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Recovering election winner probabilities from stock prices

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ABSTRACT

After the 2020 U.S. presidential election, counting votes and calling states took more time than usual, particularly in battleground states. In the days following the election, winning probabilities changed frequently as new results were tabulated. Based on the sensitivity of stocks to changes in winning probabilities observed before the election, we show how the stock market's assessment of the unobserved post-election winning probabilities can be backed out from stock prices. Our approach is based solely on publicly available data.

1. Introduction

The 2020 U.S. presidential election was special in many respects. Due to the COVID-19 pandemic more voters than ever before in U. S. election history preferred to cast their ballots by mail. This led to delays in counting the votes, particularly in those states that allow mail-in votes to arrive even after Election Day. Combined with razor-thin margins in some battleground states, calling these states proved to be more difficult and to take longer than usual. In the absence of a federal election authority, winners – both at the state and the federal levels – are called by major election reporting organizations (mainly the big networks and news agencies). Decision Desk HQ, a specialized website, was the first major election reporting organization to call the election for Joe Biden shortly before 9 a.m. ET on Friday, November 6. AP, NBC, CNN, The New York Times, and The Washington Post called the election for Biden shortly after 11 a. m. ET on Saturday.

These election reporting organizations invest sizable amounts into expert models, data access, and the required IT, but even for them a correct assessment of winning probabilities proved to be more difficult for the 2020 election compared to previous elections. Forecasts were complicated by the fact that overall a majority of in-person voters cast their ballots for Donald Trump, while a majority of mail-in ballots were for Joe Biden. Therefore, an interpretation of vote count updates required both expert modeling and additional background information on the votes that were tabulated (e.g., county, in-person vs. mail-in). This resulted both in delays in calling states where the race was close and in the risk of prematurely calling states based on an incorrect assessment of the respective winning probability.[1]

Before the election, winning probabilities for all candidates were available from political prediction markets, like the Iowa Electronic Markets (IEM). Trading on the IEM stopped after the election, with the last published prices dating from Nov. 4. For laypeople

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[1] This almost happened for Arizona, where Biden led by a seemingly comfortable margin when Associated Press and Fox News called the state already during the night following Election Day, whereas other networks were more cautious. In the following days, contrary to many other battleground states, the majority of the additional incoming votes were for Trump, which reduced the margin significantly.

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without the expert models and the additional information available to the big news agencies and networks, it was very difficult to get updated information on winning probabilities in the days following the election. In this paper, we build on Hanke et al. (2020) and show how such probabilities could be inferred from observed stock prices. The required data are publicly available, hence anyone could have implemented the approach, and anyone will be able to use it in similar future situations.

2. Literature

Outcomes of elections or referendums have an impact on financial markets (see, e.g., Lobo, 1999). They may affect all stocks in a similar way if investors anticipate changes in the general economic environment for equity markets depending on the election outcome (Snowberg et al., 2007; Addoum and Kumar, 2016), e.g., a general increase in the stock index due to a "relief effect" if a highly controversial leader is voted out of office. Alternatively (or on top of that), election outcomes may produce winners and losers in the cross-section of stocks if there are systematic differences in their effects on individual companies. Possible causes for such differences include, e.g., close links between companies and politics in the form of campaign contributions (Jayachandran, 2006; Claessens et al., 2008), or policy changes that affect firms differently depending on certain characteristics (see, e.g., Wagner et al., 2018, who analyze effects due to changes in tax and trade policy, and the literature discussed there). Wisniewski (2016) provides a literature survey that lists political connectedness of companies and/or their directors, the phase of the electoral cycle, politically relevant events such as wars or terrorist attacks, and communication by politicians as additional drivers. Examples discussed by the media in the months before the 2020 U.S. presidential election include the candidates' different stance on COVID-19 measures, banking deregulation or on energy and climate change. A number of papers try to explain/forecast winners and losers in the cross-section of stocks using regression approaches. Explanatory variables used for this purpose range from analyst recommendations (Knight, 2006) via campaign contributions (Jayachandran, 2006; Claessens et al., 2008) to firm characteristics reflecting exposure to policies announced by candidates (Wagner et al., 2018) or the economic consequences of referendums (see Hill et al., 2019, for the 2016 UK Brexit referendum).

This literature clearly shows that equity prices after the election are impacted by election outcomes. The semi-strong form of the efficient market hypothesis states that all publicly available information is already reflected by stock prices. This includes publicly available information that is useful for predicting the election outcome. Suppose there are only two parties, A and B, and only party A is expected to create an economic environment that is favorable for equities. If a large majority predicts party A to win the election, most of the resulting positive effect will already be anticipated in stock prices before the election, and stock prices will move only very little on the (unsurprising) news that party A indeed is the winner. On the contrary, if most people expect B to win the election, but A wins nonetheless, stock prices should move significantly after the election result becomes public.

In light of the myriad of potential drivers, Hanke et al. (2020) suggest an approach which differs from the literature. Instead of trying to find explanatory variables for a differential effect of election outcomes on the cross-section of stock returns, they rely on the semi-strong form of the efficient market hypothesis which implies that stock prices reflect the market's best estimate of the net effect of all potential drivers. They show that stock prices observed before the election already incorporate expectations regarding conditional (i.e. outcome-dependent) election-induced stock returns. These expectations involve risk-neutral election outcome probabilities which can be obtained from political prediction markets (such as the IEM) or betting platforms. Stocks that show positive (negative) excess returns when Republican winning probabilities increase (decrease) in the weeks and months before the election are classified as "Republican stocks", and similarly for "Democrat stocks". In contrast, stocks whose returns do not co-move with changes in betting odds are not expected to react significantly to the election outcome. For this classification of stocks, observing that the market expects certain stocks to react (or not) to a particular election outcome is sufficient. The reason for such a selective reaction does not matter, it can, e.g., be any of the causes discussed in the literature or any combination of these. As the drivers change over time, a stock's classification may, in principle, also change in the long run. For example, a company that only recently became profitable and started to pay taxes would not have been affected by tax policy in the past, but would benefit from tax cuts in the future.

Hanke et al. (2020) estimate the sensitivity of stock returns to changes in winning probabilities and form "election portfolios", i.e. long-short portfolios that show a positive return conditional on correctly forecasting the election outcome. Their approach is useful both for investors who want to speculate on the election outcome and for those who want to reduce the exposure of their portfolio to (or hedge against) the election outcome. While Knight (2006) seems to be the first paper that combines data from betting odds with stock market data to predict election-outcome-specific stock returns, he uses this approach only to "validate" his pre-selection of stocks that is based on analyst recommendations. In contrast, Hanke et al. (2020) go one step further and classify stocks purely based on the co-movement of betting odds and stock prices in the weeks and months before the election.

In this paper, we illustrate yet another application of their approach. In the days after the election, betting markets are already closed and can no longer provide updated information on election outcome probabilities. Relying on the relation between stock returns and changes in betting odds estimated *before* the 2020 U.S. presidential election, we use prices of "Biden" and "Trump" stocks observed on the days *after* the election to back out implied (changes in) election outcome probabilities on these days. Given that Hanke et al. (2020) find high stability of the relation between changes in betting odds and the returns on these stocks in the months before the election, we are confident that the stock returns observed in the first few days after the election also reflect the publicly available information (on average) correctly. To the best of our knowledge, this is the first paper that infers election outcome probabilities from stock prices, both before and after an election.

3. Data and methodology

We use the prices of all stocks in the S&P 500 index (index constituents as of Jan. 3, 2020) as well as the index itself. Daily closing prices come from Datastream and are adjusted for dividends, stock splits, etc., to make them comparable on a day-to-day basis. Intraday prices are retrieved via Alpha Vantage (www.alphavantage.co).

Election outcome probabilities come from the Iowa Electronic Markets (IEM) Winner-Takes-All market. Based on stock prices and election outcome probabilities observed between Jan. 3 and Oct. 30, 2020, we estimate individual stock sensitivities θ_i from Eq. (2) in Hanke et al. (2020). This equation extends the standard index model by an idiosyncratic component that captures the event-related return:

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

where $r_{m,t}$ is the index return, $\epsilon_{i,t}$ is a random error term with mean 0 and variance σ_i^2, and $\epsilon_{i,t}$s are pairwise uncorrelated across assets. Δq_t^R denotes the change in Republican winning probabilities between days $t-1$ and t, and α_i captures any empirically observed abnormal stock return i.

We estimate Eq. (1) for $t \le \tau - 4$. Following Hanke et al. (2020), our estimation sample ends on the Friday before Election Day ($t = \tau$). This yields estimates for the stock sensitivities θ_i as well as for α_is and β_is. Hence, we use the close of trading on Friday, Oct. 30, as our reference point. Both changes in winning probabilities and stock returns for the week around Election Day are computed relative to this reference point.

Intuitively, our idea is to invert Eq. (1) for the days of the election week. Based on realized excess returns $r_{i,t}^e = r_{i,t} - \alpha_i - \beta_i r_{m,t}$ during this week and the stock-specific sensitivities θ_i estimated before the election, we want to back out the implied changes in winning probabilities, Δq_t^R, from Eq. (1). In principle, there are two ways for implementing this idea. The first approach, which we call the *portfolio approach*, simply assumes that the excess returns observed for each stock i in the week of the election are entirely explained by the observed changes in winning probabilities:

$$\Delta q_{i,t}^R = \theta_i^{-1} r_{i,t}^e \quad \forall i \text{ and } t \in [\tau - 1, \tau + 3]. \tag{2}$$

This assumption, while it may not hold for each individual stock i, should be correct on average. Section 4 reports results for median as well as equally-weighted and value-weighted averages and various sub-samples.

The second approach, which we call the *regression approach*, starts from the long-short election portfolios used in Hanke et al. (2020). Regressing the realized excess returns $r_{i,t}^e$ (starting on Oct. 30) during the election week on the portfolio θs:

$$r_{i,t}^e = \gamma_t + \Delta q_t^R \theta_i + \nu_{i,t}, \tag{3}$$

least-squares optimal estimates for changes in winning probabilities Δq_t^R can be calculated. This approach uses Eq. (1) directly, but in contrast to its use in Hanke et al. (2020) stock sensitivities θ_i for the portfolios are known and changes in election outcome probabilities Δq_t^R are estimated. Section 4 reports results for various portfolios and weighting schemes. Using intraday stock and index data, the approach can also be used to estimate election winner probabilities on an intraday basis.

4. Results

The starting point for all our results are the stock prices and the Republican candidate's (Trump's) winning probability observed on Oct. 30, 2020. Table 1 shows the top five Democrat and Republican stocks on this day, i.e. those stocks with the highest sensitivities (in absolute terms) to changes in betting odds.

Figure 1 shows results based on closing prices for the portfolio approach (left panel) and the regression approach (right panel). Qualitatively, the results from both approaches are quite similar: Republican winning probabilities start out very low around 17% on Oct. 30, then increase until Nov. 3 (Election Day), and then fall again. Overall, while stock prices until Oct. 30 indicated a clear expectation of a Democratic victory, their development around the weekend before Election Day signals a much closer race than expected by the market in the preceding months. Although a number of battleground states remained uncalled until the end of the week, stock prices from Nov. 4 onwards clearly show that market participants interpreted the newly arriving results as increasing evidence for Joe Biden to become the next president.

Looking more closely at the results from the portfolio approach (left panel), the solid (dashed) lines indicate probabilities calculated

Table 1
Top five Democrat and Republican stocks as of Oct. 30, 2020, ranked by their sensitivities to changes in betting odds, Δq_t^R. Significance levels of θ_is are indicated by *** (1%), ** (5%) and * (10%).

Top Democrat Stocks			Top Republican Stocks		
Company	Ticker	θ_i	Company	Ticker	θ_i
ABIOMED	ABMD	–0.27***	GILEAD SCIENCES	GILD	0.24***
KROGER	KR	–0.18**	OTIS WORLDWIDE	OTIS	0.22**
AMAZON.COM	AMZN	–0.18**	MCKESSON	MCK	0.22***
BEST BUY	BBY	–0.18**	TJX	TJX	0.21***
MICROCHIP TECH.	MCHP	–0.17*	AMERISOURCEBERGEN	ABC	0.21***

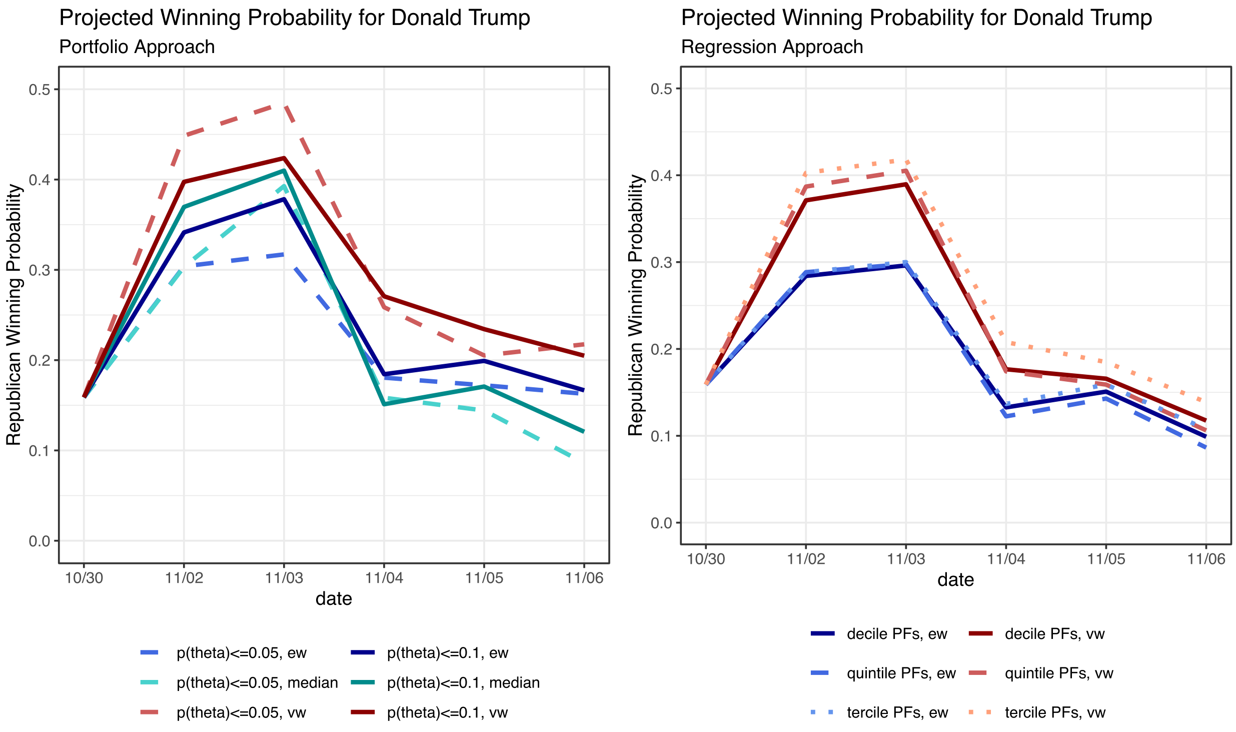

Fig. 1. Implied Republican winning probabilities around Election Day (Nov. 3, 2020). Left: Results from the portfolio approach (2), using daily closing prices. Solid (dashed) lines indicate probabilities calculated when including stocks whose sensitivities θ_i are significant at the 10% (5%) level. Results from value-weighted/equally-weighted/median portfolios are shown in red/blue/turquoise. Right: Results from the regression approach (3), using daily closing prices. Solid/dashed/dotted lines are for decile/quintile/tercile portfolios. Results from value-weighted (equally-weighted) portfolios are shown in red (blue). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

using those stocks whose sensitivities θ_is are significant at the 10% (5%) level. Results for equally-weighted, value-weighted, and median portfolios are shown in different colors. The results are quite dispersed, with winning probabilities on Election Day differing by as much as 16 percentage points.

In contrast, results from the regression approach (right panel in Fig. 1) are much more homogeneous. Solid, dashed, and dotted lines show probabilities calculated from long-short decile, quintile, and tercile portfolios, resp. (following Hanke et al., 2020), with value-weighted (equally-weighted) portfolios shown in red (blue). Probabilities computed from value-weighted portfolios are higher and more in line with the results from the portfolio approach, while probabilities computed from equally-weighted portfolios are lower by about 10 percentage points on Election Day. For each weighting scheme, differences between quantile portfolios are very small.

Comparing the two approaches, the regression approach seems to be more robust to variations in the subset of stocks used. In addition, we note that in the original application of Eq. (1) in Hanke et al. (2020), value-weighted portfolios yielded better results. Combining these observations, we regard the results from the regression approach and based on value-weighted portfolios as the most reliable. They indicate a sharp increase in the Republican winning probability in the days before the election from 17% to around 40%, reflecting that shortly before and on Election Day, markets expected a much closer race than over the weeks and months before the election. By the end of the week, the implied Republican winning probabilities decreased to values just above 10%, which is in line with mounting evidence for a majority for Biden. As mentioned before, most major election reporting organizations called the election at 11:25 a.m. ET on Saturday, Nov. 7 (when stock markets were closed).

Figure 2 illustrates the application of the regression approach to intraday data on the day after Election Day. The figure shows the development of implied Republican winning probabilities for tercile, quintile and decile portfolios. Around noon, while new (though somewhat expected) results from Ohio, Florida, and Texas arrived, Trump winning probabilities remained rather stable, with even a slight increase following the calling of Texas. In contrast, during the afternoon, when Wisconsin was called for Biden, Republican winning probabilities were decreasing steadily. The acceleration of the decrease around 3.45 p.m. ET may already anticipate Biden's victory in Michigan, which was officially called at 6 p.m. ET. Vertical lines in Fig. 2 indicate the time when the respective states were officially called by Associated Press.

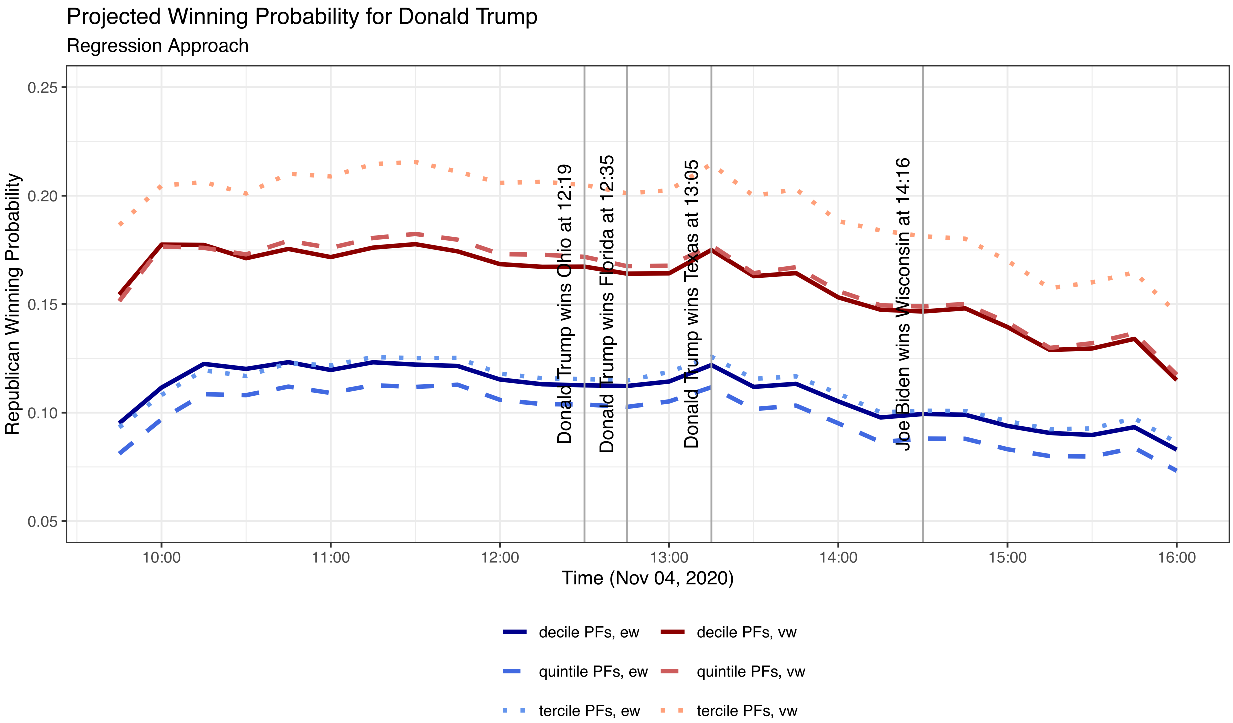

Fig. 2. Implied Republican winning probabilities on Nov. 4, 2020, calculated from intraday prices. Vertical lines indicate the time (ET) when the respective state was called by Associated Press. Solid/dashed/dotted lines are for decile/quintile/tercile portfolios. Results from value-weighted (equally-weighted) portfolios are shown in red (blue).(For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

5. Conclusion

Determining the winner after an election may take some time. During this period, updated election outcome probabilities may be difficult to retrieve. We have shown how such probabilities can be determined based on (i) stock prices observed after the election and (ii) stock sensitivities to changes in outcome probabilities, which have been estimated before the election. The approach is based solely on publicly available data, so everyone can apply it for future elections, either using closing prices or intraday data.

Declarations of Competing Interest

None

CRediT authorship contribution statement

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

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