# Access and Exposure to Local News Media in the Digital Era: Evidence from U.S. Media Markets<sup>\*</sup>

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#### Abstract

Using a new comprehensive survey of adults in large U.S. media markets we show that minority and low-skill individuals, who are heavily exposed to shocks to the local economy, typically have stronger preferences for and stronger exposure to local news than high-skill and white individuals. At the same time, these disadvantaged individuals have been negatively affected by the impact of the digital revolution on news provision. In particular, high-skill and white individuals have more rapidly embraced online and social media while low-skill and minority individuals still heavily rely on local television and other traditional news providers. These differences in provider choices are important because the digital revolution has reduced the quality of traditional news providers while the quality and quantity of online and social media have substantially increased. To gain additional insights into the welfare consequence of the digital revolution and assess potential policy interventions, we develop and estimate a model of news production and demand for local news. Our model is based on a time-allocation, discrete bundle-choice framework. Our findings suggest that the loss of the local newspaper (television) reduces welfare on average by \$923 (\$1064) which is well above the annual subscription costs in most markets. Finally, we study policies that subsidize online or social media to offset the loss of the local newspaper or television station.

### 1 Introduction

The traditional local news media - newspapers, radio, and television - have long been the prime, if not the sole, source of credible and comprehensive local news and information in the U.S. (Mondak, 1995). Yet, in the past two decades, there have been significant changes in the provision of local news. Traditional news media have been challenged by increased competition from online platforms and social media. The social and technological changes behind the restructuring of the news environment have fundamentally changed access and exposure to local news. In this paper, we show that the rise of the digital media and the resulting changes in preferred media choices have not affected all parts of society equally. In particular, disadvantaged individuals have been negatively affected by the impact of the digital revolution on news provision.<sup>1</sup>

While most individuals prefer to obtain local news from a variety of diverse providers, there are some important differences in provider choices and time allocations among providers by groups. Using a comprehensive survey of adults in large U.S. media markets which was conducted by PEW in 2018, we show that high-skill and white individuals have more rapidly embraced online and social media while low-skill and minority individuals still heavily rely on traditional news providers, in particular local television. These differences in provider choices are important because the digital revolution has reduced the quality of traditional news providers while the quality and quantity of online and social media have substantially increased. As a consequence, one may be concerned about the underlying trends in media markets as the digitalization of the media continues.

Local news is particularly important for disadvantaged individuals. There is a substantial literature in urban and labor economics that has shown that minority and low-skill individuals have lower mobility rates and fewer options in local housing markets, are stronger exposed to shocks in the local labor market, rely more heavily upon informal networks and job referrals, and are more likely to be affected by

<sup>&</sup>lt;sup>1</sup>For the purposes of this study, we define disadvantaged individuals as individuals with low skills or individuals that are likely to have experienced hardship such as racial and ethnic minorities.

shocks in neighborhood amenities such as crime and public school quality.<sup>2</sup> Since disadvantaged individuals are heavily exposed to shocks to the local economy, they should pay close attention to changes in the local environment. Our findings suggest that this conjecture is correct. We document that low-skill and minority individuals typically have stronger preferences for and stronger exposure to local news than high-skill and white individuals who prefer national and international news. These gaps exist for all relevant local news topics ranging from crime and local politics to schools and the local economy. These differences in access and exposure to local news persist after controlling for differences in political affiliation, neighborhood attachment, neighborhood quality, and city-fixed effects.

To understand access and exposure to local news in the U.S., we have to understand individuals' choice of news sources given the cost of their choices. In particular, we would like to know what bundle of providers individuals choose, the frequency and length of time they allocate to each provider, and their assessments of the relative importance to them of the various topics covered by the providers. To address these issues we develop a model of a media market with several different news providers. Local news provision is multi-dimensional covering a variety of different topics. Our model builds on the insights from Crawford and Yurukoglu (2012) and captures the demand for news providers, the time allocation among different news providers, and the resulting exposure to different local news topics. Individuals choose a bundle of providers trading off the prices associated with access to the different providers with the quality of coverage of different local news topics. The utility associated with each bundle of providers is endogenous and depends on the time-allocation choices made by individuals.

Our estimation procedure combines individual choice and time allocation data with survey data that elicit individuals' assessments of the relative importance to them of the various topics covered by the providers. We develop a new maximum likelihood estimator that captures the fact that key variables in our survey are categorical. The estimator works well in a Monte Carlo experiment and our application. We show

<sup>&</sup>lt;sup>2</sup>See, for example, Altonji and Blank (1999), Shapiro (2004), Shuey and Willson (2008), Hoynes, Miller, and Schaller (2012), and Bayer, Ferreira, and Ross (2016).

that the parameter estimates are plausible and that the model fits the data well. We find that almost all individuals prefer to obtain news from a diverse set of providers. This demand for diversity is generated in our model by a news production function that is concave in time inputs. Our findings also suggest that there are significant differences in the productivity of local news providers. Traditional news providers no longer have a comparative advantage in local news production relative to online providers and social media.

The past two decades have been pivotal for the newspaper industry, a period of immense disruption and financial distress. According to a recent study by Pew Research Center (2018), newsroom employment and print advertising were near peak levels in 2004. Since then the number of journalists employed by newspapers has been cut in half (Peterson, 2021), and print advertising revenue has fallen to record-low levels (Angelucci and Cagé, 2019). More than one in five papers has closed over the past two decades, leaving thousands of communities and cities at risk of becoming news deserts (Abernathy, 2020). Since the decline of traditional local news media is likely to continue in the future, it is useful to ask what is at stake if a city or media market loses its last printed newspaper. Using our model, we can estimate the average welfare costs associated with this loss and study what parts of society are most likely to bear the largest burden of this loss. Our findings suggest that the loss of the local newspaper reduces welfare on average by \$923 which is well above the annual subscription costs in most markets. Moreover, the welfare losses tend to be larger for disadvantaged individuals.

Similar concerns arise with respect to local news coverage by television stations. According to a recent study by PEW (2021), viewership of local affiliate news stations has declined moderately in the past decade, while TV newsroom employment has stayed constant at around 30,000. At the same, advertising and transmission fee revenues have grown moderately. As such local TV stations are not as vulnerable as printed newspapers. Nevertheless, local television is facing increased competition from a variety of streaming services, which has the potential to undermine the viability of local television. We document in this paper that local television is still the most preferred provider of local news for disadvantaged households. As a consequence, we also study the potential welfare consequences of the demise of local television. We find that the loss of the local TV station reduces welfare on average by \$1064, which is significantly larger than the welfare loss of losing the printed newspapers. Again, welfare losses tend to be larger for black and Hispanic individuals.

Given these potentially large welfare losses associated with the demise of traditional news media, we study policies that promise to offset these effects. Although online and social media have caught up with traditional news providers, there are some reasons for concern since some of the local news provided by online and via social media is unfiltered and relies on unpaid volunteers or part-time workers.<sup>3</sup> To offset the loss of the local newspaper or the local television station, policies can subsidize online or social media to entice them to raise the quality of local news production. We find that the quality of online media needs to increase by 23.3 percent to offset the loss of the local newspaper. Similarly, the quality of social media needs to increase by 49.8 percent to compensate individuals for the demise of the newspaper. The required increases are even larger for a loss of the local television station. It is, therefore, questionable whether social media can fill the shoes of traditional news providers soon. Our findings are thus consistent with the perception that it would take a serious upgrade of online or social media to fully substitute for the existing printed newspaper. These upgrades may not happen without public subsidies. As a consequence, there is much scope for carefully designed public policy interventions.

Our paper is related to several different branches of the literature that we have not already mentioned above. First, our paper is related to the literature on empirical industrial organization that has documented significant changes in the provision of local and national news. Traditional local news media have been challenged by increased competition from online platforms and social media (Seamans and Zhu (2014), Angelucci, Cagé and Sinkinson (2020), Djourelova, Durante and Martin (2021)). As a consequence, the relative importance of traditional local news providers has been diminished forcing them to save costs and downsize operations.<sup>4</sup> The decline in tra-

<sup>&</sup>lt;sup>3</sup>See, for example, Allcott and Gentzkow, (2017), Allcott, Gentzkow, and Yu (2019), and Pew Research Center (2019).

 $<sup>^4{\</sup>rm For}$  a detailed discussion see Chandra and Collard-Wexler (2009), Sweeting (2010), Fan (2013), Stahl (2016).

ditional local news providers is mirrored by a decline in the quality of local news provision (L'Heudé, 2022). Her findings suggest that the average number of local news articles per newspaper dropped by more than 50 percent during the past two decades. Online and social media have, at least, partially filled this gap (Gentzkow (2007), Gentzkow and Shapiro (2011), Kennedy and Prat (2019)). Nevertheless, there are serious concerns that the overall quality of local news provision has significantly declined during the past decades (Kirchhoff (2009), FCC (2011), Abernathy (2020)). Our paper reinforces these concerns. We find that in a counterfactual analysis where we simulate the loss of the printed newspaper, it would take a serious upgrade of the digital media to be able to fully substitute for the existing printed newspaper.

Second, this paper also adds to the literature on local news media consumption patterns. While most existing studies in the literature on the demand for news are platform-centric and revolve around the traditional news media (for instance, George and Waldfogel (2003) and Gentzkow and Shapiro (2010) in printed newspaper markets, and Siegelman and Waldfogel (2001) in the radio industry), much less is known about the impact of online and social media on local news consumption. Notable exceptions closely related to this paper are Gentzkow (2007) who studies competition between print and online newspapers and finds that print and online newspapers are substitutes using survey data from Washington, D.C., and Kennedy and Prat (2020) who document the news consumption patterns of individuals using data from the Reuters Institute for the Study of Journalism and show that people tend to rely on several platforms to get informed about news. Our paper enhances our understanding of access and exposure to local news in U.S. cities after the adjustments forced by the transition to digital media. In particular, we show that low-skill and minority individuals tend to have stronger preferences for and stronger exposure to local news than high-skill and white individuals, and that these disadvantaged individuals have been negatively affected by the digital news revolution.

Third, our analysis highlights the importance of provider choices in determining access and exposure to the local media. Not surprisingly, older individuals also prefer traditional providers while younger individuals prefer online and social media. Our news production estimates suggest that social media are relatively more effective in providing local news about economic opportunities than traditional local news providers. These findings are also consistent with previous research that has emphasized the importance of informal networks in labor markets, especially for younger, low-skill, male workers (Ioannides and Loury, 2004). Bayer, Ross, and Topa (2008) highlight neighborhood referrals and assortative matching in social networks. Bailey, Farrell, Kuchler, and Stroebel (2020) analyze data from Facebook to explore the spatial structure of social networks in the New York metro area. They find that a substantial share of urban residents' connections is to individuals who are located nearby. That suggests that even in the digital economy, most of the information about the availability and suitability of local jobs is propagated via online social networks. Chetty et al. (2022) find that differences in economic connectedness can explain wellknown relationships between upward income mobility and racial segregation, poverty rates, and inequality.

Lastly, our paper is related to the literature on political economy that has focused on the role of the media in an open society. The local media played an essential role in the functioning of democracy by informing voters, driving citizen engagement, keeping elected representatives accountable, and helping set the agenda for the debate on important local policy issues.<sup>5</sup> As traditional news sources decline, a growing proportion of Americans are getting their news online and on social media. This raises many concerns, including a decline in electoral participation, mostly among younger and less-educated voters, and the spread of misinformation and political polarization (Gavazza et al. (2019), Allcott et al. (2020), Zhuravskaya, Petrova, and Enikolopov (2020)). Our paper complements this literature in political economy by documenting how access and exposure to local and national news have shifted in the digital era.

The rest of the paper is organized as follows. Section 2 introduces our data set and characterizes differences in access and exposure to the local news media. Section 3 develops our model. Section 4 discusses the identification and estimation of the parameters of the model. Section 5 reports our main empirical results. Section 6

<sup>&</sup>lt;sup>5</sup>See Besley and Pratt (2006), DellaVigna and Kaplan (2007), Eisensee and Strömberg (2007) Snyder and Strömberg (2010), Gentzkow, Shapiro and Sinkinson (2011)

discusses the policy implications of our work while Section 7 offers some conclusions and discusses future research.

#### 2 Data Sources and Stylized Facts

Our empirical analysis focuses on the 20 largest cities in the U.S. Each city is a local media market with a variety of different news providers. As discussed in detail in Appendix A, our survey aggregates providers into five types: printed newspaper, radio, TV, online media, and social media. For each provider, we then construct annual prices as subscriber-weighted average prices in the metropolitan area. Print newspaper subscription prices come from the Alliance for Audited Media database. Basic cable and internet prices are from the Warrens Communications Television and Cable Factbook, for the year 2018. The main cost component of online news and social media is related to internet access. It is plausible that most individuals obtain internet access for other purposes besides exposure to local news. We, therefore, assume that only ten percent of the total cost of internet access is attributed to the price of online media and social media. Table 1 reports average prices for the full sample and some large U.S. cities. The average price for TV is \$254, for newspapers \$440, for online \$251, and for social media \$50. We set the price for radio to \$25 in all markets.

The main data source for our empirical analysis comes from the Pew Research Center's Local News Survey, which was conducted between October 15 and November 8, 2018.<sup>6</sup> The survey covers 99 distinct local media markets and provides a granular view of the local news landscape. The full representative sample consists of 23,857 adults. In this analysis, we restrict attention to the 20 largest media markets. That reduces our sample size to 10,352 individuals for which we have complete information.

We observe a variety of different socio-demographic characteristics including age, gender, education, race, marital status, party affiliation, and income. In addition, we observed a subjective assessment of the quality of the local neighborhood and

<sup>&</sup>lt;sup>6</sup>The data were made available to us through a data-sharing agreement.

	Printed	TV	Online	Social
	Newspaper		Media	Media
All 20 Cities	\$440	\$254	\$251	\$50
New York	\$541	\$222	\$367	\$47
Chicago	\$312	\$231	\$200	\$50
DC	\$238	\$177	\$176	\$52
Philadelphia	\$405	\$219	\$285	\$51
Miami	\$632	\$195	\$228	\$50
Detroit	\$314	\$257	\$190	\$51
Houston	\$417	\$191	\$214	\$54
St. Louis	\$374	\$324	\$193	\$36
Los Angeles	\$307	\$361	\$378	\$53
San Francisco	\$565	\$627	\$136	\$51
San Diego	\$559	\$163	\$235	\$41

Table 1: Price Heterogeneity Among Cities

a measure of the individual's attachment to the local community. Table 2 provides means of the main socio-economic variables of interest. Note that our data is an urban sample. It tracks the overall composition of the U.S. urban population reasonably well.<sup>7</sup>

One objective of the survey is to elicit detailed information about preferences for local news, national and international news. In particular, the survey asks respondents how closely they follow the three different news types. The answers are recorded as a categorical variable measured on a four-point Likert scale. Table 3 summarizes the results from ordered Logit regressions for local news, national news, and international news.

Table 3 shows that low-skill and black individuals typically follow local news much more closely than high-skill and white individuals who prefer national and international news. Note that Hispanics also have stronger preferences for local news than white individuals. However, Hispanics also pay close attention to national and international news which is probably due to their interest in immigration policies as well as political and economic news in Latin and South America. These differences in

 $<sup>^{7}</sup>$ We have used Census data to assess the representativeness of our sample. We find that we slightly oversample high-skill, white, married, and low-income individuals.

Age		Marital Status	
18-29	0.209	Married	0.456
30-49	0.352	Party Affiliation	
50-64	0.264	Republican	0.223
65+	0.175	Democrat	0.381
Gender		Independent	0.267
Male	0.507	Other	0.129
Female	0.493	Income	
Education		Less than $10,000$	0.090
College Graduate	0.307	10,000 to less than $20,000$	0.085
Some College Education	0.243	20,000 to less than $30,000$	0.104
High School Graduate	0.086	30,000 to less than $40,000$	0.095
Race		40,000 to less than $50,000$	0.099
White	0.552	50,000 to less than $75,000$	0.160
Black	0.132	75,000 to less than $100,000$	0.128
Hispanic	0.216	\$100,000 to less than \$150,000	0.133
Others	0.099	150,000  or more	0.107
Local Community Attachment		Local Community Rating	
Very much	0.224	Excellent	0.323
Somewhat	0.493	Good	0.540
Not very	0.223	Only fair	0.116
Not at all	0.061	Poor	0.021

 Table 2: Descriptive Statistics of Socio-Economic Characteristics

	How Closely Do You Follow?			
	Local	National	International	
Black	0.886***	$-0.163^{**}$	$-0.200^{***}$	
	(0.073)	(0.071)	(0.070)	
Hispanic	$0.491^{***}$	$0.221^{***}$	$0.427^{***}$	
	(0.059)	(0.060)	(0.059)	
College Grad	$-0.399^{***}$	$0.710^{***}$	$0.477^{***}$	
	(0.126)	(0.124)	(0.125)	
Age	Yes	Yes	Yes	
Income	Yes	Yes	Yes	
Political Affiliation	Yes	Yes	Yes	
Gender and Marital Status	Yes	Yes	Yes	
Community Characteristics	Yes	Yes	Yes	
City FE	Yes	Yes	Yes	

Table 3: Exposure to Local, National, and International News

preferences for local news persist after controlling for age, income, political affiliation, gender, marital status, neighborhood attachment and quality, and city-fixed effects.

The existence of these gaps in local news exposure is consistent with a substantial literature in urban and labor economics that has shown that minority and low-skill individuals have lower mobility rates than white and high-skill individuals. Low-mobility individuals have stronger incentives to invest time and effort to stay in touch with their neighborhoods and communities than those with high-mobility rates. In addition, the stakes of keeping in touch with local events may also be higher for low-skill and minority households than for whites and high-skill individuals. For example, disadvantaged individuals tend to have fewer options in local housing markets and, given their lower levels of wealth, they tend to be more exposed to housing price shocks. These individuals are more strongly exposed to shocks in the local labor market. It is well-known that they rely more heavily upon informal networks and job referrals. Finally, low-skill and minority households are more likely to be affected by shocks in neighborhood amenities such as crime and public school quality.<sup>8</sup> In

<sup>&</sup>lt;sup>8</sup>See, for example, Smith (1995), Altonji and Blank (1999), Shapiro (2004), Shuey and Willson (2008), Hoynes, Miller, and Schaller (2012), and Bayer, Ferreira, and Ross (2016).

summary, it is a lot easier for white and high-skill individuals to insure themselves against local shocks to the economy or neighborhood quality. As a consequence, they pay less attention to local news than low-skill and minority individuals.

	How Important		ant	How Easy to Get Informed		
	Crime	Politics	Community	Crime	Politics	Community
Black	0.93***	0.33***	0.43***	$0.51^{***}$	0.24***	$0.21^{***}$
	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Hispanic	$0.68^{***}$	$0.25^{***}$	$0.21^{***}$	0.05	$0.12^{*}$	-0.02
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
College Grad	$-0.61^{***}$	0.38***	$0.24^{*}$	$-0.36^{***}$	$-0.21^{*}$	-0.18
	(0.14)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
	Jobs	Schools	Economics	Jobs	Schools	Economics
Black	0.99***	0.92***	0.90***	$0.42^{***}$	$0.24^{***}$	$0.52^{***}$
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Hispanic	$0.82^{***}$	$0.66^{***}$	$0.75^{***}$	0.05	$0.14^{**}$	$0.34^{***}$
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
College Grad	$-0.43^{***}$	$-0.45^{***}$	$-0.35^{***}$	$-0.41^{***}$	$-0.38^{***}$	$-0.58^{***}$
	(0.13)	(0.12)	(0.13)	(0.13)	(0.13)	(0.13)
	Sports	Culture	Restaurants	Sports	Culture	Restaurants
Black	$0.64^{***}$	0.04	0.20***	$-0.20^{***}$	0.01	-0.01
	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)
Hispanic	$0.32^{***}$	$0.23^{***}$	0.04	$-0.22^{***}$	-0.07	$0.12^{**}$
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
College Grad	-0.16	$0.63^{***}$	$0.29^{**}$	-0.08	0.16	0.06
	(0.12)	(0.13)	(0.12)	(0.13)	(0.13)	(0.13)
	Traffic	Weather		Traffic	Weather	
Black	$0.51^{***}$	$0.24^{**}$		$0.34^{***}$	$-0.27^{***}$	
	(0.07)	(0.09)		(0.08)	(0.10)	
Hispanic	$0.42^{***}$	-0.02		0.03	$-0.25^{***}$	
	(0.06)	(0.07)		(0.06)	(0.08)	
College Grad	0.10	0.15		0.14	$0.73^{***}$	
	(0.12)	(0.15)		(0.13)	(0.14)	
Age	Yes	Yes	Yes	Yes	Yes	Yes
Income	Yes	Yes	Yes	Yes	Yes	Yes
Political Affiliation	Yes	Yes	Yes	Yes	Yes	Yes
Gender and Marital Status	Yes	Yes	Yes	Yes	Yes	Yes
Community Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Racial, Ethnics and Skill Gaps in Exposure to Local News Topics

One key objective of the survey is then to elicit detailed information about pref-

erences for a variety of local news topics. There are eleven local news topics in the survey covering diverse areas such as local politics, crime, education, the local economy, jobs, entertainment, cultural events, sports, entertainment, weather, and traffic. We observe how important these topics are to individuals and how well individuals are informed about these topics. Responses to these questions are again measured on a four-point Likert scale. We can, therefore, focus on the existence of racial, ethnic or skill gaps. Table 4 reports the estimates of the key regressors and estimated standard errors. We find that the racial and ethnic gaps exist for almost all relevant local news topics ranging from crime and local politics to schools and the local economy. The exceptions here are sports and weather-related news. The gaps between low-and high-skill individuals are equally pronounced when it comes to jobs, the economy, crime, and education. Not surprisingly high-skill individuals care more about politics, culture, and restaurants than low-skill individuals.

The survey also contains detailed information characterizing access to local news providers in each media market. Local news is provided by a variety of different firms and organizations and spread through social networks. Our analysis focuses on the following five provider types: newspapers, television stations, radio stations, social online networks, and online media.

The survey asks each respondent to name their most preferred news provider. We estimate a linear probability model for each of the five providers. Table 5 reports the coefficients of the key variables and the estimated standard errors.

Our findings show that there are some important differences in preferred provider choices in the sample. In particular, high-skill and white individuals have more rapidly embraced online and social media while low-skill and minority individuals still heavily rely on traditional news providers, in particular local television. We, therefore, conclude that the rise of digital media and the resulting changes in preferred media choices have not affected all parts of society equally. In particular, low-skill and minorities seem to lag in adopting social and online media. As we will see below, these differences in provider choices are potentially problematic given that traditional news providers are likely to continue to decline in quality in the future.

Most individuals prefer to obtain local news from a variety of diverse providers.

	Newspaper	Radio	$\mathrm{TV}$	Online	Social Media
Black	$-0.08^{***}$	$-0.04^{***}$	0.24***	$-0.10^{***}$	$-0.02^{*}$
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Hispanic	$-0.06^{***}$	$-0.02^{*}$	0.08***	$-0.05^{***}$	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
College Grad	0.05**	0.01	$-0.23^{***}$	0.18***	-0.02
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)
Age	Yes	Yes	Yes	Yes	Yes
Income	Yes	Yes	Yes	Yes	Yes
Political Affiliation	Yes	Yes	Yes	Yes	Yes
Gender and Marital Status	Yes	Yes	Yes	Yes	Yes
Community Characteristics	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes

Table 5: Preferred Provider Choices

This is reflected in the bundle choices that we observe in the sample. The distributions of the bundle choices by race are documented in Figure 1. Notice, that black individuals tend to use more providers in their bundles than white or Hispanic individuals.

Finally, we also observed time allocations for each provider choice. Again the survey captures the responses as categorical variables that measured on a four-point Likert scale. Table 6 summarizes the key results with respect to the racial, ethnic, and skill informational gaps.

Overall, we find that these differences observed in time allocation decisions (intensive margin) are similar to those observed in provider choices (extensive margin). The main difference is that Hispanics are more active in social media than black and white individuals.

In summary, we find that low-skill and minority individuals are much more engaged with local news than high-skill and white individuals. This is also true for almost all relevant local news topics including crime, politics, entertainment, schools, and the local economy. We also observed significant differences in preferred provider and bundle choices as well as time allocations for each provider. High-skill and white



Figure 1: Distribution of Bundles Choices Observed in the Sample

Table 6: Time Allocations

	Newspaper	Radio	TV	Online	Social Media
Black	0.09	0.02	0.77***	0.04	0.04
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Hispanic	$-0.12^{**}$	$-0.11^{**}$	$0.27^{***}$	0.09	$0.35^{***}$
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
College Grad	0.11	$0.35^{***}$	$-0.53^{***}$	$0.75^{***}$	$-0.20^{*}$
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
Age	Yes	Yes	Yes	Yes	Yes
Income	Yes	Yes	Yes	Yes	Yes
Political Affiliation	Yes	Yes	Yes	Yes	Yes
Gender and Marital Status	Yes	Yes	Yes	Yes	Yes
Community Characteristics	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes

individuals have more rapidly embraced the new digital media than low-skill, and minority individuals. Finally, these differences are robust to controlling for age, income, political affiliation, gender, marital status, local community engagement, and city-fixed effects. These gaps are likely to reflect the different incentives to stay in touch with events in the local community and neighborhoods. These incentives arise from differences in labor and housing markets, access to primary and secondary education, as well as exposure to crime and other shocks to neighborhood quality. In the rest of the paper, we explore how these gaps affect individual welfare and study potential interventions that may help offset the decline in the quality of traditional news media.

#### 3 Modeling Access and Exposure to Local Media

To gain additional insights we develop and estimate a model of individual behavior that captures the heterogeneity in preferences for, access, and exposure to local news. Our model is based on the time-allocation, discrete-choice framework that was developed to study demand in multichannel TV markets by Crawford and Yurukoglu (2012) and Crawford, Lee, Winston, and Yurukoglu (2018). Individuals choose a bundle of different local news providers trading off the costs associated with the different providers and the quantity of local news provision. Local news provision is multi-dimensional covering a variety of different news topics.

Let S denote the total number of local news providers. Let S denote the set of service providers. For example, this set includes radio, TV, newspaper, online media, etc. Let N be the total number of bundles available to consumers. We indicate by  $S \subset S$  a set of news providers available to an individual.

Consider the time allocation problem of an individual. Let H denote the total amount of time devoted to local news consumption during the period. Let  $h_s$  denote the time that the individual spends on service provider s. The time-allocation choices must satisfy the following constraints:

$$\sum_{s \in S} h_s \leq H$$

$$h_s \geq 0 \text{ if } s \in S \tag{1}$$

(2)

Let  $h = \{h_s\}_{s \in S}$  denote the time-allocation vector. A time-allocation vector translates into a vector of news exposure. There are K dimensions of local news. In our application, local news topics are local politics, crime, jobs, public education, entertainment, sports, entertainment, and so on. The news production for topic k, is denoted by  $t_k(h, S)$  and depends on the bundle choice and the time allocation vector. For our empirical model, we make the following assumption:

$$t_k(h,S) = \sum_{s \in S} \frac{1}{1-\rho} t_{ks} h_s^{1-\rho}$$
(3)

Note that the parameters  $t_{ks}$  capture the relative advantages of news providers in certain topics.<sup>9</sup> For each news topic, news production is additively separable across providers. However, there is some concavity in the news production since  $0 < \rho < 1$ . As a consequence, our model generates an interior solution for the time allocation problem. The concavity of the news production function also tends to create demand for diversity among providers, as discussed in detail below.

Let U(h, S) denote the utility that is associated with a bundle S and time allocation vector h. We assume that the total utility from news exposure is additively separable among news topics. For our empirical model, we use the following specification:

$$U(h,S) = \sum_{k} U_{k}(h,S) = \sum_{k} \gamma_{k} \frac{1}{1-\rho} \sum_{s \in S} t_{ks} h_{s}^{1-\rho}$$
(4)

Conditional on h and S all individuals receive the same news. However, the preferences also depend on  $\gamma_k$  and may depend on the individual's characteristics x. In the

<sup>&</sup>lt;sup>9</sup>This specification also imposes the normalizing assumption that  $t_k(h, \emptyset) = 0$ .

empirical model, we assume that  $\gamma_k(x) = \exp(x'\gamma_k)$ . As such, individuals will have different valuations of the same news that is provided to them.

Given our specifications for the news production functions and the preferences over news topics, we can obtain a closed-form solution for the optimal time allocation choices of individuals. In particular, the optimal time use vector is the solution to the following problem:

$$\max_{h_1,\dots,h_S,\mu} \sum_k \gamma_k \sum_{s \in S} \frac{1}{1-\rho} t_{ks} h_s^{1-\rho} + \mu \left(H - \sum_{s \in S} h_s\right)$$
(5)

where  $\mu$  is the Lagrange multiplier.

It is straightforward to show that the optimal time allocation for this specification satisfies:

$$h_s(H,S) = H \frac{\left(\sum_k \gamma_k t_{ks}\right)^{\frac{1}{\rho}}}{\sum_{s' \in S} \left(\sum_k \gamma_k t_{ks'}\right)^{\frac{1}{\rho}}}$$
(6)

Hence, the maximum utility attainable from bundle S and time endowment H, denoted by U(H, S), is given by

$$U(H,S) = \sum_{k} \gamma_{k} \sum_{s \in S} \frac{1}{1-\rho} t_{ks} \left( H \frac{\left(\sum_{k} \gamma_{k} t_{ks}\right)^{\frac{1}{\rho}}}{\sum_{s' \in S} \left(\sum_{k} \gamma_{k} t_{ks'}\right)^{\frac{1}{\rho}}} \right)^{1-\rho}$$
(7)

In summary, the utility associated with a time budget H and the provider choice S is endogenous and depends on the time allocation choices made by households. These choices are primarily determined by the productivities of the providers for a variety of news topics  $t_{ks}$  as well as the preferences for different topics  $\gamma_k$ .

The utility from purchasing bundle S with time endowment H, denoted by V(H, S), is then defined as:

$$V(H,S) = U(H,S) - \alpha p(S) + \epsilon(S)$$
(8)

where p(S) is the price of bundle S and  $\epsilon(S)$  is an idiosyncratic random utility shock that satisfies all the standard assumptions in McFadden (1974). In the empirical model, we also allow for heterogeneity in the price elasticity by assuming that  $\alpha(x) = \exp(x'\alpha)$ .

In summary, the bundle choices are thus driven by fundamental differences in the total time allocated to local news, preferences for local news topics, productivities of different news providers, prices as well as idiosyncratic preferences. Heterogeneity in the time allocation across providers is thus driven by fundamental differences in the total time allocated to local news and preferences for local news topics.

#### 4 Estimation

Let  $\theta$  denote the parameters of the model. We show in this section that we can estimate these parameters using the principle of maximum likelihood. The likelihood function has three components: (i) the conditional choice probabilities for the optimal provider bundle choice, (ii) the conditional choice probabilities for the optimal time allocation among the set of chosen providers, and (iii) the conditional choice probabilities for the exposure to news topics. The first type of conditional choice probabilities is straightforward to construct. The second and third types are constructed using categorical survey data.<sup>10</sup> We discuss the most important details below.

Note that we do not directly observe the total time allocation of each individual and, therefore, assume that  $H(x) = \exp(x'\beta)$ . Hence, define:

$$h_{s}(x,S) = H(x) \frac{(\sum_{k} \gamma_{k}(x) t_{ks})^{\frac{1}{\rho}}}{\sum_{s' \in S} (\sum_{k} \gamma_{k}(x) t_{ks'})^{\frac{1}{\rho}}}$$
(9)

The survey measures time use for each provider using a categorical variable measured on a four-point Likert scale. Let us define the continuous latent variables  $h_s^*$  as follows:

$$h_s^* = h_s(x, S) + \nu_s \quad s = 1, ..., n_s$$
 (10)

where  $\nu_s$  follows a logistic distribution. Define the random variable  $h_s^o$  such that:

 $<sup>^{10}</sup>$ As such our estimation strategy differs significantly from Crawford and Yurukoglu (2012).

- 1. Never:  $h_s^o = 0$  if s is not in the chosen bundle.
- 2. Hardly ever:  $h_s^o = 1$  if  $h_s^* \leq \bar{h}_l$ ,
- 3. Sometimes:  $h_s^o = 2$  if  $\bar{h}_l < h_s^* \le \bar{h}_h$
- 4. Often:  $h_s^o = 3$  if  $\bar{h}_h < h_s^*$ .

for thresholds,  $\bar{h}_l$  and  $\bar{h}_h$ . Hence, we have

$$P_{\theta}(h_{s}^{o} = 1 | x, S) = P(h_{s}^{*} \leq \bar{h}_{l}) = F(\bar{h}_{l} - h_{s}(x, S))$$

$$P_{\theta}(h_{s}^{o} = 2 | x, S) = P(\bar{h}_{l} < h_{s}^{*}) \leq \bar{h}_{h} = F(\bar{h}_{h} - h_{s}(x, S)) - F(\bar{h}_{l} - h_{s}(x, S))$$

$$P_{\theta}(h_{s}^{o} = 3 | x, S) = P(\bar{h}_{h} < h_{s}^{*}) = 1 - F(\bar{h}_{h} - h_{s}(x, S))$$

$$(11)$$

where  $F(x) = \frac{1}{1 + \exp(-x)}$  is the CDF of the logistic distribution with a location of 0 and a scale of 1. These conditional choice probabilities thus account for measurement error in the responses to the survey questions.

Similarly, the survey asks about the importance of news topics with answers on a four-point Likert scale. Define the latent variable

$$U_{k}^{*}(x,S) = \underbrace{\gamma_{k}(x) \sum_{s \in S} \frac{1}{1-\rho} t_{ks} (h_{s}(x,S))^{1-\rho}}_{U_{k}(x,S)} + \eta_{k}$$
(12)

where  $\eta_k$  follows a logistic distribution. Define the random variable  $U_k^o$  such that

- 1. Neither important nor interesting,  $U_k^o = 1$  if  $U_k^*(x, S) \leq \overline{U}_l$ ;
- 2. Interesting, but not important to me,  $U_k^o = 2$  if  $\overline{U}_l < U_k^*(x, S) \le \overline{U}_m$ ;
- 3. Important to know about, but I don't need to keep up with it daily,  $U_k^o = 3$  if  $\bar{U}_m < U_k^*(x, S) \le \bar{U}_h$ ;
- 4. Important for my daily life,  $U_k^o = 4$  if  $\overline{U}_h < U_k^*(x, S)$ .

We assume that the three thresholds do not depend on k. Hence, the probabilities of observing a particular value of  $U_k^o$  conditional on x, S are given by:

$$P_{\theta}(U_{k}^{o} = 1|x, S) = P(U_{k}^{*} \leq \bar{U}_{l}) = G(\bar{U}_{l} - U_{k}(x, S))$$
(13)  

$$P_{\theta}(U_{k}^{o} = 2|x, S) = P(\bar{U}_{l} < U_{k}^{*} \leq \bar{U}_{m})$$

$$= G(\bar{U}_{m} - U_{k}(x, S)) - G(\bar{U}_{l} - U_{k}(x, S))$$

$$P_{\theta}(U_{k}^{o} = 3|x, S) = P(\bar{U}_{m} < U_{k}^{*} \leq \bar{U}_{h})$$

$$= G(\bar{U}_{h} - U_{k}(x, S)) - G(\bar{U}_{m} - U_{k}(x, S))$$

$$P_{\theta}(U_{k}^{o} = 4|x, S) = P(\bar{U}_{h} < U_{k}^{*}) = 1 - G(\bar{U}_{h} - U_{k}(x, S))$$

where  $G(x) = \frac{1}{1 + \exp(-x)}$  is the CDF of the logistic distribution with a location of 0 and a scale of 1.

We observe the price p(S) for each bundle S. For each individual, we also observe a vector of socioeconomic characteristics x. Moreover, we observe which bundle  $S^o$ was chosen by the individual. Since errors are Type I extreme value, we can define the conditional choice probability for each bundle conditional on x:

$$P_{\theta}(S^{o}|x) = \frac{\exp[U(H(x), S^{o}) - \alpha(x) \ p(S^{o})]}{\sum_{S \in \mathcal{S}} \exp[U(H(x), S) - \alpha(x) \ p(S)]}$$
(14)

Hence, the likelihood for each observation, denoted by  $L(\theta|S^o, h^o, U^o, x)$ , can be written as

$$\prod_{S\in\mathcal{S}} \left[ P_{\theta}(S|x) * \prod_{s\in S} \left( \prod_{h=1}^{3} P_{\theta}(h_{s}^{o} = h|x, S)^{\mathbb{I}(h \text{ is observed for } s)} \right)$$

$$* \prod_{k} \left( \prod_{U=1}^{4} P_{\theta}(U_{k}^{o} = U|x, S)^{\mathbb{I}(U \text{ is observed for } k)} \right) \right]^{\mathbb{I}(S=S^{o})}$$

$$(15)$$

where  $\theta$  is the vector that includes all parameters of the model which consist of the concavity parameter  $\rho$ , the news productivity parameters  $t_{ks}$ , the preferences shifters  $\gamma_k$ , the time endowment shifters  $\beta$ , and the parameters that determine the prices elasticity of demand,  $\alpha$ , as well as the nuisance parameters of the measurement errors

and the thresholds of the ordered discrete choice models.

In summary, we have shown how to estimate the parameters the model using an MLE. Appendix C discusses identification. The issues here are fairly straightforward and common to the discrete choice literature. It also provides the details of a Monte Carlo study, that we conducted, and shows that the estimator performs well in sample sizes that are similar to the ones we use in our application.

#### 5 Empirical Results

To capture heterogeneity among cities, we use a hierarchical agglomerative clustering method to classify the 20 cities into three types.<sup>11</sup> As inputs of the clustering algorithm, we use the city fixed effects estimated from the different reduced-form regressions discussed in Section 2. Cluster 1 (Big Cities) contains New York, Chicago, Philadelphia, Washington DC, Boston, and Atlanta. Cities in Cluster 2 (Midwest-Southern Cities) are Houston, Dallas, Phoenix, Tampa, St. Louis, Detroit, Minneapolis, Detroit, and Miami. Cluster 3 (West Coast Cities) consists of Los Angeles, San Francisco, San Diego, Seattle, Riverside, and Portland. For empirical tractability, we also aggregate the eleven news topics covered in the survey into four different types of topics (politics, the economy, culture and entertainment, weather and traffic).<sup>12</sup> We then estimated a variety of different model specifications. Below we report the parameter estimates and the estimated standard errors for our preferred specification.

Table 7 reports the estimates of the production function parameters for the four topics, five providers, and three city clusters. Our findings suggest that there are significant differences in the productivity of local news providers. Traditional news providers – especially printed newspapers and TV – no longer have a comparative advantage in local news production relative to online media. In the case of the newspaper industry this probably reflects two decades of mergers, downsizing, and cost-cutting.

<sup>&</sup>lt;sup>11</sup>See Appendix B for details.

<sup>&</sup>lt;sup>12</sup>See Appendix A for details.

Parameter	Topic	Provider	Cluster 1	Cluster 2	Cluster 3
			Big	Southern	West Coast
				Midwest	
$t_{11}$	Politics	Newspaper	0.705	0.601	0.606
$t_{12}$	Politics	$\mathrm{TV}$	0.784	0.847	0.591
$t_{13}$	Politics	Radio	0.456	0.499	0.512
$t_{14}$	Politics	Online	0.834	0.786	0.844
$t_{15}$	Politics	Social Media	0.394	0.452	0.484
$t_{21}$	Economics	Newspaper	0.279	0.241	0.216
$t_{22}$	Economics	$\mathrm{TV}$	0.267	0.207	0.284
$t_{23}$	Economics	Radio	0.126	0.222	0.091
$t_{24}$	Economics	Online	0.350	0.348	0.330
$t_{25}$	Economics	Social Media	0.526	0.523	0.570
$t_{31}$	Entertainment	Newspaper	0.079	0.095	0.077
$t_{32}$	Entertainment	$\mathrm{TV}$	0.000	0.022	0.019
$t_{33}$	Entertainment	Radio	0.037	0.038	0.047
$t_{34}$	Entertainment	Online	0.095	0.071	0.074
$t_{35}$	Entertainment	Social Media	0.054	0.056	0.047
$t_{41}$	Weather, Traffic	Newspaper	0.642	0.600	0.624
$t_{42}$	Weather, Traffic	$\mathrm{TV}$	0.845	0.930	0.805
$t_{43}$	Weather, Traffic	Radio	0.804	0.734	0.630
$t_{44}$	Weather, Traffic	Online	1.112	1.077	1.089
$t_{45}$	Weather, Traffic	Social Media	0.609	0.518	0.415

Table 7: City-specific News Production

We also find that there are some notable differences in news production across cities. In particular, large cities in Cluster 1 tend to have higher-quality printed newspapers than cities in Clusters 2 and 3. However, cities in Cluster 1 do not necessarily have higher-quality TV or radio than other cities. Finally, there are no significant differences in the quality of online and social media among the twenty cities in our sample.<sup>13</sup>

Despite these differences in productivity among providers, almost all individuals prefer to obtain news from a diverse set of providers. This demand for diversity is generated in our model by a news production function that is concave in time inputs.

 $<sup>^{13}</sup>$ We use Wald Tests to formally test if the differences in productivity across providers and the difference across clusters are statistically significant.

We have estimated a variety of different model specifications. Our estimate of  $\rho$  is 0.5 which highlights the benefits of diversity when allocating time among different providers.

Table 8 summarizes our estimates of the parameters that characterize heterogeneity in time use and preferences over the four different news topics. Our empirical analysis provides new insights into the mechanisms that create the gaps in access and exposure to the local media that we documented above. In particular, we find that the racial and ethnic gaps are due to both stronger preference for local news topics as well as more time allocated to local news. Note that the coefficient for black is positive and significant in all cases. The same is true for the coefficients for Hispanics.

In contrast, the informational gap by skill type is more complicated. Our estimates suggest that high-skill individuals devote more time to local news than low-skill individuals. However, they value the local news much less than low-skill individuals. Similarly, the age gap in local news exposure is primarily due to the fact that older individuals allocate more time to local news than younger individuals. Younger individuals have stronger preferences for local news. Our structural model, therefore, provides a deeper understanding of the mechanisms that drive the gaps observed in the data.

Tables 9 summarize our estimates of the parameters that affect the price elasticity of demand. Holding income, education, and age fixed, low-skill and minority individuals tend to be more price sensitive than high-skill and white households. Similarly, younger households tend to be more price elastic than older households. There are no significant differences among city clusters. Overall, these estimates are plausible and consistent with the other estimates reported in the literature.

In summary, we find that our model can rationalize the differences in observed behavior by group that we documented in Section 2 of the paper. In addition, it provides additional insights into the productivity differences of the local news providers in the different local media markets or city. Appendix D reports goodness of fit statistics for the bundle choice probabilities, the time allocation by each provider, and the importance of the four different topics. Overall, we find that the fit of our preferred model is excellent. As a consequence, we now turn to counterfactual, prospective

Parameter	Description	Variable	Estimates	Std. Err.
$\beta_1$	Total Usage (H)	$\log(\text{Income})$	-0.036	(0.692)
$\beta_2$	Total Usage (H)	Age 18-29	-0.749	(0.022)
$\beta_3$	Total Usage (H)	Age 30-49	-0.201	(0.124)
$\beta_4$	Total Usage (H)	Age 50-64	-0.106	(0.072)
$\beta_5$	Total Usage (H)	Male	-0.178	(0.011)
$\beta_6$	Total Usage (H)	Black	0.151	(0.006)
$\beta_7$	Total Usage (H)	Hispanic	0.167	(0.027)
$\beta_8$	Total Usage (H)	College Grad	0.200	(0.030)
$\beta_9$	Total Usage (H)	Community Attachment	0.366	(0.167)
$\beta_{10}$	Total Usage (H)	Local Rating	-0.052	(0.226)
$\gamma_1$	Politics	Age 18-29	0.224	(0.020)
$\gamma_1$	Politics	Age 30-49	0.049	(0.104)
$\gamma_1$	Politics	Age 50-64	0.028	(0.057)
$\gamma_1$	Politics	Black	0.126	(0.017)
$\gamma_1$	Politics	Hispanic	0.070	(0.041)
$\gamma_1$	Politics	College Grad	-0.119	(0.047)
$\gamma_2$	Econ, Educ	Age 18-29	0.842	(0.009)
$\gamma_2$	Econ, Educ	Age 30-49	0.743	(0.050)
$\gamma_2$	Econ, Educ	Age 50-64	0.442	(0.053)
$\gamma_2$	Econ, Educ	Black	0.349	(0.015)
$\gamma_2$	Econ, Educ	Hispanic	0.299	(0.032)
$\gamma_2$	Econ, Educ	College Grad	-0.141	(0.078)
$\gamma_3$	Entertainment	Age 18-29	0.773	(0.002)
$\gamma_3$	Entertainment	Age 30-49	0.412	(0.043)
$\gamma_3$	Entertainment	Age 50-64	0.194	(0.040)
$\gamma_3$	Entertainment	Male	0.102	(0.025)
$\gamma_3$	Entertainment	Black	0.108	(0.016)
$\gamma_3$	Entertainment	Hispanic	0.035	(0.011)
$\gamma_3$	Entertainment	College Grad	0.112	(0.039)
$\gamma_3$	Entertainment	Community Attachment	0.163	(0.314)
$\gamma_4$	Weather, Traffic	Age 30-49	0.200	(0.066)
$\gamma_4$	Weather, Traffic	Age 50-64	0.146	(0.088)
$\gamma_4$	Weather, Traffic	Male	-0.025	(0.051)
$\gamma_4$	Weather, Traffic	Black	0.046	(0.022)
$\gamma_4$	Weather, Traffic	Hispanic	-0.028	(0.017)
$\gamma_4$	Weather, Traffic	College Grad	-0.067	(0.010)

Table 8: Time Allocation and Preferences

	Avg. Price	Std.		Avg. Price	Std.
	Elasticity	Error		Elasticity	Error
Overall	-1.22	(0.17)			
By Age			By Education		
Age 18-29	-3.44	(0.49)	Less than HS	-1.63	(0.21)
Age 30-49	-2.43	(0.38)	HS Grad	-1.13	(0.13)
Age $50-64$	-0.61	(0.03)	Some CL	-1.10	(0.13)
Age $65$	-0.00	(0.00)	CL Grad	-1.28	(0.19)
By Race			By City Cluster		
White	-1.04	(0.14)	Cluster1	-1.24	(0.17)
Black	-1.42	(0.17)	Cluster2	-1.16	(0.16)
Hispanic	-1.95	(0.31)	Cluster3	-1.27	(0.18)

Table 9: Price Elasticity

policy analysis. Here we focus on measuring the welfare costs associated with losing traditional news providers and study alternative policies that can compensate for these losses.

#### 6 Prospective Policy Analysis

To study the impact of the decline of traditional news providers we first study printed newspapers and then turn our attention to local television.

In 2018, half of the 3,143 counties in the U.S. had only one newspaper, attempting to cover its various communities. Almost 200 counties in the U.S. had no newspaper at all (Abernathy, 2018). Since the decline of traditional local news media is likely to continue in the future, it is useful to ask what is at stake if a city or media market loses its last local printed newspaper. Using our model, we can estimate the average welfare costs associated with this loss and study what parts of society are most likely to bear the largest burden of this loss. Figure 2 summarizes our estimates of the average willingness to pay for a variety of different groups.

Figure 2 suggests that the loss of the local newspaper reduces welfare on average by \$923 which is well above the annual subscription costs in most markets. Figure 2



Figure 2: Willingness to Pay for Keeping Local Printed Newspapers

also plots the average welfare losses by age, race, ethnicity, and city cluster. We find that the welfare losses tend to be larger for disadvantaged and older individuals. The loss of the local newspaper also results in significant reductions in news exposure even though individuals substitute to alternative providers and increase the time allocation to these alternatives. The average exposure to local political news drops by 7 percent while news exposure to the local economy drops by 3 percentage points.

Similar concerns arise with respect to local news coverage by television stations. Despite the fact that local TV stations have not been as vulnerable as printed newspapers, they face increased competition from a variety of streaming services. This competition from digital platforms has the potential to undermine the viability of traditional local news coverage by television. Hence, we also study the loss of the local television. From an equity perspective this is important since local television is the preferred provider for most disadvantaged households, i.e. the households that rely on local news the most as we have seen above. Figure 3 summarizes our estimates of the average willingness to pay for a variety of different groups. We find that the loss of the local TV station reduces welfare on average by \$1064, which is significantly larger than the welfare loss of losing the printed newspapers. Again, welfare losses tend to be larger for black and Hispanic individuals. Losing the local TV stations results in an 11% loss in local political news and a 3% loss in news about local economics and education.



Figure 3: Willingness to Pay for Keeping the Local TV Stations

Given these potentially large welfare losses associated with declines in the availability or quality of traditional news media, we study policies that promise to increase the quality of online and social media. Although online and social media have caught up with traditional news providers, there are some reasons for concern since some of the local news provided by online and via social media is unfiltered and relies on unpaid volunteers or part-time workers (Allcott and Gentzkow (2017), Allcott, Gentzkow, and Yu (2019), Pew Research Center (2019)). To offset the loss of the local newspaper, policies can subsidize online or social media to entice them to raise the quality of local news production. We find that the quality of online media needs to increase by 23.3 percent to offset the loss of the local newspaper. Similarly, the quality of social media needs to increase by 49.8 percent to compensate individuals for the demise of the newspaper. It is even more questionable that social media could fill the shoes of traditional news providers soon. To fully compensate for the loss of local television, we need to improve the online media by 26.2 % and social network by 55.6 %.<sup>14</sup>

Our findings are thus consistent with the perception that it would take a serious upgrade of online and social media to fully substitute for the existing traditional news media. These upgrades may not happen without public subsidies. As a consequence, there is much scope for carefully designed public policy interventions.

# 7 Conclusions

It is commonplace to hear discouraging assessments about polarization within the U.S. society and the seeming impossibility of meaningful communication and cooperation among different groups. An important part of understanding different views across different sub-populations is studying where individuals get information and how they assess the importance and relevance of this information. Using a comprehensive survey of adults in large U.S. media markets which was conducted by PEW in 2018, we have estimated a model that identifies the news sources different groups choose, the time spent on using those sources and individuals' assessments of the importance of different news topics.

We have shown in this paper that disadvantaged individuals have a stronger vested interest in local news coverage, including the most relevant topics such as the local economy, crime, politics, and education. These individuals still heavily rely on quality local news provided by newspapers, radio, and TV while high-skill and white individuals have more rapidly shifted towards the new online and social media. The rise of online and social media and the resulting decline of traditional media have, therefore, not affected all parts of society equally. In particular, the shift from traditional to online media has imposed the largest burden on disadvantaged households.

Our findings are consistent with the literature in urban and labor economics that documents that low-skill and minority individuals are less mobile and more heavily exposed to shocks to the local economy and neighborhood quality. If a city loses the

 $<sup>^{14}</sup>$  If the objective is to fully compensate for the loss in terms of news exposure, we need to improve the online media by 15.3 % and the social media by 33.2%.

local newspaper or local television, average welfare losses exceed subscription prices by significant amounts. It takes significant upgrades of online and social media to offset the loss of the local printed newspaper or local television. Public subsidies and incentives may be necessary to accomplish this task.

Our analysis provides ample scope for future research combing individual choice and time allocation data with survey data that elicits individuals' attitudes towards the media. An important by-product of the structure of the local news media was its concentration: I and my neighbors likely got quite similar information, albeit often with different interpretations. In 1967, Walter Cronkite's evening news broadcasts reached an estimated 28 million viewers per night, when the nation's adult population was 128 million, about 22% of the adult population. In contrast, the adult population of the U.S. is currently 258 million, and the audience for the top-rated evening news broadcast by ABC is about 7.6 million. Incidentally, Walter Cronkite was also considered to be the most trustworthy American, a title that is nowadays bestowed upon the actor Tom Hanks. This observation points to a change in the way in which people nowadays get local news. Five decades ago a large segment of the U.S. got their local news from television, radio, and printed newspapers, and they got largely the same facts regardless of their sources. The commonality of the news people got in the sixties no longer holds. More research is needed on how different individuals interpret the news that they obtain from a common source, and how these experiences shape the attitudes that individuals hold towards the media.

A 2020 poll by The Economist/YouGov asked survey respondents to rate the trustworthiness of several prominent print, broadcast and digital news providers. The survey results thus suggest that there is a substantial divergence of views on how trustworthy the news sources are. Similarly, respondents were also asked how well they thought they could tell "real news" from "fake news." The survey finds that fewer than a quarter of all respondents are very confident about their ability to separate the two. These attitudes towards the media should be taken as endogenous since they depend on the provider choices and the news content that is delivered by the different providers.

In a follow-up poll in 2023, The Economist/YouGov asked respondents to rate

forty-five print, broadcast, and digital news outlets using the same questions on trustworthiness. Each outlet got a "net trust" score equal to the percentage of respondents who answered *very trustworthy* or *trustworthy* minus the percentage who answered *untrustworthy* or *very untrustworthy*. These net ratings differ across groups. Not surprisingly, people who self-identify as Republicans are more likely to view Fox News as trustworthy than Democrats, resulting in different net trust measures for the Republicans and Democrats. More importantly, the survey also suggests individuals with different political affiliations have different assessments of the majority of news sources: each side tends to think the other has the facts wrong. More research is needed to study the interactions between provider choices, time allocations, evaluations of the importance of different news topics, and individuals' assessments of how trustworthy and relevant the news is to the individuals.

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# A Providers and Topics

As shown in Table 10 we aggregate them into the following six categories: local TV; local daily print newspaper; local radio; local news website, app or email; local news provider's social media posts; and other sources.

Table 10. Det 01 1 10vider	Table	10: S	et of F	Providers
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TV	- Local TV news station
Print newspaper	<ul> <li>Local daily newspaper's print version</li> <li>Local government agencies or officials in print</li> <li>Local organizations in print</li> <li>Print community or neighborhood newsletter</li> <li>Other community or specialized newspaper's print version</li> </ul>
Radio	- Local radio station
Online	<ul> <li>Website, app or email of local TV news station</li> <li>Website, app or email of local daily newspaper</li> <li>Website, app or email of other community or specialized newspaper</li> <li>Website, app or email of local radio station</li> <li>Local community or neighborhood digital newsletter</li> <li>Local government agencies or officials' website, app or email</li> <li>Local organizations' website, app or email</li> <li>Local online forums or discussion groups' website, app or email</li> <li>News source that publishes online only' website, app or email</li> </ul>
Social media	<ul> <li>Social media posts of local TV news station</li> <li>Social media posts of local daily newspaper</li> <li>Social media posts of other community or specialized newspaper</li> <li>Social media posts of local radio station</li> <li>Local community's social media posts</li> <li>Local government agencies or officials' social media posts</li> <li>Local organizations' social media posts</li> <li>Local online forums or discussion groups on social media</li> <li>News source that publishes online only's social media posts</li> </ul>

For the structural model, we aggregate the 11 topics covered in the survey in the following four categories:

- 1. "Politics": Local Politics: Crime, Local Government & Politics
- 2. "Economy": Local Economy & Education: Local Jobs & Unemployment, Local Prices, Local Schools

- 3. "Entertainment": Sports, Local Arts and Culture, Restaurants, Local Community
- 4. "Others":Weather and Traffic

#### **B** Clustering Analysis

We cluster the 20 cities into 3 groups based on the Hierarchical Agglomerative Clustering (HAC) method using the city-fixed effects estimated from the 14 reduced-form regressions. We use the following regression models:

- 5 linear probability models with preferred provider choices
- 5 ordered logit models with time use on each provider
- 4 ordered logit models with aggregated topic importance

The detailed procedure for the HAC analysis is as follows:

- 1. Estimate the regression models with city fixed effects and other control variables.
- 2. Predict the response variable based on the estimated city fixed effects from each regression.
- 3. Construct the coordinate matrix based on the predicted response variable.
- 4. Based on the coordinate matrix, compute the Euclidean distance between cities. This distance matrix will be used as a dissimilarity structure in HAC.
- 5. Cluster cities based on the complete linkage method. Here we provide a brief description of HAC with complete linkage:
  - (a) Initially, each city is assigned to its cluster.
  - (b) At each iteration (i.e., moving up the hierarchy), the most "similar" pairs of clusters are merged.

(c) When deciding "similar" clusters, the distance between clusters, say A and B, are computed based on the complete linkage.

$$D_{A,B} = max_{a \in A, b \in B}d(a, b)$$

where d(a, b) is the Euclidean distance between city a and b computed in Step 4.

6. Repeat the procedure until there are 3 clusters remaining.

The results are given in Table 11. Even if we do not match cities based on other characteristics than the city fixed effects in the reduced-form regressions, the clusters show meaningful correlations with some important characteristics of the cities (See Figure 4)). We named each cluster based on the observed characteristics. Cities in Cluster 1 ("Big" cities) are larger in their population sizes, have higher average house-hold income, and have higher proportions of Black individuals. In contrast, cities in cities in Cluster 2 ("Midwest-Southern" cities) have the lowest average household income and education level. Lastly, Cluster 3 ("West Coast" cities) has the highest proportion of population living in the city center, and has relatively smaller Black communities.



Figure 4: Validation of Clustering Analysis

City	Cluster	N of Obs.
Atlanta	1	496
Boston	1	431
Chicago	1	894
NewYork	1	1405
Philadelphia	1	568
Washington	1	612
Dallas	2	499
Detroit	2	431
Houston	2	468
Miami	2	507
Minneapolis	2	523
Phoenix	2	475
StLouis	2	329
Tampa	2	356
LosAngeles	3	972
Portland	3	389
Riverside	3	357
SanDiego	3	329
SanFrancisco	3	433
Seattle	3	353

Table 11: Cities in Each Cluster

# C Identification and Monte Carlo

Finally, we offer some comments on identification. Standard results from the discrete choice literature suggest that we can normalize the utility of the outside option to be equal to zero,  $U(H, \emptyset) = 0$ . The scale of U(H, S) is not identified. Hence, we can set the scale parameter of the Type 1 Extreme Value distribution to be equal to one, i.e.  $\sigma_{\epsilon} = 1$ .

The parameter  $\alpha$  is identified using a standard argument from the discrete choice literature as long as we have sufficient variation in prices (and individual characteristics x). Our Monte Carlo results suggest that we can precisely estimate  $\alpha$ s with a small number of cities in our sample. In our empirical analysis, we use cluster analysis to group the 20 cities in our sample into three groups. Hence, we can exploit variations in prices within and across cities to identify these coefficients.

Since *H* is partially latent, we can normalize the intercept of the index ( $\beta_0 = 0$ ). The time allocation question for individuals that only have access to one provider will then identify  $\beta$  and the thresholds of *h*.

Consider consumers that only have access to the first provider,  $S = \{1\}$ . Then,  $H = h_1$ . Given the normalization that the scale parameter of the measurement error is normalized to be 1, the variation in  $U_1$  will then identify the thresholds,  $\bar{U}_l$ ,  $\bar{U}_m$ , and  $\bar{U}_h$ . Next, consider the answers to the importance of other topics. These answers will identify  $t_{21} - t_{K1}$ . Compare two consumers with the same hours and characteristics, one of them has access to provider 1 ( $S = \{1\}$ ) and the other one to provider s( $S = \{s\}$ ). Differences in the answers to the importance of news topics will then identify  $t_{1s} - t_{Ks}$ . The scale of  $t_{ks}$  is identified from the normalization of the scale of  $U_k^o$  and  $\beta_0 = 0$ .

Finally, this scaling of the news production index has to be preserved by the  $\gamma_k(x)$  function. Hence, we can normalize the intercept of this index function:

$$\gamma_k(x) = \exp(\gamma_{k1}x_1 + \dots + \gamma_{kJ}x_J) \tag{16}$$

i.e. we have set  $\gamma_{k0} = 0$  for all k. The  $\gamma_k$  are identified by observed variation in  $U_k^o$  across x.

In the Monte Carlo exercise, we use a model with one city, 5 providers, and 3 news topics. Prices are calibrated based on observed prices. We pooled prices from all cities in the data to have sufficient variation in prices. We also simulate the demographic and attitude variables based on the empirical distribution observed in our data. For preference heterogeneity ( $\gamma$ s), we use a few different covariates, which are sampled from the empirical distribution of education, attitudes, race, and income in the data. For heterogeneity in overall interests in local news ( $\beta$ s), we use similar covariates (income, college, attitudes, and age). As provided in the data, many of these covariates are binary variables. We estimate the model using maximum likelihood. Bias and standard errors are computed using 100 Monte Carlo replications.

Table 12 reports the bias measured by the difference between the true parameter

Parameter	True Value	Avg. Est	Bias	RMSE
News production:				
$\overline{t_{12}}$	1.000	1.016	0.016	0.087
$t_{13}$	0.300	0.309	0.009	0.066
$t_{14}$	0.900	0.904	0.004	0.080
$t_{15}$	0.800	0.821	0.021	0.134
$t_{21}$	0.400	0.421	0.021	0.101
$t_{22}$	0.600	0.620	0.020	0.149
$t_{23}$	0.500	0.535	0.035	0.158
$t_{24}$	0.900	0.908	0.008	0.082
$t_{25}$	1.000	1.020	0.020	0.128
$t_{31}$	0.500	0.523	0.023	0.149
$t_{32}$	0.550	0.571	0.021	0.118
$t_{33}$	0.400	0.405	0.005	0.068
$t_{34}$	1.300	1.335	0.035	0.300
$t_{35}$	1.200	1.232	0.032	0.191
Preference Heterogeneity:				
$\gamma_{11}$	0.020	0.020	-0.000	0.003
$\gamma_{12}$	0.100	0.111	0.011	0.041
$\gamma_{13}$	0.400	0.406	0.006	0.087
$\gamma_{14}$	0.150	0.145	-0.005	0.025
$\gamma_{15}$	0.300	0.314	0.014	0.092
$\gamma_{21}$	0.010	0.010	0.000	0.002
$\gamma_{22}$	-0.150	-0.141	0.009	0.048
$\gamma_{23}$	0.450	0.461	0.011	0.095
$\gamma_{24}$	-0.100	-0.105	-0.005	0.036
$\gamma_{25}$	-0.200	-0.203	-0.003	0.049
$\gamma_{31}$	-0.010	-0.011	-0.001	0.003
$\gamma_{32}$	0.200	0.225	0.025	0.072
$\gamma_{33}$	0.300	0.306	0.006	0.101
$\gamma_{34}$	0.100	0.098	-0.002	0.044
$\gamma_{35}$	-0.100	-0.106	-0.006	0.050
Utility:				
$\overline{\alpha_0}$	-15.000	-14.971	0.029	2.397
$\alpha_1$	0.010	0.010	0.000	0.005
ho	0.300	0.301	0.001	0.044
<u>Time endowment:</u>				
$\beta_1$	0.000	0.000	0.000	0.000
$\beta_2$	-0.300	-0.375	-0.075	0.198
$\beta_3$	0.400	0.454	0.054	0.233
$\beta_4$	0.200	0.246	0.046	0.132
$\beta_5$	0.150	0.155	0.005	0.033
<u>Nuisance:</u>				
$\overline{h}_l$	0.300	0.301	0.001	0.044
$ar{h}_h$	0.600	0.633	0.033	0.171
$ar{U}_l$	-0.100	-0.096	0.004	0.047
$ar{U}_m$	2.500	2.570	0.070	0.415
$ar{U}_h$	20.000	21.518	1.518	7.269

Table 12: Monte Carlo Results

value and the average of our estimates as well as the root mean squared error. Overall, we find that our estimator works fairly well.

# D Goodness of Fit Analysis

Our model fits overall bundle choice distributions, time allocations across different providers, and news exposures across different topics very well. Furthermore, our estimation results replicate the racial differences observed in bundle choices, time allocations, and news exposures reasonably well. In particular, the model precisely reproduces the higher local news exposures of Black individuals across all local news topics observed in the data.



Figure 5: All Sample



Figure 6: Bundle Choice By Race



Figure 7: Time Allocation By Race



Figure 8: News Exposure By Race