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Elite Signaling and Efficient Markets: The Evaluation of Endorsements in Presidential Primaries

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Elite Signaling and Efficient Markets: The Evaluation of Endorsements in Presidential Primaries

by

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Report

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Abstract

Elite Signaling and Efficient Markets: The Evaluation of Endorsements in Presidential Primaries

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Endorsements are an integral part of American political campaigns, but despite their ubiquity, there exists only sparse literature evaluating either the impact of endorsements on electoral outcomes or the circumstances in which endorsements are offered. I hypothesized that the primary factor influencing a politician's decision to endorse was a perceived increase in a candidate's chance of success; thus politicians are more likely to endorse candidates who have demonstrated a real potential for winning the election. Using the 2012 Republican Presidential nomination and the 2008 Democratic Presidential nomination as case studies, I regressed daily proportions of endorsements given on prediction market share prices from the Iowa Electronic Markets. I used an Almon distributed lag model to account for the delay between a politician observing an increase in a candidate's chance of success and their subsequent endorsement. Though there was a weakly positive association between prediction market share prices and endorsements shares, I found little evidence to support the claim that politicians

systematically offer endorsements in response to increases in a candidate's probability of success.

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INTRODUCTION

In the 2008 Republican Presidential Primaries, John McCain and Mitt Romney were locked in a battle for the Republican Party's presidential nomination. Though McCain's war chest was far smaller than Romney's, he received an endorsement from the *New Hampshire Union Leader* one month before that state's primary. While it had a history of endorsing non-establishment candidates, the *Union Leader* was the most respected conservative publication in the state, and its endorsement was widely regarded as the pivotal moment in McCain's campaign. Indeed, he went on to win the New Hampshire primary. Though many have argued that the rise of candidate-centered campaigns and increasing independence amongst the electorate presaged the demise of political parties, this anecdote speaks to the relative importance of endorsements by political elites and leads us to consider the role of endorsements in electoral campaigns.

Endorsements are a staple of electoral campaigns in America and are given not just by politicians but also celebrities and prominent partisans. Campaigns frequently publicize coveted endorsements, and media outlets also devote coverage to endorsements. The prevalence of endorsements suggests that they play a meaningful role in campaigns, but there has been, so far, little effort to empirically evaluate their impact on electoral outcomes, the times at which they are offered, or the mechanism through which they might influence voters.

THE POWER OF PARTIES

Since the McGovern-Fraser reforms, the general trend in scholarship has pointed to the demise of political parties as powerful actors in the American political system (Polsby, Wildavsky, and Hopkins 2007; Crotty 1985; Hagen and Mayer 2000; Beck 1997). However, Cohen, et al (2004) put forth a critique of this position. While many political scientists contend that the modern nominating system has weakened parties, Cohen, et al (2004) argue in their book *The Party Decides* that "parties remain major players in presidential nominations" because "they scrutinize and winnow the field before voters get involved, attempt to build coalitions behind a single preferred candidate, and sway voters to ratify their choice" (3). They explain that "parties are a central political institution—arguably the central political institution—for organizing society's diverse demands and interests" (Cohen, et al 2004: 30). Thus these parties are composed of groups of intense policy demanders who typically form official organizations outside of the party. These intense policy demanders should also be thought of as party leaders because "the most important party business is the nomination and election of office seekers who will serve the interests of the party's intense policy demanders" (Cohen, et al 2004: 31).

Cohen, et al (2008) posit that "party insiders use the invisible primary to endow that candidate with the resources and prestige necessary to prevail in the state-by-state contests" and list endorsements as evidence of their support (9). Similarly, endorsements from party elites convey credibility insofar as they are an obviously limited campaign resource (Dominguez 2011). More importantly, endorsements convey information about

a candidate's desirability and viability; for example, an endorsement from a well-known politician might indicate to a voter that the candidate has the support of party leaders (Steger 2007). Because they contain a multitude of candidates with similar policy positions, primaries are typically considered low-information environments, and endorsements can be particularly helpful for voters attempting to differentiate between various candidates (Keeter and Zukin 1983; Popkin 1991). Thus the importance of endorsements speaks to the role of parties in the modern nominating process. In fact, evaluating the importance of endorsements can offer insight on whether establishment support influences election outcomes. Because endorsements are the most obvious sign of party elite influence, we could, through them, determine whether elites are successful in signaling party supporters through endorsements.

A vast amount of literature has shown that voters use shortcuts to make decisions in low-information environments (Popkin 1991; Kahneman, Slovic, and Tversky 1982; Nisbett and Ross 1980; Lau and Sears 1986; Fiske and Taylor 1991). Partisanship, not a viable distinguishing factor in primary elections, is widely cited as the most important heuristic for voters, and studies have shown that voters use endorsements as a shortcut in elections that they know relatively little about (Lupia 1994). Endorsements most often come from sources with clear partisan bents and can thus provide valuable information to voters (McDermott 2006). For all of these reasons, endorsements, both formal and informal, are a common heuristic (Arcenaux and Kolodny 2009; Lau and Redlawsk 2001). More specifically, endorsements from well-known political figures allow voters to assume a relationship between endorser and endorsee's policy positions (Lau and

Redlawsk 2001; Grossman and Helpman 1999). Notably, primary voters should be especially receptive to the message conveyed by endorsements because they are typically more partisan and more politically sophisticated than they average voter.

Thus one explanation for the importance of endorsements centers on their role as a heuristic. If these endorsements serve as important heuristics because they allow voters to extrapolate the candidate's issue positions from those of the endorser, then endorsements from prominent figures should provide information in addition to conferring prestige. More clearly, endorsements convey valuable information about a candidate to voters and therefore serve as an effective way for party elites to signal their preference to voters. An alternate theory suggests that elites will only offer endorsements after they receive hard evidence of a candidate's viability. This latter hypothesis does not preclude the possibility of endorsements serving as an important heuristic for the voters but does suggest that elites take their cues from the voters before offering up their endorsements.

RESEARCH HYPOTHESIS

If politicians offer endorsements in the hope that they will impact electoral outcomes, they should be giving these endorsements in a systematic fashion. In other words, what prompts politicians to endorse candidates? There are likely a multitude of factors influencing an individual politician's decision to endorse a particular candidate, and, in this study, I evaluate one of the many possible explanations for the timing of endorsements. I hypothesize that endorsements from politicians follow from changes in a candidate's probability of success. More specifically, politicians will selectively endorse candidates who show evidence of success; in other words, potential endorsers will offer their endorsements in response to a perceived increase in a candidate's probability of success.

Significantly, it is likely that the effect of this increased likelihood of success on a politician's decision to endorse another candidate is neither immediate nor permanent. With regard to the influence of endorsements on voters, Jamieson (2000) found that newspaper endorsements of particular candidates affected voters' opinions when the candidates heavily advertised those endorsements. Therefore media exposure serves as an intermediate step between a candidate receiving an endorsement and that endorsement actually increasing his public support, suggesting that the effect of an endorsement is moderated by media coverage. Despite the rapid pace of modern campaigns, it is equally likely that the temporal relationship between a candidate's likelihood of success and a politician's decision to endorse will not be immediate. Thus any analysis of the impact of endorsements on electoral outcomes must account for the possibility of delayed effects.

PREDICTION MARKETS

Prediction markets are valuable tools for estimating an individual candidate's chance of success at any given point in time (Kou and Sobel 2004; Forsythe, et al 1992). Furthermore, a number of studies have found that prediction markets are more accurate in identifying correct election outcomes than poll-based forecasts (Rothschild 2009; Leigh and Wolfers 2006; Berg, Nelson, and Rietz 2008; Berg and Rietz 2014; Chen 2008). Methodologically, prediction markets offer a number of advantages over poll-based estimates of success. First and foremost, "on any given day prior to the election, the price of a particular candidate's share should be an unbiased estimate of that candidate's probability of winning" (Shaw and Roberts 2000: 264). Participants in the market have a monetary incentive to reflect reality (meaning the actual favorability of candidate among the electorate) instead of their own particular political preferences. Secondly, prediction markets self-select for participants with very high levels of political sophistication. Thus, we can assume that any changes in share price are reflective of changes in the electoral environment (Shaw and Roberts 2000).

Prediction market share prices can, then, be an extremely powerful independent variable because they fully reflect all existing information about a particular campaign. If market participants are politically sophisticated and financially motivated, their bids should arise from broad knowledge about campaign events. In this vein, Eugene Fama argued that, under the assumption that information flows readily and is immediately incorporated into stock prices, subsequent changes in stock prices were independent of previous stock prices (Fama 1965). In his seminal article titled "Efficient Capital

Markets: A Review of Theory and Empirical Work," he argued that, because prices changes are fully random, they incorporate all known information (Fama 1965; Fama 1970). Fama's efficient market hypothesis states that an efficient market is "a market with great number of rational, profit-maximizers actively competing, with each trying to predict future market values of individual securities, and where current important information is almost freely available to all participants" (Fama 1970). Thus, under the efficient market hypothesis, market prices should fully reflect all existing information (Fama 1970; Malkiel 2003).

Fama outlined three forms of the efficient market hypothesis. The weak form claims that market prices take into account all available historical information (Fama 1970). The semi-strong form argues that, in addition to reflecting historical information, markets respond instantaneously and without bias to new information (Fama 1970). The strong form adds the additional assumption that prices fully reflect private information (Fama 1970). Though hugely influential, economists have expressed concerns about the conditions under which the efficient market hypothesis is consistent with market behavior (Jordan 1983; Allen 1981; Radner 1979; Howden 2009; Malkiel 2003). However, assuming that prediction markets are less complex than economic markets, we can conclude that any shift in prediction market share prices results from new information (Chen and Yeh 2002). Thus, we can reasonably assume that prediction market share prices accurately and without bias capture all publicly available information about a campaign.

Traders in political prediction markets are concerned with predicting mass voter behavior. Under the efficient market hypothesis, markets only change in response to new information; therefore all prediction market perturbations should be the result of campaign events (Fama 1970). In this vein, traders in prediction markets are attempting to account for how campaign events or new information about a campaign will alter that candidate's chance of success in the election.[1] Thus the efficient market hypothesis here motivates a relatively strong claim about the informational efficiency of political prediction markets that is itself grounded in an assumption about market participants' levels of political sophistication. Because politicians also have high levels of political knowledge, it is reasonable to assume that their perceptions of a candidate's likelihood of success track closely with those of market participants. Thus prediction market share prices can accurately represent politicians' perceptions of candidate's probability of success. Accordingly, we can use the correlation between endorsement share and prediction market share price to determine the degree of support for the hypothesis that politicians issue endorsements in the wake of increases in a candidate's probability of success.[2]

This analysis uses data from the Iowa Electronic Markets. All markets within the Iowa Electronic Markets are winner-take-all markets with daily high, low, average, and

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[1] This could be relatively straightforward for direct elections but slightly more nuanced for presidential nomination contests. While there is little consensus on how to maintain accurate delegate counts, it seems safe, in most instances, to assume that popular votes in primary contests translate to delegate votes at the parties' national conventions.

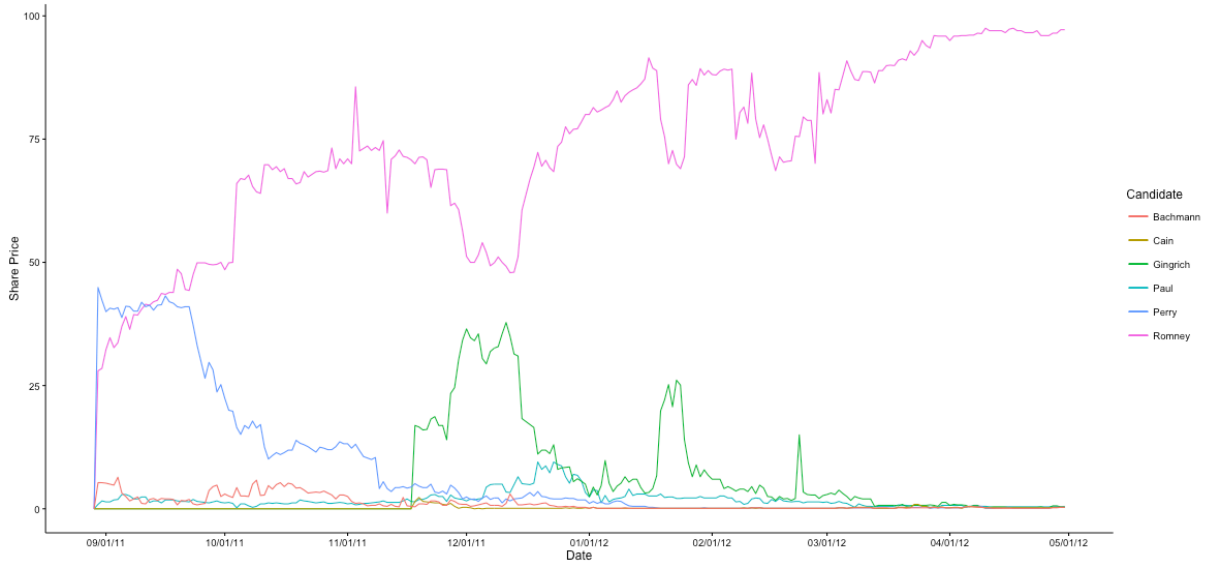
[2] Initially this would seem to raise endogeneity concerns as endorsements themselves may be considered significant campaign events. However, choosing an independent variable that could feasibly reflect endorsement information allows for bandwagon effects; more clearly, an endorsement from one politician might prompt another politician to endorse.

closing prices noted. Share prices range between zero cents and one dollar and can thus be thought of as a daily probability of a particular candidate's success in the election. The independent variable for this analysis is the daily closing share price in either the 2012 US Republican Presidential Nomination Markets or the 2008 US Democratic Presidential Nomination Markets.

PRESIDENTIAL PRIMARIES

The 2012 Republican nomination contests were notable for their wide field of candidates. Thirteen candidates participated in a series of five televised debates leading up to the Iowa caucuses; the long "invisible primary" (the months leading up to the contests in Iowa and New Hampshire) provides an ideal setting in which to gauge the role of parties in the nomination process (Cohen, et al 2008: 5). Significantly, Romney was the clear establishment candidate, but it was a wide field with a number of viable candidates who at various times led in the polls. Rick Perry, Mitt Romney, Rick Santorum, Newt Gingrich, and (to a much lesser extent) Ron Paul all racked up delegates in the early stages of the primary. On April 25, Republican National Committee Chair Reince Priebus named Romney as the presumptive nominee for the Republican Party, but Romney did not actually gather the requisite number of delegates until May 29. Closing share prices for the 2012 US Republican Presidential Nomination Markets are available from September 1, 2011 through April 30, 2012. These data capture a large amount of the invisible primary and continue past the date on which Romney was declared presumptive nominee. Figure 1 shows the closing share prices in the electronic market for six of the candidates between September 1, 2011 and April 30, 2012. Romney did not emerge as a clear favorite until after Super Tuesday on March 6, 2012.

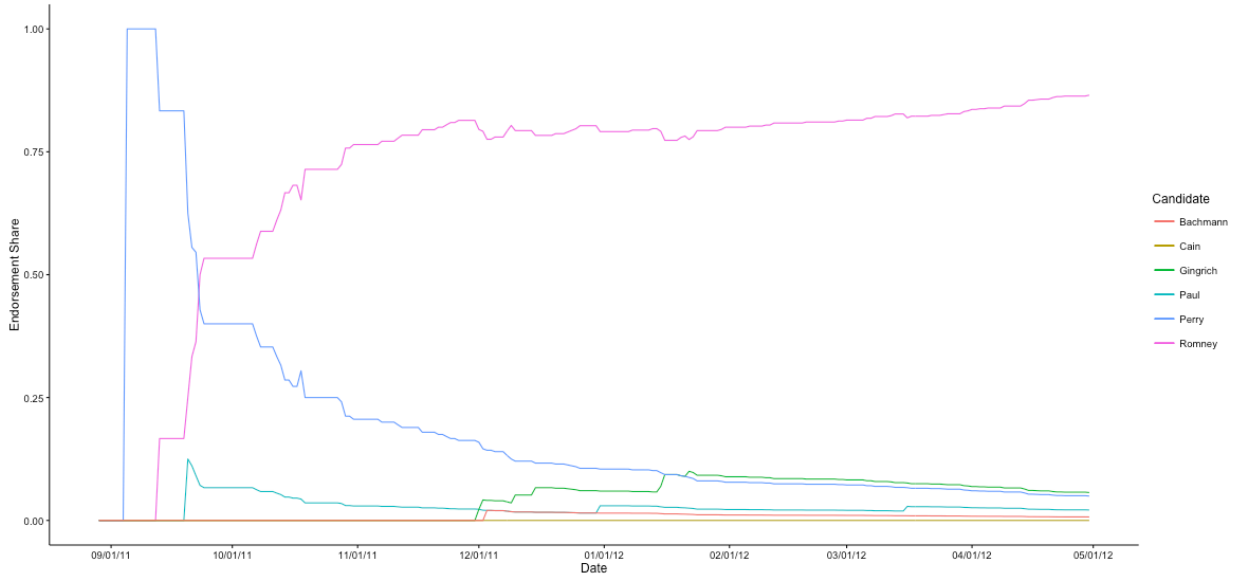
Figure 1. Closing share prices in the IEM for the 2012 Republican Presidential Primaries.



During the time of the 2012 Republican presidential primaries, there were 29 sitting Republican state governors, 3 sitting Republican Territory and Commonwealth governors, 47 sitting Republican U.S. senators, and 242 sitting Republican U.S. representatives. Because these are well-known, national politicians, presumably their endorsements will convey prestige and also offer substantial information about a particular candidate. Additionally, these endorsements should contain some information about the viability of the candidate in the presidential election. Romney, the clear establishment candidate, received endorsements from 18 sitting governors, 25 sitting U.S. senators, and 64 sitting U.S. representatives before he was named presumptive nominee on April 25, 2012. Romney received vastly more endorsements than any other nominee. The information about the endorsements and the dates on which they were given were

culled from a Lexis-Nexis search of state and local newspapers. Figure 2 shows each candidate's daily share of the total number of endorsements offered by that day. To calculate each candidate's proportion of endorsements, I created a running tally of endorsements received by each candidate and then divided that count by the total number of endorsements offered to all candidates.[3]

Figure 2. The 2012 Republican nominees' endorsement shares over time.



The 2008 Democratic nomination contests offer a valuable counterpoint to the 2012 Republican primary contests. While a number of politicians opened campaigns following the 2006 midterm elections, only three candidates went on to compete in the primaries: John Edwards, Hillary Clinton, and Barack Obama. Edwards received a number of early endorsements from other North Carolina politicians, but he suspended

[3] The data used in this study can be accurately described as panel data, with candidates as the cross-sectional object and day as the time identifier. However, both the IEM share prices and endorsement shares are compositional data and thus strain the assumption of multivariate normality central to regression-based models. A more parsimonious option, then, is to consider each candidate's time series in isolation.

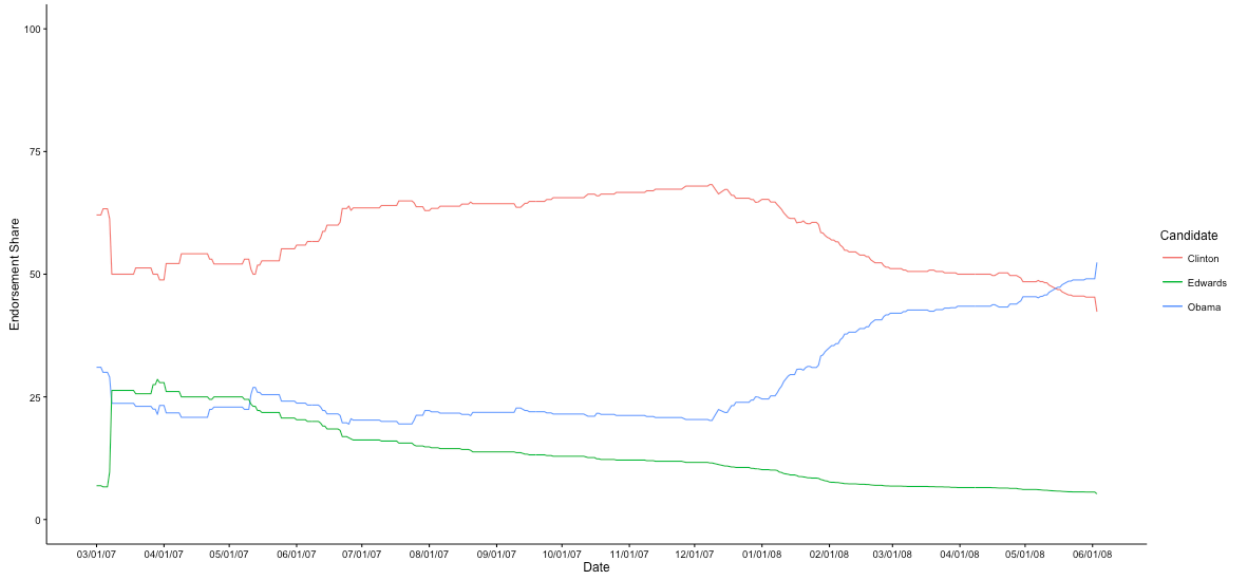
his campaign at the end of January 2008. Clinton left the invisible primary with a commanding lead in endorsements, but Obama quickly built up support in the weeks leading up to the Iowa caucuses. Thus, unlike Romney, Clinton did not maintain the lead she had built up during 2007. Instead, she received an early loss in Iowa but returned to win in New Hampshire. Clinton and Obama then drew to a tie on Super Tuesday, and Obama only surged to a lead in mid-February. Figure 3 shows the three candidates' closing share prices in the prediction market between March 1, 2007 and June 3, 2008 (the day on which Obama declared that he had amassed enough superdelegates to secure the nominate; Clinton conceded on June 7, 2008).

Figure 3. Closing share prices in the IEM for the 2008 Democratic Presidential Primaries.

Significantly, Democratic governors, U.S. Senators, and U.S. Representatives are all superdelegates, so their endorsements can also serve as the promise of votes at the

Democratic National Convention. During the time of the 2008 Democratic presidential primaries, there were 28 sitting Democratic state governors, 2 sitting Democratic Territory and Commonwealth governors, 49 sitting Democratic U.S. senators, and 233 sitting Democratic U.S. representatives. Figure 4 shows each candidate's daily share of the total number of endorsements given by that day.[4] Though Clinton built up a commanding lead in endorsements over the course of the invisible primary, she quickly lost ground to Obama once the primary contests began in January of 2008. Edwards' early departure from the primary contests is similarly reflected in his rapidly dwindling endorsement share. These endorsement shares were calculated in the same fashion for this data as they were for data drawn from the 2012 Republican nomination contests. For ease of representation, I multiplied all proportions by 100.

Figure 4. The 2008 Democratic nominees' endorsement shares over time.



[4] Both the daily share prices in the IEM and daily endorsement shares are time-series data insofar as the data points are successive and spaced equally by one day.

DISTRIBUTED LAG MODELS

Though the semi-strong form of the efficient market hypothesis states that markets respond instantaneously to new information, this is an unreasonable assumption for endorsement shares (Fama 1970). More clearly, after witnessing a particular campaign event, a politician might take some time to arrive at the decision to endorse a candidate. First and foremost, a lag structure is needed to account for the temporal delay resulting from the time needed for decision-making. Additionally, there could be logistical delays results from a need to coordinate with media outlets or even the candidate's campaign staff. Thus, the delay between a politician witnessing an increase in a candidate's probability of success and the offering an endorsement can also result from institutional interactions. Broadly speaking, then, there can be institutional, technical, and psychological reasons to expect a delay between a specific increase in a candidate's probability of success and any endorsements it may have prompted (Nerlove 1958; Griliches 1967; Gujarati 2003). Thus it is plausible that the effect of campaign events on a politician's decision to endorse a candidate is not instantaneous, and an accurate model must account for an effect that is distributed over time (Monroe 1981).

Distributed lag models are widely used in economics, marketing, and epidemiology to model event-exposure relationships that show delayed effects. These models are ideally suited for instances in which theory dictates that the dependent variable only responds to changes in the independent variable after some time interval (Alt 1942; Griliches 1967). In other words, distributed lag models can be used when there is reason to think that the effect of changes in the independent variable is distributed

over time (Jorgensen 1966). These models are a special case of the broader group of autoregressive distributed lag models and, as such, are robust to non-stationary variables (Pesaran and Shin 1999; Tsay 1985).[5]

The initial distributed lag model, commonly known as the Koyck model, assumes an infinite lag in which lag coefficient decline exponentially according to a factor λ (Koyck 1954). This model raises a number of significant estimation concerns, and the rigid lag structure it prescribes might not accord with *a priori* considerations (Gujarati 2003). The Almon distributed lag model instead assumes a finite lag in which the lag structure can be approximated by a polynomial (Almon 1965). Though the model requires that the maximum length of the lag be larger than the degree of the polynomial used to approximate the lag scheme, it still allows for a much wider array of lag structures than does Koyck's model (Almon 1965; Gujarati 2003; Monroe 1981). In addition, Almon's distributed lag model minimizes the estimation concerns that arose with Koyck's model—namely multicollinearity—and maximizes degrees of freedom (Monroe 1981). This is especially significant because Almon's model can be easily estimated through ordinary least squares procedures (Almon 1965; Gujarati 2003).[6]

A finite distributed lag model can be written as:

$$Y_t = \alpha + \beta_0 X_t + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \cdots + \beta_k X_{t-k} + \mu_t$$

[5] Distributed lag models have been shown to lose efficiency with temporally aggregated data, so the daily prediction market share prices are especially advantageous (Wei 1978).
[6] Koyck's model could also be estimated via OLS if instrumental variables are used (Gujarati 2003).

In that model, *Y* represents a candidate's daily endorsement share, *X* his or her daily share prices in the Iowa Electronic Markets, and *k* the maximum length of the lag.[7] The model can also be written as:

$$Y_t = \alpha + \sum_{i=0}^{k} \beta_i X_{t-i} + \mu_t$$

In this more compact form, *i* represents the length of the lag, and the β_i terms describe the lag distribution. Using a theorem stating that any continuous function can be uniformly approximated by a polynomial on a closed, finite interval, Almon contends that the β_i terms can be approximated by a polynomial (Almon 1965).[8] The lag distribution of that model, with *m* representing the degree of the polynomial used to approximate the lag structure and *i* representing the length of the lag, can thus be written as:

$$\beta_i = \alpha_0 + \alpha_1 i + \alpha_2 i^2 + \cdots + \alpha_m i^m$$

As described below, the specific model used here will incorporate a third-degree polynomial and a fourteen-day maximum lag length. Following Almon's claim, we can substitute the β_i terms with their third-degree polynomial approximation. Thus the model used here can be written as:

$$Y_t = \alpha + \sum_{i=0}^{14} \beta_i X_{t-i} + \mu_t$$

$$Y_t = \alpha + \sum_{i=0}^{14} (\alpha_0 + \alpha_1 i + \alpha_2 i^2 + \alpha_3 i^3) X_{t-i} + \mu_t$$

$$Y_t = \alpha + \alpha_0 \sum_{i=0}^{14} X_{t-i} + \alpha_1 \sum_{i=0}^{14} i X_{t-i} + \alpha_2 \sum_{i=0}^{14} i^2 X_{t-i} + \alpha_3 \sum_{i=0}^{14} i^3 X_{t-i} + \mu_t$$

[7] The model derivation is drawn from Gujarati 2003 and Almon 1965.

[8] This theorem is known as the Stone-Weierstrass theorem and was first proved by Karl Weierstrass in 1885.

From that equation, we can construct the variables defined below:

$$Z_{0t} = \sum_{i=0}^{14} X_{t-i}$$

$$Z_{1t} = \sum_{i=0}^{14} iX_{t-i}$$

$$Z_{2t} = \sum_{i=0}^{14} i^2 X_{t-i}$$

$$Z_{3t} = \sum_{i=0}^{14} i^3 X_{t-i}$$

With the constructed variables, we can rewrite the full equation as:

$$Y_t = \alpha + \alpha_0 Z_{0t} + \alpha_1 Z_{1t} + \alpha_2 Z_{2t} + \alpha_3 Z_{3t} + \mu_t$$

Note that in the estimating equation shown above, the dependent variable is regressed on the newly constructed variables. Moreover, with a third-degree polynomial (in other words, with *m* as three), the constructed variables are defined as:

$$Z_{0t} = \sum_{i=0}^{14} X_{t-i} = X_t + X_{t-1} + X_{t-2} + X_{t-3} + \cdots + X_{t-14}$$

$$Z_{1t} = \sum_{i=0}^{14} iX_{t-i} = X_{t-1} + 2X_{t-2} + 3X_{t-3} + \cdots + 14X_{t-14}$$

$$Z_{2t} = \sum_{i=0}^{14} i^2 X_{t-i} = X_{t-1} + 4X_{t-2} + 9X_{t-3} + \cdots + 14^2 X_{t-14}$$

$$Z_{3t} = \sum_{i=0}^{14} i^3 X_{t-i} = X_{t-1} + 8X_{t-2} + 27X_{t-3} + \cdots + 14^3 X_{t-14}$$

The α_m terms are found from the estimating equation, and the original coefficients are estimated from those α_m terms (Almon 1965; Gujarati 2003).

The primary concern surrounding the use of distributed lag models is the lack of guidance on model parameters (Pagano and Hartley 1981; Monroe 1981). While we would prefer to have theoretical considerations drive parameter selection, this is rarely the case in practice (Hanssens and Liu 1983). In the absence of any *a priori* knowledge of maximum lag length and degree of the polynomial, the model parameters must be chosen 'atheoretically' (Tsay 1983; Pagano and Hartley 1981). This is especially problematic because model results can be highly sensitive to model parameters (Hendry and Richard 1983). If bereft of theoretical guidance, common practice dictates using information criteria (either the Akaike information criterion or the Schwarz-Bayes information criterion) to guide parameter specification (Hendry and Richard 1983; Davidson and MacKinnon 1993; Gujarati 2003). It is important to note here that, without theoretical guidance, a lag structure or maximum lag length selected via information criteria could simply be an artifact of the model (Monroe 1981).[9]

In this instance, we do have substantial *a priori* information with regard to lag structure. First and foremost, it seems likely that the influence of a campaign event on a politician's decision to endorse a candidate can fluctuate over time. More specifically, given the possibility of logistical delays and the time needed for decision-making, it seems unlikely that the effect of that campaign event (in the form of an endorsement) will appear within the same day. Because we have little reason to expect that the effect of a campaign event on a potential endorser will be distributed evenly over the lag interval,

[9] For this reason, among others (such as maximizing degrees of freedom), econometricians largely use lower-order polynomials to approximate the lag structure (Gujarati 2003).

we can eliminate the first-order polynomials. Similarly, it seems unreasonable to think that the effect of a campaign event is symmetric over the course of the lag period; this suggests that second-order polynomials would not accurately approximate the lag distribution. Third-degree polynomials, however, allow for greater flexibility in the lag distribution (a necessary precaution when attempting to represent decision-making). Approximating the lag structure with a third-degree polynomial leaves room for an instantaneous impact.[10] This lag distribution also allows for the effect of campaign events to be cumulative, which accords with theoretical expectations about a politician's decision to endorse a candidate (Monroe 1981). Lastly, higher-order polynomials (such as fourth- and fifth-degree polynomials) consume degrees of freedom and have been shown to produce arbitrary coefficients (Johnston 1972).

We have slightly less specific theoretical guidance in choosing lag length and thus must rely on information criteria to determine an optimal period (Hendry and Richard 1983; Davidson and MacKinnon 1993; Gujarati 2003). Note that the maximum length of the lag is a significant decision not just for its substantive ramifications. Keeping in mind the estimating equation shown above, it is evident that an overly long maximum lag length will introduce irrelevant variables and thus bias results. An excessively short maximum lag length will result in the more deleterious 'omission of relevant variables bias' (Hendry and Richard 1983). A common approach to selecting lag length calls for testing the model with an overly long maximum lag length and then slowly decreasing

[10] A situation in which we might expect instantaneous impacts might be when candidates are named their party's presumptive nominee or when they collect the necessary number of delegates. For example, Obama received a huge number of endorsements both on the day on which he amassed the requisite number of delegates need to secure the Democratic Party's nomination and on the days immediately following.

the lag length until information criteria increase (Davidson and MacKinnon 1993). Because primary campaigns are long (particularly when considering the invisible primary), I began testing models with a maximum lag length of fourteen days.[11] Tables 1 and 2 list the information criteria by candidate and by lag length.

[11] Though primary campaigns are long, endorsements are typically offered at a rapid pace. Future studies might use media coverage of individual endorsements to determine how long they are publicized. Furthermore, studies of media coverage of campaign events might offer additional guidance on appropriate lag lengths.

Table 1. A list of AIC and BIC values for models of various lag lengths.

Lag Length (days)	**Romney**	**Perry**	**Gingrich**	**Clinton**	**Obama**	**Edwards**
14	*1679.256*	*1344.581*	*1213.459*	*2269.434*	*2274.79*	*2452.208*
13	1712.871	1388.711	1220.258	2281.468	2281.813	2461.936
12	1742.6	1422.768	1227.553	2293.42	2288.453	2470.823
11	1769.795	1451.741	1234.785	2305.63	2295.141	2479.476
10	1794.626	1477.365	1242.51	2317.857	2301.979	2487.417
9	1818.025	1498.491	1250.911	2330.019	2308.908	2498.075
8	1840.768	1516.026	1260.102	2342.329	2316.043	2508.322
7	1862.806	1532.121	1268.952	2355.533	2324.424	2518.694
6	1883.324	1569.337	1277.358	2375.029	2339.932	2525.35
5	1902.244	1700.835	1285.06	2389.399	2355.868	2536.263
4	1921.092	1779.386	1292.489	2402.626	2371.875	2548.931
3	1939.948	1832.411	1300.402	2415.581	2386.467	2562.275
2	1956.435	1876.166	1307.013	2425.457	2402.421	2574.171
1	1971.98	1913.314	1314.143	2437.201	2420.344	2587.582

Table 2. A list of SBIC values for models of various lag lengths.

Lag Length (days)	**Romney**	**Perry**	**Gingrich**	**Clinton**	**Obama**	**Edwards**
14	*1699.858*	*1365.183*	*1234.062*	*2293.982*	*2299.338*	*2476.756*
13	1733.5	1409.34	1240.887	2306.03	2306.375	2486.498
12	1763.255	1443.422	1248.207	2317.994	2313.028	2495.398
11	1790.475	1472.422	1255.466	2330.219	2319.73	2504.064
10	1815.332	1498.071	1263.217	2342.459	2326.581	2512.019
9	1838.757	1519.223	1271.643	2354.635	2333.523	2522.691
8	1861.525	1536.783	1280.86	2366.958	2340.672	2532.95
7	1883.589	1552.904	1289.735	2380.176	2349.066	2543.336
6	1904.132	1590.146	1298.167	2399.685	2364.588	2550.006
5	1923.078	1721.668	1305.894	2414.068	2380.537	2560.932
4	1941.95	1800.245	1313.348	2427.308	2396.557	2573.613
3	1960.832	1853.295	1321.285	2440.276	2411.162	2586.97
2	1973.859	1893.59	1324.437	2446.048	2423.012	2594.762
1	1985.936	1927.27	1328.098	2453.682	2436.825	2604.063

In all instances, the AIC and SBIC were minimized when the maximum length of the lag is fourteen days. Even without examining regression coefficients, the long lag length suggests that campaign events can have effects on endorsement share that persist

for quite some time. Thus, the final model assumed a lag length of fourteen days and approximated the lag distribution with a third-degree polynomial.[12] All models were run with the "dlnm" package in the R environment.

[12] I should note here that the varying AIC/SBIC values might indicate that the model parameters are not equally suitable to all of the time series. This could suggest that the model fit is not comparable across the various time series.

RESULTS

Distributed lag models offer information on both the magnitude and timing of an independent variable's effect on a dependent variable. Table 1 lists the estimated cumulative effect (along with its 95% confidence intervals and standard error) of a one-unit increase in each candidate's share price on their endorsement share over lag period of fourteen days. For example, a one-unit increase in Romney's prediction market share prices results in a 0.704-unit increase in his endorsement share over the course of fourteen days.

Table 3. Cumulative effects of a one-unit increase in a candidate's share price on endorsement share after fourteen days.

Candidate	95% Lower CI	Cumulative Effect	95% Upper CI	Standard Error
Romney	0.6249732	0.7038313	0.7826893	0.04023443
Perry	1.498725	1.55847	1.618216	0.03048313
Gingrich	0.05467511	0.1077995	0.1609238	0.02710475
Clinton	0.324725	0.3404495	0.3561739	0.008022829
Obama	0.3886653	0.4018041	0.4149429	0.006703586
Edwards	1.42386	1.533087	1.642314	0.05572911

When examining the results of a distributed lag model, graphs of the coefficients plotted by lag period can provide useful insight into the distribution of effects over time. The coefficients themselves indicate the change in the dependent variable—in this instance, endorsement shares—after k periods given a change in the independent

variable—here, prediction market share prices—on the first day. The cumulative changes represent the sum of all prior coefficients to a particular point in time.

Figure 5a shows the change in Romney's endorsement share over fourteen days associated with a one-unit increase in his prediction market share price on the first day (in other words, at a lag of zero). In Figure 5a, we can see that a one-unit increase in share price is not correlated with a change in endorsement share at a lag of zero days. This upward influence increases through a lag of three days, but then the association between Romney's share price and his endorsement share changes its trajectory. More clearly, between a lag of four to eight days, the initial one-unit increase in prediction market share price is in fact associated with a decrease in endorsement share. However, after a lag of eight days, the association again becomes strongly positive. Figure 5b depicts the sum of the contributions of all lags up to the maximum lag length of fourteen days.[13] Though the cumulative effects do not maintain a steady trend, the cumulated effects of a one-unit increase in Romney's prediction market share prices are associated with a 0.704-unit increase in his endorsement share over a lag period of fourteen days.

[13] In other words, the graph represents the additive effects of each of the lag terms included in the model. Note that the curves in Figures 5a and 5b begin at the same value along the y-axis.

Figure 5. The estimated lag distribution for a one-unit increase in Romney's prediction market share price over a lag period of fourteen days. (a) The lag-response curve. (b) The lag-response curve of cumulative effects.

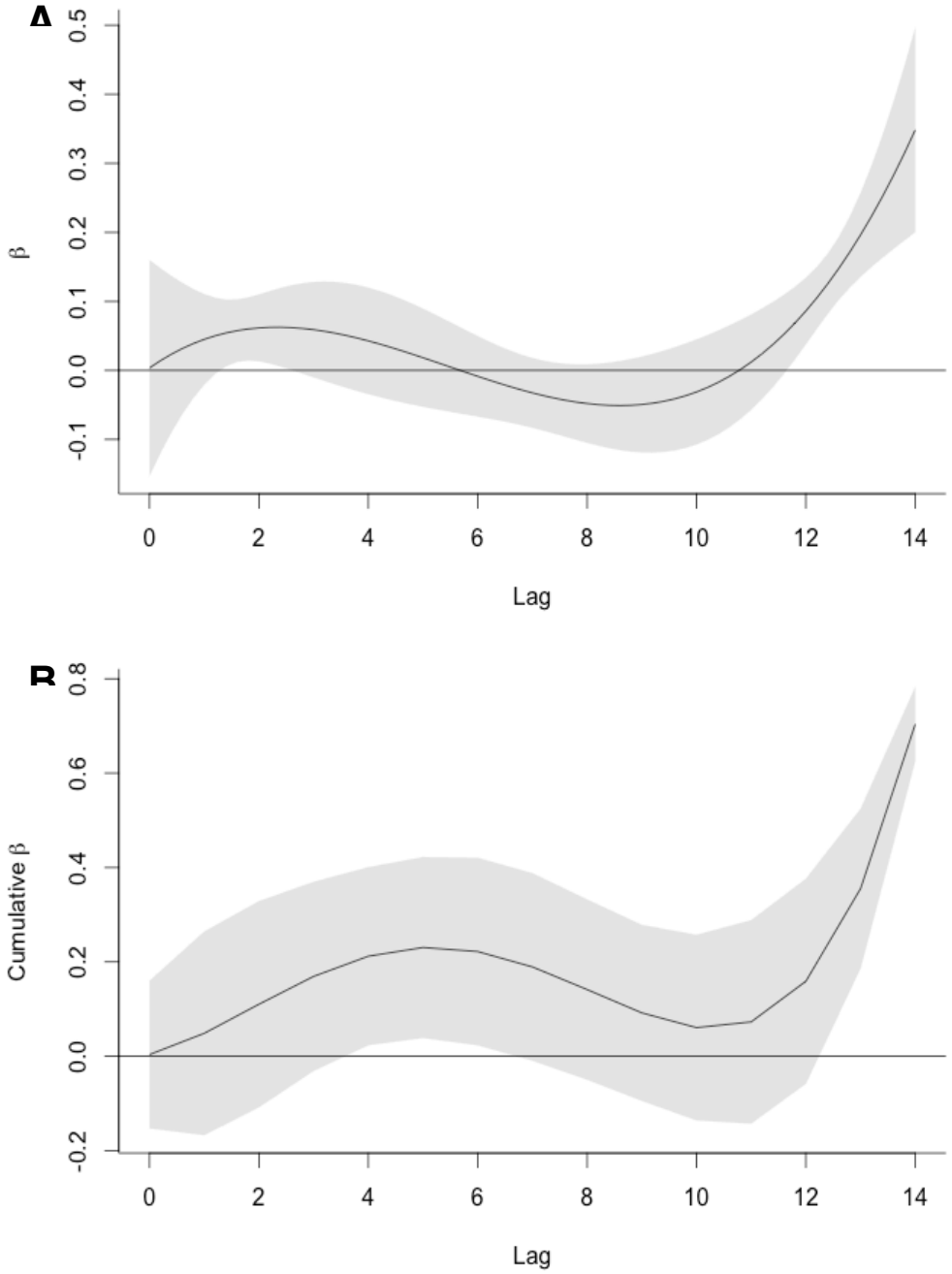


Figure 6a shows the changes in Perry's endorsement share associated with a one-unit increase in his prediction market share price. We see that, for every one-unit increase in his share price, there is a 1.5-unit increase in his endorsement share on the day that change occurred. That positive association is mitigated over time, and by the end of the lag interval, changes in Perry's share price are negatively associated with changes in his endorsement share. Figure 6b shows the cumulated effects of a one-unit increase in Perry's share price; the cumulative association after a period of fourteen days is in fact strongly positive and indicates that the initial one-unit increase is associated with a nearly 1.6-unit increase in endorsement share after fourteen days.

Figure 6. The estimated lag distribution for a one-unit increase in Perry's prediction market share price over a lag period of fourteen days. (a) The lag-response curve. (b) The lag-response curve of cumulative effects.

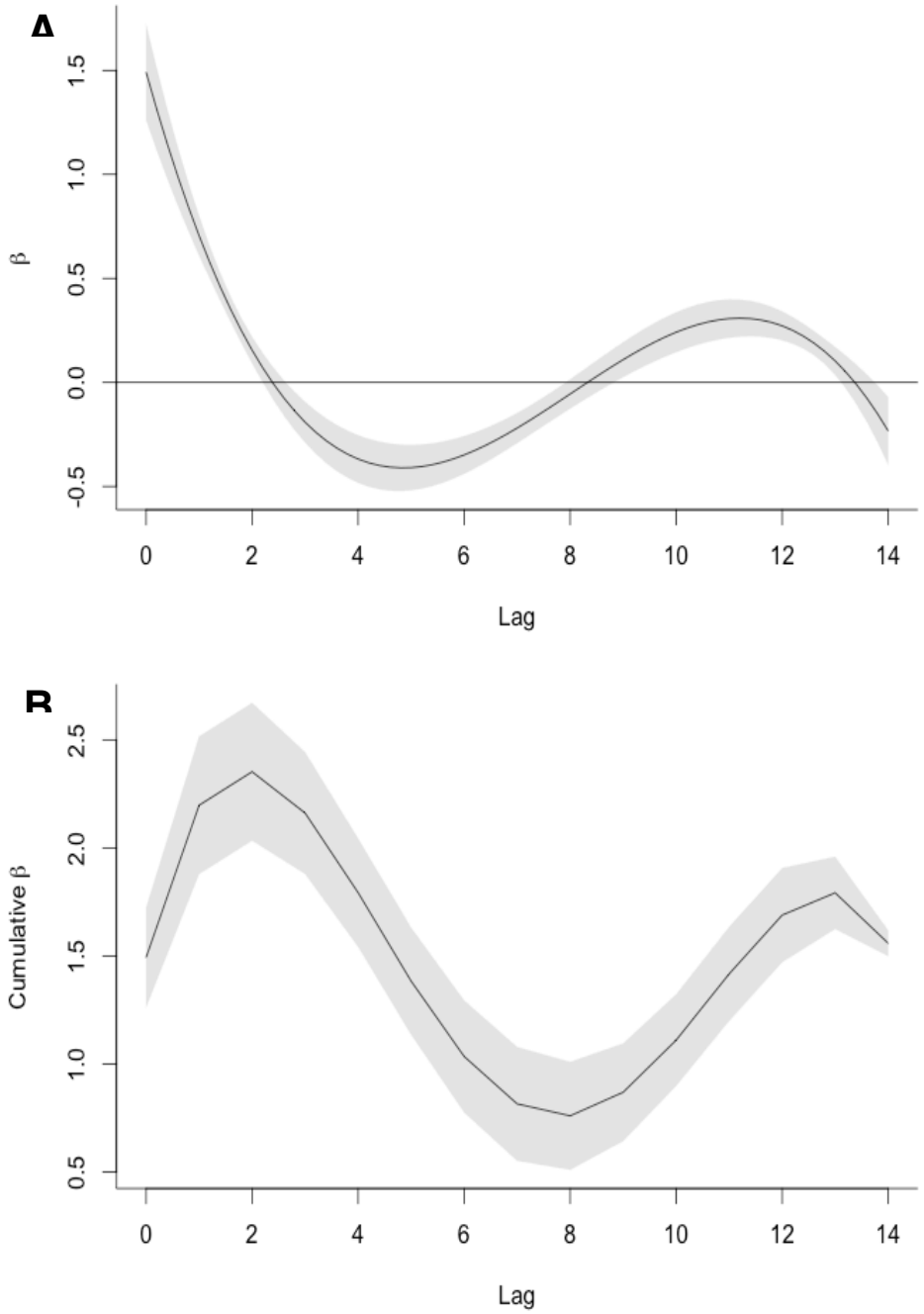
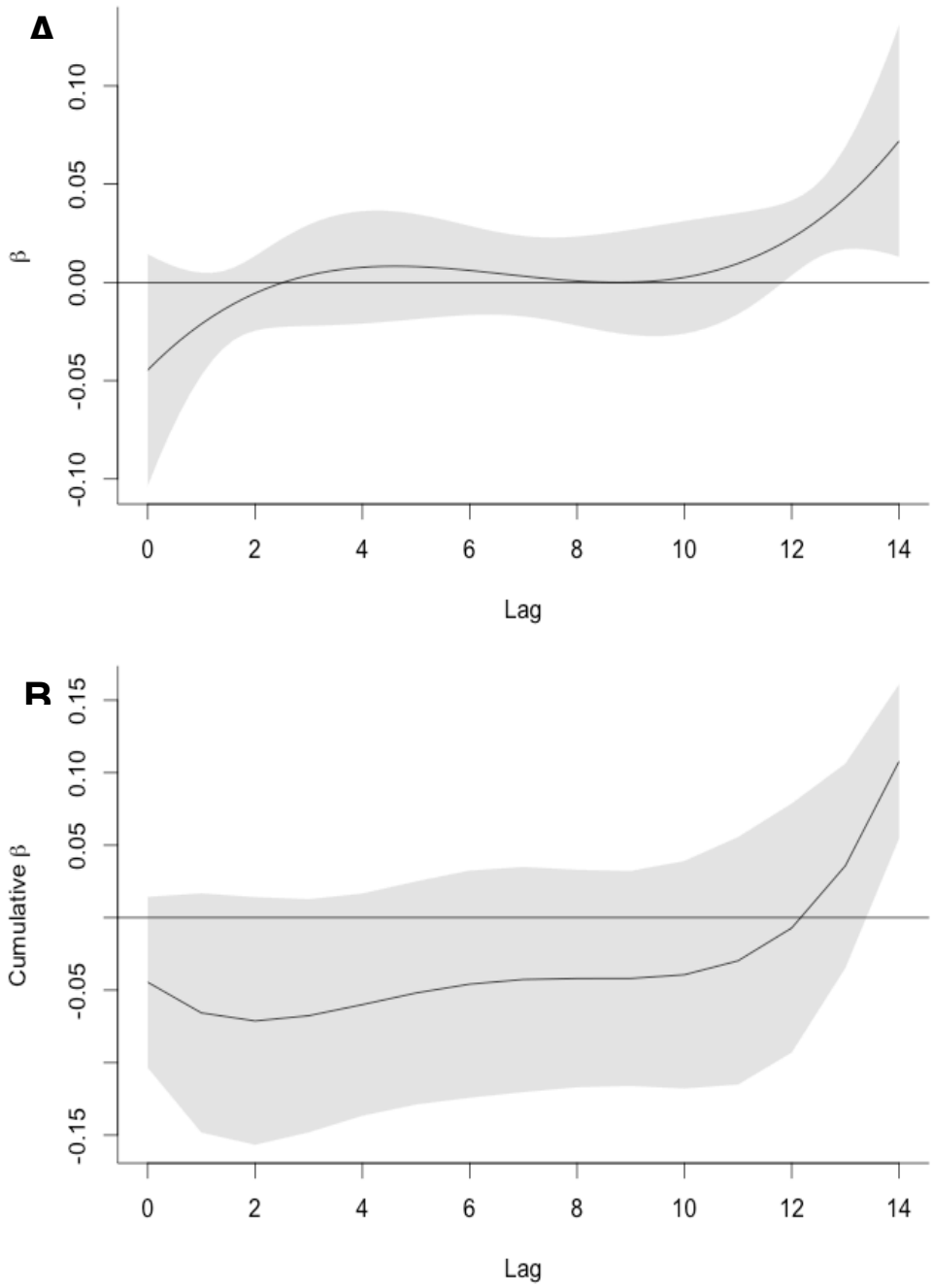


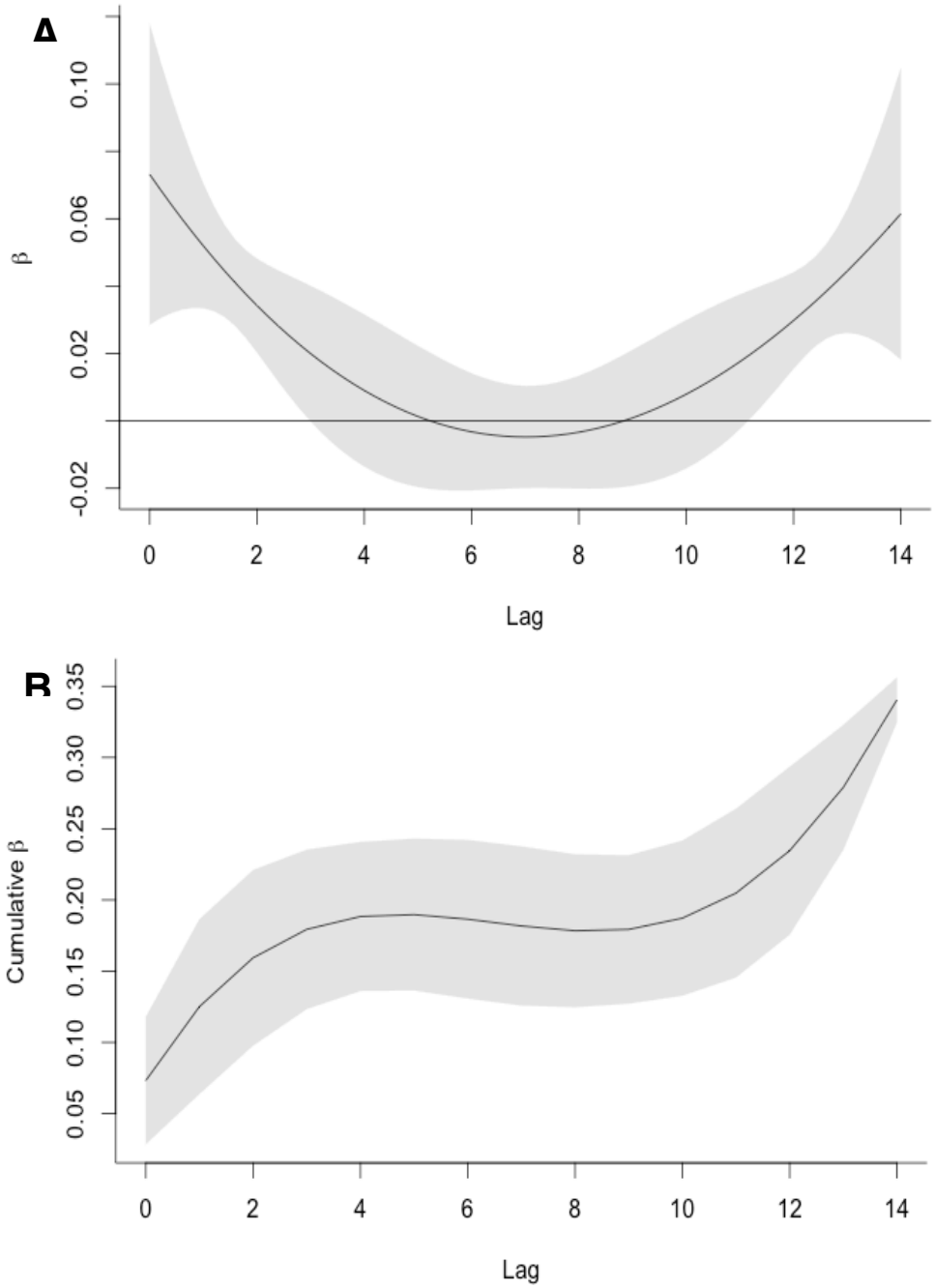
Figure 7a shows that a one-unit increase in Gingrich's prediction market share price is initially associated with miniscule decrease in his endorsement share. However, that slightly negative association remains near zero over the course of ten days. After a lag of ten days, that same one-unit increase in prediction market share price is associated with fractional increase in endorsement share. Those mild effects are reflected in Figure 7b – though the cumulative effects of Gingrich's initial increase in share price hover near zero for most of the lag period, the positive correlation seen after a lag of ten days results in a fractionally positive cumulative effect on endorsement share.

Figure 7. The estimated lag distribution for a one-unit increase in Gingrich's prediction market share price over a lag period of fourteen days. (a) The lag-response curve. (b) The lag-response curve of cumulative effects.



The association shown in Figure 8a between Clinton's endorsement share and share price strongly resembles a second degree polynomial. For Clinton, a one-unit increase in her prediction market share price is initially associated with a close to a 0.1-unit increase in her endorsement share, yet the initially positive association declines to near zero by a lag of seven days. After a period of seven days, her increase in prediction market share price is again associated with an increase in her endorsement share. The cumulative effects of a one-unit increase in Clinton's share price increase over time, with the sharpest increase starting after a lag of ten days. After a lag interval of fourteen days, a one-unit increase in Clinton's prediction market share price is associated with a 0.340-unit increase in her endorsement share.

Figure 8. The estimated lag distribution for a one-unit increase in Clinton's prediction market share price over a lag period of fourteen days. (a) The lag-response curve. (b) The lag-response curve of cumulative effects.



The association between Obama's endorsement share and his share price shown in Figure 9a is similar to that of Clinton. For a one-unit increase in Obama's prediction market share price, there is a 0.1-unit increase in his endorsement share on that same day. As it did for Clinton, that associate declines to slightly less than zero through a lag of six days but then increases again over the lag interval. Thus after a lag of fourteen days, a one-unit increase in Obama's prediction market share price is associated with a roughly 0.05-unit increase in his endorsement share. Figure 9b shows the cumulated effects of a one-unit increase in Obama's share price; the cumulated effects increase over time, and after fourteen days, that initial increase in share price is associated with an approximately 0.40-unit increase in his endorsement share.

Figure 9. The estimated lag distribution for a one-unit increase in Obama's prediction market share price over a lag period of fourteen days. (a) The lag-response curve. (b) The lag-response curve of cumulative effects.

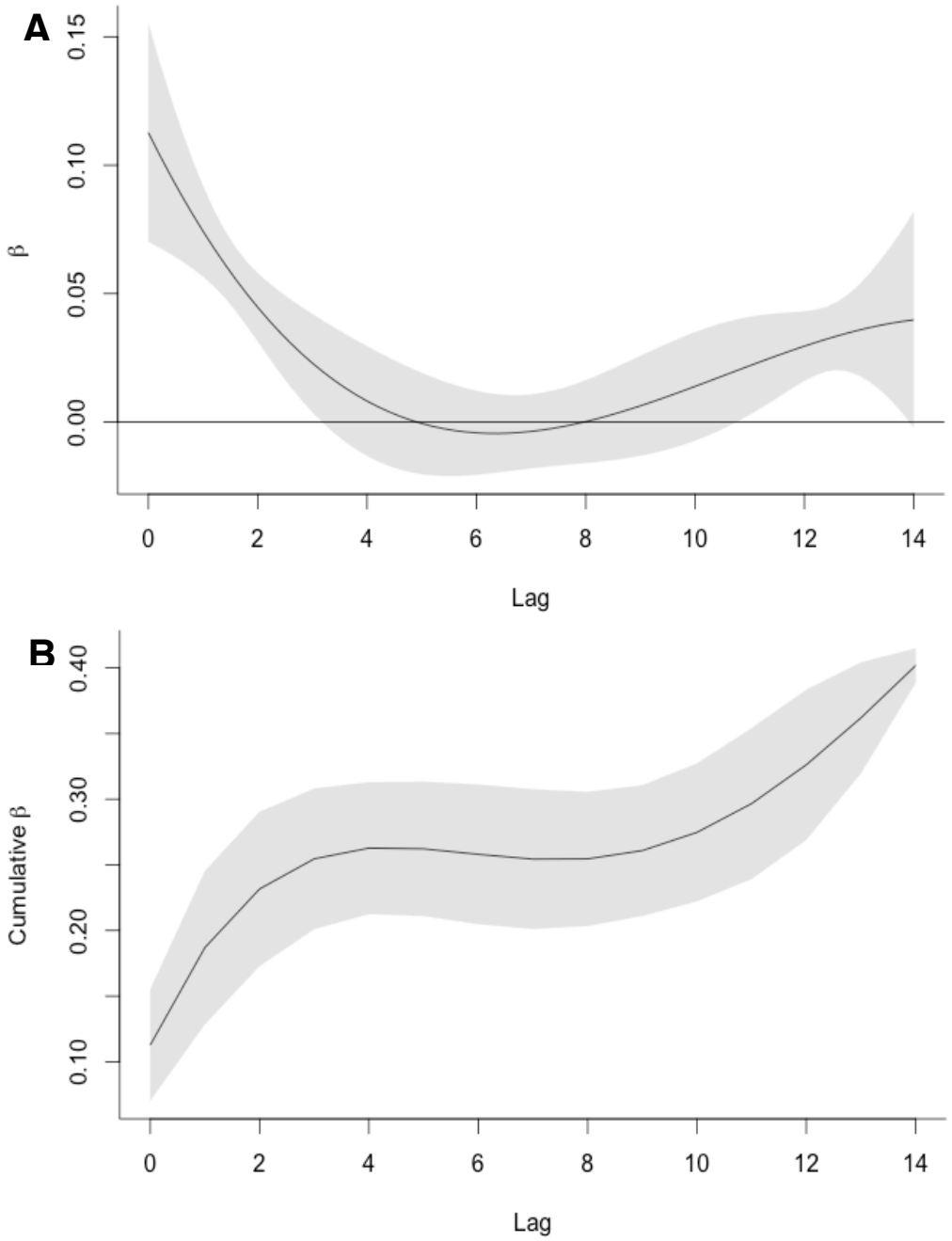
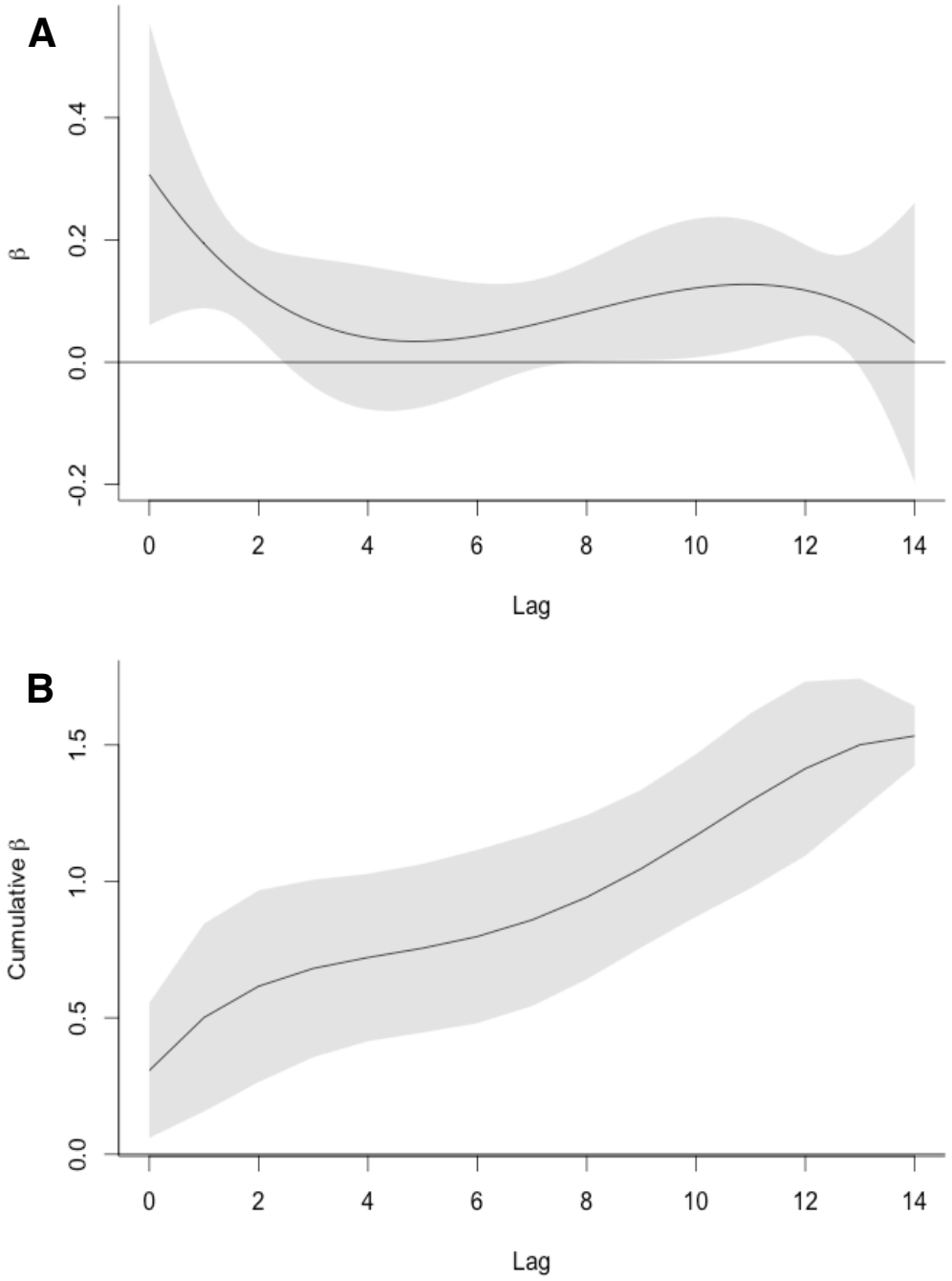


Figure 10a shows the effects of a one-unit increase in Edwards' prediction market share price over a period of fourteen days. That increase is initially associated with a roughly 0.3-unit increase in Edwards' endorsement share, but the correlation declines to near zero by a lag of five days. The correlation is again positive between a lag of seven and eleven days, but at the end of the lag period, the association between share price and endorsement share declines. Despite that ultimate decline, the cumulative effects of a one-unit increase in Edwards' share price increase fairly steadily over time. After an interval of fourteen days, a one-unit increase in Edwards' prediction market share price is associated with 1.5-unit increase in his endorsement share.

Figure 10. The estimated lag distribution for a one-unit increase in Edwards' prediction market share price over a lag period of fourteen days. (a) The lag-response curve. (b) The lag-response curve of cumulative effects.



DISCUSSION

I used distributed lag models regressing candidates' endorsement shares on their prediction market share prices to evaluate the hypothesis that politicians selectively offer endorsements in the wake of perceived increases in a candidate's probability of success. In examining candidates from the 2012 Republican Presidential primaries and the 2008 Democratic Presidential primaries, I found that there was not a uniform pattern in the correlation between prediction market share price and endorsement share. That being said, in most instances, the positive association between endorsement share and prediction market share prices increased (albeit irregularly) over time. The candidates also showed significant variability in their lag distributions. These highly variable effects are likely reflective of the candidates' varying levels of success.[14]

Broadly speaking, the distribution of coefficients over time suggests that the effect of individual campaign events is dispersed over time. Furthermore, the increasing trend in cumulative coefficients suggests that the effects of changes in a candidate's probability of success are themselves cumulative; this seems to accord with theory. With regard to specific candidates, Perry and Edwards showed the strongest cumulative effect of share price on endorsement share. Both did have similar campaigns insofar as they began with a large number of endorsements but then quickly lost ground to other candidates. This suggests that their early probabilities of success successfully netted

[14] For example, Perry dropped out of the race early on, but he received a large number of endorsements. Gingrich enjoyed some success after winning the South Carolina primary, but he quickly lost steam as well; his momentary burst of popularity might explain the small magnitude of the effect on his endorsement share.

them a substantial number of endorsements. However, it would also seem to suggest that, when candidates are trailing, politicians require more evidence of that candidate's viability before offering their endorsement. This is corroborated the barely positive correlation between Gingrich's endorsement share and his prediction market share price; though he won the South Carolina primary, it seems that the corresponding increases in Gingrich's probability of success did not prompt a large number of endorsements.

Obama and Clinton showed similar relationships between prediction market share prices and endorsement shares, likely because they were locked in a very close race. That being said, given the structure of the Democratic National Convention—governors, senators, and representatives have meaningful votes as superdelegates—it was surprising to see that the magnitude of the correlation between prediction market share prices and endorsement share was not larger for Democrats. Despite the ramifications of political endorsements for Democratic candidates, neither the Obama nor the Clinton campaign offered support for the original hypothesis. The weak correlation between their endorsement shares and their prediction market share prices suggests that changes in their probability of success did not significantly impact politicians' decisions to endorse.

Romney's share prices were also positively correlated with endorsement share. However, the weak magnitude of that effect suggests that, because his campaign was so successful, politicians were likely to endorse him even in the absence of substantial perceived increases in his probability of success. In other words, the timing of the endorsements he received was not strongly correlated with changes in his probability of success. Taken together, these results suggest that the context of campaign events—the

overall trajectory of the campaign—likely shapes the timing of a politician's decision to endorse to a much larger degree than do momentary changes in a candidate's probability of success. Not surprisingly, politicians seem to be more willing to endorse a candidate with a solid history of success. In short, the weak association between prediction market share share price—the proxy for a candidate's probability of success—and endorsement share does not offer substantial evidence in favor of the hypothesis that politicians offer endorsements in response to perceived increases in a candidate's probability of success.

Notably, the prediction market share prices are unlikely to reflect private information.[15] More clearly, the only processes affecting endorsement share that would not be captured by the markets would be those that are independent of the candidate's probability of success. Additionally, this analysis does not account for the possibility that endorsements diffuse through institutions. More clearly, it seems theoretically plausible that geography (particularly given the structure of primary contests) and institution (such the House of Representatives or the Senate or even Congressional Committees) provide venues through which politicians can influence others' decisions to endorse. Furthermore, this analysis does not account for the presence of bidirectional causality. The prevalence of endorsements suggests they could have a meaningful impact on electoral outcomes, and it seems likely that endorsements impact a candidate's probability of success as approximated by prediction markets.[16]

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[15] Note that this is a violation of the strong form of the efficient market hypothesis (Fama 1970).
[16] One way to determine the direction of (at least predictive) causality is the Granger causality test.

Moreover, if endorsements were offered as a form of political quid pro quo (a politician agrees to endorse a candidate in return for support down the road), then that exchange would be independent of other campaign events. This consideration raises further questions about the endorsement process. If candidates actively solicit endorsements from politicians, then politicians might be less concerned with events demonstrating a campaign's viability. A secondary concern is the timing of endorsements; if campaigns selectively time the release of endorsements, then a clear temporal association would not be evident. Perhaps candidates release endorsements when they are confident in their position. Alternately, politicians might be more likely to offer their endorsement on days on which the candidate has exhibited some other success, or candidates might want news of an endorsement to mask other campaign events. [17] This suggests that the timing of endorsements can then be independent of the decision to endorse.

Another consideration centers on the variables themselves; it is possible that the prediction markets do not conform to the efficient market hypothesis. Fama developed his hypothesis to explain the behavior of financial markets, which are obviously different in structure and function from political prediction markets. A more significant concern is the compositional nature of prediction market data. The efficient market hypothesis states that prices only shift in response to new information, but, within the prediction market, individual candidates' share prices are constrained by those of the other

[17] Consider a situation in which a candidate solicits an endorsement from a politician but only releases news of that endorsement after information about a scandal breaks.

candidates. For example, new information about Romney's campaign might not only result in an increase in his share price but also a corresponding decrease in other candidates' share prices. On the other hand, while prediction market share prices are touted as offering a daily, unbiased estimate of a candidate's probability of success, they do not represent voter preferences. More clearly, an investigation into the impact of endorsements must consider how individual voters perceive endorsements, and this requires individual-level data. Though obviously aggregate-level data, poll results can provide valuable information about voter opinions. Additionally, it is important to note that endorsements can also be modeled as counts. Finally, any interpretation of the distributed lag models must take into account the atheoretical aspects of model formation and the dangers they pose in creating statistical artifacts. Though our concern here was not forecasting, Freidman's famous claim that "the only relevant test of the validity of a hypothesis is comparison of its predictions with experience" still holds true (Friedman 1953: pg. 7).

CONCLUSION

To test whether politicians selectively offered endorsements to candidates in response to increases in their likelihood of success, I used a distributed lag model to represent the protracted relationship between endorsements and a candidate's prediction market share prices in both the 2012 Republican presidential primaries and the 2008 Democratic presidential primaries. I found that the cumulative association between endorsement share and prediction market share price after an interval of fourteen days was, for most candidates, weakly positive, suggesting that changes in a candidate's likelihood of success do not constitute a meaningful part of a politician's decision to endorse. Future studies should consider specific factors that might influence endorsements and whether the effect of endorsements on electoral outcomes is moderated by other factors. For example, endorsements might allow a candidate to raise more funds and only affect electoral outcomes through fundraising. Additionally, the depth and breadth of media coverage of a particular endorsement might mediate the effect of endorsements on electoral outcomes. The effect of past endorsements on future endorsements also must be taken into consideration. Furthermore, though prediction markets offer a valuable estimate of a candidate's probability of success on a given day, they do not accurately represent individual voters' perceptions of endorsements. To accurately assess the mechanism through which endorsements influence electoral outcomes, a dependent variable that captures voters' responses is necessary. Though polling data is often cited as providing voters with information about a candidate's

viability, it also contains aggregate-level information about voters' perceptions of a candidate (Bartels 1985).

The momentary effects of campaign events suggests that, though campaign events may not be significant when considered in aggregate, they can indeed affect the course of a campaign cycle. This is especially significant because the broad consensus among political scientists seems to be that campaigns have little impact on elections, particularly at the national level (Finkel 1993; Holbrook 1994; Gelman and King 1993). Scholars have suggested that campaign effects cancel out when opposing candidates have roughly similar levels of spending. However, this research often measures campaign effects in the aggregate. Stated another way, if campaigns do not influence election outcomes, then momentary campaign events—such as endorsements—should not impact a candidate's popularity. While these events might cancel out over the course of a long campaign, in the short term, campaign events might demonstrably impact the candidate's probability of success at that point in time. More clearly, it is plausible to think that campaign effects might be significant in the short term and thus subtly influence electoral outcomes through momentary shifts in a candidate's popularity. In short, momentary campaign events can have lasting effects on a candidate's probability of success, and a more fine-grained analysis of the impact of campaign events could shed light on the factors driving a candidate's electoral success.

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