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#2021-032

**Political polarization and the impact of internet and social media
use in Brazil**

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Published 30 August 2021

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UNU-MERIT Working Papers

ISSN 1871-9872

**Maastricht Economic and social Research Institute on Innovation and Technology
UNU-MERIT**

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Political Polarization and the Impact of Internet and Social Media Use in Brazil *

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August 20, 2021

Abstract

Influential scholars have pointed to the Internet and social media as a reason for the recent political divide in many countries. Greater exposure to imbalanced information in these environments would reinforce previous political positions leading voters to develop more extreme positions or greater animosity towards candidates of the opposing political group, a phenomenon known as affective polarization. This study investigates the impact of Internet and social media use on Brazil's recent affective polarization, exploring the historical peculiarities in the layout of pre-existing infrastructure that causes exogenous variation in Internet and social media usage. There is no empirical evidence that access to this new media environment explains affective polarization within the population under this study. Findings are consistent with the strand of literature suggesting that the recent phenomena of political polarization in some countries cannot be attributed to Internet and social media use. (JEL D12, D72, L82, L86)

Keywords: political polarization, broadband internet, Brazil

*I would like to thank my PhD Supervisors - Robin Cowan and Matthias Wibral - and Mark Pickup for valuable suggestions and criticisms. An earlier version this paper appeared in the 12th Annual IPSA-USP Summer School on causal Inference and Experiments. The findings, interpretations and conclusions expressed in this paper are solely mine and do not necessarily present policies or views of the UNU-MERIT or Maastricht School of Business and Economics. All remaining errors are mine.

Contents

1	Introduction	2
2	Measuring Affective Polarization	4
3	Data	7
3.1	National Trends in Political Identification	7
3.2	Affective Polarization	9
3.3	National Trends in Affective Polarization	10
3.4	Internet and Social Media Use	10
3.5	Broadband infrastructure for Brazilian municipalities	11
3.6	Control Variables	12
4	Empirical Framework	13
4.1	Identifying the Effect of Internet and Social Media Use on Political Polarization	13
4.2	Estimation Strategy	14
5	Results	18
6	Discussion	22
	Appendix A	27

1 Introduction

The debate on the effects of new technological tools on ideological fragmentation is not a new one. As early as the Internet was invented, Van Alstyne and Brynjolfsson (1996) already expressed concerns about information technologies leading to “cyber-balkanization”. The Internet would “shrink geographic distances and facilitate information exchange”, making it easier for like-minded individuals to associate with one another and strengthen communities with a common ideology.

Another influential scholar (Sunstein, 2001) has argued that the Internet would make it easier for individuals to isolate themselves into like-minded groups, which would lead to the creation of “echo chambers”. Greater exposure to imbalanced information within like-minded groups would strengthen one own confidence in a preferred ideological identity and increase the distance from opposing ideological views.¹ More recently, the concern has gained new momentum by the diffusion of social media use. These online communication tools would exacerbate selective exposure by filtering out information with algorithmic rankings (Flaxman et al., 2013; Pariser, 2011; Bakshy et al., 2015; Sunstein, 2018). Some scholars have also investigated the existence of homophily - the tendency of like-minded individuals to interact with one another - on online social media (Halberstam and Knight, 2016; Barberá et al., 2015; Bakshy et al., 2015; Barberá, 2014; Bakshy et al., 2015).

Despite the increased scholarly attention to the topic, empirical evidence on the effects of Internet and social media use on political polarization remains inconclusive. Empirical attempts to examine causal effects have been limited by identification challenges induced by self-reporting usage of Internet and social media – which typically result in biased outcomes. Much empirical evidence document pure correlations, and are unable to make claims about causality (Boxell et al., 2017; Liang and Nordin, 2013; Boulianne et al., 2020; Lawrence et al., 2010). Establishing causal inference requires finding an exogenous source of variation

¹Studies on the tendency of like-minded individuals to associate with one another and expose themselves to information that simply confirms their preexisting opinions date back to decades ago. For a review of the literature on selective exposure to information, see Sears and Freedman (1967).

of information technologies use or conducting randomized controlled experiments. To our knowledge, the only academic paper that aims to explore a causal effect of Internet or social media use in political polarization are Lelkes et al. (2017) and Levy (2021).

Moreover, most of the related studies have focused on the US context, and there is limited empirical evidence worldwide.² There are valuable scientific gains to be made from exploring the phenomena outside the usual US context. For one, most advanced democracies have multiparty systems, in contrast to the two-party political system in the US, which demands exploring the phenomena through novel political polarization measures. At the same time, scholars (Tucker et al., 2018) point out the need to further examine how online media can contribute to polarization in young democracies, where Internet and social media “disruptive role may be arguably larger than in established Western democracies” (pp.61) with relatively stronger institutions.

Brazil, a relatively new democracy with one of the highest party fragmentation of the world (Clark et al., 2006), constitutes an interesting case to study. Brazilian politics is characterized by a recent cleavage between the left and right ideological spectrum. Ranking on a left-right scale reveals a widening gap between centrist and extreme positions, especially from 2014 to 2018.³ Adding to this, Brazil is the fourth largest online news consuming nation in the world, only behind China, India, and the US (Comscore, 2019). The media and academia have stressed the rising use of the Internet and social media for electoral purposes⁴ and its association with recent political outcomes in Brazil.⁵ However, to the best of our knowledge, the relationship between the use of online media and political polarization is still unexplored from a quantitative perspective.

²For detailed literature on the effects of the Internet and social media on political outcomes, see Zhuravskaya et al. (2019); Tucker et al. (2018).

³The third section of this paper provides descriptive statistics on the trends of political identification in Brazil, which shows that the percentage of Brazilian voters who declare as extreme left or extreme right has increased since 2002 - and especially from 2014 to 2018.

⁴For a discussion of the role of social media in the last Brazilian presidential elections, see Nicolau (2020), chapter 4.

⁵For a discussion on the use of social media and political instability, desinformation and polarization in Brazil, see Evangelista and Bruno (2019) and Santos (2019).

This paper contributes to the literature by investigating the causal impact of Internet and social media use on Brazil’s recent political polarization. We employ an instrumental variable approach that follows past studies using exogenous infrastructure variations to identify the Internet’s impact on political behavior (Falck et al., 2014; Schaub and Morisi, 2019).

Another contribution is the development of a novel way to measure the degree of affective polarization in multiparty systems by exploring a political identity different from parties. Previous work has measured affective polarization mostly along partisan lines. We develop a measure that captures the extent to which citizens feel more positively toward candidates representing their ideological group and negatively toward opposing groups.

The remainder of the paper is organized as follows. Section 2 discusses the theories and reasoning behind the variable developed to measure affective polarization. Section 3 describes the study’s data and presents descriptive data on the recent trends in political identification and affective polarization in Brazil. Section 4 describes the empirical estimation strategy and discusses the instrument. Section 5 presents the main results, and section 6 discusses our findings in the context of the literature and concludes.

2 Measuring Affective Polarization

Affective polarization refers to a type of political polarization with its roots on Social Identity and Self-Categorization theories. According to such theories (Tajfel et al., 1979; Terry and Hogg, 1996; McGarty et al., 1992; Turner et al., 1987), individuals instinctively form attachments which produce favoritism towards whom they perceive as similar to themselves (in-groups) and antipathy towards groups they do not identify with (out-groups). The core mental process shaping social identity and group membership is a source of self-worth, heightened by antipathy to the out-group (Turner et al., 1979). Thus, affective polarization measures the extent to which citizens feel more negatively toward other political groups than toward their own by taking the distance between feelings towards in-groups and out-groups

members (Iyengar et al., 2012).

The US is a major case study of affective polarization. In recent years, the rise in partisan animus is a broad consensus among American scholars, illustrated by an increasing attachment to co-partisans and animosity towards opposing partisans (Westwood and Peterson, 2019; Iyengar and Westwood, 2015; Iyengar et al., 2019; Lelkes et al., 2017). While social scientists have measured affective polarization mainly along partisan lines, affective polarization is not merely a partisan matter. Social Identity Theories conceive the emergence of in-group favoritism as a result of cognitive and motivational factors related to a broad range of social identities such as real-world social cleavages, ethnic/religious groups, and arbitrary researcher-generated divisions (Mason, 2016; Huddy, 2001; Deaux et al., 1995).

Measuring partisan affect is central in long-established democracies where parties are clearly sorted into salient groups, such as the US. Less attention has been paid, however, to measuring affective polarization along other political identities,⁶ which is particularly important to democracies with multi-party systems and low levels of mass partisan identification.

In political systems exhibiting various less and salient parties, voters are less likely to rely on party identifications to make political decisions (Lau and Redlawsk, 2001, 2006) - the proliferation of parties makes it hard for the electorate to self-identify with a party or even understand which parties stand for positions that are similar to their own.

Scholars have long conceived partisan loyalties as unlikely to take root in Brazil. Political scientists do not envisage Brazilian individuals developing deep attachments to parties. One of the facts that illustrates this is that two populist presidents Bolsonaro and Collor de Mello, elected in 2018 and 1989, respectively, spend without a base party. One of the explanations relates to the fact that Brazil's party system is a relatively new phenomenon — free and multiparty elections only began after a long military regime in the 1980s (Kinzo, 2005; Samuels and Zucco, 2018; Fiorina, 1981; Huber et al., 2005). Brazil also exhibits one of the

⁶A notable exception is given by Hobolt et al. (2018), which examine social identities formed during Britain's 2016 referendum on European Union membership, and show that strong emotional attachments have emerged because of identification with opinion-based groups related to Brexit, demonstrating a strong affective polarization beyond partisanship identity.

highest degrees of partisan fragmentation in the world (Clark et al., 2006). The Brazilian political institutions not only foster party fragmentation but also make it hard for voters to attach to a party ideology or even have a clear understanding of the positions they stand for. For instance, it has an open-list system for legislative elections that promotes intraparty competition, minimizes the importance of party reputation, and strengthens individual candidacy (Samuels and Zucco Jr, 2014).

While on the one hand, the weak mass partisanship in Brazil hinders measuring affective polarization along party lines,⁷ on the other hand, the clear recognition of the left-right ideological dimension by voters offers an opportunity to construct a novel measure of affective polarization. We propose a measure that builds on a strand in the political psychology literature that advocates for adopting ideological labels as political identities (Malka and Lelkes, 2010; Mason, 2018; Kinder and Kalmoe, 2017).

In this study, affective polarization is represented by a greater attachment to the right and left ideological identities. The measure captures the extent to which voters have a positive sentiment for the candidates representing its ideological group and negative sentiment against the candidate that represents the opposing group. In the next section, we will specify the construction of the variable.

⁷Since the first presidential election held in 1989, the proportion of voters who identify with any party in Brazil have been hovering around 30 to 50%, way below average from a comparative perspective (Kitschelt et al., 2010). Samuels and Zucco Jr (2014) also highlights that the three most salient parties at the period - PSDB, PT, PMDB - “are the only ones to have obtained more than 5% of partisan preferences on average over this period”.

3 Data

We use multiple sets of data for the analysis. Individual-level data comes from the Brazilian National Election Study (Estudo Eleitoral Brasileiro – ESEB, in Portuguese). ESEB is a nationally representative survey of the voting-age population conducted shortly after the elections by the Center for Public Opinion Studies (Cesop) of the State University of Campinas (Unicamp) and contains numerous demographic variables and political measures. It asks for self-reported votes, political and ideological preferences, Internet usage, and social media for political information with a lag of one month from the election. To date, it has been undertaken in five election cycles, since 2002. For the causal analysis, we rely on the fifth wave conducted with home interviews between November 10 and 24 and comprises 2506 observations. The data is representative of the five different regions in Brazil and comprise 172 municipalities, including all state capitals. Its margin of error is two percentage points, and the confidence index is 95%.

We employ data on the availability of fiber optic backhaul at the municipality level provided by the National Telecommunications Agency (Agência Nacional de Telecomunicações - ANATEL). There are 5,570 municipalities, which are the lowest level of political division in Brazil. Population density for the municipalities was obtained from the Brazilian Institute of Geography and Statistics (Instituto Brasileiro de Geografia e Estatística - IBGE).

3.1 National Trends in Political Identification

We begin by considering how political identification have developed in Brazil over time. To visualize changes in individual political identification over time, we use ESEB ideological score that ranges from 0 (extreme left) to 10 (extreme right). A simple descriptive statistics of the five waves of ESEB ideological score shows a clear rise in political dividedness, evinced by a greater gap from centrist or moderate to extreme positions from 2002 to 2018, and especially from 2014 to 2018. Table 1 defines centrists as those with scores 4 to 6, moderates

Table 1: Percentages and changes in left-right ideological position of Brazilian residents between 2002 and 2018 using ESEB data

Year	Centrist (1)	Moderate (2)	Extreme (3)	Did not declare (4)
2002	0.113	0.093	0.188	0.606
2006	0.254	0.140	0.187	0.419
2010	0.162	0.147	0.244	0.448
2014	0.213	0.170	0.180	0.437
2018	0.206	0.159	0.422	0.213
$\Delta 2002 - 2018$	0.093	0.066	0.234	-0.394
$\Delta 2014 - 2018$	-0.007	-0.011	0.242	-0.224

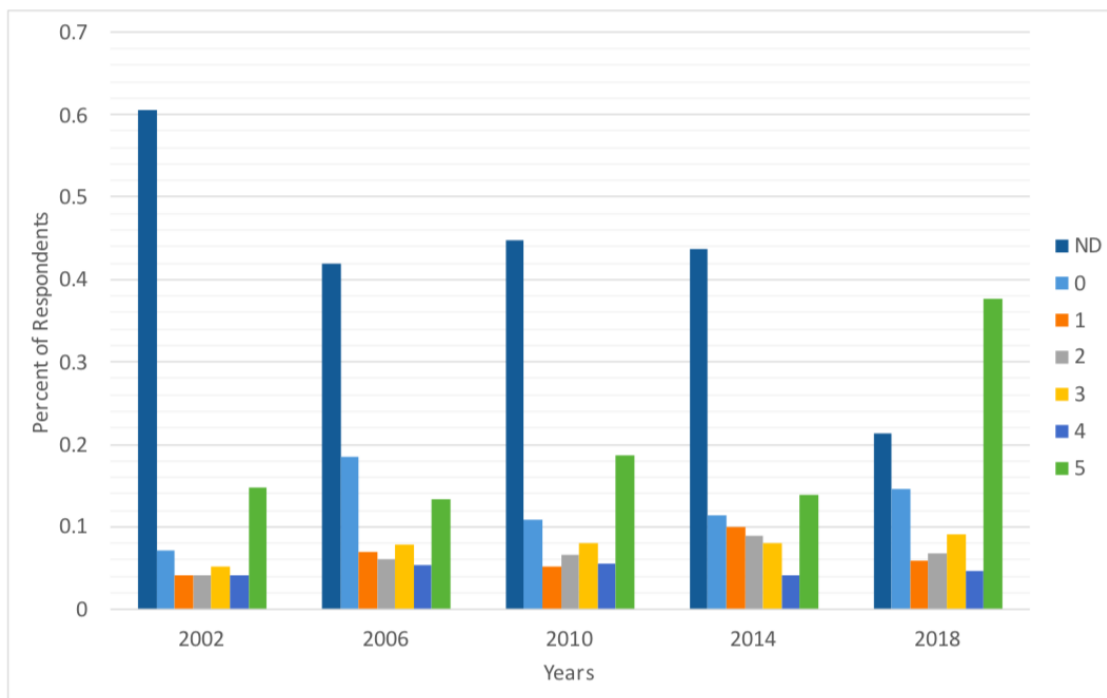
as those with scores 2,3,7,8 and extremes as 0,1,9 or 10.⁸

The percentage of respondents who declared themselves as extreme left or right increased from 0.19 in 2002 and 0.18 in 2014 to 0.42 in 2018. The percentage of respondents whose ideology was centrist or moderate fell slightly from 2014 to 2018. It is important to note that while in 2002, more than one-half of the respondents did not identify themselves as right or left-leaning, the unidentified share fell to roughly 0.4 in subsequent years reaching only 0.2 in 2018.

⁸Sample sizes of survey respondents are 2,514 in 2002, 1,000 in 2006, 2,000 in 2010, 3,136 in 2014 and 2,506 in 2018.

Data on figure 1 confirms the tendency of political divide. Data shows a sharp rise in the percentages of individuals that self-declare in the most extreme positions (defined as “5”) and a decline in the percentage of the individuals that declare a strictly neutral position (defined as “0”), from 2002 to 2018, with most of the change happening from 2014 to 2018.⁹

Figure 1: Percentages of Brazilian respondents in extreme left-right ideological position and in an indifferent position between 2002 and 2018 using ESEB data.



3.2 Affective Polarization

To construct the measure of affective polarization, we rely on data from ESEB, which asked individuals to rate feelings towards candidates on an 11-point scale, that range from 0 (“strongly dislike”) to 10 (“strongly like”). We took the difference in each individual’s feeling towards the presidential candidates¹⁰ representing the political spectrum they self-identify

⁹The most extreme respondents self-position at the furthest positions in the left-right scale. Neutral respondents self-position at the midpoint between the most extreme positions. ND represent individuals who do not declare their political ideology.

¹⁰We followed Lelkes et al., (2017) and measured affect toward the candidates in the second round of the elections.

with (right or left-wing) and the opposing one.¹¹

3.3 National Trends in Affective Polarization

Table 2 uses data of the five waves of ESEB to show national trends of affective polarization over time. Those with affective polarization scores from 0-3 are defined as neutrals, those with scores from 4-6 as moderates, and those with scores from 7-10 as extremes. The data shows a strong affective polarization in recent years. In 2018, roughly 40 per cent of respondents declared feeling extreme animosity towards other ideological groups than toward their own; in previous years, the extreme share was always under 20 per cent of respondents.

Table 2: Percentages and changes in affect towards candidates of Brazilian residents between 2002 and 2018 using ESEB data

Year	Neutral (1)	Moderate (2)	Extreme (3)
2002	0.694	0.137	0.169
2006	0.727	0.129	0.144
2010	0.683	0.132	0.185
2014	0.684	0.117	0.199
2018	0.461	0.158	0.381
$\Delta 2002 - 2018$	-0.233	0.021	0.212
$\Delta 2014 - 2018$	-0.223	0.041	0.182

3.4 Internet and Social Media Use

Our measure of the Internet and Social Media use is based on the following question of ESEB’s fifth wave (2018). Respondents were asked: “Which of the following sources do you use the most to inform yourself about politics?” Possible answers include TV, personal contacts (family or work), or internet blogs, social media and google search. We coded the variable as a dummy, assigning a value of 1 to those who used internet blogs, social media,

¹¹We followed past studies (Lelkes et al., 2017) and rescaled the measure to lie between 0 and 10. Since those below 0 do not harbor any animosity towards candidates, those scores were recoded as 0. Also, responses such as “Do not know,” “Did not answer” and “Do not know what it means” were coded as missing.

or Google search as their primary source of information, and 0 to all other responses.

3.5 Broadband infrastructure for Brazilian municipalities

The Internet provision in a country involves many infrastructure elements: regional backbones, backhauls, and access points. Each country has a regional fiber-optics backbone (in some cases, it can also use satellite or microwaves) that distributes the signal across the territory. Backhauls are intermediate links between the backbones and the peripheral data access points, which connect the final consumers to the rest of the infrastructure. The technology used in this part of the network usually is xDSL or cable technology. Thus, a backhaul is an essential piece of infrastructure that supports high-speed broadband internet services in a municipality.

Previous evidence suggests that the availability of broadband infrastructure is a crucial factor determining the time that individuals spend online. For example, Hitt and Tambe (2007) show that having access to broadband Internet increases internet usage by over 1300 min per month. Using data from the United States, Rappoport, Kridel, and Taylor (2002) show that households with high-speed internet access are uniformly more likely to be online.

In this paper, we exploit the historical peculiarities in the layout of pre-existing infrastructure that causes exogenous variation in Internet and social media usage to identify its impact on political polarization. Fiber-optic backhauls are normally placed on the basis of pre-existing infrastructures, such as electricity, gas, and oil distribution systems (Knight et al., 2016). Variations of infrastructure are commonly used to construct IVs to measure the Internet’s effect on various outcomes. For example, the exogenous variation in fiber optic backhauls’ availability was recently exploited in a paper identifying the impact of the Internet on educational outcomes in Brazil (Henriksen et al., 2019).

The strategy used in this setup is similar to other identification strategies that explore variation in technologies dissemination to identify the effects of the Internet on voting behavior and political participation. For instance, Falck et al. (2014) use the distance between

the residence and the telephone company’s data center. Schaub and Morisi (2019) exploit variation in broadband coverage as an instrument for Internet use and Lelkes et al. (2017) identifies the causal impact of broadband access on polarization by exploiting differences in broadband availability brought about by variation in state right-of-way regulations, which they assume to affect the cost of building Internet infrastructure and the price and availability of broadband access.

Data on fiber optic availability in a municipality provided by the National Telecommunications Agency was combined to individual-level data provided by ESEB at the municipality of residence of the respondents.

3.6 Control Variables

We further used a number of individual socio-demographic control variables, according to the literature on the effect of the Internet on political polarization and voting preferences (Falck et al., 2014; Schaub and Morisi, 2019; Lelkes et al., 2017). We included respondent’s age, level of income, gender, race, religion, occupation sector, residence region (Northeast, South, Southeast, or Midwest) and a dummy variable indicating whether the respondent is unemployed. We disregarded missing values on each of the variables.

4 Empirical Framework

4.1 Identifying the Effect of Internet and Social Media Use on Political Polarization

Identifying the Internet and social media effects on political polarization is complicated by endogeneity concerns. A simple regression with the key independent variable being individuals that use the Internet or social media would suffer from a potential bias, which would likely arise from unobserved factors correlated with political polarization and Internet or social media use. A related concern is of reverse causation. One may assume that polarized individuals are more likely to seek out information about politics online, which would create a causal arrow running from polarization to Internet and social media use and would bias estimates.

To address this problem, we follow recent contributions in the field and adopt an instrumental variable (IV). Variations of infrastructure are commonly used when constructing instrumental variables to measure the Internet’s effect on voting and political behavior (Falck et al., 2014; Schaub and Morisi, 2019). In this setup, we pursue a similar strategy. We exploit the exogenous variation in the availability of fiber optic backhauls – an infrastructure that allows access to broadband Internet – to identify its effect on political polarization.

Suppose the availability of fiber optic backhaul is a valid instrument. In that case, it must be (i) a relevant predictor of the potential endogenous variable and (ii) it should not be a determinant of political polarization. We show below that our instrument meets both conditions. We find that the availability of fiber optic backhaul is significantly associated with Internet and social media use. In a probit model that explains the probability of an individual to use the Internet or social media as the primary source of political information, the test statistic for a Wald test on the fiber optic variable has a p-value of 0.04, indicating that its coefficient is significantly different from 0. In a linear model, the F-statistic exceeds the

conventional benchmark of 10 set out in Stock et al. (2002) for tests for weak instruments.¹²

Furthermore, we show that the exclusion restriction is plausibly met. Although the exclusion restriction requirement cannot be tested itself, we run placebo tests to provide confidence to our instrument. We show that conditional on population density and household income, fiber optics' availability is not correlated with unobserved individual-level characteristics potentially related to political polarization. If the exclusion restriction is met, fiber optic availability should not predict behaviors linked to political or extreme preferences. In appendix A, we report the results of regressions of variables capturing political preferences on our instrument, fiber optics availability. Reassuringly, our instrument is not correlated with political preferences (left or right-wing self-placement), interest in politics, or variables capturing extreme perceptions of corruption scandals, economy, and minorities in Brazil.

4.2 Estimation Strategy

Given that the dependent variable takes the form of an ordinal variable, an ordered probit or logit model is appropriate in this setup (Long, 1997). As the standard two-stage procedure produces inconsistent estimators for ordered probit models with endogenous variables, we use a maximum likelihood estimation, which, according to Wooldridge (2010), is more efficient than any two-step procedure. The extended ordered probit model accommodates endogenous and instrumental variables while implementing the maximum likelihood estimator (Wooldridge, 2002; Drezner, 1978).

Let y_i be the ordinal variable that measures political polarization. Our extended model consists of equations (1) and (2):

$$y^* = \mathbf{x}\beta + \mathbf{w}\beta_c + \epsilon \tag{1}$$

¹²The F-test is based on Angrist (1991), who state that using linear regression for the first-stage estimates generates consistent second-stages estimates even with a dummy endogenous variable. The same strategy was used in similar studies with binary endogenous variables (Schaub and Morisi, 2019).

$$w^* = \mathbf{z}\gamma + r \quad (2)$$

$$w = 0 \quad \text{if} \quad w^* \leq \zeta$$

$$w = 1 \quad \text{if} \quad \zeta < w^*$$

where \mathbf{x} represents the exogenous covariates, and \mathbf{w} , Internet or social media use (the potentially endogenous variable) determined by a binary probit model. \mathbf{z} contains the instrumental variable that affects \mathbf{w} and exogenous variables from \mathbf{x} .

y^* is determined by a threshold model, where α_j , $j = 1, \dots, J$ are threshold parameters to be estimated:

$$\begin{aligned} y = 0 & \quad \text{if} \quad y^* \leq \alpha_1 \\ y = 1 & \quad \text{if} \quad \alpha_1 \leq y^* \leq \alpha_2 \\ & \quad \vdots \\ y = J & \quad \text{if} \quad \alpha_J < y^* \end{aligned}$$

Thus the conditional distribution of y depends on \mathbf{x} and is determined by:

$$P(y = 0|\mathbf{x}) = P(y^* < \alpha_1|\mathbf{x}) = P(\mathbf{x}\beta + \epsilon < \alpha_1|\mathbf{x}) = \Phi(\alpha_1 - \mathbf{x}\beta) \quad (3)$$

$$\begin{aligned} P(y = 1|\mathbf{x}) &= P(\alpha_1 < y^* < \alpha_2|\mathbf{x}) = P(\alpha_1 < \mathbf{x}\beta + \epsilon < \alpha_2|\mathbf{x}) \\ &= \Phi(\alpha_2 - \mathbf{x}\beta) - \Phi(\alpha_1 - \mathbf{x}\beta) \end{aligned} \quad (4)$$

\vdots

$$\begin{aligned} P(y = J|\mathbf{x}) &= 1 - P(y = J - 1|\mathbf{x}) - \dots - P(y = 0|\mathbf{x}) \\ &= 1 - P(\alpha_{J-1} < y < \alpha_J|\mathbf{x}) - \dots - P(y < \alpha_1|\mathbf{x}) \\ &= 1 - P(\alpha_{J-1} < \mathbf{x}\beta + \epsilon < \alpha_J|\mathbf{x}) - \dots - P(\mathbf{x}\beta + \epsilon < \alpha_1|\mathbf{x}) \\ &= 1 - \Phi(\alpha_J - \mathbf{x}\beta) \end{aligned} \quad (5)$$

The argument presented at the beginning of the section suggests that the correlation between ϵ_i and r_i is nonzero. That is, we expect that there are omitted covariates predicting both the probability of being polarised and of using the Internet or social media for political purposes. In order to allow for this possibility, we assume that the covariance between ϵ_i and r_i is represented by the matrix Σ .

Considering the category j of the dependent variable y , we have that the upper and lower limits of ϵ given values y and \mathbf{x} is:

$$y = j \implies \alpha_{j-1} < \mathbf{x}\beta + \epsilon < \alpha_j \implies \alpha_{j-1} - \mathbf{x}\beta < \epsilon < \alpha_j - \mathbf{x}\beta$$

$$l_{iy} = \alpha_{j-1} - x_i\beta \tag{6}$$

$$u_{iy} = \alpha_j - x_i\beta \tag{7}$$

l_{iy} e u_{iy} represent the lower and upper limits of ϵ given $y = j$ and \mathbf{x} . For the *probit* which describes the dummy variable, the conditional probability is described by:

$$P(w = 0|\mathbf{z}) = P(w^* < \zeta|\mathbf{z}) = P(\mathbf{z}\gamma + r < \zeta|\mathbf{z}) = \Phi(\zeta - \mathbf{z}\gamma) \tag{8}$$

$$\begin{aligned} P(w = 1|\mathbf{z}) &= 1 - P(w^* < \zeta|\mathbf{z}) = 1 - P(\mathbf{z}\gamma + r < \zeta|\mathbf{z}) \\ &= 1 - \Phi(\zeta - \mathbf{z}\gamma) = \Phi(\mathbf{z}\gamma - \zeta) \end{aligned} \tag{9}$$

From (8) e (9), the lower and upper limits of r given w and \mathbf{z} are:

$$w = 0 \implies \mathbf{z}\gamma + r < \zeta \implies r < \zeta - \mathbf{z}\gamma$$

$$w = 1 \implies \mathbf{z}\gamma + r > \zeta \implies r > \zeta - \mathbf{z}\gamma$$

$$l_{iw} = \begin{cases} -\infty & w = 0 \\ \zeta - \mathbf{z}\gamma & w = 1 \end{cases} \quad (10)$$

$$u_{iw} = \begin{cases} \zeta - \mathbf{z}\gamma & w = 0 \\ \infty & w = 1 \end{cases} \quad (11)$$

Equations (6), (7), (10), and (11) together imply that vectors \mathbf{l}_i and \mathbf{u}_i are defined as:

$$\mathbf{l}_i = [l_{iy}, l_{iw}]$$

$$\mathbf{u}_i = [u_{iy}, u_{iw}]$$

Thus, the log likelihood function of the two equation model that takes the covariance matrix Σ into account is:

$$\ln L = \sum_{i=1}^N \ln \Phi_2(l_i, u_i, \Sigma) \quad (12)$$

where Φ_2 represents the bivariate normal distribution, determined by:

$$\Phi_2(l_i, u_i, \Sigma) = \frac{1}{\sqrt{(2\pi)^2 |\Sigma|}} \int_{l_{iy}}^{u_{iy}} \int_{l_{iw}}^{u_{iw}} \exp\left(-\frac{1}{2} \mathbf{h}^T \Sigma^{-1} \mathbf{h}\right) \quad (13)$$

where $\mathbf{h} = [w \quad y]$. Thus, the conditional probability of $y = j$ is determined by:

$$Pr(y = j | \mathbf{x}, \mathbf{z}, w) = \Phi_2(l_i, u_i, \Sigma) \quad (14)$$

Standard errors were clustered by municipalities to allow for spatial correlation in error

terms for individuals with residency in the same municipality.¹³

5 Results

The estimates of the effects of the Internet and social media use in affective polarization are reported in Table 3. In the first column, we report the standard single ordered probit model estimates, where we find a positive and statistically significant effect (at the 1% level) of the Internet and social media. Individuals who choose to use the Internet or social media as their primary source of information for political purposes have a higher probability of being polarized than those who choose other sources of information, given their observed characteristics.

Nevertheless, we find that the standard single model and the IV estimations yield different pictures on the effect of the Internet and social media in affective polarization. In the extended model, the error terms of the equations that determine an individual’s level of affective polarization and the probability of using the Internet or social media as a primary source of information for political purposes are positively and significantly correlated. When these error terms are correlated, single-equation models may be biased, as they may attribute part of the impact of unobservable individual characteristics to Internet or social media use. In the second column of Table 3, we report the IV estimations’ results using the extended ordered probit model.¹⁴ The correlation of the error terms is reported at the end of Table 4.

A comparison of the estimates of the coefficients of Internet and social media use in the two models suggests that endogeneity is a problem in this setting. If we ignored the correlation, one might conclude that Internet and social media use play a positive and significant role in influencing affective polarization. Taking the correlation into account, the Internet and social media’s significant effect vanishes.

¹³We checked the robustness of our results to alternative clustering. Results remain unchanged across all different specifications.

¹⁴To estimate the extended model, we employ `eoprobit` Stata command, which estimates an ordered probit regression model, accommodating endogenous covariates.

The comparison of the single and the extended equation models also show that the effect of the remaining variables in political polarization is robust. Results are roughly similar in the two models. We find that the estimated coefficients for gender, religion, race, and income variables are significant and do not change signs in both models. The absolute values of most of the coefficients are roughly the same in the two models.

We have explored the robustness of our findings to changes in the specification of our model. In the third column of table 3, we ignore that the dependent variable is ordinal and present the estimation of the two-stage least squares model (2SLS). Such estimation is justified by Angrist (1991).¹⁵ The linear estimates confirm previous findings: although standard regressions show a positive correlation among Internet and social media use and political polarization, when the endogeneity is taken into account, the effect disappears. The effect of other variables is also similar for the linear and non-linear IV estimations. None of the covariates change sign, and almost all variables that had a significant effect in the linear model also have a significance in the non-linear model - except for religion and income, which showed significant effects on the non-linear model, but not on the linear one. This comparison confirms that the extended ordered probit model is most appropriate for the dataset.

To test whether there are heterogenous effects across different groups of individuals that use the internet or social media as a main source of information, we generated the IV estimates with interaction effects between our variable of interest and the covariates in the previous model. The estimates suggest that effects are uniform across different socio-demographic groups and regions.

¹⁵Using Monte Carlo simulations, he shows that linear IV estimation often have similar results to more sophisticated non-linear models.

Table 3: Affective Polarization

	Standard Model	IV estimation	2SLS
Internet/Social Media Use	0.317*** (4.21)	-0.469 (-1.23)	3.394 (0.73)
Age	0.003557 (1.52)	-0.00344 (-0.79)	0.0301 (0.66)
Male	0.237** (3.24)	0.225** (2.88)	0.727** (2.63)
Black/Indigenous	-0.135 (-1.86)	-0.137 (-1.90)	-0.427 (-1.66)
Unemployed	-0.104 (-0.94)	-0.179 (-1.51)	-0.104 (-0.16)
Protestant	0.0646 (0.65)	0.0153 (0.14)	0.347 (0.75)
Catholic	-0.230* (-2.43)	-0.296** (-3.00)	-0.694 (-1.18)
Household income Near poverty level	0.0958 (0.97)	0.157 (1.50)	0.0137 (0.03)
Low income	0.299** (3.05)	0.365** (3.24)	0.779 (1.24)
Middle class	0.395** (3.03)	0.509*** (4.04)	1.146 (1.16)
Upper middle class	0.515* (2.00)	0.554* (2.42)	1.777 (1.72)
High income	0.477 (1.06)	0.742* (2.22)	0.772 (0.34)
Highest tax brackets	-0.431 (-0.97)	-0.278 (-0.83)	-2.766 (-1.53)
Occupation sector Region	YES	YES	YES
Northeast	-0.371** (-2.90)	-0.349* (-2.55)	-1.313** (-2.74)
Southeast	-0.193 (-1.55)	-0.172 (-1.36)	-0.660 (-1.43)
South	-0.193 (-1.36)	-0.169 (-1.19)	-0.758 (-1.42)
Midwest	-0.0983 (-0.54)	-0.0765 (-0.37)	-0.195 (-0.73)
Constant			2.588 (0.64)
Observations	1136	1136	1136

* p<0.05; ** p<0.01; *** p<0.001

Table 4: Internet and Social Media Use

Optical fiber	0.276* (2.05)
Age	-0.0306*** (-8.77)
Male	0.0286 (0.32)
Black/Indigenous	-0.0102 (-0.12)
Unemployed	-0.266* (-2.01)
Protestant	-0.184 (-1.57)
Catholic	-0.294** (-2.81)
Household income Near poverty level	0.316* (2.49)
Low income	0.382** (3.20)
Middle class	0.650*** (4.09)
Upper middle class	0.447 (1.45)
High income	1.228* (2.51)
Highest tax brackets	0.576 (1.25)
Population density	-0.0000157 (-1.04)
Occupation sector Constant	YES 0.717
corr.e Internet/Social Media e.Affective Polarization)	0.525* (2.15)
Observations	1136

* p<0.05; ** p<0.01; *** p<0.001

6 Discussion

This study showed a rising affective polarization in Brazil in recent years using data from the Brazilian National Election Study. Popular accounts point to the Internet and social media as a reason for political divide through the expansion of environments that resemble “echo chambers”, where citizens are exposed to selective information (Sunstein, 2018; Parisier, 2011). Greater exposure to imbalanced information in these environments would reinforce previous political positions leading voters to develop more extreme positions or greater animosity towards candidates of the opposing political group (Lelkes et al., 2017; Iyengar et al., 2019).

In contrast with what is suggested by the mainstream literature, we found that affective polarization in Brazil cannot be attributed to Internet or social media use. Although the estimation of a straight-forward single-equation model shows a statistically significant relationship between online media use and polarization, we find evidence of selection bias, e.g. part of the impact of unobservable individual characteristics is most likely attributed to Internet or social media use. To overcome the selection bias, this study exploited exogenous variation in Internet and social media usage by using the differences in the layout of pre-existing infrastructure which permits access to broadband internet. When we treat Internet and social media use as endogenous variables and estimate a two-equation model using an IV, the effect disappears. Our findings are consistent with other work on the association between online media and political polarization in the US, Germany and Sweden (Boxell et al., 2017; Barbera, 2014; and Liang and Nordin, 2013).

One of the possible interpretations for the result is that the so-called “echo chambers” and “filter bubbles” in online media may not as strong as previously expected. It has now been suggested that exposure to diverse ideological views on online platforms - such as Facebook and Twitter - are more frequent than commonly believed (Bakshy et al., 2015) and even that online media users are more likely to be exposed to diverse news than those who use traditional media (Barnidge, 2017; Fletcher and Nielsen, 2018). New opportunities

for studies using social media data are generating attention in the literature (Zhuravskaya et al., 2019) and could advance further in understanding the role of new technologies in political behavior.

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Appendix A.

Conditional Independence

	Political Position	Interest in Politics	Extreme Perception Corruption
Optical fiber	0.241 (0.89)	-0.0894 (-1.01)	-0.0138 (-0.40)
Age	0.0162** (2.71)	0.00103 (0.61)	0.00132* (2.16)
Dummy to male	0.156 (0.86)	0.148** (2.89)	-0.0357 (-1.95)
Dummy to black and indigenous	-0.175 (-0.92)	-0.017 (-0.29)	0.0115 (0.55)
Dummy to protestant	0.905** -2.77	-0.125 (-1.45)	-0.0191 (-0.75)
Dummy to catholic	0.505 (1.74)	-0.180* (-2.25)	-0.0083 (-0.31)
Household income Near poverty level	-0.363 (-1.34)	0.156* (2.21)	0.0115 (0.39)
Low income	-0.508 (-1.86)	0.374*** (5.62)	0.0571* (1.98)
Middle class	-0.788* (-2.24)	0.522*** (5.59)	0.00790 (0.23)
Upper middle class	0.437 (0.80)	0.939*** (4.35)	0.144 (3.03)
High income	0.00206 (0.00)	0.453 (1.23)	0.0672 (0.58)
Highest tax brackets	-0.619 (-0.58)	0.202 (0.57)	-0.0448 (-0.30)
Population density	-0.0000655* (-2.14)	0.00000199 (0.20)	0.000000265 (0.07)
Constant	5.707*** (11.46)	2.182*** (14.39)	0.794*** (15.07)
Observations	1530	1524	1520
	Extreme Perception Government	Extreme Perception Minorities	Extreme Perception Economy
Optical fiber	-0.0406 (-0.71)	0.0632 (1.39)	0.00875 (0.20)
Age	-0.00357** (-2.62)	0.00384*** (4.80)	0.00342*** (3.57)
Dummy to male	-0.0881* (-2.02)	0.0553* (2.04)	-0.0845** (-3.31)

Dummy to black and indigenous	0.0378 (0.93)	-0.0168 (-0.60)	0.0573* (2.27)
Dummy to protestant	-0.0869 (-1.49)	0.0552 (1.05)	-0.000450 (-0.01)
Dummy to catholic	-0.0200 (-0.34)	0.0382 (0.77)	-0.0140 (-0.36)
Household income Near poverty level	0.108 (1.86)	-0.0404 (-1.04)	-0.0863* (-2.27)
Low income	0.138* (2.39)	-0.0677 (-1.73)	-0.0642 (-1.86)
Middle class	0.0741 (1.07)	-0.140** (-2.74)	-0.131* (-2.60)
Upper middle class	0.181 (1.19)	-0.139 (-1.47)	-0.152 (-1.71)
High income	0.581*** (9.86)	-0.159 (-0.83)	-0.915 (-0.47)
Highest tax brackets	-0.00820 (-0.04)	-0.395** (-3.07)	0.0490 (0.28)
Population density	0.00000454 (0.58)	-0.000000284 (-0.07)	0.00000338 (0.61)
Constant	0.670*** (6.25)	0.273** (3.23)	0.351*** (4.79)
Observations	614	1522	1512

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

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