Time Allocations and News Acquisition*

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Abstract

This paper studies how individuals allocate time to news acquisition. Despite the growing importance of information for economic decision-making, this topic has not gained much attention in the literature partly due to data limitation. We exploit rarely used data from the Pew Research Center's Local News Survey, complemented with quantitative time-use data from the Media Consumption Survey. We document substantial differences in news consumption across race, ethnicity, and skill. Minority and low-skill individuals devote significantly more time to local news, while white and high-skill individuals consume more national and international news. We develop and estimate a structural model of time allocation and news acquisition that combines qualitative and quantitative survey data. Our results show that observed gaps are driven primarily by differences in wages and preferences, rather than access to news providers. These findings have important implications for inequality and welfare analysis.

Keywords: Time allocations, information acquisition, stated and revealed preferences, survey data, maximum likelihood estimation, inequality in news consumption, gap analysis, decomposition of gaps.

JEL Code: C83, D83, J22.

1 Introduction

Time allocations are fundamental to economic behavior. Becker's (1965) work formed the basis of much recent research in labor economics that has studied how individuals allocate time to market activities as well as home production. This research has contributed to our understanding of important economic topics such as child care, human capital investments, child development, bargaining power, and specialization within families, and the care for the elderly. These activities are not only important for individual welfare, but they also account for a substantial portion of daily life. Much less is known about how individuals allocate time to acquire information, despite the fact that knowledge is increasingly important for decision-making and individual productivity. The lack of research on time allocation and news acquisition may largely be due to the fact that the American Time Use Survey (ATUS), which is the main data set that has been used in the U.S. to study time allocations, does not collect any detailed data about the time allocated to news acquisition. This paper aims to close this gap and study new survey data to determine how individuals allocate time to acquire news.

Our empirical analysis is primarily based on the Local News Survey (LNS) collected by the Pew Research Center. This is a comprehensive survey that has been rarely used in previous studies. It primarily uses qualitative questions to elicit time allocations for news acquisition and preferences for news topics. We document in this paper that low-skill and minority individuals typically allocate more time to local news than high-skill and white individuals. Somewhat surprisingly, these positive gaps exist for almost all relevant local news topics covered in the survey. They are most pronounced for crime, local schools, jobs and the local economy. It is important to recognize that disadvantaged individuals are only better informed about local news than other individuals. White and high-skill individuals have significantly stronger preferences for and exposure to national and international news than disadvantaged individuals. These differences in news acquisition persist after controlling for a large set of observed characteristics such as political affiliation, neighborhood attachment, neighborhood quality, and city-fixed effects. These disparities across socio-demographic groups are potentially important since they may reinforce economic inequality.

While these differences are robust in a statistical sense, the primarily qualitative nature of the survey data limits our ability to assess their economic importance. In particular, the qualitative survey data do not permit a direct quantification of how large these gaps are in terms of time or resources devoted to news consumption. A more informative approach requires measuring news acquisition on a cardinal scale, such as the number of minutes allocated to different news topics or sources. Doing so not only allows for more precise comparisons across groups, but also facilitates an evaluation of the welfare implications associated with changes in news consumption arising from policy shifts. Achieving this objective requires access to additional data and the estimation of a formal model of time allocation and news acquisition, which provides a theoretical framework for interpreting observed differences and for conducting counterfactual welfare or policy analysis.

We, therefore, develop a time allocation and news acquisition model. Each individual has a time endowment that can be allocated to market and non-market time.[1] 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 such issues 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,

[1] Following Gronau (1977) and Aguiar et al. (2021), our formation assumes a two-stage structure in which wages determine total non-market time while preferences govern its allocation across activities.

preferences for news types and specific topics, as well as the productivity differences among providers.

Next, we develop a maximum likelihood estimator for the parameters of the model. Our estimator combines traditional revealed preference data on individual time allocations with detailed survey data that elicits preferences. We implement the estimator for the structural parameters of our model by complementing the Local News Survey with data from the Media Consumption Survey (MCS), which contains traditional quantitative time-use data. Quantitative data are necessary to establish the correct scaling of time-use patterns. However, the time-use questions in the MCS are not sufficiently detailed to estimate a rich time allocation and news acquisition model. The Local News Survey provides much richer qualitative time-use data. We thus show that a comprehensive time allocation model can be identified and estimated with weaker data requirements, which is helpful since comprehensive quantitative time-use data on news acquisition do not exist in the U.S.[2]

Surveys are also an essential approach for eliciting otherwise invisible factors such as beliefs and preferences.[3] Our estimator also uses data obtained from stated preference survey questions. The stated preference 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. For example, suppose 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

[2]Qualitative data lack the numerical accuracy of quantitative data. However, qualitative time-use questions have the advantage that they are easier to answer for most survey participants, which allows researchers to elicit detailed and reliable information on a variety of time-use activities (Stantcheva, 2023). Qualitative data are also relatively cheap to collect, which matters in a world of limited research funding.

[3]Survey-based research has been widely accepted in other social sciences, such as sociology. Beggs et al. (1981) used survey data to estimate the potential demand for electric cars. Bewley (2002) forcefully argued 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 (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).

effects, we can leverage stated preference data to help us distinguish preference parameters from news production function parameters. We show that data from stated preference survey questions can be interpreted within the context of our time allocation and information acquisition model and can be used to construct additional orthogonality conditions which help to identify and estimate key parameters of the model. 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 the publicly available time-use data.[4]

Our empirical findings provide new and important insights into the observed gaps in news acquisition by race, ethnicity and skill. On average, African Americans spend about 50 minutes per day on local news, Hispanics 42 minutes, and whites 31 minutes. These differences are large, statistically significant, and economically meaningful. Using wages as opportunity costs of time, these time allocations are valued at \$13.5 for African Americans, \$12.1 for Hispanics, and \$10.85 for whites per day. 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 to international news. African Americans spend about 10 minutes on international news, Hispanics spend 15 minutes, and whites spend 13 minutes. We thus conclude that the time allocated to news acquisition is an important daily activity and that there are significant differences in time-use patterns in the population. Moreover, the racial and skill differences in time-use patterns allocated to local news acquisition documented in the news surveys are consistent with time-use patterns for entertainment documented in the ATUS. This provides an external validity test for our data sources.[5]

Finally, we decompose the observed gaps in time-use allocations into differences due to wages, preferences, and access to providers that differ in their news production

[4]Note that even if we had more comprehensive quantitative time-use data than what is currently available, the stated preference data would still be useful to construct over-identifying orthogonality conditions, which could be used to test the validity of the model.

[5]To our knowledge, the two survey data sets are the best data that are publicly available to study the research questions that we pursue in this paper.

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 preferences.

The rest of the paper is organized as follows. Section 2 provides a brief review of the literature and discusses our contributions. Section 3 introduces our data sets and discusses the survey design as well as the main survey questions used in the analysis. Section 4 summarizes the reduced form evidence regarding the observed gaps in news acquisition by race, ethnicity, and skill. Section 5 develops our time-use and information acquisition model. Section 6 discusses the identification and estimation of the parameters of the model. Section 7 reports our empirical results. Section 8 provides a detailed analysis of the informational gaps that we observe in the data based on a decomposition provided by our estimated model. Section 9 offers some conclusions and discusses future research.

2 Literature Review

Our work contributes to several strands of the literature on labor and media economics and econometrics. First, 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 affects cognitive and non-cognitive 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 include time spent acquiring news as a 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 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.

Second, the paper is related to a new literature that considers diverse data sources. In empirical economics, researchers have typically preferred revealed preference methods to estimate behavioral models. These methods are based on traditional data sources such as observed choices and objectively measured variables such as prices and individual characteristics.[6] Unquestionably, these methods have been extremely valuable to study a wide range of important research questions. However, when estimating the impact of differences in beliefs or information on behavior, traditional

[6]Some pioneering papers are by Samuelson (1938, 1948) and Arrow (1959).

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 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.[7]

Recently, a growing body of research has leveraged stated preference data to analyze subjective factors influencing behavior. This literature demonstrates the value of directly eliciting preferences and beliefs 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. This paper adds to this literature by demonstrating how stated preference and attitude data can be integrated into the estimation of a traditional time-use and information acquisition model. Our approach is promising and provides novel insights into disparities in information acquisition and the implications for labor market outcomes.

Third, the methodological approach taken in this paper is closely aligned with efforts in econometrics to integrate multiple data types for identification and estimation purposes. Imbens and Lancaster (1994) was one of the first papers that suggested combining different data sources in estimation, primarily to achieve efficiency gains. In contrast, we use quantitative data to identify the scale of the model and qualitative

[7]Most 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).

data to estimate a richer model that differentiates among a variety of different news types and news topics.

Fourth, 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.[8] Since minority 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 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 the 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 new evidence of the differences in the demand for local, national, and international news that are systematically linked to racial, ethnic, age, and skill

[8] See, for example, Altonji and Blank (1999), Shuey and Willson (2008), Hoynes et al. (2012), and Bayer et al. (2016).

heterogeneity. Moreover, it shows that most of these differences are due to preferences and opportunity costs of time.

3 Data

3.1 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.[9] One of the main objectives of the data collection efforts of the Pew Research Center is to inform the public about the issues 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 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.[10] 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%.[11] Of the 34,897 respondents in total, 10,654 came from the ATP and 24,243 came from the KnowledgePanel. Our final

[9] Both data sets are made available to researchers through data-sharing agreements with the Pew Research Center.

[10] The ATP and Ipsos KnowledgePanel use survey takers who participate in multiple surveys each month, with many participants having done so for many years. While it can be made nationally representative through weighting in terms of various demographic characteristics, the sample may be skewed towards internet users with potentially stronger news exposure, in part through the surveys themselves. It will be useful to compare this study to other data sets that use different data sources as they become available.

[11] This is a response rate among people who have previously entered and remain part of a regular online panel that completes multiple surveys per month.

sample consists of 27,563 individuals, for whom we have complete information about demographics and socioeconomic variables used in our analysis. We use the survey weights to construct a nationally representative sample.

Table 1: Descriptive Statistics of LNS

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		

Source: PEW Research Center Local News Survey.

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 the 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 the 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 income information. 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 hourly wage in our sample is 19.9, with a standard deviation of 4.65.[12]

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 to June 3, 2012.[13] Table 2 provides the MCS sample means of the main socio-economic variables of interest.

The weighted demographic compositions of the LNS and MCS samples are remarkably similar across most dimensions, which is partly expected since both surveys use weights designed to match the U.S. population. 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

[12]The 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.

[13]Both 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 non-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.

Table 2: Descriptive Statistics of the MCS

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		

Source: PEW Research Center News Consumption Survey.

MCS sample includes a higher proportion of respondents with high school education or less (39.4% versus 27.6% in LNS).

Table 3: Average time-use in Minutes in the MCS

	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

Source: PEW Research Center News Consumption Survey.

The public use file of 2012 MCS contains information on the 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 encountered when using purely qualitative or categorical time use data.

To our knowledge, these two surveys are the best data sets that are publicly available to study time allocations and news acquisition. The American Time Use Survey (ATUS) does not collect any detailed information about time allocated to news acquisition and, therefore, cannot be used to estimate our model and address the questions that we have explored in this paper. While it might be possible for researchers to collect new time allocation data based on detailed time diaries by themselves, it is well-known that assembling time-diary-based data is rather expensive. To get an idea of how costly this additional data collection may be, it is useful to consider the Well-being Module, a supplement to the ATUS. Specifically, the Module collects information about how happy, tired, sad, and stressed individuals were yesterday, and the degree to which they felt pain, for three activities randomly selected from the time diary. Collecting data on how individuals allocate time among providers or news topics as part of the ATUS is likely to be equally costly. The total estimated cost of the 2021 Well-being Module was $300,000.[14] These costs are substantial since the ATUS is based on live telephone interviews and uses open-ended questions to elicit time diaries. Coding the answers to these open-ended questions and verifying the accuracy of the responses are complex and time-consuming activities. As such, it would be rather expensive to collect detailed time diary-based data on news acquisition that has the same quality as the ATUS. We thus conclude that the data sources used in this study are the best that are currently available.

3.2 Local News Survey Design

A key problem encountered in using survey data in economic analysis is the 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 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.[15] 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

[14] This cost was borne by the University of Maryland using grant funding from the Eunice Kennedy Shriver National Institute of Child Health and Human Development (NICHD), and the University of Minnesota using grant funding from the National Science Foundation (NSF). Source: https://www.aeaweb.org/forum/1817/american-time-use-survey-well-being-module-invites-comment

[15] See Stantcheva (2023) for a detailed guide on how to run surveys in economic research.

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 revealed preference perspective. In addition, the survey also elicits stated preferences that characterize the importance of news topics and the information acquisition process.[16]

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 who 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.*[17] This is 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

[16]The complete survey, which has 32 questions, is available upon request from the authors and the Pew Research Center.

[17]As a cross-check, the survey also contains some questions about news about the local neighborhood and community.

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 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 MCS 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.*[18] 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

[18]See Appendix B for more details. The classification is based on the platform through which news is accessed, not the original producer. For example, watching a local TV station's content through its website or app is classified as online media, and reading a newspaper's digital edition is likewise classified as online rather than printed newspaper. This ensures that the provider categories reflect the actual mode of consumption.

question: *How often do you get local news and information from ...?* and the provider types are given 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.* As we discuss in detail below, we need to assume in estimation that the underlying scaling of these variables is comparable among individuals who take the survey. 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, 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?* 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.[19]

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 to traditional cardinal time-use diaries. Second, there is a variety of other questions about stated

[19]Appendix A provides a reduced-form analysis of the key outcome variables.

preferences, and the difficulty of obtaining relevant information that are 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.

4 Gap Analysis – Reduced Form Evidence

In this section, we present reduced-form evidence indicating substantial gaps in news acquisition by race, ethnicity, and skill level. As discussed in the previous section, a key variable in the LNS measures the time respondents allocate to local, national, and international news. Table 4 reports estimates from ordered logit regressions for each of these news categories.[20] The regressions control for age, income, political affiliation, gender, marital status, neighborhood attachment and quality, and city fixed effects.

Table 4: Exposure to Local, National, and International News

	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 4 shows pronounced differences in news preferences across groups. Low-skill and African American individuals are significantly more likely to follow local news

[20] Odds ratios are obtained by exponentiating the estimated coefficients.

than high-skill and white individuals, who instead devote greater attention to national and international news. These differences are sizable. For example, the coefficient of 0.863 for African Americans corresponds to an odds ratio of 2.37, implying that African Americans have more than twice the odds of reporting that they follow local news very closely (relative to all lower categories) compared to white individuals. Hispanics also exhibit a stronger preference for local news, with an odds ratio of 1.53. At the same time, Hispanics pay close attention to national and international news, plausibly reflecting interest in immigration policy as well as political and economic developments in Latin America. By contrast, the odds ratio for college graduates relative to high-school dropouts is 0.55, indicating substantially lower engagement with local news among the high-skilled. Overall, these differences are large and potentially economically meaningful.

We conducted several robustness checks by estimating a sequence of nested models with progressively richer sets of controls. We begin with a specification that includes only race and skill, and then sequentially add socio-economic demographics, city fixed effects, community attachment, and neighborhood quality, yielding five models in total. Across all specifications, the main findings remain robust. If anything, the estimated differences become larger as additional covariates are included.

We have also examined preferences across specific local news topics. The survey covers eleven such topics, and Table 5 reports coefficient estimates and standard errors from ordered logit regressions for each topic, using the same set of controls as above.

We find that racial and ethnic gaps appear for nearly all topics, including crime, local politics, schools, and the local economy. The only notable exceptions are culture- and weather-related news. The largest gaps emerge for jobs, schools, economic conditions, and crime. These topics are especially salient for the well-being of many minority individuals. Skill-based differences are similarly pronounced. Low-skill individuals care more about jobs, the economy, crime, and education, while high-skill individuals place greater weight on politics, culture, and restaurants.

We, therefore, conclude that the survey evidence points to statistically significant disparities in news acquisition across racial, ethnic, and skill-based groups. While these differences are significant and robust in a statistical sense, the primarily quali-

Table 5: Preferences for Local News Topics

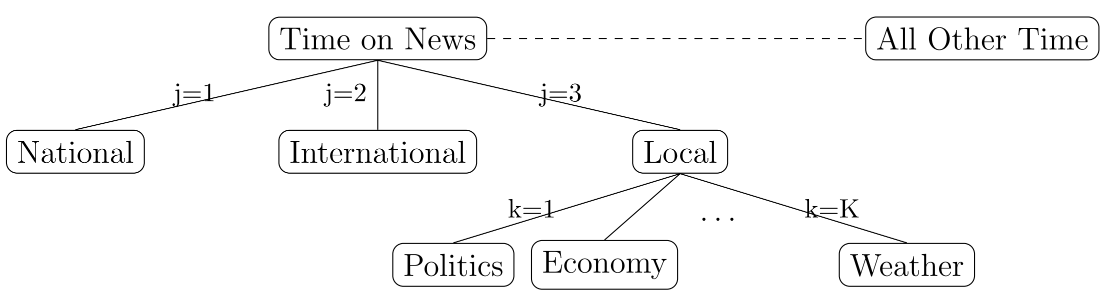
	How Important			How Easy to Get Informed		
	Crime	Politics	Community	Crime	Politics	Community
African American	0.87***	0.32***	0.35***	0.62***	0.34***	0.21***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Hispanic	0.62***	0.28***	0.20***	0.07	0.15***	0.02
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
College Grad	−0.72***	0.50***	0.24***	−0.30***	−0.20***	−0.16**
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
	Jobs	Schools	Economy	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)
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)
College Grad	−0.35***	−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***
	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
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)
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)
	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)	
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
Income	Yes	Yes	Yes	Yes	Yes	Yes
Political Affiliation	Yes	Yes	Yes	Yes	Yes	Yes
Gender and Marital Status	Yes	Yes	Yes	Yes	Yes	Yes
Community Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes

tative nature of the survey data limits our ability to assess their economic magnitude. In particular, the data do not permit a direct quantification of how large these gaps are in terms of time or resources devoted to news consumption. A more informative approach would involve measuring news acquisition on a cardinal scale, such as the number of minutes allocated to different news topics or sources. Doing so would not only allow for more precise comparisons across groups, but would also facilitate an evaluation of the welfare implications associated with changes in news consumption, whether arising from shifts in time allocation or monetary expenditures. Achieving this objective requires the estimation of a formal model of time allocation and news acquisition, which provides a theoretical framework for interpreting observed differences and for conducting counterfactual welfare analysis. The objective of the remaining parts of this paper is to conduct such an analysis.

5 A Time Allocation and News 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 types and K_j the number of news topics for each type. The information structure is illustrated in Figure 1.

Figure 1: Information Structure



There are a number of different news providers which produce content. Individuals allocate their time among these providers. Let $\mathcal{S}$ 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 $|\mathcal{S}|$ be the maximum number of providers available that could be in a consumer's choice set.[21] We indicate by $S \subset \mathcal{S}$ 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 providers for each topic.[22]

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:

$$\begin{aligned} \sum_{s \in S} h_{js} &\leq H_j \\ h_{js} &\geq 0 \text{ if } s \in S \\ h_{js} &= 0 \text{ if } s \notin S \end{aligned} \tag{1}$$

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

[21] In our application $|\mathcal{S}| = 5$.

[22] We discuss in the conclusions how to extend our model to account for endogenous bundle choices.

bundle choice and the time allocation vector. We assume that:

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

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.[23] News production is additively separable across providers.[24] The concavity in the news production generates an interior solution for the time allocation problem.[25] For our empirical model, we assume that

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

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:

$$\begin{aligned} U_j(S, x, h_j) &= \sum_{k=1}^{K_j} U_{jk}(S, x, h_j) \\ &= \sum_{k=1}^{K_j} \gamma_{jk}(x) \sum_{s \in S} t_{jks} \, f_j(h_{js}) \end{aligned} \tag{4}$$

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 $\gamma_{jk}(x) = \exp(x'\gamma_{jk})$.

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

[24] Crawford and Yurukuglu (2012) also impose this assumption. However, this separability assumption can, in principle, be relaxed and is primarily made to obtain a tractable solution for the time allocation problem.

[25] More 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.

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:

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

where μ_j is the Lagrange multiplier for news type j. For $s \in S$, the first-order conditions can be written as follows:

$$f_j'(h_{js}) \sum_{k=1}^{K} \; \gamma_{jk}(x) \; t_{jks} \; - \; \mu_j \; = \; 0 \tag{6}$$

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

$$h_{js} \;\; = \;\; f_j'^{-1} \left(\frac{\mu_j}{\sum_{k=1}^{K_j} \; \gamma_{jk}(x) \; t_{jks}} \right) \tag{7}$$

Note that we can rule out corner solutions under the assumptions we made above.[26] 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:

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

[26] Our model can be interpreted as a representative agent framework conditional on (x, S, w), with idiosyncratic variation captured by the error terms in estimation. Since we only have qualitative time allocation data at the topic or provider level, we cannot investigate corner solutions at the individual level.

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

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

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

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

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 well 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.[27]

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:

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

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

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

Summing over all news topics implies that the maximum utility that can be attained

[27] The topic mix consumed from each provider is determined by observed characteristics x. Individuals who only follow sports, for example, are not separately modeled. Incorporating unobserved heterogeneity in topic preferences is a natural extension that we leave for future work.

from a predetermined time budget H_j is

$$\begin{aligned} U_j(S,x,H_j) &= \sum_{k=1}^{K_j} U_{jk}(H_j,S,x) \\ &= u_j(S,x)\,\frac{1}{1-\rho}\,H_j^{1-\rho} \end{aligned} \tag{13}$$

where

$$u_j(S,x) = \sum_{k=1}^{K_j} \gamma_{jk}(x) \sum_{s\in S} t_{jks} \left(\frac{(\sum_k \gamma_{jk}(x)\; t_{jks})^{\frac{1}{\rho}}}{\sum_{s'\in S}(\sum_k \gamma_{jk}(x)\; t_{jks'})^{\frac{1}{\rho}}} \right)^{1-\rho} \tag{14}$$

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:

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

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:

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

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

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

Hence, we have

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

Summing over all news types, we have:

$$H = \sum_j \left(\frac{\mu}{u_j(S,x)} \right)^{-1/\rho} = \left(\sum_j u_j(S,x)^{1/\rho} \right) \mu^{-1/\rho} \tag{21}$$

Hence

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

$H_j(S,x,H)$ is thus linear in H and increasing in $u_j(S,x)$ 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 that 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:

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

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

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

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

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

which implies that

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

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 type j as a function of the wage w:

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

In summary, we follow Gronau (1977) and Aguiar et al. (2021) and model time allocation using a two-stage structure. In the first stage, wages determine the total amount of time allocated to non-market activities by shaping the trade-off between market and non-market activities. In the second stage, conditional on this total non-market time, individual preferences govern how time is allocated across different non-market activities. This allows us to characterized the optimal time allocations for news for heterogeneous individuals. Ultimately, differences in news consumption are driven by heterogeneity in wages (w), preferences ($\gamma_{jk}(x)$), and access to news providers (S).

6 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.

6.1 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:

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

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 a 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.[28] There are four categorical answers:

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

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. It should be clear

[28] The closeness question may capture attention intensity as well as time spent. However, this question is used only at the broad news-type level, where a monotone relationship between closeness and time is plausible. At the provider level, we rely on the more neutral "How often do you get local news and information from . . . ?" question, which maps more directly to time use.

from the analysis above that we need to assume that the scales used by individuals for expressing the relative importance of the different sources and types of news are the same, with the same latent variable thresholds for comparisons of local, national, and international news.[29]

Similarly, consider the time allocation problem among news providers. Note that we only observe these variables for the 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:

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

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 $\sigma_{ls}^2(\nu)$.[30]

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 $\bar{h}_l \leq h_{ls}^* < \bar{h}_h$
4. Often: $h_{ls}^o = 3$ if $\bar{h}_h < h_{ls}^*$.

[29] Common thresholds are the standard assumption in ordered choice models (Greene and Hensher, 2010; Andrich, 1978) and are necessary for identification from ordinal data alone (Bond and Lang, 2019; King et al., 2004). In our setting, all three news types use the identical response format and verbal anchors, making this assumption natural. For the stated preference questions, thresholds could in principle vary with observables, at the cost of additional parameters.

[30] We use log-log specifications to make sure that the time allocations are always positive regardless of the value of shocks.

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.

6.2 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 $\sigma^2_{lk}(\eta)$. 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^o_{lk}, that also takes four values. To map this variable into our model, we assume that

1. Neither important nor interesting: $U^o_{lk} = 1$ if $U^*_{lk} \leq \bar{U}_l$;
2. Interesting, but not important to me: $U^o_{lk} = 2$ 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:
   $U^o_{lk} = 3$ if $\bar{U}_m \leq U^*_{lk} \leq \bar{U}_h$;
4. Important for my daily life: $U^o_{lk} = 4$ 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.

6.3 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

$$
\begin{aligned}
L^N(\theta) &= \prod_{n=1}^{N} \prod_{j} \prod_{k=1}^{4} P_\theta(H_{nj}^o = k \,|S_n, x_n, w_n)^{1\{k \ observed\}} \\
&\times \prod_{n=1}^{N} \prod_{s \in S_n} \prod_{h=1}^{3} P_\theta(h_{nls}^o = h|\ S_n, x_n, w_n)^{\mathbb{I}(h \text{ is observed, } s \ in \ S_n)} \\
&\times \prod_{n=1}^{N} \prod_{k=1}^{K} \prod_{U=1}^{4} P_\theta(U_{nlk}^o = U|S_n, x_n, w_n)^{\mathbb{I}(U \text{ is observed})}
\end{aligned} \tag{32}
$$

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.

6.4 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:

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

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:

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

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.[31]

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 combine the different data to resolve the 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.[32] Finally, we would like to point out that some distributional assumptions regarding the error term could be relaxed by adopting semi-parametric discrete choice models.

7 Empirical Results

We have estimated several specifications of our model.[33] 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 func-

[31] A separate appendix is available from the authors which provides additional discussions regarding identification and presents some results from a Monte Carlo Study.

[32] Instead 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.

[33] As discussed in detail in Appendix B, we aggregate the eleven local news topics into four topics to reduce the dimensionality of the model.

tion (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 rather well.[34]

7.1 Preferences

Table 6 reports the parameter estimates and estimated standard errors for the parameters that characterize heterogeneity in preferences for news topics.[35]

Table 6: Preference Parameters

	Local				National	International
Variable	Politics	Economics Education	Entertain	Weather 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)

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

[34] Appendix C provides a more detailed discussion of the goodness of fit.

[35] Our 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.

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.

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.[36] 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.[37] Our empirical results show that this conjecture is, in fact, correct.[38]

[36]See, for example, Altonji and Blank (1999), Shuey and Willson (2008), Hoynes et al. (2012), and Bayer et al. (2016).

[37]Note that these findings are broadly consistent with the reduced form evidence that is discussed in detail in Appendix A.

[38]Research 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.

We have argued that it makes basic economic sense that African Americans and Hispanics allocate more time to local news than white Americans. As we discussed above, the American Time Use Survey does not allow us to directly test this hypothesis since it does not collect any time use data for news acquisition. However, the ATUS collects detailed data on leisure activities. The most relevant activity that is covered by the ATUS is time spent watching television for entertainment purposes. As discussed in detail in Appendix D, we can compare the time allocated to news acquisition measured in the LNS with the time allocated to television measured in the ATUS. We find that the racial and ethnic patterns observed in our LNS data and model predictions are consistent with broader television consumption patterns documented in the ATUS. Specifically, African Americans show significantly higher television usage across all measures - both for news consumption in our data and for entertainment in the ATUS. Similarly, the LNS shows that low-skill individuals tend to spend more time watching television to acquire local news. The same is true for watching television for entertainment purposes in the ATUS. We view these findings as validating our data set, i.e., the qualitative time use patterns that characterize racial and skill differences observed in the LNS are comparable to those in the ATUS.

7.2 News Production Functions

Table 7 reports the parameter estimates and estimated standard errors for the parameters of the news production functions.[39]

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 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,

[39] We 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.

Table 7: News Production Function Parameters

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.

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.

To gain some additional understanding it is useful to ask how much individuals are willing to pay for improvements in the news production function. We perform this exercise separately for local, national, and international news. More specifically, we increase the coefficients of t_{jks}, which capture the productivity of providers for different topics, by ten percent and then compute the willingness of each individual in our sample for such an increase in productivity. Table 8 summarizes our main findings.

Table 8: Willingness to Pay for a 10 Percent Productivity Increase

	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

Increases in time are measured in minutes per day.
All other outcomes are measured in dollars per day.

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 productivity of news provision. In particular, we find that a ten percent increase in the productivity 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. Similarly, a ten percent increase in the productivity of national news is valued at \$1.55 per day. Finally, a ten percent increase in the productivity of international news is valued at \$0.65 a day.[40] Note that due to the concavity of the utility function, our WTP estimates are lower than the typical back-of-the-envelope estimate that multiplies the increase in the time allocated to news by the wage rate.[41]

[40] An alternative approach for measuring the valuation of news is to design and implement a survey experiment to generate direct evidence on how people select, acquire and process information, as done by Fuster et al. (2022).

[41] These daily willingness to pay estimates can be compared to simple back-of-the-envelope calcu-

8 Differences in Time-Use and Informational Gaps

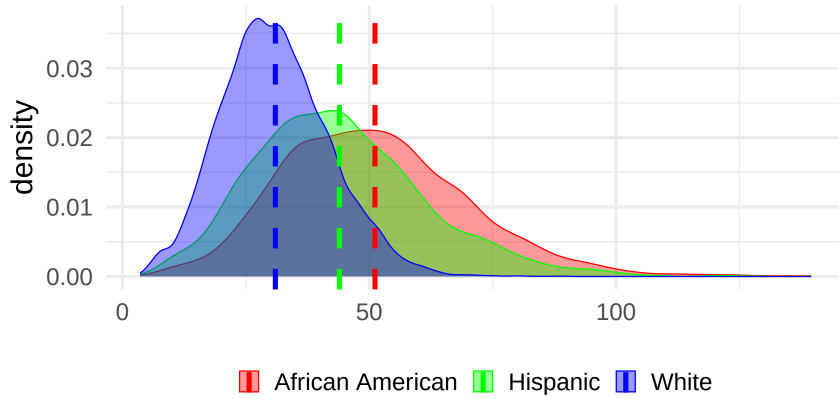
The differences in preferences, wages, and access to news providers then translate into different time-use patterns.[42] Figure 2 plots the densities of time-use allocations by race and ethnicity predicted by our model. We find large and significant differences in time allocated to local news acquisition. 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 or adoption 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 the extent to which the gaps in time-use in news consumption can be explained by these three factors.

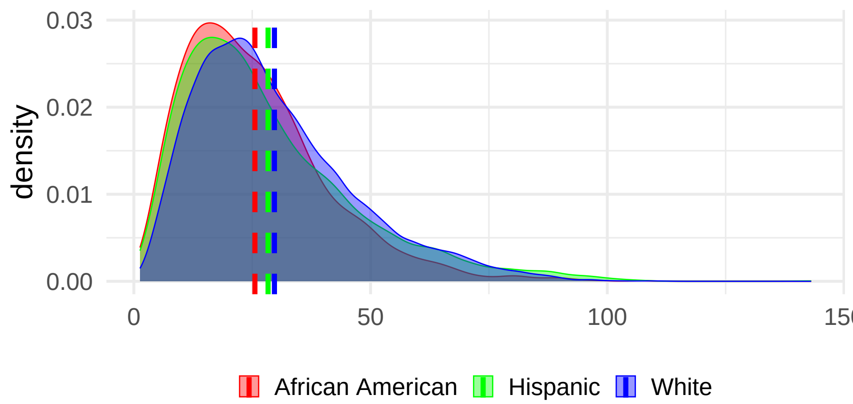
lations that multiply the predicted daily time changes by the average wage rate. Such calculations would suggest daily valuations of \$1.39, \$1.42, and \$0.59 for local, national, and international news, respectively. As a benchmark, daily subscription prices for major newspapers are typically between \$0.50 and \$1.50 per day, and basic cable television packages cost roughly \$2.00 to \$3.00 per day. Our WTP estimates for a ten percent productivity improvement are within the range of these daily expenditures on news access.

[42] The survey asks: "How often do you get local news and information from [a list of providers]?" We interpret a "Never" response as indicating that the provider is not part of the individual's bundle (choice set), and treat bundles as given in our counterfactual exercises. An alternative interpretation is that "Never" reflects a behavioral choice rather than an access constraint. Our model can accommodate this by assuming universal access and treating "Never" as the lowest time-use category. Under this interpretation, the variation attributed to the access channel would be absorbed by preferences, reinforcing our finding that preferences and opportunity costs are the primary drivers of informational gaps.

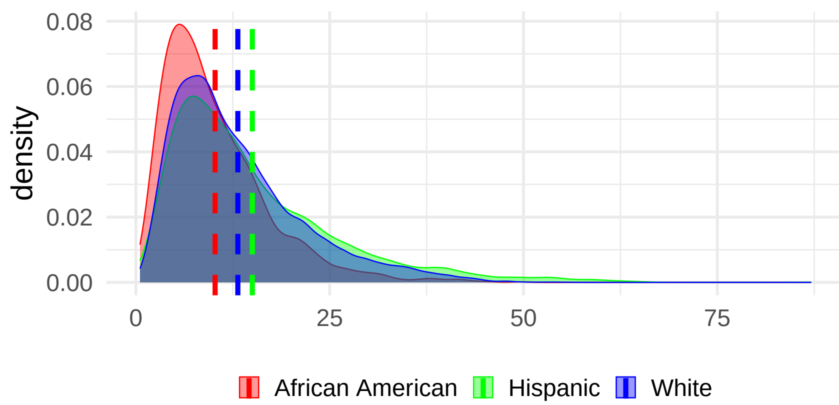
Figure 2: Predicted Time Allocations by Race and Ethnicity



(a) Local



(b) National



(c) International

Table 9: Decomposition of Time-Use Gaps by News Type and Demographic Groups

	News Type	I Base Gap	II Remove Wage Diff	III Remove Pref Diff	IV Net 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

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.

Table 9 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 preferences. 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.

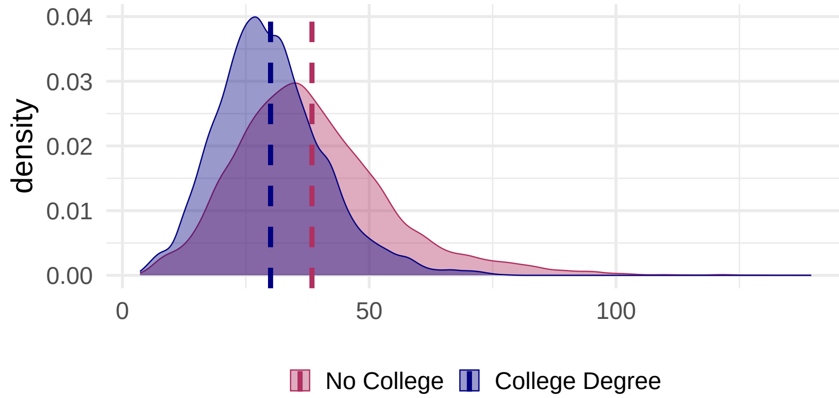
The composition of the local news gaps is similar for Hispanics. Both stronger preferences for local news and lower wages explain a significant fraction of the gap. Removing wage differences reduces the gap by about one-third, while preference differences explain about two-thirds of the gap. The net 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.

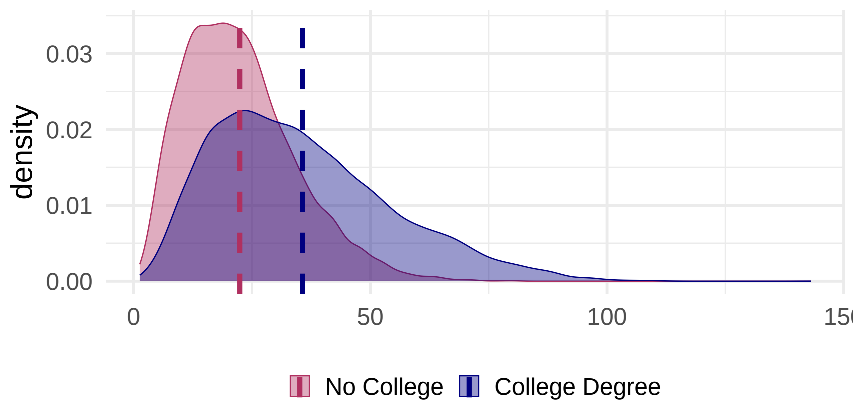
Table 9 shows the decomposition of the educational or skill gaps. Here we find that preferences and wage effects go in opposite directions. While college-educated individuals have stronger preferences for all news types, they have higher wages and hence higher opportunity costs of time. These two effects tend to offset each other. Table 9 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 or adoption of 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. There is not much variation in the choice sets in our sample. More than 60% individuals have access to 4 or 5 providers in their available bundles. Individuals with only one provider in the choice set are less than 3 percent of the sample. There are also only negligible differences by race

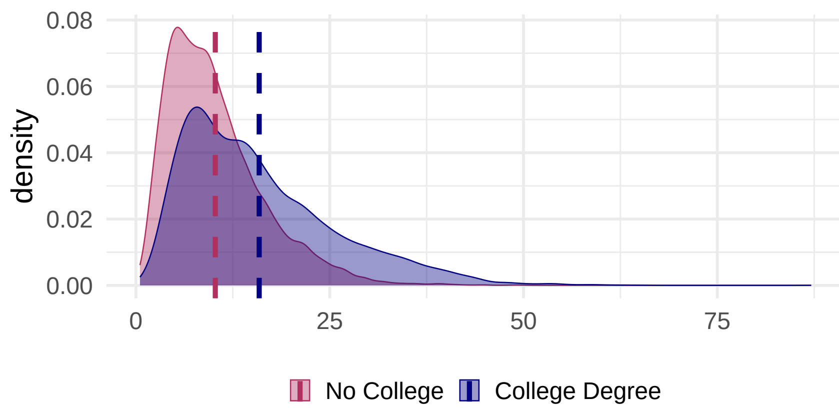
Figure 3: Predicted Time Allocations by Skill



(a) Local



(b) National



(c) International

or education. For example, African Americans have, on average, 3.86 providers in their choice set while whites have 3.78. In contrast, minorities (African Americans and Hispanics) have, on average, significantly 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.

9 Conclusions

Even though time allocations are fundamental to economic behavior, little is known about how individuals allocate time to acquire news. This lack of research is surprising since knowledge is increasingly important for decision-making. Using the LNS, we have provided compelling evidence that there are 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. 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.

The qualitative nature of the LNS survey data limits our ability to assess the economic magnitude of these differences, as it does not allow for direct measurement of time or resources devoted to news consumption. Measuring news acquisition on a cardinal scale, such as minutes allocated to different news topics, enables more precise comparisons and allows for an assessment of the associated welfare implications. To accomplish this task, 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 and non-market time devoted to news acquisition. Hence, wages serve as opportunity costs of time spent on news acquisition. We have shown how to estimate the model combining data from the LNS and the MCS.

We find that preferences, opportunity costs of time, and access to or adoption of different news sources drive the differences in informational gaps for news. 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. Our findings are supported by 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. Finally, our findings of time allocated to television for news acquisition are consistent with entertainment time-use patterns observed in the ATUS. This comparison provides some external validation of our survey data.

Our paper provides ample scope for future research. 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.[43] 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, we only observe time allocations for news consumption. Individuals allocate much more time to entertainment than to news acquisition. As a consequence, bundle choices are primarily driven by the demand for entertainment. Hence, 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 should be useful to study endogenous provider

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

choices assuming one can collect the data that currently do not exist.

Similarly, one could relax some of our assumptions if one obtained access to more comprehensive data. For example, our paper captures the explicit tradeoff between time allocated to news gathering and time spent in the labor market. Time spent on news gathering may, in reality, also compete with time spent on physical activity, entertainment, and other activities. Hence, there is also a tradeoff between non-market time alternatives, which would be interesting to study. Finally, time spent on news gathering and time spent working may also not be exclusive activities. Another natural extension would be to allow the productivity parameters to vary over time, which would capture changes in the media landscape such as the decline of print and the rise of digital platforms. Our current specification treats productivity as time-invariant, which is supported by the fact that the average time allocated to news in the MCS has been remarkably stable between 2004 and 2012 (see Table 3). Nevertheless, allowing for time-varying productivity would be a useful extension if panel data on news consumption become available. More research is needed to address these issues.

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A Gaps in Time Allocated to Different Providers

Here, 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 10 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.

Table 10: Time Allocations Among Local News Providers

	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

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 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.

B Providers and Topics

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

Table 11: Set of Providers

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 the local daily newspaper - Social media posts of other communities or specialized newspapers - 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 social media posts

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

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 overestimates the time-use for the oldest category.

Figure 4: Total Daily Minutes on News by Age Group

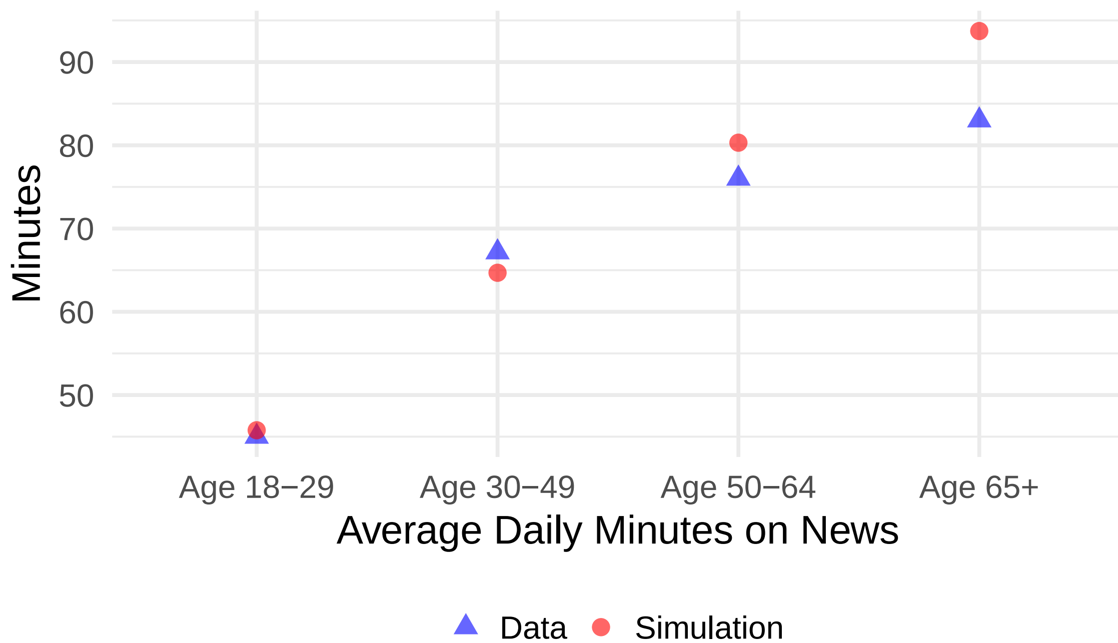


Figure 5 illustrates the fit of our model for the categorical time-use variable for each local news provider by age. This is one of the key outcomes we observe in the LNS. Figure 6 repeats this exercise conditioning on race instead of age.

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.

Finally, Figures 9 and 10 show the fit of the model for local, national, and international news by age and race.

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

Figure 5: Time-Use Conditional on Provider by Age

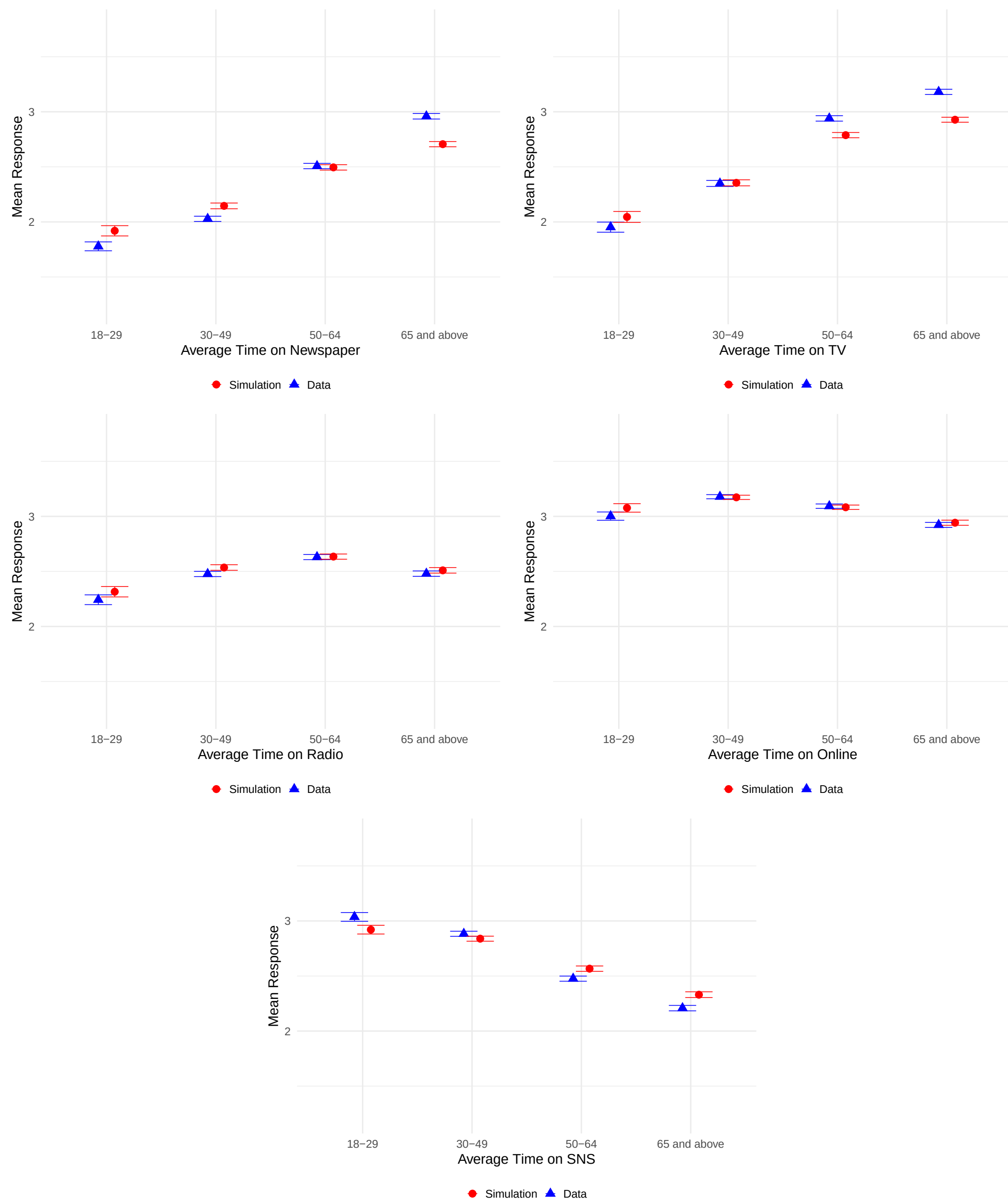


Figure 6: Time-Use Conditional on Provider by Race

Figure 7: Preferences for Local News Topics by Age

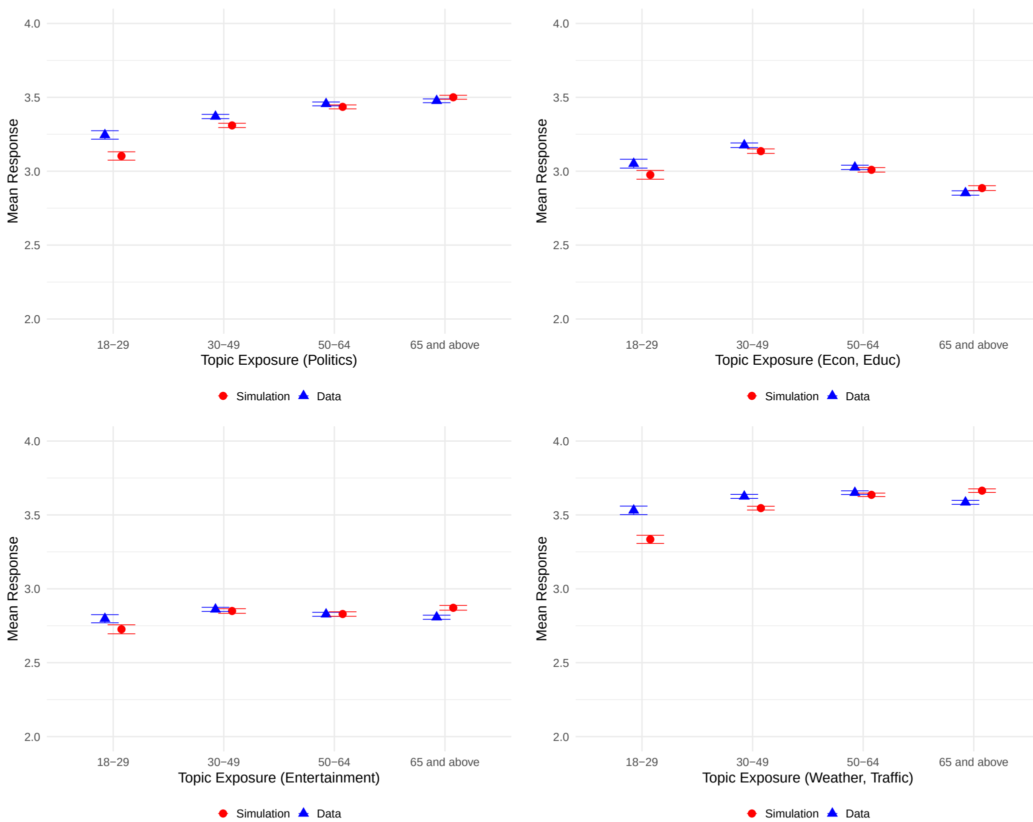


Figure 8: Preferences for Local News Topics by Race

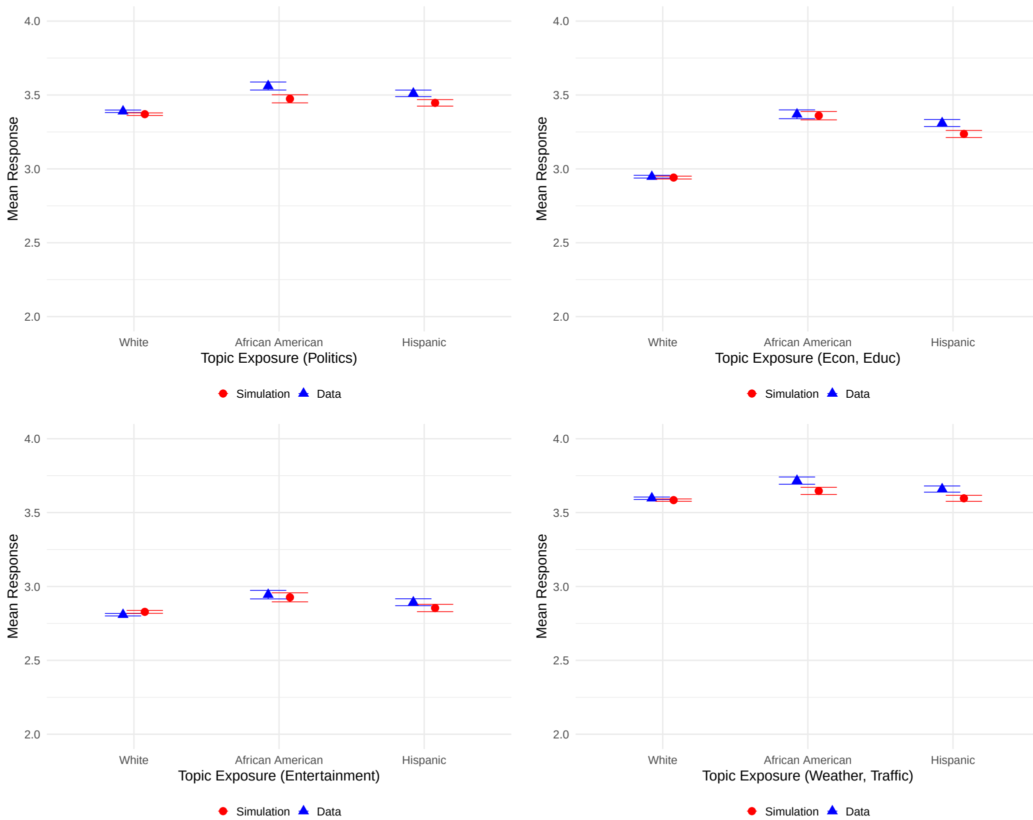


Figure 9: Time-Use Conditional on News Type by Age

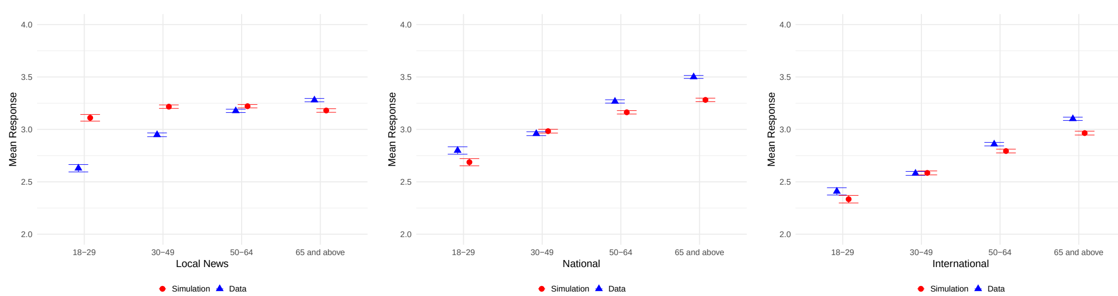
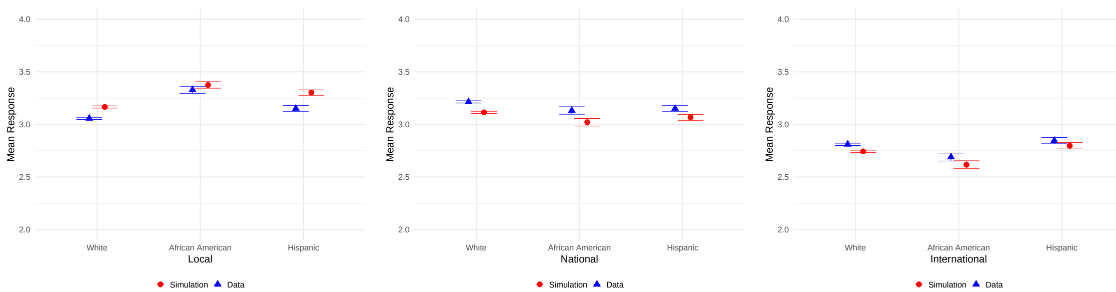


Figure 10: Time-Use Conditional on News Type by Race



D Data Validation Based on the ATUS

In this section, we compare our results with data from the American Time Use Survey (ATUS). While the ATUS does not collect detailed news consumption data, it provides comprehensive data on television watching for entertainment, allowing us to assess whether our data reflect broader media consumption patterns.

We compare three measures of TV consumption using identical control variables:

1. LNS: Categorical responses on local TV news consumption
2. Model Predictions: Daily minutes watching TV for news simulated from our structural model
3. ATUS: Daily minutes watching entertainment TV

Table 12 reveals consistent demographic patterns across all measures, providing strong validation for our data and model. In particular, African Americans show systematically higher TV consumption across all measures. They have 72% higher odds of frequent local TV news consumption (LNS), spend 4.52 additional minutes per day on local TV news (model), and watch 31.13 more minutes of entertainment TV daily (ATUS) compared to whites.

Educational patterns, age effects, and marital status show remarkable consistency across all measures, with college graduates, younger individuals, and married respondents consistently showing lower TV consumption for both news and entertainment. Some interesting dissimilarities emerge for Hispanics and by income group, which reflects higher information-seeking preferences rather than general TV viewing habits. Hispanics consume more TV news but less entertainment TV than whites, while higher income groups show increased news consumption but decreased entertainment consumption, suggesting these patterns reflect higher preferences for news content.

Table 12: Time on TV

	TV for news			TV for entertainment
	LNS	Model	Model	ATUS
		Local	All news	
	Categorical	Daily Minutes	Daily Minutes	Daily Minutes
Black	0.54***	4.52***	5.39***	31.13***
	(0.04)	(0.11)	(0.23)	(4.18)
Hispanic	0.19***	2.70***	5.78***	−22.46***
	(0.04)	(0.10)	(0.21)	(4.29)
Age	0.48***	1.46***	5.93***	2.92***
	(0.01)	(0.03)	(0.06)	(0.08)
Male	−0.10***	−1.82***	2.87***	45.00***
	(0.02)	(0.06)	(0.12)	(2.75)
Married	−0.08***	−1.54***	−3.08***	−23.89***
	(0.02)	(0.06)	(0.13)	(2.95)
HS Graduate	−0.22***	−3.76***	−5.74***	−12.08**
	(0.08)	(0.19)	(0.40)	(5.11)
Some College	−0.38***	−5.12***	−8.01***	−35.92***
	(0.07)	(0.19)	(0.38)	(5.05)
College Grad	−0.65***	−6.54***	−5.88***	−68.10***
	(0.07)	(0.19)	(0.39)	(5.11)
Income Tercile 2	0.08***	0.44***	1.53***	−23.92***
	(0.03)	(0.08)	(0.15)	(3.53)
Income Tercile 3	0.13***	0.82***	2.93***	−34.97***
	(0.03)	(0.08)	(0.17)	(4.01)
Constant		8.17***	1.94	92.99***
		(0.62)	(1.27)	(6.41)
City FE	Yes	Yes	Yes	Yes
Observations	27,352	27,352	27,352	17,879
R^2		0.26	0.30	0.14