Surprise Me if You Can: The Influence of Newspaper Endorsements in US Presidential Elections*

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Abstract

We here evaluate the heterogeneous effects of newspaper endorsements of US Presidential candidates in the 100 days preceding the 2008 and 2012 elections on the probability that they win the election. Our identification strategy relies on daily variations in the winning probabilities (obtained from the *Intrade* prediction market) and the fact that newspapers decide their endorsements weeks before their announcement. Endorsements that are classified as surprising and consistent have the largest effect. An endorsement is surprising when the newspaper has not traditionally endorsed the candidate's party (Ansolabehere et al. (2006)). An endorsement is inconsistent when the newspaper leans ideologically to one party (Gentzkow and Shapiro (2005)) but endorses a candidate from another party.

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1 Introduction

Most American newspapers traditionally, explicitly endorse one presidential candidate per electoral cycle, in a printed *editorial page* stating the case for their support. Whether such endorsements affect electoral outcomes is still open to debate, and not simple to pin down empirically. The main difficulty is to distinguish unobserved common factors, which are correlated with both endorsements and the winning probability, from any causal effect of endorsements. A cross-election finding that candidates with more endorsements also obtain more votes does not prove that the former caused the latter. This may instead simply reveal that some candidates are better than others. Even if we consider the same candidates in multiple elections, inference remains problematic if perceived candidate quality changes across elections (see Druckman and Parkin (2008)).

We here address this difficulty and quantify the causal effect of newspaper endorsements on election outcomes using a novel daily measure of the winning probability and exploiting the timing of endorsements, which are decided weeks before they are printed (Meltzer (2007)) . The existing literature (Chiang and Knight (2011), Puglisi and Snyder (2015)) suggests a larger effect from endorsements that are unexpected. We split the latter into two groups, using well-known measures of media bias to show that not all unexpected endorsements affect winning probabilities.

Although endorsements mostly mirror the political stance of the corresponding newspapers, and are therefore expected, unexpected endorsements may come as (i) a `surprise`, when a newspaper traditionally endorsing one Party goes for another Party; equally, they may appear as (ii) `inconsistent`, when they are at odds with the newspaper's typical discourse (political language). The measure of the (historical) "propensity to endorse democrat candidates" in Ansolabehere et al. (2006) is used to define surprise endorsements, while we appeal to the measure of "media slant" in Gentzkow and Shapiro (2005) to capture inconsistent endorsements. For instance, while the *Chicago Tribune* historically endorses Republican candidates, the newspaper's content is **relatively** appealing to Democratic voters. Its endorsement of Barack Obama would thus be classified as a consistent surprise endorsement. These two correlated but separate measures, used

in both the economics and political science literatures, allow us to distinguish between types of unexpected endorsements and their effects (see Table 1 for a summary of this classification; we will detail how we classify newspapers endorsements as being a surprise or inconsistent endorsement in Section 2.2).

Our key variables come from the daily trading prices of the contract "Obama to win the election" from the prediction market site Intrade, combined with newspaper endorsement dates from "The American Presidency Project". We cover the 2008 and 2012 presidential elections. Our identification strategy relies on the daily variation in both endorsements and the winning probability. Our analysis is thus *within election*, so that we control for unobserved candidate characteristics. In addition, the fact that endorsements are typically decided weeks before their public disclosure (Meltzer (2007)) allows us to separately determine the effects of endorsements and candidates' attributes, and eliminate concerns regarding reverse causality. We further show that there is considerable stability over time in the timing of announcements: most newspapers announce their endorsements at the same point in the electoral campaign across elections.

Were the likelihood of a candidate winning the election and receiving an endorsement to be jointly determined by the candidate's unobserved quality, any information on the candidates or from the campaign that was used to decide the endorsement would already be reflected in the closing price of the previous day.[1] Therefore, newspaper endorsements are orthogonal to the prediction market *daily prices*, absent any endorsement effect.

Our empirical strategy consists in estimating the causal relationship between endorsements and the winning probability, following a simple model of probabilistic voting with horizontal and vertical differentiation (Banks and Duggan (2005)). Nevertheless, we abstain from the mechanism behind the endorsement effects: independently of whether they are informative signals of a candidate's type, or extra publicity for a candidate, we consider them chiefly as vertical differentiation.[2]

[1] Leigh and Wolfers (2006) produce convincing evidence that prediction markets are efficient

[2] For instance, event studies in the finance literature also highlight the type and tone of news content as a mechanism affecting trading prices, beyond any dichotomous type of information (for an example, see Boudoukh et al. (2012)).

We find heterogeneous average endorsement effects[3] that depend on the endorsed party, the circulation of the newspaper, and our classification of unexpected endorsements - surprise and inconsistent. The average Republican endorsement[4] effect does not depend on newspaper circulation, while the Democrat endorsement effect is only significant for high-circulation newspapers.

One of our most novel results relates to the effect of endorsements that are unexpected: inconsistent endorsements have no effect in any of our specifications. On the contrary, we show that surprise endorsements do affect both parties' winning probabilities. This differentiation between consistent and surprise endorsements helps to further clarify the informational role of "unexpected" endorsements, which is widespread in the literature (Chan and Suen (2008); Chiang and Knight (2011)).

Electoral endorsements, and media bias in general, can be split into demand-driven (determined by market factors) and supply-driven (decided mostly by the preferences of the owner or Editorial Board) elements. Work considering the effect of endorsements on voting behavior and electoral outcomes (including the current paper) usually consider the latter (Garthwaite and Moore (2012), Chiang and Knight (2011), Ladd and Lenz (2009), Druckman and Parkin (2008) and, to some extent, Chan and Suen (2008)). Our results are generally consistent with this literature ; however, our work is different in two fundamental ways. First, we use prediction markets rather than individual voter surveys to estimate the effects. Prediction markets have the advantage of aggregating more information, and are not susceptible to response bias and other survey problems (see, for example, Leigh and Wolfers (2006) for a comparison between polls and prediction-market data). Second, we take a step further in the classification of unexpected endorsements, and distinguish between inconsistent and surprise support. We do indeed find that not all unexpected endorsements have the same impact.

In the remainder of the paper we first set out a simple model that aggregates voter individual utilities into an equation that can be applied to the data. We then describe

[3]Our data cover endorsements from the top 100 newspapers in the U.S.

[4]We use the terms Republican and *GOP* (a commonly-used acronym for the party's nickname: "Grand Old Party") interchangeably.

the data that we use, and discuss our empirical strategy. Finally, we present the main results and robustness checks, and then conclude.

2 Estimation Strategy

Our baseline estimation model of the effect of endorsements on the probability of winning an election comes from a standard model of voting with vertical differentiation (see for examplee Groseclose (2001)). From individual behavior, we derive the expected share of the Democratic Party for each of the 100 days (t) before the election, $S_{dem,t}$, and the probability that the Democratic Party wins at time t, i.e. $\Pr_{dem,t} \equiv \Pr_t(S_{dem,t} > S_{gop,t})$. We then estimate our model using Intrade data for the winning probability.

2.1 The empirical model

There is a continuum of voters in this economy who have preferences over the parties and their candidates. There are two Parties, the Democratic and Republican Party, indexed by $p \in \{dem, gop\}$, with one candidate each. Voter utility has both horizontal and vertical components. While the former depends on the parties' ideological distance to the voters' ideal policies, the latter depends on the quality of the political candidates - or valence - an attribute that is positively appreciated by all voters, independently of their individual preferences.[5]

Let $x_p \in \mathbb{R}$ be the parties' political platforms (observed by everybody), and $x_i \in \mathbb{R}$ the voters' ideological position in the same policy space. The interim utility of voter i who would vote for party p at time t, can be written as

$$u_{i,p,t} = -d_t(x_i, x_p) + q_{p,t}.$$

The horizontal and vertical differentiation components of utility contain information unobserved by the econometrician (i.e. ideologies and voters' perception of quality) that

[5]Valence is a term that comes from the political science literature (Stokes (1963)) and refers to characteristics that are not only orthogonal to ideology, but also equally-valued by all voters. In economics, this would be similar to vertical differentiation.

we model as random variables. We moreover assume that endorsements provide information about the vertical dimension (i.e. quality), which we model as

$$q_{p,t} = \alpha_p I_{p,t-1} + \beta_p Endors_{p,t} + \tilde{\eta}_{p,t}, \tag{1}$$

where $I_{p,t-1}$ is all information available up to the previous period, $Endors_{p,t}$ are the current period's endorsements, and $\tilde{\eta}_{p,t}$ is new information about the candidate that is unobservable to the econometrician, which is also modeled as an independent random variable.

As individual i will vote for p at time t if $u_{i,p,t} > u_{i,p',t}$, we can derive the probability that i votes for p at t (see Banks and Duggan (2005)). Integrating this probability over voters' ideologies, we obtain the expected share of each party, and integrating over the random component in the vertical dimension yields the winning probability of each party at t: $Pr_{dem,t}$ and $Pr_{dem,t}$.[6]

After some manipulation, the ratio of probabilities $\frac{Pr_{dem,t}}{Pr_{gop,t}}$ can be written as a function of the endorsements for each party at time t, and all the information available up to t:

$$\ln\left(\frac{\Pr_{dem,t}}{\Pr_{gop,t}}\right) = \beta_{dem} Endors_{dem,t} - \beta_{gop} Endors_{gop,t} + \alpha_{dem} I_{dem,t-1} - \alpha_{gop} I_{gop,t-1}. \tag{2}$$

We assume that there is an unobserved noise term, ϵ_t, which may affect the Intrade quotes but is not necessarily related to the voting model.[7] Also, assuming efficient markets allows us to use the quotes from the previous period to capture all information on candidate quality up to $t-1$, ie. $\alpha Pr_{dem,t-1} = \alpha_{dem} I_{dem,t-1} - \alpha_{gop} I_{gop,t-1}$. We can thus estimate equation (2) linearly:

$$\ln\left(\frac{\Pr_{dem,t}}{\Pr_{gop,t}}\right) = \beta_{dem} Endors_{dem,t} - \beta_{gop} Endors_{gop,t} + \alpha Pr_{dem,t-1} + \epsilon_t. \tag{3}$$

[6]See the Appendix for the full model. We assume that both random variables are distributed with Type-I extreme-value distributions, which allows us to obtain closed-form solutions, as is standard in multinomial logit models (Nevo (2000)).

[7]As is often argued, there could be movements in the intrade quotes that are unrelated to voter ideologies, party platforms, or candidate quality, such as traders with "fat fingers".

The above specification can also be adapted to include not only the number of Democrat and Republican endorsements but also newspaper characteristics such as circulation and ideological bias (surprise and consistency). [8]

We thus interpret endorsements as providing voters with information about the vertical differentiation between candidates. An extension of the model could allow for the effect of endorsements to depend on whether voter i reads the endorsing newspaper; however, the main qualitative (and aggregate) predictions of the model would not be substantially affected. The main intuition here is that, even if voters assign a greater weight to their preferred newspaper, they can still learn from the newspapers that they do not read, especially if the endorsements are unexpected or come from high-circulation newspapers.

The updating of voter intentions after unexpected endorsements can be modelled as follows: a consistent endorsement, but which goes against the historical tradition of the newspaper, provides voters with useful information and will increase the winning probability of the endorsed candidate. On the other hand, inconsistent or unsurprising endorsements may not yield additional information about candidate quality, and may thus not affect winning probabilities.[9]

2.2 Data and discussion of the main variables

Our information on the endorsements of the top-100 circulation newspapers for the US Presidential elections comes from "The American Presidency Project". The pricing of future contracts in the 100 days before the 2008 and 2012 election day is retrieved from the "Intrade" prediction-market website.[10]

[8] Alternatively, we also estimate a linear version of this equation so that the coefficients represent the change in the probability of winning. The results are similar in both significance and size. The alternative model is:

$$\frac{\Pr_{dem,t} - \Pr_{dem,t-1}}{\Pr_{dem,t-1}} = \beta_{dem} Endors_{dem,t} - \beta_{gop} Endors_{gop,t} + \epsilon_t \tag{4}$$

[9] Inconsistent endorsements may even confuse voters, and thus be treated as uninformative.

[10] The data from "The American Presidency Project" can be downloaded at http://www.presidency.ucsb.edu/, while the prediction markets data was available at http://www.intrade.com, which is closed now.

As all endorsements in our dataset appear in the 100 days before the election, we focus on this period for both elections. In addition, the volume of trade in future contracts is almost zero until the end of August, when the Democratic and Republican Conventions traditionally take place (see Figure 1). Each observation in our data refers to one day, and our main dependent variable is the log of the odds ratio $\Pr_{dem,t} / \Pr_{gop,t}$, which captures the perceived relative probability of Obama winning.

Prediction Markets. Intrade offers winner-take-all contracts linked to the victory of the two candidates. The price per share of these contracts lies between 0 and \$10, and transactions occur when bid and ask orders meet, at a price that reflects the average probability of each candidate's victory as estimated by market participants (e.g. a price of \$5.25 is interpreted as a 52.5% probability of Obama winning). These binary options pay \$10 if the chosen candidate wins, and 0 otherwise. Hence, an investor buying a "Obama to be (re-)elected" future at \$7 will earn a net payoff of \$3 if Obama is elected.

The use of prediction-market data as winning probabilities is not new in the political economics literature: Mattozzi (2008) exploits such data to reveal the existence of stock portfolios that may be used as hedging in political markets, and Malhotra and Snowberg (2009) consider the effect of the US 2008 primary elections and caucuses on candidates' winning probabilities, measured via the Intrade futures price. Prediction-market data is theoretically motivated in Mattozzi (2010), Musto and Yilmaz (2003) and partly Manski (2006), while its empirical validity was demonstrated in Forsythe et al. (1992); Rothschild (2010); Wolfers and Zitzewitz (2004); Saxon (2010); Chen et al. (2008).[11]

These Intrade stock prices, linked to the victory of each candidate, would then appear to be an accurate reflection of their underlying probability of victory.

[11] Forsythe et al. (1992), confirm the external validity of their results on prediction-market data via a survey of participants in the prediction market. Although they find judgement biases in the trading behavior of market participants, they show that this bias is driven by average traders, while the "marginal traders" (those who determine the prices in their dataset) do not exhibit the same behavior. In our case, this means that even though some traders may buy/sell contracts because they think that endorsements affect the probability of winning, the marginal traders would find arbitrage possibilities and close the gap produced by those average traders.

Endorsements. Traditionally, most newspapers make one explicit endorsement per electoral cycle in an *editorial page* where they state their reasons for supporting one particular candidate. This page is clearly separated from the news content of the newspaper and is usually not signed, as it is decided by the *Editorial Board*. These editorial endorsements are typically presented along with some of the candidate's achievements, and the reasons why he/she is the most suitable candidate for the office. Although endorsements are not mandatory, in the 2008 US elections 90 out the top 100 newspapers endorsed a presidential candidate (and 76 did so in 2012) (see Table 3).[12]

These editorial decisions may be taken to match readers' preferences or, on the contrary, to influence their support for the newspapers' candidate; as such, the literature on the effects of newspapers on elections can be split into the demand and supply sides. In the former, endorsements "match" readers' expectations by choosing their preferred candidate; this branch of the literature is also referred as the "profit-maximizing" view of media outlets (for instance, de Leon (2010) considers how media-market structure determines endorsements). In the latter, which is where our paper is situated, the publisher, owner or journalists (Baron (2006)) in the Editorial Board determine endorsements according to their own preferences (for instance, Garthwaite and Moore (2012) analyse the impact of Oprah Winfrey's endorsement of Obama in 2008, while Chiang and Knight (2011) estimate a model in which voters derive information cues from endorsements).

Unexpected endorsements. As noted above, a newspaper's endorsement may come as a surprise; we here draw on previous measures to show that not all unexpected endorsements are the same. We create two unexpected endorsement variables: one that captures inconsistent endorsements (i.e. ideologically "unexpected"), and another for surprise endorsements ("unexpected" following the newspaper's endorsement history). An endorsement is defined as *inconsistent* when the ideology of the journal, as measured by the measure of media slant in Gentzkow and Shapiro (2005), and that of the candidate differ. This media-slant measure results from comparing the language used by

[12]For a more detailed account of the wide range of mechanisms to endorse candidates, see Meltzer (2007).

newspapers to that used by congressmen from each party (from congressional records). A higher value is associated with more Republican content, in terms of language used.[13] This information, combined with the endorsement, is used to classify an endorsement as (in)consistent.

A surprise endorsement, on the other hand, occurs when issued by a newspaper which traditionally endorses the opposing Party. We replicate Ansolabehere et al. (2006) to obtain a measure of the historical propensity to endorse the Democratic candidate, based on data on newspaper endorsements going back to 1940.[14] A newspaper endorsement which deviates from this historical trend is considered as a surprise.

Both of our media-slant and propensity-to-endorse-Democrats variables are normalized to lie between 0 and 1. We then divide newspapers into four quartiles for slant and propensity. Table 5 presents the endorsement behavior of all newspapers, as a function of the slant and propensity quartiles. The greater their slant, the more likely the newspapers are to endorse the Republican candidate. In particular, the first three slant quartiles are more aligned with the Democratic Party, while the fourth is Republican. A Republican endorsement coming from a newspaper in the first three quartiles will be classified as inconsistent. This applies to Democratic endorsements from a newspaper in the 4th slant quartile. With respect to the propensity measure, the endorsement pattern across quartiles is straightforward: the greater the propensity to endorse Democrats, the more Democrat endorsements we observe (see also Figure 5).

In other words, as shown in Tables 3 and 5, and as noted in Ansolabehere et al. (2006), since 1940s newspapers have developed a tendency to endorse more Democratic than Republican candidates. This historical trend in media markets appears to be even stronger today for high-circulation newspapers, so that there are very few large newspapers that endorse Republican candidates.

These classifications allow for a more subtle interpretation of unexpected endorse-

[13]This index of media slant follows the tradition of "content analysis" and has been widely used in the literature, for instance in Gentzkow and Shapiro (2010).

[14]In short, the measure is the newspaper's estimated coefficient from a regression of endorsements (Democrat, Republican, or no endorsement) on the electoral race, period, incumbency and other variables. We replicate their analysis in order to obtain the coefficients for each newspaper in our set (Ansolabehere et al. (2006) only display the coefficients corresponding to a dozen newspapers).

ments: for instance, a Republican newspaper (i.e. using a language more inclined toward the Republican Party) that endorses a Democrat candidate, although unexpected, may be interpreted as contradictory, with no subsequent positive impact on the Democrat's probability of winning. However, it may still be the case that unexpected (but consistent) endorsements that break a newspaper's historical tradition come as a surprise to voters, and impact the electoral outcome.

2.3 Identification

Our identification strategy relies on the fact that newspapers do not decide their endorsements or the timing of their publication on the basis of the daily probability of winning. That is, the main identifying assumption is that endorsements are orthogonal to any other shocks received by the candidate on the same day. In terms of our model above, this is equivalent to saying in equation 1 that $\tilde{\eta}_{p,t} \perp Endors_{p,t}$, for all p and t.[15]

This assumption will be violated if newspapers choose either i) the candidate endorsed or ii) the timing of the endorsement based on campaign news from the day that their endorsement becomes public. Although we have no direct way of testing this assumption, neither of these two would seem to be a concern in our setting, especially given that our data exhibits *daily* variation in the predicted outcomes for each election.

First of all, we can exploit the editorial process to isolate the effect of endorsements on the winning probabilities. Editorial Boards decide on endorsements several weeks before their public announcement (Meltzer (2007)); newspapers' endorsements are thus exogenous to trading prices or other events the day of the announcement. Second, it could be argued that once a newspaper has decided which candidate to endorse, the timing of the announcement may be manipulated strategically. However, in our setting this is not the case; on the contrary, the timing of endorsement announcements varies little across elections.

Table 2 shows that 28% of newspapers announced their 2012 endorsements the same number of days before the election as for the 2008 election. Moreover, 59% make this

[15] We also show that there is no serial correlation in the residuals: see Figure 4.

announcement within a window of one week.[16] It should furthermore be taken into account that endorsements appear in the printed first edition of the newspapers (known as the bulldog edition in the U.S.), which is typically sent to press in the evening or at midnight of the previous day. Were a given newspaper to choose its endorsement day based on campaign events, the newspaper would have to have private information on the campaign news that will take place the next day and base its decisions on that private information for this to affect our results. With fast-spreading news due to social media and internet, this is not only unlikely, but may also lead our coefficients to be under-estimated, if newspapers act strategically.[17]

Last, events may take place the same day as the endorsement which, without affecting our identification strategy, may contaminate our regressions. In particular, few events during the electoral campaign are supposed to affect candidates' winning probabilities like the official Presidential debates (see, for example, Holbrook (1996)). During both of the campaigns analyzed here, the two candidates agreed to face each other three times, while their potential vice-presidents debated together once. Figure 2 plots the price of Obama victory contracts over the 100 days preceding the 2008 and 2012 elections, and shows that the price of Obama victory contracts varied in line with the candidates' perceived performance during these debates: the largest changes in Obama's stock in the 2008 and 2012 campaigns took place the day after a Presidential debate: +9.8 percentage points after the second debate in 2008, which Obama "won" according to 54% of those surveyed in a CNN poll (only 30% felt McCain had won); -9.6 points after the first presidential debate in 2012, which he unambiguously "lost" according to CNN polls (67% said Romney had won, against 25% for Obama; this debate was also the most widely-viewed Presidential debate in 32 years). We therefore add controls not only for weekends, months and years, but also for the days following these debates.

[16] Figure 2 shows that the timing of endorsements does not exhibit any strange patterns, within or across elections.

[17] If a given newspaper had such private information on the next day's events, it is likely that it would choose to release this information on days where their favorite candidate receives bad news. This would bias the results in our favor, in the sense that our estimated coefficients would be under-estimates of the true effects.

3 Results

We here discuss the estimates from our baseline specification (equation (3)) for the effect of endorsements. In particular, we not only explore whether endorsements matter, but also which endorsements matter more. In all of our specifications, if the estimated coefficient on Democratic endorsement is positive, it means that a day with at least one Democrat endorsement increases the market's estimated probability that Obama win the election. The impact of endorsements on the Democratic winning probability is given by the following equation

$$P_{dem} = \frac{e^{\beta} OR}{e^{\beta} OR + 1},$$

where β is the coefficient of interest and OR is the "odds ratio" (P_{dem}/P_{gop}). Analogously, a negative estimated coefficient on Republican (or GOP) endorsements implies a positive effect on the Republican candidates' winning probability (McCain in 2008 and Romney in 2012).

Do endorsements matter? Table 7 reveals that endorsements (a dummy for days where there was at least one endorsement) work as expected. In the first two columns, on average, endorsements of the Republican candidate have a moderate effect on the candidates' winning probability: in a tied election a GOP endorsement reduces Obama's probability from 50% to 47%. More interestingly, in columns (5) to (7), we find that the Republican endorsement effect does not depend on newspaper circulation, whereas the Democratic endorsement effect is only significant for high-circulation newspapers. For the Democrats, this effect is largest when the newspaper's circulation is over 400 000: a day with a Democratic endorsement from a large newspaper increases Obama's probability from 50% to 58%. In a less-close election (suppose that he had a 60% of winning) the effect would be smaller (from 60% to 63%). With both a GOP endorsement and a high-circulation DEM endorsement, in a tied election the balance would tip to the Democrats, increasing the Democratic winning probability to 53% approximately. For Republicans the negative effect on Obama's probability of winning does not work via larger-circulation newspapers, as was the case for the Democrats. We will explore this asymmetry further

below when introducing our media bias measures, but from the descriptive statistics in Table 6, we already see that approximately 75% of GOP endorsements come from newspapers with circulation below 200 000, while this is the case for under half of Democratic endorsements. Larger-circulation newspapers then tend to lean toward the Democrats (in these elections).

Which endorsements matter the most? The main result in Tables 8 to 10 is that inconsistent endorsements have no effect, while consistent endorsements and surprise endorsements have large, positive, significant and robust effects. In addition, except for the noted asymmetric effect regarding circulation, the size of the effect of Democratic and Republican endorsements on the winning probability is very similar.

Table 8 uses a coarser classification of newspapers according to their endorsement consistency: consistent Democratic endorsements come from the first three quartiles of the media slant distribution, while consistent Republican endorsements come from newspapers in the fourth quartile.[18] When we split into consistent and inconsistent endorsements, only consistent GOP endorsements have a significant (negative) effect on Obama's winning probability: one consistent Republican endorsement reduces Obama's winning probability from 50% to 41% approximately. In a less-close election, the same effect would reduce the Democratic winning probability from 60% to 47%. The effect of Democratic endorsements is insignificant, although the sign and size of the coefficients are in line with our results in Table 7 across all different specifications. Inconsistent endorsements are never significant, whether using a dummy or the number of endorsements in a day (which we refer to as the *Count* variable).

Our regrouping of consistency quartiles allows us to reduce potential collinearity: as we have 200 observations, and endorsements occur over a relatively short time period, the more covariates we add, the more likely they will share considerable correlation, as endorsements from the individual quartiles may take place on the same days. Neverthe-

[18] We split slant according to the number of DEM and GOP endorsements in each quartile (see Table 5): only the fourth quartile is GOP-leaning (with 24 of the 53 newspapers which endorsed the GOP candidate, and only 13 of the 99 DEM endorsements), which is why a GOP endorsement will be classified as consistent if issued by a newspaper in this particular quartile.

less, the regrouping of the first three quartiles may mask a particular impact of DEM endorsements for one quartile. We thus include all quartiles separately in Table 9. Here there is a significant positive effect of Democratic endorsements from relatively neutral newspapers (in the third quartile of media slant, i.e. the most conservative of the Democratic newspapers), on Obama's odds of winning in all specifications. On the contrary, consistent Republican endorsements reduce this probability. Overall, a consistent Republican endorsement and a neutral Democratic endorsement cancel each other out (their sum is not significantly different from zero).

In both of the models estimated in Tables 8 and 9, we add a specification including high-circulation endorsements (from newspapers with over 400 000 copies) to check that our consistency results are not driven by high circulation (at least for Democrats, for whom only high-circulation endorsements matter in Table 7). Introducing a dummy for days with high-circulation endorsements, or the number of high circulation endorsements per day, changes neither the magnitude nor the significance of our main results. The descriptive statistics in Table 6 also confirm that consistent but more neutral newspapers endorsing the Democratic candidate are not the largest ones: out of 11 high-circulation newspapers endorsing Obama, only one comes from the third quartile.

Regarding the *count* variables, the coefficients on consistent GOP endorsements remain significant. They are somewhat smaller, but are in line with our previous results.[19] The number of DEM endorsements in both the second and third quartiles (and particularly the second) have a significant effect (whereas a dummy for the existence of such endorsements was not significant). We again interpret these endorsements as being consistent coming from Democratic newspapers, but probably less obviously so than those from the first quartile of slant.

The results above complement the documented effect of unexpected endorsements. From the construction of media slant in Gentzkow and Shapiro (2005), an inconsistent

[19] As we estimate linear models, a day with four consistent GOP endorsements will reduce Obama's winning odds four times more (meaning by 4*(0.188) than a day with only one consistent GOP endorsement, in the last specification of Table 8). This may seem to be at odds with the coefficient of -0.366 for a day with at least one consistent GOP endorsement, but as there are 14 days with at least one consistent GOP endorsements, with some of these days having two, three or four such endorsements, the coefficient on the dummy variable is actually an average of those on the count variable.

endorsement comes from a newspaper that esteems one type of policy, but does not support the candidate that proposes those policies. Such endorsements are unexpected, but may be more confusing than informative for their readers. Applying this reasoning, while Republicans only value consistent endorsements, the effect for Democrats is larger when endorsements come from relatively neutral newspapers (and are not necessarily expected, but relatively consistent).

Moreover, although the media-slant measure is correlated with Democratic endorsements in Ansolabehere et al. (2006), evaluating the effect of endorsements according to the paper's historical propensity to endorse Democrats yields new and interesting results: in Table 10, newspapers with a greater propensity to endorse Democrats (quartiles 3 and 4) have a large effect when they instead endorse the Republican candidate (that is, when their endorsements come as a surprise). Likewise, when we use the coarser classification, Democratic endorsements from newspapers with a low probability of endorsing Democrats (quartiles 1 and 2) increase Obama's winning probability. Even though we would require more observations to test the simultaneous effect of both measures, our evidence here suggests that consistent but surprising endorsements might be those with the greatest effect on candidates' winning probabilities.[20]

4 Conclusion

We add to the growing literature on media and politics by pinning down the effect of printed newspaper endorsements on candidates' winning probabilities. Chiang and Knight (2011) used survey data to show that endorsements make readers more likely to vote for the endorsed candidate, and that this effect is larger when the endorsements are unexpected. Our results are consistent with this latter finding, which we extend by showing that not all unexpected endorsements have the same effect. In particular, using the newspaper ideology measures in Gentzkow and Shapiro (2005) and Ansolabehere et al. (2006), we show that, even though unexpected, inconsistent endorsements have no effect.

[20]For instance, in our data set, only three endorsements are classified as "consistent and surprising" for the GOP endorsements, i.e in the fourth quartile of slant and quartiles 3 and 4 (and vice versa for DEM endorsements). As such we only evaluate the effects of consistent and surprise endorsements separately.

On the contrary, endorsements that are consistent with respect to the newspaper's discourse, and which come as a surprise compared to the newspaper's endorsement history, have a large and potentially decisive effect in tied contests.

If, as argued elsewhere, endorsements inform voters about candidates' attributes, they will be welfare-improving if they make the "better" candidate more likely to win. However, knowing their effect on winning probabilities, campaign managers may try to persuade newspapers to endorse their candidates. Could this strategy negate the potentially welfare-improving effect of endorsements? According to our results, on aggregate, society is not influenced by inconsistent endorsements. Hence, any such persuasion would work only if the endorsement is consistent, for which the campaign manager should not have to put in any effort.

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5 Appendix

5.1 The underlying voting model

In this economy there is a continuum of voters who have preferences over the parties and their candidates. There are two Parties, Democratic and Republican, indexed by $p \in \{dem, gop\}$, with one candidate each. Voter utility has horizontal and vertical differentiation components. While the former depends on the parties' ideological distance to the voters' ideal policies, the latter depends on the quality of the political candidates - or valence - an attribute that is positively appreciated by all voters, independently of their individual preferences.

Let $x_p \in R$ be the parties' political platforms (observed by everybody), and $x_i \in R$ the voter's ideological position in the same policy space. The interim utility of voter i who would vote for party p at time t can be written as

$$u_{i,p,t} = -d_t(x_i, x_p) + q_{p,t}.$$

The horizontal-differentiation component of utility - unobserved to the econometrician - is modeled as a random variable $\tilde{x}_{i,p,t}$. The vertical differentiation component of utility at time t contains all the information about candidate quality, up to the last period, plus the new information arriving at time t. We can hence write

$$q_{p,t} = \alpha_p I_{p,t-1} + \beta_p Endors_{p,t} + \tilde{\eta}_{p,t},$$

where $\tilde{\eta}_{p,t}$ is the new information about the candidate that is unobservable to the econometrician, also modeled as a random variable. Thus, from the econometrician's point of view, we can re-write utility as follows:[21]

[21] All the non time-varying information about a candidate is already captured in $I_{p,t-1}$.

$$
\begin{aligned}
U_{i,p,t} =& - d_t(\tilde{x}_i, x_p) + \tilde{q}_{p,t} \\
=& \tilde{x}_{i,p,t} + I_{p,t-1} + Endors_{p,t} + \tilde{\eta}_{p,t}, \\
=& \tilde{x}_{i,p,t} + \bar{U}_{p,t}, \\
=& \tilde{x}_{i,p,t} + V_{p,t} + \tilde{\eta}_{p,t}
\end{aligned} \tag{5}
$$

A voter i will vote for candidate p at time t if $U_{i,p,t} > U_{i,p,'t}$, so that $\Pr(U_{i,dem,t} > U_{i,gop,t}) \equiv S_{dem,t}$ is the expected share for the Democratic party. Assume that $\tilde{x}_{i,p,t}$ is randomly-drawn from a Type0I extreme-value distribution (as is standard in multinomial estimations, as in Nevo (2000)), then

$$
S_{dem,t} = \frac{e^{\bar{U}_{dem,t}}}{e^{\bar{U}_{dem,t}} + e^{\bar{U}_{gop,t}}}.
$$

The shares of the parties depend on the uncertainty in the vertical component, $\tilde{\eta}_{p,t}$. Hence, to obtain the probability that party p, say $p = dem$, wins, we need to calculate $Pr_{dem,t} = Pr(S_{dem,t} > S_{gop,t})$. As before, assuming $\tilde{\eta}_{p,t}$ to be drawn a Type-I extreme-value distribution, we obtain the following closed-form expression

$$
Pr_{dem,t} = \frac{e^{V_{dem,t}}}{e^{V_{dem,t}} + e^{V_{gop,t}}}.
$$

The ratio of probabilities can be written as $\frac{Pr_{dem,t}}{Pr_{gop,t}} = \frac{e^{V_{dem,t}}}{e^{V_{gop,t}}}$. The logarithm of the odds ratio is hence linear in $V_{p.t}$, and can be written as

$$
\ln\left(\frac{\Pr_{dem,t}}{\Pr_{gop,t}}\right) = \beta_{dem} Endors_{dem,t} - \beta_{gop} Endors_{gop,t} + \alpha_{dem} I_{dem,t-1} - \alpha_{gop} I_{gop,t-1}. \tag{6}
$$

We assume that there is an unobserved noise term, ϵ_t, which may affect the Intrade quotes but is not necessarily related to the voting model.[22] Also, the assumption of efficient markets allows us to use the quotes from the previous period to capture all

[22] As is often argued, there could be movements in the intrade quotes that are unrelated to voter ideologies, party platforms, or candidate quality, such as traders with "fat fingers".

information on candidate quality up to $t-1$, i.e. $\alpha Pr_{dem,t-1} = \alpha_{dem} I_{dem,t-1} - \alpha_{gop} I_{gop,t-1}$. We can therefore estimate equation (6) linearly:

$$\ln\left(\frac{\mathrm{Pr}_{dem,t}}{\mathrm{Pr}_{gop,t}}\right) = \beta_{dem} Endors_{dem,t} - \beta_{gop} Endors_{gop,t} + \alpha Pr_{dem,t-1} + \epsilon_t.$$

5.2 Figures

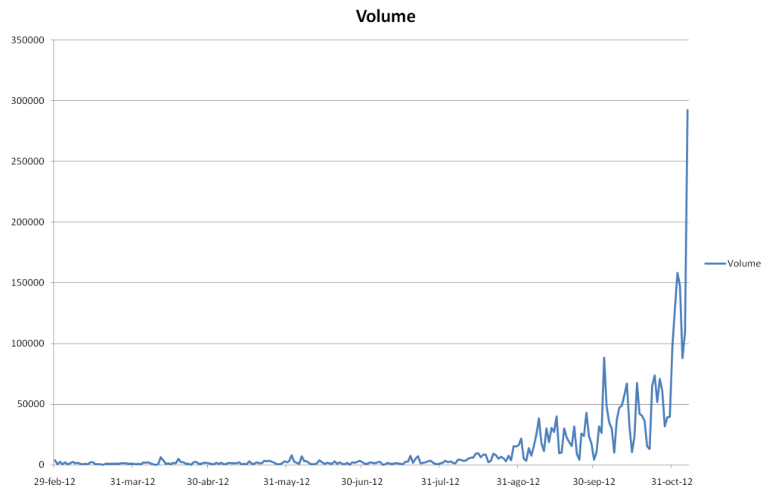

Figure 1: Volume of trade (weights) over the months prior to the Election Day in 2012

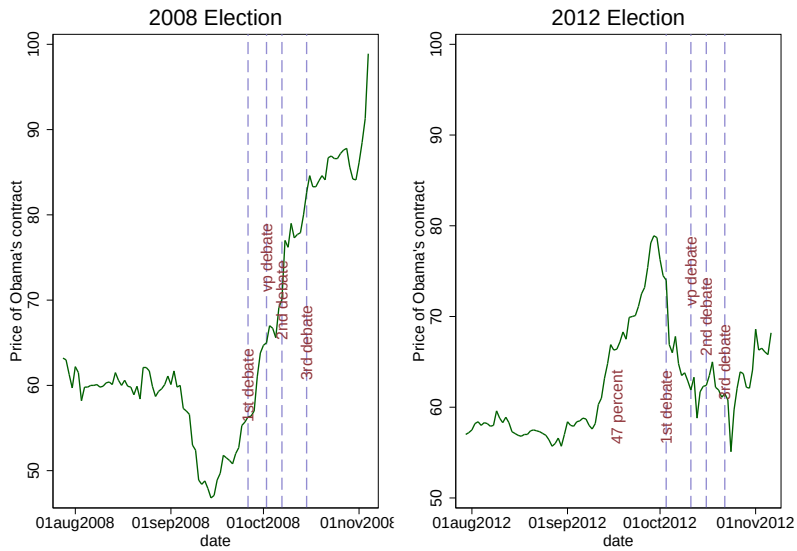

Figure 2: Daily Obama stock prices in the 2008 and 2012 Presidential elections.

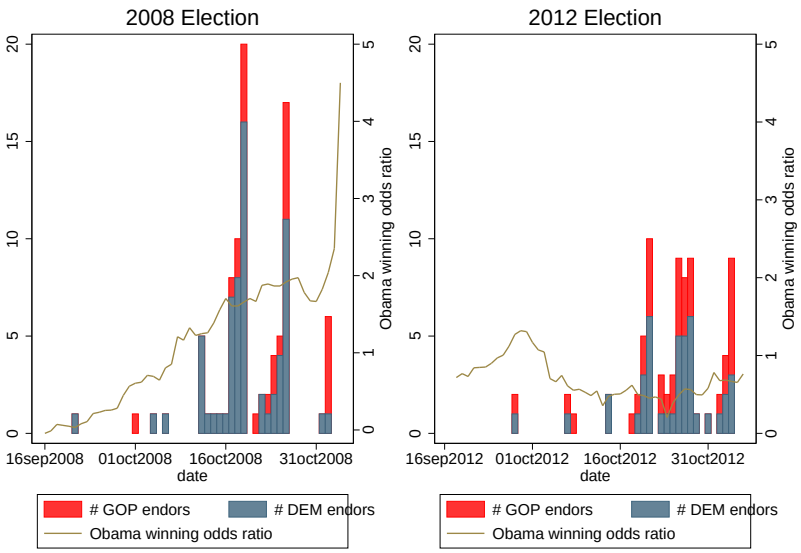

Figure 3: Number of endorsements and Obama's winning odds ratio in the 2008 and 2012 Presidential elections.

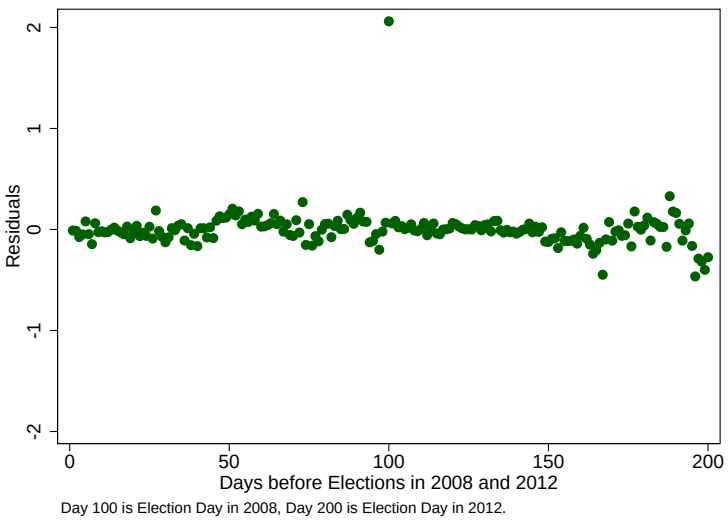

Figure 4: Residuals of the WLS regression plotted over time: regression of Obama's winning odds-ratio on dummies for DEM and GOP endorsements, with month and weekend FE, and weighted by volume (corresponding to Table 7, Column (2).

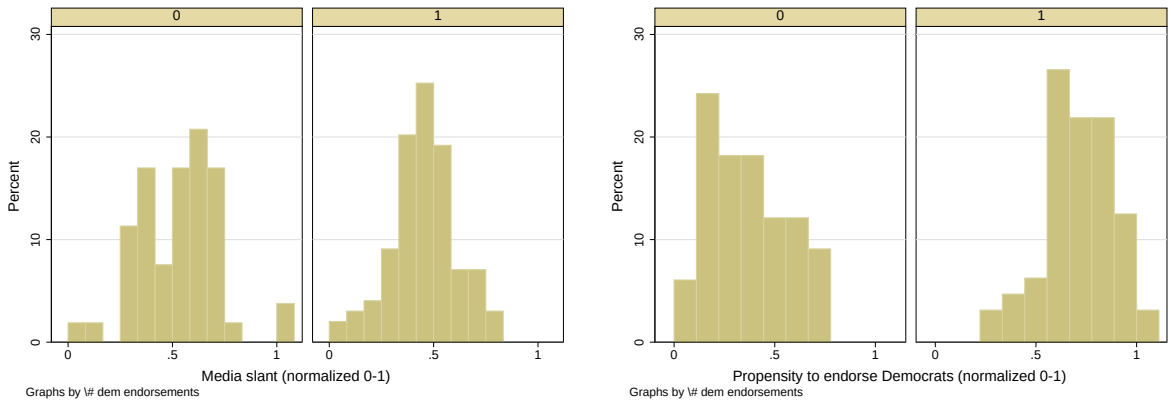

Figure 5: This graph shows Republican and Democrat endorsements according to our normalized measures of media slant (left panel, with 1 being the most Republican) and propensity to endorse Democrats (right panel, with 1 being the most Democratic).

6 Tables

Table 1: Unexpected endorsements: surprise vs inconsistent

	surprise	**inconsistent**
measure used	propensity to endorse Democrats	media slant
based on	Ansolabehere et al. (2006)	Gentzkow and Shapiro (2005)
for GOP	$Q3 - Q4 = surprise$	$Q1 - Q3 = inconsistent$
	$Q1 - Q2 = anticipated$	$Q4 = consistent$
for DEM	$Q1 - Q2 = surprise$	$Q4 = inconsistent$
	$Q3 - Q4 = anticipated$	$Q1 - Q3 = consistent$

Qi refers to the ith quartile of the corresponding measure.

Table 2: Timing of newspaper endorsements: difference between the 2008 and 2012 elections, in weeks and days.

	Weeks			**Days**	
	Newspapers	Percentage		Newspapers	Percentage
1 or fewer	44	58.6	1 or fewer	21	28
2	17	22.6	2-3	7	9.3
3	11	15.6	4-5	9	12
4	2	2.6	6-7	15	20
5	0	0	8-9	3	4
6	0	0	10-11	2	2.7
7 or more	1	1.3	12 or more	18	24
Total	75	100	Total	75	100

Table 3: Top 100 newspapers: endorsement statistics, by Presidential candidate during the US 2008 and 2012 elections

	2008		2012	
	Obama	McCain	Obama	Romney
Circulation endorsement (millions)	16.099	5.194	10.015	6.476
Days with an endorsement	18	11	17	16
Total endorsements	65	25	41	35

Table 4: Number and days of endorsements, by circulation, for each party

	DEM endorsements		**GOP endorsements**		**Total**	
Circulation (in thousands)	# Newspapers	# Days	# Newspapers	# Days	# Newspapers	# Days
≻100	97	33	51	27	148	40
≻200	50	22	16	13	66	25
≻400	12	8	5	5	17	12
≻600	6	6	1	1	7	7
≻800	2	2	0	0	2	2
Total	106	35	60	27	166	40

Table 5: Number and days of endorsements, by slant and propensity quartiles, for each party.

	DEM endorsements		**GOP endorsements**		**Total**	
Slant quartiles	# Newspapers	# Days	# Newspapers	# Days	# Newspapers	# Days
Q1	29 (3)	16 (3)	10 (2)	9 (2)	39 (5)	21 (5)
Q2	28 (6)	17 (6)	10 (2)	9 (2)	38 (8)	23 (7)
Q3	29 (1)	15 (1)	9 (0)	9 (0)	38 (1)	16 (1)
Q4	13 (1)	11 (1)	24 (1)	14 (1)	37 (2)	19 (2)
Total	99 (11)	33 (8)	53 (5)	27 (5)	152 (16)	39 (12)
Propensity quartiles	# Newspapers	# Days	# Newspapers	# Days	# Newspapers	# Days
Q1	5 (2)	5 (2)	20 (3)	14 (3)	25 (5)	17 (5)
Q2	14 (2)	11 (2)	10 (0)	5 (0)	24 (2)	13 (2)
Q3	22 (0)	16 (0)	3 (0)	3 (0)	25 (0)	17 (0)
Q4	23 (5)	15 (4)	0 (0)	0 (0)	23 (5)	15 (4)
Total	64 (9)	26 (7)	33 (3)	18 (3)	97 (12)	31 (10)

The figures in parenthesis are the corresponding high-circulation (>400 000) number of endorsements. Example: 23 newspapers in the 4th propensity quartile endorsed the DEM candidate (5 were high circulation), on 15 days (4 days).

Table 6: Newspaper circulation summary statistics (in millions)

Newspapers	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
DEM endorsements	0.246	0.208	0.078	1.587	106
GOP endorsements	0.194	0.129	0.083	0.702	60
1st quartile slant	0.242	0.141	0.094	0.703	39
2nd quartile slant	0.325	0.31	0.083	1.587	38
3rd quartile slant	0.187	0.076	0.088	0.401	38
4th quartile slant	0.173	0.097	0.078	0.494	37
All	0.228	0.185	0.078	1.587	166

Table 7: Endorsement baseline effects (Dummy).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DEM Endorsement Dummy	0.010	0.024	-0.061	-0.054	-0.003	0.010	0.011
	(0.07)	(0.07)	(0.10)	(0.10)	(0.08)	(0.08)	(0.08)
GOP Endorsement Dummy	-0.118*	-0.109	-0.095	-0.096	-0.191**	-0.184**	-0.186*
	(0.07)	(0.07)	(0.09)	(0.09)	(0.09)	(0.09)	(0.10)
Circulation > 200 000 x DEM			0.200**	0.218**			
			(0.10)	(0.10)			
Circulation > 200 000 x GOP			-0.098	-0.064			
			(0.14)	(0.13)			
Circulation > 400 000 x DEM					0.342**	0.339***	0.337**
					(0.13)	(0.13)	(0.13)
Circulation > 400 000 x GOP					0.043	0.046	0.048
					(0.11)	(0.10)	(0.10)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekend FE	No	Yes	No	Yes	No	Yes	Yes
Debate FE	No	No	No	No	No	No	Yes
R2	0.76	0.76	0.77	0.77	0.77	0.78	0.78
N	200	200	200	200	200	200	200

Standard errors in parentheses

In all specifications the dependent variable is $\ln\left(\frac{\mathrm{Pr}_{dem,t}}{\mathrm{Pr}_{gop,t}}\right)$.

All regressions are weighted and include a lagged dependent variable.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Consistency (slant). Dummies and Count.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dummy								
Consistent DEM endorsement (`Q1-Q3`)	0.065	0.070	0.085	0.037				
	(0.06)	(0.07)	(0.07)	(0.08)				
Inconsistent DEM endorsement (`Q4`)	-0.051	-0.052	-0.066	-0.079				
	(0.08)	(0.09)	(0.09)	(0.06)				
Consistent GOP endorsement (`Q4`)	-0.336**	-0.344*	-0.354**	-0.336**				
	(0.17)	(0.18)	(0.17)	(0.16)				
Inconsistent GOP endorsement (`Q1-Q3`)	0.091	0.091	0.101	0.049				
	(0.08)	(0.09)	(0.09)	(0.07)				
Count								
Consistent DEM endorsement (`Q1-Q3`)					0.024	0.025	0.017	0.012
					(0.02)	(0.02)	(0.02)	(0.03)
Inconsistent DEM endorsement (`Q4`)					-0.010	-0.014	-0.035	-0.003
					(0.09)	(0.09)	(0.08)	(0.08)
Consistent GOP endorsement (`Q4`)					-0.174*	-0.167*	-0.169*	-0.188*
					(0.09)	(0.10)	(0.09)	(0.10)
Inconsistent GOP endorsement (`Q1-Q3`)					0.065	0.068	0.089	0.052
					(0.05)	(0.05)	(0.06)	(0.06)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekend FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Debate FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	No	No	Yes	Yes
Circulation	No	No	No	Yes	No	No	No	Yes
R2	0.78	0.78	0.80	0.81	0.77	0.78	0.80	0.80
N	200	200	200	200	200	200	200	200

Standard errors in parentheses.

In all specifications the dependent variable is $\ln\left(\frac{\Pr_{dem,t}}{\Pr_{gop,t}}\right)$.

All regressions are weighted and include a lagged dependent variable.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Quartiles of consistency (slant). Dummy and count variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dummy								
High consistency DEM (`Q1`)	-0.097	-0.099	-0.095	-0.100				
	(0.10)	(0.10)	(0.11)	(0.11)				
Medium consistency DEM (`Q2`)	0.042	0.041	-0.055	-0.046				
	(0.10)	(0.10)	(0.13)	(0.17)				
Low consistency DEM (`Q3`)	0.188***	0.206**	0.211**	0.182*				
	(0.07)	(0.08)	(0.08)	(0.09)				
Inconsistent DEM (`Q4`)	-0.101	-0.103	-0.144	-0.127				
	(0.09)	(0.09)	(0.10)	(0.11)				
High inconsistency GOP (`Q1`)	0.129	0.127	0.229*	0.185				
	(0.09)	(0.10)	(0.13)	(0.13)				
Medium inconsistency GOP (`Q2`)	0.102	0.108	0.094	0.088				
	(0.08)	(0.09)	(0.09)	(0.07)				
Low inconsistency GOP (`Q3`)	0.019	0.014	0.070	0.049				
	(0.13)	(0.13)	(0.15)	(0.16)				
Consistent GOP (`Q4`)	-0.296**	-0.296*	-0.289*	-0.283*				
	(0.14)	(0.16)	(0.15)	(0.15)				
Count								
High consistency DEM (`Q1`)					-0.073	-0.074	-0.082	-0.082
					(0.07)	(0.07)	(0.07)	(0.07)
Medium consistency DEM (`Q2`)					0.165***	0.163**	0.112*	0.140*
					(0.06)	(0.07)	(0.06)	(0.07)
Low consistency DEM (`Q3`)					0.078*	0.081*	0.074	0.091
					(0.04)	(0.05)	(0.05)	(0.06)
Inconsistent DEM (`Q4`)					0.047	0.042	-0.008	-0.031
					(0.06)	(0.07)	(0.07)	(0.07)
High inconsistency GOP (`Q1`)					0.053	0.052	0.126	0.157
					(0.07)	(0.07)	(0.08)	(0.11)
Medium inconsistency GOP (`Q2`)					0.071	0.077	0.057	0.061
					(0.07)	(0.08)	(0.08)	(0.07)
Low inconsistency GOP(`Q3`)					-0.122	-0.117	-0.033	-0.014
					(0.10)	(0.10)	(0.13)	(0.14)
Consistent GOP (`Q4`)					-0.218**	-0.214**	-0.194**	-0.208**
					(0.10)	(0.11)	(0.09)	(0.10)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekend FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Debate FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	No	No	Yes	Yes
Circulation	No	No	No	Yes	No	No	No	Yes
R2	0.79	0.79	0.81	0.82	0.78	0.79	0.81	0.81
N	200	200	200	200	200	200	200	200

Standard errors in parentheses

In all specifications the dependent variable is $\ln\left(\frac{\mathrm{Pr}_{dem,t}}{\mathrm{Pr}_{gop,t}}\right)$.

All regressions are weighted and include a lagged dependent variable.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Surprise (propensity). Dummy variables.

	(1)	(2)	(3)	(4)	(5)	(6)
Very surprising DEM (`Q1`)	0.207	0.167	0.153			
	(0.13)	(0.14)	(0.16)			
Surprising DEM (`Q2`)	0.191	0.212	0.238			
	(0.14)	(0.15)	(0.16)			
Anticipated DEM (`Q3`)	-0.182	-0.174	-0.160			
	(0.15)	(0.16)	(0.15)			
Very Anticipated DEM (`Q4`)	-0.035	-0.009	-0.037			
	(0.08)	(0.08)	(0.10)			
Very Anticipated GOP (`Q1`)	0.110	0.110	0.109			
	(0.09)	(0.10)	(0.10)			
Anticipated GOP (`Q2`)	-0.175	-0.135	-0.184			
	(0.15)	(0.16)	(0.18)			
Surprising GOP (`Q3`)	-0.223**	-0.217*	-0.212*			
	(0.11)	(0.12)	(0.13)			
Anticipated DEM (`Q3-Q4`)				-0.184	-0.172	-0.175
				(0.14)	(0.14)	(0.13)
Surprise DEM (`Q1-Q2`)				0.233*	0.257*	0.259*
				(0.14)	(0.15)	(0.15)
Anticipated GOP (`Q1-Q2`)				0.041	0.062	0.051
				(0.09)	(0.09)	(0.09)
Surprise GOP (`Q3-Q4`)				-0.213	-0.211	-0.193
				(0.14)	(0.16)	(0.16)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Weekend FE	No	Yes	Yes	No	Yes	Yes
Debate FE	No	Yes	Yes	No	Yes	Yes
Year FE	No	No	Yes	No	No	Yes
R2	0.77	0.77	0.80	0.77	0.77	0.79
N	200	200	200	200	200	200

Standard errors in parentheses.

In all specifications the dependent variable is $\ln\left(\frac{\Pr_{dem,t}}{\Pr_{gop,t}}\right)$.

All regressions are weighted and include a lagged dependent variable.

Note: there are no GOP endorsements in the the fourth propensity quartile.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$