Selective Media Exposure and Polarization in Presidential Campaigns

by

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Thesis submitted in partial fulfillment of the requirements for the degree of Master of Arts in the Department of Political Science in the Graduate School of Duke University 2013
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This paper analyzes the influence of political selective exposure to cable news stations on mass-polarization, operationalized as radicalization in issue attitudes during the 2004 Presidential campaign. Various studies have demonstrated at length how political predispositions guide news media choices, which holds especially true for TV news. In contrast, my empirical analyses focus on the effects of exposure to congenial news sources. Using panel data, I show that, first, selective exposure to ideologically leaning cable news has a radicalizing effect on issue attitudes salient in the presidential campaign, even in states where intense campaigning was absent. Second, I demonstrate that the effect of selective exposure on economic attitudes is much more powerful than its effect on social issues. I conclude by discussing the relevance of the findings as well as its long-term implications.
I dedicate this work to Mom and Dad, for their infinite love and generosity
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I thank Sunshine Hillygus, John Aldrich and Christopher Johnston for their patient advice, Shahryar Minhas and Rotem Ben-Shachar for advice and questions and the DAAD and the Duke Graduate School for funding.
Introduction

Polarization at the mass-level has become one of the fundamental issues in the study of public opinion. Scholars themselves are polarized on this issue: Do Americans intuitively converge to the political center (Fiorina & Abrams 2009, Fiorina & Abrams 2008, Fiorina et al. 2006), or do the masses become increasingly polarized (Abramowitz 2010, Abramowitz & Saunders 2008, Levendusky 2009)? Some scholars who see evidence for mass-level polarization have attributed a catalyst role to processes of fragmentation in the media environment (Iyengar & Hahn 2009, Jamieson & Cappella 2008, Prior 2007, Stroud 2011, 2007).

Today’s news environment, so goes the argument, provides plenty of opportunities to avoid discourse intransigent with one’s political views by selecting into news that have a clear, known and salient political leaning, and there is a panoply of evidence supporting this selection-hypothesis. Numerous studies have shown that political identities such as self-reported ideology or party identification oftentimes determine selection of news sources, and this correlation is especially true for the selection of cable news: liberals and Democrats favor exposure to MSNBC and CNN, conservatives and Republicans favor exposure to Fox News (Jamieson & Cappella

While these studies meticulously document explanatory factors of news choice, the analysis of effects of this type of selective exposure is more cursory, and only recently has become more prominent. But even today, clear evidence for a direct link between polarization and selective exposure remains scarce and most findings pertain to phenomena mediating polarization. Some scholars argue that exposure to partisan news environments entails differences in perceived importance of political issues (Stroud 2011) via priming, others demonstrate that selective exposure leads to enhanced accessibility of political attitudes (Iyengar & Kinder 1987, Knobloch-Westerwick 2012) or document how selective exposure induces different perceptions of political candidates and fosters affect-based polarization (Iyengar et al. 2012, Jamieson & Cappella 2008, Stroud 2010).

In contrast, this paper establishes a direct link between selective exposure and polarization on relevant political issues by demonstrating that consistent exposure to politically congenial news entails a process of radicalization on a latent political dimension comprised by attitudes on political issues initially less salient to the self. In adapting parts of Social Identity Theory and Bayesian Learning, I develop a theory showing how issue attitudes become more salient to the self in the course of selective exposure and thereafter polarize. In addition, I argue that selective exposure should be most visible in times when the news agenda is extremely political – as it is the case primarily during Presidential elections. I test the hypotheses using data from the 2004 Presidential election and focus on exposure to cable news. In concluding, I address long-term consequences of issue-based polarization as a function of selective exposure and identify points of departure for future research.
2.1 Choosing News – Cognitive harmony and accessibility of political identity

Selective exposure, the choice of news congenial to one’s political predisposition, has been a controversial topic in political science (Arceneaux & Johnson 2010, Donohew & Palmgreen 1971, Stroud 2011, 2007, Sunstein 2001, Zaller 1992). While there has been agreement on the need for “cognitive harmony” and on the human proclivity to avoid cognitive dissonance in order to maintain emotional stability (Festinger 1957), there is considerable controversy whether the need for “cognitive harmony” can be seen as a major factor in explaining media choice. On the one hand, it is reasonable to assume that consumption of news that have a slant in the opposite direction of one’s political leaning entails this kind of discomfort and that thus people tend to avoid exposure to the “hostile” news sources. On the other hand, psychologists have pointed out that these instincts could be overridden by proclivities of openness-mindedness, a trait certainly subject to high variation at the individual level, or other mediating factors (Donohew & Palmgreen 1971, McGuire 1968). Also, Kruglanski has shown that the need for cognitive closure, or what I referred to earlier as cognitive
harmony, equally varies from individual to individual (Kruglanski et al. 2006).

It is thus not surprising that, in the wake of the rise in importance of political psychology, especially Zaller in his influential monograph “The Nature and Origins of Mass Opinion” (1992) is highly skeptical of selective exposure effects. He argues, much in the tradition of Converse (1964), that people might simply lack the political sophistication to engage in this kind of selectivity (Zaller 1992). However, the news environments predominant in the earlier studies summoned by Zaller were characterized by the pervasiveness of network news, and opportunities to preselect into news niches were scarce. Today, citizens are able to select from a wide range of news niches that allow them to avoid being confronted with opposing political viewpoints altogether (Iyengar & Hahn 2009, Piror 2007, Stroud 2011, Sunstein 2001). There is considerable evidence that, used to tendencies of balkanization in the news environment, people are more prone to engage in selective exposure than had been the case in the past. Valentino and colleagues find that feelings of anxiety might increase selective exposure if there is no specific utility to seek out counter-attitudinal information (Valentino et al. 2009). Similarly, findings suggest that when presented with different options of exposure to information, people will seek out confirming over disconfirming arguments, all else equal (Taber & Lodge 2006).

But certainly, Zaller's key assessment that people lack sophistication and political interest to engage in hyper-selectivity still holds. Naturally, strength of political predispositions thus constitutes another dimension relevant for the likelihood of selective exposure. Politically interested citizens that possess strong predispositions should be especially likely to rely on these when it comes to news choice. For them, political predispositions are highly accessible knowledge structures that are inherently more likely to be activated and subsequently applied to the decision-making-process, and news choice is an obvious case in which political predispositions become extremely relevant (Higgins 1996, Stroud 2007).
Thus, both hypotheses explaining selective exposure assume that political pre-
dispositions take on the form of an identity (Stroud 2007). The need for cognitive
harmony or strong political predispositions can only trigger selective exposure if there
is certainty about congruence of political reality shared in the group environment of
the news chosen and one’s own political reality (Kruglanski et al. 2006), and it makes
sense that these tasks of categorization of news and self-categorization happen on a
dimension that is visible and highly salient to the self, such as partisan identification
or ideology (Stroud 2007). But it also limits the group of interest to the politically
minded and engaged for they have the skills necessary to engage in the categoriza-
tion tasks described. In this sense, selective exposure is not a potential mechanism
of mass-level polarization, but affects only the few, a politically interested subgroup
of the population.

So what kind of partisan affiliation triggers exposure to what kind of news?
Various content analyses show that Fox News tends to lean to the right politically,
whereas CNN and MSNBC tend to lean to the left (Groseclose 2011, Stroud 2010,
Jamieson & Capella 2008). Thus I assume that selective exposure occurs when self-
reported Republicans tune in to Fox News, or when self-reported Democrats tune in
to CNN or MSNBC.¹

2.2 Effects of News Choice – The psychology of issue-based radical-
ization

One of the most well-bread theoretical frameworks of selective exposure effects was
initiated by Cass Sunstein. Those who engage in selective exposure, claims Cass Sun-
stein in Republic.com, are likely to become more extreme in their political viewpoints,
because the different media audiences that are stratified according to political be-

¹There is considerable debate whether CNN has a clear liberal leaning or not. It is included as
“liberal news” because not doing so would severely shrink the sample-size.
liefs essentially form deliberative enclaves (Sunstein 2001). In these enclaves, voters are not confronted with opposing viewpoints anymore and “views will not be reinforced, but instead will be shifted to more extreme point[s]” (Sunstein 2001: 101). In short, “the central factor behind group polarization is the existence of a limited argument pool” (Sunstein 2001: 68).

Central to this relocation of political position, besides a lack of communicative contacts with members of enclaves that are centered on the other end of the hypothetical unidimensional ideology-spectrum (Sunstein 2001), is a high responsiveness to political messages of the news, and there is considerable support for this assumption. For example, Tajfel and Turner, in developing Social Identity Theory, have shown that people are likely to display a certain degree of ingroup bias, even in a setting of minimal history of group relations and affiliations, such as a participation in the same communicative enclave of cable news (Huddy 2001, Tajfel & Turner 1979, Kruglanski et al. 2006). As a consequence, positions by the group, or in this case the enclave, are seen more favorably. Members of communicative enclaves, as all ingroup members, are inclined to “reduce one’s sense of individuality, minimize ingroup differences, and promote conformity to the group prototype” (Huddy 2001: 145). However, enclave members have fundamental uncertainty as to what issue attitudes exactly the prototype of the enclave holds, although they know the general direction of these attitudes. In an attempt to reduce uncertainty, members will be likely to display group conformity by imitating the political positions inherent in the ideological belief system of the news they watch, as they know these positions must be reasonably close to the prototype’s. In other words, because they know that the general leaning of the news correspond to their political identity, they are likely to display a “positive bias” and engage in motivated reasoning, accepting issue-attitudes presented more or less at face value (Taber & Lodge 2006).

Most of the empirical studies seeking to apply this theoretical framework and
to demonstrate effects of selective exposure struggle with a severe problem of endogeneity, a loop of causality between main explanatory and dependent variable. Is it selective exposure that leads to polarized political predispositions, or is it political predispositions that lead to selective exposure? In the early days of selective exposure scholarship, cause and effect of selective exposure were believed to be entirely congruent (Berelson et al. 1954, Klapper 1960). Klapper for example derived the minimal-effect-hypothesis of his groundbreaking work (1960) from the observation that people were likely to engage in selective exposure and that this kind of media-consumption reinforces prior political beliefs in lieu of changing them (Klapper 1960). While Klapper’s hypothesis of minimal effects has not endured, the idea that cause and effect of selective exposure point to the same individual phenomenon has. Stroud (2010) points out that the causal arrow between affective polarization and news choice points in both directions and Slater (2007) essentially delineates a spiral, in which a higher degree of polarization entails the consumption of more homogeneous news, which in return leads to even more polarization etc.

The argumentative structure presented here is diametrical to this canon. The media agenda constantly revolves around concrete political issues such as the new health care bill or the stimulus, not abstract concepts of political identities. Thus, the effects of selective exposure should become most pronounced on a latent score of ideology comprised by attitudes on political issues. In contrast, political identities guiding news choice should remain stable over time, as has been shown by researchers numerous times (Campbell et al. 1960, Green & Palmquist 1994). In addition, it is unlikely that people would choose cable news based on issue attitudes. Not only is the task of categorizing different news according to their stance on political issues nearly impossible and would require complete information, it is also reasonable to assume that while political identities are salient to the self, one’s attitudes on political issues are not as well formed and come, to say the least, with high uncertainty. Exposing
oneself to cable news consistent in framing of political issues should decrease this uncertainty in stance on political issues overtime and move the issue-position in the direction of the positions advocated by the news.

2.3 Effects of News Choice – A Bayesian-learning-based model of attitude polarization as a function of selective Exposure

One of the most well-bread theoretical frameworks of selective exposure effects was initiated by Cass Sunstein. Those who engage in selective exposure, claims Cass Sunstein in Republic.com, are likely to become more extreme in their political viewpoints, because the different media audiences that are stratified according to political beliefs essentially form deliberative enclaves (Sunstein 2001). In these enclaves, voters are not confronted with opposing viewpoints anymore and “views will not be reinforced, but instead will be shifted to more extreme point[s]” (Sunstein 2001: 101). In short, “the central factor behind group polarization is the existence of a limited argument pool” (Sunstein 2001: 68).

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145). However, enclave members have fundamental uncertainty as to what issue attitudes exactly the prototype of the enclave holds, although they know the general direction of these attitudes. In an attempt to reduce uncertainty, members will be likely to display group conformity by imitating the political positions inherent in the ideological belief system of the news they watch, as they know these positions must be reasonably close to the prototype’s. In other words, because they know that the general leaning of the news correspond to their political identity, they are likely to display a “positive bias” and engage in motivated reasoning, accepting issue-attitudes presented more or less at face value (Taber & Lodge 2006).

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2.4 Effects of News Choice – A Bayesian-learning-based model of attitude polarization as a function of selective Exposure

This move of political positions can best be illustrated by the concept of Bayesian learning or position-taking. While people engaging in selective exposure based on concepts highly salient to the self have uncertainty in less salient issue attitudes held prior to selective exposure, these prior beliefs are updated if new information about the given issue is encountered, which leads to a new posterior belief about the given issue. When the new information, or likelihood, is politically homogeneous over time in its message and focuses on concrete political matters, as it is the case for ideologically leaning news, one should expect the strengths of the posterior beliefs to be greater due to a higher salience of these issues in the likelihood and the positions of the beliefs to be constantly shifting in the direction of the likelihood (Bartels 2002, Bullock 2009, Gerber & Green 1999). In consequence, the median voter of
each stratified enclave moves to the poles of a hypothetical unidimensional ideology spectrum.

As a point of departure for a formalized model of Bayesian-learning-based polarization in issue-attitudes as a function of selective exposure, it is notable that the simple Bayesian model of political learning postulates that voters have some political belief $\theta$ about a given political issue but they have some uncertainty as to how strong they feel about it. The prior beliefs are then updated if new information about the given issue, the likelihood, is encountered, which leads to a new posterior belief about the given issue, where we expect the variance to be smaller and the mean to be shifted in the direction of the likelihood. Formally, the process of Bayesian updating can be written as $P(\theta|D) \propto P(\theta)P(D|\theta)$ where $P(\theta|D)$ is the posterior density function of a belief about any given issue, $P(\theta)$ is the prior density function and $P(D|\theta)$ represents the likelihood. It makes intuitive sense to assume that the posterior will be a combination of the information priorly held and the new information at hand. This justifies assumption 1:

**Assumption 1**: People update their political beliefs as a combination of prior beliefs and new information encountered.

Bullock argues that political beliefs differ in certainty because the signal is weak and thus attributes strength of beliefs, hereafter referred to as precision $\tau$ to remain consistent with the Bayesian terminology, to quality and scope of information available (Bullock 2009). In this case, I attribute belief-strength to the amount of information available. Thus it is important to note that realistically, $\theta$ will always be distributed, and its precision is an expression of the relative “completeness” of information used to construct the belief. In consequence, $\theta$ would only become a point-estiamte in cases of complete information, a scenario highly unrealistic when
it comes to political issues.

It is reasonable to assume that people who have uncertainty about their political belief due to incomplete information choose a mean of the distribution of $\theta$ such that half the uncertainty falls on one side of the mean and half the uncertainty falls on the other side of the mean. Hence, on a one-dimensional scale of any given attitude where one pole represents the conservative and the other represents the liberal extreme, voters who feel uncertain about their own position due to incomplete information intuitively assume that their position could shift to the right or left with equal probability. Also, it is important to note that both, precisions and means, vary across individuals. This justifies assumption 2:

**Assumption 2:** People’s prior beliefs are distributed $\mathcal{N}(\mu_i, \frac{1}{\tau_i})$

Imagine two voters with different distributions of prior attitudes on the issue of abortion. If abortion attitudes are conceptualized to fall on a single dimension ranging from liberal to conservative (1-7), the beliefs could be characterized by the following probability density functions:
These two densities could represent possible respondents of the survey used in the statistical analysis of this paper: The red respondent has a moderately conservative stance on abortion (e.g. only allowing abortion after rape or if the mother’s life is in danger), but feels strongly about it, while the blue respondent has a moderately liberal stance on abortion (e.g. allowing abortions until a certain time after conception), and does not feel very strongly about it (e.g. her stance could become more conservative or more liberal with equal probability, depending on the new information received).

If these two voters encountered the same likelihood (“new information”), given that voter A and voter B have political beliefs about abortion with means (e.g. prior positions) $\mu_1$ and $\mu_2$ and uncertainties $\tau_1$ and $\tau_2$ and that $\theta$ represents their belief on a political issue if they were in an environment of complete information, the prior beliefs should be updated according to $\mu_1 = \frac{\mu_0 \tau_1 + \tau_0 \mu_1}{\tau_0 + \tau_1}, \tau_1 = \tau_0 + \tau_x$, (DeGroot and Schervish 2011). It makes intuitive sense to see that the “new” position will have
shifted in the direction of the likelihood while the precision of the posterior has become stronger.²

**Assumption 3:** People’s posterior beliefs are a combination of their prior beliefs and the likelihood, weighed by the precision of each.

These simple updating rules demonstrate an updating process where the likelihood is congruent across individuals. With regards to the phenomenon of selective exposure, the assumption of congruent likelihoods does not hold. In fact, likelihoods are entirely determined by prior attitudes. In addition, it is important to note that the likelihood necessarily has to be defined as the information *used* in the updating-process, not the raw new information at hand. As a consequence, the same likelihood could still lead to different updating processes if interpretation of the message differs.

In consequence, selective exposure and its effects entail corrections of the propositions derived in the previous two sections.

**Correction 1:** The Likelihoods cannot be compared across individuals, as they are not encountered at random, but determined as a function of prior information.

To model processing of likelihoods determined by the prior, selective exposure, we need a three-stage “path model” to account for these corrections. Graphically, the model should describe the following:

In a Bayesian framework, if it is reasonable to assume that strong prior political attitudes salient to the self lead to the determination of the likelihood, the likelihood

---

²This updating rule is based on the assumption that the likelihood is also $\mathcal{N}(\mu_i, \frac{1}{\tau_i})$ and that the precision of the population is known, which does make sense when the case of “complete information” is conceptualized as the population and hence, the population variance is as low as possible.
is chosen so that it minimizes the difference between salient political predisposition, such as party identification, $\delta$, and political leaning of the news, $\gamma$. In accordance, the likelihood is chosen according to $\min(\delta_i - \gamma_j) = \ell_{ji}$, where $i$ individuals choose from $j$ available different likelihoods.

If the prior predispositions are strong enough and individual 1 one can minimize the difference between her predispositions and all possible likelihoods $j$ by choosing MSNBC/CNN, denoted $M$, and individual 2 can minimize the difference between her predispositions and all possible likelihoods $j$ by choosing Fox News, denoted $F$ we expect the updating process to be a function of different priors and different
likelihoods such that

\[
P(\theta_1|D) \propto P(\theta_1) \ell_M(D|\theta_1)
\]

\[
P(\theta_2|D) \propto P(\theta_2) \ell_F(D|\theta_2)
\]

and it is reasonable to assume that the beliefs of the individuals about any given issue diverge as a consequence of differences in \(\tau_F\) and \(\tau_M\) and more importantly in \(\mu\)s of the likelihoods such that the posterior beliefs of the two individuals are in a process of constant divergence, e.g. \(\mu_1 \neq \mu_2\). Thus the entire process can be expressed mathematically as

\[
\min(\delta_1 - \gamma_j) = \ell_M \Rightarrow P(\theta_{\text{polarized-liberal}}|D) \propto P(\theta) \ell_M(D|\theta_1)
\]

\[
\min(\delta_2 - \gamma_j) = \ell_F \Rightarrow P(\theta_{\text{polarized-conservative}}|D) \propto P(\theta) \ell_F(D|\theta_2)
\]

Accordingly, we should expect that selective exposure leads to a radicalization in attitudes on political issues (H1). There is also considerable evidence that the leanings of the communicative enclaves point in the same ideological direction across issue clusters, or ideology dimensions respectively (Stroud 2011). Thus, in accordance with the mechanisms described, it is reasonable to assume that selective exposure contributes independently to issue based polarization in each of two prominently named dimensions of the political space: the economic dimension and the cultural dimension (H2)
3

Modeling Media Effects on issue attitudes

3.1 Dataset and related shortcomings

The paper demonstrates how political selective exposure independently contributes to a radicalization in issue-based ideology. For measuring radicalization in issue attitudes, I rely on panel data of the National Annenberg Election Survey 2004 conducted between a pre-election period, July 15 – Nov. 1, 2004, and a post-election period, Nov. 4 – Dec. 28, 2004, as I try to demonstrate a procedural change in issue attitudes.

As much as the Annenberg dataset is preferable to the National Election Studies because of its in-depth media variables, it faces a severe problem of missingness, which is especially the case for my dependent variable, an overall score in issue attitudes. As most of the issue-related questions were only asked at certain time points, all respondents are coded as “NA” in at least one issue question. The amount of missingness for the particles of the key dependent variable averages 36% across issues, and thus can easily be described as “severe”. However, given the sample size and advanced techniques of data imputation discussed later, there is still considerable
inference to be made.\footnote{Instead of relying on imputations, a more rigid method is to code those that did not respond in one panel with the same response they gave in the other panel and equally hold all NAs constant. This approach would essentially attribute a null-effect to all those respondents that are coded as missing in at least one of the two panels in any given issue and thus artificially deflate effects. Even in this most rigid approach, the relevant statistical coefficients are still statistically significant. The missingness statistics for the elements of the dependent variable and the lagged version are included in the Appendix.}

**Figure 3.1**: Missingness-patterns in the unimputed data for particles of the dependent variable, colored as tan

Most statistical programs deal with missingness by list-wise deletion in regression analyses, resulting in a severely diminished sample size that undermines statistical inference. Also, list-wise deletion would delete cases that might be very relevant, such as respondents who displayed radically conservative attitudes in all issues but one, because they were not asked this one specific issue question. This limitation of the data has arguably lead researchers who worked with this dataset to shy away from an
issue-based conceptualization of polarization (Stroud 2007, 2010). The question then arises how to deal with missingness in the data. Coding missing issue attitudes as the median of the given category or the mean of all non-missing responses in this category might be convenient, but it can severely bias the estimates. Additionally, it artificially inflates the standard error because of the newly entered data’s null-deviance from the column mean and might thus lead to artificial statistical significance (Howel 2008).

A more promising approach lies in multiple data imputation, such as the EMB-algorithm-based Amelia program developed by Honacker, King and Blackwell (2011). Amelia assumes that the complete data are distributed multivariate normal, and that the missing data are missing at random (MAR) such that the underlying pattern of missingness is only dependent on the observed, and not on the unobserved data (Honacker et al. 2011). If the entire $n \times k$ dataset is represented as $D$ (with $D^{obs}$ and $D^{unobs}$ indicating if data is observed or unobserved), the data are distributed as

$$D \sim \mathcal{N}(\mu, \sum)$$

where $\mu$ is a vector of means and $\sum$ the covariance-variance matrix of the dataset. Indeed, such an assumption makes sense if the missingness originates from a failure of the interviewer to survey the respondent on a particular issue, and not from a failure of the respondent to answer the question.\footnote{In this paper, imputation is only used for those who were not asked the specific question. Those who did not chose to answer or did not know how to respond, were left unchanged and were deleted from the dataset as “NAs”, because the MAR-assumption does not hold for these respondents.}

The observed data consists of a vector indicating missingness, $M$, and $D^{obs}$. Thus the likelihood of the observed data is given by $p(D^{obs}, M|\theta)$, where $\theta$ represents a vector of complete data parameters. As we only care about the observed data, we can rewrite the likelihood as $p(D^{obs}|\theta)$ (Honacker et al. 2011). According to Bayes’
Law, the new posterior is given by

\[ p(D_{\text{obs}}|\theta) = \int p(D|\theta) d_{\text{mis}} \]

The algorithm then finds the mode of the posterior and takes fundamental uncertainty into account. The final imputation is made “by drawing values of \( D_{\text{mis}} \) from its distribution conditional on \( D_{\text{obs}} \) and the draws of \( \theta \)” (Honacker et al. 2011: 4).

In this case, the imputation is computed according to the distribution of predictor variables. Predictor variables were voting behavior, political attitudes, responses to political issues, demographics and similar variables that are believed to be of highly predictive power for issue-related responses.\(^3\)

### 3.2 The Model – Definitions and Variables

Using the imputed dataset, I model issue-based radicalization in a typical ordinary-least-squares environment as an autoregressive model. For liberal selective exposure, I rely on a subset of the data comprised of these reporting their party identification as “leaning Democrat”, “weak Democrat” or “strong Democrat” and for conservative selective exposure, I rely on a subset of the data comprised of these describing themselves as “leaning Republican”, “weak Republican” or “strong Republican”. This procedure allows to compare changes in issue attitudes of liberally (or conservatively respectively) exposed self-reported Democrats (or self reported Republicans respectively) to a baseline of non-exposed self-reported Democrats (or self-reported Republicans respectively).\(^4\) The regression model can be expressed as the following:

---

\(^3\)Imputations were used for the particles of the lagged dependent variable, relying on the same technique and same theoretical justification. A complete set of predictor variables as well as diagnostics of the imputation are available in the Appendix.

\(^4\)Descriptive Statistics of the distributions of the variables discussed may be found in the Appendix. The fully specified models that include controls for education, political knowledge, political interest, a measure for political discussion and exposure to cable-news in general, income and attention to national news may also be found in the Appendix.
\[ Y_t = \beta_0 + \beta_1 Y_{t-1} + \beta_2 v + \beta_3 i_{t-1} + \beta_4 p_{t-1} + \beta_5 b + \beta_6 h + c + \epsilon \]

whereby \( \beta_0 \) represents the intercept, \( v \) represents the gender of the respondent coded as a dummy, \( i_{t-1} \) represents self-reported ideology at time-point \( t - 1 \) ranging from very conservative to very liberal (1-5), \( p_{t-1} \) represents party-identification at time-point \( t - 1 \) ranging from strong Republican to strong Democrat (1-7), \( b \) represents a dummy-variable for blacks, \( h \) represents a dummy-variable for Hispanics, \( c \) represents the controls mentioned in the Appendix and their coefficients and \( \epsilon \) represents the error term.

The dependent variable \( Y_t \) is coded as a relative score on 16 political issues relevant during the Presidential campaign 2004, ranging from 0, the most conservative score possible, to 1, the most liberal score possible. This procedure allows me to treat my dependent variable as quasi-continuous.\(^5\) The normal appearance of the distribution of the dependent variable and the normal appearance of the QQ-plot justify the use of OLS.

\(^5\) A list of policy items used to create the variable may be found in the Appendix.
To assess the independent influence of selective exposure on ideology at time point $t$, a lagged version of the dependent variable is included on the right-hand-side of the equation. The main independent variable captures conservative selective exposure and liberal selective exposure respectively, coded as 1 if the respondent had
named Fox News as her primary news source at time point \( t \) and time point \( t - 1 \) and 0 if the respondent neither named Fox News her primary news source at time point \( t \) nor at time point \( t - 1 \) for the Fox News model, and 1 if the respondent had named CNN/MSNBC as her primary news source at time point \( t \) and time point \( t - 1 \) and 0 if the respondent neither named CNN/MSNBC her primary news source at time point \( t \) nor at time point \( t - 1 \) for the CNN/MSNBC model.\(^6\) Accordingly, we should expect that Republicans exposing themselves to Fox News should have become more ideologically conservative in issue attitudes at time point \( t \) than their non-exposed Republican counterparts and Democrats exposing themselves to CNN/MSNBC should have become more liberal in their issue attitudes at time point \( t \), compared to their non-exposed Democratic counterparts.

To model change in issue attitudes in the respective dimensions of the political space, I rely on three controversial policy items that may be attributed to the cultural dimension, gay marriage, stem-cell research and abortion, and seven distinctive policy items that may be attributed to the economic dimension, tax cuts, eliminating tax breaks for overseas profits, minimum wage, employer’s responsibility to provide health care, government’s responsibility to provide health care for underprivileged children, allowing workers to invest some of their Social Security contributions in the stock market, and the government placing limits on how much people could collect when a jury finds that a doctor has committed medical malpractice, to compute economic and cultural/social issue attitudes.\(^7\) To model the independent association of selective exposure with a move to the margins of the respective policy dimensions,

\(^6\) A point can be made that it is hard to make a causal claim that selective exposure entails issue-based polarization, as I only consider respondents who constantly watch CNN/MSNBC or Fox News. However, it is somewhat reasonable to assume that many respondents engage in selective exposure only temporarily because they seek information about the political campaign and will stop doing so once the election is over. Thus, I assume that albeit coded as “constant exposers”, many respondents expose themselves temporarily. Thus, especially because I compare the exposers only to those who have not been exposed at either panel, inference about the political impact of exposure can be made.

\(^7\) A complete list of variables used can be found in the Appendix.
I additionally control for issue attitudes not being included in the cultural attitudes or in the economic attitudes respectively at time point $t - 1$.\footnote{Details on these policy items may be found in the Appendix.}
Descriptive data analyses show that Republicans constantly watching Fox News have a more conservative latent ideology score at time point $t$ than Republicans who watched cable news at least one day during the week prior to the interview, but did not name Fox News as the channel watched most. Similarly, Democrats constantly exposed to CNN or MSNBC have a more liberal latent ideology score at time point $t$ than Democrats who watched cable news at least one day during the week prior to the interview, but did not name CNN or MSNBC as the channel watched most. Both, Republicans and Democrats who were subject to political selective exposure have also undergone a process of radicalization in issue attitudes.
Figure 4.1: Issue attitudes or Republicans at $t$ mapped against Issue attitudes at $t-1$ (above) and Issue attitudes or Republicans at $t$ mapped against Issue attitudes at $t-1$ (above)
A locally weighted line of best fit between score on the latent ideology scale at time point \( t - 1 \) and latent ideology score at time point \( t \) for Republicans and Democrats clearly shows that for both models, changes in issue attitudes between panels become most visible for Republicans and Democrats initially having a moderate score on the latent ideology scale at time point \( t - 1 \).
Figure 4.2: Issue attitudes or Republicans at $t$ mapped against Issue attitudes at $t - 1$ (above) and Issue attitudes or Republicans at $t$ mapped against Issue attitudes at $t - 1$ (above); locally weighted regression line
Table 4.1: Change in issue attitudes for Republicans after constant exposure to Fox News and Democrats after constant exposure to CNN or MSNBC

The assumption that selective exposure does have an independent predictive impact on radicalization in the latent ideology score is supported by the fully specified regression models.\(^1\) As is visible in Table 1, selective exposure to MSNBC/CNN for Democrats predicts a radicalization in issue attitudes between panels (e.g. those who selectively exposed themselves to liberal-leaning news were more liberal in their issue attitudes than those not selectively exposed) and selective exposure to Fox News for Republicans also predicts a radicalization in issue attitudes between panels (e.g. those who selectively exposed themselves to conservative-leaning news were more conservative in their issue attitudes than those not selectively exposed).

\(^1\)Models that hypothesize that selective exposure is based on ideology instead of party identification show the same results.
This trend is also visible graphically as the effect of selective exposure is significantly different from a null-effect in both models.
Figure 4.3: Coefficient plot showing coefficients of interest for the Fox News model (left), CNN/MSNBC model (right)
The effect-sizes are admittedly small, which is certainly no surprise given the conservative nature of the model. In addition, the number of controls introduce a vast amount of uncertainty into the model. However, the results are still of meaningful and substantive magnitude, as indicated by the non-overlapping confidence intervals (or barely overlapping confidence intervals in the liberal model) of the graphs visualizing the effect of selective exposure on issue attitudes at time-point $t$ by holding all other covariates constant at meaningful values.
Figure 4.4: Substantive effects of exposure of selective exposure on issue-attitudes for the Fox News model (above), for the MSNBC model (below)
A minor point that has to be made is that both, Republicans and Democrats have undergone a subtle process of radicalization between the two panels ($\mu_{R,t-1} = 0.548, \mu_{R,t} = 0.542, \mu_{D,t-1} = 0.738, \mu_{D,t} = 0.758$). Both changes in means are statistically significant in a two-sided student’s t-test of differences in means.$^2$

If intervals are based on the true error-term instead of just the sample and used to predict the range of issue attitudes at time-point $t$ in which an individual $Y_{n+1}$ will fall, the effect of selective exposure becomes indistinguishable from a null-effect.

$^2$Although the change in means for Republicans barely misses statistical significance at the conventional 0.05 level, $p=0.06$
Figure 4.5: Substantive predictive effects of exposure of selective exposure on issue-attitudes for the Fox News model (above), for the MSNBC model (below)
However, that does not mean that the effect in itself is insignificant. Selective exposure in the Republican model accounts for a move in the conservative direction on the scale of issue attitudes at time-point $t$ of size of roughly one fourth of a standard deviation and selective exposure in the Democratic model accounts for a move in the liberal direction on the scale of issue attitudes at time-point $t$ of size of roughly one tenth of a standard deviation.

While the effects are thus of statistical significance, the failure to demonstrate substantive predictive effects that take the true error term into account indicate that while the model allows for attributing a selective-exposure effect to the sample, its statistical power is not fully sufficient to make predictions about future outcomes. Hence, there is certainly need for a more rigorous panel study that offers data for longer time-spans and allows for replication of the results and a more meaningful testing for substantiveness of effects.

If broken down to the two hypothetical dimensions of the political space, it is clearly visible that political selective exposure has an independent and significant effect on the economic political dimensions for Republicans and Democrats, as hypothesized. The effect of selective exposure on political attitudes associated with the cultural dimension are mixed. While the effect of selective exposure for Republicans is statistically significant and in the expected direction, the effect of selective exposure for Democrats is indistinguishable from zero.\footnote{Again, models that hypothesize that selective exposure is based on self-reported ideology instead of self-reported party-identification show the same results.}
Table 4.2: Independent change in issue attitudes for Republicans after constant exposure to Fox News and Democrats after constant exposure to CNN or MSNBCS on two dimensions of the political space

<table>
<thead>
<tr>
<th>Models</th>
<th>self-reported Republicans on economic dimension</th>
<th>self-reported Democrats on economic dimension</th>
<th>self-reported Republicans on cultural dimension</th>
<th>self-reported Democrats on cultural dimension</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.241*</td>
<td>0.138*</td>
<td>-0.070</td>
<td>0.060</td>
</tr>
<tr>
<td>(0.022)</td>
<td>(0.024)</td>
<td>(0.038)</td>
<td>(0.036)</td>
<td></td>
</tr>
<tr>
<td>Economic/Social Issue-ideology at $t - 1$</td>
<td>0.556*</td>
<td>0.491*</td>
<td>0.639*</td>
<td>0.521*</td>
</tr>
<tr>
<td>(0.019)</td>
<td>(0.020)</td>
<td>(0.018)</td>
<td>(0.018)</td>
<td></td>
</tr>
<tr>
<td>Control for unrelated Issue-ideology at $t - 1$</td>
<td>0.154*</td>
<td>0.217*</td>
<td>0.252*</td>
<td>0.279*</td>
</tr>
<tr>
<td>(0.022)</td>
<td>(0.021)</td>
<td>(0.040)</td>
<td>(0.037)</td>
<td></td>
</tr>
<tr>
<td>Self-reported Ideology at $t - 1$</td>
<td>0.007*</td>
<td>0.006*</td>
<td>0.032*</td>
<td>0.029*</td>
</tr>
<tr>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.005)</td>
<td>(0.004)</td>
<td></td>
</tr>
<tr>
<td>Self-reported Party-identification at $t - 1$</td>
<td>0.005</td>
<td>0.005</td>
<td>0.012*</td>
<td>-0.005</td>
</tr>
<tr>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.005)</td>
<td>(0.004)</td>
<td></td>
</tr>
<tr>
<td>Constant Selective Exposure</td>
<td>-0.026*</td>
<td>0.013*</td>
<td>-0.026*</td>
<td>0.009</td>
</tr>
<tr>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.010)</td>
<td>(0.008)</td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>0.013*</td>
<td>-0.010*</td>
<td>-0.015</td>
<td>-0.010</td>
</tr>
<tr>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.008)</td>
<td>(0.006)</td>
<td></td>
</tr>
<tr>
<td>Black</td>
<td>0.037</td>
<td>0.001</td>
<td>-0.020</td>
<td>-0.047*</td>
</tr>
<tr>
<td>(0.019)</td>
<td>(0.007)</td>
<td>(0.033)</td>
<td>(0.011)</td>
<td></td>
</tr>
<tr>
<td>Hispanic</td>
<td>0.004</td>
<td>-0.010</td>
<td>-0.035</td>
<td>-0.022</td>
</tr>
<tr>
<td>(0.011)</td>
<td>(0.009)</td>
<td>(0.019)</td>
<td>(0.014)</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>2294</td>
<td>2156</td>
<td>2294</td>
<td>2156</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.489</td>
<td>0.444</td>
<td>0.497</td>
<td>0.502</td>
</tr>
<tr>
<td>adj. $R^2$</td>
<td>0.485</td>
<td>0.439</td>
<td>0.493</td>
<td>0.499</td>
</tr>
<tr>
<td>Resid. sd</td>
<td>0.100</td>
<td>0.097</td>
<td>0.174</td>
<td>0.144</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

* indicates significance at $p < 0.05$

This trend of radicalization—effects of selective exposure on the economic dimension is also visible graphically, as the effects of selective exposure are again significantly different from a null-effect in both models.
Figure 4.6: Coefficient plot showing coefficients of interest for the Fox News model (above), CNN/MSNBC model (below)
The effect-sizes are again admittedly small for the above mentioned reasons. As in the general model however, the effect of selective exposure is visible and substantive for the sample analyzed (although confidence intervals are slightly overlapping in the model for Democrats). Selective exposure in the Republican model accounts for a move in the conservative direction on the scale of issue attitudes in the economic dimension at time-point $t$ of size of roughly 23% of a standard deviation and selective exposure in the Democrat model accounts for a move in the liberal direction on the scale of issue attitudes in the economic dimension at time-point $t$ of size of roughly 12% of a standard deviation.
Figure 4.7: Coefficient plot showing coefficients of interest for the Fox News model (above), CNN/MSNBC model (below)
5

Alternative Hypotheses and Robustness-Checks

5.1 Media Effects or Campaign Effects?

Any empirical survey-based study assessing the independent impact of media exposure faces a severe limitation: the isolation of media effects as the causal mechanism. Are reported “media effects” genuine media effects or do they capture the effect of omitted variables? This seems especially problematic for changes in issue attitudes in the course of a Presidential campaign, which lies at the heart of this paper. In these analyses, observed media effects might merely reflect the impact of other campaign stimuli. The history of both campaign-effect- and media-effect-research has shown that the two are conceptually difficult to disentangle. As a robustness check, I replicate my analysis for states that are least exposed to campaign-stimuli – so called safe states. In these safe states, campaign expenditure is comparably weaker to other states (Shaw 2006, Gimpel et al. 2007). Thus, campaign-exposure is usually minimal in these states, especially when compared to battleground-states (Gimpel et al. 2007). In 2004, these “safe” states were Alabama, Alaska, Georgia, Idaho, Indiana, Kansas, Kentucky, Mississippi, Montana, Nebraska, North Dakota,
Oklahoma, South Carolina, South Dakota, Tennessee, Texas, Utah and Wyoming (Republican base) and California, Connecticut, District of Columbia/Washington, Hawaii, Illinois, Maryland, Massachusetts, New York, Rhode Island and Vermont (Democrat base) (Shaw 2006).

The graphs below show that during campaigns, selective exposure also has an effect on change in issue attitudes if only non-battleground states are considered. The absence of significant campaign stimuli allows for isolation of media exposure during the campaign independent of other campaign stimuli accidentally captured in one of the independent variables. That is, the changes in issue attitudes during the campaign should reflect information obtained by selective exposure, and not information provided by the campaigns directly.
Figure 5.1: Coefficient plot showing coefficients of interest for the Fox News model (above), for the CNN/MSNBC-model (below), only safe states
5.2 Causes and Effects – Political Identities vs. latent ideology

The disentanglement of cause and effect undertaken earlier postulates that while salient political predispositions determine selective exposure, it should not be affected by it. Political identities, such as partisan identification or ideology that today seem to capture the same underlying political identity (Sniderman & Stiglitz 2012, in press), are highly stable over time and as a consequence of processes of political socialization and identity formation rather static (Campbell et al. 1960, Green & Palmquist 1994).

Indeed, party identification proves to be rather stable during the two panels and is not significantly affected by selective exposure for either self-reported Democrats or Republicans, as the ordered logistic regression indicates. However, it should be noted that the autoregressive model is a very conservative test to reject the null-hypothesis. While the rejection of the null-hypothesis postulating a null-effect lied at the heart of the statistical analysis for the earlier models, the argument used here relies on a failure to reject the null-hypothesis that the true coefficient size is zero.

However, the failure to reject the null-hypothesis might not be as meaningful. By definition, autoregressive modeling in this form minimizes the probability of committing a Type-I-error. As there is always a trade-off between Type-I and Type-II error, the probability of accepting the null although it does not hold rises (Type-II-error).
<table>
<thead>
<tr>
<th>Models</th>
<th>Democrats</th>
<th>Republicans</th>
</tr>
</thead>
<tbody>
<tr>
<td>Issue Ideology at $t - 1$</td>
<td>4.52*</td>
<td>4.43*</td>
</tr>
<tr>
<td></td>
<td>(0.54)</td>
<td>(0.52)</td>
</tr>
<tr>
<td>Self-reported Party-identification at $t - 1$</td>
<td>1.79*</td>
<td>1.89*</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>Self-reported ideology at $t - 1$</td>
<td>0.14*</td>
<td>0.26*</td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Constant Selective Exposure</td>
<td>0.05</td>
<td>-0.23</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td>(0.12)</td>
</tr>
<tr>
<td>Female</td>
<td>0.20*</td>
<td>-0.26*</td>
</tr>
<tr>
<td></td>
<td>(0.09)</td>
<td>(0.09)</td>
</tr>
<tr>
<td>Black</td>
<td>0.50*</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>(0.17)</td>
<td>(0.41)</td>
</tr>
<tr>
<td>Hispanic</td>
<td>-0.11</td>
<td>0.20</td>
</tr>
<tr>
<td></td>
<td>(0.18)</td>
<td>(0.22)</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>1—2</td>
<td>9.63*</td>
<td>5.92*</td>
</tr>
<tr>
<td></td>
<td>(0.61)</td>
<td>(0.47)</td>
</tr>
<tr>
<td>2—3</td>
<td>10.55*</td>
<td>7.57*</td>
</tr>
<tr>
<td></td>
<td>(0.59)</td>
<td>(0.48)</td>
</tr>
<tr>
<td>3—4</td>
<td>11.23*</td>
<td>9.85*</td>
</tr>
<tr>
<td></td>
<td>(0.59)</td>
<td>(0.50)</td>
</tr>
<tr>
<td>4—5</td>
<td>11.73*</td>
<td>10.38*</td>
</tr>
<tr>
<td></td>
<td>(0.59)</td>
<td>(0.51)</td>
</tr>
<tr>
<td>5—6</td>
<td>13.99*</td>
<td>11.26*</td>
</tr>
<tr>
<td></td>
<td>(0.61)</td>
<td>(0.52)</td>
</tr>
<tr>
<td>6—7</td>
<td>15.47*</td>
<td>12.44*</td>
</tr>
<tr>
<td></td>
<td>(0.63)</td>
<td>(0.56)</td>
</tr>
<tr>
<td>AIC</td>
<td>4462.12</td>
<td>4411.96</td>
</tr>
<tr>
<td>BIC</td>
<td>4581.31</td>
<td>4532.46</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-2210.06</td>
<td>-2184.98</td>
</tr>
<tr>
<td>Deviance</td>
<td>4420.12</td>
<td>4369.96</td>
</tr>
<tr>
<td>Num. obs.</td>
<td>2156</td>
<td>2294</td>
</tr>
</tbody>
</table>

* $p < 0.05$

Table 5.1: Ordered Logistic Regression of party-id at time-point $t$ on its lagged version, selective exposure and covariates
5.3 Genetic Matching

As a second robustness check, I apply the concept of genetic matching, conceptualizing political selective exposure as *treatment*. Genetic matching allows for testing the two related but different hypotheses of comparative radicalization as a function of selective exposure (do those engaging in selective exposure become more radical compared to their non-exposed counterparts) vs. absolute radicalization as a function of selective exposure (have those that engage in selective exposure become more radical in their issue attitudes than they were before?).

Genetic matching relies on the statistical concept of propensity score matching, a technique that is somewhat controversially believed to be adequate for isolating treatment-effects (Diamond & Sekhon 2012, forthcoming, see however Morgan & Winship 2007). The basic idea is that treated and non-treated observations that have a similar propensity of treatment contingent on the joint distribution of its covariates are matched pairwise and that the variable of interest, the dependent variable of the models, is compared across the range of pairs for treated and non-treated observations. In other words, the data-set will be sub-sampled, as only pairs that could be matched by means of a mathematical algorithm are subject to statistical analysis. Genetic matching is a balance between propensity-score-matching and covariate-matching (Diamond & Sekhon 2012).

Mathematically, propensity score matching relies on the Rubin causal model that “conceptualizes causal inference in terms of potential outcomes under treatment and control, only one of which is observed for each unit” (Sekhon 2011: 3). The treatment-effect is thus defined as

\[ \tau_i = Y_{i1} - Y_{i0} \]
whereby $\tau_i$ denotes the treatment-effect for each observation $i$ that is treated (denoted as 1) or not treated (denoted as 0). However, this equation is not solvable as treatment and non-treatment never occur at the same time (Sekhon 2011). If $T_i$ is a treatment indicator denoted 1 if the element receives treatment and 0 otherwise, the observed outcome of each element can be denoted as

$$Y_i = T_iY_{1i} + (1 - T_i)Y_{0i}$$

Theoretically, causal inference would be possible if assignment to treatment would be randomized and is independent of covariates. However, this is hardly the case in lab-experiments, where some elements have an intrinsically higher propensity to be assigned to treatment. Thus, the propensity of treatment $\pi$ is dependent on certain covariates ($\pi(X_i) = P(T = 1)|X_i$). Applied to survey-data-analysis, matching can also be used to simply balance across the covariates. In essence, non-parametric matching then enables one to control for certain covariates similar to parametric multivariate regression techniques.

In this notion, progress towards accurate estimation of the treatment effect can be made by achieving balance in the covariate distribution of $X_i$, which in turn is achieved by matching observations pairwise with regard to their propensity score $\pi$. Matching pairs dependent on the true propensity score then results in the observed covariates (X) being asymptotically balanced between treatment and control groups such that indeed $T \perp X$ (Diamond & Sekhon 2012, forthcoming). This approach however is heavily constrained: the “true” propensity-score that asymptotically balances the observed covariates remains unknown and hence, the propensity-score must be adjusted by iteratively comparing the achieved covariate balance and readjusting the score.

Genetic Matching makes use of another means of matching, a generalized version
of a scalar measuring the multivariate distance between the covariates of two different units, known as Mahalanobis Distance \(MD(X_i, X_j) = \sqrt{X_i - X_j^T \ast S^{-1} \ast (X_i - X_j)}\) by introducing an additional weight-parameter \(W\) (Diamond & Sekhon 2012, forthcoming):

\[
GMD(Z_i, Z_j, W) = \sqrt{Z_i - Z_j^T \ast (S^{-\frac{1}{2}})^T \ast WS^{-\frac{1}{2}} \ast (Z_i - Z_j)}
\]

The \(Z\)-matrix in this case consists of both the propensity-score \(\pi(X)\) and the underlying covariates \(X\), whereas the \(W\)-matrix represents a \(k \times k\)-matrix that in its diagonal specifies the weight to each variable in \(Z\). Genetic Matching can thus be seen as a method to reduce the loss-function by finding the right balance between propensity-score matching (in the case of pure propensity-score matching, \(W\) carries a zero-weight for every variable in \(Z\) except \(\pi\)) and minimization of \(MD\) (in the case of pure matching based on \(MD\), \(W\) carries a zero-weight for \(\pi\) and a weight of one for every other variable in \(Z\), Diamond & Sekhon 2012, forthcoming).

I conceptualize the propensity of treatment, \(\pi\), as a vector of fitted values for two logistic regression models

\[
pFOX - NEWS = \frac{1}{1 + e^{-x \ast \beta}}
\]

\[
pCNN/MSNBC = \frac{1}{1 + e^{-x \ast \beta}}
\]

whereby \(x \ast \beta\) represents the link-function or linear part of the model. In this case, the link function is given by

\[
\beta_1q + \beta_2w + \beta_3f + \beta_4r + \beta_5u + \beta_6v + \beta_7h + \beta_8t + \beta_9d + e
\]

whereby \(q\) represents latent issue-ideology at time-point \(t - 1\), \(w\) represents self-reported party-identification at time-point \(t - 1\), \(f\), \(r\) and \(u\) represent dummies for
Blacks, Hispanics and women, $v$ represents the number of days respondents had watched a 24-hours-cable-news-station the week prior to the interview, $h$ represents political ideology at time-point $t - 1$, $t$ represents a measure of political discussion, $s$ represents a measure of political interest, $d$ represents a measure of political knowledge and $e$ represents the error term. The explanatory variables of the propensity score model are also included in the $Z$-matrix for the genetic matching algorithm.

Genetic Matching also relies on an iterative process, “checking and improving overall covariate balance and guarantees asymptotic convergence to the optimal matched sample” (Diamond & Sekhon 2012, forthcoming). The outcome reports the standardized mean difference over pairs with similar propensity scores for the treated and the untreated for each covariate as the average treatment effect (ATE), which gives information as to how treated and untreated observations differ in issue attitudes at time-point $t$ on average, as well as the average treatment effect of the treated (ATT), the average gain in the dependent variable from treatment for those who actually were treated.

As is visible in the comparison of the pre- and post-matching statistics, the genetic matching algorithm has significantly improved covariate balance for the conservative model in almost all covariates for the ATT and the ATE model. The statistics provided in the tables below include the means for the treatment and control groups, the standardized difference in means, the variance ratio of treatment over control (which should equal 1 if there is perfect balance), and the t-test of difference of means (the paired t-test is provided post-matching).¹

¹Complete match-balance results that include the mean, median and maximum differences in the standardized empirical-QQ plots and summary statistics from the raw empirical-QQ plots are presented in the Appendix.
<table>
<thead>
<tr>
<th></th>
<th>mean.Tr</th>
<th>mean.Co</th>
<th>sdiff</th>
<th>var.ratio</th>
<th>T</th>
<th>pval</th>
</tr>
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<tbody>
<tr>
<td>Issue Attitudes t-1</td>
<td>0.50</td>
<td>0.58</td>
<td>-84.35</td>
<td>0.83</td>
<td>0.00</td>
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</tr>
<tr>
<td>Self-reported Ideology at t-1</td>
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<td>2.38</td>
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<td>0.00</td>
<td></td>
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<tr>
<td>Self-reported PID at t-1</td>
<td>1.60</td>
<td>1.88</td>
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<td>1.01</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td>0.44</td>
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<td>-15.25</td>
<td>0.99</td>
<td>0.00</td>
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</tr>
<tr>
<td>Hispanic</td>
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<td>0.05</td>
<td>-14.98</td>
<td>0.54</td>
<td>0.00</td>
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</table>

Table 5.2: Covariate Balance for the conservative ATT model before and after Matching

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<th>pval</th>
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</thead>
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<td>Issue Attitudes t-1</td>
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<td>24.72</td>
<td>0.79</td>
<td>0.00</td>
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<td>Self-reported Ideology at t-1</td>
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<td>3.40</td>
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<td>0.90</td>
<td>0.00</td>
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<td>Self-reported PID at t-1</td>
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<td>6.24</td>
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<td>0.77</td>
<td></td>
</tr>
<tr>
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<td>0.56</td>
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<td>0.04</td>
<td>0.00</td>
<td>1.00</td>
<td>1.00</td>
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</tr>
</tbody>
</table>

Table 5.3: Covariate Balance for the conservative ATE model before and after Matching

For the liberal model, the genetic matching algorithm increased covariate-balance for both, the ATT and the ATE model in general, and performed equally strong as
it did for the conservative model.\(^2\)

<table>
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<tr>
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<th>sdiff</th>
<th>var.ratio</th>
<th>T</th>
<th>pval</th>
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</thead>
<tbody>
<tr>
<td>Issue Attitudes t-1</td>
<td>0.75</td>
<td>0.72</td>
<td>34.36</td>
<td>0.77</td>
<td>0.00</td>
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<td>Self-reported PID at t-1</td>
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<td>Gender</td>
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<td>0.59</td>
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<td>1.02</td>
<td>0.16</td>
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<td>Black</td>
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<td>0.09</td>
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<td>0.96</td>
<td>0.75</td>
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<tr>
<td>Hispanic</td>
<td>0.04</td>
<td>0.08</td>
<td>-21.29</td>
<td>0.52</td>
<td>0.00</td>
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</table>

Table 5.4: Covariate Balance for the liberal ATT model before and after Matching

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<tr>
<th></th>
<th>mean.Tr</th>
<th>mean.Co</th>
<th>sdiff</th>
<th>var.ratio</th>
<th>T</th>
<th>pval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Issue Attitudes t-1</td>
<td>0.75</td>
<td>0.73</td>
<td>24.04</td>
<td>0.98</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>Self-reported Ideology at t-1</td>
<td>3.50</td>
<td>3.44</td>
<td>6.54</td>
<td>1.16</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>Self-reported PID at t-1</td>
<td>6.24</td>
<td>6.23</td>
<td>0.88</td>
<td>1.07</td>
<td>0.55</td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td>0.56</td>
<td>0.56</td>
<td>0.00</td>
<td>1.00</td>
<td>1.00</td>
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</tr>
<tr>
<td>Black</td>
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<td>0.08</td>
<td>1.77</td>
<td>1.05</td>
<td>0.66</td>
<td></td>
</tr>
<tr>
<td>Hispanic</td>
<td>0.04</td>
<td>0.03</td>
<td>3.37</td>
<td>1.19</td>
<td>0.31</td>
<td></td>
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</tbody>
</table>

Table 5.5: Covariate Balance for the liberal ATE model before and after Matching

The non-parametric regression technique holds what the various OLS regressions have indicated: selective exposure has a strong independent predictive impact on

\(^2\)Complete Balance-tables are in the Appendix.
radicalization in issue attitudes, as there is also considerable support for my hypo-
theses if the elements of the treatment- and the control-group are paired on the basis of the joint distribution of their covariates.

Republicans exposing themselves to Fox News are more conservative at time point $t$ and Democrats exposing themselves to CNN/MSNBC are more liberal at time point $t$ compared to their non-exposed counterparts in their latent ideology, as indicated by the statistically significant average treatment effect (ATE).

\[
\begin{array}{|c|c|c|}
\hline
\text{Matching} & \text{Fox-News} & \text{CNN/MSNBC} \\
\hline
\text{Average Treatment Effect} & -0.05 & 0.04 \\
\text{Abadie-Imbens Standard Errors} & 0.01 & 0.01 \\
\text{T-Statistics} & -6.02 & 4.22 \\
\text{P-Value} & 0.00 & 0.01 \\
\text{Original Number of Observations} & 2294 & 2156 \\
\text{Original Number of treated Observations} & 956 & 1195 \\
\text{Matched Number of Observations} & 956 & 1195 \\
\text{Matched Number of Observations (unweighted)} & 956 & 1195 \\
\hline
\end{array}
\]

Table 5.6: Average Treatment Effect after Matching

Also, those who engaged in selective exposure have undergone a process of issue-based radicalization and have become more liberal and respectively conservative in their ideology score between the two panels, as indicated by the statistically significant average treatment effect for the treated (ATT).

\[
\begin{array}{|c|c|c|}
\hline
\text{Matching} & \text{Fox-News} & \text{CNN/MSNBC} \\
\hline
\text{Average Treatment Effect} & -0.04 & 0.04 \\
\text{Abadie-Imbens Standard Errors} & 0.01 & 0.01 \\
\text{T-Statistics} & -5.26 & 4.22 \\
\text{P-Value} & 0.00 & 0.05 \\
\text{Original Number of Observations} & 2294 & 2156 \\
\text{Original Number of treated Observations} & 956 & 1195 \\
\text{Matched Number of Observations} & 956 & 1195 \\
\text{Matched Number of Observations (unweighted)} & 956 & 1195 \\
\hline
\end{array}
\]

Table 5.7: Average Treatment Effect for the Treated after Matching
The findings presented here demonstrate how selective exposure entails a process of polarization in issue-attitudes independent of political predispositions. Democrats tuning in to CNN/MSNBC become more liberal in their issue attitudes while Republicans tuning in to Fox News become more conservative. As a consequence, those who selectively expose themselves to congenial news sources as a consequence of political predispositions move in the direction of their initial leaning on the latent, issue-based ideology measure and the ideological difference between those exposed to liberal-leaning news and those exposed to conservative-leaning news becomes starker.

To be sure, the magnitude of the effects is small, especially with regards to the general model. When accounting for the true error and trying to generate predictive inference, the significance of selective-exposure-effects diminishes. While allowing statistical inference on the sample analyzed, the findings presented here do not pass the threshold of making predictive inference for future observations. In order to replicate the findings here and draw additional predictive inference about the effects of selective exposure, media-effect-scholarship is in desperate need for a new survey that offers longer panels, more variability in the media exposure variables and less
missingness in the issue-attitude-items. But a survey that combines the methodological rigor of for example the National American Election Studies with the media focus of the National Annenberg Election Survey remains to be conducted. I thus believe that the significance of the independent effect of selective exposure demonstrated here not only proves to be preliminary evidence that supports the theory developed here, it also justifies the development of such a survey.

Certainly, this paper has further numerous shortcomings. Most prominently, it incorporates a vast amount of uncertainty into its analyses, for there is not one respondent who had answered every issue question asked. As much as Amelia might produce realistic imputations, and as correct as the MAR-assumption seems to be in this case, imputations remain imputations, or educated guesses. Furthermore, predictive variables used for the imputation process, as self-reported ideology or party identification, are concepts that are conceptually distinguished from issue attitudes in this paper, thus producing an endogeneity effect for the dependent variable.

Finally, I took great care to disentangle causes and effects of selective exposure, although I by no means claim that cause and effect are entirely unrelated. However, the simple assumption that there is a causal loop between independent and dependent variable has hindered scholars to develop a more rigorous framework of selective exposure effects (Slater 2007, Stroud 2010). If cause and effect were equal, the question as to what sets the causal spiral in motion has not been answered sufficiently. In addition, there is plenty of evidence that news niche audiences differ in knowledge and perceived importance of newly arising political issues. And while these tendencies by no means prove that cause and effect of selective exposure point to different underlying political and psychological phenomena, they invalidate the assumption that cause and effect of selective exposure are entirely congruent. A theoretical framework of selective exposure effects necessarily has to focus on causes and effects, but only a conceptual disentanglement provides researchers with the op-
portunity to derive distinctive and testable hypotheses for both. In lieu of the many limitations of this study, it thus provides a point of departure for a new paradigm in both, theoretical and empirical scholarship of selective exposure.
Conclusion

As my results suggest, there is evidence for polarization as a function of selective exposure to the partisan media. At first glance, these findings seem to be intransigent with Fiorina and colleagues, who argue that Americans are, at the aggregate level, much more moderate politically than their representatives (Fiorina et al. 2006). In line with Converse (1964), it is reasonable to assume that many citizens have little interest in politics, and accordingly many people chose to entirely opt out of political news, are drawn to less political sources or have a more inconsistent news consumption. That, however, is not to say that polarization at the mass-level is neglectable. My results suggest that regardless of news-consumption, citizens were subject to issue-based polarization in the course of the campaigns. Furthermore, research that has predominantly focused on aggregate data is not apt to identify polarization processes at subsets of society, as trends in different subsets might cancel out at the aggregate. In this light, my findings that demonstrate how selective exposure induces polarization are not and should not be treated as accounts that prove the minimal-mass-polarization hypothesis wrong, but as a demonstration of group-level polarization.
In addition, these findings, especially if they are corroborated by analyses accounting for fundamental certainly, raise macro behavioral questions. What are the long-term consequences of exposure to enclave discourse? Do people regress to their previously held issue attitudes after the intensely political tone in coverage of Presidential campaigns mellows in non-campaign times? Or do the updated issue attitudes become the new prior and are subject to another updating during the next campaign cycle which then again leads to a new posterior, in a never ending cycle of a Bayesian-updating-based process of polarization? What unforeseeable events might disrupt the cycle? Are party identification and ideology brought in line with the new issue attitudes, are vice-versa issue attitudes brought in line with party identification and ideology and thus is the process of polarization only terminally visible, or does correlation between these political identities and issue attitudes weaken over time? If the latter were true, polarization as a function of selective exposure would go completely unnoticed if the academic focus lies on self-placement concepts or affect to political leaders (Stroud 2010).

Also, the question as to what consequences the observed process of issue-based radicalization entails needs to be addressed. One could somewhat correctly point out that, if not reflected in vote choice, issue-based polarization is not a tendency as threatening as assumed here. Nevertheless, polarization at the group-level can have severe consequences, especially if it occurs among the audience of what has been framed as the partisan media: CNN/MSNBC on the political left and Fox News on the political right. If the country is hypothetically dividable into red and blue states, it certainly is also dividable into red and blue cable news. And although this cleavage might only divide the few, it is reasonable to assume that issue-based polarization as a consequence of selective exposure certainly reduces the potential for cross-cutting discourse. Polarization in issue attitudes is more threatening than affect-based polarization (Stroud 2010), because it bears potential for a further po-
itical gentrification of communicative enclaves. Topics in informal social networks revolve around issues, such as the new health care bill or the new government stimulus, much more than they revolve around political affect or thermometer scores. If informal social networks become more ideologically homogeneous, one of the consequences might be that grand bargains that not only enjoy bipartisan support but also are supported by a vast majority of the American electorate might become less likely, and our Democracy in consequence less deliberative (Mutz 2006).
Appendix A

Tables and Additional Summary Statistics

A.1 Dependent variable

Average issue, attitudes, ranges from 1 (very conservative) to 5 (very liberal). The item is created by averaging 16 issue-question. For each issue-attitude, 1 is the most conservative and 5 the most liberal answer. The questions read:

1) Making recent federal tax cuts permanent-do you favor or oppose this?

2) Eliminating tax breaks for overseas profits and using money to cut taxes for businesses that create jobs in the United States do you favor or oppose this?

3) Do you favor or oppose increasing the $5.15 minimum wage employers now must pay their workers?

4) The federal government helping to pay for health insurance for all children—do you favor or oppose this?
5) The federal government helping employers pay the cost of their workers health insurance—do you favor or oppose this?

6) Changing the recently passed Medicare prescription drug law to allow reimporting drugs from Canada—do you favor or oppose this?

7) Do you favor or oppose allowing workers to invest some of their Social Security contributions in the stock market?

8) As far as you know, has the No Child Left Behind education law made American public schools much better, somewhat better, somewhat worse, much worse, or hasn’t it made a difference?

9) Since the attacks on the World Trade Center and the Pentagon on Sept. 11, 2001, the United States government has done a number of things both at home and abroad intended to protect Americans from future attacks. How safe have these efforts made you feel much more safe, somewhat more safe, somewhat less safe, or much less safe?

10) Laws making it more difficult for a woman to get an abortion—do you favor or oppose this?

11) Making additional stem cell lines from human embryos available for federally funded research on diseases like Parkinson’s—do you favor or oppose this?

12) Would you favor or oppose an amendment to the U.S. Constitution saying
hat no state can allow two men to marry each other or two women to marry each other?

13) Extending the federal law banning assault weapons–do you favor or oppose this?

14) The government placing limits on how much people could collect when a jury finds that a doctor has committed medical malpractice–do you favor or oppose this?

15) In the next administration, the president may have the opportunity to nominate two or three Supreme Court justices to replace retiring ones. How comfortable are you with George W. Bush making those nominations – very comfortable, somewhat comfortable, neither comfortable nor uncomfortable, somewhat uncomfortable, or very uncomfortable?

16) From what you know about John Kerrys anti-Vietnam war statements made to Congress after he returned from Vietnam in 1971, do you approve or disapprove of what he said?

Items used for economic dimension: 1,2,3,4,5,7,14

Items used for cultural dimension: 10,11,12
A.2 Patterns of Missingness

Predictor variables used for the imputation process were all issue-related questions that are part of the main dependent variable, ideology, party identification and demographics, the main independent variables were not included as predictors for imputation to avoid problems of endogeneity. Patterns of missingness can be tracked by distributions of unimputed and imputed variables. The distribution of mean imputations (in red) is overlayed on the distribution of observed values (in black) for each variable. The distributions of fully observed variables are colored blue.

**Figure A.1**: Tax cuts

**Figure A.2**: Oversea Tax Cuts

**Figure A.3**: Increase Minimum Wage for workers

**Figure A.4**: Subsidize Health Insurance for Children
**Figure A.5:** Subsidize Health Insurance for Workers

**Figure A.6:** Stance on Kerry’s Anti-War statements

**Figure A.7:** Allow Drug reimports from Canada for Medicare

**Figure A.8:** Limiting medical malpractice charges in court
Figure A.9: Allow reinvesting Social Security in Stock-Market

Figure A.10: Stance on the No Child Left Behind programs initiated by the bush Administration

Figure A.11: Stance on Abortion

Figure A.12: Stance on Stem-cell Research
A.3 Model and Descriptive Statistics of variables

\[ Y_t = \beta_0 + \beta_1 Y_{t-1} + \beta_2 v + \beta_3 i_{t-1} + \beta_4 p_{t-1} + \beta_5 b + \beta_6 h + c + \epsilon \]

whereby \( \beta_0 \) represents the intercept, \( v \) represents the gender of the respondent coded as a dummy, \( i_{t-1} \) represents self-reported ideology at time point \( t - 1 \) ranging from very conservative to very liberal (1-5), \( p_{t-1} \) represents party-identification at time point \( t - 1 \) ranging from strong Republican to strong Democrat (1-7), \( b \) represents a
dummy-variable for blacks, $h$ represent a dummy-variable for Hispanics, $c$ represents the controls mentioned and their coefficients and $\epsilon$ represents the error term. The dependent variable $Y_t$ is coded as a relative score on 17 political issues relevant during the Presidential campaign 2004, ranging from 0, the most conservative score possible, to 1, the most liberal possible. A lagged version of the independent variable is included as $Y_{t-1}$ on the right-hand-side of the equation. The main independent variable $p$ signifies conservative selective exposure and liberal selective exposure respectively, coded as 1 if the respondent had named Fox News as her primary news source at time point $t$ and time point $t - 1$ and 0 if the respondent neither named Fox News her primary news source at time point $t$ nor at time point $t - 1$ for the conservative selective exposure model, and 1 if the respondent had named CNN/MSNBC as her primary news source at time point $t$ and time point $t - 1$ and 0 if the respondent neither named CNN/MSNBC her primary news source at time point $t$ nor at time point $t - 1$.

$v$ is coded 0 for male and 1 for female, range=0,1 $\sigma=0.5$ [Fox], 0.48 [CNN/MSNBC] $\mu=0.52$ [Fox], 0.62 [CNN/MSNBC]

$i_{t-1}$ has range=1,5 very conservative to very liberal, $\sigma=0.43$ [Fox], 0.42 [CNN/MSNBC] $\mu=1.75$ [Fox], 4.236 [CNN/MSNBC]

$p_{t - 1}$ has range=1,7 strong Democrat to strong Republican, $\sigma=1.93$ [Fox], 1.54 [CNN/MSNBC] $\mu=2.48$ [Fox], 5.82 [CNN/MSNBC]

$b$ is coded 1 for black, range=0,1 $\sigma=0.20$ [Fox], 0.25 [CNN/MSNBC] $\mu=0.04$ [Fox], 0.07 [CNN/MSNBC]
$h$ is coded 1 for hispanic, $\text{range} = 0, 1 \ \sigma = 0.23 \ \text{[Fox]}, \ 0.23 \ \text{[CNN/MSNBC]} \ \mu = 0.05 \ \text{[Fox]}, \ 0.05 \ \text{[CNN/MSNBC]}

$Y_t$ has $\text{range} = 0, 1, \ \sigma = 0.12 \ \text{[Fox]}, \ 0.11 \ \text{[CNN/MSNBC]} \ \mu = 0.54 \ \text{[Fox]}, \ 0.79 \ \text{[CNN/MSNBC]}

$Y_{t-1}$ has $\text{range} = 0, 2, \ \sigma = 0.11 \ \text{[Fox]}, \ 0.11 \ \text{[CNN/MSNBC]} \ \mu = 0.54 \ \text{[Fox]}, \ 0.79 \ \text{[CNN/MSNBC]}

$p$ has $\text{range} = 0, 1, \ \sigma = 0.49 \ \text{[Fox]}, \ 0.50 \ \text{[CNN/MSNBC]} \ \mu = 0.39 \ \text{[Fox]}, \ 0.51 \ \text{[CNN/MSNBC]}

\textit{Coefficients for controls in the models}

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<th>self-reported Democrats</th>
<th>self-reported Republicans in non-battleground states</th>
<th>self-reported Democrats in non-battleground states</th>
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<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
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<td>-0.000</td>
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<td>-0.001</td>
<td>0.003*</td>
</tr>
<tr>
<td>political_interest_pre</td>
<td>-0.003</td>
<td>0.009*</td>
<td>-0.003</td>
<td>0.010*</td>
</tr>
<tr>
<td>political_knowledge</td>
<td>-0.003*</td>
<td>0.008*</td>
<td>-0.004*</td>
<td>0.009*</td>
</tr>
<tr>
<td>N</td>
<td>2294</td>
<td>2156</td>
<td>922</td>
<td>934</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.643</td>
<td>0.622</td>
<td>0.643</td>
<td>0.608</td>
</tr>
<tr>
<td>adj. $R^2$</td>
<td>0.641</td>
<td>0.619</td>
<td>0.637</td>
<td>0.601</td>
</tr>
<tr>
<td>Resid. sd</td>
<td>0.069</td>
<td>0.070</td>
<td>0.068</td>
<td>0.071</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
* indicates significance at $p < 0.05$

Table A.1: Change in issue attitudes for Republicans after constant exposure to Fox News and Democrats after constant exposure to CNN or MSNBC

A.4 Matching-tables
<table>
<thead>
<tr>
<th>Models</th>
<th>self-reported Republicans on the economic dimension</th>
<th>self-reported Democrats on the economic dimension</th>
<th>self-reported Republicans on the cultural dimension</th>
<th>self-reported Democrats on the cultural dimension</th>
</tr>
</thead>
<tbody>
<tr>
<td>education</td>
<td>-0.002* (0.001)</td>
<td>0.000 (0.001)</td>
<td>0.002 (0.002)</td>
<td>0.002 (0.002)</td>
</tr>
<tr>
<td>income</td>
<td>-0.000* (0.000)</td>
<td>-0.000* (0.000)</td>
<td>0.000* (0.000)</td>
<td>0.000* (0.000)</td>
</tr>
<tr>
<td>age</td>
<td>-0.000 (0.000)</td>
<td>0.000 (0.000)</td>
<td>-0.000 (0.000)</td>
<td>-0.000* (0.000)</td>
</tr>
<tr>
<td>watched_24h_cable_news_pre</td>
<td>0.001 (0.001)</td>
<td>-0.002* (0.002)</td>
<td>0.004* (0.002)</td>
<td>-0.001 (0.002)</td>
</tr>
<tr>
<td>attention_national_news_pre</td>
<td>-0.001 (0.002)</td>
<td>0.001 (0.002)</td>
<td>0.004 (0.004)</td>
<td>0.003 (0.003)</td>
</tr>
<tr>
<td>political_discussion_pre</td>
<td>-0.002* (0.001)</td>
<td>0.004* (0.002)</td>
<td>-0.004* (0.002)</td>
<td>0.002 (0.003)</td>
</tr>
<tr>
<td>political_interest_pre</td>
<td>-0.006* (0.001)</td>
<td>0.008* (0.002)</td>
<td>0.010* (0.005)</td>
<td>0.008* (0.004)</td>
</tr>
<tr>
<td>political_knowledge</td>
<td>-0.000* (0.001)</td>
<td>0.008* (0.002)</td>
<td>-0.004* (0.002)</td>
<td>0.010* (0.002)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>N</th>
<th>2294</th>
<th>2156</th>
<th>2294</th>
<th>2156</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R^2$</td>
<td>0.489</td>
<td>0.444</td>
<td>0.497</td>
<td>0.502</td>
</tr>
<tr>
<td>adj. $R^2$</td>
<td>0.485</td>
<td>0.439</td>
<td>0.493</td>
<td>0.499</td>
</tr>
<tr>
<td>Resid. sd</td>
<td>0.100</td>
<td>0.097</td>
<td>0.174</td>
<td>0.144</td>
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</table>

Standard errors in parentheses indicate significance at $p < 0.05$.

Table A.2: Independent change in issue attitudes for Republicans after constant exposure to Fox News and Democrats after constant exposure to CNN or MSNBC on two dimensions of the political space.
<table>
<thead>
<tr>
<th>Models</th>
<th>Democrats</th>
<th>Republicans</th>
</tr>
</thead>
<tbody>
<tr>
<td>education</td>
<td>0.01</td>
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</tr>
<tr>
<td>income</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>age</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>watched24hcable</td>
<td>-0.01</td>
<td>0.06***</td>
</tr>
<tr>
<td>newspre</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>attentionnationalnewspre</td>
<td>0.01</td>
<td>-0.13**</td>
</tr>
<tr>
<td>(0.05)</td>
<td>(0.05)</td>
<td></td>
</tr>
<tr>
<td>politicaldiscussionpre</td>
<td>0.01</td>
<td>0.00</td>
</tr>
<tr>
<td>(0.02)</td>
<td>(0.02)</td>
<td></td>
</tr>
<tr>
<td>politicalinterestpre</td>
<td>0.09</td>
<td>0.07</td>
</tr>
<tr>
<td>(0.06)</td>
<td>(0.06)</td>
<td></td>
</tr>
<tr>
<td>politicalknowledge</td>
<td>-0.06**</td>
<td>0.03</td>
</tr>
<tr>
<td>(0.03)</td>
<td>(0.03)</td>
<td></td>
</tr>
<tr>
<td>1—2</td>
<td>9.63***</td>
<td>5.92***</td>
</tr>
<tr>
<td></td>
<td>(0.61)</td>
<td>(0.47)</td>
</tr>
<tr>
<td>2—3</td>
<td>10.55***</td>
<td>7.57***</td>
</tr>
<tr>
<td></td>
<td>(0.59)</td>
<td>(0.48)</td>
</tr>
<tr>
<td>3—4</td>
<td>11.23***</td>
<td>9.85***</td>
</tr>
<tr>
<td></td>
<td>(0.59)</td>
<td>(0.50)</td>
</tr>
<tr>
<td>4—5</td>
<td>11.73***</td>
<td>10.38***</td>
</tr>
<tr>
<td></td>
<td>(0.59)</td>
<td>(0.51)</td>
</tr>
<tr>
<td>5—6</td>
<td>13.99***</td>
<td>11.26***</td>
</tr>
<tr>
<td></td>
<td>(0.61)</td>
<td>(0.52)</td>
</tr>
<tr>
<td>6—7</td>
<td>15.47***</td>
<td>12.44***</td>
</tr>
<tr>
<td></td>
<td>(0.63)</td>
<td>(0.56)</td>
</tr>
<tr>
<td>conservativelyexposed</td>
<td>-0.23*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Democrats</th>
<th>Republicans</th>
</tr>
</thead>
<tbody>
<tr>
<td>AIC</td>
<td>4462.12</td>
<td>4411.96</td>
</tr>
<tr>
<td>BIC</td>
<td>4581.31</td>
<td>4532.46</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-2210.06</td>
<td>-2184.98</td>
</tr>
<tr>
<td>Deviance</td>
<td>4420.12</td>
<td>4369.96</td>
</tr>
<tr>
<td>Num. obs.</td>
<td>2156</td>
<td>2294</td>
</tr>
</tbody>
</table>

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.3: Independent effects of selective exposure on Party Identification for Republicans and Democrats
<table>
<thead>
<tr>
<th>Covariate</th>
<th>sd.diff.pooled</th>
<th>var.ratio</th>
<th>T.pval</th>
<th>KS.pval</th>
<th>qqmean.diff</th>
<th>qqmed.diff</th>
<th>qqmax.diff</th>
</tr>
</thead>
<tbody>
<tr>
<td>Issue Attitudes t-1</td>
<td>-104.85</td>
<td>0.83</td>
<td>0.00</td>
<td>0.00</td>
<td>0.12</td>
<td>0.08</td>
<td>0.31</td>
</tr>
<tr>
<td>Self-reported Ideology at t-1</td>
<td>-65.62</td>
<td>0.77</td>
<td>0.00</td>
<td>0.00</td>
<td>0.08</td>
<td>0.05</td>
<td>0.22</td>
</tr>
<tr>
<td>Self-reported PID at t-1</td>
<td>-46.21</td>
<td>1.01</td>
<td>0.00</td>
<td>0.00</td>
<td>0.09</td>
<td>0.06</td>
<td>0.21</td>
</tr>
<tr>
<td>Education</td>
<td>16.22</td>
<td>0.92</td>
<td>0.01</td>
<td>0.01</td>
<td>0.04</td>
<td>0.05</td>
<td>0.06</td>
</tr>
<tr>
<td>Income</td>
<td>29.09</td>
<td>1.11</td>
<td>0.00</td>
<td>0.00</td>
<td>0.06</td>
<td>0.07</td>
<td>0.10</td>
</tr>
<tr>
<td>Gender</td>
<td>-21.43</td>
<td>0.99</td>
<td>0.00</td>
<td>0.00</td>
<td>0.04</td>
<td>0.04</td>
<td>0.08</td>
</tr>
<tr>
<td>Age</td>
<td>27.71</td>
<td>0.94</td>
<td>0.00</td>
<td>0.00</td>
<td>0.04</td>
<td>0.04</td>
<td>0.10</td>
</tr>
<tr>
<td>Black</td>
<td>-8.47</td>
<td>0.56</td>
<td>0.14</td>
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<td>0.00</td>
<td>0.00</td>
<td>0.01</td>
</tr>
<tr>
<td>Hispanic</td>
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<td>0.54</td>
<td>0.00</td>
<td>0.00</td>
<td>0.01</td>
<td>0.01</td>
<td>0.02</td>
</tr>
<tr>
<td>Days/Week watched Cable-News</td>
<td>172.18</td>
<td>0.44</td>
<td>0.00</td>
<td>0.00</td>
<td>0.45</td>
<td>0.51</td>
<td>0.56</td>
</tr>
<tr>
<td>Attention to News</td>
<td>110.24</td>
<td>0.52</td>
<td>0.00</td>
<td>0.00</td>
<td>0.20</td>
<td>0.26</td>
<td>0.29</td>
</tr>
<tr>
<td>Political Discussion</td>
<td>94.19</td>
<td>0.95</td>
<td>0.00</td>
<td>0.00</td>
<td>0.21</td>
<td>0.24</td>
<td>0.30</td>
</tr>
<tr>
<td>Political Interest</td>
<td>72.83</td>
<td>0.64</td>
<td>0.00</td>
<td>0.00</td>
<td>0.11</td>
<td>0.09</td>
<td>0.26</td>
</tr>
<tr>
<td>Political Knowledge</td>
<td>5.86</td>
<td>1.13</td>
<td>0.33</td>
<td>0.00</td>
<td>0.03</td>
<td>0.02</td>
<td>0.06</td>
</tr>
</tbody>
</table>

Table A.4: Covariate Balance for the conservative ATT model before Matching

<table>
<thead>
<tr>
<th>Covariate</th>
<th>sd.diff.pooled</th>
<th>var.ratio</th>
<th>T.pval</th>
<th>KS.pval</th>
<th>qqmean.diff</th>
<th>qqmed.diff</th>
<th>qqmax.diff</th>
</tr>
</thead>
<tbody>
<tr>
<td>Issue Attitudes t-1</td>
<td>-15.80</td>
<td>1.03</td>
<td>0.00</td>
<td>0.00</td>
<td>0.02</td>
<td>0.01</td>
<td>0.09</td>
</tr>
<tr>
<td>Self-reported Ideology at t-1</td>
<td>-1.15</td>
<td>1.06</td>
<td>0.05</td>
<td>0.80</td>
<td>0.00</td>
<td>0.00</td>
<td>0.01</td>
</tr>
<tr>
<td>Self-reported PID at t-1</td>
<td>7.80</td>
<td>1.17</td>
<td>0.01</td>
<td>0.01</td>
<td>0.02</td>
<td>0.01</td>
<td>0.06</td>
</tr>
<tr>
<td>Education</td>
<td>4.96</td>
<td>0.98</td>
<td>0.19</td>
<td>0.02</td>
<td>0.03</td>
<td>0.03</td>
<td>0.06</td>
</tr>
<tr>
<td>Income</td>
<td>6.64</td>
<td>1.28</td>
<td>0.00</td>
<td>0.02</td>
<td>0.03</td>
<td>0.04</td>
<td>0.06</td>
</tr>
<tr>
<td>Gender</td>
<td>-7.79</td>
<td>0.99</td>
<td>0.08</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.04</td>
</tr>
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<td>Age</td>
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<td>1.38</td>
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<td>0.00</td>
<td>0.03</td>
<td>0.02</td>
<td>0.09</td>
</tr>
<tr>
<td>Black</td>
<td>9.18</td>
<td>Inf</td>
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<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.01</td>
</tr>
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<td>7.07</td>
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<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>Days/Week watched Cable-News</td>
<td>-3.37</td>
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<td>0.00</td>
<td>0.01</td>
<td>0.02</td>
<td>0.01</td>
<td>0.06</td>
</tr>
<tr>
<td>Attention to News</td>
<td>-5.65</td>
<td>1.34</td>
<td>0.09</td>
<td>0.20</td>
<td>0.02</td>
<td>0.02</td>
<td>0.03</td>
</tr>
<tr>
<td>Political Discussion</td>
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<td>1.13</td>
<td>0.00</td>
<td>0.00</td>
<td>0.03</td>
<td>0.01</td>
<td>0.09</td>
</tr>
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<td>Political Interest</td>
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<td>1.04</td>
<td>0.79</td>
<td>0.67</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>Political Knowledge</td>
<td>-2.86</td>
<td>1.00</td>
<td>0.00</td>
<td>0.20</td>
<td>0.01</td>
<td>0.01</td>
<td>0.04</td>
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</tbody>
</table>

Table A.5: Covariate Balance for the conservative ATT model after Matching
<table>
<thead>
<tr>
<th>Covariate</th>
<th>sdiff.pooled</th>
<th>var.ratio</th>
<th>T pval</th>
<th>KS pval</th>
<th>qqmeandiff</th>
<th>qqmeddiff</th>
<th>qqmaxdiff</th>
</tr>
</thead>
<tbody>
<tr>
<td>Issue Attitudes t-1</td>
<td>-104.85</td>
<td>0.83</td>
<td>0.00</td>
<td>0.00</td>
<td>0.12</td>
<td>0.08</td>
<td>0.31</td>
</tr>
<tr>
<td>Self-reported Ideology at t-1</td>
<td>-65.62</td>
<td>0.77</td>
<td>0.00</td>
<td>0.00</td>
<td>0.08</td>
<td>0.05</td>
<td>0.22</td>
</tr>
<tr>
<td>Self-reported PID at t-1</td>
<td>-46.21</td>
<td>1.01</td>
<td>0.00</td>
<td>0.00</td>
<td>0.09</td>
<td>0.06</td>
<td>0.21</td>
</tr>
<tr>
<td>Education</td>
<td>16.22</td>
<td>0.92</td>
<td>0.01</td>
<td>0.01</td>
<td>0.04</td>
<td>0.05</td>
<td>0.06</td>
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<tr>
<td>Income</td>
<td>29.09</td>
<td>1.11</td>
<td>0.00</td>
<td>0.00</td>
<td>0.06</td>
<td>0.07</td>
<td>0.10</td>
</tr>
<tr>
<td>Gender</td>
<td>-21.43</td>
<td>0.99</td>
<td>0.00</td>
<td>0.00</td>
<td>0.04</td>
<td>0.04</td>
<td>0.08</td>
</tr>
<tr>
<td>Age</td>
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<td>0.94</td>
<td>0.00</td>
<td>0.00</td>
<td>0.04</td>
<td>0.04</td>
<td>0.10</td>
</tr>
<tr>
<td>Black</td>
<td>-8.47</td>
<td>0.56</td>
<td>0.14</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.01</td>
</tr>
<tr>
<td>Hispanic</td>
<td>-17.30</td>
<td>0.54</td>
<td>0.00</td>
<td>0.00</td>
<td>0.01</td>
<td>0.01</td>
<td>0.02</td>
</tr>
<tr>
<td>Days/Week watched Cable-News</td>
<td>172.18</td>
<td>0.44</td>
<td>0.00</td>
<td>0.00</td>
<td>0.45</td>
<td>0.51</td>
<td>0.56</td>
</tr>
<tr>
<td>Attention to News</td>
<td>110.24</td>
<td>0.52</td>
<td>0.00</td>
<td>0.00</td>
<td>0.20</td>
<td>0.26</td>
<td>0.29</td>
</tr>
<tr>
<td>Political Discussion</td>
<td>94.19</td>
<td>0.95</td>
<td>0.00</td>
<td>0.00</td>
<td>0.21</td>
<td>0.24</td>
<td>0.30</td>
</tr>
<tr>
<td>Political Interest</td>
<td>72.83</td>
<td>0.64</td>
<td>0.00</td>
<td>0.00</td>
<td>0.11</td>
<td>0.09</td>
<td>0.26</td>
</tr>
<tr>
<td>Political Knowledge</td>
<td>5.86</td>
<td>1.13</td>
<td>0.33</td>
<td>0.00</td>
<td>0.03</td>
<td>0.02</td>
<td>0.06</td>
</tr>
</tbody>
</table>

Table A.6: Covariate Balance for the conservative ATE model before Matching

<table>
<thead>
<tr>
<th>Covariate</th>
<th>sdiff.pooled</th>
<th>var.ratio</th>
<th>T pval</th>
<th>KS pval</th>
<th>qqmeandiff</th>
<th>qqmeddiff</th>
<th>qqmaxdiff</th>
</tr>
</thead>
<tbody>
<tr>
<td>Issue Attitudes t-1</td>
<td>-27.22</td>
<td>1.05</td>
<td>0.00</td>
<td>0.00</td>
<td>0.04</td>
<td>0.02</td>
<td>0.13</td>
</tr>
<tr>
<td>Self-reported Ideology at t-1</td>
<td>-9.48</td>
<td>1.36</td>
<td>0.00</td>
<td>0.00</td>
<td>0.02</td>
<td>0.01</td>
<td>0.09</td>
</tr>
<tr>
<td>Self-reported PID at t-1</td>
<td>3.02</td>
<td>1.08</td>
<td>0.09</td>
<td>0.26</td>
<td>0.01</td>
<td>0.00</td>
<td>0.03</td>
</tr>
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Table A.7: Covariate Balance for the conservative ATE model after Matching
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Table A.8: Covariate Balance for the liberal ATT model before Matching

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Table A.9: Covariate Balance for the liberal ATT model after Matching
### Table A.10: Covariate Balance for the liberal ATE model before Matching

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### Table A.11: Covariate Balance for the liberal ATE model after Matching

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