An Event Long-Short Index: Theory and Applications

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Abstract

We propose a stock-market-based measure to capture initial beliefs about an event's effect on firm profits, which may be used to measure whether initial expectations are subsequently realized. Our "Event Long-Short Index" is the difference in market-capitalization-weighted returns of firms that outperform versus underperform the market on the event date. We use post-event index returns to measure whether initial beliefs are reinforced or attenuated. We apply our approach to the 2016 U.S. presidential election and Brexit referendum to illustrate the index and its interpretation and to validate it, showing that it moves as expected following subsequent political and business news.

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1 Introduction

Stock markets have proven to be a useful testing ground for the expected business effects of a wide range of phenomena, including natural disasters, covert CIA operations, and especially unexpected political turnover.[1]

While these studies crisply capture investors' contemporaneous expectations of an event's impact, the results of event studies also raise the question of the extent to which these expectations are borne out in practice. In this paper, we propose a stock-market-based index which aims to capture the extent to which initial expectations of the effects of an event are well-calibrated relative to eventual outcomes. While the examples we examine below are surprise election results, the same approach and similar interpretation could be applied to other unexpected events.

For a given event, we use the firms which outperform the market on the event date to form an "Event Long Index" and similarly construct an "Event Short Index" comprised of underperforming stocks. We weight stocks in these indices by the product of market capitalization and the absolute value of their out/underperformance. The difference between the two – the Event Long-Short Index – increases by construction on the event date. We take subsequent returns as a summary measure of investors' beliefs in the extent to which their expectations of changes anticipated on the event date are likely to be realized in practice. Our summary statistic has the useful and intuitive property that the ratio of the change in the index on date t to the change in the index at the event date is equal to the coefficient from a (market capitalization-weighted) least squares regression of date-t returns on event-date returns.

Conceiving of the the Event Long-Short Index in this way helps to highlight the circumstances under which it serves as a useful barometer for changes in the anticipated impact of the event. As is typical of event studies, our index yields cleaner results when there is little other relevant news for stock returns on the event date. It is helpful in settings in which companies cannot easily be sorted ex ante into likely winners and losers, as our approach allows stock prices to provide this information. For the elections that will be our focus, if there are post-event shifts in the winning politician or party's desired policies, our index will capture their success to the extent that their new goals are correlated (in terms of their impacts on firms) with the policies anticipated immediately following the event. (In Section 2 we discuss in greater detail the settings that will be suited to our methodology, as well as its limitations.)

We apply our methodology to two unanticipated political outcomes: the 2016 U.S. presidential election, and the 2016 Brexit referendum.[2] Focusing first on the 2016 election, while the market

[1]For an event study of earthquakes, see Shelor et al. [1992]; for CIA coups, see Dube et al. [2011]. Faccio [2006] provides a multi-country perspective on investors' responses to unexpected political turnover. For work focused on the U.S., see, for example, Fisman et al. [2012], for an event study on expected political turnover induced by Vice-President Richard Cheney's heart attacks.

[2]We are not the first to study market reaction to the 2016 election, or elections broadly. Our innovation is in the creation of a new tool for examining how investor beliefs about a set of policies evolve subsequent to an election. See

overall saw gains the day after the election (the trading day in which Trump's victory became apparent), this overall effect masked considerable heterogeneity in the cross-section of returns. For example, for-profit universities, large banks, and coal companies experienced large gains, while alternative energy stocks and hospitals declined. These patterns were, we argue, broadly reflective of differences in the Trump versus Clinton campaign platforms. We show that our Trump Long-Short Index moves in expected ways in the year following the election, if we are to interpret it as a measure of Trump's ability to enact his agenda: the index declined in the weeks following FBI Director James Comey's firing, then recovered after his Senate testimony, which failed to deliver impeachment-worthy revelations. Our index declined again with the indictment of Trump campaign manager Paul Manafort, and increased with the passage of the Senate tax bill, which may have indicated that Trump's agenda was back on track. We show that more standard measures of an administration's success – presidential approval ratings as well as the probability of early departure or reelection based on Betfair wagers – move in the same direction as our index, but are less responsive to some of the pivotal events in the Trump administration's first year. Overall, we see the analysis of the 2016 election and its aftermath as a validation of our methodology.

To demonstrate some of the features of our approach that may prove useful in future applications, we provide several decompositions of the overall Trump Long-Short Index, which are informative of the particular policy effects that were expected from a Trump administration. These allow us to consider, for example, whether Trump's policies were expected to have sector- versus firm-specific effects, and the extent to which particular policies accounted for both initial and subsequent movements in our index (e.g., by contructing tax-correlated and tax-ortogonal components).

In a second application, we construct a Brexit Long-Short Index based on the unexpected "leave" vote in the Brexit referendum on June 23, 2016. While the mapping from post-referendum news to the economic consequences of the Brexit vote is less clear than in the case of Trump's election, we argue that subsequent movements in the Brexit index are plausibly consistent with its interpretation as a measure of Brexit's impact. When "hard" Brexit proponent Boris Johnson – who risked splitting the vote with fellow Leaver Michael Gove – dropped out of the leadership race, the index increased. After Gove was eliminated, and expectations solidified that the next prime minister would be Theresa May, a more moderate candidate, the index declined. Our Brexit index reverted overall in the months following the leave vote, suggesting that investors initially over-estimated the profit consequences of Brexit.

While our two case studies emphasize political applications, our methodology may potentially be applied to any setting in which an unexpected event has possible consequences across a range of businesses that may be difficult to sort ex ante on the basis of, say, geography or industry. Consider, for example, the Fukushima earthquake in 2011, which damaged a nearby nuclear power plant and

Knight [2006] for an analysis of the impact of the 2000 U.S. presidential election on stock prices. For event studies focused on the 2016 election, see Wagner et al. [2018a] and Massound and Zhou [2018].

led to a two-day decline of nearly 16 percent in Tokyo's Nikkei index. While it might be natural to focus on companies operating near the quake's epicenter, as Carvalho et al. [2016] observe, the earthquake led to much wider reverberations via supply chain disruptions. And given the stock market declines worldwide (especially in Asia), a Fukishima Long-Short Index might shed light on expected versus realized profit consequences globally. The terrorist attacks on September 11, 2001 present another possible setting, given the wide-ranging consequences, and related subsequent events (invasion of Iraq; near-capture of Osama bin Laden) that investors might interpret as (in)validation of beliefs in the immediate wake of the World Trade Center attack.

Our goal is to provide a relatively versatile tool for examining the consequences of unanticipated events, political or otherwise. Prediction markets are perhaps the most natural comparator for our methodology. We view our approach as providing information that is complementary to prediction markets, which may not attract sufficient liquidity for some types of outcomes, like Trump's reelection probability, which was too far in the future in the period immediately following his election, or the rules governing trade in financial services under Brexit, which is too technical to interest bettors.[3]

2 Index Construction and Properties

We begin by defining an intuitive index which captures the distribution of benefits and costs as a result of an unexpected event. Given our applications, we will frame the exposition in terms of an unanticipated election outcome (though as emphasized in the introduction we view potential applications to be somewhat broader).

Specifically, on event date e, let the returns of firm i be denoted by R_i^e, which we assume reflects the change in firm value as a result of changes in expected policy at date e. We further denote average returns on date e, weighted by market capitalization, by $\overline{R^e}$. For ease of exposition, we treat as two separate groups the firms that beat the market at date e (expected beneficiaries) and those that lag the market (expected losers), and use these two groups to construct an Election Long Index and an Election Short Index respectively. In each case, we give proportionately more weight to firms with higher anticipated benefits or costs, and further weight these returns by pre-event market capitalization MV_i^e. Thus, each firm is assigned a weight in its portfiolio of:

$$w_i = MV_i^e(R_i^e - \overline{R^e}). \tag{1}$$

These weights collectively sum to zero, so the positive and negative weights can each be rescaled to sum to one. Let L be the set of firms in the long index and S be the set of firms in the short index.

[3] See Snowberg et al. [2007] for the application of prediction markets to U.S. presidential elections, Wolfers and Zitzewitz [2018] for a prediction market-based analysis of aggregate market effects of the 2016 election, and Wolfers and Zitzewitz [2004] for a discussion of prediction markets applications more generally

We set the index equal to 100 at date $e-1$, and let it change according to subsequent returns, so that the long index at date T is given by:

$$E_L^T = 100 \sum_{i \in L} w_i \prod_{t=e}^{T} (1 + (R_i^t - \overline{R^t})) \tag{2}$$

where R_i^t and $\overline{R^t}$ are firm i and (market cap weighted) mean returns on date t respectively. We similarly define the short index E_S^T. Our summary measure of the extent to which investors at date T continue to anticipate implementation of profit-relevant policies expected at date e is given by our Election Long-Short Index, which is simply $E_{LS} = E_L - E_S$.

Our index captures the intuition that, if investors' beliefs about the incidence of benefits and costs anticipated as a result of the election are maintained, the index should remain high. If initial uncertainty about policies' implementation is resolved favorably, our index should appreciate further, while the index should decline if expected policies fail to materialize or fall short of expectations.[4]

The index allows us to follow the extent to which investors believe that profit-relevant policies are on track. It also has the intuitive property that the ratio of the change in the index at date T and the change in the index at date e is given by the coefficient from a regression of date-T returns on date-e returns, weighted by market value, since

$$\frac{\Delta E_{LS}^T}{\Delta E_{LS}^e} = \frac{\sum_{i \in \{S,L\}} w_i (R_i^T - \overline{R^T})}{\sum_{i \in \{S,L\}} w_i (R_i^e - \overline{R^e})} = \frac{\sum_{i \in \{S,L\}} MV_i (R_i^e - \overline{R^e})(R_i^T - \overline{R^T})}{\sum_{i \in \{S,L\}} MV_i (R_i^e - \overline{R^e})(R_i^e - \overline{R^e})}$$

We can thus think of the change in the index at time T as reflecting whether beliefs moves *toward* or *against* initial expectations. The size of the coefficient reflects the fraction of initial beliefs that are reversed (or augmented) at date T.

A few caveats are in order for the application and interpretation of the index. Most importantly, the weights in the long-short index (including whether a firm is assigned to the long index or the short index) will capture beliefs about changed policy expectations at date e measured with noise. The signal-to-noise ratio is a function of (a) the extent that beliefs about policies are affected at e; (b) whether policy changes will have a substantial effect on firm valuation; and (c) whether other relevant information appears on date e. Increasing the first two will improve the signal value of the index, whereas the third will reduce it. Assuming no short-run changes in expected policies, (a) and (b) are largely a function of the unexpectedness of the election outcome as well as the differences in platforms between candidates. For the 2016 U.S. presidential election, for example, we can expect the index will perform relatively well, given the unexpected outcome, and the stark

[4]Note that our index captures changes in the beliefs implicit in stock returns, without regard for the rationality of the beliefs or the efficiency with which the market reflects them. If markets initially underreact or overreact to an event, our index will reflect subsequent appreciation or depreciation, respectively.

differences in policy platforms on issues ranging from tax policy to regulation. Movements in the index lend themselves to several interpretations: they reflect the combined effect of success in implementing anticipated policy objectives as well as shifts in policy objectives after the event date e. In the example of the U.S. presidential election, our index may be best-suited to interpreting index changes through the lens of efficacy in implementation rather than policy shifts, given that the administration stayed true to the Trump campaign's focus on slimming regulations, cutting taxes, repealing the Affordable Care Act, and sabre rattling on trade.

The multiplicity of effects that were expected as a result of Trump's election also highlights the circumstances in which our measure may be particularly useful – if his administration was expected to focus its reform efforts on a single industry or issue, one could simply assess policy successes and failures by focusing directly on the affected firms (e.g., if banking reform were the expected focus one could look directly at financial industry returns). Our approach is useful when the effects of an election are expected to be multi-faceted and, more broadly, when the researcher has no direct proxies to classify firms as expected winners and losers, as our approach does this indirectly via stock returns.

The interpretation of our index as a regression coefficient naturally suggests possible extensions. For example, just as the variation in stock returns on date e can be decomposed into its within-industry and between-industry components, we can construct within-industry and between-industry versions of our index. The within-industry index will maintain the same industry mix in L and S and take positions in firms that out/underperfomed their industry on date e, while the between-industry index takes positions in industries that outperformed the overall market. In the same way that a overall regression coefficient is a weighted average of within- and between-regression coefficients, the performance of our overall index reflects a weighted average of its within- and between-industry components. Other decompositions of date-e stock returns, and thus of our index, are possible, such as into components that are correlated with or orthognal to, for example, corporate tax rates or other variables correlated with date-e returns.

Finally, the regression interpretation also gives us guidance for statistical inference. Given that the date-T return on our index is proportional to a cross-sectional regression coefficient of date-T returns on date-e returns, standard errors for the index return can be calculated using standard techniques.

3 Applications

3.1 2016 Presidential Election

The data for our Trump Long-Short Index come from the North American version of the Compustat Security Daily files. We include only common stocks whose primary market is in the United States.

To classify firms into industries we use the GICS codes available in the Compustat data. We extract from Compustat information on firms' cash tax payments and income in order to calculate tax rates according to the definition in Wagner et al. [2018a].

We present the Trump Long-Short Index in Figure 1. Recall that, by construction, the index goes up on November 9, the date investors incorporated the election outcome into market prices. The magnitude of the first-day rise reflects the high cross-sectional variance in individual stock returns – the variance in individual returns on November 9 was six times higher than its average during October 1 - November 8.[5] The index rose again on November 10 and stayed high – at about 115 – through the first part of 2017, before starting to decline in mid-March.[6]

Some of the index's movements coincide with eventful periods for the Trump Administration, which we have shaded in the figure. Some of these highlighted events primarily involve shocks to Trump's expected political longevity (e.g., the firing and testimony of FBI Director Comey, and the indictment of Trump campaign manager Paul Manafort), while others involve news about the passage of, or failure to pass, new policies (e.g., ACA repeal and tax cuts).

Focusing first on key legislative efforts during the administration's first year, the index fell between the introduction of the American Health Care Act (AHCA), which would have repealed the Affordable Care Act (ACA), and its subsequent failure to pass in the House of Representatives (on March 7 and 24, respectively). The index increased slightly when the U.S. Senate voted 51-50 to open debate on ACA repeal on July 25 and fell when repeal failed to pass (51-49) on July 28. The index also increased sharply in the week leading up to the passage of the Senate's tax reform bill in late November 2017, showing that the index responds to policy outcomes that may have been of concern to investors at the time of the election. The size of the increase – 45 percent of the November 9, 2016 gain – indicates that a sizeable fraction of the post-election rally was in anticipation of tax cuts. We also label a pair of events that speak to investors' possible uncertainty about the administration's longevity and/or its political capital to act on its policy goals. The first, labeled "Comey," begins with the firing of James Comey on May 9, which led to a sharp decline in the index over the following weeks, amidst speculation that Comey would provide damning information on Trump when he appeared before the Senate. More than a third of the index's initial gains were lost during this period, indicating a substantial decline in beliefs that Trump could execute his agenda. The index then recovered on June 8, when the testimony failed to produce damaging evidence. Finally, we observe a sharp decline in the index with the indictment of Trump campaign manager Paul Manafort on October 30, 2017.

[5] Relative to the political events studied by Cutler et al. [1989], this suggests that investors put more weight on the 2016 election than political shifts that took place in prior decades.

[6] Broadly consistent with the patterns we observe in Figure 1, Wagner et al. [2018b] find that stock returns continued increasing on November 10 and 11, then reverted somewhat on November 14 and 15 (the next two trading days after November 11). They thus conclude that the stock market required as much as 5 days to fully process Trump's election. We construct a version of our index that is weighted using returns from November 9 – 15 rather than November 9 and obtain nearly identical results.

For comparison, in Appendix Figure A1 we show the probabilities of Trump's reelection and survival through the end of calendar year 2019 (from the Betfair.com prediction market, where individuals could place wagers on political events), as well as his approval rating (as aggregated by fivethirtyeight.com, a political statistics website), shading the same set of events. In many cases, these more traditional measures of presidential success move in the same direction as our index, though often the effects are more muted.

To better understand the sources of these movements in our index, we present summary statistics in Table 1 for the firms in the Long and Short portfolios of the Trump index. The sector shares of the Long and Short portfolios reflect stated positions of the Trump campaign (relative to Clinton's). The Long portfolio is heavily weighted toward pharmaceuticals, biotechnology and financials, reflecting expectations of deregulation. The Long portfolio is also weighted toward Industrials whereas the Short portfolio includes a high proportion of information technology firms, perhaps reflecting the Trump campaign's promises of promoting domestic manufacturing. The sector-wide distribution also masks some interesting within-sector variation. For example, while the Long portfolio is overweighted toward energy at the sector-level overall, coal is entirely contained in the Long portfolio, while renewable electricity is entirely in the Short portfolio.

Various characteristics of the two portfolios also line up with popular narratives of the winners and losers under Trump policies, and also some of the findings in Wagner et al. [2018a]: Long portfolio firms paid cash tax rates that were 7 percent higher than Short portfolio firms, consistent with investor expectations of tax cuts. Small-cap stocks also tended to outperform large-caps on November 9, as indicated by the much lower median market capitalization of the Long portfolio; value stocks and previously low-performing stocks also did well, as suggested by the higher book-to-market and lower prior returns in the Long portfolio.

One feature of our approach is that we may generate decompositions of the index, which may provide additional insights on particular expected consequences of an event. For our Trump Long-Short Index, we focus on within- versus between-industry effects, and effects driven by anticipated tax reform versus those orthogonal to taxes. In Figure 2, Panel A, we decompose our index into within and between-industry components, using GICS subindustries as the level of aggregation (there are 164 subindustries in our sample). The between index reflects the performance of industries that outperformed or underperformed the overall market when Trump was elected, while the within index reflects the subsequent performance of firms that outperformed or underperformed their industries. Some of the between-industry gains can readily be tied to the performance of particular sectors or subindustries. Financial stocks, the largest component in the long portfolio, track the overall index, for example waxing and waning with Trump's fortunes during the Comey and Manafort events.[7] The within-industry index, by contrast, exhibits a steady reversion of its post-

[7] We refer the interested reader to Fisman and Zitzewitz [2017] or Wagner et al. [2018a] for further discussion of industry-level patterns.

election gain. We can offer some speculative explanations for the within-industry pattern. First, many of big gains on November 9 were tied to expectations of infrastructure spending, which has yet to materialize. The anticipated beneficiaries were spread across a range of industries, including chemicals, construction equipment, and construction management companies, many of which have given up their (relative) gains. Even more speculatively, the reversion may reflect that it has proven more challenging than investors anticipated to assist (or remove assistance from) narrowly targeted groups of firms, rather than entire industries.[8]

The signature legislative achievement of the Trump administration at the time of writing was the passage of the Tax Cuts and Jobs Act in 2017, satisfying Republican supporters' expectations of a corporate tax cut. In Panel B, we thus we decompose our overall index into components that are orthogonal to and correlated with firms' cash tax rates.[9] As shown in Wagner et al. [2018a], firms with high tax rates outperformed the market when Trump was elected. It is understandable (and indeed reassuring for our methodology) that high tax firms also outperformed during the week when it became clear that the Senate would pass the corporate tax cut (a pattern also documented in Wagner et al. [2018c]); this is reflected in the sharp jump in the correlated index. The orthogonal index also appreciates that week, likely reflecting both imperfections in our proxy for which firms benefit from the tax bill and the increased expectation for other Trump-supported policy changes as a result of the bill's passage. Earlier events are accompanied by larger movements in the orthogonal index; while changes in the tax-correlated index are far more muted, they are generally of the same sign as the tax-orthogonal index.

Our primary interest in looking at the 2016 election is as a validation exercise for our methodology – there are cleanly identifiable and largely unanticipated events that can credibly be associated with the successes, failures, and likely longevity of the Trump administration. If our index captures these changes, we should see it move in expected directions around these events. Table 2 presents estimates of changes in our index (and its decompositions), with associated standard errors for a set of post-election event periods. We estimate these changes in panel regressions of the following form:

$$R_i^t - \overline{R^t} = \gamma_t + \sum_E \sum_{t \in E} \beta_E (R_i^e - \overline{R^e}) + e_i^t$$

where β_E captures the average daily return of our index during event window E (divided by its return on November 9) and γ_t is a date fixed effect. We multiply these estimates by the November 9 index return and the length of each event window to obtain (noncompounded) index returns during

[8] One widely-reported case was that of biofuels, which Trump advisor (and biofuels investor) Carl Icahn had advocated – ultimately unsuccessfully – for deregulation. The administration similarly allowed preexisting subsidies to remain in place, leading, for example, to reversion in valuations of fertilizer, solar, and wind producers.

[9] The cash tax rate is the ratio of taxes paid to net income before tax. We follow Wagner et al. [2018a] in focusing on this measure of a firm's tax rate, but the results are similar if we use accrued tax liability in the numerator. The tax-correlated index replaces November 9 returns with the predicted values from a market-capitalization-weighted regression of these returns on cash tax rates; the tax-orthogonal index uses the residuals from the same regression.

each window. We calculate standard errors that allow for two-dimensional clustering by date and by the 26 GICS industry groups represented in the sample. We provide these estimates for each event window shaded in Figure 1, as well as for the first and second half of our sample period (the halfway point happens to be June 7, the day before FBI director Comey's testimony). The events that we judged ex ante to involve increases in the likelihood of Trump's agenda being implemented (Events 3, 4, and 7) were accompanied by increases in our indices, while the others were accompanied by decreases. While the tax-correlated index had, as expected, strong gains when the Senate passed its 2017 tax cuts, it also moved consistently with the overall index during the event windows related to health care (Events 1, 4, and 5), as well as during events that were primarily about the longevity of the Trump administration (Events 2, 3, and 6). During the shorter event windows, for most of the index changes, we can reject that they are equal to zero at least at the 5 percent level.[10] Below the 7 individual events, we summarize the index movements during our seven event windows by presenting estimates of the difference between those accompanying the events that were positive (3, 4, and 7) and negative (1, 2, 5, and 6) for Trump's agenda. The positive and significant coefficient estimates in this row indicate that all 5 indices moved consistently with our a priori expectations. Overall, we take our results on post-event market movements during these key events as indicating that our index captures investors' policy expectations, and that subsequent shifts reflect changes in these expectations.

At the bottom of Table 2, we show the changes in our indices, and associated standard errors, for the first and second halves of our sample. If we view the first part of Table 2 as a validation exercise, these long window comparisons may be seen as an application of the index to understand the overall state of Trump's agenda during the first part of his administration. We begin the first half on November 10, after a second positive day for our index, and break the sample before Comey's testimony, when concerns about Trump's longevity were heightened. For our overall index, we find statistically significant evidence that the first seven-month period was a poor one for President Trump; the components of the index each declined over the first half of the sample, though overall these effects are imprecisely measured. With the exception of the within-industry index, our indices recovered somewhat in the second half of our sample period, which began with Comey's testimony and ended with the passage of the tax cuts, but these recoveries were not statistically significant at conventional thresholds. Overall, the first-half decline and second-half recovery are large relative to our index's initial movement, yet are not consistently statistically significant. We take two lessons from this exercise. First, it illustrates the application of our method to explore thow the effects of an event unfold over time relative to initial expectations, potentially in the absence of discrete unexpected changes that allow for crisp event study analyses. It also illustrates the diminishing precision with which our index is likely to measure policy implementation with the passage of time,

[10] Our results are similar if we use unweighted returns for our index and also for subsequent returns, so long as we exclude micro caps (the bottom quintile of firms by market capitalization using NYSE breakpoints).

as other factors come to influence stock prices.

Finally, we turn to examining how the returns of our overall index are affected if we control for the performance of the overall market and for the performance of other commonly used asset pricing factors. In a typical event study of a single firm, the performance of the market and other factors is usually assumed to be unaffected by the event in question, and the primary focus is on the stock's "alpha" (its return beyond what would be expected given factor returns). In our setting though, it is reasonable to expect the market and other factors to be affected by Trump's election and subsequent political news. Thus, the inclusion of factor controls can be viewed as providing another decomposition of our index returns, into returns that can be explained (and left unexplained) by firm characteristics such as market beta, size, and value.

Appendix Table A1 reports betas for the most commonly used asset pricing models – the CAPM and the three and five-factor Fama-French models, with and without momentum. Our Trump index has a positive CAPM beta of 0.43, reflecting the fact that higher beta stocks outperformed following Trump's election. Our index also has a positive loading on the SMB and HML factors and a negative correlation with momentum, consistent with the portfolio characteristics reported in Table 1. In Appendix Table A2, we repeat our event-window returns for our overall index from Table 2, and then introduce controls for various asset pricing factors. U.S. equities performed well during our sample period, and if we control for the positive CAPM beta of our index, its reversion during the first half of our sample is even stronger. In our shorter event windows, accounting for market returns and the relative performance of small-cap stocks has only a small impact on the estimated event returns. Including the value factor substantially reduces the estimated event returns for most event windows, as well as the standard errors for these estimates. As noted above, this is because the stocks that Trump was expected to help tended to have high book-to-market values. Overall, we conclude that the patterns in our main index partly reflect the expectation that Trump's election would help value stocks, and partly reflect expectations, and revisions thereof, that are independent of the value factor.

3.2 The Brexit Referendum

As a second application, we create the Brexit Long-Short Index for the June 23, 2016 British referendum on leaving the European Union. As with Trump's victory, the Brexit "leave" vote was largely unanticipated by the markets, and only became apparent long after the end of the European trading day. We therefore use returns from June 24, 2016, the day after the referendum, to construct our index. We use return data from the Global version of the Compustat Security Daily files and include common stocks of firms whose primary market and headquarters are both in Europe (i.e., in a member country of the European Union, European Economic Area, or Switzerland). Returns are converted to a common currency using daily exchange rates from the Federal Reserve (publication

H.10).[11]

We present the Brexit Long-Short Index in Figure 3, which rises (again by construction) on the first day that index returns are calculated. The index continued to rise in the days that followed, with a sharp increase coinciding with the exit of "hard" Brexiteer Boris Johnson from the leadership race. Johnson had risked splitting the vote with fellow Leaver, Michael Gove, so the departure may have raised expectations of a hard-line Brexit prime minister. The index's subsequent reversion coincides roughly with the shift toward (and ultimate selection of) Theresa May – a candidate with, at minimum, more moderate views on the E.U. – as successor to Cameron. The index subsequently declined, returning to its pre-referendum level by late 2016, plausibly reflecting a range of factors: investors had apparently shrugged off the consequences of Brexit, at least for large, publicly traded firms; there remained uncertainty over its implementation (for example, whether the British parliament would approve the use of Article 50, as required in order to withdraw from the E.U.); and other world events, most notably the U.S. presidential election, also had a substantial effect on market prices.

In Appendix Table A3, we report summary statistics for the Brexit Long and Brexit Short portfolios. The Short portfolio, containing stocks expected to suffer greater harm under Brexit, is disproportionately comprised of UK stocks, as well as stocks in financial and consumer discretionary industries. The Long portfolio is comprised of a disportionately high share of stocks in other countries that might be expected to benefited from Brexit. Figure 3 also reports a UK-only version of our index, and Appendix Figure 2 we presents a within versus between industry decomposition of our Europe-wide index. The patterns are very similar for each, though with a smaller initial gain and less subsequent reversion for the within-industry index.

In contrast to the 2016 U.S. election, with Brexit, we feel less comfortable identifying short event windows for which we had strong ex ante priors about the sign of changes in expectations about the effects of Brexit, since there were many elements to the discussion in the weeks following the "leave" vote. Nevertheless, we find the index movements in the weeks following the referendum, as well as the significant reversion by the end of 2016, consistent with our understanding of the evolution of beliefs about the business consequences of Brexit. This second application thus also serves as an illustration of our method's utility in tracking the evolution of investors' beliefs about Brexit's business consequences.

4 Conclusion

In this paper we provide a new stock-market-based measure of revisions to initial expectations of the effects of an event. When applied to elections, this measure largely tracks changes to expected government policy through their impact on firm's stock prices.

[11] The choice of common currency does not affect the results.

Our Trump and Brexit Indexes potentially add to what we can learn from alternative metrics. Existing prediction markets capture a limited set of outcomes and are often illiquid for events that are far in the future (e.g., reelection), too esoteric for many bettors (e.g., Article 50), or too complex to capture in a security (e.g, ACA repeal, the terms of Brexit). Voter opinion can be readily polled, but its relevance for policy is often at a minimum immediately after elections, when victorious politicians have flexibility in interpreting their mandate. In contrast, our approach works best in the period immediately following a surprise event – political or otherwise – potentially providing a useful complementary tool for understanding the ultimate effects of events on firms and the economy.

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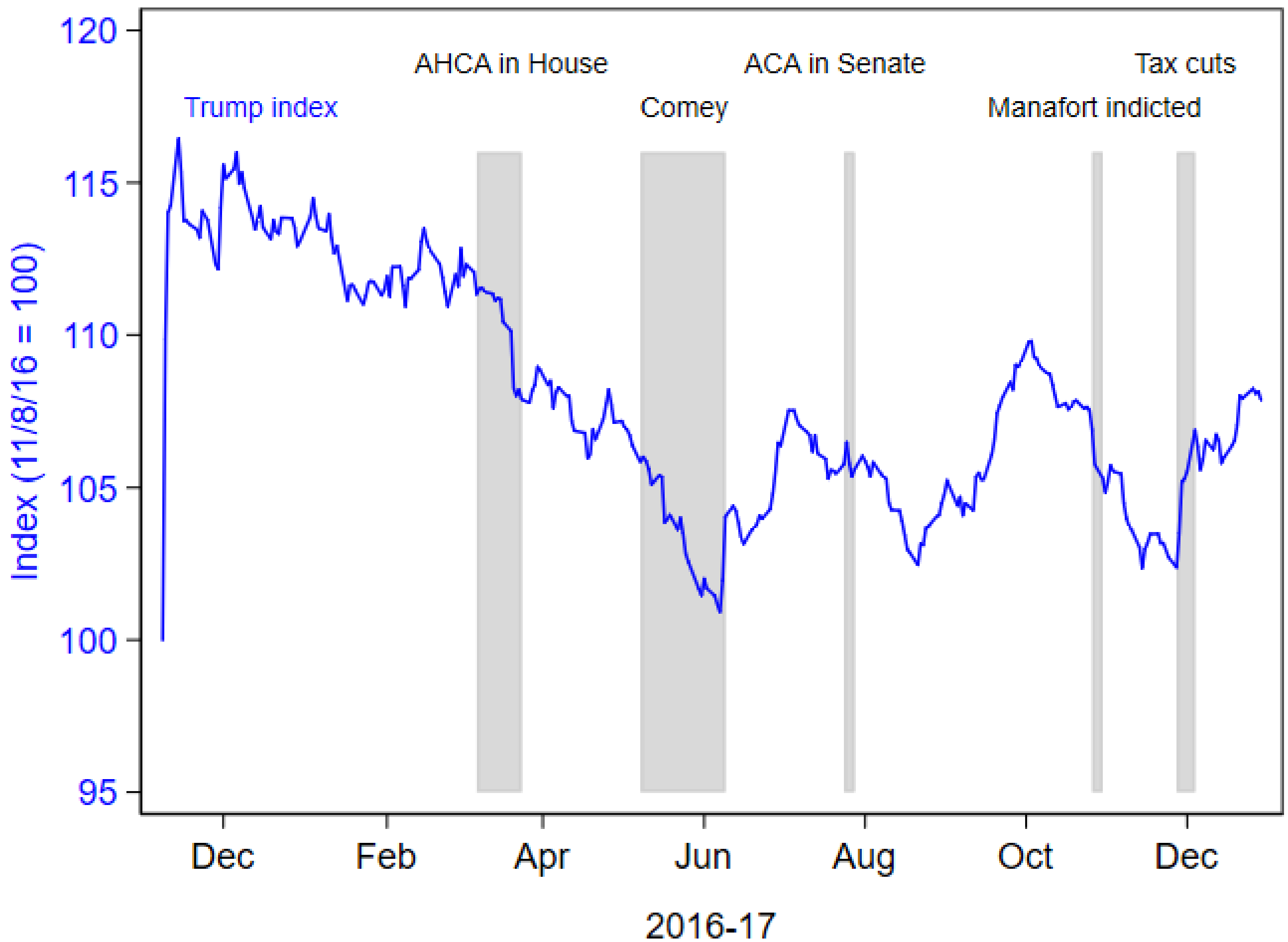
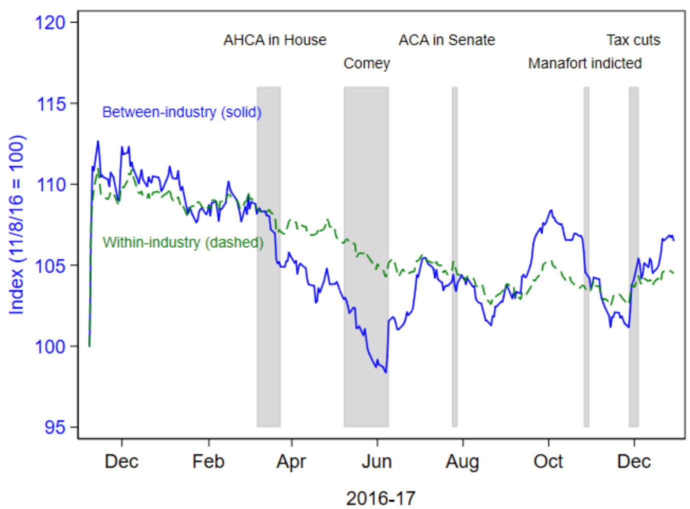
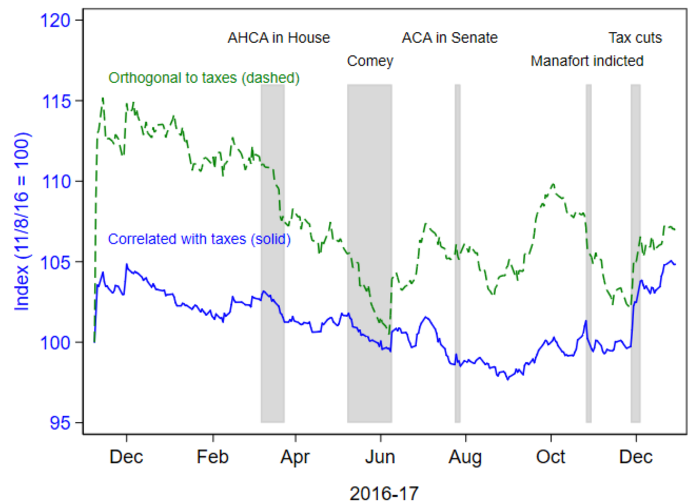
Figure 1 – The Trump Long-Short Index



This figure shows the Trump Long-Short Index, calculated based on the market-capitalization weighted stock returns of U.S. equities on November 9, 2016. See Section 2 for details of its construction.

Figure 2 – Decompositions of the Trump Long-Short Index

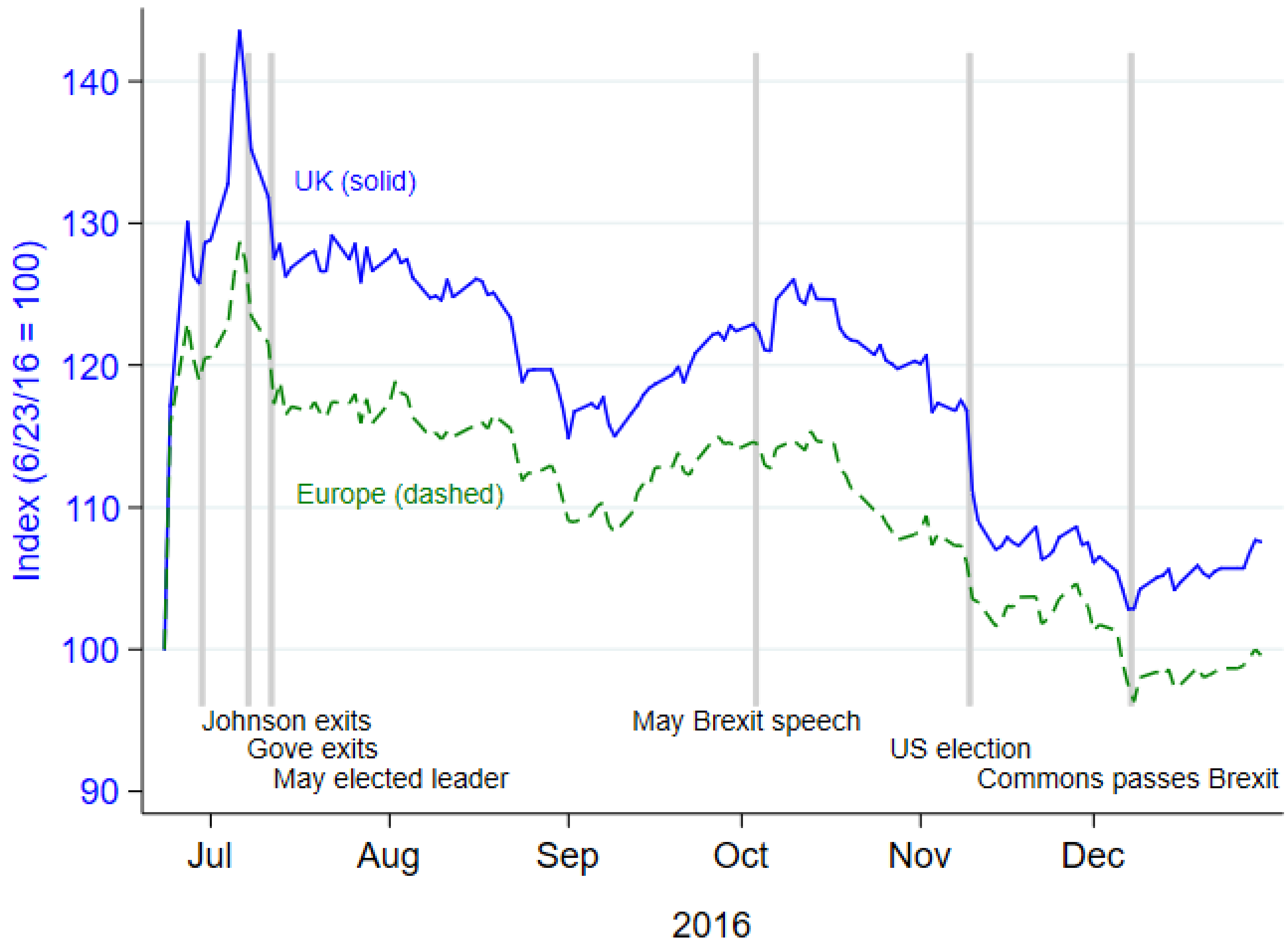




Panel A: Within vs between industry **Panel B: Tax-correlated vs tax-orthogonal**

Panel A provides a decomposition of our Trump Long-Short Index into indices calculated based on returns relative to the GICS sub-industry average (Within-industry) and GICS sub-industry average returns relative to overall market returns (Between-industry). Panel B shows a decomposition of the Trump Long-Short Index constructed by regressing the index on tax rates paid by firms in the year prior to the 2016 U.S. presidential election (using the tax rate measure from Wagner, 2017). The predicted component is the “Correlated with taxes” index and the residual from this regression is the “Orthogonal to taxes” index.

Figure 3 – The Brexit Long-Sort Index



This figure shows the Brexit Long-Short Index, calculated based on the market-capitalization weighted stock returns of equities on June 24, 2016. The UK version includes equities whose headquarters and primary stock market are in the United Kingdom; the Europe version includes those whose headquarters and primary stock market are in the European Union, European Economic Area, or Switzerland.

Table 1. Summary Statistics for Trump Long-Short Portfolios (and component indices)

	Overall index		Correlated with taxes		Orthogonal to taxes		Between industry		Within industry	
	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long
Number of firms	1945	2599	1304	1149	972	1481	1950	2557	2094	2413
Total market cap ($T)	15.2	10.9	10.9	10.5	12.8	8.64	14.6	11.4	13.5	12.5
Portfolio characteristics										
Mean market cap ($B)	102	60.9	86.2	93.5	117	71.3	107	71.0	67.3	45.5
Median market cap ($B)	39.0	29.2	30.5	58.4	52.0	40.5	43.6	40.5	29.0	14.6
Return on event day	-2.7%	7.1%	0.4%	2.2%	-2.5%	6.4%	-1.6%	5.4%	-1.5%	6.1%
Cash tax rate	18.1%	25.2%	7.3%	36.2%	22.0%	22.0%	17.9%	23.5%	19.7%	24.4%
Accrual tax rate	22.8%	26.1%	19.6%	30.8%	24.8%	25.2%	23.2%	25.4%	23.0%	25.8%
Book-to-market	31.0%	49.8%	46.8%	36.4%	27.0%	50.8%	30.8%	46.2%	35.1%	46.7%
Prior returns	12.7%	1.6%	11.6%	6.1%	11.8%	2.8%	12.1%	4.0%	11.0%	2.9%
Share of portfolio by GICS sector										
10 Energy	2.8%	8.5%	5.7%	5.1%	1.4%	5.9%	0.8%	4.9%	9.1%	9.1%
15 Materials	1.8%	4.9%	2.2%	3.5%	1.8%	3.9%	1.8%	15.5%	3.6%	3.6%
20 Industrials	3.5%	13.9%	5.5%	15.1%	4.7%	14.7%	11.6%	2.0%	11.7%	11.7%
25 Consumer Discretionary	11.0%	3.1%	8.6%	12.3%	13.3%	3.0%	22.9%	0.8%	7.8%	7.8%
30 Consumer Staples	19.5%	1.2%	2.3%	15.0%	22.6%	0.8%	8.9%	2.4%	5.8%	5.8%
3510 Health Care Equipment & Services	10.0%	4.4%	1.7%	10.9%	11.2%	3.7%	0.5%	37.8%	10.1%	10.1%
3520 Pharmaceuticals, Biotechnology	1.0%	29.4%	5.9%	6.5%	1.0%	27.3%	1.0%	34.3%	12.8%	12.8%
40 Financials	3.9%	29.2%	16.8%	20.3%	2.2%	35.5%	18.0%	0.3%	17.7%	17.7%
45 Information Technology	16.6%	2.1%	12.7%	8.0%	17.9%	1.6%	10.3%	2.0%	9.7%	9.7%
50 Telecommunication Services	9.4%	2.5%	14.1%	3.0%	8.3%	2.1%	13.2%	0.0%	4.8%	4.8%
55 Utilities	11.0%	0.1%	12.3%	0.1%	9.6%	0.1%	11.0%	0.0%	2.6%	2.6%
60 Real Estate	9.7%	0.6%	12.1%	0.3%	6.1%	1.4%	0.0%	0.0%	4.3%	4.3%
Portfolio shares of selected GICS subindustries										
10102050 Coal & Consumable Fuels	0.02%	0.26%	0.07%	0.01%	0.00%	0.19%	0.00%	0.32%	0.22%	0.22%
25302010 Education Services	0.00%	0.28%	0.01%	0.13%	0.00%	0.19%	0.00%	0.37%	0.18%	0.18%
25401030 Movies & Entertainment	0.57%	0.00%	0.25%	0.06%	0.66%	0.00%	0.69%	0.00%	0.04%	0.04%
55105020 Renewable Electricity	0.20%	0.00%	0.03%	0.00%	0.01%	0.00%	0.24%	0.00%	0.11%	0.11%
60101080 (part) Prisons	0.00%	0.32%	0.05%	0.00%	0.00%	0.42%	0.04%	0.00%	0.00%	0.66%

This table reports average characteristics for stocks in the long and short portfolios of the indicated indices. Characteristics are weighted by each stock's portfolio share. Portfolio shares in various GICS sectors and subindustries are reported below.

Table 2. Changes in indexes during event windows

		Industry indexes		Cash tax rate indexes	
	Overall	Between	Within	Correlated	Orthogonal
1. AHCA in U.S. House (3/7-3/24)	-3.34	-3.23	-1.29	-1.30	-3.37
	(1.85)	(1.78)	(0.81)	(0.70)	(1.79)
2. Comey fired (5/8-6/7)	-4.80	-4.58	-1.97	-2.00	-4.89
	(2.20)	(2.02)	(1.22)	(1.26)	(1.92)
3. Comey testifies (6/8-6/9)	3.09	3.21	0.86	1.03	3.39
	(0.88)	(1.02)	(0.19)	(0.92)	(0.87)
4. Senate opens debate on ACA repeal (7/24-7/25)	0.67	0.43	0.59	0.65	0.66
	(0.34)	(0.39)	(0.11)	(0.11)	(0.28)
5. ACA repeal fails in Senate (7/25-7/28)	-0.87	-0.54	-0.80	-0.75	-0.55
	(0.55)	(0.73)	(0.13)	(0.42)	(0.69)
6. Manafort indicted (10/26-10/30)	-1.56	-1.64	-0.40	-1.71	-1.84
	(0.64)	(0.74)	(0.24)	(0.43)	(0.84)
7. Senate passes tax cuts (11/27-12/4)	4.44	4.30	1.74	3.96	4.45
	(2.10)	(2.14)	(0.98)	(1.50)	(2.06)
Positive events (3, 4, 6) less negative (1, 2, 5, 7)	19.78	18.81	8.18	11.98	20.02
	(7.00)	(7.22)	(2.87)	(3.68)	(6.40)
First half of sample (11/10/16 - 6/7/17)	-13.01	-12.94	-4.51	-3.94	-12.55
	(6.27)	(5.72)	(3.24)	(2.60)	(6.09)
Second half of sample (6/7/17 - 12/31/17)	6.65	8.00	0.26	5.40	6.08
	(6.01)	(5.68)	(3.06)	(3.63)	(6.21)

This table reports estimates of the sum of daily changes in the indicated long-short index during the indicated event window. Changes are estimated using regressions of stock returns on either stock returns from 11/9/2016 (for the overall index), the within or between industry component of these returns, or the component of these returns that is correlated or orthogonal to cash tax rates. Observations in these regressions are weighted by market capitalization, regressions include day fixed effects, and standard errors allow for two-dimensional clustering by date and GICS industry group. To convert the regression coefficients to cumulative index changes, coefficients are multiplied by the number of trading days in each window and by the Nov 9 index change (see text for details). Event windows begin and end at 4 PM ET on the indicated date.

"An Event Long-Short Index: Theory and Application"

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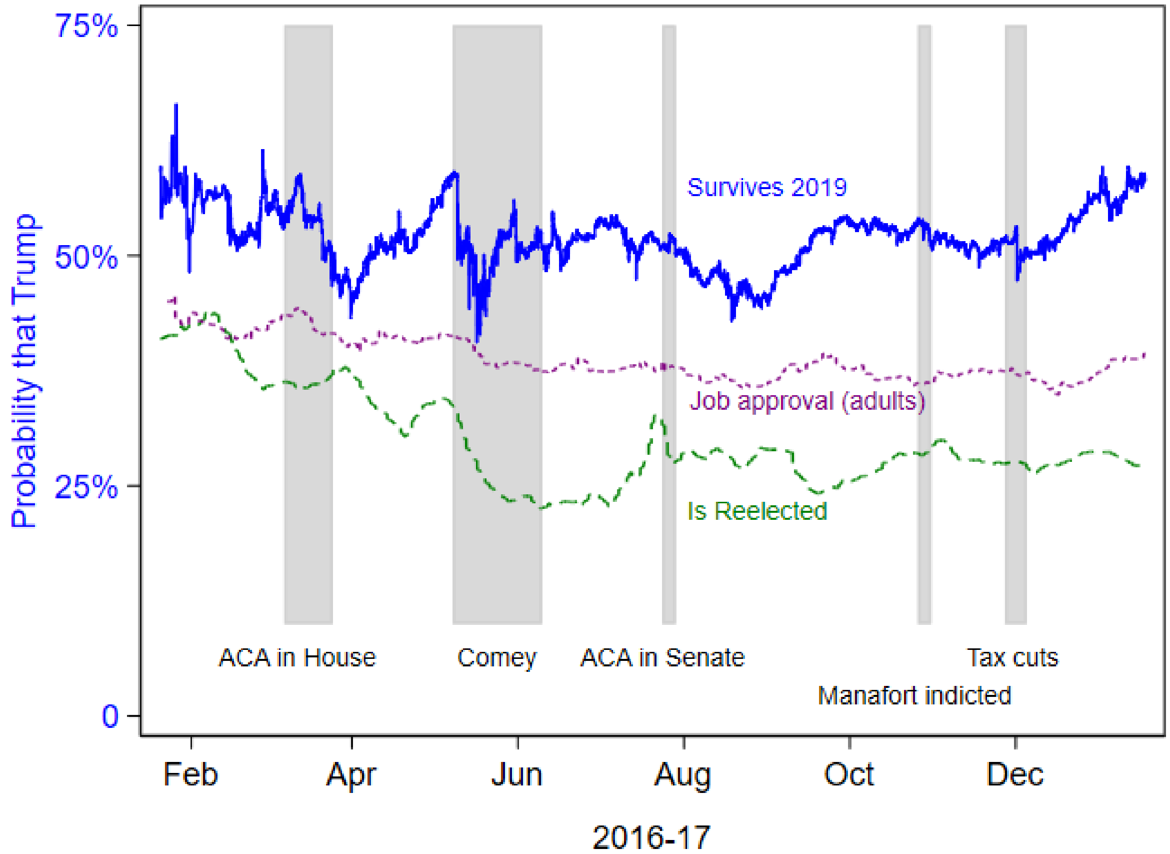
Online Appendix

Appendix Figure A1 – Alternative measures of the Trump administration's performance



This figure provides the fraction of U.S. adults that approve of President Trump's performance ("Job approval (adults)"), as well as Betfair probabilities of Trump's survival through to the end of 2019 and of his reelection in 2020.

Appendix Table A1. Betas for Trump Long-Short Index

Estimation period: 11/10/2016 to 12/31/2017

Model	Mkt-RF	SMB	HML	UMD	RMW	CMA
CAPM	0.43					
	(0.08)					
FF3	0.18	0.35	0.62			
	(0.07)	(0.06)	(0.07)			
FF3+Momentum (Carhart)	0.24	0.35	0.59	-0.14		
	(0.08)	(0.06)	(0.06)	(0.05)		
FF5	0.16	0.33	0.58		-0.35	-0.01
	(0.07)	(0.06)	(0.07)		(0.11)	(0.09)
FF5+Momentum	0.22	0.32	0.59	-0.17	-0.38	-0.14
	(0.07)	(0.06)	(0.06)	(0.06)	(0.10)	(0.11)

This table reports betas from regressions of daily returns of the Trump Long-Short Index on various asset pricing factors. Factor returns are from Ken French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

Appendix Table A2. Raw and factor-adjusted returns for overall index during event windows

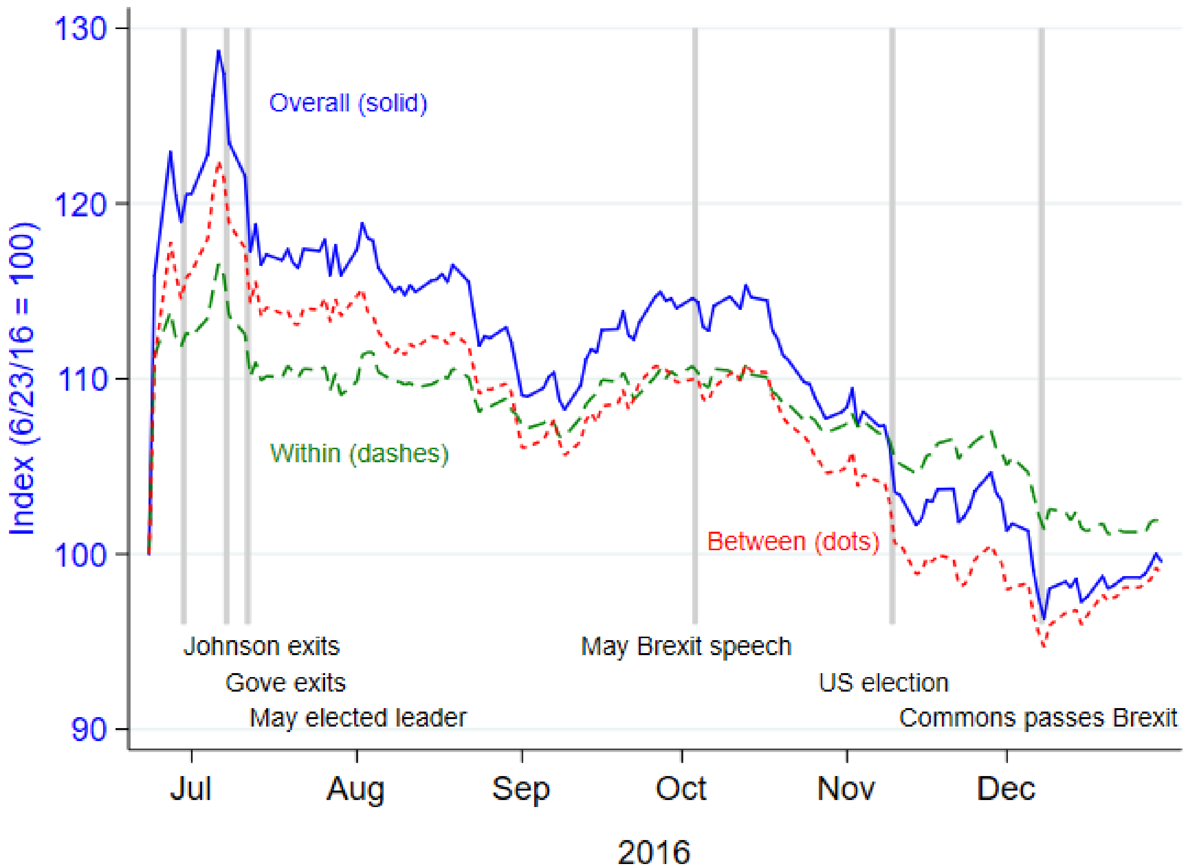
	Raw returns	CAPM	CAPM+SMB	FF3	FF3+Mom	FF5	FF5+Mom
1. AHCA in U.S. House (3/7-3/24)	-3.34	-2.76	-3.39	-0.88	-1.70	-0.70	-1.49
	(1.85)	(1.15)	(1.25)	(1.26)	(1.20)	(1.19)	(0.91)
2. Comey fired (5/8-6/7)	-4.80	-5.72	-4.96	-1.81	-1.23	-1.65	-1.06
	(2.20)	(1.87)	(1.78)	(0.82)	(0.95)	(0.72)	(0.90)
3. Comey testifies (6/8-6/9)	3.09	3.05	2.37	0.18	0.28	-0.03	0.03
	(0.88)	(0.96)	(1.31)	(0.67)	(0.54)	(0.74)	(0.53)
4. Senate opens debate on ACA repeal (7/24-7/25)	0.67	0.45	0.34	-0.25	-0.46	-0.25	-0.37
	(0.34)	(0.30)	(0.29)	(0.18)	(0.32)	(0.12)	(0.33)
5. ACA repeal fails in Senate (7/25-7/28)	-0.87	-0.65	-0.13	-0.19	-0.56	-0.26	-0.49
	(0.55)	(0.58)	(0.44)	(0.22)	(0.42)	(0.16)	(0.21)
6. Manafort indicted (10/26-10/30)	-1.56	-1.77	-1.17	-0.49	-0.39	-0.83	-1.14
	(0.64)	(1.08)	(1.11)	(0.64)	(0.57)	(0.60)	(0.66)
7. Senate passes tax cuts (11/27-12/4)	4.44	3.52	4.51	2.22	0.53	3.19	1.53
	(2.10)	(2.19)	(2.04)	(0.76)	(1.32)	(1.05)	(1.02)
Positive events (3, 4, 6) less negative (1, 2, 5, 7)	19.78	17.20	16.85	5.71	4.41	7.08	5.90
	(7.00)	(6.26)	(6.28)	(2.28)	(2.45)	(2.50)	(2.23)
First half of sample (11/10/16 - 6/7/17)	-13.01	-19.42	-16.48	-11.32	-13.03	-8.37	-10.86
	(6.27)	(5.48)	(4.91)	(3.70)	(4.00)	(2.37)	(2.65)
Second half of sample (6/7/17 - 12/31/17)	6.65	1.19	4.47	3.27	3.85	4.30	4.60
	(6.01)	(5.39)	(5.20)	(2.39)	(2.30)	(2.34)	(2.44)

This table reports changes in the overall index during the indicated event windows, as well as index changes that are adjusted for changes in asset pricing factors. Col 1 is the same as Col 1 in Table 2. Subsequent columns control for changes in asset pricing factors by adding interactions of the factors with November 9 returns.

Appendix Table A3. Summary Statistics for Brexit Long-Short Portfolios

	Brexit Index	
	Short	Long
Number of firms	1668	4025
Total market cap ($T)	4.794	7.401
Averages (weighted as in portfolios)		
Return on event day (in USD)	-13.9%	-5.0%
Share of portfolio by sector		
10 Energy	5.4%	5.6%
15 Materials	6.1%	6.7%
20 Industrials	14.8%	13.9%
25 Consumer Discretionary	19.0%	9.4%
30 Consumer Staples	2.3%	21.4%
35 Health Care	1.2%	17.4%
40 Financials	34.5%	8.0%
45 Information Technology	2.6%	7.6%
50 Telecommunication Services	4.6%	4.2%
55 Utilities	7.2%	2.3%
60 Real Estate	2.4%	3.5%
Share of portfolio by headquarters location		
United Kingdom	34.7%	17.2%
France	19.6%	13.5%
Germany	13.1%	13.7%
Switzerland	3.1%	16.4%
Spain	11.8%	1.6%
Netherlands	3.1%	7.4%
Italy	8.3%	1.6%
Sweden	0.0%	7.1%
Ireland	1.8%	4.4%
Belgium	1.0%	5.0%
Denmark	0.5%	4.3%
Norway	0.6%	2.5%
Finland	0.0%	2.7%
Greece	0.7%	0.1%

Appendix Figure A2 – Within and between-industry versions of Brexit Long-Short Index



This figure provides a decomposition of the Europe-wide version of our Brexit Long-Short Index into indices calculated based on returns relative to GICS groups for UK and non-UK firms (Within) and returns for these groups relative to overall market returns (Between).