Journal of Banking and Finance 118 (2020) 105883

Contents lists available at ScienceDirect

Journal of Banking and Finance

journal homepage: www.elsevier.com/locate/jbf

Political event portfolios[☆]

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ARTICLE INFO

Article history:
Received 12 February 2019
Accepted 8 June 2020
Available online 10 June 2020

JEL classification:
G11
D72

Keywords:
Betting odds
Political event portfolios
Political uncertainty

ABSTRACT

We use data from betting markets to analyze the sensitivity of stock returns to potential outcomes of political events such as elections. By classifying stocks into expected conditional winners and losers prior to such an event, we form portfolios that generate large positive returns after the event date, conditional on correctly anticipating the outcome. The approach is illustrated using data from the 2016 US presidential election and the 2016 Brexit referendum. We show that these sensitivities contain information about event-related returns beyond that of firm characteristics whose predictive power has been documented in the literature.

1. Introduction

Election outcomes have various financial and economic effects. Aside from a possible impact on the overall market or on certain asset classes, election outcomes produce relative winners and losers in the cross-section of stocks. This is because the policies of the winning party or candidate may be favorable for certain sectors, industries, or particular companies and unfavorable for others. Market participants analyze these potential consequences of different election outcomes, resulting in stock prices that reflect this information. Reacting to corresponding client requests, financial institutions even create "candidate baskets" in the run-up to elections, i.e. bundles of investments that are designed to benefit from certain election outcomes (Kelly, 2019).

A substantial number of studies have analyzed the possible links between politics and the returns of stock markets and industries, both in general and around elections. Most of these studies have attempted to find variables linking industries and single stocks to political parties, e.g., via campaign contribution data (Jayachandran, 2006) or based on a longer-term analysis of performance differences depending on which political party was in power (Addoum and Kumar, 2016).

While approaches based on economic variables such as campaign contributions or firm characteristics allow for an analysis of the potential causes of the existence of relative winners and losers in the cross-section of stocks, the necessary data may be difficult for investors to obtain. The data may only be available for a relatively small subset of stocks and advanced econometric methodology may be required. For an investor who is not interested in the underlying economic causes but only in predicting relative performance around election events, a simple approach that classifies stocks into expected winners and losers, conditional on the election outcome, might be preferable. In this paper, we present an approach, which is based on observable prices only and relies on market expectations being quickly and (on average) correctly reflected in these prices. Two types of market expectations are important in this regard. First, election outcome probabilities are assumed to be reflected in betting odds or prices from political prediction markets. Second, the expected effects of different election outcomes, weighted by the changes in the outcome probabilities, are assumed to be reflected in stock returns. The magnitude of potential effects can then be estimated using only the observed stock returns and risk-neutral event outcome probabilities implied in the betting odds.

Information on risk-neutral probabilities from either betting odds or prediction markets has been used before to forecast conditional returns for different possible outcomes of political events. While Wolfers and Zitzewitz (2018) attempt to predict conditional returns in a broad stock index (a similar approach has also been used by Snowberg et al., 2007), Hanke et al. (2018) focus on conditional exchange rate movements around political events using the

☆ We thank the Editor, Geert Bekaert, three anonymous referees, Demelza Hays, and conference participants of the 2019 Quantitative Methods in Finance Conference in Sydney for helpful comments and discussions.

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https://doi.org/10.1016/j.jbankfin.2020.105883
0378-4266/

2016 UK Brexit referendum and the 2016 US presidential election as showcases. Knight (2006) uses data from political prediction markets to relate the probability of Bush winning against Gore in the 2000 US presidential election to the returns of 70 companies. In his regressions, he uses indicator variables for stocks being positively influenced by either a potential Bush or Gore victory based on financial analyst coverage. Combining these indicator variables with changes in winning probabilities for the two candidates, he finds significant differences in returns between the two groups of stocks.

In various aspects, our approach described in this paper differs from those in the literature. We focus on a single political event for which the date and possible outcomes are known ex ante. Based on a simple model, which requires only stock returns and risk-neutral election outcome probabilities implied from betting (prediction) markets, we classify stocks into expected relative winners and losers, conditional on the election outcome. This allows us to systematically analyze a large cross-section of stocks without any prior knowledge regarding the possible effects of event outcomes on companies or additional proxies such as campaign contributions, yet with less data and econometric complexity compared to some existing studies. The approach is agnostic regarding the causes for the event effect. It only assumes that stock returns at least partly reflect the corresponding available information, i.e. capture the net effect across possible causes, as expected by market participants at the time. We illustrate the approach using data from two recent political events, the 2016 US presidential election and the 2016 UK Brexit referendum.

There is already some literature on these events, but our paper provides additional insights. The potential impact of the 2016 US presidential election on American stock markets has been discussed at length, both in the press (Strain, 2016) and in scientific publications (e.g., Wolfers and Zitzewitz, 2018). Wagner et al. (2018a,c) and Ramelli et al. (2019) empirically investigate individual stock price reactions to the 2016 US presidential election. They explain the differences in reaction by different levels of exposure to major policy changes expected by the markets as a result of Trump's victory, particularly regarding taxes and foreign trade. Initially, they find an overall underreaction, leading to a positive return momentum in the days after the election for stocks that reacted positively to Trump's win. Individual paths to convergence and explanations via firm characteristics are investigated by Wagner et al. (2018b) who also document a positive short-term momentum effect after the election and attribute this effect to the slow but predictable diffusion of information into stock prices. Aiming at constructing an index of policy implementation success, Fisman and Zitzewitz (2019) analyze the relation between (individual) stock returns on election day and in subsequent periods. In light of the observed return momentum after the election event, this implies that positive returns could be achieved even by investors who did not want to place a bet on a particular election outcome via candidate baskets but who classified stocks into winners and losers based on their returns observed on the first day after the election. Hill et al., 2019 search for the drivers of stock returns around the 2016 Brexit referendum. They separately analyze the dependence of both stock returns and a sensitivity measure based on betting odds on a number of firm characteristics. Although they find that both dependent variables show similar relations to these drivers, they do not take the additional step of using the betting odds observed prior to the event to predict the conditional returns after the event, which is the main topic of the present paper.

The remainder of this paper is organized as follows. Our methodology is presented in Section 2. Section 3 describes the data used for the empirical analysis. Section 4 discusses our results, and Section 5 concludes the paper.

2. Methodology

We use the 2016 US presidential election to present our approach, with ex ante possible outcomes of R, the Republican (Donald Trump), or D, the Democratic candidate (Hillary Clinton) winning. The analogous outcomes for the 2016 UK Brexit referendum are Leave and Remain. When we use the term "election," this is meant to include similar political events such as referendums. In the absence of any election, daily returns on stock i, $r_{i,t}$, are assumed to follow the standard single-index model (Sharpe, 1963). Time is measured in days, and the one-day risk-free interest rate is set to zero for simplicity of exposition. In the run-up to elections that are expected to have an impact on individual stock prices, there is an additional driver of stock returns. This event-related driver may have a systematic component, which affects stock returns indirectly via their dependence on the index, and an idiosyncratic component. We start by deriving this idiosyncratic component. Extending the index model for this idiosyncratic component leads to our main regression equation.

We assume that some of the stocks in our sample will be positively (negatively) affected if the Democratic (Republican) candidate wins and vice versa for others, while other stocks may not react at all to the election outcome. There are many potential reasons for this, e.g., policies announced by candidates that may affect the entire cross-section of stocks to varying degrees, or the political proximity of board members, which may be expected to have a positive effect on individual firm values via additional business from public procurement. For each stock, the mix of relevant factors will vary and so will the expected impact of each factor. Instead of trying to identify and aggregate individual factors that are cross-sectionally relevant, such as the effects of announced changes in tax policy (see, e.g., Wagner et al., 2018a), we rely on the market's ability to correctly anticipate the net effect on the resulting postevent returns when pricing individual stocks.

The election outcome becomes publicly known between times τ and $\tau+1$. Suppose that the market expects election outcome D (R) to lead to an idiosyncratic stock return of D_i (R_i) when comparing the stock price at time $\tau+1$ to the hypothetical stock price at this time in the absence of the election. Once the market has converged on estimates regarding D_i and R_i, these values are assumed to be constant over time and correct.[1] The conditional event returns are anticipated in stock prices observed before the election, in accordance with the market's assessment of the election outcome probabilities. This is in line with views of practitioners in the field. As stated by an investment strategist responsible for so-called *candidate baskets* in the run-up to the 2020 US presidential elections, "...the market will price in the probabilities around these outcomes" (Kelly, 2019). Our approach is based on standard no-arbitrage pricing which requires *risk-neutral* event outcome probabilities q_t^R ($q_t^D = 1 - q_t^R$) that can be inferred from betting odds or from political prediction markets.[2]

Denote the range of the conditional returns by $\theta_i := R_i - D_i$. Since their risk-neutral expectation, $q_t^R R_i + q_t^D D_i = D_i + q_t^R \theta_i$, is already priced in at time t, the conditional returns remaining for the time interval $[t, \tau+1]$ are $r^R_{i,t,\tau+1} = (1 - q_t^R)\theta_i$ conditional on an outcome of R, and $r^D_{i,t,\tau+1} = -q_t^R \theta_i$ for an outcome of D. The market's assessment of risk-neutral probabilities changes over time as new information becomes available. These changes imply an id-

[1] Our model can be viewed as a restricted version of the mixture of normal densities model used in Hanke et al. (2018) for currency returns, in which the means of the component densities are constant in time and the volatilities of the component densities are equal to zero.

[2] In contrast, we could not use poll data for our purpose, as these provide expected vote shares rather than winning probabilities (this important distinction is discussed, e.g., by Knight, 2006, p. 755).

iosyncratic component of $\theta_i(q^R_{t+1} - q^R_t) = \theta_i \Delta q^R_{t+1}$ in daily stock returns, together with corresponding changes in conditional returns remaining for the time interval $[t+1, \tau+1]$.[3] The risk-neutral expectation of the idiosyncratic return is zero:

$$\mathbb{E}^Q_t[r_{i,t,\tau+1}] = q^R_t(1-q^R_t)\theta_i - q^D_t(1-q^D_t)\theta_i = 0 \quad \forall t \le \tau. \qquad (1)$$

We illustrate this by using a simple example. E.g., for $q^R_t = q^D_t = 1/2$, the conditional idiosyncratic event returns for the remaining time interval $[t, \tau+1]$ are $r^R_{i,t,\tau+1} = -r^D_{i,t,\tau+1} = \theta_i/2$. If, on the next day, q^R_{t+1} increases to 2/3, this change implies an election-induced component of $\theta_i \Delta q^R_{t+1} = \theta_i/6$ in the daily return $r_{i,t+1}$. Consequently, the remaining conditional returns for the time interval $[t+1, \tau+1]$ decrease to $r^R_{i,t+1,\tau+1} = \theta_i/2 - \theta_i/6 = \theta_i/3$ and $r^D_{i,t+1,\tau+1} = -\theta_i/2 - \theta_i/6 = -2\theta_i/3$.

Extending the standard index model for this idiosyncratic component of the event-related return, we obtain the following:

$$r_{i,t} = \alpha_i + \beta_i r_{m,t} + \theta_i \Delta q^R_t + \epsilon_{i,t}, \quad t \le \tau + 1, \qquad (2)$$

where $r_{m,t}$ is the index return, $\epsilon_{i,t}$ is a random variable with mean 0 and variance σ^2_i, and ϵs are pairwise uncorrelated across assets.[4] α_i captures any empirically observed abnormal stock return i.

If we were able to forecast the direction of changes in risk-neutral election outcome probabilities, i.e. the sign of Δq^R_t, the knowledge of the corresponding sensitivities θ_i for each stock would allow us to form portfolios at time $t-1$ with positive expected returns. For the special case of portfolios formed at time τ, this would require a correct forecast for the election outcome. To estimate θ_i prior to the event, the regression in Eq. (2) can be applied for each stock and $t \le \tau$. Stocks with a large positive θ_i are expected to benefit from a Republican victory and/or to suffer from a Democratic victory (over and above any systematic election effect on the index), while the opposite interpretation holds true for stocks with a large negative θ_i. Stocks with $\theta_i \approx 0$ should not show any idiosyncratic reactions to the election outcome according to market expectations.

Eq. (2) corresponds to the "empirical model" used by Knight (2006, equation (3)). As previously mentioned, our derivation is agnostic regarding the reasons for election-induced returns (which may be neoclassical, behavioral, or a combination of both) and only assumes that these returns are anticipated in market prices. Our approach differs from Knight (2006) in several aspects. First, whereas he directly establishes his equations as an "empirical model," we explicitly derive the idiosyncratic event-related return component. Second, Knight (2006) starts from a subset of stocks that have been identified by others (i.e. analysts) as being expected to benefit from either of the two candidates, whereas we take all stocks contained in the respective indices as our starting point. Finally, he uses changes in event probabilities mainly to "validate" his preselection, whereas we use them as the sole basis for selecting stocks for portfolios, which allows us to systematically analyze the entire cross-sections of stocks.

Based on the θ_is estimated individually from Eq. (2), we will sort stocks into quantile portfolios. These quantile portfolios can then be used to form long-short portfolios, which are expected to show positive absolute returns around the election day, conditional on correctly predicting the election outcome. Given that perfect predictions of the outcome are not possible, these portfolios can then be used to bet on a particular outcome. Using stock portfolios for this purpose may be desirable for investors who are not allowed to bet directly on the outcome in betting markets (e.g., US investors, who are legally prohibited from political betting, or those who are confined to investing only in financial securities) or for financial institutions designing "candidate baskets" in the run-up to elections. Following the logic of Eq. (2), the approach could also be used to bet on changes in betting odds prior to the election, e.g., as a result of political debates or similar events. This strategy provides a recipe to test the approach prior to the event.

Based on our approach, investors can quantify the sensitivity of their portfolios to the potential outcomes (and prior to the election to changes in outcome probabilities).[5] If their portfolio θ differs from zero, knowing the θ_is of all stocks in their investment universe allows them to make their portfolios "θ-neutral," i.e. to remove any undesired sensitivity to the election outcome.

3. Data

The estimation of regression (2) requires stock returns, index returns, and risk-neutral election outcome probabilities. In what follows, we describe our data separately for the two events we analyze in Section 4.

3.1. US Presidential election

Risk-neutral election outcome probabilities are proxied by data from the 2016 US Presidential Election Winner-Takes-All Market (Iowa Electronic Markets, IEM). Data from prediction markets have been used previously in similar contexts, see, e.g., Herron et al. (1999) and Knight (2006). Compared to data from real betting markets, our data have some drawbacks. In particular, participants in the IEM may only wager between 5 and 500 dollars. This restriction reflects the nature of these markets as being primarily for academic and educational purposes, which allows these markets to remain unregulated. In the US, unlike in Europe, political bets are illegal. However, we prefer the IEM data to the alternative of using betting odds from European bookmakers or betting exchanges for two reasons. First, due to the time difference between Europe and the US, liquidity in European odds is markedly lower around the closing time of US stock exchanges (late evening in Europe), making risk-neutral probabilities potentially less responsive and informative. Second, information in the IEM data comes mainly from US citizens that are active in this market, whereas US citizens are legally prohibited from political betting outside of scientific markets such as the IEM. Assuming that US-based investors are (at least) not worse at estimating outcome probabilities for US elections than people living in other parts of the world, IEM data should more accurately reflect the election outcome expectations of the US electorate. The risk-neutral election outcome probabilities implied by the IEM data are shown in Fig. 1. Similar to the effects we see in some derivatives markets close to the maturity of contracts, these probabilities become very volatile shortly before the election. For this reason, we exclude the election day itself and the immediately preceding business day from all our estimations. Hence, we use all data from Jan. 1, 2016, to Nov. 4, 2016, for estimating Eq. (2).

Stock returns are computed from daily closing prices of the stocks in the S&P 500 index. We include all stocks that are part of the index as of Nov. 8, 2016 (the election day), and the index itself. Stock prices come from Datastream and are adjusted for dividends, stock splits, etc., to make them comparable on a day-to-day basis. In line with risk-neutral outcome probabilities, stock returns until Nov. 4 are used for estimation, and stock returns from Nov. 9 onward are used for our postevent analysis.

[3] At any point in time before the election, the difference between the remaining conditional returns is $r^R_{i,t,\tau+1} - r^D_{i,t,\tau+1} = \theta_i$.

[4] In light of the small weighting of each index component in broad stock indices, the impact of D_i and R_i on the index itself is ignored in the index model; i.e. the index is treated as an exogenous factor.

[5] "The goal for investors, of course, is to make money off their wagers – or at least to avoid losing it due to some unforeseen political outcome." (Kelly, 2019).

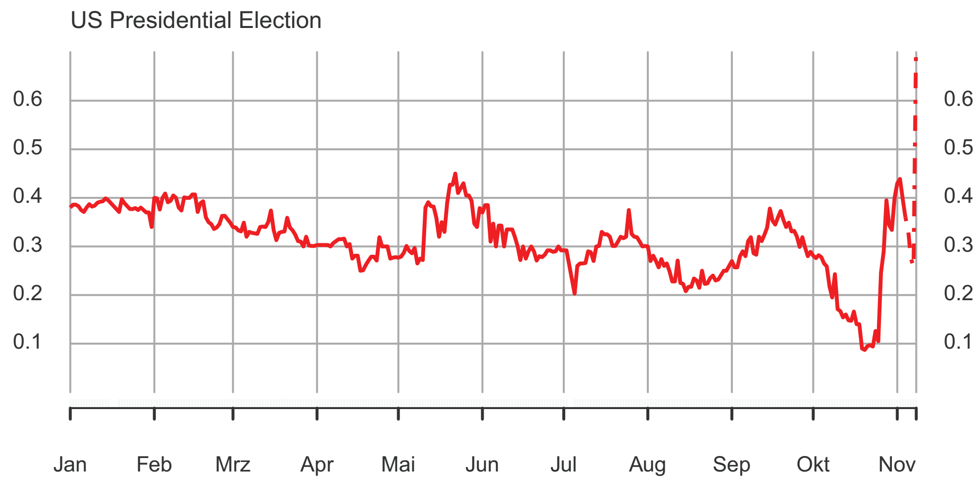

Fig. 1. Risk-neutral probabilities of Trump winning the US presidential election held on Nov. 8, 2016, obtained from Iowa Electronic Markets. We use data until Nov. 4, 2016 (two business days before the election), in the estimation. For a few days in January and July, data are missing.

To show that the stock sensitivities θ_i contain incremental information relative to variables that have been used successfully in the previous literature to explain cross-sectional returns around the 2016 US presidential election (Wagner et al., 2018a), we use various firm characteristics, e.g., proxies for sensitivity to tax and foreign trade policies. The required data are retrieved from Datastream/Worldscope, and we follow Wagner et al. (2018a) for calculating these variables for the fiscal year 2016.[6] Some of these data are not available for all the stocks in our sample, which eliminates some stocks contained in the S&P 500 from these analyses.

In Section 4.2, we provide a test of our approach on data prior to the election and show that portfolios sorted on θ_is show positive alphas relative to Fama-French factor portfolios. The factor returns for the US come from Kenneth French's data library (French, 2020).

3.2. Brexit referendum

Risk-neutral election outcome probabilities are derived from betting odds quoted on Betfair, a large internet betting platform. These data have also been used by Hanke et al. (2018) in the context of FX forecasting. Ex ante possible outcomes were either Leave or Remain, and the risk-neutral Leave probabilities extracted from Betfair odds are shown in Fig. 2. Similar to the US election case, we drop the referendum day itself and the immediately preceding business day from our sample, leaving all data from Feb. 26, 2016 (the first day for which we have betting odds data), to June 21, 2016, for our estimations.

Stock returns are computed from the daily closing prices of all stocks that are part of the FTSE 350 index as of June 23, 2016 (the day of the referendum), plus the index itself. Data from June 24 onward are used for the analysis of postevent returns. As for the US data, we work with adjusted prices from Datastream.

To show that our stock sensitivities contain incremental information relative to variables that have been used successfully in the previous literature to explain cross-sectional returns around the 2016 Brexit referendum (Hill et al., 2019), we use various firm-specific variables, e.g., return on equity or capital expenditure. The required data are retrieved from Datastream/Worldscope, and we follow Hill et al., 2019 for calculating these variables for the fiscal year 2015. Some of the data are not available for all the stocks in our sample, which eliminates some stocks from these analyses.

In Section 4.2, we provide a test of our approach on data prior to the election and show that portfolios sorted on θ_is show positive alphas relative to Fama-French factor portfolios. The factor returns for the UK come from the University of Exeter (see Gregory, 2020); details on the construction of factors can be found in Gregory et al., 2013.

4. Results

For both events analyzed in this paper, we start in Section 4.1 by showing that in line with our model stock sensitivity-based portfolios formed before the election indeed show significant returns after the event day. As robustness checks, we use different weighting schemes and investment universes (indices) and demonstrate that hedging out market risk would have had only a very small impact on the returns of these portfolios. To assess the predictive power of the stock sensitivities estimated from Eq. (2), we show that the long-short portfolios based on our θ_is perform better than those based on firm characteristics—which were used successfully in previous literature—for the two events analyzed here. Furthermore, sorting on both firm characteristics and θ_is always improves the results achievable from sorting based on firm characteristics alone. Together with very low correlations of the θ_is with these firm characteristics, this approach shows that our stock sensitivities indeed contain incremental information over and above these firm characteristics.

In Section 4.2, we present insights gained from testing our model prior to the event day. They can be used to detect whether or not the market actually expects outcome-dependent conditional returns on the event day. Whereas the empirical results in Section 4.1 focus on cumulative returns of long-short portfolios in *short time intervals immediately after* the election, the pre-event tests in Section 4.2 yield time series of similarly constructed portfolios over *several months prior to* the election. These portfolios show high Sharpe ratios and positive alphas relative not only to the index model but also to the Fama-French 3-factor and 4-factor models.

As an interesting side result of our analysis in Section 4.1, we also find the postevent return drift documented by, e.g., Wagner et al. (2018b) and Fisman and Zitzewitz (2019), in our datasets.

[6] Contrary to Wagner et al. (2018a), we do not use values from previous years for cases for which 2016 values are not available. Avoiding such "backfilling," which they found necessary because many 2016 observations were missing at the time they downloaded the data (February 2017), yields better results for portfolios based on firm characteristics.

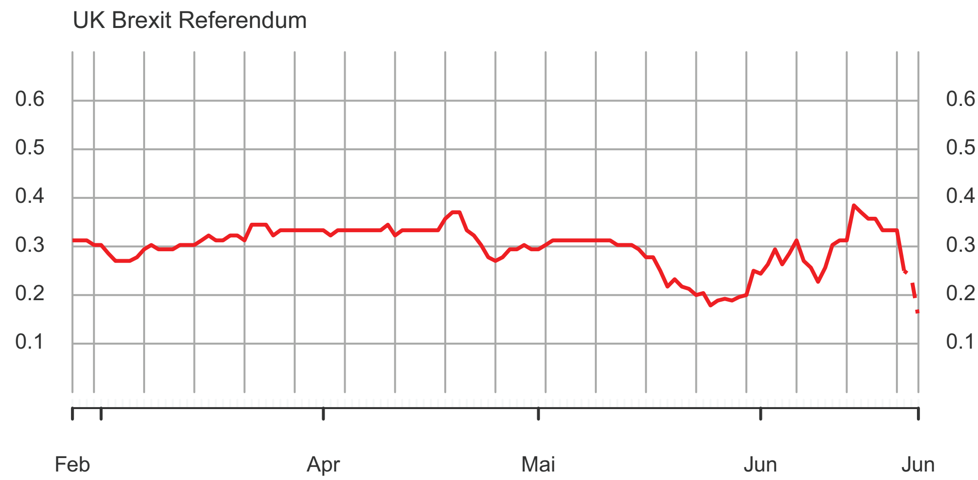

Fig. 2. Risk-neutral probabilities of a majority voting for Leave in the Brexit referendum held on June 23, 2016, calculated from Betfair betting odds. We use data until June 21, 2016 (two business days before the referendum), in the estimation.

This effect is outside the scope of our model and may be due to initial underreaction. Its presence implies that even when investing only after the election result becomes known, based only on returns observed on the first day after the event, investors could still have achieved abnormal returns. This effect is analyzed in Section 4.3, where we show that our θ_is have incremental explanatory power relative to first-day returns.

4.1. Postevent returns of portfolios formed before the election

We estimate the regression in Eq. (2) with OLS for each stock separately.[7] Based on the results, we form portfolios that are expected to provide a positive absolute return conditional on correctly forecasting the election outcome. Most of the θ_is estimated from Eq. (2) are insignificant. Appendix A provides the empirical distribution of the estimates (Figures A.4 and A.5) together with their significance levels (Tables A.1 and A.2). Restricting our sample to only those stocks with significant θ_is would eliminate a large number of observations. Instead, we follow a common approach in such situations, especially in the presence of large cross-sections, which is to sort stocks based on their regression coefficients and then compare the performance of their quantile portfolios. We form value-weighted median,[8] tercile and quintile portfolios. To capture the event effect as purely as possible, we form the portfolios at time τ, i.e. just before any information on the event outcome could have become known to the markets. Starting earlier would only serve to contaminate our results with effects that are unrelated to the event.

After sorting stocks on their θ_is from Eq. (2), we expect stocks with higher coefficients to outperform around the election date due to Trump's victory. Given that stocks with high θ_i reacted positively to (relatively small) increases in q_t^R prior to the election, their prices should also go up when q_t^R increases to 1 after the election. In short, stocks with high θ_is could be called "Trump stocks" for the US presidential election and "Leave stocks" for the Brexit referendum. Later in this section, we will compare the performance of portfolios sorted on θ_i to portfolios sorted on firm characteristics, the predictive power of which around the two events analyzed here has been shown in the previous literature (Hill et al., 2019; Wagner et al., 2018). Descriptive statistics are shown in Table 1, which provides the means and medians of these firm characteristics for the (equally weighted) upper/lower median portfolios of each of the two datasets, sorted on θ_i. Trump stocks tend to have higher cash ETRs and revenue growth but lower foreign exposure. Leave stocks tend to show lower sales growth and foreign income but higher R&D. For profitability, market-to-book and capital expenditure, comparisons based on means and medians lead to mixed results. Trump stocks are somewhat smaller firms, while Leave stocks are larger firms.

Fig. 3 shows the performance of the value-weighted quantile portfolios sorted on θ_i for the S&P 500 (top) and the FTSE 350 (bottom). The upper part of each graph presents the cumulative performance of each of the extreme quantile portfolios. In addition, Fig. 3 (lower part of each graph) shows the performance of value-weighted long-short portfolios using the portfolios at the extreme ends of the sort; e.g., long the highest quintile portfolio, and short the lowest quintile portfolio. For both events, all long-short portfolios deliver positive returns, and the ordering is as expected throughout the three weeks following the Brexit referendum. A similar pattern can be observed for the US presidential election, with tercile and quintile portfolios alternating closely between first and second rank.

Tables 2 and 3 provide numerical results corresponding to Fig. 3. Panel A reports results for median portfolios, Panel B for tercile portfolios, and Panel C for quintile portfolios based on a ranking according to θ_i. The numbered rows contain results for the quantile portfolios themselves, followed by results for long-short portfolios constructed by going long (short) on the highest (lowest) quantile portfolio in each panel. Column (1) shows the value-weighted average θ_i of stocks in the respective quantile portfolio. Column (2) provides the portfolio betas, indicating that the observed performance differences between quantile portfolios are not driven by systematic risk (this will be discussed later in this section). Column (3) shows the total market capitalization of all companies in the respective portfolios. Column (4) provides the number of stocks in each portfolio, and column (5) shows the return of the respective portfolios on the day immediately after the event. The maximum returns of long-short portfolios can be observed for an interval of 4 (8) days after the event for the US presidential election (the UK Brexit referendum). Columns (6)-(9) in these ta-

[7] The potential endogeneity between the index and betting odds is discussed in Appendix B.

[8] As an alternative to median portfolios, we also form portfolios based on the sign of θ_i. This yields portfolios with different numbers of assets but with similar performance. For comparison with tercile and quintile portfolios, we report the results for median portfolios in this paper.

Table 1
Descriptive statistics: Means and medians of θ_i and selected firm characteristics, calculated for upper-/lower-θ_i median portfolios. The predictive power of these firm characteristics has been demonstrated in previous studies. Panel A: Following Wagner et al. (2018a), cash effective tax rate (cash ETR), revenue growth, profitability, and foreign income are based on 2016 accounting data from Datastream/WorldScope. Cash ETR is calculated as cash taxes paid relative to current year pretax income (adjusted for special items), revenue growth is computed as the relative growth rate of sales, profitability is pretax income relative to total assets, and foreign income is equal to international operating income relative to operating income (all values in percent). Panel B: Following Hill et al., 2019, sales growth, return on equity, market-to-book ratio, foreign income, capital expenditure, and a dummy for R&D expenses are based on 2015 accounting data from Datastream/WorldScope. Sales growth is the 3-year moving average of relative growth in sales (corresponding to revenue growth in Table 5), CAPEX is capital expenditure relative to total assets, and foreign income is equal to international operating income relative to operating income (Hill et al. use different proxies for foreign exposure, which are partly hand-collected and can therefore not be easily replicated; all values are in percent). R&D is a dummy variable indicating whether or not a firm reports positive R&D expenses. For both panels, ln(market value of equity) is based on the market capitalization at the time of the respective event (τ).

Panel A (S&P 500)

	No. of Stocks	θ_i	Cash ETR	Revenue Growth	Profitability	Foreign Income	ln(Market Value of Equity)
		Mean					
Lower Median (θ_i)	253	−0.0281	26.8480	3.2285	9.2757	9.9125	10.0550
Upper Median (θ_i)	252	0.0361	28.7230	3.6188	8.9685	8.0149	9.9265
		Median					
Lower Median (θ_i)	253	−0.0204	28.3408	2.3492	7.0761	0.0000	9.9918
Upper Median (θ_i)	252	0.0292	30.0950	2.8956	7.2632	0.0000	9.7899

Panel B (FTSE 350)

	No. of Stocks	θ_i	Sales Growth	ROE	MB Ratio	Foreign Income	CAPEX	R&D	ln(Market Value of Equity)
		Mean							
Lower Median (θ_i)	176	−0.1068	0.6514	39.5018	2.6368	22.6624	0.0580	0.2292	7.5362
Upper Median (θ_i)	175	0.0303	0.2045	35.5864	1.4842	19.1950	0.0468	0.4621	8.0569
		Median							
Lower Median (θ_i)	176	−0.0908	0.0701	16.4950	2.0800	0.0000	0.0320	0.0000	7.2937
Upper Median (θ_i)	175	0.0209	0.0270	13.9800	2.6000	0.0000	0.0412	0.0000	7.8302

bles show the aggregate buy-and-hold returns for time intervals around this maximum (2–5 days for the US data and 7–10 days for the UK data). Columns (10)-(11) in both tables show the cumulative returns of the quantile and long-short portfolios for time windows after the initial reaction to the events (i.e. after $\tau+5$ for the US presidential election and after $\tau+10$ for the Brexit referendum). The returns of long-short portfolios are tested for significance using both a two-sample t-test and corresponding two-sample bootstrapping (with 10,000 resamplings).[9] While the t-test assumes normal distributions with equal variances for upper and lower quantile portfolios, the bootstrapping method does not require these assumptions. The returns in columns (5)-(9) are highly significant, except for the quintile portfolios for the US presidential elections, which show significance levels of around 7%. In contrast, the returns in columns (10)-(11) are statistically indistinguishable from zero.

As a robustness check, we provide the results for alternative portfolio weighting schemes. The results for equally weighted quantile portfolios are shown in Appendix C (Tables C.1 and C.2). Returns are lower compared to the value-weighted case but still highly statistically significant. An alternative weighting scheme employs weights that are proportional to the product of each stock's market capitalization and its stock price sensitivity, θ_i.[10] The results are shown in Tables C.3 and C.4. For the US presidential election, this weighting scheme does not improve our results (the highest return, $r_{\tau,\tau+4}$, is essentially the same for the median long-short portfolios but lower for the tercile and quintile long-short portfolios when comparing Table C.3 to Table 2). For the Brexit referendum, this alternative weighting scheme improves the results for all long-short quantile portfolios by up to four percentage points, with the highest improvement for median portfolios, but only a smaller difference of less than one percentage point for quintile portfolios (compare $r_{\tau,\tau+8}$ in Table C.4 to Table 3). We attribute this difference in results to the relatively high noise in the estimated θ_is (see Appendix A) combined with a more favorable signal-to-noise ratio in the Brexit referendum case. Finally, to investigate any possible dependence on the investment universe used we also conducted our analysis with the smaller index portfolios of the S&P 100 and the FTSE 100, yielding similar results to those shown here (available upon request).

Since our goal is to generate positive absolute returns conditional on forecasting the election outcome correctly, we do not use the index itself as a benchmark. As shown in column (2) of Tables 2 and 3, the betas of our long-short portfolios are around 0.13 for the US presidential election and around −0.22 for the Brexit referendum. Hence, the index exposure of the long-short portfolios is low, including the exposure to any election effect on the index itself. To assess the impact of hedging out the market risk from these long-short portfolios, we provide the cumulative returns of the two stock indices around the respective events in Table 4. The time intervals shown are the same as in Tables 2 and 3. With the exception of the FTSE 350 return on the day after the Brexit referendum, the magnitude of all returns is relatively low. For an investor who formed the quintile long-short portfolios at time τ, as described in Table 3, but did not want to bear the market risk and therefore hedged it out based on the estimated beta of his portfolio, this hedge would have reduced his return by 0.21 times the FTSE 350 return for the respective time interval. For instance, when hedging all market risk from the long-short portfolios in Table 3, the highest correction relative to the results for the quintile portfolios would occur for the first-day return,

[9] A nonparametric Wilcoxon test shows similar p-values. The results are available upon request.

[10] This is inspired by Fisman and Zitzewitz (2019) who weight stocks by the product of their market capitalization and their return.

Table 2
US presidential election: value-weighted event-window returns for quantile portfolios based on S&P 500 stocks, formed at time τ (shortly before information on the event outcome is revealed), according to θ_i estimated from Eq. (2) and weighted according to the market capitalization at this time. The table shows the median portfolios (Panel A), tercile portfolios (Panel B), and quintile portfolios (Panel C). Column (1) provides the value-weighted average of θ_i for the respective portfolios, and column (2) provides the portfolio β relative to the index. Column (3) shows the sum of the market caps of the companies in the respective portfolios in billion USD, and column (4) provides the number of stocks in each portfolio. Columns (5)-(11) show cumulative portfolio returns $r_{s,t}$ for various time windows (from s to t). Long-short portfolios are formed by going long (short) on the highest (lowest) quantile portfolio. [p-val] depicts one-sided significance levels for a parametric two-sample t-test and bootstrapping with 10,000 resamplings.

Portfolio	(1) θ_i	(2) β_i	(3) Size	(4) No. of Stocks	(5) $r_{\tau,\tau+1}$	(6) $r_{\tau,\tau+2}$	(7) $r_{\tau,\tau+3}$	(8) $r_{\tau,\tau+4}$	(9) $r_{\tau,\tau+5}$	(10) $r_{\tau+5,\tau+10}$	(11) $r_{\tau+10,\tau+15}$
Panel A (Median Portfolios)											
1 (Short)	−0.0224	0.91	10,739	253	0.0075	0.0034	−0.0019	−0.0065	0.0018	0.0106	0.0008
2 (Long)	0.0305	1.06	8433	252	0.0152	0.0242	0.0277	0.0333	0.0409	0.0122	0.0021
Long-Short	0.0529	0.15			0.0076	0.0209	0.0296	0.0398	0.0391	0.0016	0.0013
t-test [p-val]					[0.0375]	[0.0063]	[0.0003]	[0.0002]	[0.0000]	[0.3745]	[0.2855]
Bootstrap [p-val]					[0.0329]	[0.0049]	[0.0001]	[0.0000]	[0.0000]	[0.3685]	[0.2885]
Panel B (Tercile Portfolios)											
Portfolio	θ_i	β_i	Size	No. of Stocks	$r_{\tau,\tau+1}$	$r_{\tau,\tau+2}$	$r_{\tau,\tau+3}$	$r_{\tau,\tau+4}$	$r_{\tau,\tau+5}$	$r_{\tau+5,\tau+10}$	$r_{\tau+10,\tau+15}$
1 (Short)	−0.0352	0.99	6831	169	0.0072	0.0025	−0.0035	−0.0080	0.0035	0.0114	−0.0015
2	0.0048	0.85	6727	168	0.0082	0.0070	0.0049	0.0014	0.0074	0.0130	0.0042
3 (Long)	0.0401	1.11	5614	168	0.0185	0.0313	0.0364	0.0457	0.0517	0.0093	0.0014
Long-Short	0.0752	0.13			0.0113	0.0288	0.0400	0.0537	0.0482	−0.0021	0.0029
t-test [p-val]					[0.0230]	[0.0049]	[0.0003]	[0.0003]	[0.0003]	[0.6210]	[0.1795]
Bootstrap [p-val]					[0.0197]	[0.0020]	[0.0001]	[0.0001]	[0.0001]	[0.6004]	[0.1842]
Panel C (Quintile Portfolios)											
Portfolio	θ_i	β_i	Size	No. of Stocks	$r_{\tau,\tau+1}$	$r_{\tau,\tau+2}$	$r_{\tau,\tau+3}$	$r_{\tau,\tau+4}$	$r_{\tau,\tau+5}$	$r_{\tau+5,\tau+10}$	$r_{\tau+10,\tau+15}$
1 (Short)	−0.0493	1.05	3835	101	0.0096	0.0041	−0.0024	−0.0052	0.0065	0.0127	−0.0047
2	−0.0123	0.86	4745	101	0.0072	0.0039	−0.0017	−0.0078	−0.0005	0.0056	0.0039
3	0.0066	0.86	4276	101	0.0056	0.0031	0.0016	−0.0025	0.0054	0.0197	0.0037
4	0.0250	1.04	3445	101	0.0135	0.0224	0.0315	0.0362	0.0445	0.0115	0.0022
5 (Long)	0.0524	1.16	2871	101	0.0234	0.0403	0.0402	0.0540	0.0576	0.0063	0.0008
Long-Short	0.1017	0.11			0.0138	0.0362	0.0427	0.0592	0.0511	−0.0063	0.0055
t-test [p-val]					[0.0704]	[0.0242]	[0.0089]	[0.0066]	[0.0089]	[0.7373]	[0.1427]
Bootstrap [p-val]					[0.0650]	[0.0159]	[0.0028]	[0.0014]	[0.0028]	[0.7310]	[0.1451]

which would be adjusted downward by $0.21 \times 0.0385 = 0.008$. For the quintile portfolios in the case of the US presidential election, the corrections would be even smaller due to the lower beta values of long-short portfolios and lower S&P 500 returns, as shown in Table 4. For both events, the return reduction arising from hedging out systematic risk (if desired by an investor) is small relative to the magnitude of the long-short portfolio returns.

For the 2016 US presidential election, Wagner et al. (2018a) identify the firm characteristics linked to expected changes in economic policies as the major drivers behind the cross-sectional differences in stock price reactions. For instance, companies with a higher tax burden were expected by the market to benefit more from the announced tax reductions. For the UK Brexit referendum, Hill et al., 2019 classify stocks into expected (relative) winners and losers based on firm characteristics. These findings in the literature raise the question if our stock sensitivities θ_i essentially capture the same information as some of these variables or if they contain incremental information relative to these firm characteristics. To investigate this question, we follow two paths: (i) We provide a statistical analysis via regressions, as in Wagner et al. (2018a) and Hill et al., 2019. (ii) We analyze the economic significance of firm characteristics and the incremental information contained in θ_is via long-short quantile portfolios. The descriptive statistics of the firm characteristics used in this paper are provided in Table 1.

For the US presidential election, we start by applying a regression similar to Wagner et al. (2018a, Table 2), who use all Russell 3000 constituents, to our sample of S&P 500 companies. To analyze the significance of both θ_i and firm characteristics for explaining the cross-section of postelection stock returns, we run a cross-sectional regression of stock returns on these variables. We begin with θ_i and $\ln(\text{market value of equity})$, which Wagner et al. (2018a) use as a control variable, and we subsequently add firm characteristics, such as the cash effective tax rate (cash ETR) and foreign income, one at a time. The sample size changes when adding more variables due to the fact that not all firm-specific variables are available for all stocks. The results of this exercise are shown in Table 5.[11] Odd-numbered columns cover the period from τ to $\tau + 4$, which is the holding period with the highest returns in Table 2, while even-numbered columns cover—for comparison with Table 2 in Wagner et al. (2018a)—the period from the election day until Dec. 30, 2016. Column (9) in Table 5 shows that the coefficient for θ is highly significant, even in the presence of all firm characteristics. Furthermore, the stepwise addition of firm characteristics does not materially change the magnitude of its coefficient. Firm characteristics are also highly significant, with the exception of profitability. The coefficient for θ in column (10) is not significant at the 5% level, which can be attributed to the longer estimation period. Several coefficients for firm characteristics in column (10), particularly that for cash ETR, are quite similar

[11] We use estimated θ_is, which may cause issues related to errors in variables. We have checked our results using an error-in-variables linear regression, specifying a variety of different reliabilities for θ_i. In line with the literature, we find that setting lower reliabilities (starting at $0.966 = 1/(1 + \text{var}(\theta))$ and decreasing until 0.5) increases our coefficient but does not substantially change its significance level (results are available upon request). Additionally, the coefficients and significance levels of the other predictors are hardly affected. For this reason, we are confident that using estimated θ_is does not cause a problem.

Table 3
UK Brexit referendum: value-weighted event-window returns for quantile portfolios based on FTSE 350 stocks, formed at time τ (shortly before information on the event outcome is revealed), according to θ_i estimated from Eq. (2) and weighted according to the market capitalization at this time. The table shows the median portfolios (Panel A), tercile portfolios (Panel B), and quintile portfolios (Panel C). Column (1) provides the value-weighted average of θ_i for the respective portfolios, and column (2) provides the portfolio β relative to the index. Column (3) shows the sum of the market caps of the companies in the respective portfolios in billion GBP, and column (4) provides the number of stocks in each portfolio. Columns (5)-(11) show cumulative portfolio returns $r_{s,t}$ for various time windows (from s to t). Long-short portfolios are formed by going long (short) on the highest (lowest) quantile portfolio. [p-val] depicts one-sided significance levels for a parametric two-sample t-test and bootstrapping with 10,000 resamplings.

Panel A (Median Portfolios)											
Portfolio	(1) θ_i	(2) β_i	(3) Size	(4) No. of Stocks	(5) $r_{\tau,\tau+1}$	(6) $r_{\tau,\tau+7}$	(7) $r_{\tau,\tau+8}$	(8) $r_{\tau,\tau+9}$	(9) $r_{\tau,\tau+10}$	(10) $r_{\tau+10,\tau+15}$	(11) $r_{\tau+15,\tau+20}$
1 (Short)	−0.1007	1.18	514	176	−0.2048	−0.1677	−0.1882	−0.1690	−0.1451	0.0499	0.0105
2 (Long)	0.0330	0.96	1581	175	−0.0209	0.0755	0.0687	0.0780	0.0831	0.0079	0.0093
Long-Short	0.1337	−0.22			0.1839	0.2432	0.2569	0.2470	0.2281	−0.0419	−0.0012
t-test [p-val]					[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[1.0000]	[0.5685]
Bootstrap [p-val]					[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[1.0000]	[0.5828]
Panel B (Tercile Portfolios)											
Portfolio	θ_i	β_i	Size	No. of Stocks	$r_{\tau,\tau+1}$	$r_{\tau,\tau+7}$	$r_{\tau,\tau+8}$	$r_{\tau,\tau+9}$	$r_{\tau,\tau+10}$	$r_{\tau+10,\tau+15}$	$r_{\tau+15,\tau+20}$
1 (Short)	−0.1299	1.21	307	117	−0.2248	−0.1997	−0.2192	−0.1985	−0.1725	0.0535	0.0141
2	−0.0271	1.01	604	117	−0.0916	−0.0167	−0.0286	−0.0159	−0.0041	0.0242	0.0125
3 (Long)	0.0478	0.97	1183	117	−0.0118	0.0884	0.0815	0.0903	0.0948	0.0061	0.0069
Long-Short	0.1776	−0.24			0.2130	0.2881	0.3007	0.2888	0.2672	−0.0474	−0.0072
t-test [p-val]					[0.0001]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.9997]	[0.8172]
Bootstrap [p-val]					[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[1.0000]	[0.8243]
Panel C (Quintile Portfolios)											
Portfolio	θ_i	β_i	Size	No. of Stocks	$r_{\tau,\tau+1}$	$r_{\tau,\tau+7}$	$r_{\tau,\tau+8}$	$r_{\tau,\tau+9}$	$r_{\tau,\tau+10}$	$r_{\tau+10,\tau+15}$	$r_{\tau+15,\tau+20}$
1 (Short)	−0.1586	1.34	187	71	−0.2518	−0.2391	−0.2648	−0.2434	−0.2146	0.0622	0.0081
2	−0.0768	1.03	211	70	−0.1783	−0.1271	−0.1445	−0.1270	−0.1079	0.0433	0.0118
3	−0.0416	1.10	195	70	−0.1606	−0.1069	−0.1237	−0.1074	−0.0863	0.0395	0.0098
4	0.0027	0.85	890	70	−0.0130	0.0813	0.0727	0.0815	0.0848	0.0030	0.0135
5 (Long)	0.0849	1.13	611	70	−0.0175	0.0871	0.0842	0.0935	0.0998	0.0115	0.0035
Long-Short	0.2436	−0.21			0.2343	0.3262	0.3489	0.3369	0.3144	−0.0507	−0.0046
t-test [p-val]					[0.0036]	[0.0002]	[0.0004]	[0.0002]	[0.0001]	[0.9907]	[0.6893]
Bootstrap [p-val]					[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.9996]	[0.7082]

to the corresponding values in Wagner et al. (2018a, Table 2), despite the different investment universe (Russell 3000 vs. S&P 500).

Table 6 conducts a similar analysis for the Brexit referendum. Here the choice of variables is based on Hill et al., 2019, Table 2). The structure follows that of Table 5, where we sequentially add firm characteristics to the regression. The findings are similar to those for the US election: Even in the presence of all firm characteristics, θ remains highly significant for the first few days after the event (column 13). However, it becomes insignificant when extending this postevent interval until the end of 2016 (column 14). Its coefficient changes only moderately when new variables are added, with part of the changes being attributable to the change in the sample (decrease in the number of observations). Most of the firm characteristics are significant at the 5% level for both time intervals shown in columns (13) and (14). Excepted are the market-to-book ratio (insignificant for both postevent intervals), foreign income, and ln(market value of equity), which are only significant for the shorter postevent window. In line with our model, R^2 values are higher for the shorter time intervals (odd-numbered columns) compared to the longer time intervals (even-numbered columns) shown in Tables 5 and 6. As expected, the differences in R^2s between these time intervals are markedly higher for the Brexit referendum, where the longer time interval covers more than half a year.

An analysis of the pairwise correlations among all explanatory variables in these regressions reveals relatively low values for most of the pairs (results are shown in Tables 7 and 8). θ_i correlates most with the control variable ln(market value of equity) in both cases, with −13.76% for the US data and 22.56% for the UK data: in line with the signs of the corresponding coefficients in Tables 5 and 6, large companies were expected to be more negatively affected by a Trump victory and to suffer comparatively less from a Leave vote. The correlations of θ_i with cash ETR (9.62%) and foreign income (−1.6%) are even lower. This shows that θ does not "just capture the same information" as one of these firm characteristics, and it supports our interpretation in Section 2 of θ_i being a mix of many different event-related, company-specific effects. For instance, when Table 6 shows that both sales growth and ROE have a significant impact on returns around the Brexit referendum but their correlation in Table 8 is only −1.54%, it should not come as a surprise that θ_i, which according to our model, captures the combined effect of these two factors (and many other factors of influence), shows low correlations with both.

Table 4
Cumulative index returns for various time intervals around the 2016 US presidential election and the 2016 Brexit referendum. For ease of comparison, the time intervals shown are the same as in Tables 2 and 3.

Panel A (S&P 500)					
	(1) $r_{\tau,\tau+1}$	(2) $r_{\tau,\tau+2}$	(3) $r_{\tau,\tau+3}$	(4) $r_{\tau,\tau+4}$	(5) $r_{\tau,\tau+5}$
Cumulative return	0.0111	0.0132	0.0118	0.0118	0.0196
Panel B (FTSE 350)					
	$r_{\tau,\tau+1}$	$r_{\tau,\tau+7}$	$r_{\tau,\tau+8}$	$r_{\tau,\tau+9}$	$r_{\tau,\tau+10}$
Cumulative return	−0.0385	0.0121	0.0113	0.0000	0.0118

Table 5
US presidential election: results of OLS regressions of cumulative postevent returns on stock sensitivities θ_i and on firm characteristics selected based on the previous literature. Following Wagner et al. (2018a, Table 2), we use ln(market value of equity) as a control variable, and we add firm characteristics (cash effective tax rate (cash ETR), revenue growth, profitability, and foreign income, all based on 2016 accounting data from Datastream/WorldScope) one at a time. Cash ETR is calculated as cash taxes paid relative to current year pretax income (adjusted for special items), revenue growth is computed as the relative growth rate of sales, profitability is pretax income relative to total assets, and foreign income is equal to international operating income relative to operating income (all values in percent). Regressions account for the Fama-French 30 industry effects. The number of observations in each regression depends on the availability of the data for all variables in the respective regressions. Odd-numbered columns cover the time period November 9, 2016, to November 14, 2016, while even-numbered columns cover November 9, 2016, to December 30, 2016. p-values based on robust standard errors are shown in parentheses.

	Cumulative Return Since the Election									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$r_{\tau,\tau+4}$	$r_{\tau,Dec30}$	$r_{\tau,\tau+4}$	$r_{\tau,Dec30}$	$r_{\tau,\tau+4}$	$r_{\tau,Dec30}$	$r_{\tau,\tau+4}$	$r_{\tau,Dec30}$	$r_{\tau,\tau+4}$	$r_{\tau,Dec30}$
θ	26.2250	24.1715	28.2776	31.6187	26.7099	30.6395	25.4575	28.8651	29.9751	34.1268
	[0.0009]	[0.0672]	[0.0018]	[0.0688]	[0.0018]	[0.0765]	[0.0029]	[0.0966]	[0.0020]	[0.0932]
Cash ETR (in %)			0.1695	0.1660	0.1638	0.1624	0.1669	0.1668	0.1458	0.1198
			[0.0000]	[0.0013]	[0.0000]	[0.0013]	[0.0000]	[0.0011]	[0.0001]	[0.0273]
Revenue Growth (in %)					−0.1524	−0.0952	−0.1544	−0.0981	−0.1537	−0.0809
					[0.0000]	[0.0842]	[0.0000]	[0.0823]	[0.0003]	[0.2054]
Profitability (in %)							−0.0836	−0.1185	−0.0626	−0.0541
							[0.0901]	[0.1041]	[0.2802]	[0.5356]
Foreign Income (in %)									−0.0546	−0.0656
									[0.0008]	[0.0063]
ln(Market Value of Equity)	−1.1875	−0.0994	−0.6863	0.3613	−0.6733	0.3695	−0.6324	0.4274	−0.5585	0.5566
	[0.0003]	[0.8210]	[0.0483]	[0.4609]	[0.0436]	[0.4455]	[0.0595]	[0.3747]	[0.1284]	[0.2935]
Constant	17.5439	8.1865	9.1734	0.2586	9.7397	0.6123	9.9775	0.9492	7.9187	−0.2650
	[0.0002]	[0.1804]	[0.0642]	[0.9708]	[0.0342]	[0.9294]	[0.0311]	[0.8913]	[0.2151]	[0.9784]
Observations	502	502	412	412	412	412	412	412	350	350
R^2	0.3180	0.2545	0.4124	0.3120	0.4518	0.3208	0.4555	0.3252	0.4743	0.3476

Table 6
UK Brexit referendum: results of OLS regressions of cumulative postevent returns on stock sensitivities θ_i and on firm characteristics selected based on the previous literature. The structure follows Table 5 for ease of comparison, with ln(market value of equity) as a control variable. Based on Hill et al., 2019, we use sales growth, return on equity, market-to-book ratio, foreign income, capital expenditure, and a dummy for R&D expenses as firm characteristics (all based on 2015 accounting data from Datastream/WorldScope). Sales growth is the 3-year moving average of relative growth in sales (corresponding to revenue growth in Table 5), foreign income is equal to international operating income relative to operating income, CAPEX is capital expenditure relative to total assets (all these values are given in percent), and R&D is a dummy variable indicating whether or not a firm reports positive R&D expenses. For comparison with Hill et al., 2019, we do not include industry fixed effects here. The number of observations in each regression depends on the availability of the data for all variables in the respective regressions and is reduced due to the exclusion of financials for CAPEX and R&D expenses. Odd-numbered columns cover the time period June 24, to July 6, 2016, while even-numbered columns cover June 24, to December 30, 2016. p-values based on robust standard errors are shown in parentheses.

	Cumulative Return Since the Referendum													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	$r_{\tau,\tau+8}$	$r_{\tau,Dec30}$	$r_{\tau,\tau+8}$	$r_{\tau,Dec30}$	$r_{\tau,\tau+8}$	$r_{\tau,Dec30}$	$r_{\tau,\tau+8}$	$r_{\tau,Dec30}$	$r_{\tau,\tau+8}$	$r_{\tau,Dec30}$	$r_{\tau,\tau+8}$	$r_{\tau,Dec30}$	$r_{\tau,\tau+8}$	$r_{\tau,Dec30}$
θ	93.2002	58.5521	97.9280	61.4433	102.9498	61.6240	104.4287	62.5547	108.5260	42.1820	100.9121	37.2935	97.7263	32.7002
	[0.0000]	[0.0004]	[0.0000]	[0.0000]	[0.0000]	[0.0001]	[0.0000]	[0.0000]	[0.0000]	[0.0179]	[0.0000]	[0.1081]	[0.0000]	[0.1751]
Sales Growth			−0.1972	−0.1555	−0.1933	−0.1566	−0.1919	−0.1700	−0.1951	−0.2236	−0.2598	−0.2140	−0.2304	−0.1716
(in %)			[0.0002]	[0.1523]	[0.0002]	[0.1515]	[0.0002]	[0.0987]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0001]
ROE (in %)					−0.4286	−0.7298	−0.4092	0.1353	−0.4504	−0.7294	−0.8568	−0.7007	−1.0272	−0.9463
					[0.0000]	[0.0315]	[0.0357]	[0.8822]	[0.0030]	[0.1866]	[0.0000]	[0.1289]	[0.0000]	[0.0161]
MB Ratio							−0.0097	−0.5667	−0.0669	−0.7240	0.0245	−0.5952	0.0461	−0.5641
							[0.9439]	[0.0333]	[0.7125]	[0.0047]	[0.9148]	[0.0636]	[0.8208]	[0.0904]
Foreign Income									0.0152	0.0161	0.0412	0.0802	0.0492	0.0917
(in %)									[0.0840]	[0.2111]	[0.0657]	[0.1040]	[0.0311]	[0.0653]
CAPEX											45.0264	−24.5468	46.1973	−22.8585
											[0.0000]	[0.0145]	[0.0000]	[0.0159]
R&D Expense													6.1078	8.8061
Dummy													[0.0062]	[0.0044]
ln(Market Value	0.4524	−0.4630	0.7759	0.7676	0.9023	0.8145	0.8805	0.6963	0.8586	0.7718	2.7749	0.9875	2.3811	0.4198
of Equity)	[0.5293]	[0.6805]	[0.2906]	[0.4449]	[0.2158]	[0.4161]	[0.2307]	[0.4940]	[0.2965]	[0.4696]	[0.0103]	[0.4913]	[0.0251]	[0.7773]
Constant	−8.6262	12.8599	−11.0284	2.6021	−11.8232	2.4007	−11.5785	5.2691	−11.6099	3.5136	−30.0227	0.5253	−29.3885	1.4396
	[0.1446]	[0.1680]	[0.0699]	[0.7514]	[0.0517]	[0.7703]	[0.0602]	[0.5212]	[0.0771]	[0.6698]	[0.0007]	[0.9624]	[0.0008]	[0.8967]
Observations	351	351	307	307	302	302	296	296	226	226	153	153	153	153
R^2	0.2883	0.0571	0.3376	0.0880	0.3582	0.0886	0.3645	0.1003	0.3515	0.0729	0.4146	0.0937	0.4423	0.1416

Table 7
Correlations among explanatory variables from the regressions corresponding to Columns (9) and (10) in Table 5.

	θ	ln(Market Value of Equity)	Cash ETR	Rev. Growth	Profitability
ln(Market Value of Equity)	−0.1376				
Cash ETR	0.0962	−0.1015			
Revenue Growth	−0.0826	0.0210	−0.0163		
Profitability	−0.0854	0.1028	0.1027	−0.0043	
Foreign Income	−0.0160	0.0906	−0.1260	0.0068	0.1231

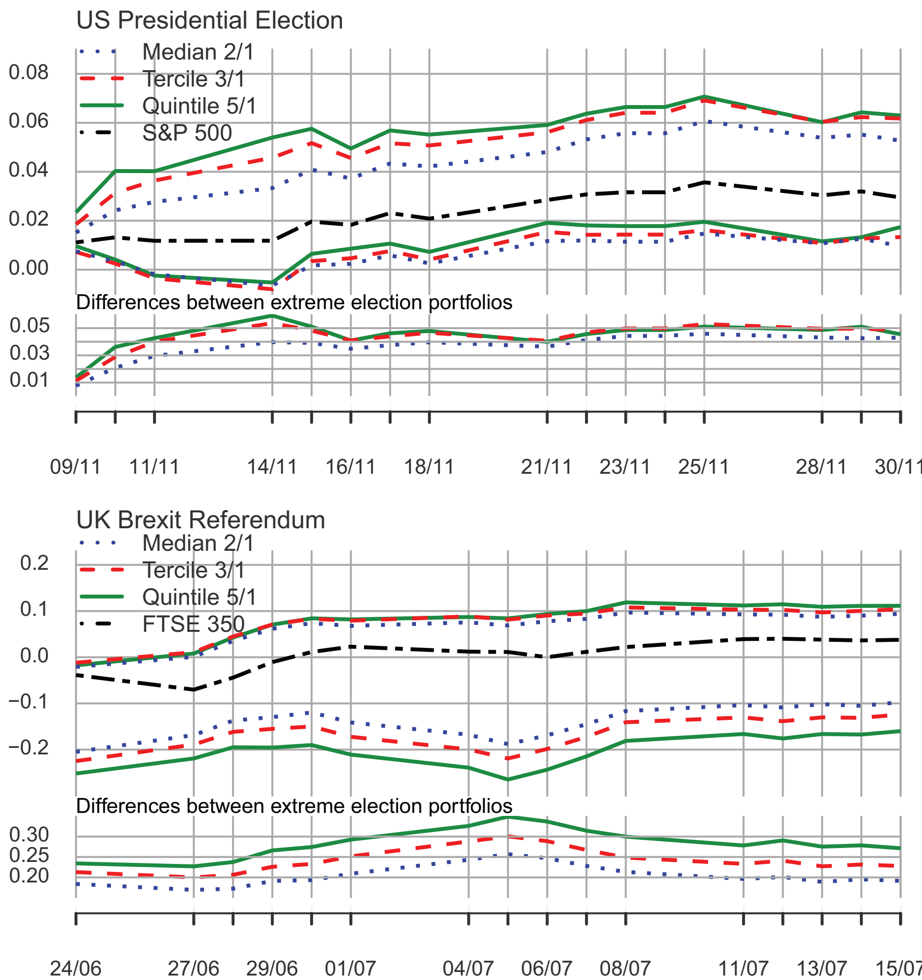

Fig. 3. Extreme (top and bottom quantile) election portfolios and corresponding long-short portfolios for the US presidential election (top) and the Brexit referendum (bottom). The upper part of each plot shows the cumulative returns of the top and bottom median (blue & dotted), tercile (red & dashed) and quintile (green & solid) value-weighted portfolios that are built by sorting on θ_i from Eq. (2). The lower part of each plot shows the cumulative returns of long-short portfolios, which are formed from the extreme quantile portfolios. For reference purposes, we also provide the cumulative performance of the corresponding index (S&P 500 and FTSE 350) in black (dot-and-dash). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 8
Correlations among explanatory variables from the regressions corresponding to Columns (13) and (14) in Table 6.

	θ	ln(Market Value of Equity)	Sales Growth	ROE	MB Ratio	Foreign Income	CAPEX
ln(Market Value of Equity)	0.2256						
Sales Growth	−0.0761	−0.0109					
ROE	0.0199	0.2135	−0.0154				
MB Ratio	0.0235	0.1980	−0.0384	0.1257			
Foreign Income	−0.0211	0.2539	−0.0340	0.0518	0.1210		
CAPEX	0.0152	−0.0468	0.0454	0.0494	−0.0177	0.0604	
R&D Expense Dummy	0.0096	0.0870	−0.0227	0.0627	0.0327	0.0068	−0.1024

In addition to these regressions, we provide results for long-short portfolios similar to those provided in Tables 2 and 3 but sorted based on firm characteristics instead of θ_i. For the US presidential election (Brexit referendum), we use all firm characteristics that turned out to be significant in Table 5 (Table 6, with the exception of the dummy variable R&D and of ROE, which shows the weakest results and has been left out for space reasons). To analyze the incremental information contained in our θ_is, we compare the returns of long-short portfolios sorted only on firm characteristics to the returns of long-short portfolios based on double sorts on both firm characteristics and θ_i. For space reasons and also to ensure sufficiently large portfolios after applying the double sorts, we confine ourselves to median portfolios for this analysis. The results are provided in Tables 9 and 10. Table 9 shows that long-short portfolios sorted on the cash effective tax rate (alone) yield significant cumulative returns of about 2.5% but only for $\tau+4$ and $\tau+5$. Long-short portfolios sorted on revenue growth or foreign income do not show significant returns at any horizon. For all three firm characteristics, however, double sorts on each characteristic and θ_i yield significant returns on the order of 3.2–7.3%, with the highest values occurring at $\tau+4$ or $\tau+5$. Interestingly, in particular the double sort on cash ETR and θ_i, with a cumulative return of 7.28% for $\tau+4$ (Table 9), exceeds the return of long-short portfolios based solely on θ_i (Table 2). For the Brexit case, Table 10 shows that the only firm characteristic that delivers significant returns when used for sorting portfolios is sales growth (no significance

Table 9
US presidential election: value-weighted event-window returns for median portfolios based on S&P 500 stocks and double sorted according to three different firm characteristics and on θ_i estimated from Eq. (2). The firm characteristics used are those that showed explanatory power in the regressions reported in Table 5 (Panel A: cash effective tax rate, Panel B: revenue growth, and Panel C: foreign income). Columns (1)-(3) show the value-weighted averages of the first sorting variable and θ_i, as well as the index beta of the respective portfolios. Column (4) indicates the sum of the market caps of the companies in the respective portfolios in billion USD. Column (5) provides the number of stocks in each portfolio (the total number of stocks for each panel depends on the availability of data on the particular variable). Columns (6)-(12) show cumulative portfolio returns $r_{s,t}$ for various time windows (from s to t), where τ is the last point in time before information on the event outcome is revealed. The top part of each panel provides results for double-sorted median portfolios. Below, we show the results for two types of long-short portfolios: first, long-short portfolios sorted only on the respective firm characteristic and, second, long-short portfolios sorted on both the firm characteristic and θ_i. [p-val] depicts one-sided significance levels for a parametric two-sample t-test and bootstrapping with 10,000 resamplings.

Panel A (Cash Effective Tax Rate)

Portfolio		(1) Cash ETR (in %)	(2) θ_i	(3) β_i	(4) Size	(5) No. of Stocks	(6) $r_{\tau,\tau+1}$	(7) $r_{\tau,\tau+2}$	(8) $r_{\tau,\tau+3}$	(9) $r_{\tau,\tau+4}$	(10) $r_{\tau,\tau+5}$	(11) $r_{\tau+5,\tau+10}$	(12) $r_{\tau+10,\tau+15}$
1 (Low Cash ETR)	1 (Low θ)	20.4133	−0.0184	0.87	5942	104	0.0077	0.0008	−0.0049	−0.0155	−0.0095	0.0063	0.0014
1 (Low Cash ETR)	2 (High θ)	20.8644	0.0298	1.11	4214	103	0.0130	0.0173	0.0225	0.0247	0.0338	0.0119	0.0014
2 (High Cash ETR)	1 (Low θ)	36.5628	−0.0160	0.83	3634	103	0.0052	0.0035	0.0032	0.0059	0.0136	0.0248	0.0085
2 (High Cash ETR)	2 (High θ)	34.0888	0.0365	0.98	2544	103	0.0214	0.0385	0.0416	0.0572	0.0615	0.0088	0.0020
Long-Short (High-Low Cash ETR)		14.9437	0.0040	−0.07			0.0020	0.0103	0.0125	0.0259	0.0249	0.0096	0.0044
t-test [p-val]							[0.3322]	[0.1409]	[0.1009]	[0.0224]	[0.0132]	[0.0608]	[0.0777]
Bootstrap [p-val]							[0.3370]	[0.1432]	[0.0962]	[0.0208]	[0.0126]	[0.0533]	[0.0813]
Long-Short (High Cash ETR/High θ - Low Cash ETR/Low θ)		13.6755	0.0549	0.11			0.0138	0.0377	0.0465	0.0728	0.0711	0.0025	0.0006
t-test [p-val]							[0.0350]	[0.0109]	[0.0024]	[0.0002]	[0.0001]	[0.3555]	[0.4267]
Bootstrap [p-val]							[0.0272]	[0.0041]	[0.0009]	[0.0000]	[0.0000]	[0.3415]	[0.4448]

Panel B (Revenue Growth)

Portfolio		(1) Revenue Growth (in %, RG)	(2) θ_i	(3) β_i	(4) Size	(5) No. of Stocks	(6) $r_{\tau,\tau+1}$	(7) $r_{\tau,\tau+2}$	(8) $r_{\tau,\tau+3}$	(9) $r_{\tau,\tau+4}$	(10) $r_{\tau,\tau+5}$	(11) $r_{\tau+5,\tau+10}$	(12) $r_{\tau+10,\tau+15}$
1 (High RG)	1 (Low θ)	14.7078	−0.0223	0.91	5789	126	0.0051	0.0024	−0.0029	−0.0103	−0.0027	0.0125	0.0029
1 (High RG)	2 (High θ)	11.5732	0.0324	1.06	3657	125	0.0181	0.0315	0.0382	0.0458	0.0510	0.0147	0.0006
2 (Low RG)	1 (Low θ)	−6.8051	−0.0225	0.93	4828	125	0.0114	0.0070	0.0021	0.0014	0.0101	0.0080	−0.0015
2 (Low RG)	2 (High θ)	−4.3015	0.0289	1.04	4811	125	0.0120	0.0158	0.0166	0.0201	0.0296	0.0112	0.0027
Long-Short (Low-High RG)		−19.0498	0.0043	0.02			0.0016	−0.0022	−0.0037	−0.0007	0.0018	−0.0037	−0.0014
t-test [p-val]							[0.3509]	[0.6028]	[0.6695]	[0.5241]	[0.4237]	[0.7543]	[0.7062]
Bootstrap [p-val]							[0.3459]	[0.5955]	[0.6619]	[0.5107]	[0.4121]	[0.7617]	[0.7105]
Long-Short (Low RG/High θ - High RG/Low θ)		−19.0093	0.0512	0.13			0.0069	0.0135	0.0195	0.0304	0.0324	−0.0013	−0.0001
t-test [p-val]							[0.1012]	[0.1007]	[0.0381]	[0.0191]	[0.0055]	[0.5614]	[0.5115]
Bootstrap [p-val]							[0.0953]	[0.1007]	[0.0353]	[0.0157]	[0.0044]	[0.5606]	[0.5203]

Panel C (Foreign Income)

Portfolio		(1) Foreign Income (in %, FI)	(2) θ_i	(3) β_i	(4) Size	(5) No. of Stocks	(6) $r_{\tau,\tau+1}$	(7) $r_{\tau,\tau+2}$	(8) $r_{\tau,\tau+3}$	(9) $r_{\tau,\tau+4}$	(10) $r_{\tau,\tau+5}$	(11) $r_{\tau+5,\tau+10}$	(12) $r_{\tau+10,\tau+15}$
1 (High FI)	1 (Low θ)	21.7102	−0.0223	0.92	5291	108	0.0022	−0.0038	−0.0057	−0.0130	−0.0045	0.0181	−0.0010
1 (High FI)	2 (High θ)	18.8913	0.0282	1.03	3796	108	0.0144	0.0235	0.0292	0.0346	0.0420	0.0124	0.0030
2 (Low FI)	1 (Low θ)	0.0000	−0.0262	0.88	3868	108	0.0158	0.0168	0.0077	0.0063	0.0124	0.0012	−0.0002
2 (Low FI)	2 (High θ)	0.0000	0.0296	1.05	3583	108	0.0129	0.0208	0.0235	0.0278	0.0356	0.0140	0.0017
Long-Short (Low-High FI)		−20.5326	0.0018	−0.01			0.0071	0.0112	0.0064	0.0098	0.0087	−0.0084	0.0000
t-test [p-val]							[0.0673]	[0.1091]	[0.2381]	[0.2020]	[0.2037]	[0.9197]	[0.4944]
Bootstrap [p-val]							[0.0616]	[0.1029]	[0.2386]	[0.2041]	[0.2002]	[0.9196]	[0.5021]
Long-Short (Low FI/High θ - High FI/Low θ)		−21.7102	0.0519	0.12			0.0107	0.0246	0.0292	0.0408	0.0401	−0.0041	0.0027
t-test [p-val]							[0.0241]	[0.0301]	[0.0131]	[0.0093]	[0.0030]	[0.6746]	[0.2137]
Bootstrap [p-val]							[0.0170]	[0.0212]	[0.0071]	[0.0044]	[0.0006]	[0.6805]	[0.2125]

for CAPEX and foreign income, and similarly for ROE, not shown). Using θ_i as an additional sorting criterion leads to substantially higher returns for the combinations of (i) sales growth and θ_i and (ii) foreign income and θ_i (Table 10) compared to θ_i alone (top panel of Table 3).[12]

We conclude from the results in this section that betting odds contain valuable information for predicting conditional stock returns around political events. θ_is estimated from our model exhibit low correlations with selected firm characteristics, which have been shown in the literature to have high explanatory power for the cross-sectional effects of election outcomes. Long-short portfolios based solely on firm characteristics of this type yield inferior returns to those based on θ_i, even for firm characteristics that the literature finds to have explanatory power for the cross-section of stock returns around the two political events analyzed here. However, their returns improve markedly when performing additional sorting based on θ_i, which provides additional evidence for stock sensitivities θ_i containing incremental information relative to firm characteristics. According to our model, θ_i should represent the sum of all relevant effects regarding conditional event returns. In some cases, however, long-short portfolios based on double sorts on both firm characteristics and θ_i yield higher returns than those sorted on θ_i alone. While all our results show that θ_is reflected in market prices contain valuable information on conditional event returns, this observation indicates that the market fails to aggregate *all* relevant information *in a perfect manner*.

[12] In addition to the firm characteristics shown in Tables 9 and 10, we have conducted the same analysis for firm size. In both cases, θ_i shows significant incremental information also relative to firm size. The returns of long-short quantile portfolios based on firm size alone are insignificant in the US presidential election case and are comparable to those from sorting on sales growth around the Brexit referendum. The results are available upon request.

Table 10
UK Brexit referendum: value-weighted event-window returns for median portfolios based on FTSE 350 stocks and double sorted according to three different firm characteristics and on θ_i estimated from Eq. (2). The firm characteristics used are a subset of those that showed explanatory power in the regressions reported in Table 6 (Panel A: sales growth, Panel B: foreign income, and Panel C: CAPEX; ROE is not shown for space reasons). Columns (1)-(3) show the value-weighted averages of the first sorting variable and θ_i, as well as the index beta of the respective portfolios. Column (4) indicates the sum of the market caps of the companies in the respective portfolios in billion GBP. Column (5) provides the number of stocks in each portfolio (the total number of stocks for each panel depends on the availability of data on the particular variable). Columns (6)-(12) show cumulative portfolio returns $r_{s,t}$ for various time windows (from s to t), where τ is the last point in time before information on the event outcome is revealed. The top part of each panel provides results for double-sorted median portfolios. Below, we show the results for two types of long-short portfolios: first, long-short portfolios sorted only on the respective firm characteristic and, second, long-short portfolios sorted on both the firm characteristic and θ_i. [p-val] depicts one-sided significance levels for a parametric two-sample t-test and bootstrapping with 10,000 resamplings.

Panel A (Sales Growth)

Portfolio		(1) Sales Growth (in %, SG)	(2) θ_i	(3) β_i	(4) Size	(5) No. of Stocks	(6) $r_{\tau,\tau+1}$	(7) $r_{\tau,\tau+7}$	(8) $r_{\tau,\tau+8}$	(9) $r_{\tau,\tau+9}$	(10) $r_{\tau,\tau+10}$	(11) $r_{\tau+10,\tau+15}$	(12) $r_{\tau+15,\tau+20}$
1 (High SG)	1 (Low θ)	2.2857	−0.0987	1.07	172	77	−0.2095	−0.1736	−0.1890	−0.1696	−0.1500	0.0527	0.0115
1 (High SG)	2 (High θ)	0.2434	0.0183	0.99	323	77	−0.0824	0.0047	0.0006	0.0154	0.0284	0.0291	0.0289
2 (Low SG)	1 (Low θ)	−0.1146	−0.1014	1.27	293	77	−0.1968	−0.1592	−0.1831	−0.1638	−0.1378	0.0487	0.0089
2 (Low SG)	2 (High θ)	−0.0283	0.0355	0.97	1187	76	−0.0046	0.0951	0.0877	0.0958	0.0988	0.0026	0.0026
Long-Short (High-Low SG)		−1.0001	0.0308	0.01			0.0840	0.1022	0.0995	0.0935	0.0857	−0.0255	−0.0189
t-test [p-val]							[0.0000]	[0.0007]	[0.0012]	[0.0024]	[0.0036]	[0.9998]	[0.9216]
Bootstrap [p-val]							[0.0001]	[0.0006]	[0.0018]	[0.0026]	[0.0036]	[1.0000]	[0.9733]
Long-Short (Low SG/High θ - High SG/Low θ)		−2.3140	0.1342	−0.10			0.2049	0.2687	0.2768	0.2654	0.2488	−0.0500	−0.0088
t-test [p-val]							[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[1.0000]	[0.9516]
Bootstrap [p-val]							[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[1.0000]	[0.9518]

Panel B (Foreign Income)

Portfolio		(1) Foreign Income (in %, FI)	(2) θ_i	(3) β_i	(4) Size	(5) No. of Stocks	(6) $r_{\tau,\tau+1}$	(7) $r_{\tau,\tau+7}$	(8) $r_{\tau,\tau+8}$	(9) $r_{\tau,\tau+9}$	(10) $r_{\tau,\tau+10}$	(11) $r_{\tau+10,\tau+15}$	(12) $r_{\tau+15,\tau+20}$
1 (Low FI)	1 (Low θ)	−0.6401	−0.1077	1.23	192	63	−0.2273	−0.1950	−0.2181	−0.1974	−0.1740	0.0567	0.0010
1 (Low FI)	2 (High θ)	0.0000	0.0253	1.09	516	62	−0.0305	0.0758	0.0683	0.0796	0.0854	0.0100	0.0018
2 (High FI)	1 (Low θ)	34.8307	−0.0840	1.16	206	63	−0.1879	−0.1497	−0.1732	−0.1549	−0.1282	0.0447	0.0145
2 (High FI)	2 (High θ)	82.4423	0.0265	0.79	768	62	−0.0082	0.0798	0.0721	0.0799	0.0831	0.0029	0.0114
Long-Short (High-Low FI)		72.5379	0.0139	−0.26			0.0377	0.0289	0.0296	0.0257	0.0233	−0.0109	0.0104
t-test [p-val]							[0.0696]	[0.2557]	[0.2516]	[0.2805]	[0.2925]	[0.9405]	[0.0306]
Bootstrap [p-val]							[0.0600]	[0.2530]	[0.2476]	[0.2792]	[0.2960]	[0.9469]	[0.0200]
Long-Short (High FI/High θ - Low FI/Low θ)		83.0825	0.1342	−0.43			0.2191	0.2748	0.2903	0.2773	0.2571	−0.0537	0.0104
t-test [p-val]							[0.0008]	[0.0001]	[0.0002]	[0.0002]	[0.0001]	[0.9995]	[0.1140]
Bootstrap [p-val]							[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[1.0000]	[0.1003]

Panel C (CAPEX)

Portfolio		(1) CAPEX	(2) θ_i	(3) β_i	(4) Size	(5) No. of Stocks	(6) $r_{\tau,\tau+1}$	(7) $r_{\tau,\tau+7}$	(8) $r_{\tau,\tau+8}$	(9) $r_{\tau,\tau+9}$	(10) $r_{\tau,\tau+10}$	(11) $r_{\tau+10,\tau+15}$	(12) $r_{\tau+15,\tau+20}$
1 (Low CAPEX)	1 (Low θ)	0.0175	−0.0937	0.97	99	55	−0.1947	−0.1644	−0.1715	−0.1544	−0.1319	0.0540	0.0088
1 (Low CAPEX)	2 (High θ)	0.0208	0.0300	0.70	722	55	−0.0026	0.0923	0.0856	0.0947	0.0955	0.0001	0.0188
2 (High CAPEX)	1 (Low θ)	0.1013	−0.0407	1.06	263	55	−0.1005	−0.0263	−0.0435	−0.0320	−0.0195	0.0233	0.0057
2 (High CAPEX)	2 (High θ)	0.0734	0.0576	1.22	526	55	−0.0200	0.0936	0.0883	0.0971	0.1043	0.0118	−0.0089
Long-Short (High-Low CAPEX)		0.0623	0.0097	0.43			−0.0211	−0.0079	−0.0104	−0.0108	−0.0052	0.0090	−0.0216
t-test [p-val]							[0.9074]	[0.5757]	[0.6043]	[0.6038]	[0.5516]	[0.0484]	[0.9903]
Bootstrap [p-val]							[0.9135]	[0.5732]	[0.6010]	[0.6058]	[0.5530]	[0.0431]	[0.9997]
Long-Short (High CAPEX/High θ - Low CAPEX/Low θ)		0.0559	0.1513	0.25			0.1747	0.2580	0.2597	0.2515	0.2362	−0.0423	−0.0177
t-test [p-val]							[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[1.0000]	[0.9981]
Bootstrap [p-val]							[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[1.0000]	[0.9994]

4.2. Pre-Event testing of the model

There is no guarantee that our approach will work for all future elections. Before forming long-short portfolios as described above, an investor would find it reassuring to have some evidence that the approach can be expected to work for a particular future event. In this section, we provide a simple check which can be applied prior to the event.

While Section 4.1 has shown that our model correctly predicted conditional returns *after* the events when winning probabilities jumped to 0 or 1, this test was based on the implications our model has for returns *prior* to the events. For instance, Eq. (2) implies positive idiosyncratic returns of Trump stocks (with $\theta_i > 0$) when Trump probabilities q^R increase, and vice versa. To obtain an indication of whether our approach works for a particular election, we check whether the long-short portfolios based on θ_is analyzed in Section 4.1 behave as predicted by the model in the weeks/months prior to the event. To this end, we proceed as follows. To ensure a sufficient number of observations for the initial estimation of our model, we use data from the beginning of each dataset (described in Section 3) until 12 weeks prior to its end to estimate θ_is from Eq. (2). Assuming that we correctly anticipate the direction of changes in betting odds on the next day, we form long-short portfolios similar to those described in Section 4.1. For the next day, we repeat this exercise with an estimation set that grows by including the previous day's returns and betting odds and so on until two business days prior to the event. This yields 12 weeks of one-day returns of long-short portfolios formed based on data available at this time and conditional on correctly anticipating the direction of the next day's change in betting odds. For the resulting portfolios, we calculate the mean returns, Sharpe ratios, and alpha values relative to the Fama-French 3-factor and 4-factor models (as a robustness check based on well-known alternatives to the index model).

The results of this exercise are described in Table 11, with all values provided on an annual basis and t-statistics in square brack-

Table 11
Portfolio statistics from testing the model on stock prices observed *prior to* the respective events. θ_is are estimated repeatedly from Eq. (2) using expanding windows, starting 12 weeks before the end of our samples described in Section 3. Assuming perfect foresight regarding the direction of change in the next day's betting odds, long-short quantile portfolios are formed and adjusted daily. Panel A shows the annualized results for the US presidential election, and Panel B shows those for the Brexit referendum. Column (1) provides the mean return, and column (2) shows the Sharpe ratio of our strategies. The remaining columns indicate the alpha values of the long-short portfolios against the Fama-French 3-factor and 4-factor models. Factor returns for the US data are taken from Kenneth French's data library, and those for the UK data are taken from the University of Exeter, with details on the construction of factors described in Gregory et al., 2013. t-statistics are given in square brackets. For columns (1), (3) and (4), they are based on Newey-West standard errors. For column (2), they are based on Memmel (2003).

Panel A (S&P 500)								
	(1)		(2)		(3)		(4)	
Portfolios	Mean Return		Sharpe Ratio		Alpha (3F)		Alpha (4F)	
Median	0.2513	[1.88]	5.8593	[2.54]	0.2379	[2.46]	0.2397	[2.51]
Tercile	0.3870	[2.33]	6.1790	[2.68]	0.3584	[2.55]	0.3604	[2.71]
Quintile	0.4614	[2.34]	5.5579	[2.42]	0.3995	[2.11]	0.3981	[2.09]
Panel B (FTSE 350)								
Portfolios	Mean Return		Sharpe Ratio		Alpha (3F)		Alpha (4F)	
Median	0.5919	[1.47]	5.9513	[1.86]	0.6473	[3.53]	0.4609	[2.28]
Tercile	0.8038	[1.96]	6.9269	[2.18]	0.8729	[3.97]	0.6413	[2.66]
Quintile	1.0236	[2.37]	7.0312	[2.27]	1.1060	[3.96]	0.8222	[2.68]

ets. As predicted by our model, we find positive mean returns, high Sharpe ratios, and positive alpha values relative to the factor models. The results improve when moving from median via tercile to quintile portfolios (the only exception to this is the Sharpe ratio of the quintile relative to tercile portfolios for the S&P 500). This is reassuring evidence for that the model's predictions are correct over an extended time period prior to the event: If the observed returns prior to the event did not contain such expectations, we should not see any significant returns or alpha values, while Sharpe ratios should be at levels commonly observed for diversified stock portfolios. We note that the purpose of the pre-event test is an ex ante assessment of whether or not our approach can be expected to work for a particular election. The results reported here are not indicative of what could have been achieved in practice for these events, as the pre-event test assumes that the sign of daily changes in betting odds can be predicted without error and does not consider transaction costs. We note that pre-event tests along the lines suggested in this section could also be conducted for strategies based on firm variables (Hill et al., 2019; Wagner et al., 2018) to assess potential dependencies on such variables prior to the event: If the market considers, e.g., foreign income to be an important characteristic regarding the election effect, the returns of quantile portfolios sorted based on this variable should covary with changes in betting odds in the weeks and months prior to the election.

4.3. Postevent return drift

Similar to Fisman and Zitzewitz (2019) and Wagner et al. (2018a,b), Fig. 3 as well as Tables 2 and 3 show positive return autocorrelation in the first few days after the event, which leads to an inverse U-shaped pattern: The maximum long-short portfolio returns for the S&P 500 are on the order of 4–5.9%. They are reached four days after the election (see column (8) in Table 2). For the FTSE 350, this short-term momentum effect is observable as well. Long-short portfolio returns are much higher at around 25.7–34.9% and are reached after a holding period of 8 days (see column (7) in Table 3). One-sided significance levels for these maximum returns are all below 1% for both events and for the t-test as well as the bootstrap.

In light of this momentum effect, abnormal returns were also achievable around both events for investors who formed long-short portfolios on the day after the event, i.e. when the election outcome was already publicly known. This effect has previously been documented for larger stock universes including smaller stocks as well (cf. Wagner et al. (2018a,b) for the US presidential election and Fisman and Zitzewitz (2019) for both the US presidential election and the Brexit referendum). One possible explanation is that markets needed some time to fully process all relevant information after the event. Alternatively, there may be behavioral reasons for the initial underreaction, which then caused a short-term momentum effect. Fisman and Zitzewitz (2019) and Wagner et al. (2018b) analyze simple strategies which select long-short portfolios on the first postevent day purely based on this day's returns, $r_{\tau,\tau+1}$. Due to the empirically observed postevent return drift, these portfolios yield remarkable returns over 4–10 days. We use their approach as the basis for our analysis in this section.

From the point of view of our model, the postevent return drift means that it takes a couple of days until the election effect is fully incorporated into the stock prices. An interesting question is whether information from our approach, although it has been designed to select stocks ex ante, could also have been used by investors who wanted to exploit the postevent return drift. This hope is justified as follows. When classifying stocks purely based on $r_{\tau,\tau+1}$, two types of stocks will be selected: (i) stocks that have been affected by the event, but the effect has not been fully incorporated into the stock price on the first day after the event, and (ii) stocks whose prices increased or decreased on this day for other reasons. Double sorting on both first-day returns and the stock sensitivities θ_i estimated from our model should allow us to distinguish between these two groups of stocks, which should increase the returns achievable based on first-day returns alone. Hence, an investor who wants to benefit from the postevent return drift should buy only stocks that went up on the first postevent day *and* have a high θ_i, whereas he/she should shun stocks with high returns but low θ_i because these stocks' high returns came unexpectedly (from the point of view of our model) and are, thus, most likely not election-related.

Table 12
Value-weighted event-window returns for median portfolios double sorted according to the first postevent return ($r_{\tau,\tau+1}$) and θ_i estimated from Eq. (2). Panel A shows the results for the US presidential election, and Panel B shows those for the Brexit referendum. Columns (1)-(3) provide the value-weighted average first postevent return and θ_i, as well as the index beta of the respective portfolios. Column (4) indicates the sum of the market caps of the companies in the respective portfolios in billion USD/GBP. Column (5) provides the number of stocks in each portfolio. Columns (6)-(11) show cumulative portfolio returns $r_{s,t}$ for various time windows (from s to t), where τ is the last point in time before information on the event outcome is revealed. The top part of each panel provides results for double-sorted median portfolios. Below, we show the results for two types of long-short portfolios: first, long-short portfolios sorted only on $r_{\tau,\tau+1}$ and, second, long-short portfolios sorted on both $r_{\tau,\tau+1}$ and θ_i. [p-val] depicts one-sided significance levels for a parametric two-sample t-test and bootstrapping with 10,000 resamplings.

Panel A (S&P 500)

	Portfolio	(1) $r_{\tau,\tau+1}$	(2) θ_i	(3) β_i	(4) Size	(5) No. of Stocks	(6) $r_{\tau+1,\tau+2}$	(7) $r_{\tau+1,\tau+3}$	(8) $r_{\tau+1,\tau+4}$	(9) $r_{\tau+1,\tau+5}$	(10) $r_{\tau+5,\tau+10}$	(11) $r_{\tau+10,\tau+15}$
1 (Low $r_{\tau,\tau+1}$)	1 (Low θ)	−0.0123	−0.0249	0.89	5838	127	−0.0170	−0.0196	−0.0291	−0.0171	0.0170	0.0014
1 (Low $r_{\tau,\tau+1}$)	2 (High θ)	−0.0101	0.0251	0.93	4651	126	−0.0097	−0.0065	−0.0131	−0.0012	0.0199	0.0042
2 (High $r_{\tau,\tau+1}$)	1 (Low θ)	0.0353	−0.0192	0.95	4900	126	0.0132	0.0055	0.0081	0.0116	0.0032	0.0000
2 (High $r_{\tau,\tau+1}$)	2 (High θ)	0.0408	0.0369	1.21	3784	126	0.0266	0.0298	0.0474	0.0502	0.0028	−0.0004
Long-Short (High-Low $r_{\tau,\tau+1}$)		0.0490	0.0080	0.15			0.0328	0.0299	0.0472	0.0384	−0.0153	−0.0028
t-test [p-val]							[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.9985]	[0.8627]
Bootstrap [p-val]							[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.9994]	[0.8693]
Long-Short (High $r_{\tau,\tau+1}$/High θ - Low $r_{\tau,\tau+1}$/Low θ)		0.0531	0.0618	0.32			0.0435	0.0494	0.0765	0.0672	−0.0142	−0.0018
t-test [p-val]							[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.9726]	[0.7246]
Bootstrap [p-val]							[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.9848]	[0.7419]

Panel B (FTSE 350)

	Portfolio	(1) $r_{\tau,\tau+1}$	(2) θ_i	(3) β_i	(4) Size	(5) No. of Stocks	(6) $r_{\tau+1,\tau+7}$	(7) $r_{\tau+1,\tau+8}$	(8) $r_{\tau+1,\tau+9}$	(9) $r_{\tau+1,\tau+10}$	(10) $r_{\tau+10,\tau+15}$	(11) $r_{\tau+15,\tau+20}$
1 (Low $r_{\tau,\tau+1}$)	1 (Low θ)	−0.2602	−0.1376	1.31	246	88	−0.1037	−0.1313	−0.1044	−0.0689	0.0632	0.0126
1 (Low $r_{\tau,\tau+1}$)	2 (High θ)	−0.1996	−0.0184	1.09	311	88	−0.0457	−0.0675	−0.0418	−0.0182	0.0437	−0.0031
2 (High $r_{\tau,\tau+1}$)	1 (Low θ)	−0.0226	−0.0214	0.93	587	88	0.0825	0.0744	0.0832	0.0898	0.0068	0.0244
2 (High $r_{\tau,\tau+1}$)	2 (High θ)	0.0011	0.0552	0.97	950	87	0.0946	0.0890	0.0962	0.0995	0.0053	0.0038
Long-Short (High-Low $r_{\tau,\tau+1}$)		0.2184	0.0970	−0.23			0.1613	0.1790	0.1606	0.1364	−0.0465	0.0078
t-test [p-val]							[0.0000]	[0.0000]	[0.0000]	[0.0000]	[1.0000]	[0.1291]
Bootstrap [p-val]							[0.0000]	[0.0000]	[0.0000]	[0.0000]	[1.0000]	[0.1233]
Long-Short (High $r_{\tau,\tau+1}$/High θ - Low $r_{\tau,\tau+1}$/Low θ)		0.2613	0.1928	−0.34			0.1983	0.2202	0.2006	0.1684	−0.0579	−0.0088
t-test [p-val]							[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.9997]	[0.8929]
Bootstrap [p-val]							[0.0000]	[0.0000]	[0.0000]	[0.0000]	[1.0000]	[0.8875]

The results for double-sorted quantile portfolios are shown in Table 12, which also provides returns for long-short portfolios sorted only on first-day returns for comparison. The results in both panels confirm that double sorting on both first-day returns and θ_i leads to higher returns than sorting on first-day returns alone, with an incremental effect attributable to the additional sort on θ_i of about 3 (4) percentage points for the US (UK) data. For both cases, the maximum return still occurs for the same time intervals as before, i.e. 4 (8) days after the event for the US (UK) data. However, the two cases differ markedly when comparing the returns of portfolios formed based on $r_{\tau,\tau+1}$ to those from sorting only on θ_i (Tables 2 and 3): For the US data, the maximum return achievable based on first-day returns (double-/single-sorted, 7.65%/4.72%) is higher than for portfolios formed based on θ_i alone (3.98%). In contrast, for the UK data, portfolios formed based on θ_i alone (25.69%) outperform those based on first-day returns with/without taking θ_i into account (22.02%/17.9%).

We conclude this part by noting that our model has neither been designed to capture nor explain the postevent return drift. The economic reasoning behind our approach, which aims at selecting stocks before the event, applies to any political event as long as its date and possible outcomes are known ex ante. In contrast, the postevent drift in returns, as documented for both the US presidential election and the UK Brexit referendum, may or may not persist in the future. The lack of a solid explanation for this empirical observation means that strategies aiming at exploiting the postevent return drift may or may not work for future events.

5. Conclusion

In this paper, we have shown how to classify the cross-section of stocks into expected winners and losers around political events by combining event outcome probabilities from betting markets (political prediction markets) with stock price data. Compared to previous literature, our approach selects profitable portfolios prior to the event from a large cross-section of stocks, without relying on firm-specific variables that may only be available for a subset of these stocks. Instead, we use a simple and parsimonious model which infers all required information directly from stock prices and betting odds. Aside from forming portfolios designed to benefit from a particular event outcome ("candidate baskets"), the approach can also be used to measure the sensitivity of existing portfolios to the event outcome and to remove any undesired corresponding exposure. Moreover, prior to political events, the approach also provides the possibility to check whether or not stock prices reflect any outcome-dependent return expectations.

The approach has been applied to the constituents of major US and UK stock indices, using data that were publicly available before the 2016 US presidential election and the 2016 Brexit referendum. Long-short portfolios constructed according to this approach show strong outperformance around the election date, which is both economically and statistically significant. The stock sensitivities estimated from our model show low correlations to firm-specific variables which have been used successfully in the previous literature analyzing these events. In both datasets, we find postevent return drift, which has been documented previously for these events but is outside of the scope of our model. Using both regression approaches and double-sorted quantile portfolios, we show that stock sensitivities to betting odds contain incremental information compared to both firm characteristics and first-day returns.

Appendix A. Empirical distribution of θ_is from Eq. (2)

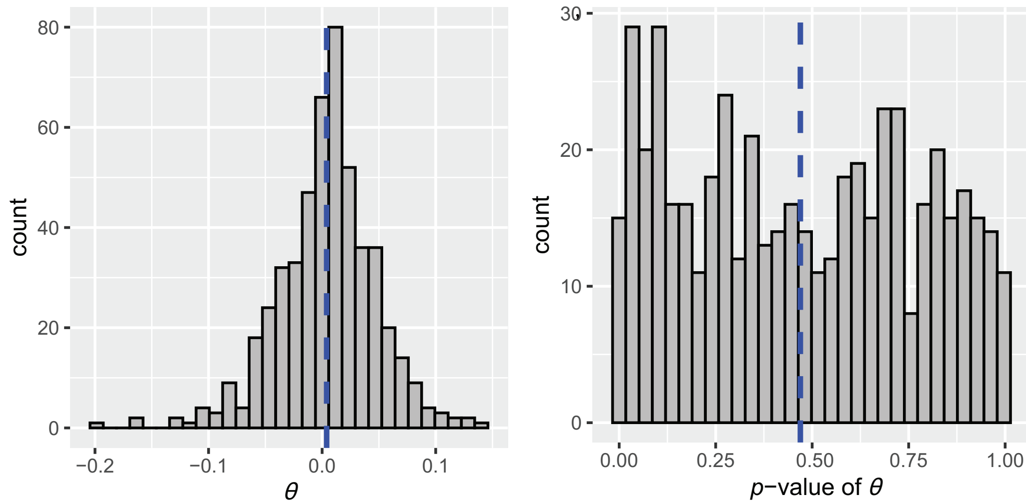

Fig. A.4. US presidential election (S&P 500): Empirical distribution of 505 θ_is and their significance levels $p(\theta_i)$. The dashed vertical line indicates the mean.

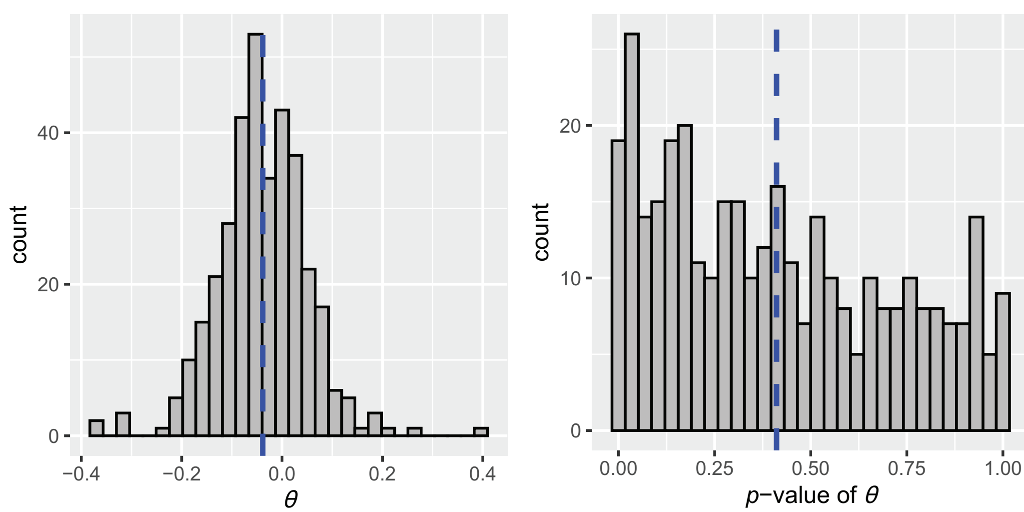

Fig. A.5. Brexit referendum (FTSE 350): Empirical distribution of 351 θ_is and their significance levels $p(\theta_i)$. The dashed vertical line indicates the mean.

Table A.1
Descriptive statistics for the cross-section of θ_is and their respective p-values. Panel A: US presidential election, Panel B: UK Brexit referendum.

Panel A (S&P 500)									
	Min	q(25)	Mean	Median	q(75)	Max	SD	Skew	Kurt
θ	−0.20	−0.02	0.00	0.01	0.03	0.13	0.04	−0.48	1.88
$p(\theta)$	0.00	0.19	0.47	0.46	0.73	1.00	0.30	0.06	−1.29
Panel B (FTSE 350)									
	Min	q(25)	Mean	Median	q(75)	Max	SD	Skew	Kurt
θ	−0.37	−0.09	−0.04	−0.04	0.02	0.39	0.09	0.02	2.32
$p(\theta)$	0.00	0.15	0.41	0.37	0.66	1.00	0.30	0.39	−1.07

Table A.2
Number of p-values below standard significance levels. Panel A: US presidential election, Panel B: UK Brexit referendum.

Panel A (S&P 500)				
	# of Stocks	# of $p <= 0.01$	# of $p <= 0.05$	# of $p <= 0.1$
1	505	10	43	78
Panel B (FTSE 350)				
	# of Stocks	# of $p <= 0.01$	# of $p <= 0.05$	# of $p <= 0.1$
1	351	10	44	68

Appendix B. Potential endogeneity between index returns and risk-neutral probabilities

In our model in Section 2, we assume that changes in risk-neutral probabilities cause (part of the) changes in stock prices. In principle, both might be simultaneously driven by market-wide sentiment or economic conditions. Regarding the possible causes of endogeneity, we conjecture that due to the small size of the election-induced effect relative to total idiosyncratic volatility, single stock returns cannot influence betting odds, but the market (proxied by the index) might potentially do so. In this section, we check for a potential endogeneity between index returns and risk-neutral probabilities.

In Eq. (2) in Section 2, we regress the stock returns on index returns and changes in risk-neutral probabilities (restated here for convenience):

$$r_{i,t} = \alpha_i + \beta_i r_{m,t} + \theta_i \Delta q_t^R + \epsilon_{i,t}. \tag{B.1}$$

As a robustness check, we regress changes in risk-neutral probabilities on market returns:

$$\Delta q_t^R = \alpha_R + \gamma r_{m,t} + \epsilon_{R,t}. \tag{B.2}$$

The slope parameter γ is not significantly different from zero. We then plug the estimated residuals $\hat{\epsilon}_{R,t}$ from Eq. (B.2) into Eq. (B.1), which obtains

$$r_{i,t} = \alpha_{i,2} + \beta_{i,2} r_{m,t} + \theta_{i,2} \hat{\epsilon}_{R,t} + \varepsilon_{i,t}, \tag{B.3}$$

and check the difference between θ_i and $\theta_{i,2}$ estimated from Eqs. (B.1) and (B.3). Results computed based on θ_i and $\theta_{i,2}$ are statistically indistinguishable.

Appendix C. Robustness Check: Equally weighted Portolios

Table C.1
US presidential election: equally weighted event-window returns for quantile portfolios based on S&P 500 stocks, formed at time τ (shortly before information on the event outcome is revealed), according to θ_i estimated from Eq. (2). The table shows the median portfolios (Panel A), tercile portfolios (Panel B), and quintile portfolios (Panel C). Column (1) provides the equally weighted average of θ_i for the respective portfolios, and column (2) provides the portfolio β relative to the index. Column (3) shows the sum of the market caps of the companies in the respective portfolios in billion USD, and column (4) provides the number of stocks in each portfolio. Columns (5)–(11) show cumulative portfolio returns $r_{s,t}$ for various time windows (from s to t). Long-short portfolios are formed by going long (short) on the highest (lowest) quantile portfolio. [p-val] depicts one-sided significance levels for a parametric two-sample t-test and bootstrapping with 10,000 resamplings.

Panel A (Median Portfolios)											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Portfolio	θ_i	β_i	Size	No. of Stocks	$r_{\tau,\tau+1}$	$r_{\tau,\tau+2}$	$r_{\tau,\tau+3}$	$r_{\tau,\tau+4}$	$r_{\tau,\tau+5}$	$r_{\tau+5,\tau+10}$	$r_{\tau+10,\tau+15}$
1 (Short)	−0.0281	1.05	10,739	253	0.0077	0.0101	0.0050	0.0110	0.0201	0.0078	0.0010
2 (Long)	0.0361	1.13	8433	252	0.0173	0.0293	0.0340	0.0452	0.0511	0.0110	−0.0002
Long-Short	0.0642	0.08			0.0096	0.0192	0.0289	0.0342	0.0310	0.0032	−0.0011
t-test [p-val]					[0.0025]	[0.0001]	[0.0000]	[0.0000]	[0.0000]	[0.1439]	[0.7052]
Bootstrap [p-val]					[0.0021]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.1446]	[0.7101]
Panel B (Tercile Portfolios)											
Portfolio	θ_i	β_i	Size	No. of Stocks	$r_{\tau,\tau+1}$	$r_{\tau,\tau+2}$	$r_{\tau,\tau+3}$	$r_{\tau,\tau+4}$	$r_{\tau,\tau+5}$	$r_{\tau+5,\tau+10}$	$r_{\tau+10,\tau+15}$
1 (Short)	−0.0420	1.11	6831	169	0.0079	0.0115	0.0055	0.0145	0.0249	0.0073	−0.0019
2	0.0064	0.97	6727	168	0.0101	0.0155	0.0144	0.0169	0.0238	0.0111	0.0053
3 (Long)	0.0478	1.18	5614	168	0.0193	0.0322	0.0385	0.0529	0.0580	0.0098	−0.0022
Long-Short	0.0898	0.07			0.0114	0.0207	0.0330	0.0384	0.0332	0.0025	−0.0003
t-test [p-val]					[0.0048]	[0.0009]	[0.0000]	[0.0000]	[0.0000]	[0.2552]	[0.5475]
Bootstrap [p-val]					[0.0048]	[0.0009]	[0.0000]	[0.0000]	[0.0001]	[0.2584]	[0.5441]
Panel C (Quintile Portfolios)											
Portfolio	θ_i	β_i	Size	No. of Stocks	$r_{\tau,\tau+1}$	$r_{\tau,\tau+2}$	$r_{\tau,\tau+3}$	$r_{\tau,\tau+4}$	$r_{\tau,\tau+5}$	$r_{\tau+5,\tau+10}$	$r_{\tau+10,\tau+15}$
1 (Short)	−0.0583	1.20	3835	101	0.0113	0.0156	0.0084	0.0213	0.0340	0.0054	−0.0056
2	−0.0135	0.96	4745	101	0.0039	0.0051	0.0016	0.0041	0.0095	0.0078	0.0056
3	0.0066	0.94	4276	101	0.0088	0.0133	0.0105	0.0121	0.0201	0.0137	0.0057
4	0.0234	1.12	3445	101	0.0208	0.0345	0.0434	0.0547	0.0611	0.0102	0.0011
5 (Long)	0.0617	1.22	2871	101	0.0174	0.0299	0.0334	0.0483	0.0531	0.0100	−0.0049
Long-Short	0.1200	0.02			0.0062	0.0143	0.0250	0.0270	0.0191	0.0046	0.0007
t-test [p-val]					[0.1386]	[0.0474]	[0.0027]	[0.0062]	[0.0331]	[0.2110]	[0.4325]
Bootstrap [p-val]					[0.1356]	[0.0469]	[0.0025]	[0.0055]	[0.0304]	[0.2042]	[0.4216]

Table C.2
UK Brexit referendum: equally weighted event-window returns for quantile portfolios based on FTSE 350 stocks, formed at time τ (shortly before information on the event outcome is revealed), according to θ_i estimated from Eq. (2). The table shows the median portfolios (Panel A), tercile portfolios (Panel B), and quintile portfolios (Panel C). Column (1) provides the equally weighted average of θ_i for the respective portfolios, and column (2) provides the portfolio β relative to the index. Column (3) shows the sum of the market caps of the companies in the respective portfolios in billion GBP, and column (4) provides the number of stocks in each portfolio. Columns (5)-(11) show cumulative portfolio returns $r_{s,t}$ for various time windows (from s to t). Long-short portfolios are formed by going long (short) on the highest (lowest) quantile portfolio. [p-val] depicts one-sided significance levels for a parametric two-sample t-test and bootstrapping with 10,000 resamplings.

Panel A (Median Portfolios)											
Portfolio	(1) θ_i	(2) β_i	(3) Size	(4) No. of Stocks	(5) $r_{\tau,\tau+1}$	(6) $r_{\tau,\tau+7}$	(7) $r_{\tau,\tau+8}$	(8) $r_{\tau,\tau+9}$	(9) $r_{\tau,\tau+10}$	(10) $r_{\tau+10,\tau+15}$	(11) $r_{\tau+15,\tau+20}$
1 (Short)	−0.1068	0.94	514	176	−0.1835	−0.1523	−0.1612	−0.1440	−0.1241	0.0477	0.0153
2 (Long)	0.0303	0.87	1581	175	−0.0817	−0.0105	−0.0120	−0.0015	0.0095	0.0266	0.0107
Long-Short	0.1372	−0.08			0.1018	0.1418	0.1492	0.1425	0.1337	−0.0211	−0.0046
t-test [p-val]					[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[1.0000]	[0.8700]
Bootstrap [p-val]					[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[1.0000]	[0.8651]
Panel B (Tercile Portfolios)											
Portfolio	θ_i	β_i	Size	No. of Stocks	$r_{\tau,\tau+1}$	$r_{\tau,\tau+7}$	$r_{\tau,\tau+8}$	$r_{\tau,\tau+9}$	$r_{\tau,\tau+10}$	$r_{\tau+10,\tau+15}$	$r_{\tau+15,\tau+20}$
1 (Short)	−0.1326	0.97	307	117	−0.1977	−0.1686	−0.1787	−0.1619	−0.1407	0.0495	0.0173
2	−0.0382	0.85	604	117	−0.1379	−0.0931	−0.1002	−0.0847	−0.0698	0.0378	0.0094
3 (Long)	0.0554	0.89	1183	117	−0.0626	0.0169	0.0184	0.0277	0.0380	0.0244	0.0123
Long-Short	0.1879	−0.09			0.1351	0.1856	0.1971	0.1896	0.1787	−0.0250	−0.0050
t-test [p-val]					[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[1.0000]	[0.8272]
Bootstrap [p-val]					[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.9999]	[0.8335]
Panel C (Quintile Portfolios)											
Portfolio	θ_i	β_i	Size	No. of Stocks	$r_{\tau,\tau+1}$	$r_{\tau,\tau+7}$	$r_{\tau,\tau+8}$	$r_{\tau,\tau+9}$	$r_{\tau,\tau+10}$	$r_{\tau+10,\tau+15}$	$r_{\tau+15,\tau+20}$
1 (Short)	−0.1623	1.00	187	71	−0.2177	−0.1961	−0.2086	−0.1937	−0.1707	0.0573	0.0156
2	−0.0792	0.91	211	70	−0.1631	−0.1242	−0.1312	−0.1125	−0.0955	0.0404	0.0178
3	−0.0390	0.85	195	70	−0.1440	−0.1039	−0.1132	−0.0973	−0.0807	0.0381	0.0077
4	0.0067	0.69	890	70	−0.0900	−0.0237	−0.0221	−0.0125	−0.0028	0.0247	0.0192
5 (Long)	0.0833	1.07	611	70	−0.0477	0.0416	0.0427	0.0528	0.0638	0.0254	0.0048
Long-Short	0.2455	0.06			0.1700	0.2377	0.2513	0.2465	0.2345	−0.0319	−0.0108
t-test [p-val]					[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[1.0000]	[0.9781]
Bootstrap [p-val]					[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[1.0000]	[0.9794]

Table C.3
US presidential election: event-window returns for quantile portfolios based on S&P 500 stocks, formed at time τ (shortly before information on the event outcome is revealed), according to θ_i estimated from Eq. (2). The weights used for this table are proportional to the product of each stock's market capitalization and θ_i. The table shows the median portfolios (Panel A), tercile portfolios (Panel B), and quintile portfolios (Panel C). Column (1) provides the weighted average of θ_i for the respective portfolios, and column (2) provides the portfolio β relative to the index. Column (3) shows the sum of the market caps of the companies in the respective portfolios in billion USD, and column (4) provides the number of stocks in each portfolio. Columns (5)–(11) show cumulative portfolio returns $r_{s,t}$ for various time windows (from s to t). Long-short portfolios are formed by going long (short) on the highest (lowest) quantile portfolio. [p-val] depicts one-sided significance levels for a parametric two-sample t-test and bootstrapping with 10,000 resamplings.

Panel A (Median Portfolios)											
Portfolio	(1) θ_i	(2) β_i	(3) Size	(4) No. of Stocks	(5) $r_{\tau,\tau+1}$	(6) $r_{\tau,\tau+2}$	(7) $r_{\tau,\tau+3}$	(8) $r_{\tau,\tau+4}$	(9) $r_{\tau,\tau+5}$	(10) $r_{\tau+5,\tau+10}$	(11) $r_{\tau+10,\tau+15}$
1 (Short)	−0.0475	1.03	10,739	253	0.0114	0.0091	0.0015	−0.0001	0.0111	0.0088	−0.0053
2 (Long)	0.0433	1.12	8433	252	0.0172	0.0281	0.0313	0.0404	0.0468	0.0100	0.0012
Long-Short	0.0908	0.09			0.0058	0.0189	0.0298	0.0405	0.0357	0.0012	0.0065
t-test [p-val]					[0.1657]	[0.0429]	[0.0033]	[0.0022]	[0.0027]	[0.4195]	[0.0518]
Bootstrap [p-val]					[0.1639]	[0.0379]	[0.0015]	[0.0006]	[0.0011]	[0.3995]	[0.0354]
Panel B (Tercile Portfolios)											
Portfolio	θ_i	β_i	Size	No. of Stocks	$r_{\tau,\tau+1}$	$r_{\tau,\tau+2}$	$r_{\tau,\tau+3}$	$r_{\tau,\tau+4}$	$r_{\tau,\tau+5}$	$r_{\tau+5,\tau+10}$	$r_{\tau+10,\tau+15}$
1 (Short)	−0.0503	1.05	6831	169	0.0117	0.0097	0.0019	0.0006	0.0122	0.0087	−0.0060
2	0.0086	0.89	6727	168	0.0085	0.0082	0.0074	0.0050	0.0134	0.0148	0.0048
3 (Long)	0.0478	1.15	5614	168	0.0184	0.0305	0.0340	0.0445	0.0503	0.0090	0.0008
Long-Short	0.0981	0.10			0.0067	0.0208	0.0322	0.0440	0.0381	0.0004	0.0068
t-test [p-val]					[0.1518]	[0.0435]	[0.0040]	[0.0026]	[0.0037]	[0.4750]	[0.0552]
Bootstrap [p-val]					[0.1527]	[0.0349]	[0.0018]	[0.0006]	[0.0014]	[0.4505]	[0.0458]
Panel C (Quintile Portfolios)											
Portfolio	θ_i	β_i	Size	No. of Stocks	$r_{\tau,\tau+1}$	$r_{\tau,\tau+2}$	$r_{\tau,\tau+3}$	$r_{\tau,\tau+4}$	$r_{\tau,\tau+5}$	$r_{\tau+5,\tau+10}$	$r_{\tau+10,\tau+15}$
1 (Short)	−0.0588	1.09	3835	101	0.0135	0.0116	0.0032	0.0035	0.0154	0.0093	−0.0081
2	−0.0173	0.90	4745	101	0.0056	0.0030	−0.0026	−0.0098	−0.0003	0.0057	0.0022
3	0.0087	0.89	4276	101	0.0060	0.0027	0.0012	−0.0028	0.0076	0.0214	0.0050
4	0.0265	1.06	3445	101	0.0134	0.0216	0.0315	0.0363	0.0449	0.0118	0.0019
5 (Long)	0.0575	1.18	2871	101	0.0209	0.0350	0.0350	0.0482	0.0526	0.0074	0.0004
Long-Short	0.1164	0.09			0.0074	0.0234	0.0318	0.0447	0.0372	−0.0019	0.0085
t-test [p-val]					[0.2011]	[0.0781]	[0.0255]	[0.0157]	[0.0238]	[0.5918]	[0.0608]
Bootstrap [p-val]					[0.1954]	[0.0715]	[0.0185]	[0.0082]	[0.0101]	[0.5700]	[0.0439]

Table C.4
UK Brexit referendum: event-window returns for quantile portfolios based on FTSE 350 stocks, formed at time τ (shortly before information on the event outcome is revealed), according to θ_i estimated from Eq. (2). The weights used for this table are proportional to the product of each stock's market capitalization and θ_i. The table shows the median portfolios (Panel A), tercile portfolios (Panel B), and quintile portfolios (Panel C). Column (1) provides the weighted average of θ_i for the respective portfolios, and column (2) provides the portfolio β relative to the index. Column (3) shows the sum of the market caps of the companies in the respective portfolios in billion GBP, and column (4) provides the number of stocks in each portfolio. Columns (5)-(11) show cumulative portfolio returns $r_{s,t}$ for various time windows (from s to t). Long-short portfolios are formed by going long (short) on the highest (lowest) quantile portfolio. [p-val] depicts one-sided significance levels for a parametric two-sample t-test and bootstrapping with 10,000 resamplings.

Panel A (Median Portfolios)											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Portfolio	θ_i	β_i	Size	No. of Stocks	$r_{\tau,\tau+1}$	$r_{\tau,\tau+7}$	$r_{\tau,\tau+8}$	$r_{\tau,\tau+9}$	$r_{\tau,\tau+10}$	$r_{\tau+10,\tau+15}$	$r_{\tau+15,\tau+20}$
1 (Short)	−0.1274	1.24	514	176	−0.2223	−0.1923	−0.2143	−0.1949	−0.1696	0.0551	0.0091
2 (Long)	0.1080	1.45	1581	175	−0.0269	0.0828	0.0816	0.0933	0.0997	0.0247	−0.0067
Long-Short	0.2353	0.21			0.1953	0.2751	0.2959	0.2882	0.2693	−0.0304	−0.0158
t-test [p-val]					[0.0002]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.9627]	[0.9642]
Bootstrap [p-val]					[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.9684]	[0.9695]
Panel B (Tercile Portfolios)											
Portfolio	θ_i	β_i	Size	No. of Stocks	$r_{\tau,\tau+1}$	$r_{\tau,\tau+7}$	$r_{\tau,\tau+8}$	$r_{\tau,\tau+9}$	$r_{\tau,\tau+10}$	$r_{\tau+10,\tau+15}$	$r_{\tau+15,\tau+20}$
1 (Short)	−0.1479	1.28	307	117	−0.2367	−0.2145	−0.2362	−0.2159	−0.1891	0.0582	0.0107
2	−0.0481	1.08	604	117	−0.1521	−0.0921	−0.1112	−0.0963	−0.0783	0.0398	0.0059
3 (Long)	0.1179	1.49	1183	117	−0.0218	0.0910	0.0904	0.1022	0.1082	0.0246	−0.0081
Long-Short	0.2658	0.21			0.2149	0.3055	0.3266	0.3181	0.2973	−0.0336	−0.0188
t-test [p-val]					[0.0011]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.9522]	[0.9716]
Bootstrap [p-val]					[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.9610]	[0.9791]
Panel C (Quintile Portfolios)											
Portfolio	θ_i	β_i	Size	No. of Stocks	$r_{\tau,\tau+1}$	$r_{\tau,\tau+7}$	$r_{\tau,\tau+8}$	$r_{\tau,\tau+9}$	$r_{\tau,\tau+10}$	$r_{\tau+10,\tau+15}$	$r_{\tau+15,\tau+20}$
1 (Short)	−0.1691	1.37	187	71	−0.2541	−0.2391	−0.2650	−0.2443	−0.2160	0.0642	0.0063
2	−0.0785	1.03	211	70	−0.1806	−0.1308	−0.1475	−0.1299	−0.1102	0.0434	0.0131
3	−0.0453	1.13	195	70	−0.1675	−0.1149	−0.1315	−0.1146	−0.0919	0.0410	0.0098
4	0.0091	0.79	890	70	−0.0114	0.0807	0.0720	0.0807	0.0827	0.0045	0.0085
5 (Long)	0.1277	1.56	611	70	−0.0239	0.0906	0.0910	0.1031	0.1096	0.0269	−0.0093
Long-Short	0.2968	0.20			0.2301	0.3297	0.3559	0.3474	0.3256	−0.0373	−0.0156
t-test [p-val]					[0.0064]	[0.0003]	[0.0005]	[0.0003]	[0.0001]	[0.9292]	[0.9109]
Bootstrap [p-val]					[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.9405]	[0.9172]

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jbankfin.2020.105883.

CRediT authorship contribution statement

Michael Hanke: Conceptualization, Methodology, Validation, Formal analysis, Writing - original draft, Writing - review & editing. **Sebastian Stöckl:** Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Visualization, Writing - review & editing. **Alex Weissensteiner:** Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing - review & editing.

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