presence of judgement bias amongst traders). Forsythe et al. (1992) finds that 'the [Iowa] market worked extremely well, dominating opinion polls' for the 1988 US presidential election. Different constituent groups apparently tended to place bets on their preferred candidates, indicating judgement bias. However, the paper concludes that prices are set by the marginal trader, removing this bias in prices. Oliven (2004) also considers whether the Iowa market is skewed by biased participants. They conclude that market-making traders are more rational than price takers, the implication being that arbitrageurs are indeed making prices efficient. The analysis and conclusions are repeated for the 1993 Canadian federal election in Forsythe et al. (1995). Both these studies focus on shorter-term market predictions. A later study, Joyce E. Berg and Rietz

[1]Following the inclusion of Mexico in 1994 the CUSFTA became the North American Free Trade Association in 1994.

[2]Modern examples of electronic election markets include University of Iowa's Iowa Electronic Markets, introduced for the 1988 US presidential election, the University of British Columbia's (UBC) Election Stock Market (now superseded by the Sauder School of Business Prediction Markets) and the Betfair Exchange, prices for which are used in this paper.

(2008) compares vote share prices from the Iowa market with 964 polls over the five US presidential elections from 1988 to 2004. They find that the prediction market is closer than the polls 74% of the time. Further 'the market significantly outperforms the polls in every election when forecasting more than 100 days in advance'. There is evidence that election markets are not only accurate at times close to a vote but have superior explanatory power months from an election.

The literature is clear that both election markets are powerful tools to forecast elections and that the outcome of elections have effects on asset prices. It naturally follows that prediction and financial markets should be related in some way. There are many event studies in the literature that consider elections, but they typically only consider either financial markets, or political markets and rarely both, and when they do they typically only uncover an empirical relationship and are not based on economic theory. The few studies in the literature that consider both types of market are discussed below.

There are two studies in the literature that directly relate political prediction market prices to the residuals of CAPM models. Both consider only the 2014 Scottish independence referendum. Acker and Duck (2015) find that the residuals of an estimated CAPM model are significantly positively related to a weighted sum of the Betfair exchange odds for 'No'. Similarly Darby et al. (2019) study equities listed on the LSE that were headquartered in Scotland. They find that uncertainty betas help predict cross-sectional returns. Hanna et al. (2021) find that increases in the odds for leave on the Betfair exchange precede falls in the prices of UK equities and the pound in the following 5 minutes. Spillover effects to EU equities were also observed.

We find very few examples of economically derived relationships between prediction markets and asset prices in the literature. These are, firstly, Auld and Linton (2019) and the associated corrigendum Auld and Linton (2023). This paper examines the behaviour of the pound and the betting markets on the night of Brexit. Using a Bayesian electoral forecasting model that updates throughout the night they conclude that both the betting and pound markets were slow in reflecting the information contained in the referendum results. Secondly, Auld (2022) builds a model of betting and financial markets restricted to the very particular setting of the hours after an election. Finally, Manasse et al. (2020) considers the months prior to the Brexit referendum. The authors build a simple portfolio model for currencies. This implies that currencies are cointegrated with betting prices for Brexit. Under risk neutrality they find a linear cointegrating relationship whereas risk aversion leads to the presence of a non-linear term risk factor related to uncertainty. Manasse et al. (2020) find that currency and Betfair data are consistent with their model. However, we do not believe the assumptions behind their model are valid. For it to be so, one would have to believe that the only determinant of the GBPUSD price in the weeks and months preceding the Brexit vote is the result of that vote. We believe this is not plausible. News and information beyond that relating to the referendum, including US economic releases, are likely to affect the British Pound and United States Dollar exchange rate in the period under study. We believe a longer term VAR or factor model, such as the one presented here, is more appropriate to describe the longer term relationship between currency and betting market prices, in the run up to the Brexit referendum.

Contrary to the existing literature, this paper presents a pricing model of political and financial markets that is based on economic principles and applies to a general political vote. We believe the fact that there are no similar studies or models presented in the literature speaks to the contribution of this work.

3 Pricing model

We begin by outlining the scenario of the model. There exists a betting market which is liquid and trades multiple times a day in the run up to a scheduled event. Contracts are listed on the market relating to the outcome of a binary political event. Say $E = 1$ if this event occurs and $E = 0$ otherwise. The outcome of the election or event occurs at time $t = T$. For $t < T$ let PB_t be the price of the contract that pays out £1 when $E = 1$. There are N financial assets indexed $i = 1, \dots, N$ whose prices are p_{it} at time t. For much of this section we consider only a single financial asset and then we label the price p_t. The unit time period ($\triangle t$=1) is equal to one day.

The key assumption in this model is that there is a constant effect of the election on the condition expectations of financial prices given the outcome of the event E.

CE – Constant effect of the event

We seek a condition that the outcome of a binary election or some other event has some expected fixed effect on financial prices. As an example, ex-ante, the market could believe Trump winning the 2016 Presidential election would have a 10% negative effect on the stock price of the Mexican bank Inbursa, versus a Clinton win[3]. This would be equivalent to

$$\frac{\mathbb{E}_t\left(\text{INBURSA}_T | E = 1\right)}{\mathbb{E}_t\left(\text{INBURSA}_T | E = 0\right)} = 0.9 \quad \forall\, t < T. \tag{3.1}$$

Similarly, for the duration of the election campaign, the market may have believed that

[3]Inbursa closed around 5.6% lower the day after Trump win, although it did initially trade significantly lower.

the price would be 3 Pesos lower if Trump versus Clinton won[4]. This could be expressed as

$$\mathbb{E}_t\left(\text{INBURSA}_T|E=1\right) \; - \; \mathbb{E}_t\left(\text{INBURSA}_T|E=0\right) = 3 \quad \forall\, t < T. \tag{3.2}$$

In either case some function of the two conditional expectations is fixed for the time period before the event, and not allowed to vary. Our model applies typically to a relatively small period of time. As long as the stock price does not vary too much the above two formulations of the CE assumptions will be approximately equivalent. Taking logarithms of the first formulation would, for a general price p_t, recover

$$log(\mathbb{E}_t\left(p_T|E=1\right)) \; - \; log(\mathbb{E}_t\left(p_T|E=0\right) = \gamma \quad \forall\, t < T.$$

To make the assumption operational we make a further approximation. Stocks typically vary by much less than order 100% over a period of a few weeks. As such, $log(p_t)$ will be approximately linear over the support of $p_t|E$. So

$$log\left(\mathbb{E}_t(p_T|E=i)\right) \;\approx\; \mathbb{E}_t\left(log(p_T)|E=i\right) \quad \forall\, t < T.$$

Thus if either of the above forms of the CE assumption for Imbursa hold (equations 3.1 and 3.2), the quantity

$$\gamma_t = \mathbb{E}_t\left(log(p_T)|E=1\right) \; - \; \mathbb{E}_t\left(log(p_T)|E=0\right) = \gamma$$

will be approximately fixed in time for $t < T$. This is the mathematical form that our CE assumption takes.

The CE assumption will not hold for all assets all of the time. As an example, consider the case of a UK based bank unexpectedly announcing the opening of European operations during the Brexit referendum campaign. This may reduce the firm's reliance on cross-border regulations between the UK and the EU, reducing any negative effect of a vote for Brexit. As such it would be reasonable to expect the magnitude of γ to reduce for this bank over the announcement. Nonetheless this would be a fairly rare and specific event. Other scenarios could be systematic and affect large numbers of assets. For example, had the Brexit leave campaign unexpectedly announced that they had settled upon a policy of remaining in the EU single market ('softening' any Brexit), then one would expect the difference in conditional expectations to reduce. This would

[4]Inbursa was trading in the range 27–30 Pesos in the weeks prior to the election.

create a structural break in the political sensitivities γ. The strength of this assumption is a matter for debate. However, we believe for most assets and most elections it is fairly weak.

Derivation

In what follows below we assume a single asset price with price p_t at time t. $r_t = log(p_t/p_{t-1}) = log(p_t) - log(p_{t-1}) = \triangle log(p_t)$, the return of the asset on day t.

First we write down an equation linking the price of a financial asset today, and the expected value in the future. This is

$$\mathbb{E}_t(log(p_T)) = \mu_{Tt} + log(p_t)$$

where

$$\mu_{Tt} = \mathbb{E}_t(log(p_T) - log(p_t)).$$

Simply put, the expected log price of the asset price at the point the election result becomes known, $\mathbb{E}_t(log(p_T))$, is the price today, p_t, plus the expected return of the asset μ_{Tt} from t to T.[5] This is of course equivalent to

$$log(p_t) = -\mu_{Tt} + \mathbb{E}_t(log(p_T). \tag{3.3}$$

The purpose of this equation is to link future expected prices with the price today. Financial economics has many instances of such equations. These include the uncovered interest parity (UIP) relation applied to currencies. Another example is the cash and carry relationship linking the arbitrage relationship between forward or futures and spot prices. The common feature of these relationships is that any changes in future expectations of an asset's price are immediately reflected in changes to today's price.

The first difference of equation 3.3 recovers

$$r_t = \triangle log(p_t) = -\triangle\mu_{Tt} + \triangle\mathbb{E}_t(log(p_T)). \tag{3.4}$$

For notational convenience write

[5] For convenience we assume no dividends, coupons or other cash-flows.

$$\begin{aligned}
E_t^i &= \mathbb{E}_t\left(p_T | E = i\right) \qquad i = 1, 2 \\
P_t^i &= \mathbb{P}_t^f(E = i) \qquad\quad\;\; i = 1, 2 \\
\gamma_t &= E_t^1 - E_t^0.
\end{aligned}$$

where $\mathbb{P}_t^f(\cdot)$ represents the probability of an event as evaluated by a representative investor in the financial markets.

Next we expand the expectation of the log price using the total law of expectation.

$$\begin{aligned}
\mathbb{E}_t(log(p_T)) &= P_t^1.E_t^1 + P_t^0.E_t^0 \\
&= P_t^1.E_t^1 + (1 - P_t^1).E_t^0 \\
&= E_t^0 + (E_t^1 - E_t^0).P_t^1 \\
&= E_t^0 + \gamma_t.P_t^1
\end{aligned}$$

Taking first differences gives an expression for the second term of equation 3.4.

$$\begin{aligned}
\triangle\mathbb{E}_t(log(p_T)) &= \triangle E_t^0 + \gamma_t.P_t^1 - \gamma_{t-1}.P_{t-1}^1 \\
&= \triangle E_t^0 + (\gamma_{t-1} + \triangle\gamma_t).P_t^1 - \gamma_{t-1}.P_{t-1}^1 \\
&= \triangle E_t^0 + \gamma_{t-1}.(P_t^1 - P_{t-1}^1) + \triangle\gamma_t.P_t^1 \\
&= \triangle E_t^0 + \gamma_{t-1}.\triangle P_t^1 + \triangle\gamma_t.P_t^1
\end{aligned}$$

Note that $\triangle E_t^0 = \triangle E_t^1$ and that this quantity is the change in the expected future log price of the asset at time T, $log(p_T)$, that is not related to the political event. Further, our CE assumption is precisely that $\triangle\gamma_t = 0$ and $\gamma_t = \gamma \; \forall \, t$. So CE $\Rightarrow$

$$\triangle\mathbb{E}_t(log(p_T)) = \triangle E_t^0 + \gamma.\triangle P_t^1 \tag{3.5}$$

for some fixed political sensitivity γ. Thus the CE assumption implies that the expectation of the log price from time $t-1$ to t can be split up into a change not related to the upcoming election ($\triangle E_t^i$ $i = 1$ or 2) and the change due to the political event ($\gamma.\triangle P_t^1$). The latter term is simply a constant multiplied by the change in the financial market's evaluation of the probability of $E = 1$, P_t^1. Assets that are expected to appreciate when $E = 1$ have $\gamma > 0$ whereas expected depreciation results in $\gamma < 0$. The greater the sensitivity to the political event the larger the magnitude of γ.

Weak market efficiency and risk neutral pricing in betting markets.

We now equate the probability of $E = 1$ as assessed by a representative investor in the betting markets with that of beliefs in the prediction market,

$$\mathbb{P}_t^f(E = 1) = \mathbb{P}_t^B(E = 1),$$

where $\mathbb{P}_t^b(\cdot)$ is the probability of an event as evaluated by participants in the betting market. This is a condition that is consistent with weak market efficiency.

Next, the condition of risk neutral pricing in betting markets with an effective discount factor of unity[6] implies that for a contract that pays out £1 when $E = 1$

$$PB_t = \mathbb{P}_t^B(E = 1).$$

Thus the additional restrictions of equal beliefs in the two markets and risk neutral investors in betting markets ⇒

$$\mathbb{P}_t^f(E = 1) = PB_t.$$

Taking first differences and substituting into equation 3.5 ⇒

$$\triangle \mathbb{E}_t(log(p_T)) = \triangle E_t^0 + \gamma . \triangle PB_t. \tag{3.6}$$

To recover an expression for the daily return of an asset we still need to consider the change in the expected appreciation of the asset to the election result, $\triangle \mu_{Tt}$. This can be achieved using the fact that market efficiency implies that returns have a martingale difference property. First write

[6] Our model applies only to the campaign period of an election of a few weeks or months. Thus any discount factor related to the payout of binary options that payout on the election result will be very close to one.

$$
\begin{aligned}
\mu_{Tt} &= \mathbb{E}_t(log(p_T) - log(p_t)) \\
&= \mathbb{E}_t(log(\frac{p_T}{p_t})) \\
&= \mathbb{E}_t(log(\frac{p_T}{p_{T-1}}.\frac{p_{T-1}}{p_{T-2}}.\dots.\frac{p_{t+1}}{p_t})) \\
&= \mathbb{E}_t(log(\frac{p_T}{p_{T-1}}) + \dots + log(\frac{p_{t+1}}{p_t})) \\
&= \mathbb{E}_t(log(\frac{p_T}{p_{T-1}})) + \dots + \mathbb{E}_t(log(\frac{p_{t+1}}{p_t})).
\end{aligned}
$$

The final line uses the fact that the expectations are separable due to the martingale difference property of returns. If we assume an expected constant rate of daily return for the asset of μ then $\mathbb{E}_t(log(\frac{p_{t+i}}{p_{t+i-1}})) = \mathbb{E}_{t-1}(log(\frac{p_{t+i}}{p_{t+i-1}})) = \mu$ and

$$\mu_{Tt} = (T - t) \times \mu.$$

$\Rightarrow$

$$
\begin{aligned}
\triangle\mu_{tT} &= \mu_{tT} - \mu_{t-1\,T} \\
&= (T - t)\mu - (T - t + 1)\mu \\
&= -\mu. \qquad (3.7)
\end{aligned}
$$

Substituting equations 3.6 and 3.7 into equation 3.4 $\Rightarrow$

$$r_t = \mu + \triangle E_t^0 + \gamma.\triangle PB_t. \qquad (3.8)$$

This is linear equation linking changes in prices of betting market binary options and financial market returns. Changes in the odds of $E = 1$ affect returns directly through the factor loading γ. This is similar to the βs in the capital asset pricing model (CAPM). Whereas β in the CAPM relates to the sensitivity of the asset to the single factor market return, γ in our model represents the sensitivity to the political event.

Errors in market efficiency

We now consider what happens when beliefs in the betting and financial markets about the probability of $E = 1$ diverge. This would be consistent with deviations of weak market efficiency. To do this we add an error ϵ_t to the condition linking beliefs in the two markets,

$$\mathbb{P}_t^f(E=1) = \mathbb{P}_t^B(E=1) + \epsilon_t = PB_t + \epsilon_t.$$

We assume that $\mathbb{E}(\epsilon_t) = 0$, so there are no systematic differences in beliefs, and ϵ_t is weakly dependent so that errors in beliefs are transient. Equation 3.6 now becomes

$$\triangle\mathbb{E}_t(log(p_T)|\epsilon_t, \epsilon_{t-1}) = \triangle E_t^0 + \gamma.\triangle PB_t + \gamma.\triangle\epsilon_t$$

and equation 3.8 is varied to

$$r_t = \mu + \triangle E_t^0 + \gamma.PB_t + \gamma.\triangle\epsilon_t.$$

The factor model is now

$$\begin{aligned} r_t &= \mu + \gamma.\triangle PB_t + \zeta_t \\ \zeta_t &= \triangle E_t^0 + \gamma.\triangle\epsilon_t. \end{aligned}$$

If market efficiency generally holds, but with some transient fleeting errors between beliefs about the probability of the political event, the residual error of the factor model will be serially correlated.

Extension to multi-factor Fama–French model

We now consider a large portfolio of stocks, with returns r_{it}, $i = 1, \ldots, N$. The single political factor model is

$$\begin{aligned} r_{it} &= \mu_i + \gamma_i.\triangle PB_t + \zeta_{it} \\ \zeta_{it} &= \triangle E_{it}^0 \\ \mathbb{E}(\zeta_{it}) &= 0 \end{aligned} \tag{3.9}$$

The error ζ_{it} is allowed, indeed expected, to be correlated across different stocks. Under strict market efficiency it will be serially uncorrelated but fleeting deviations from efficiency (on the timescale of days) will result in auto-correlation. Nonetheless the model above allows a parsimonious description of the covariance matrix of returns when a political event is upcoming. γ_i is the political factor loading and is a measure of stock i's sensitivity to the upcoming election. Ceteris paribus, stocks with higher or lower γs will have higher or lower correlation. $\mu_i + \zeta_{it}$ is the part of the return not related to the political event. Indeed when there is no upcoming vote the returns model reduces to $r_{it} = \mu_i + \zeta_{it}$. This is a poor description of the covariance structure of the portfolio of stocks as there are no common factors. We now extend the model by applying the ubiquitous Fama–French factor model to describe this part of stock returns.

The Fama–French factor model for equities is:

$$r_{it} - r_f = \alpha_i + \sum_{j=1}^{K} b_{ij} f_{jt} + \varepsilon_{it} \qquad \mathbb{E}(\varepsilon_{it}) = 0 \qquad i = 1, \dots, N \; j = 1, \dots, K. \tag{3.10}$$

There are N financial assets and K factors. r_{it} is the return of the i'th stock at time t and r_f is the risk free return. The factors $f_{1t}, \dots, f_{Kt}$ are K univariate random variables that vary with time. B is a $N \times K$ constant matrix describing the loading of the factors within the space of the N stocks (the elements of which are $\{b_{ij}\}$). ε is a vector of shocks, assumed to be serially uncorrelated and weakly correlated across different stocks as $N \to \infty$.

The aim of factor models is to explain the cross-section of returns, where premia can only be earned from a small number of 'risk-factors'. The key result of these models comes from arbitrage pricing theory and is

$$\mu_i = \mathbb{E}(r_i) = r_f + \sum_{j=1}^{K} b_{ij} \mathbb{E}(f_{jt}).$$

Equivalently $\alpha_i = 0 \; \forall \, i$ in equation 3.10. This implication has been studied in numerous papers and contexts, too many to discuss here. It is also not the topic of this paper.

The mainstay of finance asset pricing courses is the single factor capital asset pricing model (CAPM). Expected returns are explained solely by the stocks sensitivity β, to the single market factor R_m. Returns can only be increased by increasing exposure to this factor, with correspondingly higher risk. However, discrepancies in data led to Fama and French to extend CAPM with two additional factors related to the returns of small versus large cap stocks and the returns of cheap versus expensive companies (measured by book-to-value ratios), Fama and French, 1992. When this was found to be insufficient, two more factors relating to operating profitability and investment were added in Fama and French (2015). At the same time, the number of supposed risk-factors in the literature exploded, leading to Cochrane referring to a 'zoo' of factors in his American Finance Association Presidential Address, Cochrane (2011). Subsequent research has found that the vast majority of these findings were simply "data-mining". Harvey et al. (2016), studied 315 factors from the literature, concluding that only a handful are significant once "data-snooping" is adjusted for.

We have no wish to enter the debate about which particular factors lead to excess returns and are indeed risk factors. We also make no claims about whether or not the political factor is a risk-factor. Indeed, we will not even impose the arbitrage pricing condition $\alpha_i = 0 \; \forall \, i$ in equation 3.10. We simply wish to use some common factors to describe the non-political part of stock returns. Doing so will enable us to study if prediction markets are explanatory of returns *once common factors have been controlled for.* We chose the five Fama-French factors for two reasons. Firstly, they are common in the literature. Secondly Professor French has also gone to the trouble of publishing their daily values for a variety of equity markets on his website, so we do not need to calculate them.

Following the convention in the literature, we write the excess return of stock i as $Z_{it} = r_{it} - r_f$. We proceed by replacing the non-political part of the return, $\mu_i + \zeta_{it}$, in our one factor political model (equation 3.9) with the general factor expression above (equation 3.10). The result is

$$Z_{it} = \alpha_i + f_{1t}.b_{i1} + \cdots + f_{Kt}.b_{iK} + \triangle PB_t.\gamma_i + \eta_{it}, \tag{3.11}$$

where $K = 5$ and $\{f_{jt}\}$ are the daily returns of the five Fama-French factors. The shock has been replaced by η in the full model above to distinguish it from the Fama–French residual, ε. We now have a characteristic $K + 1$ (six) factor model which includes the additional political component.

$\triangle PB_t$ is unlikely to be uncorrelated with the factors $\{f_{jt}\}$. Indeed, the outcome of most political events will be expected to have an overall effect on the prices of stocks. Changes in the probability of $E = 1$ will be highly likely to affect the returns of the market R_m. When this is the case it is important to note that the factor loadings in the full political factor model (equation 3.11), will be different from those in the standard Fama–French model (equation 3.10). This is also the case for the political loadings $\{\gamma_i\}$. These loadings in the full model will differ from those in the single political factor model (equation 3.9). Only in the unlikely event of $\triangle PB_t$ being uncorrelated with $\{f_{jt}\}$ would loadings be equal between the full model and the sub-factor models.

In this paper we are not interested in the accurate estimation of Fama-French factor loadings in any one of these particular models. The purpose of the investigation is to examine whether political markets are explanatory of stock returns, and if so, what the political loadings can tell us about different stocks. As long as both the political loadings $\{\gamma_i\}$ are non-zero in either model, and $\triangle PB_t$ is not collinear with $\{f_{jt}\}$, $\triangle PB_t$ will explain returns. It will also follow that $\triangle PB_t$ will be explanatory of the Fama–French residuals $\{\varepsilon_{it}\}$. When collinearity occurs, loadings in the full model are not identifiable, but, more importantly, adding betting market information to the model does not help describe stock returns. This would be because changes in the betting markets would already be fully explained by the Fama–French factors.

4 Empirical specification

Our theoretical model for stock returns is summarised as the full factor model

$$Z_{it} = \alpha_i + f_{1t}.b_{i1} + \cdots + f_{Kt}.b_{iK} + \triangle PB_t.\gamma_i + \eta_{it} \qquad i = 1, \ldots N,\ t \leq T.$$

If we assume $\triangle PB_t$ is not collinear with $\{f_{jt}\}$ then the betting markets are explanatory of stock returns if and only if $\gamma_i \neq 0$. Testing the validity of our model is equivalent to testing that the set of parameters $\{\gamma_i\}$ are significant. Rejecting $H_0 : \gamma_i = 0\ \forall\, i$ would be strong evidence in favour for the model holding.

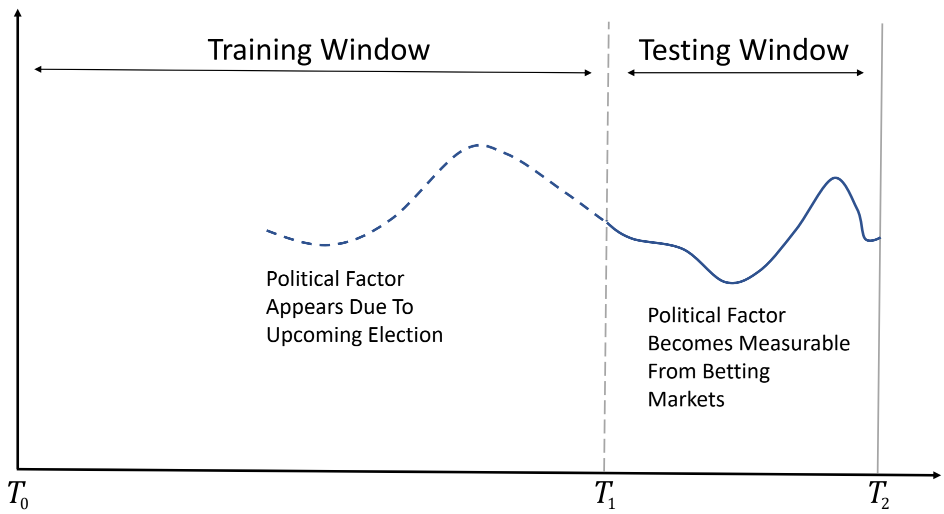
The model itself is a $K + 1$ characteristic factor model. The historical daily K Fama–French factor returns are readily available from Professor K.R. French's website[7]. Histories from around 1990 are provided for download. The final political factor $\triangle PB_t$ is available from betting markets for periods preceding a political event. In this paper we rely on data solely from the Betfair exchange platform. This acts like a limit order book. Contracts may be listed months and even years before an election. However, liquidity generally increases as the event approaches. Far out from an election there may be no trading at all on most days. $\triangle PB_t$ appears in the model as a measurement of the changes in the probability of a political event $\mathbb{P}_t(E = 1)$. However, unless the betting market is trading and liquid then the measurement will not be valid. Care will be required to ensure there is sufficient liquidity when choosing which time period to apply the model to. In practice only a small number of months or a few weeks directly prior to the election will be considered sufficiently liquid.

One could proceed by estimating the full model above on this small period and attempting to generate significance for γ. However, this would be inefficient. The much longer history of the Fama–French factors would not be exploited for estimation.

First we must choose a period where we judge the betting market to be sufficiently liquid to be a valid measure of beliefs about the odds for the political event. Call this

[7] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

period the testing period. Say it starts at T_1 and ends at T_2. (In practice T_2 will be the day before the election result is announced, $T-1$). Define a longer period starting at T_0 and ending at $T_1 - 1$. Call this the training period. Fama–French factor data from both the testing and training periods will be used but only betting data from the testing set is considered. The approach is illustrated in Figure 1.



Fama–French factor loadings are estimated in the training window. Explanatory power of the betting market on the Fama–French residual is tested in the testing window.

Figure 1: Schematic of the empirical approach.

One way to proceed would be to estimate the following regression

$$Z_{it} = \hat{\alpha_i} + f_{1t}.\hat{b_{i1}} + \cdots + f_{Kt}.\hat{b_{iK}} + \left[\delta_{t,\{T_1,T_2\}} \times \triangle PB_t\right].\hat{\gamma_i} + \hat{\eta_{it}} \qquad t = T_0, \ldots, T_2 \quad (4.1)$$

where

$$\delta_{t,\{T_1,T_2\}} = I\left(t \in \{T_1 + 1, T_2\}\right).$$

This replaces the political factor with $\delta_{t,\{T_1,T_2\}} \times \triangle PB_t$. This forces the factor to zero outside of the liquid testing period. However, this is a flawed approach. Political risk may still be present prior to the testing period, and changing. An election, say, three or four months in the future may be well known and the prospects for each of the candidates varying. However, it just may be too far in the future to be in the minds of those that choose to place bets in a political market. Lack of participation in a betting market may make an evaluation of the probability of an election outcome unmeasurable. This is not the same as it being constant and unchanging though. Conducting a regression where it is assumed to be zero in the training period will lead to invalid results.

To overcome this issue, and to use more of the history of the Fama–French factors, we proceed as follows:

1. Estimate the Fama–French loadings $\hat{\alpha}, \hat{B}$ during the training period $t = T_0, \ldots, T_1 - 1$.

2. Evaluate the Fama–French estimated residuals $\hat{\varepsilon_{it}} = Z_{it} - \hat{\alpha_i} - \sum_{j=1}^{K} \hat{b_{ij}} f_{jt}$ on the testing period $t = T_1, \ldots, T_2$.

3. Regress the estimated Fama–French residuals $\hat{\varepsilon_{it}}$ on changes in the political factor $\triangle PB_t$ on the testing period $t = T_1, \ldots, T_2$, without intercept.

The above approach involves the same regression as that of equation 4.1 under the null hypothesis. For most event studies it would also produce identical statistics under alternatives of interest. However, if the political factor is in fact changing in the training set then the two step approach has greater power. This is demonstrated in Appendix A.

As discussed in the previous section the Fama–French loadings estimated in step 1 above will not be the same as the loadings in the full factor model. This is due to the very likely correlation of $\triangle PB_t$ with the other factors $\{f_{1t}, \ldots, f_{Kt}\}$. However, significance of γ_i in the regression

$$\hat{\varepsilon_{it}} = \alpha + \gamma_i . \triangle PB_t + \xi_{it} \qquad t = T_1, \ldots, T_2$$

is equivalent to significance of γ_i in the full factor model. Note that we allow an intercept in the first stage regression as we do not impose the arbitrage pricing theory constraint. However, for the second stage we drop the intercept. This is because both $\mathbb{E}(\hat{\varepsilon_{it}}) = 0$ and $\mathbb{E}(\triangle PB_t) = 0$. The level of PB_t will change in the testing period but the unconditional expectation is zero. Of course there will be estimation error in $\hat{\alpha}, \hat{B}$. This will lead to estimation error of $\hat{\varepsilon_{it}}$. However, the error will be in the dependent variable in the second stage regression. Further, as the training and testing periods are disjoint, the estimation error will be independent of the residual of the final equation ξ_{it}. No endogeneity will be present in the final step and estimates of γ_i will be unbiased, although there will be a reduction in precision.

4.1 Significance tests

In the next section we will test our model on a series of political events from recent years. For each event we will select an appropriate universe of stocks and a betting contract and follow the process described above. There are two tests we will perform which are outlined below.

4.1.1 Portfolio test

The first test we apply is to consider the univariate regression for an equally weighted portfolio of the stocks of the chosen universe. If $\hat{\varepsilon_{it}}$ is the estimated Fama–French residual for stock i then define $\bar{\hat{\varepsilon}}_t = \frac{1}{N}\sum_{i=1}^{N}\hat{\varepsilon_{it}}$, the average estimated residual. We then conduct the following regression

$$\bar{\hat{\varepsilon}}_t = \bar{\gamma}.\triangle PB_t + \xi_t \qquad t = T_1, \ldots, T_2.$$

If $\gamma_i = 0\ \forall\, i$ then $\bar{\gamma} = 0$ in the above regression. Thus rejection of the null hypothesis $\bar{\gamma} = 0$ rejects the null hypothesis of insignificance of the betting market. This is a simple test to perform. It can also easily be made robust to serially correlated errors that may occur due to the presence of errors in market efficiency, as well as heteroskedasticity. However, the test is not robust to alternatives where the set of individual stock γs can take different signs.

4.1.2 J_α tests of Pesaran and Yamagata

The above portfolio test may suffer from a lack of power. There is loss of information by grouping all securities together in a single portfolio. As we are only conducting tests over periods where the betting market will be liquid, T is likely to be of the order of 10s, and certainly not much greater than 100. This is small compared to the number of stocks available. For example, there are around 5000 stocks listed in the US alone. There is the possibility of using large number of assets to generate significance, but this will require a test for which $N > T$.

The problem of testing the arbitrage pricing condition $\alpha_i = 0$ when $N > T$ was solved in Pesaran and Yamagata (2012). They propose a test based on a normalised Wald statistic, J_α, of the individual t-statistics of univariate regressions, adjusted for (threshold applied) cross sectional correlations. It is robust to weak cross sectional dependence and asymptotically valid in the case of non-normal errors.

We modify the J_α test to apply to the slope γ_i. It is this test that will be primarily relied upon in the next section. Call this the J_γ test. We describe it further in Appendix B. The test has been demonstrated to have excellent properties for our setting where there may be non-normal errors and some correlation amongst stock residuals. For example, Monte Carlo evidence shows the test performs well with minimal size distortions, for samples of size $T = 60$ and 100 and N ranging from 50 to 500. These are similar sizes of

N and T to those used in this paper. The test however is not demonstrated to be robust in the presence of serial correlation (possibly in existence due to market inefficiencies) or heteroskedasticity. In practice we will test the residuals of the second stage regression for the presence of these effects. The lower power univariate portfolio test does have one advantage over this large N test, which is that it is simple to apply robust errors.

Comment on power improvements to the J_α test

Improvements to the J_α (and other similar tests) have been proposed by Fan et al. (2015). They demonstrate that the J_α test lacks power against sparse alternatives where, for example, a finite number of stocks have significant αs. They add a power enhancement term to the test statistic which vanishes asymptotically under the null, but has power against such sparse alternatives. This may well be relevant when testing arbitrage pricing theory, where a small number of stocks may be responsible for failures in market efficiency. The empirical application in their paper, studying returns of the S&P500 index components, certainly suggests so. However, we do not believe this is relevant in our application. If betting markets are significant, we expect explanatory effects beyond a small number of stocks or particular industry sector. The number of stocks with significant αs is likely to grow as $N \to \infty$. The J_α (or J_γ) tests should have power against the alternatives of interest and we rely solely on them without power adjustment.

5 Results

We study six elections from recent years. To apply the method several choices need to be made for each event. These are; what particular betting contract to use, what portfolio of stocks to consider and what training and testing periods to use? A plot of the logarithm of trailing 7-day average daily volume on the Betfair exchanges for our chosen event is shown in Figure 2. Any key announcement concerning the event is also shown on the figure. As can be seen, liquidity explodes exponentially as the day of voting approaches, but can be very low a few months out. For example, the daily volumes trading on exchange are under £10k, 5 months from several of the elections. We treat data from lower liquidity days cautiously. Below, we discuss each event in more detail. Table 1 in Appendix C lists each election along with their chosen specifications for testing. Note that we test two portfolios for the Brexit referendum as well as the 2016 US presidential election. Also, 1, 3 and 5 factor models are available for each Fama–French choice, the 1 factor equating to CAPM.

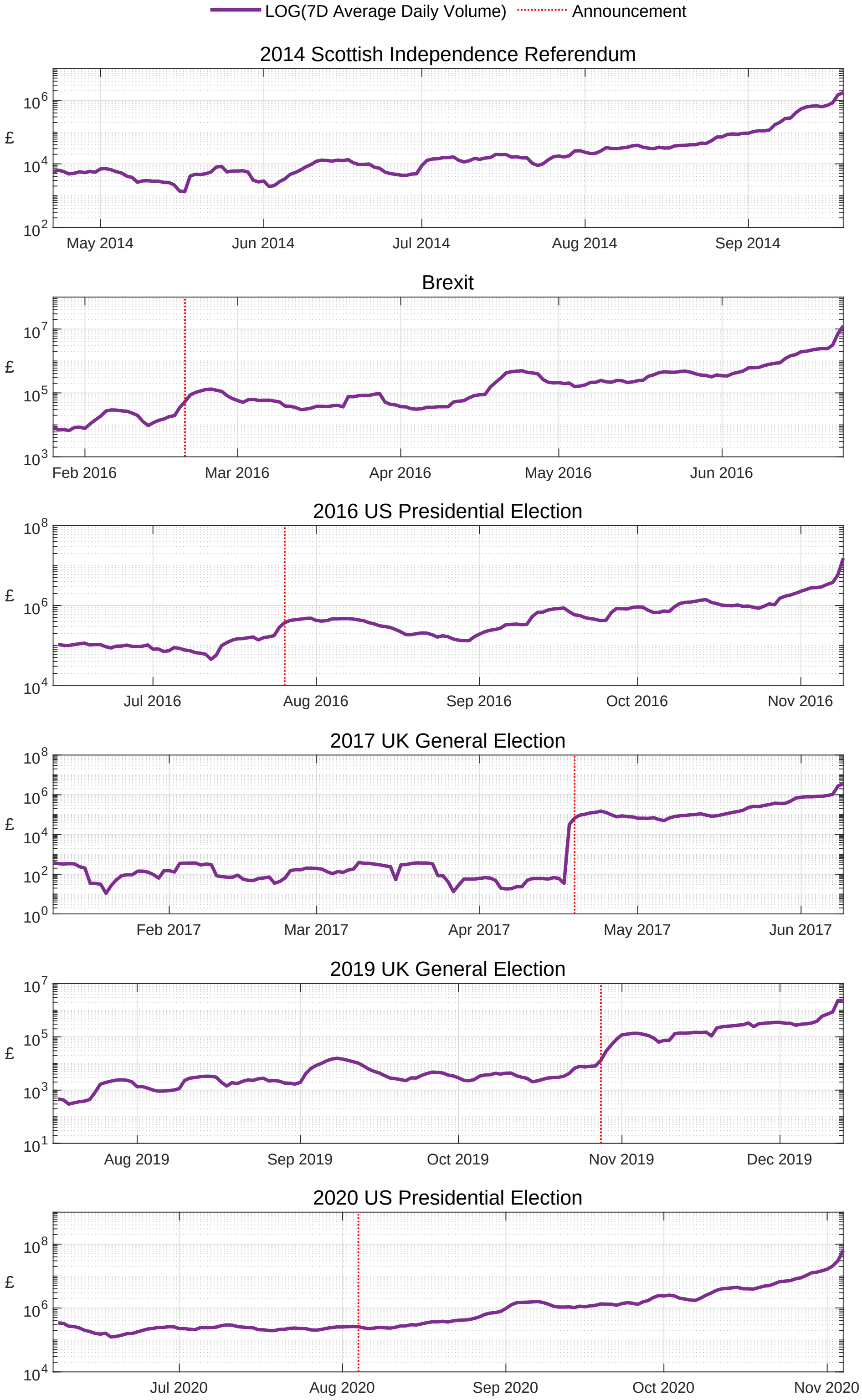


Figure 2: Liquidity on Betfair in the months prior to our chosen political events.

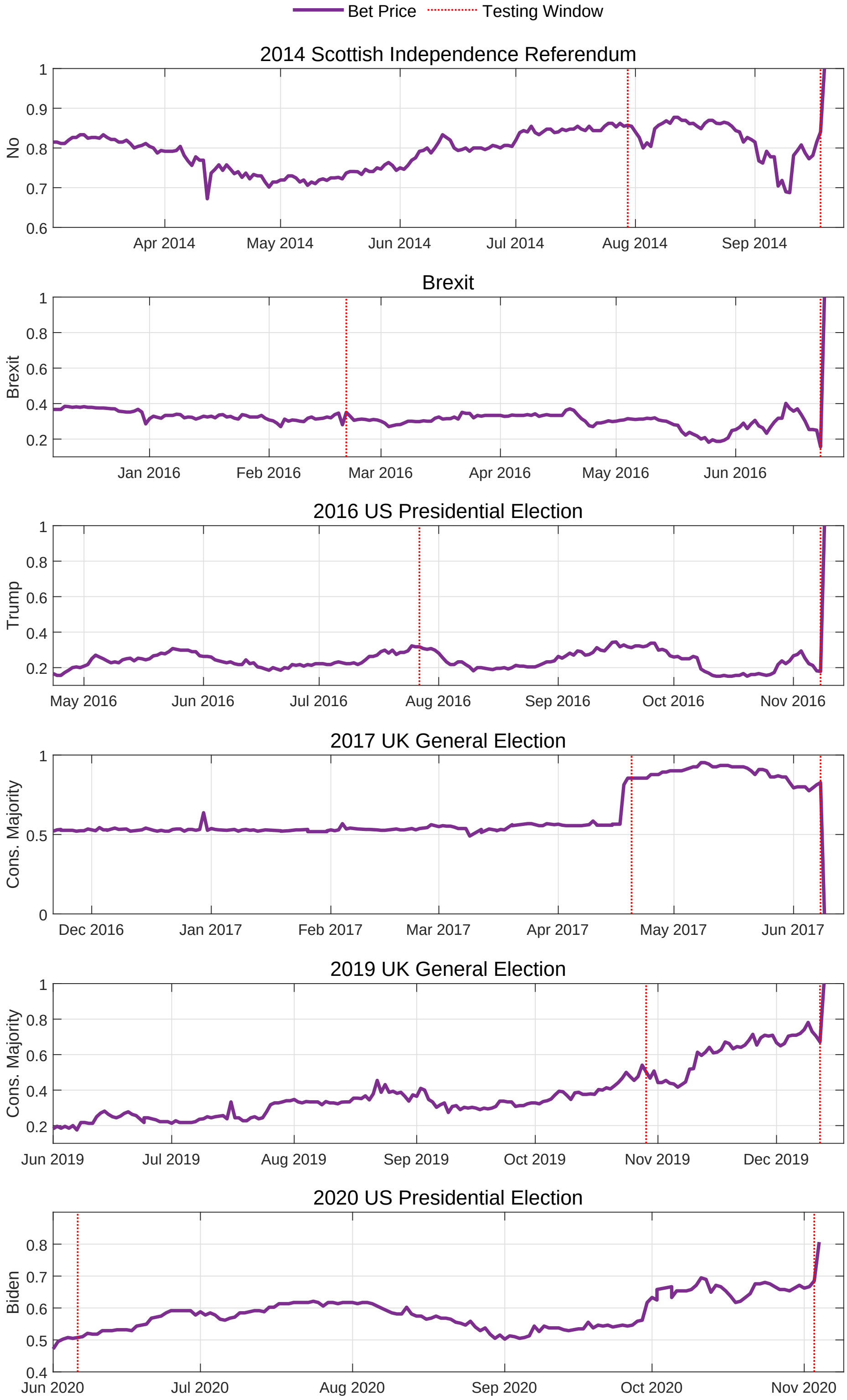


Figure 3: Betfair implied probabilities.

5.1 Events

2014 Scottish independence referendum

The vote took place on 18th September 2014. The question on the ballot paper was 'Should Scotland become an independent country'. Polls showed a consistent lead for 'No' during July and August of that year but tightened in September. In fact, on 6th September a poll was announced showing a small lead for 'Yes'. The pound and companies linked to Scotland depreciated on that day and the betting contract paying out £1 for 'Yes' rallied to 35p. Ultimately though, polls reverted and the 'No' side prevailed. The risk neutral Betfair implied probabilities can be seen from Figure 3. The figure shows the prices along with the chosen testing windows for this and the other political events. As this was a binary Yes/No referendum the choice of betting contract is simple. We chose the 'No' bet in our model. For stocks we chose all companies listed on the London Stock Exchange (LSE), from Q2 2014, domiciled in the UK. Many small less liquid companies will be removed from the portfolio according to a further screening step. This is discussed at the end of this subsection and is applied to all the portfolios studied in this paper. Fama–French daily factor returns are available for the European market and we utilise this as the most appropriate choice[8]. The choice of testing period is not straightforward. The Scottish Government announced the date of the referendum on 21 March 2013, around 18 months prior to the vote itself. Liquidity on betting markets was muted though. Little more than around a few thousand pounds exchanged hands per day on Betfair through April, May and June 2014. The volume increased to around £10k per day in July and peaked at well over £1m a day in the week before the referendum. We chose to start the testing window on July 30th to give us sufficient time samples in the testing window. The volume did start to significantly increase from around £25k per day from this point.

2016 Brexit referendum

This is a binary vote and so the choice of betting contract is straight forward. We use the contract for 'Leave'. On 20th February 2016 David Cameron announced the date of the referendum to parliament as 23rd June 2016. Liquidity improved on Betfair from this point with around £100k per day trading the week after the announcement, with volume peaking at around £50m on the overnight session following the vote. This makes our choice of testing period easier. We chose the day after the announcement to begin the testing window. The betting percentage odds during this period put the probability of leaving the EU from between the high teens to the high 30s. However, by the day of the vote there was a widespread (misplaced) belief that the country would vote to remain.

[8] Daily developed market factors are also available but the European centric-data set is preferred.

The implied probability of a Leave vote bottomed out around 10%, just after the vote closed. We make the similar choices for the equity universe and Fama–French factors as the 2014 Scottish independence referendum, using stocks listed on the UK based LSE from Q1 2016. We also separately test a portfolio of stocks that are made up of EU27 based companies that earned at least 25% of their revenues in the UK according to their 2015 full year accounts.

2016 US presidential election

The election of Donald Trump as the 45th president of the United States was the second political surprise of 2016. As election day is set under statute as 'the Tuesday next after the first Monday in the month of November', the date is known well in advance. However, the two candidates are not nominated until the summer before the vote. Recall that our model assumes a fixed difference between an expectation of a particular outcome (say X) and the complement of that outcome ($\overline{X}$). Even if one candidate is known, the complement, that is the opponent, may not be. Thus the expectation of the complement can change without the betting odds for the known candidate changing. For example, Donald Trump's nomination came before the Democratic candidate. The odds of the particular Democratic candidate can change, effecting asset prices, without a corresponding change to the odds of Donald Trump winning. So our model will not hold. Until both candidates are known the model will not apply. The vote is not binary.[9] Trump was officially nominated at the Republican national convention on 19th July, Clinton, on July 26th at the Democrat event. Liquidity for the election was much higher than the preceding events, with hundreds of thousands of pounds exchanging hands on Betfair around the time of the nominations. We are comfortable with using the betting markets from the day after both nominations were known. We chose the contract for Donald Trump for the model. Trump was (incorrectly) never seen as the stronger candidate. The percentage odds of him winning never rose above the mid 30s during the testing window. For this event we will use two different stock universes and test both. The first will be the index stocks of the S&P500 in Q2 of 2016; the second, publicly traded stocks domiciled in Mexico. We do not limit ourselves to companies listed on the major Mexican exchanges as many top Mexican stocks trade off-shore. It was expected that a Trump win would be very bad for trade with Mexico and hence its markets. The relevant Fama–French factors for both these portfolios are the North American ones.

[9] The vote for US president is in fact never completely binary. There is always the chance that a candidate may become incapacitated during the campaign. Running mates often trade with very small but positive likelihoods. The morbidly interested reader can look at the betting odds for Kamala Harris in the 2020 election to impute the market's belief about the probability of the elderly president Biden passing during his campaign!

2017 UK General Election

The result of the 2016 Brexit referendum was a surprise. The ruling Conservative party had a working majority of 17 in the house of commons.[10] There was no election due under the Fixed-term Parliaments Act until May 2020. However, following the UK's triggering of Article 50 of the Treaty on European Union, the Prime Minister Theresa May called a surprise election. This was to 'strengthen her hand' in negotiations with the EU. Ultimately though she failed in that aim. She lost her majority and following the result governed as the leader of a minority government with the support of the Democratic Unionist party.

Legislation to enact a general election was ratified by parliament on 19th April, 2017. The date was set for 8th June 2017. Until 18th April, the day before the announcement, liquidity for this event on Betfair was minimal, struggling to reach even £100 per day. However, trading jumped to around £100k a day once it became clear an election was imminent. It increased to over £1m per pay in the days before the vote. The choice of testing set is clear with this event as there is simply no liquidity prior to the date of the election's announcement.

Until the snap election became public, the odds for a Conservative majority were barely trading. For the few trades that did occur, the implied probability was around 50%. The lack of liquidity was likely due to the fact that the election was not scheduled for several years. Gamblers were neither interested in, nor informed about, the details of the election. This observation is remarkably consistent with the findings of Page and Clemen (2013) that there is a 'bias of the price towards 50%' for events far into the future. Until the announcement of the election date, the vote was indeed expected to be 'far into the future'. Going into the campaign, opinion polls consistently showed a lead for the Conservatives. They tightened as the vote approached. Implied odds for a majority rallied to over 80% when the election was announced. They stayed in the range 78–95 until the vote. The choice of which contract to use is not straightforward. If the Conservatives did not achieve a majority, then there were were potentially multiple alternatives. Bets for a 'Labour majority', a 'hung parliament' or 'anything else' were listed. However, the Conservative's lead over the Labour party was such that the probability of an actual Labour majority was very small. For the most part of the campaign, odds for this outcome hovered around 1–2.5%. It did increase a little as the polls tightened going into the election but was never implied to be higher than 4%, except for a few trades on election day. This means the event was close to binary with the majority of the probability distributed between a Conservative majority and a hung parliament. However, we should note our model does not hold exactly. In terms of the universe of stocks, we will stick with

[10] There are 650 seats in the house of commons and 17 is considered a small majority which makes governing difficult.

all stocks headquartered in the UK listed on the LSE (in Q1 2017), with the European Fama–French factors.

2019 UK General Election

Following the UK government losing its majority in the house of commons in 2017 there was prolonged political deadlock. This led to Theresa May resigning as Prime Minister. Boris Johnson was elected as her replacement by the Conservative party in the summer of 2019. Johnson could not, though, convince the house of commons to pass a revised withdrawal agreement[11]. This caused him to call a snap election, the third general election in four years. Legislation was passed on 28th October 2019 and the date was set for 12th December. As was the case with the 2017 general election, trading on Betfair rose significantly over the announcement. For example, the day before only £2,600 traded, whereas the day after volume jumped to over £100k. Volumes generally increased from this point with over £2m per day trading in the final week. Given the uptick in volume we will again start the testing period the day after the announcement.

Throughout the campaign period, the Conservatives held a strong lead over the Labour party. However, the implied odds of a Conservative majority was relatively low compared to opinion polls. It traded in the range 40–55% in the first fortnight of the campaign. This was likely due to the underperformance of the Conservatives versus initial polling and expectations in the 2017 election. The odds did steadily increase to around 70–80% as Labour failed to significantly tighten the polls. The Conservatives ultimately gained a landslide win with a huge majority of 80 seats in the house of commons. We again use the bet for 'Conservative majority'. The prices for a labour majority did initially imply odds as high as 6% but this soon dropped to the 2–3% range as they failed to make ground. The alternative to a Conservative majority was again dominated by a hung parliament. We again use the same choices for the equity universe as the preceding UK events, with UK stocks listed on the LSE in Q3 2019.

2020 US presidential election

In 2020 the presidential election was scheduled for 3rd November. There was never any doubt that Trump, as sitting president, would run for a second term. However, there was a political battle for the heart of the Democratic party between establishment Joe Biden and the left winger Bernie Sanders. On June 5th Joe Biden gained the required number of delegates from the Democratic national convention to secure the nomination. Volume on Betfair for this event was in the hundreds of thousands of pounds a day at

[11]The withdrawal agreement was made between the UK and the EU and established the terms of the UK's withdrawal from the EU.

the time of the nomination. This increased to around £1m a day in the days immediately prior to the vote. As we now know, president Biden did not secure the Presidency the day after the election. In the days and weeks after voting day there were numerous recounts. There were also several (seemingly baseless) legal challenges by the Trump campaign looking to overturn what was apparently a clear win for the Democratic ticket. Contracts continued to trade on Betfair until 14th December 2020. The electoral college confirmed Joe Biden's victory in the election on that date. There is no doubt that there are numerous opportunities to study financial and political markets in the period 9th November to 14th December 2020. However, we do not believe the model presented in this paper will apply. This is because the prospects of a Joe Biden win and its alternative will have fundamentally changed. Instead of political risk relating to this election disappearing overnight on 8th November, it substantially increased. The prospect of Donald Trump retaining the presidency via a typical presidential election and one where the apparent rightful winner is deposed by the courts (or worse) is very different. The risk becomes less about what the electorate is voting for and more about the strength of US institutions. Political implications aside, the conditional expectations of asset prices given a Biden or Trump win certainly changed on 4th November 2020. Given this, we have no confidence the model will hold. We end the testing set on 3rd November. We use two equity universes to test this event; the index stocks of the S&P500 in Q2 of 2020 and stocks domiciled in Mexico in Q2 2016.

5.2 Data sources and handling

Equity data

For each event we have selected a universe of stocks and Fama–French factors. Our aim is to ascertain if there is evidence to reject the null hypothesis $\gamma = 0$. We sue CRSP adjusted close data to calculate stock returns.[12] We use a variety of sources to conduct stock screens and source price data, including S&P Capital IQ, Thomson Reuters Datastream and Yahoo Finance. We do not exclude data points for days with specific company results or other announcements. This will no doubt introduce variance unrelated to either the political event or the Fama–French factors. Removing the corresponding return for such announcements would 'clean' the data set. Doing so would likely reduce the variance of the unexplained part of our regressions and potentially improve significance. It would also involve a considerable computational effort. We do not take this step, choosing to focus on testing a greater number of events, rather than a smaller number with cleaner data. This means there is an implicit assumption in our method. This is that the frequency of

[12] Adjustment methodology can be found at `https://www.crsp.org/products/documentation/crsp-calculations`.

such stocks specific events is similar in training and testing sets. There is no reason to believe that this assumption is not valid.

Many of the stock universes we have chosen include all equities listed on a particular exchange, or domiciled in a particular country. This will include many illiquid and infrequently traded stocks. They may not respond to changes in the odds of a political event as they simply may not be traded. There may also be stocks included that do not exist for all of the training and testing sets. The estimates of the factor loadings may not be accurate for such stocks. To remove such securities we apply a filter to the portfolio. Firstly we remove any stocks that were not trading at the start of the training set. Secondly we only consider stocks that have trades, and non-zero returns, for 90% of days in both the training and testing sets. In practice this reduces the size of our stocks universes significantly.

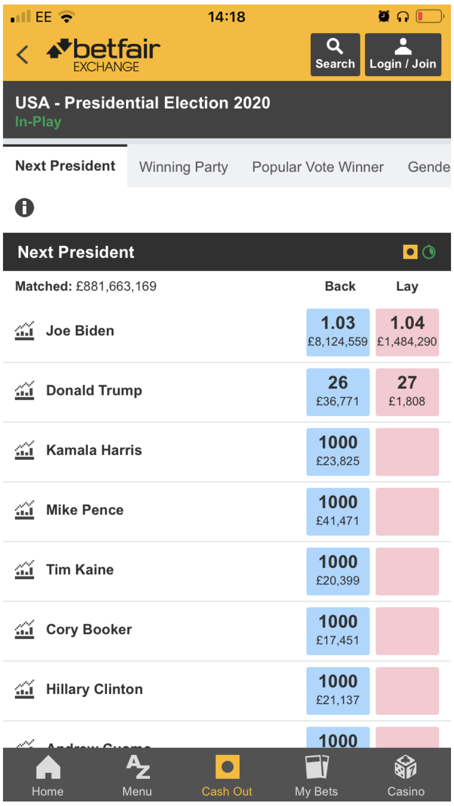


Figure 4: Betfair Exchange market for the 'Next President' on 21st Nov 2020, 18 days after voting closed.

Betting data

The betting company Betfair runs a platform called Betfair Exchange. This functions like a limit order book. For sporting, political and other events they list markets where orders for bets can be placed and executed. For each market, various selections are listed. Only one of the selections on each market will ultimately win. Participants can either 'back' or 'lay' each selection. The prices quoted are in terms of odds. Backers of the winners receive the odds multiplied by their stake, less a small percentage commission levied by Betfair. The payout, gross of commission, is paid by the participant that laid the relevant matched bet. The risk neutral probability, ignoring commission, for a selection with odds o is $1/o$. In this paper we only quote probabilities and not odds. We consider each bet listed to be a binary option pays out £1 and costs £$1/o$. Figure 4 shows a screen shot of the Betfair market for the 2020 US presidential election on 21st November 2020. This was in the height of the political mayhem that followed the election when Donald Trump was contesting results with various legal challenges. It can be seen that the risk neutral probability of him winning is seen at almost 4%,[13] although we believe the discount to the payout from a Biden win is largely due to risk and cost of capital matters. Note that all contenders apart from Trump and Biden have orders to lay at 1000 to 1 (1000 is the maximum odds allowed on the exchange). The market has reflected the removal of the other candidates from the presidential race.

The raw data we use from Betfair are matched trades on the exchange for the relevant market. For non-binary markets, which have multiple possible outcomes, such as the US presidential election shown in Figure 4, we only consider trades in a single selection (corresponding to $E = 1$). We handle binary events (Brexit and the Scottish independence referendum) differently. Here we use both selections, converting the alternative probability to the chosen selection via $\mathbb{P}(E = 1) = 1 - \mathbb{P}(E = 0)$. The market is sufficiently efficient that arbitrage opportunities do not exist by holding every selection on a market (doing so guarantees a risk-free fixed payout). Trades also happen at multiple times throughout the day and at various prices. We need to convert the trades into a daily difference that aligns with the stock returns. We do this by choosing the trade that happens closest to the time of the relevant equity market close on each day.

Fama–French factor data

Fama–French daily factor returns are available for download from Professor French's website[14]. We use data for the five factor model for both the training and testing periods. The factors are labelled MktRF, the market return, SMB, the small minus big size

[13] The binary option that pays out £1 in the event of Trump being named as next president is bid at £1/27 and offered at £1/26.
[14] `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

companies, HML, high minus low value stocks, RMW, robust minus weak operating profitability and CMA, conservative minus aggressive investment. We use two years worth of data immediately prior to the testing set to estimate the Fama–French loadings. We judge this period sufficient to estimate the factor loadings. We avoid choosing a longer training set to avoid the possibility of structural breaks in stock loadings. Over long periods of time the factor loadings may change for a stock. For example, small companies can become large ones.

5.3 Results

Firstly we examine relationships between the factor returns and the betting markets. We regress each factor on $\triangle PB_t$ and an intercept in the event window for each political event. Note we exclude the day after the election. This is because both the changes in betting odds, and market moves, can be very large on that day. Including this day will dominate any OLS regression. Further, returns, and Fama-Franch factors, are calculated based on market close. If we were to include the day after the election, it would be better to look at the market open as this will be the first snapshot of prices post-result. There can be large intra-day volatility the day after the outcome becomes known. For example, the market rout that followed Trump's shock win 2016 was completely reversed within the day following a reassuring morning address from the new president. If there is a relationship between the betting and stock markets we want to test that it is persistent over a reasonable length of time and not just when the election result becomes known. Results for the slope for these regressions are shown in Table 2. Errors robust to heteroskedasticity are used. The betting markets do not explain the variation in the European factors for the Scottish independence referendum. This is not surprising as this was a UK based event and the factors are based on the whole of the European market. Correspondingly though for the Brexit referendum, there is a significant relationship at the 99% level for the market return, and at the 90% level for the SMB factor. Brexit was an event that had potential effects beyond the UK and could affect many large European economies and exporters. (The Fama–French European factor covers both the UK and mainland Europe.) The estimated slopes in the regressions suggests a difference in price of the average European company of 17% ($\pm$5%) between the UK remaining in the EU and leaving. Smaller companies would be expected to outperform by 3% ($\pm$1.9%) under Brexit, perhaps as smaller EU companies are less likely to export to the UK than large ones. The 2017 UK general election has surprising results. MktRF and SMB do not appear related to the betting market, but the other three factors do. This election was called by the Prime Minister Theresa May to 'strengthen her hand' in any Brexit negotiations. The outcome of this election could have been expected to have an effect on the type of deal the UK and the EU would ultimately strike. It then follows that the probability of Theresa May gaining a majority could have an effect on stock prices throughout Europe. However, it is puzzling that effects were seen on stock prices according to their relative value, operating profitability and investment strategy, but not on the overall level of the market. Further, no significant effects were seen on the Fama–French factors in the general election two years later, where the new Prime Minister Boris Johnson was vowing to 'Get Brexit Done'. For the 2016 US presidential elections, there are significant effects in the SMB and CMA factors. The relationship between MktRF and $\triangle PB_t$ is not significant though. This is a surprise given the huge sell off in asset prices following Donald Trump's unexpected win. We do note that the estimated slope coefficient does suggest the market would be 5.2% ($\pm$4.8%) lower if Trump were to win[15]. For the 2020 election, no significant effects are seen on the Fama–French factors from the betting market.

To experiment to see if the betting markets become more informative as the election approaches we re-run the regressions, but begin the event window only a calendar month before the dates of the election. The new results are shown in Table 3 and are striking. All factors are now significant for the 2016 election bar RMW and MktRF and CMA are significant for the 2020 election. Biden is now seen as having a rather unbelievable positive effect of around 25% ($\pm$8%) on the stock market if he were to replace Trump as president. This suggests that the betting markets become more informative as the election nears which is consistent with the observation that liquidity exponentially increases during this time too.

5.3.1 Significance tests

We now turn to results of significance tests for the model. Results tables for the tests are found in Appendix D. As with the Fama–French factor regressions, we exclude the day after the election from the testing period. Including the day would almost certainly generate significance. However this does not test that the model holds over a general period and would relate to significance 'after the fact'. We apply the steps in the empirical specification for the residuals of the K=0, 1 and 5 factor Fama–French models. For K=0 we simply regress stock returns, less their mean from the training set, on $\triangle PB_t$. K=1 corresponds to residuals from the CAPM model. Both the mean weighted portfolio and individual stock Pesaran and Yamagata tests are run. Results are shown in Table 4. We perform various diagnostics to check for serial correlation and heteroskedasticity.

From the pricing model recall that the presence of serial correlation in the regression errors is consistent with errors in market efficiency. It would also invalidate the results of the $J_{\gamma,2}$ test. Ljung Box statistics are calculated for all regressions, including the

[15]The S&P500 future initially sold off by 4.8% overnight. The odds for Trump increased from around 20% to 99% during this time.

multivariate form of the statistic. There is little evidence of serial correlation from the mean weighted portfolio regressions. Of the 24 regressions conducted a single one has a significant Ljung-Box statistic at the 95% level. This is for the one factor model for the 2016 US presidential election. This is not repeated for the other factor models, nor for the individual stock regressions for that election. We ascribe little relevance to this observation. There is also no evidence for serial correlations from the portfolio regressions with no significant Ljung-Box statistics. The conclusion is that the data demonstrate no evidence of market failure. The election night model of Auld (2022) found deviations of weak market efficiency of the order of minutes to tens of minutes. However, it is not surprising that no inefficiency was found here as we are using much less frequent daily data. Discovering an inefficiency on this time-scale would be a much more surprising result.[16]

Turning now to heteroskedasticity we conduct both the Breusch-Pagan and Engle ARCH tests for the univariate portfolio regressions. The Engle test provides some evidence of deviations from homoskedasticity in these univariate regressions. We note though that only one event, the 2019 UK general election, is significant, at the 95% level, once the first market wide factor has been controlled for. However, results of these regressions will be valid as heteroskedasticity robust errors are employed. For the $J_{\gamma,2}$ tests we conduct the Ling and Li (1997) test. We observe a single significant value, (at the 95% level), for the zero factor model in the Brexit test. Again we do not ascribe any relevance to this finding as it is not repeated for the higher factor models. In general we are confident that conclusions drawn from the modified Pesaran and Yamagata $J_{\gamma,2}$ tests are valid.

In short, we observe highly significant values of γ for four of the six events studied. We also note that, as expected, the $J_{\gamma,2}$ tests have higher power than the univariate mean-weighted portfolio test. Significance of the portfolio test is only ever found when the $J_{\gamma,2}$ is significant, but the opposite is not true. We discuss the results below in more detail.

For the 2014 Scottish independence referendum, $J_{\gamma,2}$ is significant at the 95% level for K=0 and at the 99.9% level for K=1 and 5. This is consistent with the conclusions of Darby et al. (2019) and Acker and Duck (2015) that showed that the CAPM residuals are related to betting odds. However, we go further and demonstrate that there is still explanatory power in the betting markets when the additional Fama–French factors are controlled for. We note that the average value of γ implies an average decrease in the price of UK stocks of 2.5% between Scotland voting for independence and voting to remain in the UK. The regressions on the residuals of the higher factor models estimates

[16]Given the number of regressions performed, we would expect a small number of seemingly significant Ljung Box statistics at the 95% level under the null hypothesis of no serial correlation.

the decline relative to the European wide market. This is because the factors used are Europe wide. The underperformance of UK stocks relative to their European peers is estimated at 1.7–1.8% given a vote for independence versus Scotland remaining in the UK.

The 2016 Brexit referendum also produced highly significant findings for UK based equities listed on the LSE. All the models produced $J_{\gamma,2}$ significant at the 99.9% level. Two of the three univariate regressions are also significant at the 99.9% level for K=0, and at the 90% level for K=1. Estimated values of γ imply very steep falls in stocks given a vote for Brexit. The K=0 model suggests an overall decline of 15% (individual regressions) relative to a vote to Remain. The K=1 and 5 models estimate declines for UK stocks relative to the overall European market of around 2.6–2.8%. Results for the Brexit referendum for the European exporters portfolio are interesting. Recall that the betting markets were highly explanatory for this European wide market factor. γ is significant for K=0 but once we control for the first market factor, MktRF, they become insignificant. The significance seen for European exporters in the raw returns is due to $\triangle PB_t$ driving the wider European market. However, $\triangle PB_t$ does not explain the CAPM residual, even for European companies that generated over 25% of their revenues in the UK in 2015. These companies were not expected to perform significantly differently than the wider European stock market, given a vote for Brexit. We note that the estimated fall for these European exporters of 13% is consistent with both the estimated fall of UK stocks (around 15%) and the estimated underperformance of UK stocks (3%), to within standard errors. Recall also that a regression of the European wide MktRF factor on the betting market for this event was significant. The estimated effect of a 1% change in the odds of Brexit led to a fall of $0.16\% \pm 0.05\%$. Again this is broadly consistent with the fall of European exporters estimated in the portfolio regressions.

The 2016 US presidential election was a major event for Mexico. Changes in the probability of a Trump victory were highly significant for Mexican stocks, both outright and relative to the North American market. All univariate and multivariate tests were significant at the 99.9% level. The difference between a Clinton and a Trump win was estimated to have an average effect on Mexican stock prices of 18%. The decline relative to the North American market was estimated at around 16%. We note that for the $J_{\gamma,2}$ test $N < T$. Although the test is not asymptotically valid in such cases, Monte Carlo simulation of test statistics presented in Pesaran and Yamagata (2012) suggest good performance for similar values of N and T, when $N < T$. They also demonstrate for these values superior performance to the standard multivariate test of Gibbons et al. (1989). Furthermore we do not need to rely on the modified test of Pesaran and Yamagata here as the weaker mean-weighted portfolio test generated significance anyway. For the historical S&P500 constituents our tests do not generate significance, even for K=0. This is particularly surprising given the sell-off on the night of the election itself. This is a surprising result, but not dissimilar to the finding that $\triangle PB_t$ did not explain MktRF when regressing over the full event window. This will be explored further later.

Our final significant event was the 2019 UK general election. Boris Johnson was the firm favourite to win this election promising to 'Get Brexit Done'. His opponent Jeremy Corybn had doubled down on his left wing policies after failing to win the 2017 election. He launched what was seen as the most left wing set of policy ideas seen for a generation, Pickard (2019). Policies included raising taxes sharply for companies and higher earners as well as nationalising key UK companies. A failure for Boris Johnson to gain a majority may have opened up the possibility of a reversal of Brexit as opposition parties were suggesting a second referendum. However, for asset markets, Jeremy Corbyn was now apparently seen as the bigger threat. Also, failure to gain a majority could likely continue the intense political uncertainty that had dogged the UK for the preceding few years. A Conservative majority was seen as significantly positive for UK stocks, both outright and relative to the European market. $J_{\gamma,2}$ is significant for all three models (at the 99.9% level). Estimated values of γ imply an average premium for stocks of 1.4% under a Conservative majority.

The two events that did not generate significant γ are the 2017 UK general election and the 2020 US presidential election. It may be the case for these events that either, one, $\gamma = 0$, and the political event is not informative for asset prices, or two, that the elections are informative but that noise in the data fail to generate statistically significant regression coefficients due to γ being small relative to the variance of the full model residual η_t. We cannot be certain of the answer. However, it is plausible that neither event is in fact, for the average stock, informative for prices. $\gamma = 0$ appears consistent with the very muted reaction seen in the markets for the 2017 General election on what was in effect a shock result. Prior to this election there was political gridlock due to disagreements about Brexit. Although the opposition Labour party was seen as less friendly to business, power for them would have made the odds of remaining in the EU more likely. Results for the market were not clear. However, by the time of the 2019 election, opposition policies had become either more extreme or more progressive, depending upon one's political viewpoint. Either way, in 2019 the implications for the UK stock prices from a Corbyn win were generally seen as being more negative than from the certainty of Brexit under the more generally perceived business friendly Conservatives. The possibility that the outcome of the 2017 election was not informative for stock prices at all, and that $\gamma = 0$, is also suggested by the very small values of the t-statistics in the stock by stock regressions. This is -0.07 (or -0.13 for K=1) and $\sqrt{\overline{t^2}} = 0.99 - 1.00$. Similarly for the 2020 presidential election, as the US stock market had been on a roar during Trump's presidency (contrary to 2016 fears), implications for stocks were not at all clear either in that election. Either result is less surprising than the failure of the 2016 presidential election to generate significance for the S&P500 constituents.

5.3.2 Weighted regression tests

The failure to demonstrate that betting markets significantly explained the returns of the S&P500 stock returns (and their Fama–French residuals) was a puzzling result for the 2016 US presidential election. This is a similar result though to the failure of the betting markets to explain the returns of the first market factor, MktRF, over the same period. However, significance was found when regressing MktRF over the shorter period of the month preceding the election, both for this election and the 2020 presidential election. Could it be that the betting market's explanatory power increases closer to an election? This would be consistent with the findings of Page and Clemen (2013). They demonstrated the performance of prediction markets is negatively correlated with time to expiry of the market. As the election nears it tends to dominate the news cycle and will more likely be on the minds of potential bettors. Betting volumes also increase hugely.

To explore the idea we apply a weighted regression scheme to our significance tests, with the weights increasing as the election nears. The J_γ tests of Pesaran and Yamagata allow this as long as the same weighting is used for each individual stock regression. The weighted estimates of correlation coefficients are also required when adjusting for cross sectional dependence of returns. This is trivial to apply. A weighting scheme will need to be chosen. It would be natural to weight by the volume traded in the betting markets. However, as Table 2 shows, the liquidity can increase by several orders of magnitude during the testing period, and peaks just before the election. Using raw volume will simply put all the weight on the final few days. Using the logarithm of volume could be a choice but probably does not increase sharply enough given the large increases in volume. Rather than come up with a scheme whereby we make some choice of function of volume to use, we will simply weight in the time dimension. We chose to increase the weighting exponentially by a relatively modest 5% per week.[17] Regressions and significance tests are run for both individual stocks as well as the equally weighted portfolio. Results are shown in Table 5.

For the previously significant stock universe and event pairs, results are repeated but with increased significance. Absolute values of t-statistics and estimates of $J_{\gamma,2}$ are higher. Values of γ are also similar. We will not in general discuss these results individually. One meaningful change is with the European exporters portfolio during Brexit. Not only has the significance of the betting markets improved for the K=0 model (and become significant in the univariate test) but the K=1 and 5 models now produce

[17] Schemes whereby weightings of 2.5% and 10% were also tried. The same 'sharpening of results' was also observed albeit to different degrees. Results are available by contacting the author directly.

significant results (at the 99.9% level). A small outperformance of these stocks versus the European average given Brexit over Remain of 1.4–1.9% is estimated. This is surprising as this author expected European exporters to the UK to underperform given a Brexit scenario. There may be other factors at play here, such as these companies exporting more outside Europe, potentially mitigating a downturn in EU revenues, than the average European company.

With regards to the S&P500 universe in the 2016 presidential election, results are now highly significant using the weighted regression. All $J_{\gamma,2}$ tests are significant at the 99.9% level and the K=0 univariate equally weighted portfolio test is significant at the 95% level. It appears that the information content of the betting markets may indeed improve as the election is approached. The K=0 models imply a fall in price of the average S&P500 stock of 8% given a win for Trump versus Biden. The K=1 and 5 models actually predict a small outperformance of 0.4–0.8% of the S&P500 versus the North American market as a whole. This may be highly significant but it is an economically small effect.

The 2017 UK general election remains insignificant using the weighted regressions. Again very small values of t-statistics are found in the stock by stock regressions. $\bar{t}$ is in the range -0.04 to -0.11 and $\sqrt{\overline{t^2}} = 1.06$. We conclude that our model is not relevant for this event and indeed $\gamma = 0$.

Finally we see that using a weighted regression generates some significance for S&P500 stocks in the 2020 US presidential election. For K=0 the results are significant at the 99.9% level for the stock by stock test and at the 95% level for the equally weighted portfolio regression. The typical index stock is expected to outperform by 20% given a Biden win over a Trump win. The K=5 model also generates a significant $J_{\gamma,2}$ at the 99% level. However, the predicted outperformance of the index stocks of 0.3% versus the wider North American market is economically insignificant. We note that using the weighted scheme has generated significance for the S&P500 portfolios for both US elections studied in this paper. Betting markets do explain the moves in outright stock returns. However, despite the betting markets having significant explanatory effects on the residuals of the Fama–French model for these index stocks the predicted effects are very small and economically insignificant.

In general, using significance tests based on the weighted regressions has sharpened our results. Events that were deemed to be significant using the standard regression over the whole testing period remain significant but more so. We have also demonstrated that the betting markets explain the returns of S&P500 stocks using the weighted scheme. This suggest that the information content increases as the election nears. This is a not unexpected result given the explosion in trading volumes on betting exchanges as the election is approached. However, we do not generate results of economically meaningful magnitude for the Fama–French residuals of the S&P500 index stocks. Finally our model does not appear to hold in that $\gamma = 0$ for the 2017 UK general election. The results of that election did not seem clear for Brexit and hence stock prices given the particular political situation in the UK at that time.

5.3.3 Political factor loading characteristics

Next we investigate the political factor loadings γ and how they vary with any common observable characteristics of the stocks. We examine how γ varies for the 5 factor model. This will identify the political sensitivity of individual stocks, controlled for common characteristics related to the Fama–French factors. We need to caveat our results. We regress the loadings against some observable characteristics. However, not all stocks had the necessary data we sought. As such we cannot discount the possibility of some sample selection bias in what we report. However, most events had reasonably good data coverage and the relationships uncovered were generally strong. We are confident of the direction of the relationships revealed if not their exact magnitude.

For the 188 stocks listed on the LSE that survived our selection process for the 2014 Scottish independence referendum, 158 of them published easy to access percentages of revenues for the UK in their 2013 full year accounts. We expect a greater sensitivity to independence for stocks that generate more of their revenues onshore, as the UK economy would likely suffer more than international peers. Thirteen of the companies were also headquartered in Scotland. These latter stocks would be much more likely to affected by independence than companies based in the rest of the UK.

Table 6 shows the results of a cross-sectional regression of γ against these two characteristics. Results for similar regressions from the other events are also shown in the table. Both characteristic's coefficients are significant. For every additional 1% revenue earned onshore in 2013, γ would be 0.0008 higher. This means the sensitivity of the stock price to the election increases eight basis points (0.08%) from that 1% additional UK based revenue. By sensitivity here we mean the expected difference of prices between Scotland leaving or remaining as part of the UK. The coefficient of the 'HQ in Scotland' indicator implies an increased sensitivity due to being based in Scotland of 7.3%. Darby et al. (2019) demonstrated that sensitivity to betting odds helped predict cross sectional returns of Scottish based companies. The work in this paper goes further and shows that Scottish headquartered companies had significantly more risk to the 2014 Scottish independence referendum than other UK firms.

For stocks listed on the LSE in the Brexit referendum, we use percentage of revenue generated in developed European markets published in the 2015 full year accounts. This includes the revenue earned in the UK. This developed EU markets figure is found to be very similar to the revenue figure for the UK only. (Most of the revenue earned by UK companies in developed European markets is earned in the UK.) Joint regression of γ on both these figures is problematic due to co-linearity. We chose the European number to include any effects on exporters to the EU (who are also likely to be affected by Brexit). These figures are available for 183 of the 219 stocks used in the regressions. European revenue is significantly explanatory for γ at the 99.9% level. The political sensitivity increases by about ten basis points for every additional percent of developed European revenue earned. Put another way, for every additional percent of revenue earned outside of developed European markets, stocks are expected to have prices eight basis points higher in price under Brexit (versus Remain). We also regress γ on revenue earned in the UK in 2015 for the EU exporters portfolio (available for all the exporters). No relationship was found. The UK sales figure was not informative with a very low R^2 of 0.008.

For the 2016 election where Trump won the presidency, we study both the S&P500 index stocks as well as Mexican companies. For the index stocks we source percentage of sales earned locally in the US in 2015 (we hypothesise that exporters would have more sensitivity to a Trump win given the potential for increased trade disruption). The characteristic was available for 461 of the 488 index stocks that were used in the significance tests. The local percentage of revenue figure was highly significant with γ falling 7.5 basis points for every additional percent of revenue earned locally. This is puzzling, as this means γ was increasing with increasing exports and that exporters would be likely to perform better under a Trump versus a Clinton presidency. We have no explanation for this result but do note that the estimated values of γ for this model had on average an expectantly positive sign, although the effect was very small ($\bar{\gamma} = 0.004$).

For the Mexican portfolio we use the percentage of revenue earned in the US in 2015. Unfortunately this was only reported for 16 of the 51 stocks used. The regression does not generate significant results, not unexpectedly since N is so low. The coefficient is estimated at -0.199 ± 0.174 ($p = 0.271$). This suggests a Mexican stock that earns all revenue from the US is estimated to have prices 20% lower under Trump versus Clinton than a Mexican company that earns no revenue in the US.

For the 2017 UK general election we do not proceed as we have concluded our model does not hold ($\gamma = 0$). For the 2019 UK general election portfolio we use the 2015 reported percentage revenue earned in the UK. This is available for 202 of the 243 stocks considered. Jeremy Corbyn, the opposition Labour party leader, also promised to nationalise seventeen UK based companies, if he won, Rees (2019). We regress γ on the UK revenue percentage and an indicator based on whether or not the company would be nationalised under Labour. UK Revenue is significant at the 99.9% level. Political sensitivity increases with UK revenue, eleven basis points for every additional percentage point revenue earned onshore in 2018. This means UK focused businesses were expected to perform relatively poorly had the Conservatives failed to get a majority, relative to

exporters. The coefficient on the indicator of nationalisation risk under Corbyn is not significant, but is estimated at 3.9%. We note that the average γ for stocks identified as being nationalised under Corbyn is 0.055 $\pm$ 0.12 versus 0.012 $\pm$ 0.17 for the other stocks. We thus test equivalence of the distributions of γ amongst stocks conditional on nationalisation risk, versus conditional on no nationalisation risk. We apply a one-sided two-sample Kolmogorov–Smirnov test. The null is that the two samples come from the same distribution versus an alternative that the CDF for the sample given nationalisation risk is higher. The Kolmogorov–Smirnov test statistic is 0.325 with a p-value of 0.028. The 17 stocks Corbyn named as nationalisation targets are significantly more sensitive to the result of the election than others at the 95% level.
Finally we seek a relationship for the S&P500 index stocks for the 2020 US presidential election. 2019 local percentage revenue is available for 404 of the 487 stocks used in the model estimation stage. This is not explanatory for γ with a very low R^2 reported of 0.002.

Elections often involve domestic or geographical risks. It is likely that companies that earn more revenue offshore or internationally are more able to diversify away from election risks. Some evidence for this hypothesis was present in the literature for Brexit, Hill et al. (2019). Internalisation was found to decrease the sensitivity of UK stock prices to the betting odds for Brexit as well as the day-after-result return. In this paper we have extended these findings, testing this idea for all six events. We included a proxy for national revenue (or developed EU revenue for Brexit), finding that internalisation is indeed significantly explanatory for four of the six events. These results both complement Hill et al. (2019) and improve them. Not only do we consider more events, we check the explanatory power after the five Fama–French factors have been controlled for.

Similarly we have repeated an observation made in one of the oldest studies of elections risk and financial markets (Gemmill, 1992). For the 1987 UK general election this paper showed there was a much larger increase as the election was approached in option volatility of stocks that were at risk of nationalisation under the Labour opposition. History appears to have repeated itself in 2019. The then Labour leader Jeremy Corbyn threatened to nationalise various utility and other companies if he won. Here we measure political risk as the sensitivity to betting odds of the Conservatives failing to get a majority, finding the risk significantly larger for companies at risk of nationalisation.

6 Conclusion

The information content of political prediction markets is well documented. As is the effect on asset prices of elections and other political risks. Given this, it is natural to ask is there a way to formally link prices between political markets and financial markets?

Auld (2022) sought to answer this question in the very particular circumstances of the overnight session following a vote. However, this paper aims to describe the relationship between these two types of markets in the weeks and months leading up to a political event. There are a small number of examples in the literature that study this question (see Manasse et al. (2020), Hanna et al. (2021), Acker and Duck (2015) and Darby et al. (2019)). However, they consider only a single event and typically study only empirical relationships. We build a pricing model for the asset pricing relationship from the 'ground-up' using an economic assumption and common pricing restrictions from the asset pricing literature. That we recover a relationship between asset price returns and the first difference of betting markets is perhaps no surprise. Indeed other papers have studied this relationship empirically. However, this work differs in that we have an economic basis for the model, and also test it on multiple events. Indeed the main contribution of this paper is to present a model that is grounded in economic assumptions and can be applied to *any* political event. In fact the model applies in more general settings; it can be used for any events where there is a liquid prediction market and whose outcome has an effect on asset prices. There are no comparable studies in the literature.

To build the model we make a key assumption. This is that the difference of the conditional expectations of asset prices (given the result of the election) is fixed. This leads to a relationship in first differences. The variance of returns of asset prices are separated into a political part, explained by political markets, and a residue, related to commercial, economic and other non-political factors. The model is naturally extended using the Fama–French factors to describe the variance of the non-political component. The resulting model is an extended characteristic factor model, where all factors, both Fama–French and political, are observed.

We test the model on six recent elections. We find strong evidence in favour of our model for four of the six events. One election has mixed results (the 2020 presidential election). A weighting scheme was required there to generate significance. Data closer to the election was weighted more highly than data far from the vote. Although a modification of the original model, this can be explained by political markets having greater information content the closer we are to an election. Some justification for the approach is from Page and Clemen (2013), which showed that the forecasting ability of prediction markets is negatively correlated with time to expiry. We find that in general the weighting scheme increases the significance of our results. This improvement is explained by the huge increases in volumes observed on betting platforms as elections draw near. Finally, we find no support for our model for a single event, the 2017 UK general election. We conclude that this election was not informative for asset prices, with the weighting on the political factor, γ, being in fact zero.

An exploration of the factor loadings reveals some pleasing relationships. Consistent with Hill et al. (2019) we find that domestic (or EU based) revenue is a strong explanatory factor of political risk. Indeed, this characteristic was significant for four of the six elections studied. This provides evidence for the hypothesis that companies with a greater reliance on international sales are more able to diversify domestic political risk. We also extend findings of the existing literature with the observation that the location of company headquarters, and nationalisation risk are significantly explanatory of political risk.

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Appendix

A Power of two-step empirical specification versus a single regression approach

We demonstrate that using our two step approach to testing political betting significance (outlined in section 4) has superior power than using a single larger factor model regression (equation 4.1). The latter (falsely) assumes an unchanging political probability on the training set. The key assumption is that the political factor, although not necessarily observable, has non-zero variance in some part of the training period. To show this consider the simple univariate regression

$$r_t = \alpha + \beta \triangle P_t + \epsilon_t \qquad t = 1, \ldots, T_1, T_1 + 1, \ldots, T_2 \qquad \mathbb{E}(\epsilon_t) = \sigma_\epsilon^2 \tag{A.1}$$

where r_t is the return of a financial asset at time t and $\triangle P_t$ is the change in the probability of the upcoming event. Assume that this is the correct model, that $\beta \neq 0$ and note that $\mathbb{E}(\triangle P_t) = 0$. Data is available for r_t for entire period $t = 1, \ldots, T_2$. $\triangle P_t$ is in general not observed for the first period $t = 1, \ldots, T_1$ but can be measured by the betting market prices $\triangle PB_t$ for $t = T_1 + 1, \ldots, T_2$. Consider the regression on the period where we have data for both r_t and $\triangle P_t$, $(t = T_1 + 1, \ldots, T_2)$. This is analogous to regressing the estimated Fama-French residual on changes in the political markets on the testing set only. The t-statistic for β in this regression is t_β where

$$t_\beta \longrightarrow \sqrt{T_2 - T_1} \times \frac{COV(r_t, \triangle P_t)}{\sigma_\epsilon . \sigma_{\triangle P_t}}.$$

Next define

$$\tilde{\triangle P_t} = I(t > T_1) . \triangle PB_t$$

which is $\triangle P_t$ forced erroneously to zero on the first set $T = 1, \ldots T_1$ where data is lacking. Now consider a regression of r_t on $\tilde{P}_t$ on the whole period for $t = 1, \ldots, T_2$

$$r_t = \alpha + \beta \tilde{\triangle P_t} + \tilde{\epsilon}_t \qquad t = T_1 + 1, \ldots, T_2 \quad \mathbb{E}(\tilde{\epsilon}_t) = \tilde{\sigma}_\epsilon^2$$

This is analogous to the single regression empirical approach where we jointly estimate the Fama-French loadings with a false assumption that the political probability is unchanging in the first period. The relevant t-statistic for β is now

$$
\begin{aligned}
\tilde{t}_\beta &= \sqrt{T_2} \times \frac{\frac{1}{T_2}\sum_{t=1}^{T_2} r_t(\widetilde{\triangle P}_s - \frac{1}{T_2}\sum_{s=1}^{T_2}\widetilde{\triangle P}_s)}{\hat{\sigma\epsilon} \times \sqrt{\frac{1}{T_2}\sum_{t=1}^{T_2}(\widetilde{\triangle P}_t - \frac{1}{T_2}\sum_{s=1}^{T_2}\widetilde{\triangle P}_s)^2}} \\
&= \sqrt{T_2} \times \frac{\frac{1}{T_2}\sum_{t=1}^{T_2} r_t(\widetilde{\triangle P}_t - \frac{1}{T_2}\sum_{s=T_1+1}^{T_2}\triangle P_s)}{\hat{\sigma\epsilon} \times \sqrt{\frac{1}{T_2}\sum_{t=1}^{T_2}(\widetilde{\triangle P}_t - \frac{1}{T_2}\sum_{s=T_1+1}^{T_2}\triangle P_s)^2}} \\
&= \sqrt{T_2 \times} \frac{\frac{1}{T_2}\sum_{t=1}^{T_2} r_t(\widetilde{\triangle P}_t - \frac{(T_2-T_1)}{T_2}\hat{\overline{\triangle P}})}{\hat{\sigma\epsilon} \times \sqrt{\frac{1}{T_2}\sum_{t=1}^{T_2}(\widetilde{\triangle P}_t - \frac{(T_2-T_1)}{T_2}\hat{\overline{\triangle P}})^2}} \\
&= \sqrt{T_2} \times \frac{\frac{1}{T_2}\sum_{t=T_1+1}^{T_2} r_t \triangle P_t \; - \; \frac{T_1(T_2-T_1)}{T_2^2}\hat{\overline{\triangle P}}}{\hat{\sigma\epsilon} \times \sqrt{\frac{1}{T_2}\sum_{t=T_1+1}^{T_2}\triangle P_t^2 - \frac{2(T_2-T_1)^2}{T_2^2}\hat{\overline{\triangle P}}^2}} \\
&= \sqrt{T_2} \times \frac{\frac{(T_2-T_1)}{T_2} C\hat{O}V(r_t, \triangle P_t) \; - \; \frac{T_1(T_2-T_1)}{T_2^2}\hat{\overline{\triangle P}}}{\hat{\sigma\epsilon} \times \sqrt{\frac{(T_2-T_1)}{T_2} V\hat{A}R(\triangle P_t) - \frac{(T_2-T_1)^2}{T_2^2}\hat{\overline{\triangle P}}^2}}
\end{aligned}
$$

where we have used the fact that $\widetilde{\triangle P}_t = 0$ for $t \leq T_1$ and

$$
\begin{aligned}
\hat{\overline{\triangle P}} &= \frac{1}{(T_2 - T_1)} \sum_{s=T_1+1}^{T_2} \triangle P_s \longrightarrow 0 \\
\hat{\sigma\epsilon} &= \sqrt{\frac{1}{T_2} \sum_{t=1}^{T_2} \hat{\tilde{\epsilon}}_t^2} \longrightarrow \sigma_{\tilde{\epsilon}} \\
C\hat{O}V(r_t, \triangle P_t) &= \frac{1}{(T_2 - T_1)} \sum_{t=T_1+1}^{T_2} r_t \triangle P_t \longrightarrow COV(r_t, \triangle P_t) \\
V\hat{A}R(\triangle P_t) &= \frac{1}{(T_2 - T_1)} \sum_{t=T_1+1}^{T_2} \triangle P_t^2 \longrightarrow \sigma^2_{\triangle P_t}.
\end{aligned}
$$

The first result comes from the fact that $\mathbb{E}(\triangle P_t) = 0$. Thus

$$
\tilde{t}_\beta \longrightarrow \sqrt{T_2} \frac{\frac{(T_2-T_1)}{T_2} COV(r_t, \triangle P_t)}{\sqrt{\frac{(T_2-T_1)}{T_2}} \sigma_{\tilde{\epsilon}} . \sigma_{\triangle P_t}} = \sqrt{T_2 - T_1} \times \frac{COV(r_t, \triangle P_t)}{\sigma_{\tilde{\epsilon}} . \sigma_{\triangle P_t}}
$$

Note that $t_{\tilde{\beta}}$ is very similar to t_β and differs only in the denominators σ_ϵ and $\sigma_{\tilde{\epsilon}}$. However, we have assumed that

1. $\beta \neq 0$
2. $\{x_1, \ldots, x_{T_1}\}$ is not everywhere zero

3. Equation (A.1) represents the *true* model.

However, if the model is indeed true it cannot provide a worse fit than the model

$$y_t = \alpha + \beta \tilde{x}_t + \tilde{\epsilon}_t \qquad t = 1, \ldots, T_2.$$

When assumptions 1 and 2 above hold, the fit must be strictly worse. Thus, asymptotically, $\sigma_{\tilde{\epsilon}} > \sigma_{\epsilon}$. The limit of the second t-statistic has smaller absolute size than that of the first t-statistic. Thus under an alternative hypothesis $\beta \neq 0$ the second t-statistic will never reject the null hypothesis $\beta = 0$ unless the first t-statistic does. t_β has greater asymptotic power then $\tilde{t}_\beta$.

If we are testing the hypothesis $\beta \neq 0$ in a univariate regression and we lack data for the explanatory variable for some part of a sample set, then a higher power test is provided by regressing on only the sub-sample where data is known for both the explanatory and dependent variables rather than regressing on the whole set and forcing the dependent variable to zero where there are no observations. This is exactly analogous to showing that jointly estimating the Fama-French residuals along with the political component, whilst forcing the political factor to be zero, has lower power than the two step approach we employ.

B Modified J_α tests of Pesaran and Yamagata

The J_α test of Pesaran and Yamagata (2012) is summarised as follows. Consider the following factor model in the form of a panel data regression and stacked by cross-sectional regressions

$$\boldsymbol{y}_t = \boldsymbol{\alpha} + \boldsymbol{B}\boldsymbol{f}_t + \boldsymbol{u}_t.$$

y_i are the individual stock returns, and $\boldsymbol{f}_t$ are K known factors. $\boldsymbol{B}$ is an $N \times K$ matrix of factor loadings. The Wald statistic for $\boldsymbol{\alpha} = 0$ can be estimated as

$$\hat{W}_\alpha = \sum_{i=1}^{N} t_{\alpha,i}^2$$

where $t_{\alpha,i}$ is the t-ratio of the intercept of the OLS regression of $(\boldsymbol{y}_t)_i$ on intercept and $\boldsymbol{f}_t$. In the case of cross sectionally independent errors it can be shown that under various regularity conditions

$$\begin{aligned}
\mathbb{E}(W_\alpha) &\to \frac{\nu N}{\nu - 2} \\
\mathbb{VAR}(W_\alpha) &\to \frac{2N(\nu-1)}{(\nu-4)}\left(\frac{\nu}{\nu-2}\right)^2
\end{aligned}$$

as $N \to \infty$, $T \to \infty$ and $N/T \to \infty$ where $\nu = T - K - 1 > 4$. The following is an exactly standardised statistic

$$\hat{J}_{\alpha,1} = \frac{N^{-1/2}\sum_{i=1}^{N}\left(t_{\alpha,i}^2 - \frac{\nu}{\nu-2}\right)}{\left(\frac{\nu}{\nu-2}\right)\sqrt{\frac{2(\nu-1)}{(\nu-4)}}}$$

and thus is distributed as $N(0,1)$ asymptotically under the null. The result holds in the case of non-normal errors. A second statistic $\hat{J}_{\alpha,2}$ is derived that is adjusted for correlation of the individual t-statistics when the errors are cross-sectionally correlated. The adjustment is based on a consistent estimate of the correlation matrix of the disturbances $\boldsymbol{u}_t$. Define

$$\hat{\bar{\rho}^2} = \frac{2}{N(N-1)}\sum_{i=2}^{N}\sum_{j=1}^{i-1}\hat{\rho}_{ij}^2 I(\nu\hat{\rho}_{ij}^2 \geq \theta_N)$$

where $\hat{\rho}_{ij}$ is the sample correlation of the regression residuals $\hat{\boldsymbol{u}}_t$ and θ_N is some threshold value. The latter is chosen so that the number of non-zero correlations decline steadily with N. We will follow the protocol set out in Pesaran and Yamagata (2012) with $\sqrt{\theta_N} = \Phi^{-1}(1 - \frac{p_N}{2})$ and $p_N = 0.1$. The adjusted statistic is now

$$\hat{J}_{\alpha,2} = \hat{J}_{\alpha,1} \times \frac{1}{\sqrt{\left[1 + (N-1)\,\hat{\bar{\rho}^2}\right]}} = \frac{N^{-1/2} \sum_{i=1}^{N} \left(t_{\alpha,i}^2 - \frac{\nu}{\nu-2}\right)}{\left(\frac{\nu}{\nu-2}\right) \sqrt{\frac{2(\nu-1)}{(\nu-4)} \left[1 + (N-1)\,\hat{\bar{\rho}^2}\right]}}.$$

Pesaran and Yamagata (2012) show that $\hat{J}_{\alpha,2}$ is asymptotically distributed as $N(0,1)$ under various stricter regularity conditions and weak cross sectional correlation. They also show, via Monte Carlo simulation, small deviations from correct sizes for sample sizes similar to those used in this paper. Of course $|\hat{J}_{\alpha,2}| < |\hat{J}_{\alpha,1}|$ since it has lower variance due to the correlation adjustment of the t-statistics. $\hat{J}_{\alpha,2}$ will never reject the null when $\hat{J}_{\alpha,1}$ does not. We will not consider the first statistic at all as we do expect that errors will indeed have some correlation.

The test generalises simply to the slope parameter. We thus consider

$$\hat{J}_{\gamma,2} = \frac{N^{-1/2} \sum_{i=1}^{N} \left(t_{\gamma,i}^2 - \frac{\nu}{\nu-2}\right)}{\left(\frac{\nu}{\nu-2}\right) \sqrt{\frac{2(\nu-1)}{(\nu-4)} \left[1 + (N-1)\,\hat{\bar{\rho}^2}\right]}}$$

where $t_{\gamma,i}$ is the t-statistic for slope in the regression of the Fama–French residual $\hat{\varepsilon_{it}}$, on intercept and changes in the betting market, $\triangle PB_t$. This is the statistic we evaluate in the results section.

C Event specifications

Table 1: Specifications for each political event.

Event	**Bet**	**Portfolios**	**Factors**	**StartTest**	**EndTest**[1]
2014 Scottish independence referendum	No	Stocks listed on LSE in Q2 2014	Fama/French European	30-Jul-2014	18-Sep-2014
Brexit	Yes	Stocks listed on LSE in Q1 2016	Fama/French European	21-Feb-2016	23-Jun-2016
		European stocks with $>25\%$ revenues from UK in 2015	Fama/French European		
2016 US presidential Election	Trump	S&P500 in Q2 2016	Fama/French North American	27-Jul-2016	8-Nov-2016
		Stocks domiciled in Mexico in Q2 2016	Fama/French North American		
2017 UK General Election	Conservative Majority	Stocks listed on LSE in Q1 2017	Fama/French European	20-Apr-2017	8-Jun-2017
2019 UK General Election	Conservative Majority	Stocks listed on LSE in Q3 2019	Fama/French European	29-Oct-2019	12-Dec-2019
2020 US presidential Election	Biden	S&P500 in Q2 2020	Fama/French North American	6-Jun-2020	3-Nov-2020

[1]The test period ends on the day of the vote. The result is generally known one day later.

D Results tables

Table 2: Regression of Fama–French factor returns on $\triangle PB_t$ for political events in the testing window.

	European Factors				**American Factors**			
	Slope	Error	tStat	pValue	Slope	Error	tStat	pValue
	2014 Scottish independence ref.				**2016 US election**			
MktRF	1.15	3.24	0.36	0.722	-5.24	4.76	-1.10	0.272
SMB	-0.21	1.06	-0.20	0.840	**-2.71***	1.51	-1.80	**0.072**
HML	-0.67	1.31	-0.51	0.608	2.07	2.41	0.86	0.390
RMW	0.89	1.17	0.76	0.445	1.37	1.36	1.01	0.313
CMA	-0.70	0.89	-0.79	0.431	**2.98****	1.39	2.14	**0.033**
				$T = 36$				$T = 74$
	2016 Brexit referendum				**2020 US election**			
MktRF	**-16.28*****	5.00	-3.26	**0.001**	10.69	7.51	1.42	0.155
SMB	**3.16***	1.90	1.66	**0.097**	-0.69	4.93	-0.14	0.889
HML	-0.83	1.81	-0.46	0.646	-2.11	7.51	-0.28	0.779
RMW	0.57	1.47	0.39	0.698	-0.78	2.89	-0.27	0.788
CMA	0.34	0.62	0.54	0.588	1.76	3.92	0.45	0.654
				$T = 88$				$T = 106$
	2017 UK GE							
MktRF	0.23	4.92	0.05	0.963				
SMB	0.35	1.88	0.19	0.851				
HML	**5.34****	2.15	2.48	**0.013**				
RMW	**-3.41***	1.77	-1.93	**0.053**				
CMA	**2.70***	1.39	1.94	**0.053**				
				$T = 35$				
	2019 UK GE							
MktRF	-0.30	1.66	-0.18	0.856				
SMB	0.91	0.98	0.93	0.353				
HML	-1.30	1.25	-1.04	0.297				
RMW	0.22	0.60	0.36	0.716				
CMA	0.64	0.74	0.86	0.390				
				$T = 32$				

Heteroskedastic robust errors are used.

Table 3: Regression of Fama–French factor returns on $\triangle PB_t$ for US presidential elections from the month prior to election day.

	2016 US election				**2020 US election**			
	Slope	Error	tStat	pValue	Slope	Error	tStat	pValue
MktRF	**-12.03****	(5.92)	-2.03	**0.042**	**23.42****	(10.54)	2.22	**0.026**
SMB	**-4.89****	(2.22)	-2.20	**0.028**	2.18	(7.34)	0.30	0.766
HML	4.45	(2.96)	1.50	0.133	**18.27***	(11.02)	1.66	**0.097**
RMW	1.82	(1.60)	1.14	0.254	3.12	(4.83)	0.65	0.517
CMA	**5.09*****	(1.61)	3.16	**0.002**	**13.62****	(5.60)	2.43	**0.015**
				$T = 22$				$T = 22$

Heteroskedastic robust errors are used.

Table 4: Results of the significance tests for γ.

	Univariate regressions[a]								**Individual stock regressions**						
K	$\hat{\gamma}$	$\hat{\sigma_{\gamma}}$	t	p	R^2	p_Q[b]	p_{LM}^{BP}[c]	p_{LM}^{E}[d]	$\bar{\hat{\gamma}}$	$\bar{t}$	$\sqrt{\bar{t^2}}$	$\hat{J_{\gamma,2}}$	$P_{J_{\gamma,2}}$	p_Q[e]	p_{LL_n}[f]
	2014 Scottish independence referendum														
0	0.025	(0.036)	0.70	0.483	0.016	0.234	0.575	0.138	0.025	0.29	1.17	**2.01*****	**0.022**	1.000	0.898
1	0.017	(0.016)	1.06	0.290	0.028	0.676	0.543	0.179	0.017	0.22	1.22	**3.33*****	**<0.001**	1.000	0.193
5	0.018	(0.016)	1.08	0.282	0.032	0.798	0.276	0.354	0.018	0.21	1.22	**3.37*****	**<0.001**	1.000	0.426
	$N = 188$, $T = 36$														
	2016 Brexit referendum - LSE stocks														
0	**-0.147*****	(0.042)	**-3.51**	**<0.001**	0.171	0.848	0.946	**0.006*****	-0.147	-1.92	2.28	**15.66*****	**<0.001**	1.000	**0.014****
1	**-0.028***	(0.016)	**-1.70**	**0.089**	0.025	0.775	0.600	0.192	-0.028	-0.30	1.39	**6.02*****	**<0.001**	1.000	0.970
5	-0.026	(0.016)	-1.63	0.103	0.021	0.795	0.588	0.328	-0.026	-0.27	1.34	**5.88*****	**<0.001**	1.000	0.705
	$N = 219$, $T = 85$														
	2016 Brexit referendum - European exporters to UK														
0	**-0.133*****	(0.041)	**-3.26**	**0.001**	0.121	0.755	0.773	**0.071***	-0.133	-1.64	1.89	**9.06*****	**<0.001**	1.000	0.723
1	0.010	(0.021)	0.48	0.631	0.002	0.186	0.251	0.487	0.010	0.15	0.91	-1.16	0.878	1.000	0.909
5	0.014	(0.020)	0.71	0.479	0.004	0.112	0.341	0.593	0.014	0.18	0.94	-0.85	0.802	1.000	0.843
	$N = 102$, $T = 87$														
	2016 US presidential election - S&P500 constituents														
0	-0.041	(0.049)	-0.82	0.413	0.016	**0.031****	0.575	0.136	-0.040	-0.52	1.07	0.52	0.300	1.000	0.536
1	0.009	(0.007)	1.51	0.132	0.021	0.414	**0.092***	0.772	0.011	0.17	1.06	0.49	0.313	1.000	0.531
5	0.005	(0.006)	0.92	0.356	0.006	0.558	0.575	0.410	0.006	0.04	1.03	0.32	0.376	1.000	0.557
	$N = 488$, $T = 74$														
	2016 US presidential election - Mexican stocks														
0	**-0.180*****	(0.047)	**-3.86**	**<0.001**	0.229	0.569	0.311	0.969	-0.180	-2.05	2.35	**14.91*****	**<0.001**	0.520	0.644
1	**-0.156*****	(0.029)	**-5.32**	**<0.001**	0.270	0.970	0.749	0.895	-0.155	-1.85	2.20	**15.66*****	**<0.001**	0.518	0.795
5	**-0.158*****	(0.030)	**-5.24**	**<0.001**	0.281	0.906	0.603	0.985	-0.158	-1.88	2.22	**16.33*****	**<0.001**	0.421	0.675
	$N = 51$, $T = 75$														
	2017 UK general election - LSE stocks														
0	-0.008	(0.030)	-0.28	0.781	0.001	0.606	0.910	0.743	-0.008	-0.07	0.99	-0.66	0.745	1.000	0.661
1	-0.012	(0.039)	-0.31	0.754	0.004	0.151	0.194	0.595	-0.012	-0.13	1.00	-0.46	0.677	1.000	0.924
5	-0.011	(0.040)	-0.27	0.789	0.003	0.196	0.211	0.679	-0.011	-0.07	0.99	-0.63	0.735	1.000	0.438
	$N = 215$, $T = 34$														
	2019 UK general election - LSE stocks														
0	0.014	(0.019)	0.72	0.472	0.007	0.648	0.527	0.821	0.014	0.344	1.28	**3.72*****	**<0.001**	1.000	0.945
1	0.014	(0.010)	1.30	0.193	0.019	0.772	0.338	**0.043****	0.014	0.36	1.37	**6.86*****	**<0.001**	1.000	0.947
5	0.014	(0.010)	1.35	0.178	0.018	0.984	0.414	**0.047****	0.014	0.38	1.47	**9.18*****	**<0.001**	1.000	0.871
	$N = 243$, $T = 33$														
	2020 US presidential election - S&P500 constituents														
0	0.083	(0.092)	0.79	0.432	0.004	0.598	0.509	0.210	0.074	0.49	0.86	-0.43	0.672	1.000	0.860
1	0.004	(0.049)	-0.11	0.911	0.000	0.194	0.429	0.368	-0.005	0.01	0.84	-0.81	0.417	1.000	0.396
5	0.006	(0.022)	-0.15	0.884	0.000	0.868	0.521	0.114	-0.003	-0.01	0.88	-1.13	0.260	1.000	0.330
	$N = 487$, $T = 105$														

[a] Heteroskedastic robust errors are used for the univariate portfolio regression
[b] Ljung-Box serial correlation test p-value
[c] Breusch-Pagan heteroskedasticity test p-value
[d] Engle ARCH test p-value

[e] Multivariate Ljung-Box serial correlation test p-value
[f] Ling-Li multivariate heteroskedasticty test p-value

Table 5: Results for weighted regressions, with the weight increasing by 5% each week.

	Univariate regressions[a]								**Individual stock regressions**						
K	$\hat{\gamma}$	$\hat{\sigma_\gamma}$	t	p	R^2	p_Q [b]	p_{LM}^{BP} [c]	p_{LM}^{E} [d]	$\bar{\hat{\gamma}}$	$\bar{t}$	$\sqrt{\bar{t^2}}$	$\hat{J_{\gamma,2}}$	$P_{J_{\gamma,2}}$	p_Q [e]	p_{LL_n} [f]
	2014 Scottish independence referendum														
0	0.023	(0.030)	0.78	0.438	0.017	0.234	0.575	0.142	0.023	0.30	1.27	**3.60*****	**<0.001**	1.000	0.768
1	0.014	(0.017)	0.82	0.412	0.019	0.693	0.543	0.143	0.014	0.19	1.31	**5.23*****	**<0.001**	1.000	0.580
5	0.014	(0.016)	0.90	0.366	0.023	0.824	0.276	0.347	0.014	0.19	1.32	**5.34*****	**<0.001**	1.000	0.512
	$N = 187$, $T = 37$														
	2016 Brexit referendum - LSE stocks														
0	**-0.170*****	(0.029)	**-5.93**	**<0.001**	0.289	0.666	0.946	**0.017**	-0.170	-2.88	3.34	**32.62*****	**<0.001**	1.000	0.286
1	**-0.030****	(0.015)	**-1.98**	**0.048**	0.044	0.805	0.600	0.199	-0.030	-0.45	1.85	**15.49*****	**<0.001**	1.000	**0.026**
5	**-0.028***	(0.015)	**-1.84**	**0.065**	0.037	0.823	0.588	0.338	-0.028	-0.41	1.79	**15.73*****	**<0.001**	1.000	0.554
	$N = 218$, $T = 85$														
	2016 Brexit referendum - European exporters to UK														
0	**-0.156*****	(0.030)	**-5.15**	**<0.001**	0.232	0.906	0.773	0.119	-0.156	-2.53	2.89	**24.00*****	**<0.001**	1.000	0.139
1	0.014	(0.018)	0.79	0.430	0.005	0.199	0.251	0.457	0.014	0.27	1.32	**4.30*****	**<0.001**	1.000	0.106
5	0.019	(0.018)	1.02	0.309	0.010	0.119	0.341	0.550	0.019	0.32	1.35	**4.64*****	**<0.001**	1.000	0.403
	$N = 101$, $T = 87$														
	2016 US presidential election - S&P500 constituents														
0	**-0.080****	(0.036)	**-2.23**	**0.026**	0.068	0.032	0.587	**0.061**	-0.080	-1.09	1.61	**5.39*****	**<0.001**	1.000	0.954
1	0.008	(0.007)	1.10	0.273	0.013	0.338	0.398	0.764	0.008	0.16	1.30	**4.22*****	**<0.001**	1.000	0.372
5	0.004	(0.006)	0.62	0.537	0.003	0.569	0.720	0.822	0.004	0.04	1.29	**4.31*****	**<0.001**	1.000	0.223
	$N = 488$, $T = 74$														
	2016 US presidential election - Mexican stocks														
0	**-0.215*****	(0.036)	**-5.91**	**<0.001**	0.320	0.569	0.311	0.821	-0.215	-2.74	3.06	**24.71*****	**<0.001**	0.501	0.736
1	**-0.172*****	(0.028)	**-6.11**	**<0.001**	0.333	0.966	0.751	0.813	-0.172	-2.30	2.69	**23.65*****	**<0.001**	0.499	0.843
5	**-0.175*****	(0.028)	**-6.27**	**<0.001**	0.345	0.897	0.601	0.893	-0.175	-2.34	2.73	**24.82*****	**<0.001**	0.441	0.736
	$N = 50$, $T = 75$														
	2017 UK general election - LSE stocks														
0	-0.012	(0.037)	-0.32	0.747	0.002	0.586	0.910	0.749	-0.012	-0.11	1.06	0.48	0.316	1.000	0.194
1	-0.009	(0.044)	-0.20	0.842	0.004	0.157	0.194	0.601	-0.009	-0.11	1.06	0.46	0.325	1.000	0.944
5	-0.007	(0.044)	-0.15	0.882	0.003	0.205	0.211	0.689	-0.007	-0.04	1.06	0.45	0.328	1.000	0.893
	$N = 214$, $T = 34$														
	2019 UK general election - LSE stocks														
0	0.016	(0.025)	0.65	0.518	0.011	0.679	0.527	0.874	0.016	0.41	1.28	**3.67*****	**<0.001**	1.000	0.748
1	0.014	(0.017)	0.81	0.418	0.019	0.784	0.338	**0.042**	0.014	0.39	1.37	**6.70*****	**<0.001**	1.000	0.336
5	0.015	(0.019)	0.78	0.433	0.019	0.970	0.414	**0.045**	0.015	0.40	1.47	**9.17*****	**<0.001**	1.000	0.979
	$N = 242$, $T = 33$														
	2020 US presidential election - S&P500 constituents														
0	**0.200*****	(0.090)	2.24	**0.025**	0.045	0.595	0.493	0.228	0.200	1.41	1.71	**3.41*****	**<0.001**	1.000	0.390
1	0.026	(0.046)	0.58	0.561	0.003	0.170	0.658	0.488	0.026	0.21	1.12	0.84	0.201	1.000	0.840
5	0.003	(0.019)	0.15	0.881	0.000	0.947	0.202	0.108	0.003	0.01	1.19	**2.93*****	**0.002**	1.000	0.321
	$N = 487$, $T = 105$														

[a] Equally weight portfolio regression
[b] Ljung-Box serial correlation test p-value
[c] Breusch-Pagan heteroskedasticity test p-value
[d] Engle ARCH test p-value
[e] Multivariate Ljung-Box serial correlation test p-value
[f] Ling-Li multivariate heteroskedasticty test p-value

Table 6: Regressions of factor loadings γ against stock characteristics for different events.

Dependent Variable	Estimate	Error	tStat	pValue
γ				
2014 Scottish independence referendum				
Intercept	**-0.030****	0.012	-2.56	**0.011**
% 2013 UK revenue	**0.080*****	0.018	4.54	**<0.001**
I(HQ in Scotland)	**0.073****	0.036	2.03	**0.044**
		$N = 158$, $R^2 = 0.136$		
2016 Brexit referendum - UK Stocks				
Intercept	**0.036****	0.014	2.50	**0.013**
% 2015 developed Europe revenue	**-0.098*****	0.021	-4.78	**<0.001**
		$N = 183$, $R^2 = 0.112$		
2016 Brexit referendum - EU Exporters				
Intercept	-0.000	0.023	0.00	0.999
% 2015 UK revenue	0.044	0.050	0.87	0.385
		$N = 101$, $R^2 = 0.008$		
2016 US presidential election - S&P500				
Intercept	**0.058*****	0.013	4.50	**<0.001**
% 2015 US revenue	**-0.075*****	0.017	-4.41	**<0.001**
		$N = 461$, $R^2 = 0.041$		
2016 US presidential election - Mexican stocks				
Intercept	-0.094	0.063	-1.50	0.156
% 2015 US revenue	-0.199	0.174	-1.15	0.271
		$N = 16$, $R^2 = 0.086$		
2019 UK general election				
Intercept	**-0.041***	0.021	-1.97	**0.051**
% 2016 UK revenue	**0.111*****	0.033	3.41	**<0.001**
I(Corbyn to nationalise)	0.004	0.050	0.07	0.944
		$N = 202$, $R^2 = 0.071$		
20206 US presidential election - S&P500				
Intercept	-0.030	0.019	-1.56	0.120
% 2015 US revenue	0.033	0.025	1.32	0.187
		$N = 404$, $R^2 = 0.002$		