Estimating a Time Allocation and Information Acquisition Model using Revealed and Stated Preference Data^{*}

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Abstract

This paper develops and estimates a new time allocation and news acquisition model using revealed and stated preference data. Stated-preference survey data provide additional information about the underlying preferences for specific news topics and the information acquisition process. Combining these two types of data allows us to separately identify and estimate preferences over news topics and news production functions, which would be harder using time allocation data alone. We find important differences in news consumption patterns across racial, ethnic, and skill groups. In particular, low-skill and minority individuals typically allocate more time to local news than high-skill and white individuals who allocated more time to national and international news. These differences in informational gaps for news are driven by differences in preferences, opportunity costs of time, and access to news providers. We assess the relative importance of each channel. Finally, we provide new estimates of the willingness to pay for improvements in the quality of news.

Keywords: Time allocations, information acquisition, stated and revealed preference methods, survey data, maximum likelihood estimation, inequality in news consumption.

JEL Code: C8, J2, L82

1 Introduction

In empirical economics, researchers have typically preferred revealed preference methods to estimate behavioral models.¹ These methods are based on traditional data sources such as observed choices and objectively measured variables such as prices and individual characteristics. Unquestionably, these methods have been extremely valuable to study a wide range of important research questions. However, when estimating the impact of differences in attitudes, beliefs, or information on behavior, traditional revealed preference approaches face some inherent challenges and limitations. A new literature has, therefore, emerged that uses more diverse data sources. Data on subjective beliefs, attitudes, and stated preferences offer the potential to complement more traditional data and allow the estimation of rich behavioral models that may also rest on weaker identifying assumptions.²

The purpose of this paper is to develop and estimate a new time allocation and information acquisition model combining traditional revealed preference data with state-of-the-art survey data. Surveys are an essential approach for eliciting otherwise invisible factors such as perceptions, knowledge, beliefs, attitudes, and preferences.³ The survey data used in this analysis complement the more traditional time allocation data by eliciting detailed information on how well individuals are informed about various news topics and how important these topics are for their lives. We show that data from these types of survey questions can be interpreted within the context of our time allocation and information acquisition model and can, therefore, be used to estimate key components of the model which would be harder to estimate purely based on time use data.

¹The pioneering papers are by Samuelson (1938, 1948) and Arrow (1959).

²Most notably, Orazio Attanasio argued in his 2020 Presidential Address to the Econometric Society that a more flexible and broader approach to measurement can lead to new insights. For a survey of the literature and some new results see Almas et al. (2024).

³Survey-based research has been widely accepted in other social sciences such as sociology. Bewley (2002) was one of first economists to argue that surveys are a valid empirical tool in economics. More recently, several studies have used large-scale surveys to shed new light on a diverse set of topics such as macroeconomic dynamics dynamics (Andre et al., 2022), social preferences (Almas et al., 2020) people's understanding of policies (Stantcheva, 2021), and eliciting key factors in decision making (Geiecke and Jaravel, 2024). For a review of this growing literature see, for example, Stantcheva (2023).

The starting point of our analysis is a new time allocation and news acquisition model. Each individual has a time endowment that can be allocated to market and non-market time. An important component of non-market time is spent on the acquisition of information from various news sources. The model considers individuals in a media market who have access to several different news providers that produce a variety of different types of news, such as local, national, and international. Local news refers to the coverage of events in a local context and differs from national and international news which are also of interest to individuals in other localities. Local news, therefore, is almost exclusively relevant to members of a local community, and it has little value to outsiders. As such it largely covers topics such as crime and justice, local businesses and labor markets, primary and secondary education and schools, municipal and state politics, regional entertainment and sports, as well as weather and traffic. In contrast, national and international news tends to cover a wide range of content, that is of common interest to individuals in the same country. For each type of news, individuals allocate time among different news providers that are in their choice set. Time allocations are determined by the opportunity costs of time, preferences for news types and specific topics as well as the productivity differences among providers.

This paper develops a new maximum likelihood estimator for the parameters of the time allocation and information acquisition model. Our estimator combines traditional revealed preference data on individual time allocations with detailed survey data. The estimator, therefore, draws on two different types of data. First, we exploit detailed qualitative and quantitative data on time use allocations. Qualitative time use questions have the advantage that they are easier to answer for most survey participants which allow researchers to elicit detailed and reliable information on a variety of time use activities. Quantitive data are necessary to establish the correct scaling of time use patterns but may be harder for survey participants to answer (Stantcheva, 2023). Both qualitative and quantitative time use data are revealed preference data. Second, we use data obtained from stated preference survey questions. These data provide direct information about the underlying preferences for specific news topics, attitudes, and the information acquisition process. For example, if an individual allocates a lot of time to watching local news on television, that can either reflect stronger preferences for the news topics covered by television or a greater productivity of television in delivering local news content than other news outlets. To disentangle these two effects, we can leverage stated preference data to help us distinguish preference parameters from news production function parameters. As such the stated preference survey data help us to estimate the parameters of a rich time use and information acquisition model which would be more difficult to estimate solely based on traditional time use data.

We implement the estimator using data from two comprehensive surveys collected by the Pew Research Center, the Local News Survey and the Media Consumption Survey. The Media Consumption Survey contains traditional quantitative time use data. The Local News Survey complements this data with much richer qualitative time use data as well as rich survey data on preferences, attitudes, and the information acquisition process.

Our empirical analysis provides new and important insights into differences in the exposure to and the valuation of news in the U.S. Our estimates indicate that traditional news providers no longer hold a comparative advantage in news production compared to online providers. We find important gaps in news consumption by race, ethnicity, and skill. In particular, low-skill and minority individuals typically allocate more time to local news than high-skill and white individuals. These differences in time allocations exist for almost all relevant local news topics covered in the survey. They are most pronounced for crime, schools, and jobs. White and high-skill individuals allocate more time to national and international news.

One key advantage of our empirical approach is that it allows us to decompose the observed gaps in time use allocations in differences due to wages, preferences, and access to providers which differ in their news production technologies. We show in the paper that the first two channels matter the most, i.e. differences in access to news providers only explain a small fraction of the observed informational gaps. We thus conclude that differences in wages and preferences are much more important than differences in access to news providers. Minorities (African Americans and Hispanics) have, on average, both lower opportunity costs of time and stronger preferences for local news. Both factors explain approximately half of the differences in time allocations to local news. In contrast, whites have much stronger preferences for national and international news than minorities. Stronger preferences are, however, partially offset by the fact that whites have higher opportunity costs of time than minorities. Similarly, the differences in news consumption by skill or education are also primarily driven by opportunity costs of time and differences in preferences.

Finally, we turn to policy analysis and estimate the willingness to pay for discrete changes in the quality of news production. We consider a ten percent increase in the quality of local, national, and international news. We find the demand for news is fairly elastic to the quality of news provision. The average annual willingness to pay for a 10 percent improvement in quality is \$485, \$566, and \$237 for local, national, and international news, respectively. These estimates of the average willingness to pay mask important heterogeneity within the population. As discussed above, minorities and low-skill individuals have, on average, lower wages than non-minority or highskill individuals. Hence, the opportunity costs of time are lower for these individuals. Lower opportunity costs of time then translate into a lower willingness to pay for improvements in the quality of news. Despite these lower opportunity costs of time, we find that the average annual willingness to pay for the quality improvement in local news for African Americans is \$605 while the average willingness to pay for whites is only \$467. The skill gap operates differently. Our model suggests that the higher opportunity costs associated with time lead to lower local news acquisition among college graduates. However, when we factor in the college graduates' stronger preference for news, we find that their willingness to pay for quality improvements is significantly higher than that of high school graduates. Since it is in the public interest that individuals are well-informed, there is some scope for well-designed public policies that support the provision of quality news coverage.

Our work contributes to several strands of the literature on labor and media economics, and econometrics. First, the methodological approach taken in this paper is closely aligned with recent efforts to integrate multiple data types for identification purposes.⁴ Recently, a growing body of research has leveraged stated preference data

 $^{^{4}}$ Imbens and Lancaster (1994) was one of the first papers that suggested to combine different data sources in estimation, primarily to achieve efficiency gains.

to analyze subjective factors influencing behavior. This literature demonstrates the value of directly eliciting preferences, beliefs, and attitudes through carefully designed survey data. Manski (2004) emphasized their potential in addressing identification challenges. Recent studies have highlighted the utility of stated preference data in understanding heterogeneity in labor market preferences (Wiswall and Zafar, 2018), valuation of non-wage job attributes (Maestas et al., 2018), maternal expectations on children's cognitive skill development (Cunha et al., 2013), and the formation of expectations across demographic groups (Dominitz and Manski, 1997). Our work advances this literature by applying stated preference data to decompose demographic differences in news consumption, revealing how preferences and time constraints interact to shape information acquisition. As in Almas et al. (2024), we combine revealed and stated preference data to disentangle the relative contributions of preferences, technology, and the opportunity costs of time in explaining the observed behaviors. This dual approach offers a robust framework for addressing difficult identification questions. By applying this methodology to news consumption, we also provide novel insights into disparities in access to information and the implications for labor market outcomes.

Second, this paper is related to research in labor economics that has studied time use patterns. The pioneering theoretical frameworks were developed by Becker (1965) and Gronau (1977). Ghez and Becker (1975) and Juster and Stafford (1985) are classic examples of early analysis of time use data in economics. Kooreman and Kapteyn (1987) and Biddle and Hamermesh (1990) developed and estimated structural models incorporating time allocation data. More recently, Aguiar and Hurst (2007) have documented recent changes in time use patterns in the U.S. leading to significant shifts in leisure and labor supply. Fiorini and Keane (2014) study how the allocation of children's time affect cognitive and noncognitive development. Blundell et al. (2016) integrated time use data with income and expenditure information to examine family labor supply and saving behavior, highlighting the role of non-market activities. Rogerson and Wallenius (2019) used time use surveys to study labor supply dynamics among older couples. Bastian and Lochner (2022) study, in detail, the time allocation responses of mothers to state and federal expansions in the earned income tax credit with an emphasis on time spent with children. Note that the American Time Use Surveys, which are the most commonly used data to study time allocations in the U.S., do not specifically ask about time spent acquiring news as its own category. Our paper complements this literature by integrating survey-based stated preference data, enabling a more nuanced analysis of preferences for different types of news acquisition and differences in technologies among news providers.

Time use information has also been widely used in the family economics literature to identify household preferences, production functions, and bargaining protocols. Notable examples include Chiappori et al. (2002) who use time allocation patterns to identify household bargaining parameters, Cherchye et al. (2012) who analyze collective labor supply with detailed time use data, and Lise and Yamada (2019) who study household sharing and commitment. Our paper treats the individual and not the family as the unit of analysis. However, integrating survey-based stated preference data with traditional time use data may also enable a more nuanced analysis of preferences in family economics.

Third, our paper is related to research in labor and urban economics which has documented that minority and low-skill individuals are more heavily exposed to shocks to the local economy than white and high-skill individuals. In particular, they have lower mobility rates, are more strongly exposed to shocks in the local labor market, rely more heavily upon informal networks for job referrals, have fewer options in the local housing markets, and are more likely to be affected by shocks in neighborhood amenities such as crime and public school quality than other individuals.⁵ Since African American and low-skill individuals are more exposed to local shocks, they should pay closer attention to changes in the local environment than white and high-skill individuals. Our paper shows that this hypothesis is correct.

Finally, the interplay between content analysis and the demand for news has been explored in media economics. George and Waldfogel (2006) examine how the New York Times' expansion influenced local newspaper markets and consumer behavior, highlighting the importance of local news consumption patterns. Gentzkow and Shapiro (2010) develop a novel measure of media slant by comparing the language

 $^{^5 \}mathrm{See},$ for example, Altonji and Blank (1999), Shuey and Willson (2008), Hoynes et al. (2012), and Bayer et al. (2016).

of newspapers with that of congressional representatives. Yildirim et al. (2013) analyze newspapers' decision to expand their product lines by adding online editions that incorporate user-generated content. Recent work by Athey et al. (2021) investigates how algorithmic changes affect local news consumption using detailed web traffic data. Chen and Yang (2019) conduct a large-scale field experiment to study demand for news, while Martin et al. (2024) analyze how willingness to pay varies across different types of news content. Using text analysis techniques to study the content of a large number of U.S. newspapers, L'Heude (2022) has documented a shift from local news to national and international news in print newspapers, which is largely driven by cost-cutting measures in response to a shrinking subscription base. Our paper provides some evidence of the differences in the demand for local, national and international news that are systematically linked to racial, ethnic, age, and skill heterogeneity.

The rest of the paper is organized as follows. Section 2 introduces our data sets and discusses the key survey data used in the empirical analysis. Section 3 discusses the survey design and the main survey questions used in the analysis. Section 4 develops our time use and information acquisition model. Section 5 discusses the identification and estimation of the parameters of the model. Section 6 reports our empirical results. Section 7 conducts some welfare analysis and provides new estimates of the willingness to pay for improvements in the quality of news. Section 8 offers some conclusions and discusses future research.

2 Data Sources and Descriptive Statistics

We use two detailed surveys that were collected by the Pew Research Center, which is mainly funded by the Pew Charitable Trusts.⁶ One of the main objectives of the data collection efforts of the Pew Research Center is to inform the public about the issues, attitudes and trends shaping news habits and the media. As a consequence, the Pew Research Center has been a leader in survey design and data collection since

 $^{^6\}mathrm{Both}$ data sets are made available to researchers through data-sharing agreements with the Pew Research Center.

its inception in 1990.

The first data source for our empirical analysis is the Local News Survey (LNS), which was conducted between October 15 and November 8, 2018. It is based on both the Center's American Trends Panel (ATP) and Ipsos's KnowledgePanel. The ATP and KnowledgePanel are national probability-based online panels of U.S. adults. Panelists participate via self-administered web surveys. The sample only includes non-institutionalized individuals aged 18 and over, English- and Spanish-speaking. The survey responses were collected via online, mail, or computer-assisted telephone interviewing. The survey covers 932 core-based statistical areas, and provides a granular view of the news landscape. A total of 34,897 panelists responded out of 62,757 who were sampled, for a response rate of 56%. Of the 34,897 respondents in total, 10,654 came from the ATP and 24,243 came from the KnowledgePanel. Our final sample consists of 27,563 individuals, for which we have complete information about demographics and socioeconomic variables used in our analysis. We use the survey weights to construct a nationally representative sample.

As mentioned above, the LNS is based on two professional samples that are repeatedly used in surveys. Hence, we observe a broad set of socio-economic characteristics that are likely to shift preferences and affect time use and news acquisition decisions. The data characterizing panel participants have been carefully vetted and are generally regarded as accurate. In particular, we observe age, gender, education, race, marital status, party affiliation, and income. In addition, the LNS asks some other questions that provide additional useful information regarding subjective assessment of the quality of the local neighborhood and individuals' attachments to the local community. Table 1 provides the LNS sample means of the main socio-economic variables of interest.

In LNS, the annual income of the respondents is aggregated to 9 income levels, as shown in Table 1. We supplement this with the Current Population Survey (CPS) to get more detailed information on income. Using CPS, we estimate a model predicting log hourly wages using various observable characteristics. Then, using the estimated model, we impute the hourly wages of respondents in LNS. The average predicted

Age		Marital Status	
18-29	0.209	Married	0.483
30-49	0.348	Party Affiliation	
50-64	0.262	Republican	0.263
65+	0.181	Democrat	0.331
Gender		Independent	0.276
Male	0.490	Other	0.130
Female	0.510	Income	
Education		Less than $10,000$	0.097
College Graduate	0.314	10,000 to less than $20,000$	0.100
Some College Education	0.321	20,000 to less than $30,000$	0.115
High School Graduate	0.276	30,000 to less than $40,000$	0.104
Race		40,000 to less than $50,000$	0.102
White	0.644	50,000 to less than $75,000$	0.166
African American	0.116	75,000 to less than $100,000$	0.124
Hispanic	0.159	\$100,000 to less than \$150,000	0.116
Others	0.081	\$150,000 or more	0.076
Local Community Attachment		Local Community Rating	
Very much	0.225	Excellent	0.312
Somewhat	0.485	Good	0.550
Not very	0.228	Only fair	0.118
Not at all	0.061	Poor	0.020
Hourly Wages			
Mean	19.94		
St. Dev.	4.65		

Table 1: Descriptive Statistics of LNS

Source: PEW Research Center Local News Survey.

hourly wage in our sample is 19.9, with a standard deviation of 4.65.⁷

The second data source used in this analysis is the Media Consumption Survey (MCS). This biennial survey includes a nationally representative sample of 3,003 adults in the U.S. In this paper, we focus on the latest MCS survey conducted from May 9 and June 3, 2012.⁸ Table 2 provides the MCS sample means of the main socio-economic variables of interest.

The demographic compositions of the LNS and MCS samples are remarkably similar across most dimensions. The age distributions are nearly identical, with differences of less than one percentage point across all age categories. Similarly, both surveys have almost identical gender balances and racial/ethnic compositions. The most notable difference appears in educational attainment, where the MCS sample includes a higher proportion of respondents with high school education or less (39.4% versus 27.6% in LNS).

The public use file of 2012 MCS contains information on distributions of daily time allocated to news consumption by age group. Table 3 summarizes the results for 2012 and compares the time use data to earlier versions of the sample that were conducted between 2004 and 2010. On average individuals spend between 66 and 72 minutes per day on news consumption. Younger individuals aged between 18-29 spend on average 45 minutes while individuals over 65 spend on average approximately 83 minutes. Table 3 also shows that the average time use patterns have been remarkably stable during the last eight years that the survey was conducted. We use these quantitative time use data to anchor our model estimates and resolve the scaling issues that are

⁷The average hourly wage translates into the annual earnings of 41,400 dollars which is consistent with income data from the LNS. Our data is an urban sample. It tracks the overall composition of the U.S. urban population reasonably well. We have also used Census data to assess the representativeness of our sample.

⁸Both landlines and cell phone numbers were sampled to represent all adults in the U.S. who have access to either a landline or cellular number. The landline numbers were sampled based on active blocks that contained three or more residential directory listings. The cellular sample was drawn through a systematic sampling from dedicated wireless 100-blocks and shared service 100-blocks with no directory-listed landline numbers. As many as 7 attempts were made to contact every sampled telephone number. There are 53,627 landlines and 31,096 cell phone numbers ever dialed, and after excluding non-residential, computer, children, and other not working numbers, there are 16,076 landlines and 17827 cell numbers. The completed sample consists of 1,801 landlines and 1,202 cellulars with response rates of 11.2% and 6.7%, respectively.

Age		Marital Status	
18-29	0.229	Married	0.513
30-49	0.333	Party Affiliation	
50-64	0.269	Republican	0.249
65+	0.168	Democrat	0.334
Gender		Independent	0.373
Male	0.489	Other	0.045
Female	0.511	Income	
Education		Less than $$10,000$	0.116
College Graduate	0.288	10,000 to less than $20,000$	0.136
Some College Education	0.285	20,000 to less than $30,000$	0.117
High School Graduate	0.305	30,000 to less than $40,000$	0.096
Race		40,000 to less than $50,000$	0.085
White	0.681	50,000 to less than $75,000$	0.154
African American	0.115	75,000 to less than $100,000$	0.126
Hispanic	0.139	\$100,000 to less than \$150,000	0.096
Others	0.066	\$150,000 or more	0.073
Hourly Wages			
Mean	19.94		
Std. Dev.	4.65		

Table 2: Descriptive Statistics of the MCS

Source: PEW Research Center News Consumption Survey.

	2004	2006	2008	2010	2012	Average
Total	72	69	66	70	67	69
Age 18-29	45	49	46	45	45	46
Age 30-39	70	65	63	68	62	66
Age 40-49	73	64	67	74	71	70
Age 50-64	82	76	74	81	76	78
Age $65+$	88	79	84	83	83	83
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Table 3: Average Time Use in Minutes in the MCS

Source: PEW Research Center News Consumption Survey.

encountered when using purely qualitative or categorical time use data.

3 Survey Design

A key problem encountered in using survey data in economic analysis is to design of the survey and its questionnaire. A good survey needs to be designed for a specific set of research questions. The questionnaire needs to be carefully phrased with that research goal in mind. The main objective of the LNS is to learn about differences in exposure and attitudes to news, with a special focus on local news. While survey design can always be subject to criticism, several rules have emerged in the literature that characterize best practices in survey design which help researchers avoid common pitfalls encountered in survey analysis.⁹ It should be emphasized that we did not design or conduct this survey ourselves. Instead, we use an existing survey that was collected by the Pew Research Center. Pew has conducted surveys since its inception in 1990 and is, therefore, highly experienced in this research domain.

It is not surprising that the LNS largely follows best practices in survey design. In particular, the LNS is comprehensive and thorough. It uses simple, clear, and mostly neutral language, avoiding vague questions that can mean different things to different respondents. It primarily relies on closed-ended qualitative questions with a small number of answer options. It avoids direct quantitative questions that may be hard to answer for many individuals in favor of categorical questions with options that have a natural and simple ordinal ranking. The ordinal scales that are used in the survey are typically unipolar. The LNS includes multiple questions on the same issues that allow the researchers to cross-check and validate the answers. Moreover, it uses a variety of simple initial questions to set up more complicated questions, which may lead to more accurate responses. The LNS, therefore, avoids many pitfalls that may be encountered in surveys collected by less experienced researchers.

Overall, the LNS contains a variety of qualitative questions about time allocated to news topics and local news providers. These are traditional data that are useful from a

 $^{^{9}}$ See Stantcheva (2023) for a detailed guide on how to run surveys in economic research.

revealed preference perspective. In addition, the survey also elicits stated preferences that characterize the importance of news topics, the information acquisition process, and attitudes that the individuals have towards the media.¹⁰

The LNS starts by asking some personal questions about the perceived quality of the local community and the attachment of the person to the local community. It then continues to ask whether individuals perceive the media to be influential and whether they think that the media is in touch with their lives. These initial questions are meant to engage the respondents and capture their interests. These are elements of a well-designed survey since it is well-understood that the quality of survey data often depends on the degree of engagement of the individuals that participate in the survey.

Next, the LNS asks respondents *How closely do you follow ...?* and the news types are international news, national news, and local news.¹¹ This a closed-ended question and the answers are recorded as a categorical variable measured on a four-point Likert scale. The four categories are not at all closely, not very closely, somewhat closely, and very closely. Answers are recorded retrospectively for three-week periods in 2018, 2017, and 2016, respectively. While this survey question is designed to elicit differences in time use or exposure to various types of news, it should be pointed out that the question differs from standard time use surveys (such as the Media Consumption Survey). In particular, the LNS does not ask quantitative time use questions. Instead, it uses categorical variables to measure differences in time allocations. There are some advantages and disadvantages of this approach. The main advantage of the approach taken in the LNS is that qualitative questions are easy to understand. Individuals may be more comfortable answering closed-ended questions with a small number of options that have a natural order. Furthermore, individuals may not be able to precisely assess the exact time they allocate for different activities, even if these activities are fairly routine. Forcing individuals to give precise quantitative answers may induce respondents to make errors. An unknown fraction of

 $^{^{10}\}mathrm{The}$ complete survey which has 32 questions is available upon request from the authors and the Pew Research Center.

 $^{^{11}\}mathrm{As}$ a cross-check the survey also contains some questions about news about the local neighborhood and community.

the variation in the answers may, therefore, be due to noise (Stantcheva, 2023). The main drawback of these types of categorical questions is that the researcher loses the natural scale that is inherent in quantitative time use questions. As a consequence, we pursue an estimation strategy that combines both types of time use questions. Direct quantitative time use questions from the CMS have a natural cardinality and are used to establish the scale that is impossible to identify from categorical data. The question from the CMS only elicits the total time allocated to news. Indirect, qualitative time use questions from the LNS are more detailed and allow us to identify time allocations on a more granular level. In particular, we use qualitative time use questions from the LNS to measure time allocations to different types of news as well as local news providers, as discussed in detail below.

Another focus of the LNS is to characterize the set of news providers from which individuals obtain local news. The LNS focuses on the following five provider types: printed newspapers, television, radio, social media (such as Facebook, YouTube, and Snapchat), and online media.¹² After introducing the different providers that are potentially available to the respondents, the survey asks some qualitative questions about how intensively each provider is used. In particular, the LNS asks the following question: How often do you get local news and information from ...? and the provider types which are provided in randomized order. The survey captures the responses as categorical variables that are measured on a four-point Likert scale. The four categories have a natural ordering and are often, sometimes, hardly ever, never. Again the question lacks the cardinality of quantitative time use questions, but is easier to answer for the individuals who participate in the survey, as we discussed in detail above.

The LNS also elicits stated preferences on the importance of a large number of local news topics and how difficult it is for individuals to stay informed about these topics. The LNS covers eleven distinct local news topics such as local politics, crime, education, the local economy, jobs, entertainment, cultural events, sports, entertainment, weather, and traffic. In our model estimation, we focus on the following question: *How important is it for you to know about each of the following local news topics?*

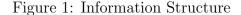
¹²See Appendix B for more details.

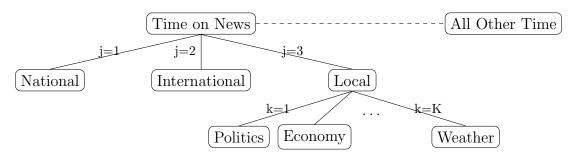
Responses to these questions are ordered as follows: neither important nor interesting, interesting, but not important, important to know about, but I don't need to keep up with it daily, important for my daily life. Similarly, the survey asks: How easy it is for you to stay informed about these topics? Responses to these questions are very hard, somewhat hard, somewhat easy, and very easy. Not surprisingly the answers to these two questions are strongly positively correlated. While the first question can be interpreted as a stated preference question, the second question is slightly different and focuses on the difficulty of obtaining information that may be relevant to their lives. Note that these types of questions provide insights into individuals' preferences and information sets that are almost impossible to obtain from traditional data sources that are used in revealed preference analysis.¹³

Finally, the survey focuses on engagement with and attitudes towards the media and the role of journalists. Here the LNS covers a variety of questions regarding *access, fairness, transparency, inclusiveness, accuracy, thoroughness, and influence of the local media.* While these questions are potentially interesting and highlight the usefulness of survey data, they are not as informative about the model we estimate below as the questions we discussed in detail above.

In summary, we have seen that the LNS survey contains a variety of questions that complement traditional, quantitative time use surveys such as the MCS. Two types of questions are potentially useful for economic modeling and estimation. First, there are categorical time use questions that elicit similar information than traditional cardinal time use diaries. Second, there is a variety of other questions about attitudes, stated preferences, and the difficulty of obtaining relevant information that is well outside of traditional data sets. Below we discuss how to integrate both types of data sets into our strategy to estimate a rich time use and information acquisition model under fairly weak identifying assumptions.

¹³Appendix A provides a reduced-form analysis of the key outcome variables.





4 A Time Allocation and Information Acquisition Model

We consider a model in which the information structure can be partitioned into a two-dimensional nesting structure. The first layer of the structure consists of the different types of news. In our application, there are three types: local, national, and international news. The second layer of the news structure then consists of several distinct topics for each news type. For example, local news can be divided into news on the local economy, crime, and education. Let J denote the number of news topics and K_j the number of news topics for each type. The information structure is illustrated in Figure 1.

There are a number of different news providers which produce content. Individuals allocate their time among these providers. Let S denote the set of news providers. In our empirical application, there are five types of providers: radio, television, printed newspaper, online media, and social media. Let |S| be the maximum number of providers available that could be in a consumer's choice set.¹⁴ We indicate by $S \subset S$ the set of news providers that are available to an individual. Let |S| denote the number of providers in bundle S. For example, an individual may have access to radio, television, social media, and online media, but does not subscribe to a printed newspaper, hence $S = \{radio, television, online media, social media\}$ and |S| = 4. We take these bundle choices as given and study the time allocation among the

¹⁴In our application $|\mathcal{S}| = 5$.

providers for each topic.¹⁵

We solve the optimal time allocation and information acquisition problem sequentially. First, we characterize preferences over news topics and derive the optimal time allocations among providers for an arbitrary time allocation among news types. Second, we characterize the optimal time allocation among news types and derive the optimal time allocated to news acquisition.

Consider an individual with a predetermined time budget H_j that has been allocated to news type j. Let h_{js} denote the time that the individual spends on service provider s. Hence, $h_j = \{h_{js}\}_{s \in S}$ denotes the full time allocation vector for news type j. The time allocation choices of an individual must satisfy the following constraints:

$$\sum_{s \in S} h_{js} \leq H_{j}$$

$$h_{js} \geq 0 \text{ if } s \in S$$

$$h_{js} = 0 \text{ if } s \notin S$$
(1)

A time allocation vector translates into a vector of news or information acquisition. The total news production for topic k is denoted by $t_{jk}(S, h_j)$ and depends on the bundle choice and the time allocation vector. We assume that:

$$t_{jk}(S,h_j) = \sum_{s \in S} t_{jks} f_j(h_{js})$$
(2)

where $f_j(\cdot)$ is strictly concave, differentiable, and strictly monotonically increasing in h_{js} . Moreover $f_j(0) = 0$. Note that the parameters t_{jks} capture the relative advantages of news providers in certain topics.¹⁶ News production is additively separable across providers. The concavity in the news production generates an interior solution

¹⁵We discuss in the conclusions how to extend our model to account for endogenous bundle choices. ¹⁶This apprication also improve the permetricing accountion that $t_{-}(-\phi) = 0$

¹⁶This specification also imposes the normalizing assumption that $t_{jk}(\cdot, \emptyset) = 0$.

for the time allocation problem.¹⁷ For our empirical model, we assume that

$$f_j(h_{js}) = \frac{1}{1-\rho} h_{js}^{1-\rho}$$
 (3)

Let x denote an observed vector of individual characteristics that shift preferences. Let $U_j(S, x, h_j)$ denote the utility of news type j associated with a bundle S and time allocation vector h_j for an individual with characteristics x. We assume that the total utility of news type j is additively separable among news topics:

$$U_{j}(S, x, h_{j}) = \sum_{k=1}^{K_{j}} U_{jk}(S, x, h_{j})$$

=
$$\sum_{k=1}^{K_{j}} \gamma_{jk}(x) \sum_{s \in S} t_{jks} f_{j}(h_{js})$$
(4)

where $\gamma_{jk}(x)$ captures heterogeneity in preferences for topic k or the intensity with which individuals consume topic k. For example, some individuals pay more attention to sports while others are more interested in politics. In the empirical model, we assume that $\gamma_{jk}(x) = \exp(x'\gamma_{jk})$.

Given a pre-determined time budget H_j , individuals optimally allocate the time among the providers in their choice sets. Hence, individuals maximize utility in equation (4) subject to the time constraints in equations (1). The Lagrangian for this optimization problem can be written as:

$$\max \sum_{k=1}^{K_j} \gamma_{jk}(x) \sum_{s \in S} t_{jks} f_j(h_{js}) + \mu_j \left(H_j - \sum_{s \in S} h_{js} \right)$$
(5)

where μ_j is the Lagrange multiplier for news type j. For $s \in S$, the first-order

¹⁷More generally the concavity of the news production function also tends to create demand for diversity among providers. Kennedy and Andrea Prat (2020) document the news consumption patterns of individuals using data from the Reuters Institute for the Study of Journalism. They also show that people tend to rely on several platforms to get informed about news.

conditions can be written as follows:

$$f'_{j}(h_{js}) \sum_{k=1}^{K} \gamma_{jk}(x) t_{jks} - \mu_{j} = 0$$
(6)

while $s \notin S$ we have $h_{js} = 0$, Solving equation (6) for h_s we obtain for each $s \in S$:

$$h_{js} = f_{j}^{\prime-1} \left(\frac{\mu_{j}}{\sum_{k=1}^{K_{j}} \gamma_{jk}(x) t_{jks}} \right)$$
(7)

We can obtain closed-form solutions for h_{js} for a class of production functions that satisfy strict monotonicity and differentiability conditions. Consider, for example, the specification of the news production function we use in the empirical analysis in equation (3). Equation (7) then implies that:

$$h_{js} = \left(\frac{\sum_{k=1}^{K_j} \gamma_{jk}(x) t_{jks}}{\mu_j}\right)^{\frac{1}{\rho}}$$
(8)

Note that equations (1) and (8) imply that:

$$H_j = \sum_{s \in S} h_{js} = \sum_{s \in S} \left(\frac{\sum_{k=1}^{K_j} \gamma_{jk}(x) t_{jks}}{\mu_j} \right)^{\frac{1}{\rho}}$$
(9)

and hence we get the following solution for the optimal time allocation among providers for topic j:

$$h_{js}(S, x, H_j) = \frac{\left(\sum_k \gamma_{jk}(x) \ t_{jks}\right)^{\frac{1}{\rho}}}{\sum_{s' \in S} \left(\sum_k \gamma_{jk}(x) \ t_{jks'}\right)^{\frac{1}{\rho}}} H_j$$
(10)

Note that the time allocation is linear in H_j and the weights associated with news provider s dependent on the efficiency of news production t_{jks} as we as the individual preferences for news topics $\gamma_{jk}(x)$. For example, if the television is good at covering local politics, and the individual cares about local politics, the individual allocates a higher fraction of her time to television. The maximum utility for news type j and topic k attainable from bundle S and time endowment H_j , denoted by $U_{jk}(S, x, H_j)$, is given by:

$$U_{jk}(S, x, H_j) = \gamma_{jk}(x) \sum_{s \in S} t_{jks} f_j(h_{js}(S, x, H_j))$$
(11)

In our empirical specification, we obtain the following closed-form solution:

$$U_{jk}(S, x, H_j) = \gamma_{jk}(x) \sum_{s \in S} \frac{1}{1 - \rho} t_{jks} \left(\frac{\left(\sum_k \gamma_{jk}(x) t_{jks}\right)^{\frac{1}{\rho}}}{\sum_{s' \in S} \left(\sum_k \gamma_{jk}(x) t_{jks'}\right)^{\frac{1}{\rho}}} H_j \right)^{1 - \rho} (12)$$

Summing over all news topics implies that the maximum utility that can be attained from a predetermined time budget H_j is

$$U_{j}(S, x, H_{j}) = \sum_{k=1}^{K_{j}} U_{jk}(H_{j}, S, x)$$

$$= u_{j}(S, x) \frac{1}{1-\rho} H_{j}^{1-\rho}$$
(13)

where

$$u_{j}(S,x) = \sum_{k=1}^{K_{j}} \gamma_{jk}(x) \sum_{s \in S} t_{jks} \left(\frac{\left(\sum_{k} \gamma_{jk}(x) t_{jks}\right)^{\frac{1}{\rho}}}{\sum_{s' \in S} \left(\sum_{k} \gamma_{jk}(x) t_{jks'}\right)^{\frac{1}{\rho}}} \right)^{1-\rho}$$
(14)

These equations then completely characterize the optimal allocation of time among providers for each news type for an arbitrary vector of time budgets. Note that the utility of news type j is concave in H_j which helps to obtain an interior solution to the full time allocation problem discussed below.

Next, we discuss how to allocate time among the different news types in the first layer of the information structure. Let H denote the total time endowment devoted to news consumption. Recall that $(H_1, ..., H_J)$ describes the time allocation vector for the J news types. This vector needs to satisfy the following time budget constraint:

$$H = \sum_{j=1}^{J} H_j \tag{15}$$

Assuming separability among topics, the total utility from the time allocation vector $(H_1, ..., H_J)$ is then given by:

$$U(S, x, H) = \sum_{j=1}^{J} U_j(S, x, H_j)$$
(16)

In our parametric model, $U_j(S, x, H_j)$ is given by equation (13). We can derive the optimal budgets allocated across news types j by solving the following decision problem:

$$\max_{H_1,\dots,H_J} \sum_{j=1}^J U_j(S,x,H_j) + \mu \left(H - \sum_{j=1}^J H_j\right)$$
(17)

The first-order conditions for this decision problem are given by:

$$\frac{\partial U_j(H_j, S, x)}{\partial H_j} - \mu = 0 \tag{18}$$

In our parametric model, the first-order condition can be written as

$$u_j(S,x) H_j^{-\rho} - \mu = 0$$
 (19)

Hence, we have

$$H_j = u_j(S, x)^{1/\rho} \mu^{-1/\rho}$$
(20)

Summing over all news types, we have:

$$H = \sum_{j} \left(\frac{\mu}{u_{j}(S,x)}\right)^{-1/\rho} = \left(\sum_{j} u_{j}(S,x)^{1/\rho}\right) \mu^{-1/\rho}$$
(21)

Hence

$$H_j(S, x, H) = \frac{u_j(S, x)^{1/\rho}}{\sum_i u_i(S, x)^{1/\rho}} H$$
(22)

 $H_j(S, x, H)$ is thus linear in H and increasing $u_j(S, x)$ holding the other utilities constant. Note that the optimal decision rules $H_j(S, x, H)$ depend on the full set of preferences over the two dimensional nesting structure and the effectiveness of the news providers for each topic.

To derive the optimal time allocated to news consumption, we assume that each individual has a total time endowment which can be normalized to be equal to one. Time can be allocated between market time L (labor supply) and non-market time H (news consumption). Market time is compensated at a constant wage rate of w. Preferences are defined over news consumption and a numeraire good. Let's assume that the utility function is quasi-linear in the numeraire good. Then the decision problem that characterizes the optimal allocation of time is:

$$\max_{H} \ \beta \ U(S, x, H) \ + \ w \ (1 - H)$$
(23)

The first-order condition of this problem is given by:

$$\beta \frac{\partial U(S, x, H)}{\partial H} = w \tag{24}$$

which can be solved for the optimal decision rule, H(S, x, w). In our parametric model, we have

$$U(S, x, H) = \sum_{j=1}^{J} u_j(S, x) \frac{1}{1-\rho} \left(\frac{u_j(S, x)^{1/\rho}}{\sum_i u_i(S, x)^{1/\rho}} H \right)^{1-\rho}$$

= $\left(\sum_{j=1}^{J} u_j(S, x) \left(\frac{u_j(S, x)^{1/\rho}}{\sum_i u_i(S, x)^{1/\rho}} \right)^{1-\rho} \right) \frac{1}{1-\rho} H^{1-\rho}$
= $u(S, x) \frac{1}{1-\rho} H^{1-\rho}$ (25)

The first-order condition can, therefore, be written as

$$\beta u(S,x) H^{-\rho} = w \tag{26}$$

which implies that

$$H(S, x, w) = \left(\beta \frac{u(S, x)}{w}\right)^{1/\rho}$$
(27)

Hence H is increasing in u(S, x) and decreasing in the wage w, i.e. the wage measures the opportunity cost for time spent on non-market time such as news or information acquisition.

Substituting (27) into equation (22), gives us the optimal time allocation to news topic j one as a function of the wage w:

$$H_j(S, x, w) = \frac{u_j(S, x)^{1/\rho}}{\sum_i u_i(S, x)^{1/\rho}} \left(\beta \frac{u(S, x)}{w}\right)^{1/\rho}$$
(28)

In summary, we have characterized the optimal time allocations for news for heterogeneous individuals. Differences in news consumption are driven by heterogeneity in wages (w), preferences $(\gamma_{jk}(x))$, and access to news providers (S). One of the key empirical objectives of this paper is to understand the relative importance of these channels. To accomplish this task, we need to identify and estimate the parameters of the model given the observed data structure.

5 Estimation

There are three challenges encountered in estimating our time use and information acquisition model. The first challenge is to model the categorical time use data from the LNS. The second challenge is to incorporate the stated preference data from the LNS into the estimation procedure. The final challenge is converting the categorical time use into quantitative time use information measured in daily minutes. We can accomplish the first two tasks within a Maximum Likelihood framework. Finally, we need to add moment restrictions that are based on the quantitative time use data from the MCS. To impose the moment conditions, we add a penalty function to the likelihood function. Below we discuss the challenges in detail and derive the estimator for the parameters of the model.

5.1 Modeling the Categorical Time Use Data

Consider the problem of modeling the qualitative time use data that characterize time allocated to different news types. Let us define the continuous latent variables H_j^* as:

$$\ln H_i^* = \ln H_j(S, x, w|\theta) + \epsilon_j \quad j = l, n, i$$
⁽²⁹⁾

where $\ln H_j(S, x, w|\theta)$ is given by equation (28). The error term ϵ_j can be interpreted as ex-post shocks to the time allocations realized after the decision problem has been solved. Alternatively, the error may reflect differences in how survey participants interpret and answer the survey questions. We assume that these errors follow a logistic distribution with common scale parameter $\sigma_j(\epsilon)$. Since the responses in the data are measured as categorical variables, it is well known that the scale and the location parameter of the error term ϵ_j are not identified from the conditional choice probabilities. To resolve these scaling problems, we add moments based on quantitative time use data as discussed below to resolve this identification problem.

Define the observed random variables H_j^o such that they reflect the answers to the survey question on how closely the individuals follow each news type. There are four categorical answers:

- 1. Not at all closely: $H_i^o = 0$ if s if $H_i^* \leq \overline{H}_l$
- 2. Not very closely: $H_j^o = 1$ if $\bar{H}_l < H_j^* \le \bar{H}_m$,
- 3. Somewhat closely: $H_j^o = 2$ if $\bar{H}_m < H_j^* \le \bar{H}_h$
- 4. Very closely: $H_j^o = 3$ if $\overline{H}_h < H_j^*$.

Note the thresholds values $(\bar{H}_l, \bar{H}_m, \bar{H}_h)$ do not depend on j. This restriction guarantees that the three indices are comparable and on the same scale. Integrating out the error terms, we obtain the standard ordered logit probabilities.

Similarly, consider the time allocation problem among news providers. Note that we only observe these variables for time allocated to local news in our survey, and not for national or international news. Define a latent variables h_{ls}^* as the total local news time allocated to provider s:

$$\ln h_{ls}^{*} = \ln h_{ls}(S, x, w|\theta) + \nu_{ls} \quad s = 1, .., |S|$$
(30)

where $h_{ls}(S, x, w, |\theta)$ is obtained by substituting equation (28) into equation (10). Again, the error ν_{ls} captures ex-post shock to the time allocation problem and idiosyncratic differences in responses to survey questions. As before, we assume that ν_{ls} follows a logistic distribution with a location parameter of 0 and a scale parameter of $\sigma_{ls}^2(\nu)$.¹⁸

Recall that the survey asks the question: "How often do you get local news and information from each of the following types of sources?" The answer is a categorical variable, denoted by h_s^o , that takes four values. To map this variable into our model, we assume that

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

Again, the thresholds do not depend on *s*. This restriction makes sure that the indices are comparable and on the same scale. Integrating out the error terms, we obtain the conditional choice probabilities. Note that these categorical variables are particularly informative about the productivity of each provider.

 $^{^{18} \}rm We$ use log-log specifications to make sure that the time allocations are always positive regardless of the value of shocks.

5.2 Modeling the Stated-Preference Data

Next, we discuss how to integrate the stated preference data into the estimation strategy. Recall that our survey also elicits data on the valuations of the different news topics. To match the model to the data, define another latent variable

$$\ln U_{lk}^* = \ln U_{lk}(S, x, w) + \eta_{lk} \quad k = 1, .., K_l \tag{31}$$

where $U_{lk}(S, x, w)$ is obtained by substituting equation (28) into equation (12). We assume that the error term η_{lk} follows a logistic distribution with location parameter of 0 and the scale parameter of $\sigma_{lk}^2(\eta)$. Recall that the survey asks "How important is it for you to know about each of the following topics?" The answer is a categorical variable, denoted by U_{lk}^o , that also takes four values. To map this variable into our model, we assume that

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

Given these assumptions, we can compute the conditional choice probability for each response. These survey questions provide direct information about preferences for individual news topics. The observed variation in these variables are particularly useful to identify the preferences for each news topic. They also help to identify the productivity parameters that are associated with each topic.

5.3 The Likelihood Function

We have a random sample of size N. We assume that the errors are independently distributed across individual n. The likelihood function of observing the three types

of categorical variables can be written as

$$L^{N}(\theta) = \prod_{n=1}^{N} \prod_{j} \prod_{k=1}^{4} P_{\theta}(H_{nj}^{o} = k \mid S_{n}, x_{n}, w_{n})^{1\{k \text{ observed}\}}$$

$$\times \prod_{n=1}^{N} \prod_{s \in S_{n}} \prod_{h=1}^{3} P_{\theta}(h_{nls}^{o} = h \mid S_{n}, x_{n}, w_{n})^{\mathbb{I}(h \text{ is observed}, s \text{ in } S_{n})}$$

$$\times \prod_{n=1}^{N} \prod_{k=1}^{K} \prod_{U=1}^{4} P_{\theta}(U_{nlk}^{o} = U \mid S_{n}, x_{n}, w_{n})^{\mathbb{I}(U \text{ is observed})}$$

$$(32)$$

The first term captures the likelihood of the time allocated to the three news types. The second term captures the time for local news allocated to each provider in the choice set. The third term reflects the utility of the local news topics.

5.4 Adding Moment Restrictions based on Quantitative Time Use Data

To resolve the scaling issues encountered in discrete choice estimation and to anchor the time use model, we add moments based on the quantitative survey data from the MCS to the objective function. Recall that the MCS provides the conditional means of the total time allocated to news conditional on age as shown in Table 3. The optimal time use $H(S, x, w, |\theta)$ is given by equation (27). As a consequence, we can form additional moments of the form:

$$\frac{1}{N} \sum_{n=1}^{N} [H_n - H(w_n, x_n, S_n | \theta)]$$
(33)

for different age groups. Time use is measured in minutes per day in the MCS. This determines the scale of our model and, therefore, identifies the scale parameters of the error terms that are not identified based on categorical variables alone.

We use these moments to define a penalty function. Adding the penalty function

to the likelihood function, we obtain the following objective function:

$$L_N^P(\theta_2) = L^N(\theta) + \lambda \left(\frac{1}{N} \sum_{n=1}^N [H_n - \omega \ H(w_n, x_n, S_n | \theta)] \right)$$
(34)

where λ is a bandwidth parameter. Our estimator of the parameters of the model then maximizes the penalized likelihood function. We have assumed that errors in the time use model are independent of the errors in the attitude models. We can, in principle, extend the estimation procedure and allow for correlations in errors between the three different components of the model.¹⁹

Note that this estimator builds on Imbens and Lancaster (1994), who proposed to combine micro and aggregate data in a constrained MLE framework. While they are primarily concerned with increasing the efficiency of the estimator we need to combine the different data to resolve some scaling issues encountered in discrete choice estimation as discussed in detail in the paper. Moreover, the moments that we add are nonlinear in the parameters which makes implementing a constrained MLE estimator difficult.²⁰

6 Empirical Results

We have estimated several specifications of our model.²¹ Our preferred model is relatively parsimonious, it has nine production parameters, 48 parameters that capture heterogeneity in preferences, the concavity parameter in the news production function (ρ), the parameter that captures the opportunity costs of time (β), and a variety of nuisance parameters that capture variances of error terms and thresholds for the ordered discrete choice models. Overall, we find that our model fits the observed data

 $^{^{19}\}mathrm{A}$ separate appendix is available from the authors which provides additional discussions regarding identification and presents some results from a Monte Carlo Study.

²⁰Instead of using a penalized likelihood estimator we could use a GMM estimator which stacks the moments associated with the score of the likelihood function and the moments obtained from the MCS.

 $^{^{21}}$ As discussed in detail in Appendix B, we aggregate the eleven local news into four topics to reduce the dimensionality of the model.

rather well.²² Table 4 reports the parameter estimates and estimated standard errors for the parameters that characterize heterogeneity in preferences for news topics.²³

		Local			National	International
Variable	Politics	Economics	Entertain	Weather		
		Education		Traffic		
log(Income)	0.03	-0.16	0.05	0.08	0.09	0.09
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age 25-34	-0.54	0.16	-0.05	-0.46	-1.00	-1.01
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)
Age 35-54	-0.33	0.40	-0.03	-0.23	-0.56	-0.67
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
Age 55-65	-0.15	0.18	-0.11	-0.09	-0.25	-0.32
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
Male	0.05	-0.12	-0.02	0.02	0.44	0.52
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
African American	0.13	0.33	0.00	0.03	-0.10	-0.13
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
Hispanic	0.17	0.29	0.01	0.07	0.10	0.22
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
College Grad	0.13	0.04	0.17	0.26	0.53	0.52
-	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)

 Table 4: Preference Parameters

Estimated standard errors in parentheses.

We have heterogeneity in preferences for four local news topics as well as national and international news. We find much heterogeneity in preferences for news topics by race, ethnicity, age, gender, skill or education. Not surprisingly, we find that preferences for most news topics, with the exceptions of Economics and Education, tend to increase with income and age. Males also have stronger preferences for national and international news than females. In addition, there is important heterogeneity associated with skills or education. High-skill individuals (college graduates) have stronger preferences for all types of news than low-skill individuals. These differences are most pronounced for national and international news.

²²Appendix C provides a more detailed discussion of the goodness of fit.

²³Our estimate of β is 0.37 with an estimated standard error of 0.01. The parameter estimates and estimated standard errors of the nuisance parameters are available upon request from the authors.

An important finding is that minority individuals typically have stronger preferences for local news than white individuals. Interestingly, these differences in preferences exist for almost all relevant local news topics covered in the survey. They are most pronounced for crime, schools, and jobs. In contrast, white individuals have stronger preferences for national and international news than African Americans. Astonishingly, Hispanics have stronger preferences for national and international news than whites. These findings are consistent with recent research in labor and urban economics which has documented that minority individuals are more heavily exposed to shocks to the local economy than white individuals. In particular, they have lower mobility rates, are more strongly exposed to shocks in the local labor market, rely more heavily upon informal networks for job referrals, have fewer options in the local housing markets, and are more likely to be affected by shocks in neighborhood amenities such as crime and public school quality than other individuals.²⁴ Since African Americans and Hispanics are more exposed to local shocks, they should pay closer attention to changes in the local environment than white individuals.²⁵ Our empirical results show that this conjecture is, in fact, correct.²⁶

Table 5 reports the parameter estimates and estimated standard errors for the parameters of the news production functions.²⁷ We find that television and online are the most productive providers of news, with coefficients of 0.26 and 0.29 respectively. This indicates that one traditional news provider, namely television, has maintained

 $^{^{24}}$ See, for example, Altonji and Blank (1999), Shuey and Willson (2008), Hoynes et al. (2012), and Bayer et al. (2016).

 $^{^{25}}$ Note that these findings are broadly consistent with the reduced form evidence that is discussed in detail in Appendix A.

²⁶Research in labor economics has also emphasized the importance of informal networks in labor markets, especially for younger, low-skill, male workers. Ioannides and Loury (2004) and Bayer et al. (2008) highlight neighborhood referrals and assortative matching in social networks. Bailey et al. (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 information about the availability and suitability of local jobs is propagated via online social networks. We also find that individuals rely on a variety of formal and informal news outlets to stay informed.

²⁷We assume for simplicity in our model that the fixed effects are additively separable, i.e. $t_{jks} = t_{jk} + t_s$. Note that national and international news have one topic while local news is decomposed into four topics in our application. We experimented with more general specifications but found that the additive separable model fits the data almost as well as the more general specifications.

Parameters	Estimates	Std. Errors.			
Newspaper	0.11	(0.01)			
TV	0.26	(0.01)			
Radio	0.10				
Online	0.29	(0.01)			
Social Network	0.11	(0.01)			
Politics	0.72	(0.04)			
Economics	0.58	(0.04)			
Entertainment	0.10				
WeatherTraffic	0.86	(0.04)			
National	1.55	(0.05)			
International	0.87	(0.03)			
Curvature ρ	0.62	(0.01)			
Estimated standard errors in parentheses.					

 Table 5: News Production Function Parameters

its effectiveness in news delivery, while online platforms have achieved comparable or even slightly higher productivity. Radio, printed newspapers, and social media show lower productivity than television or online. The estimated coefficients range between 0.10 and 0.11. Taken together, these findings indicate that the traditional advantages of print media in news production have largely been eroded, with online platforms now exceeding their productivity. Among news types, national news emerges as the most relevant (coefficient of 1.55), followed by international news (0.87). Among local news topics, weather & traffic is the most important (0.86), followed by politics (0.72), with economics & education in third place (0.58) and entertainment last (0.10). Our estimate of the concavity parameter of news production, denoted by ρ , is 0.62 with an estimated standard error of 0.01. This suggests that there is much concavity in the news production function which rationalizes the observation that most individuals obtain news from multiple sources.

The differences in preferences, wages, and access to news providers then translate into different time use patterns. Figures 2 plot the densities of time use allocations by race and ethnicity predicted by our model. We find large and significant differences in time allocated to local news acquisition. On average, African Americans spend about 50 minutes on local news, Hispanics 42 minutes and whites 31 minutes. These differences are large, statistically significant, and economically meaningful. In contrast, we find only small differences in the time allocated to national news. On average African Americans spend about 23 minutes on national news, Hispanics 24 minutes and whites 26 minutes. The least amount of time is allocated to international news. However, there are some substantial differences in the time allocations. African Americans spend about 10 minutes on international news, Hispanics 15 minutes and whites 13 minutes.

Our empirical analysis provides new insights into the mechanisms that create these gaps in time allocations and news acquisition. In our model, three factors account for differences in time use patterns. These are preferences, opportunity costs of time, and access to news providers. Recall that the opportunity costs of time are measured by wages. Our model predicts that individuals with high wages tend to spend less time on non-market activities. Using the estimated model, we can quantify to what extent the gaps in time use in news consumption can be explained by these three factors.

		Ι	II	III	IV
	News Type	Base Gap	Remove	Remove	Net
			Wage Diff	Pref Diff	Effect
African American	Local	20.18	12.85	11.42	5.39
vs White	National	-4.13	-7.71	0.12	-4.09
	International	-2.93	-4.36	-0.45	-2.24
Hispanic	Local	12.98	8.77	4.40	1.06
vs White	National	-1.34	-4.01	-5.38	-7.64
	International	1.87	0.44	-2.68	-3.65
College	Local	-10.05	10.57	-17.55	-2.09
vs High School	National	12.93	37.43	-7.64	2.72
	International	5.60	16.52	-3.47	1.23

Table 6: Decomposition of Time Use Gaps by News Type and Demographic Groups

All outcomes are measured in minutes per day

The Base Gap reports the predicted differences in time allocation between groups.

The Wage Effect shows the impact of removing wage differences.

The Preference Effect shows the impact of removing preference differences.

The Net Effect represents the remaining gap after accounting for both wage and preference effects.

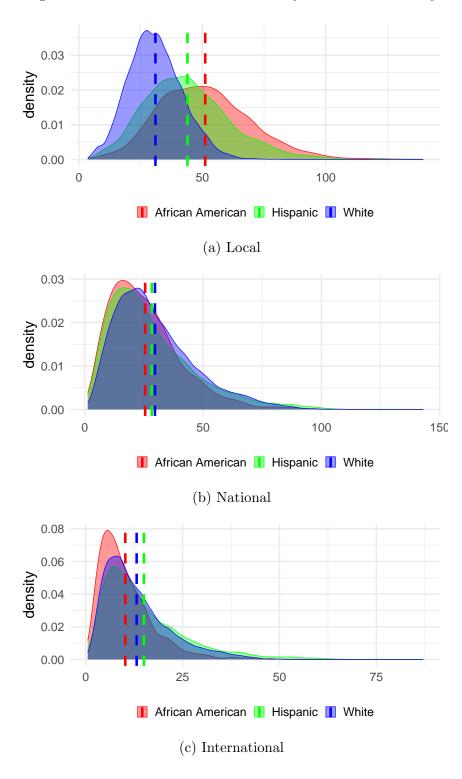


Figure 2: Predicted Time Allocations by Race and Ethnicity

Table 6 reports the findings from the decomposition exercises. The baseline gap in Column I represents observed differences in time allocation between groups. Column II shows the impact of removing wage differences. In Column III we remove differences in differences. Finally, we report the net effect which represents the remaining gap after accounting for both wage and preference effects in Column IV. The net effect, therefore, measures the importance of differences in access to news providers.

Recall that the largest gap between African Americans and whites is in local news consumption. The difference in average time allocations to local news acquisition is 20 minutes per day. African Americans have stronger preferences for local news than whites. They also have lower wages and hence lower opportunity costs to acquire news. We find that both channels explain about 50 percent of the predicted differences in time allocated to local news. In contrast, differences in access to news providers explain a much smaller fraction of the gap.

The composition of the local news gaps is similar for Hispanics. Both stronger preferences for local news and lower wages explain a significant fraction of the gap. Removing wage differences reduces the gap by about one-third, while preference differences explain about two-thirds of the gap. The net effect that can be attributed to differences in access to providers is small. Unlike African Americans, Hispanics also consume more international news than whites which is largely due to differences in opportunity costs.

Figure 3 illustrates the differences in the densities of time allocations by skill type. We find that there are large and significant differences in local news consumption. On average low-skill individuals spend 38 minutes per day on local news, while high-skill individuals spend 30 minutes. These differences are large, statistically significant, and economically meaningful. In contrast, we find that high-skill individuals spend significantly more time on national (22 versus 35 minutes) and international news (10 versus 16 minutes). Again this finding is consistent with research in labor economics that low-skill individuals are more exposed to shocks in the local economy and rely more heavily on local referrals to obtain jobs. High-skill individuals tend to participate in regional or national labor markets.

Table 6 shows the decomposition of the educational or skill gaps. Here we find

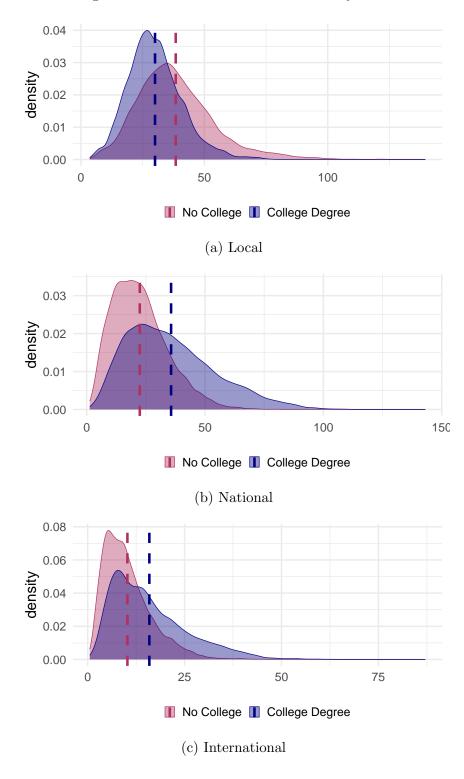


Figure 3: Predicted Time Allocations by Skill

that preferences and wage effects go in opposite directions. While college-educated individuals have stronger preferences for all news types, they have higher wages and hence higher opportunity costs of time. These two effects tend to offset each other. Table 6 shows that the wage effect tends to dominate the preference effect for local news, while the preference effect dominates the wage effect for national and international news. Differences in access to news providers are not important.

In summary, we have shown that the observed differences in informational gaps for all news types are driven by differences in preferences, opportunity costs of time (wages), and access to news providers. We find that the first two channels matter the most, i.e. differences in access to news providers only explain a small fraction of the observed informational gaps. Minorities (African Americans and Hispanics) have, on average, lower opportunity costs of time and stronger preferences for local news than whites. Each factor explains a significant fraction of the differences in predicted time allocations to local news. In contrast, whites have stronger preferences for national and international news than African Americans. These stronger preferences are partially offset by higher opportunity costs of time. The differences in time allocations by skill follow a similar pattern. Wage effects dominate for local news, while preference effects are most salient for national and international news.

7 Willingness to Pay for News

In this section, we report estimates of the willingness to pay for improvements in the quality of news. We implement the analysis by considering a ten percent quality increase in the productivity of all news providers. We perform this exercise separately for local, national, and international news. Table 7 summarizes our main findings.

Overall, we find that our WTP estimates are plausible and generate important new insights into the distribution of welfare effects associated with changes in the quality of news provision. In particular, we find that a ten percent increase in the quality of local news leads to an average increase of 4.2 minutes per day of local news consumption which is valued at \$1.33 per day or \$485 a year. Similarly, a ten percent increase in national news is valued at \$1.55 per day or \$566 a year. Finally, a ten

	Leel	National	T
	Local	National	International
Overall	1.33	1.55	0.65
Age 18-29	0.90	0.43	0.19
Age 30-49	1.27	0.99	0.37
Age 50-64	1.40	1.62	0.65
Age 65 or above	1.46	2.40	1.07
White	1.28	1.63	0.67
African American	1.66	1.12	0.42
Hispanic	1.49	1.31	0.64
HS Grad	1.28	0.93	0.39
CL Grad	1.40	2.12	0.88
Women	1.39	1.06	0.40
Men	1.27	2.21	0.98
Married	1.33	1.73	0.73
Single	1.35	1.32	0.55
Democrat	1.40	1.51	0.62
Republican	1.31	1.66	0.70
Increase in Time	4.2	4.3	1.8

Table 7: Willingness to Pay for a 10 Percent Quality Increase

Increases in time are measured in minutes per day.

All other outcomes are measured in dollars per day.

percent increase in the quality of international news is valued at \$0.65 a day or \$237 a year. Note that due to the concavity of the utility function, our WTP estimates are lower than the typical off-the-envelope estimate that multiplies the increase in the time allocated to news with the wage rate.²⁸

These estimates of the average willingness to pay mask important heterogeneity within the population. We have seen above that minorities and low-skill individuals have, on average, lower wages than non-minority or high-skill individuals. Hence, their opportunity costs of time are lower for these individuals. Lower opportunity costs of time then translate into a lower willingness to pay for improvements in local news quality. Despite these lower opportunity costs of time, we find that the average annual

²⁸These annual willingness to pay estimates can be compared to simple 'back-of-the-envelope' calculations that multiply the predicted daily time changes by the average wage rate and annualize them. Such calculations would suggest yearly valuations of \$509, \$521, and \$218 for local, national, and international news respectively.

willingness to pay for the quality improvement in local news for African Americans is \$1.66 a day or \$605 a year while the average willingness to pay for whites is only \$1.28 a day or \$467 a year.

The willingness to pay estimates increase in age. Women have higher willingness to pay for local news, but lower for national and international news than men. Similar results are found when comparing singles to married individuals. The willingness to pay for all types of news improvements also increases in the level of education. Note that college graduates' willingness to pay for quality improvements in local news is nine percent higher than that of high school graduates, despite the fact that the spend on average eight minutes less on local news.

These counterfactuals are also informative about the elasticity of the demand for news with respect to quality. Note that a 10 percent increase in the quality of local news, leads to a 12 percent increase in the time allocated to local news. Hence, the elasticity of demand with respect to local news quality is greater than one. The implied elasticities for national and international news are even larger according to Table 7. As such, we find that the demand for news is fairly responsive to changes in the overall quality of news. If traditional news providers continue to decline in quality in the future, online and other digital providers need to improve to offset this decline and meet the demand for quality news. Since it is in the public interest that individuals are well-informed about local, national ,and international news, there is some scope for well-designed public policies that support, for example, innovative new digital news providers.

8 Conclusions

We have developed a new time allocation and news acquisition model. Individuals have preferences defined over local, national, and international news. The information production functions depend on the productivity of the news providers as well as the time an individual allocates to each provider. Individuals also choose between market time (labor supply) and non-market time devoted to news acquisition. Hence, wages serve as opportunity costs of time. We have shown how to estimate the model using revealed and stated preference data. We use survey data for two different purposes. First, we exploit detailed qualitative data on time use allocations. Qualitative time use questions have the advantage that they are easier to answer for most survey participants which allow researchers to elicit detailed and reliable information on a variety of time use activities. However, the estimation of the model also requires some quantitive data which are necessary to establish the correct scaling of time use patterns. Second, stated preference survey data provide additional information about the underlying preferences for specific news topics and the information acquisition process. Without such data it would be challenging to estimate a rich model of information acquisition.

We find important gaps in news acquisition by race, ethnicity, and skill. In particular, low-skill and minority individuals typically allocate more time to local news than high-skill and white individuals. Somewhat interestingly, these differences in time allocations exist for almost all relevant local news topics covered in the survey. They are most pronounced for crime, schools, and jobs. White and high-skill individuals allocated more time to national and international news. 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.

The differences in informational gaps for news are driven by preferences, opportunity costs of time, and access to different news providers. Our model allows us to assess the relative importance of each channel. We find that the gaps in local news acquisition between minorities and whites are due to lower wages and stronger preferences for local news. These two effects reinforce each other. In contrast, the gaps in national and international news acquisition between African Americans and whites are largely due to differences in preferences. Differences in the opportunity costs of time tend to mitigate these gaps.

Finally, we have provided estimates of the willingness to pay for improvements in the quality of news. We have shown that the demand for news is fairly responsive to changes in the overall quality of news. Moreover, the average annual willingness to pay for a 10 percent improvement in the quality of local (national, international) news is \$485 (\$566, \$237). These estimates of the average willingness to pay mask important heterogeneity within the population. These results illustrate that our empirical approach improves our understanding of disparities in news acquisition among important socio-demographic groups. Since it is in the public interest that individuals are well-informed, there is some scope for well-designed public policies that support the provision of quality news coverage.

Our paper provides ample scope for future research. The surveys also elicit detailed information about attitudes towards the media. For example, the survey asks whether the media can be trusted, is fair and transparent, inclusive, accurate, thorough, and in touch. This part of the survey reveals attitudes towards the media which may be the outcome of the time allocation and news acquisition decisions that we have studied in this paper. More research is needed to understand how these attitudes are formed and how they are affected by time use patterns.

Moreover, we have shown how to identify and estimate the parameters of our time allocation and information acquisition model conditioning on access to news providers. We have treated the bundle of news providers as predetermined. Modeling bundle choices is, in principle, possible and can be done using techniques from the differentiated product demand literature.²⁹ However, estimating models of bundle choice for the media is difficult since news providers are also a main source of entertainment. To estimate a joint model of bundle choice and time allocations, we probably need to observe time allocations for both news acquisition and entertainment. In our data, set we only observe time allocations for news consumption. As a consequence, we treat bundle choices as predetermined. Our results suggest that differences in access to providers only explain a small fraction of the observed informational gaps. Nevertheless, it can be useful to account for endogenous provider choices. More research is needed to address this issue.

²⁹See, for example, Crawford and Yurukuglu (2012) who study multi-channel television markets.

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A Reduced Form Empirical Evidence

In this appendix, we provide some additional reduced form evidence for the key outcome variables used in this paper.

A.1 Local, National, and International News

One key variable in the LNS is the time allocated to local, national, and international news. Table 8 summarizes the estimates from ordered Logit regressions for local news, national news, and international news.³⁰ In this model, we control for covariates such as age, income, political affiliation, gender, marital status, neighborhood attachment and quality, and city-fixed effects.

	How Closely Do You Follow?			
	Local	National	International	
African American	0.863***	-0.038	-0.082^{*}	
	(0.048)	(0.047)	(0.046)	
Hispanic	0.428^{***}	0.215^{***}	0.432^{***}	
	(0.041)	(0.042)	(0.041)	
College Grad	-0.604^{***}	0.712***	0.457^{***}	
	(0.076)	(0.074)	(0.074)	
Age	Yes	Yes	Yes	
Income	Yes	Yes	Yes	
Political Affiliation	Yes	Yes	Yes	
Gender and Marital Status	Yes	Yes	Yes	
City FE	Yes	Yes	Yes	

Table 8: Exposure to Local, National, and International News

Table 8 shows that low-skill and African American individuals typically follow local news much more closely than high-skill and white individuals who prefer national and international news. Note that these differences are quite large. Consider, for example, the coefficient of 0.863 for African Americans which translates into an odds

 $^{^{30}\}mathrm{The}$ odds are computed by taking the exponent of the coefficient.

ratio of 2.37. That means African Americans have more than two times the odds of responding that they follow local news very closely (vs. somewhat closely, not very closely, and not at all closely) compared to white individuals. Hispanics also have stronger preferences for local news than white individuals. Here, the odds ratio is 1.53. 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. Finally, the odds ratio for college graduates relative to high-school dropouts is 0.55. Again, these differences are large and potentially economically meaningful.

We conducted several additional robustness checks and estimated a sequence of models that control for smaller subsets of the co-variates that we use in the specification of the model reported in Table 8. In particular, we started with a model that only controls for race and skill level. We then sequentially added socio-economic demographics, city fixed effects, community attachment, and, finally, local neighborhood ranking. That gave us a sequence of five nested models. Overall, we find that the main findings reported above are robust to these specification changes. If anything, the results get stronger, as we control for more co-variates.

A.2 Time Allocations Among Local News Providers

Next, we consider the time allocated among local news providers. Recall that our analysis focuses on five provider types: printed newspapers, television, radio, social media, and online media. The survey asks how often an individual gets local news and information from each provider. Table 9 summarizes the key coefficient estimates and estimated standard errors from ordered Logit regressions for time allocations for each of the five providers. Again, we control for a variety of covariates.

Overall, we find that minorities allocate significantly more time to local news providers than non-minorities. The differences between African Americans and whites are positive for all five providers and statistically significant for television, printed newspaper, radio, and social media. These effects are large, especially for television, where the odds ratio is approximately 2.08. The differences between Hispanics and

	Newspaper	Radio	TV	Online	Social Media
African American	0.11**	0.10**	0.73***	0.06	0.09^{*}
	(0.05)	(0.04)	(0.05)	(0.05)	(0.04)
Hispanic	-0.03	-0.09^{**}	0.23^{***}	0.10^{**}	0.27^{***}
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
College Grad	0.12	0.34^{***}	-0.59^{***}	0.61^{***}	-0.41^{***}
	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)
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 9: Time Allocations Among Local News Providers

whites are smaller, but again we find that Hispanics allocate significantly more time to television and social media. The gaps between low- and high-skill individuals are more nuanced. High-skill individuals allocate more time to online news media as well as some traditional media such as radio and printed newspaper while low-skill individuals allocate more time to television and social media.

A.3 Local News Topics

Finally, we consider preferences over local news topics. There are eleven local news topics that are covered in the survey. Table 10 summarizes the coefficient estimates and estimated standard errors from ordered Logit regressions for all topics. Again, we control for a variety of covariates such as age, income, political affiliation, gender, marital status, neighborhood attachment and quality, and city-fixed effects.

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 only exceptions are culture- and weather-related news. We observe the biggest gaps for Jobs, Schools and Economics and Crime. These are the topics that strongly affect

African American 0.87^{***} 0.32^{***} 0.35^{***} 0.62^{***} 0.21^{***} Hispanic 0.62^{***} 0.28^{***} 0.20^{***} 0.07 0.15^{***} 0.02 Hispanic 0.62^{***} 0.20^{***} 0.20^{***} 0.07 0.15^{***} 0.02^{***} College Grad -0.72^{***} 0.55^{***} 0.24^{***} -0.30^{***} -0.16^{***} Microan American 1.00^{***} 0.53^{***} 0.24^{***} -0.30^{***} -0.16^{***} Mispanic 0.08 (0.08) (0.08) (0.08) (0.08) (0.05) Hispanic 0.77^{***} 0.44^{***} 0.69^{***} 0.11^{**} 0.21^{***} 0.33^{***} (0.04) (0.05) <th></th> <th colspan="3">How Important</th> <th colspan="3">How Easy to Get Informed</th>		How Important			How Easy to Get Informed		
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$		Crime	Politics	Community	Crime	Politics	Community
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	African American	0.87^{***}	0.32***	0.35^{***}	0.62***	0.34^{***}	0.21***
1 (0.04) (0.08) (0.08) (0.08) (0.08) (0.08) (0.08) (0.08) (0.08) (0.08) (0.08) (0.08) (0.05) (0.05) (0.05) (0.05) (0.05) (0.05) (0.05) (0.05) (0.05) (0.05) (0.05) (0.06) (0.04) (0.04) (0.04) (0.04) (0.04) (0.04) (0.04) (0.08) (0.08) (0.08) (0.08) (0.08) (0.08) (0.08) (0.05) (0.05) (0.05) (0.05) (0.05) (0.05) (0.05) (0.05) (0.05) (0.05) (0.05) (0.05) (0.05) (0.05) (0.05) (0.05) $(0.0$							
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Hispanic	0.62^{***}	0.28^{***}	0.20^{***}	0.07	0.15^{***}	0.02
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $					(0.04)	(0.04)	(0.04)
Jobs Schools Event Jobs Schools Economy African American 1.00*** 0.93*** 0.87*** 0.51*** 0.40*** 0.66*** (0.05) (0.05) (0.05) (0.05) (0.05) (0.05) (0.05) Hispanic 0.77*** 0.64*** 0.69*** 0.11** 0.21*** 0.33*** (0.04) (0.08) (0.08) (0.08) (0.08) (0.08) (0.08) (0.08) (0.08) (0.08) (0.08) (0.08) (0.08) (0.08) (0.08) (0.08) (0.08) (0.08) (0.06) (0.05) (0.05) (0.05) (0.05) (0.05) (0.05) (0.06) (0.04) (0.04) (0.04) (0.04) (0.04) (0.04) (0.04	College Grad	-0.72^{***}	0.50^{***}	0.24^{***}	-0.30^{***}	-0.20^{***}	-0.16^{**}
African American 1.00^{***} 0.93^{***} 0.51^{***} 0.40^{***} 0.66^{***} (0.05) (0.05) (0.05) (0.05) (0.05) (0.05) (0.05) Hispanic 0.77^{***} 0.64^{***} 0.69^{***} 0.11^{**} 0.21^{***} 0.33^{***} (0.04) (0.04) (0.04) (0.04) (0.04) (0.04) (0.04) College Grad -0.38^{***} -0.49^{***} -0.37^{***} -0.42^{***} -0.66^{***} (0.08) (0.07) (0.08) (0.08) (0.08) (0.08) Sports Culture Restaurants Sports Culture Restaurants African American 0.68^{***} 0.05 0.20^{***} -0.07 0.12^{**} 0.16^{***} Hispanic 0.33^{***} 0.28^{***} 0.13^{**} -0.19^{***} 0.01 0.12^{***} Micrian American 0.57^{***} 0.21^{***} 0.12^{**} 0.10^{**} Mispanic 0.33^{***} 0.21^{***}		(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$		Jobs	Schools	Economy	Jobs	Schools	Economy
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$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Hispanic	0.77^{***}	0.64^{***}	0.69^{***}	0.11^{**}	0.21^{***}	0.33^{***}
$\begin{tabular}{ c c c c c c c c c c c c c c c c c c c$							
$\begin{tabular}{ c c c c c c c c c c c c c c c c c c c$	College Grad	-0.35^{***}	-0.38^{***}	-0.49^{***}	-0.37^{***}	-0.42^{***}	-0.66^{***}
African American 0.68^{***} 0.05 0.20^{***} -0.07 0.12^{**} 0.16^{***} Hispanic (0.04) (0.05) (0.04) (0.04) (0.04) (0.04) (0.04) (0.04) (0.04) (0.04) (0.04) (0.04) (0.04) (0.04) (0.04) (0.04) (0.04) (0.04) (0.04) (0.04) (0.08) (0.08) (0.08) (0.08) (0.08) (0.08) (0.08) (0.08) (0.07) (0.06) (0.05) (0.07) (0.06) (0.05) (0.07) (0.08) (0.08) (0.08) (0.08) (0.08) (0.08) (0.08) (0.09) (0.08) (0.09) (0.08) (0.09) (0.08) (0.09)		(0.08)	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)
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Hispanic 0.33^{***} 0.28^{***} 0.13^{***} -0.19^{***} 0.01 0.12^{***} (0.04) (0.04) (0.04) (0.04) (0.04) (0.04) (0.04) College Grad -0.17^{**} 0.68^{***} 0.21^{***} 0.12 0.11 -0.17^{**} (0.07) (0.08) (0.07) (0.08) (0.08) (0.08) (0.08) Traffic WeatherTraffic WeatherAfrican American 0.57^{***} 0.12^* 0.46^{***} -0.13^{**} (0.05) (0.06) (0.05) (0.07) $(0.08)^*$ $(0.07)^*$ Hispanic 0.44^{***} -0.02 0.08^{**} -0.21^{***} (0.04) (0.05) (0.09) (0.08) (0.09) AgeYesYesYesYesYesYesYesYesYesYesYesPolitical AffiliationYesYesYesYesYesYesYesYesYesYesYesYesCommunity CharacteristicsYesYesYesYesYesYesYesYesYesYesYesYesYesYes	African American	0.68^{***}	0.05	0.20***	-0.07	0.12^{**}	0.16***
$\begin{array}{c c c c c c c c c c c c c c c c c c c $						(0.05)	
College Grad -0.17^{**} 0.68^{***} 0.21^{***} 0.12 0.11 -0.17^{**} (0.07) (0.08) (0.07) (0.08) (0.08) (0.08) (0.08) Traffic Weather Traffic Weather Traffic Weather African American 0.57^{***} 0.12^* 0.46^{***} -0.13^{**} (0.05) (0.06) (0.05) (0.07) Hispanic 0.44^{***} -0.02 0.08^{**} -0.21^{***} (0.04) (0.05) (0.04) (0.06) (0.04) (0.06) College Grad -0.06 0.09 0.08 0.57^{***} 0.12^* (0.08) (0.09) (0.08) (0.09) 0.08 0.57^{***} (0.08) (0.09) (0.08) (0.09) 0.08 0.57^{***} (0.08) (0.09) (0.08) (0.09) 0.08 0.57^{***} Income Yes Yes Yes Yes Yes Yes Political Affiliation Yes Yes Yes Yes Yes	Hispanic	0.33^{***}	0.28^{***}	0.13^{***}	-0.19^{***}	0.01	0.12^{***}
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $		(0.04)			(0.04)	(0.04)	(0.04)
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	College Grad	-0.17^{**}	0.68^{***}	0.21^{***}	0.12	0.11	-0.17^{**}
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $		(0.07)	(0.08)	(0.07)	(0.08)	(0.08)	(0.08)
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$		Traffic	Weather		Traffic	Weather	
Hispanic 0.44^{***} -0.02 0.08^{**} -0.21^{***} (0.04) (0.05) (0.04) (0.06) College Grad -0.06 0.09 0.08 0.57^{***} (0.08) (0.09) (0.08) (0.09) Age Yes Yes Yes Yes Yes Yes Yes Income Yes Yes Yes Yes Yes Yes Yes Yes Political Affiliation Yes Yes Yes Yes Yes Yes Yes Gender and Marital Status Yes Yes Yes Yes Yes Yes Yes Community Characteristics Yes Yes Yes Yes Yes Yes Yes	African American	0.57^{***}	0.12^{*}		0.46***	-0.13^{**}	
$\begin{array}{c c c c c c c c c c c c c c c c c c c $		(0.05)	(0.06)		(0.05)	(0.07)	
College Grad-0.060.090.080.57***(0.08)(0.09)(0.08)(0.09)AgeYesYesYesYesIncomeYesYesYesYesPolitical AffiliationYesYesYesYesGender and Marital StatusYesYesYesYesYesYesYesYesYesYesCommunity CharacteristicsYesYesYesYesYesYesYesYesYesYes	Hispanic	0.44^{***}	-0.02		0.08^{**}	-0.21^{***}	
(0.08)(0.09)(0.08)(0.09)AgeYesYesYesYesYesIncomeYesYesYesYesYesYesPolitical AffiliationYesYesYesYesYesYesGender and Marital StatusYesYesYesYesYesYesCommunity CharacteristicsYesYesYesYesYesYes		(0.04)	(0.05)		(0.04)		
AgeYesYesYesYesYesYesIncomeYesYesYesYesYesYesPolitical AffiliationYesYesYesYesYesYesGender and Marital StatusYesYesYesYesYesYesCommunity CharacteristicsYesYesYesYesYesYes	College Grad	-0.06	0.09		0.08	0.57^{***}	
IncomeYesYesYesYesYesYesPolitical AffiliationYesYesYesYesYesYesGender and Marital StatusYesYesYesYesYesYesCommunity CharacteristicsYesYesYesYesYesYes		(0.08)	(0.09)		(0.08)	(0.09)	
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City FE Yes Yes Yes Yes	•						
	City FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Preferences for Local News Topics

the well-being of most minority individuals. The gaps between low- and high-skill individuals are equally pronounced when it comes to jobs, the economy, crime, and education. High-skill individuals care more about politics, culture, and restaurants than low-skill individuals.

Again, we conducted additional robustness checks for the four most important topics: crime, schools, the local economy, and jobs. We considered a sequence of models that control for smaller subsets of co-variates that we use in the model above. Overall, we find that the main findings reported above are robust to these specification changes.

B Providers and Topics

Table 11 shows how we aggregated news providers into five types. We have three traditional news providers: television, print newspaper, and radio. The new non-traditional news providers are online media and social media.

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

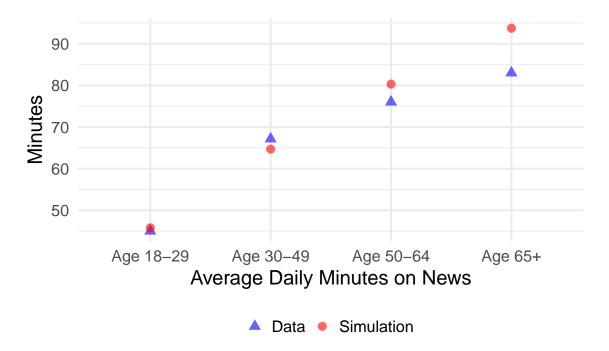
- 1. "Politics": Local Politics: Crime, Local Government & Politics
- 2. "Economy": Local Economy & Education: Local Jobs & Unemployment, Local Prices, Local Schools
- 3. "Entertainment": Sports, Local Arts and Culture, Restaurants, Local Community
- 4. "Others":Weather and Traffic

TV	- Local TV news station
Print newspaper	 Local daily newspaper's print version Local government agencies or officials in print Local organizations in print Print community or neighborhood newsletter Other community or specialized newspaper's print version
Radio	- Local radio station
Online	 Website, app or email of local TV news station Website, app, or email of local daily newspaper Website, app, or email of other community or specialized newspaper Website, app, or email of local radio station Local community or neighborhood digital newsletter Local government agencies or officials' website, app, or email Local organizations' website, app or email Local online forums or discussion groups' website, app, or email News source that publishes online only' website, app, or email
Social media	 Social media posts of local TV news station Social media posts of local daily newspaper Social media posts of other community or specialized newspaper Social media posts of local radio station Local community's social media posts Local government agencies or officials' social media posts Local organizations' social media posts Local online forums or discussion groups on social media News source that publishes online only's social media posts

Table 11: Set of Providers

C Goodness of Fit

The following figures illustrate the goodness of fit of our model. Figure 4 shows how well our model matches the quantitative time use moments from the MCS. Recall that we observe the average daily minutes spent on total news by age group. Our model fits the data remarkably well for three age groups, and slightly underestimates the time use for the oldest category.



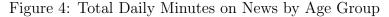


Figure 5 illustrates the fit of our model for the categorical time use variable for each local news provider by age. This is one of the key outcomes we observe in the LNS. Figure 6 repeats this exercise conditioning on race instead of age.

Figure 7 illustrates the fit of our model for the local news topics variable by age. This is another key outcome we observe in the LNS. Figure 8 repeats this exercise conditioning on race instead of age.

Overall, we find that our model fits these conditional distributions rather well.

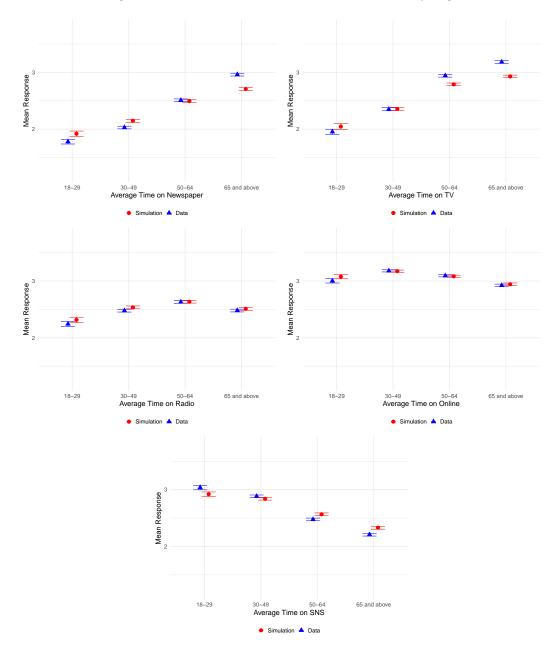


Figure 5: Time Use Conditional on Provider by Age

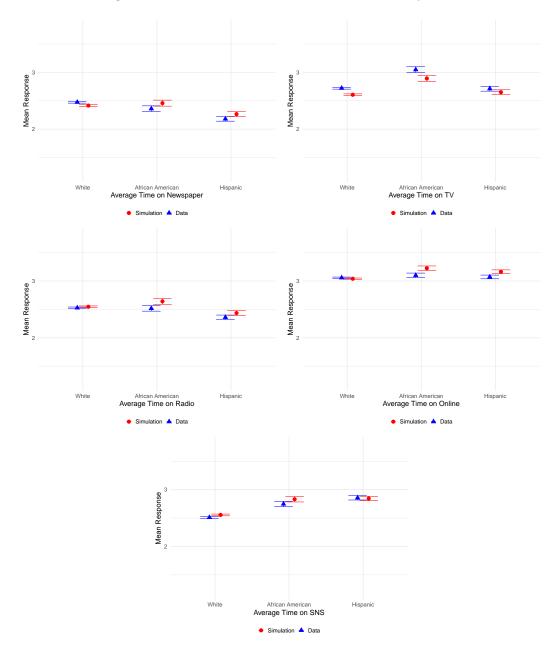


Figure 6: Time Use Conditional on Provider by Race

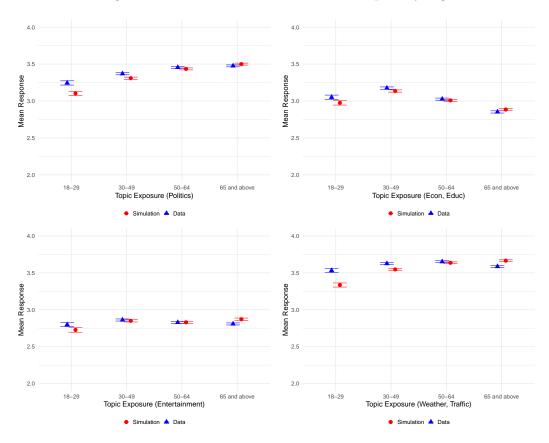


Figure 7: Preferences for Local News Topics by Age

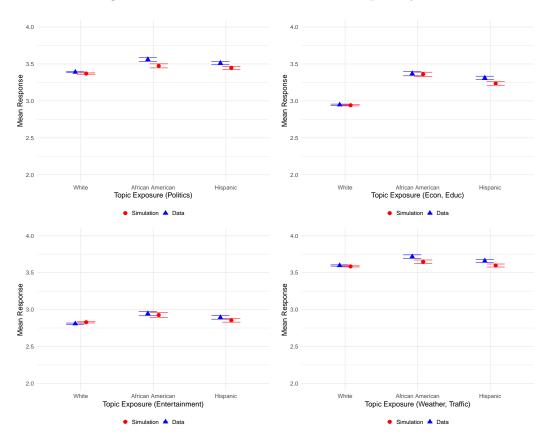
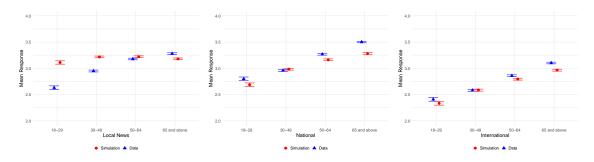


Figure 8: Preferences for Local News Topics by Race

Figure 9: Time Use Conditional on News Type by Age



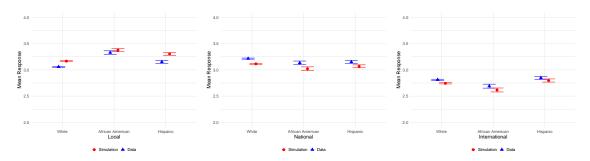


Figure 10: Time Use Conditional on News Type by Race