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2 What Are We Not Doing When We Are Online?

Scott Wallsten

2.1 Introduction

The Internet has transformed many aspects of how we live our lives, but the magnitude of its economic benefits is widely debated. Estimating the value of the Internet is difficult, in part, not just because many online activities do not require monetary payment, but also because these activities may crowd out other, offline, activities. That is, many of the activities we do online, like reading the news or chatting with friends, we also did long before the Internet existed. The economic value created by online activities, therefore, is the incremental value beyond the value created by the activities crowded out. Estimates of the value of the Internet to the economy that do not take into account these transfers will, therefore, overstate the Internet's economic contribution.

This observation is, of course, not unique to the Internet. In the 1960s Robert Fogel noted that the true contribution of railroads to economic growth was not the gross level of economic activity that could be attributed to them, but rather the value derived from railroads being better than previously existing long-haul transport such as ships on waterways (Fogel 1962,

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1964). The true net economic benefit of the railroad was not small, but was much smaller than generally believed.

This chapter takes to heart Fogel's insight and attempts to estimate changes in leisure time spent online and the extent to which new online activities crowd out other activities. If people mostly do online what they used to do offline, then the benefits of time spent online are biased upward, potentially by a lot. In other words, if online time substitutes for offline time then that online time purely represents an economic transfer, with the net incremental benefit deriving from advantages of doing the activity online, but not from the time doing the activity, per se. By contrast, brand new online activities or those that complement offline activities do create new value, with activities crowded out representing the opportunity cost of that new activity.

Using the available data, this chapter does not evaluate which online activities substitute or complement offline activities. Instead, it estimates the opportunity cost of online leisure time. The analysis suggests that the opportunity cost of online leisure is less time spent on a variety of activities, including leisure, sleep, and work. Additionally, the effect is large enough that better understanding the value of this opportunity cost is a crucial issue in evaluating the effects of online innovation.

To my knowledge, no empirical research has investigated how leisure time online substitutes for or complements other leisure activities.[1] In this chapter I begin to answer that question using detailed data from the American Time Use Survey, which allows me to construct a person-level data set consisting of about 124,000 observations from 2003 to 2011.

I find that the share of Americans reporting leisure time online has been increasing steadily, and much of it crowds out other activity. On average, each minute of online leisure is associated with 0.29 fewer minutes on all other types of leisure, with about half of that coming from time spent watching TV and video, 0.05 minutes from (offline) socializing, 0.04 minutes from relaxing and thinking, and the balance from time spent at parties, attending cultural events, and listening to the radio. Each minute of online leisure is also correlated with 0.27 fewer minutes working, 0.12 fewer minutes sleeping, 0.10 fewer minutes in travel time, 0.07 fewer minutes in household activities, and 0.06 fewer minutes in educational activities, with the remaining time coming from sports, helping other people, eating and drinking, and religious activities.

Among the interesting findings by population groups, the crowd-out effect of online leisure on work decreases beyond age thirty, but remains fairly con-

1. One existing study tries to investigate the effects of information technology (IT) use using the same data I use in this chapter, though only from 2003 to 2007. The author finds no particular effect of IT use on other time spent on other activities, though the empirical test is simply whether IT users and nonusers spend significantly different amounts of time on various activities. See Robinson (2011).

stant with income. Online leisure has a large crowd-out effect on time spent on education among people age fifteen to nineteen, but the effect decreases steadily with age.

2.2 Existing Research on the Economic Value of the Internet

The value of the Internet is intrinsically difficult to estimate, in part, because it enables so many activities and, in part, because many of the most popular online activities are "free" in the sense that they have no direct monetary cost to consumers. Several tools exist for valuing nonmarket goods, such as contingent valuation surveys to revealed preference inferred by related market activities (Boardman et al. 1996). Those mechanisms have shortcomings. In principle, contingent valuation can tell you willingness to pay, but people often have no reason to respond truthfully to contingent valuation surveys. Measuring spending on relevant complements reveals how much people spend on an activity, but not how much they would be willing to spend.

Given those weaknesses, perhaps the most common approach to valuing time spent on activities outside of work is to value that time at the wage rate under the implicit assumption that the marginal minute always comes from work. Of course, that assumption may be problematic, as those who employ that approach readily admit. Nevertheless, it is a useful starting point.

Goolsbee and Klenow (2006) were among the first to apply this approach to the Internet. They estimated the consumer surplus of personal (i.e., nonwork) online time using the wage rate as the measure of time value and an imputed demand curve. They estimated a consumer surplus at about $3,000 per person. Setting aside the question of whether the wage rate is an accurate measure of the value of all leisure time, this approach provides an estimate of gross consumer surplus as it does not measure incremental benefits.

Brynjolfsson and Oh (2012) improves on Goolsbee and Klenow with newer survey data from 2003 to 2010 to measure the value of incremental time spent online. Although they also use the wage rate to estimate surplus, their estimates are smaller in magnitude because they focus on the increase in time spent online over this time period rather than the aggregate time spent online. Based on that approach, they estimate the increase in consumer surplus from the Internet to be about $33 billion, with about $21 billion coming from time spent using "free" online services.

Both Goolsbee and Klenow (2006) and Brynjolfsson and Oh (2012) almost certainly overestimate the true surplus created by the Internet, even setting aside the question of whether all leisure time should be valued at the wage rate. In particular, they neglect to factor in the extent to which consumers are simply doing some things online that they used to do offline and that new activities must, at least partially, come at the expense of activities they are no longer doing. Spending an hour reading the paper online shows up as a "free" activity, assuming no subscriber paywall, but is not intrinsically more valuable than the same hour spent reading the news on paper. Similarly, the net benefit of reading an electronic book on a Kindle, for example, does not include the time spent enjoying the book if it would have otherwise been read in dead-tree format. Instead, the net benefit is only the incremental value of reading an electronic, rather than paper, book.

To be sure, the online version of the newspaper must generate additional consumer surplus relative to the offline version or the newspaper industry would not be losing so many print readers, but not all time spent reading the paper online reflects the incremental value of the Internet. Additionally, at a price of zero the activity might attract more consumers than when the activity was paid, or consumers might read more electronic books than paper books because they prefer the format, or because e-books are so much easier to obtain. But even if lower prices increase consumption of a particular activity, the cost of that additional consumption is time no longer spent on another activity.

Activities that once required payment but became free, such as reading the news online, represent a transfer of surplus from producers to consumers, but not new total surplus. Of course, these transfers may have large economic effects as they can lead to radical transformations of entire industries, especially given that consumers spend about $340 billion annually on leisure activities.[2] Reallocating those $340 billion is sure to affect the industries that rely on it. Hence, we should expect to see vigorous fights between cable, Netflix, and content producers even if total surplus remains constant. Similarly, as Joel Waldfogel shows in this volume (chapter 14), the radical transformation in the music industry does not appear to have translated into radical changes in the amounts of music actually produced. That is, the Internet may have thrown the music industry into turmoil, but that appears to be largely because the Internet transferred large amounts of surplus to consumers rather than changing net economic surplus.

As the number and variety of activities we do online increases, it stands to reason that our Internet connections become more valuable to us. Greenstein and McDevitt (2009) estimate the incremental change in consumer surplus resulting from upgrading from dialup to broadband service based on changes in quantities of residential service and price indices. They estimate the increase in consumer surplus related to broadband to be between $4.8 billion and $6.7 billion.

2. See table 57 at http://www.bls.gov/cex/2009/aggregate/age.xls. The $340 billion estimate includes expenditures on entertainment, which includes "fees and admissions," "audio and visual equipment and services," "pets, toys, hobbies, and playground equipment," and "other entertainment supplies, equipment, and services." I added expenditures on reading to entertainment under the assumption that consumer expenditures on reading are likely to be primarily for leisure.

Rosston, Savage, and Waldman (2010) explicitly measure consumer willingness to pay for broadband and its various attributes using a discrete choice survey approach. They find that consumers were willing to pay about $80 per month for a fast, reliable broadband connection, up from about $46 per month since 2003. In both years the average connection price was about $40, implying that (household) consumer surplus increased from about $6 per month in 2003 to $40 per month in 2010. That change suggests an increase of about $430 per year in consumer surplus between 2003 and 2010. Translating this number into total consumer surplus is complicated by the question of who benefits from each broadband subscription and how to consider their value from the connection. That is, a household paid, on average, $40 per month for a connection, but does each household member value the connection at $80? Regardless of the answer to that question, Rosston, Savage, and Waldman's (2010) estimate is clearly well below Goolsbee and Klenow (2006).

In the remainder of the chapter I will build on this research by explicitly estimating the cost of online activities by investigating the extent to which online activities crowd out previous activities.

2.3 The American Time Use Survey, Leisure Time, and Computer Use

Starting in 2003, the US Bureau of Labor Statistics and the US Census began the American Time Use Survey (ATUS) as a way of providing "nationally representative estimates of how, where, and with whom Americans spend their time, and is the only federal survey providing data on the full range of nonmarket activities, from childcare to volunteering."[3]

Each year the survey includes about 13,000 people (except in 2003, when it included about 20,000) whose households had recently participated in the Current Population Survey (CPS).[4] From the relevant BLS files we constructed a 2.5 million-observation data set at the activity-person-year level for use in identifying the time of day in which people engage in particular activities, and a 124,000-observation, person-year-level data set for examining the crowd-out effect.

The ATUS has several advantages for estimating the extent to which online time may crowd out or stimulate additional time on other activities. First, each interview covers a full twenty-four-hour period, making it

3. http://www.bls.gov/tus/atussummary.pdf.

4. More specifically, BLS notes that "Households that have completed their final (8th) month of the Current Population Survey are eligible for the ATUS. From this eligible group, households are selected that represent a range of demographic characteristics. Then, one person age 15 or over is randomly chosen from the household to answer questions about his or her time use. This person is interviewed for the ATUS 2–5 months after his or her household's final CPS interview." See http://www.bls.gov/tus/atusfaqs.htm.

possible to study how time spent on one activity might affect time spent on another activity. Second, it is connected to the CPS, so it includes copious demographic information about the respondents.

Third, the survey focuses on activities, not generally on the tools used to conduct those activities. So, for example, reading a book is coded as "reading for personal interest" regardless of whether the words being read are of paper or electronic provenance.[5] As a result, the value of the time spent reading would not be mistakenly attributed to the Internet when using these data. Similarly, time spent watching videos online would be coded as watching TV, not computer leisure time.

The survey does, however, explicitly include some online activities already common when the survey began in 2003. In particular, time spent doing personal e-mail is a separate category from other types of written communication.[6] Online computer games, however, are simply included under games.

The ATUS coding rules therefore imply that any computer- or Internet-based personal activity that did not exist in 2003 as its own category would be included under "Computer use for leisure (excluding games)," which includes "computer use, unspecified" and "computer use, leisure (personal interest)."[7] For example, Facebook represents the largest single use of online time today, but ATUS has no specific entry for social media, and therefore Facebook would almost certainly appear under computer use for leisure.

This feature of the ATUS means that increases in computer use for leisure represent incremental changes in time people spend online and that it should be possible to determine the opportunity cost of that time—what people gave up in order to spend more time online. It is worth noting, however, that the ATUS does not code multitasking, which is a distinct disadvantage to this research to the extent that online behavior involves doing multiple activities simultaneously. In principle the survey asks whether the respondent is doing multiple activities at a given time, but only records the "primary" activity.

To reiterate, the ATUS does not make it possible to determine, say, how much time spent watching video has migrated from traditional television to online services like Netflix. It does, however, tell us how new online activities since 2003 have crowded out activities that existed at that time and—to extend the video example—how much those activities have crowded out (or in) time spent watching video delivered by any mechanism.

A significant disadvantage of the survey, however, is that as a survey,

5. More explicitly, reading for pleasure is activity code 120312: major activity code 12 (socializing, relaxing, and leisure), second-tier code 03 (relaxing and leisure), third-tier code 12 (reading for personal interest). http://www.bls.gov/tus/lexiconwex2011.pdf.

6. Code 020904, "household and personal e-mail and messages," which is different from code 020903 "household and personal mail and messages (not e-mail). See http://www.bls.gov/tus/lexiconwex2011.pdf, p.10. Inexplicably, however, any time spent doing volunteer work on a computer is its own category (150101) (http://www.bls.gov/tus/lexiconwex2011.pdf, p.44).

7. See http://www.bls.gov/tus/lexiconwex2011.pdf, p. 34.

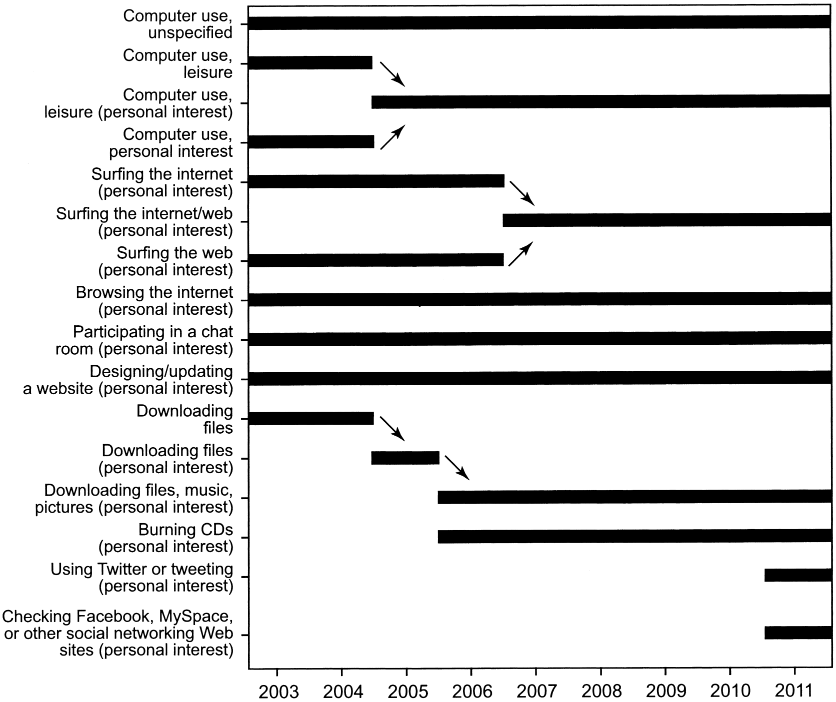

Fig. 2.1 Evolution of examples of "computer use for leisure" provided for ATUS coders

Source: "ATUS Single-Year Activity Coding Lexicons," 2003–2011, http://www.bls.gov/tus/lexicons.htm.

as discussed above, respondents have little reason to respond truthfully, especially about sensitive subjects. For example, would viewing pornography online be categorized under "computer use for leisure" (based on the "unspecified" example in the codebook), or under "personal/private activities" (also the "unspecified" example under this subcategory)?

2.3.1 "Computer Use for Leisure" is Online Time

The relevant ATUS category is time spent using a computer for leisure.[8] This measure explicitly excludes games, e-mail, and computer use for work and volunteer activities. While some computer leisure activities may not necessarily involve the Internet, nearly all of the many examples provided to interviewers under that heading involve online activities (figure 2.1). Addi-

8. Computer games are simply recorded as "leisure/playing games," and e-mail is coded as "household and personal e-mail and messages." Text messaging is recorded as "telephone calls." Bureau of Labor Statistics (2010).

Table 2.1 Top ten online activities by time spent on them

		Share of time			Position change
Rank	Category	May–11 (%)	Jun–10 (%)	Jun–09 (%)	'10–'11 (%)
1	Social networks	22.50	22.70	15.80	↔
2	Online games	9.80	10.20	9.30	↔
3	E-mail	7.60	8.50	11.50	↔
4	Portals	4.50	4.40	5.50	↔
5	Videos/movies[a]	4.40	3.90	3.50	↑1
6	Search	4.00	3.50	3.40	↑1
7	Instant messaging	3.30	4.40	4.70	↓2
8	Software manufacturers	3.20	3.30	3.30	↔
9	Classifieds/auctions	2.90	2.70	2.70	↑1
10	Current events and global news	2.60	—	—	↑1
	Multicategory entertainment	—	2.80	3.00	↓2
	Other[b]	35.10	34.30	37.30	

Source: Nielsen NetView (June 2009–2010) and Nielsen State of the Media: The Social Media Report (Q3 2011).

[a]Nielsen's videos/movies category refers to time spent on video-specific (e.g., YouTube, Bing Videos, Hulu) and movie-related websites (e.g., IMDB, MSN Movies, and Netflix). It does not include video streaming non–video-specific or movie-specific websites (e.g., streamed video on sports or news sites).

[b]Other refers to 74 remaining online categories for 2009–2010 and 75 remaining online categories for 2011 visited from PC/laptops.

tionally, while the measure is coded as "computer use for leisure," based on the coding instructions it also likely includes mobile device use.

Based on what the ATUS measure excludes and other sources of information detailing what online activities include, we can get a good idea of what people are probably spending their time doing. Nielsen identifies the top ten online activities (table 2.1). Of the top ten, the ATUS variable excludes online games, e-mail, and any Internet use for work, education, or volunteer activities. Based on this list, it is reasonable to conclude that the top leisure uses included in the ATUS variable are social networks, portals, and search.

2.3.2 How Do Americans Spend Their Time?

The *New York Times* produced an excellent representation of how Americans spend their time from the ATUS (figure 2.2). As the figure highlights, ATUS data track activities by time of day and activity, as well as by different population groupings due to coordination with the CPS. Each major activity in the figure can be broken down into a large number of smaller activities under that heading. The figure reveals the relatively large amount of time people spend engaged in leisure activities, including socializing and watching TV and movies.

The ATUS includes detailed data on how people spend their leisure time.

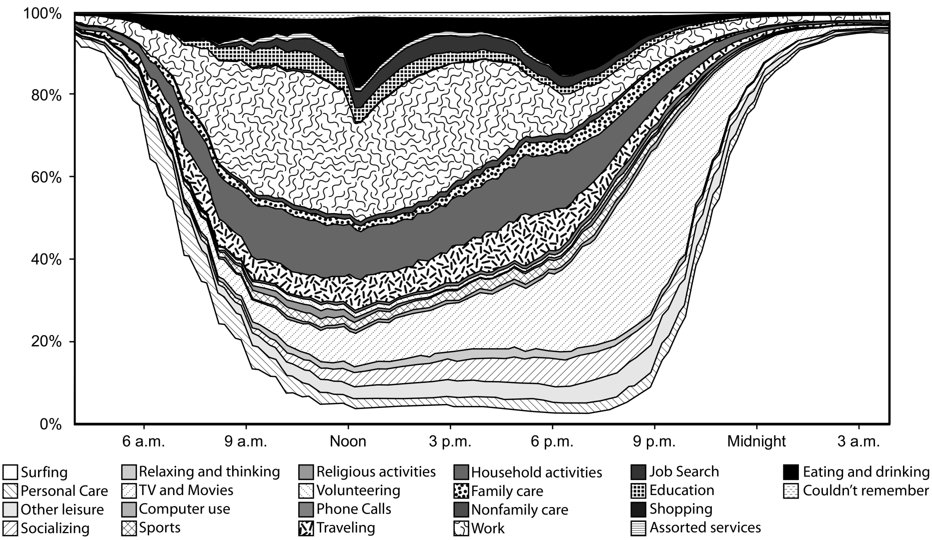

Fig. 2.2 How Americans spent their time in 2008, based on ATUS
Source: New York Times (2009). http://www.nytimes.com/interactive/2009/07/31/business/20080801–metrics-graphic.html.

The ATUS has seven broad categories of leisure, but I pull "computer use for leisure" out of the subcategories to yield eight categories of leisure. Figure 2.3 shows the share of time Americans spent on these leisure activities in 2011.

The total time Americans engage in leisure on average per day has remained relatively constant at about five hours, increasing from 295 minutes in 2003 to about 304 minutes in 2011, though it has ranged from 293 to 305 minutes during that time.

Figure 2.4 shows the average number of minutes spent per day using a computer for leisure activities. While the upward trend since 2008 is readily apparent, the data also show that, on average, at about thirteen minutes per day, leisure time online is a small share of the total five hours of daily leisure activities the average American enjoys.

This average is deceptively low, in part, not just because it does not include time spent doing e-mail, watching videos, and gaming, but also because it is calculated across the entire population, so is not representative of people who spend any time online. Figure 2.5 shows that the average is low primarily because a fairly small share of the population reports spending any leisure time online (other than doing e-mail and playing games). However, the figure shows that the share of the population who spend nongaming and non–e-mail leisure time online is increasing, and, on average, people who spend any leisure time online spend about 100 minutes a day—nearly one-third of their total daily leisure time.

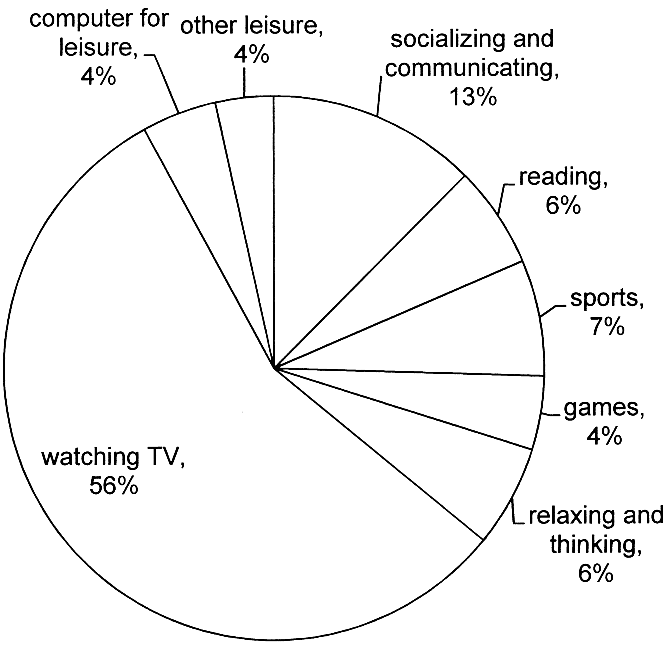

Fig. 2.3 Share of leisure time spent on various activities, 2011
Source: ATUS 2011 (author's derivation from raw data).
Note: Average total daily leisure time is about five hours.

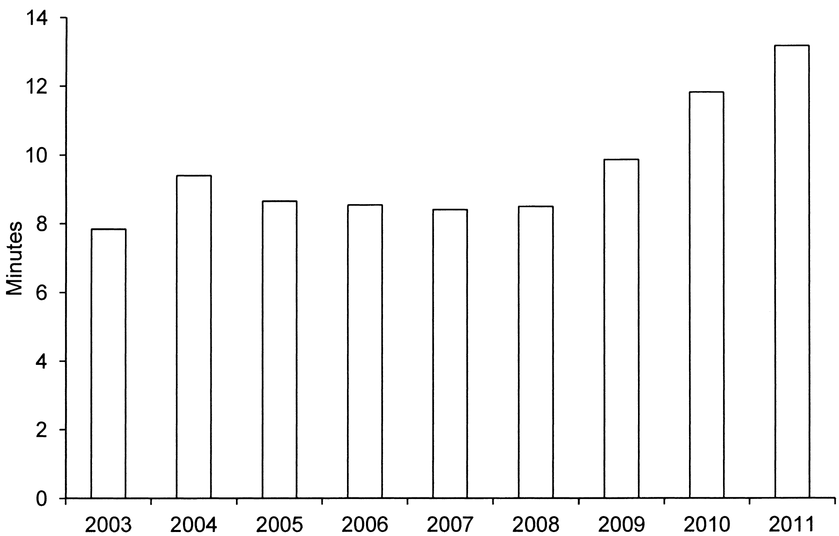

Fig. 2.4 Average minutes per day spent using computer for leisure

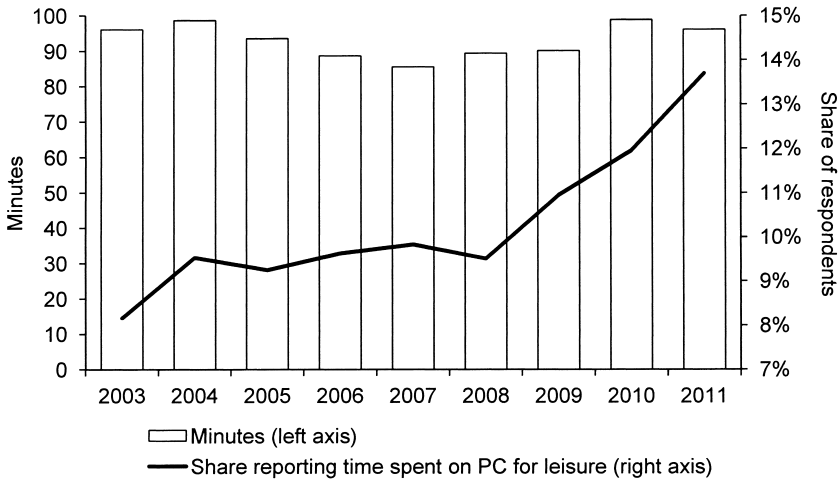

Fig. 2.5 Share of population using computer for leisure and average number of minutes per day among those who used a computer for leisure

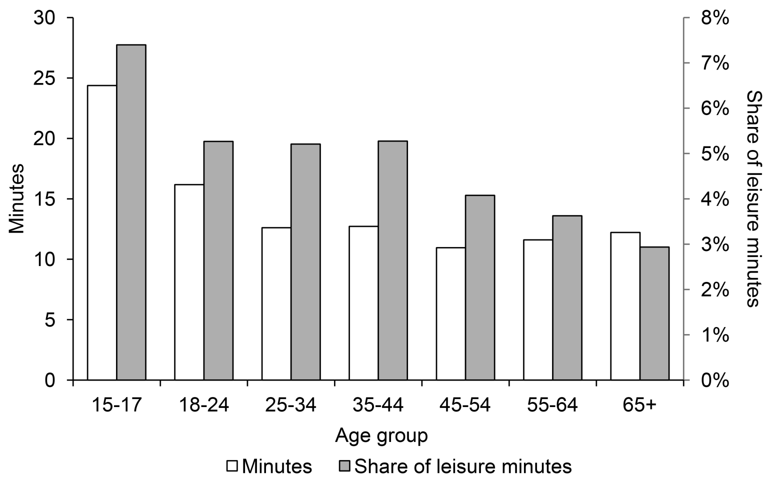

Fig. 2.6 Minutes and share of leisure time online by age group in 2010

2.3.3 Who Engages in Online Leisure?

Online leisure time differs across many demographics, including age and income. As most would expect, the amount of online leisure time decreases with age, more or less (figure 2.6). People between ages fifteen and seventeen spend the most time online, followed by eighteen- to twenty-four-year-olds. Perhaps somewhat surprisingly, the remaining age groups report spending similar amounts of time engaged in online leisure. However, because total

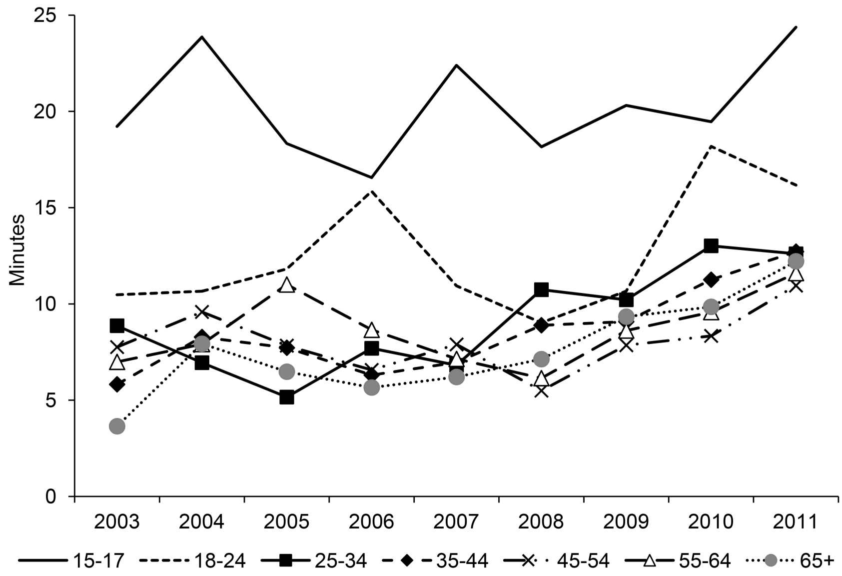

Fig. 2.7 Time spent using computer for leisure by age and year

leisure time increases with age, beginning with the group age thirty-five to forty-four, the share of leisure time spent online continues to decrease with age.

Perhaps not surprisingly given the trends discussed above, both the amount of leisure time spent online (figure 2.7) and the share of respondents reporting spending leisure time online is generally increasing over time (figure 2.8).

Leisure time also varies by income. Figure 2.9 shows average total leisure time excluding computer use and computer use for leisure by income. The figure shows that overall leisure time generally decreases with income. Computer use for leisure, on the other hand, appears to increase with income.

People with higher incomes, however, are more likely to have computer access at home, meaning average computer use by income is picking up the home Internet access effect.

Goldfarb and Prince (2008) investigated the question of online leisure by income in a paper investigating the digital divide. Based on survey data from 2001, they find that conditional on having Internet access, wealthier people spend less personal time online than poorer people. Their key instrument identifying Internet access is the presence of a teenager living in the house, which may make a household more likely to subscribe to the Internet but not more likely to spend personal time online except due to having Internet access.

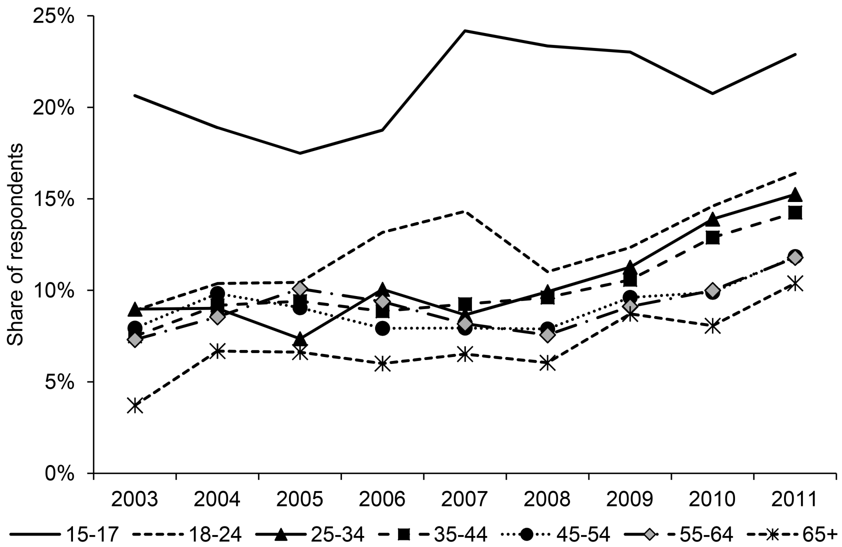

Fig. 2.8 Share of respondents reporting using computer for leisure by age and year

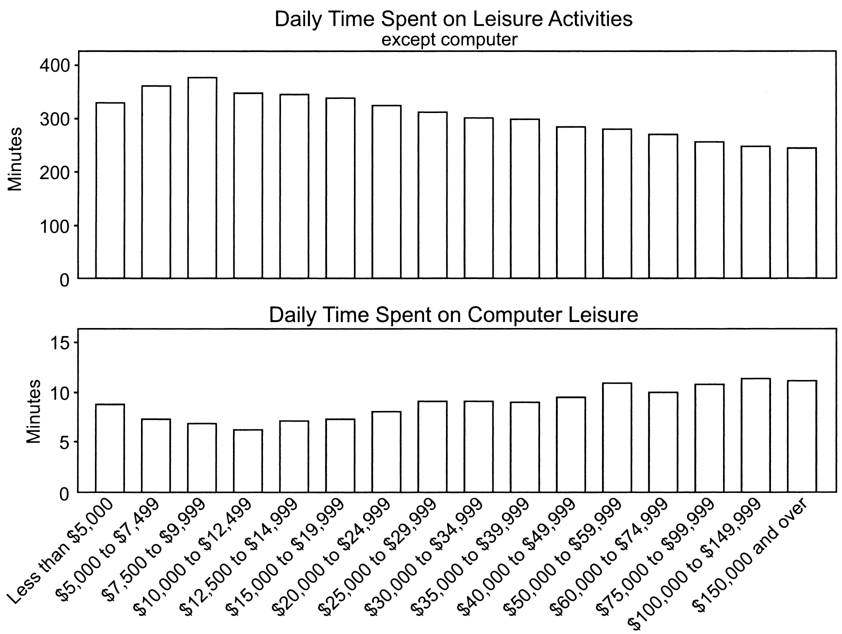

Fig. 2.9 Leisure time by income

With the ATUS data I can attempt to replicate their instrumental variables results using this more recent data. While I know the ages of all household members, the data do not indicate whether a household has Internet access. However, I can identify some households that have access. In particular, any ATUS respondent who spends any time at home involved in computer leisure, e-mail, or using a computer for volunteer work must have home Internet access. Following Goldfarb and Prince, I estimate the following two simultaneous equations using two-stage least squares:

$$\text{home Internet access}_i =$$

$$(1) \qquad f\left(\begin{array}{c} \text{income}_i, \text{education}_i, \text{ age}_i, \text{ sex}_i, \text{ race}_i, \text{ married}_i, \text{ number of children} \\ \text{in household}_i, \text{ Spanish-speaking only}_i, \text{ labor force status}_i, \\ (\text{metro, suburban, rural})_i, \text{ leisure excluding computer use}_i, \text{ year}_t, \\ \text{survey day of week}_i, \text{ teenager in house}_i \end{array}\right)$$

$$(2) \qquad \text{computer use for leisure}_i = f\left((\mathbf{Z}), \widehat{\text{home Internet access}_i}\right),$$

where i indicates a respondent, and **Z** is the vector of independent variables included in the first equation. Note the absence of a t subscript—no individual appears more than once in the survey, so the data are a stacked cross section rather than a pure time series. "Labor force status" is a vector of dummy variables indicating whether the respondent is employed and working, employed but absent from work, employed but on layoff, unemployed and looking for work, or not in the labor force. I include year dummy variables to control for time trends. I include an indicator for the day of the week the survey took place since certain activities—leisure time especially—differs significantly across days. As mentioned, my indicator for home Internet access identifies only a portion of households that actually have Internet access. This method implies that only 17 percent of households had access in 2010 when the US Census estimated that more than 70 percent actually had access.[9] Nevertheless, in the first stage of this two-stage model the variable is useful in creating a propensity to have access for use in the second stage in that while the level is wrong, the fitted trend in growth in Internet access tracks actual growth in access reasonably well. The fitted propensity to have access increases by about 70 percent while actual home Internet access increased by about 78 percent during that same time period.[10]

Table 2.2 shows the (partial) results of estimating the set of equations above. The first column replicates Goldfarb and Prince. These results mirror theirs: conditional on home Internet access, computer leisure time decreases with income. In order to see whether computer leisure looks different from

9. See http://www.ntia.doc.gov/files/ntia/data/CPS2010Tables/t11_2.txt.
10. See http://www.pewinternet.org/Trend-Data-(Adults)/Internet-Adoption.aspx.

Table 2.2 **Computer leisure as a function of income**

Variable	Computer leisure	Computer as share of leisure	Variable	Computer leisure	Computer as share of leisure
$10k–$19.9k	0.00264	0.00124	Black	3.078***	0.0101***
	(0.00453)	(0.748)		(4.590)	(5.414)
$20k–$29k	–1.015	–0.00238	American Indian	1.176	0.00801**
	(–1.371)	(–1.134)		(0.829)	(1.975)
$30k–$49k	–2.352***	–0.00622**	Asian	2.250***	0.0122***
	(–2.621)	(–2.477)		(3.194)	(5.864)
$50k–$75k	–3.510***	–0.0101***	White	–2.314*	–0.00195
	(–3.079)	(–3.148)	American Indian	(–1.842)	(–0.545)
$75k–$99k	–3.993***	–0.0108***	White Asian	8.130***	0.0227***
	(–3.257)	(–3.155)		(3.112)	(3.026)
$100k–$149k	–4.690***	–0.0122***	White Asian	42.55***	0.450***
	(–3.530)	(–3.241)	Hawaiian	(4.270)	(15.62)
> = $150k	–4.701***	–0.0124***	Spanish only Hhld	0.906*	0.00177
	(–3.699)	(–3.447)		(1.741)	(1.254)
Age	–0.0244	–6.83e–05	Monday	–2.568***	0.00127
	(–1.355)	(–1.241)		(–5.955)	(0.875)
Male	4.164***	0.00661***	Tuesday	–3.292***	–0.000695
	(18.00)	(9.131)		(–7.548)	(–0.461)
Grade 6	3.459**	0.0119***	Wednesday	–4.565***	–0.00189
	(2.086)	(2.582)		(–9.920)	(–1.107)
Grades 7, 8, 9	2.044**	0.00827***	Thursday	–3.374***	–0.00289*
	(2.180)	(3.005)		(–7.596)	(–1.853)
High school, no	3.450***	0.0100***	Friday	–0.781*	0.00240**
diploma	(3.910)	(3.903)		(–1.758)	(1.975)
High school grad.	1.777**	0.00345	Saturday	0.217	0.00127
	(2.154)	(1.429)		(0.498)	(1.030)
Some college	0.0904	–0.00229	Constant	1.988	0.00500
	(0.144)	(–1.281)		(1.067)	(1.289)
Associate/vocational	–0.0462	–0.00250	Observations	110,819	106,869
degree	(–0.0563)	(–1.067)	*R*-squared	0.176	0.238
Bachelor's	–4.004***	–0.00969***			
Master's	–5.909***	–0.0163***			
	(–5.276)	(–5.321)			
Professional	–2.928**	–0.0116***			
	(–2.374)	(–3.292)			
Doctoral	–5.557***	–0.0116***			
	(–3.809)	(–2.820)			

Notes: Other variables included but not shown: year fixed effects; number of household children; urban, rural, suburban status; labor force status. (Abridged results of second stage only; full results, including first stage, in appendix at http://www.nber.org/data-appendix/c13001/appendix-tables.pdf.)

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

other types of leisure, I change the dependent variable to computer leisure as a share of total leisure (column [2]). These results are similar in that conditional on home Internet access, computer time as a share of total leisure time decreases with income, although the effect is fairly small in magnitude above $50,000 in annual family income.

I also find that computer use for leisure decreases with education, conditional on access, although the effect on computer use as a share of leisure is less straightforward. For example, online leisure as a share of total leisure is less for people with master's degrees than for people with doctorate degrees. By race, people who identify as "White-Asian-Hawaiian" spend the most time engaged in online leisure, followed by "White-Asian," "Black," and finally "White." Not surprisingly, the largest amount of online leisure takes place on Saturday and Sunday, followed closely by Friday. Wednesday appears to have the least online leisure.

As Goldfarb and Prince note, these results shed some light on the nature of the digital divide. In particular, while we know from census and other data that a significant gap remains on Internet access conditional on access, poorer people and minorities are more likely to engage in computer leisure than are rich people and white people. Goldfarb and Prince note that these results are consistent with poorer people having a lower opportunity cost of time. These results, using ATUS data, are also consistent with that hypothesis. However, because, as shown above, poorer people engage in more leisure time overall, the results also suggest that online leisure may not be so different from offline leisure, at least in terms of how people value it.

2.3.4 What Times Do People Engage in Online Leisure?

As discussed, to better understand the true costs (and benefits) of time spent online, it is important to figure out the source of the marginal minute online—What activities does it crowd out? It is reasonable to assume that much of it comes from other leisure activities, since leisure time has remained unchanged for so many years, but it need not necessarily come only from other leisure time. To begin to understand where online time comes from, we first look at it in the context of some other (major) activities throughout the day. Figure 2.10 shows how sleep, work, leisure (excluding computer time), and computer time for leisure are distributed throughout the day. Not surprisingly, most people who work begin in the morning and end in the evening, with many stopping mid-day, presumably for lunch. People begin heading to sleep en masse at 9:00 p.m. with nearly half the population over age fifteen asleep by 10:00 p.m. and almost everyone asleep at 3:00 a.m. Leisure time begins to increase as people wake up and increases steadily until around 5:00 p.m. when the slope increases and the share of people engaged in leisure peaks at about 8:45 p.m. before dropping off as people go to sleep.

Time engaged in computer leisure, a subcategory of leisure, tracks overall

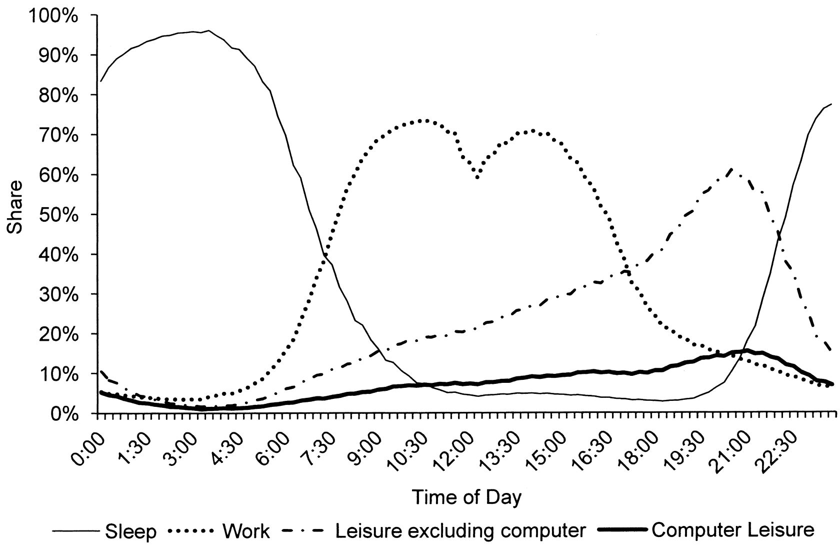

Fig. 2.10 Percentage of people who engage in major activities doing that activity throughout the day

leisure fairly well, but exhibits somewhat less variation. In particular, the peak in the evening is not as pronounced and continues later in the evening. This time distribution suggests that computer leisure may, in principle, crowd out not just other leisure activities, but also work, sleep, and other (smaller) categories. The next section investigates the extent to which online leisure crowds out these other categories.

2.4 What Does Online Leisure Crowd Out?

The ATUS has seventeen major categories of activities (plus one unknown category for activities that the interviewer was unable to code). Each of these major categories includes a large number of subcategories. The first step in exploring where online leisure time comes from is to investigate its effects at the level of these major categories. The second step will be investigating the effects within those categories.

2.4.1 Major Activity Categories

Figure 2.11 shows the average time spent on each of the eighteen major categories. Personal care, which includes sleep, represents the largest block of time, followed by leisure, work, and household activities.

To explore potential crowd-out effects, I begin by estimating eighteen versions of equation (3), once for each major activity category.

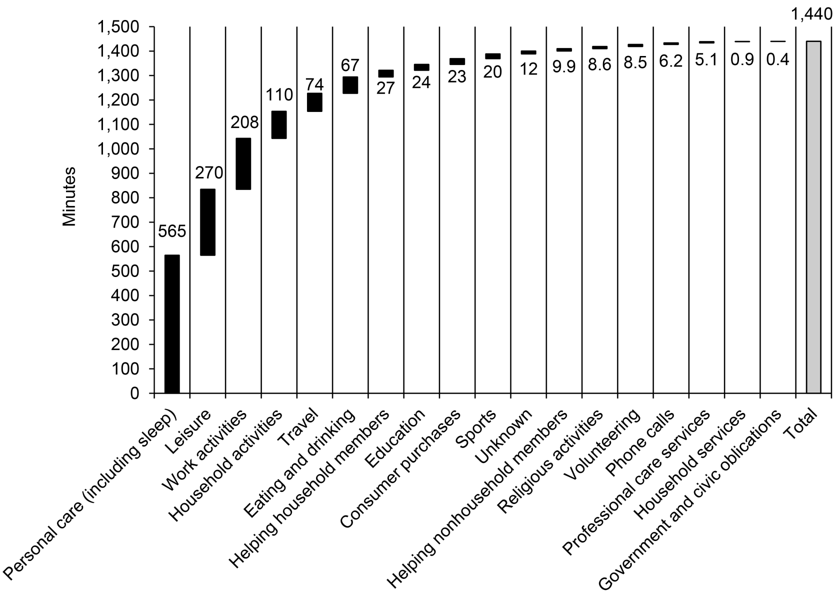

Fig. 2.11 Average time spent on daily activities, 2003–2011

$$\text{major activity}_i =$$

$$(3)\quad f\left(\begin{array}{c} \text{computer leisure}_i,\ \text{income}_i, \text{education}_i,\ \text{age}_i,\ \text{sex}_i,\ \text{race}_i,\ \text{married}_i, \\ \text{number children in household}_i,\ \text{occupation}_i \\ \text{Spanish-speaking only}_i,\ \text{labor force status}_i, (\text{metro, suburban, rural})_i, \\ \text{year}_t,\ \text{survey day of week}_i \end{array}\right).$$

Table 2.3 shows the coefficient (and t-statistic) on the computer leisure variable from each of the eighteen regressions.[11] Figure 2.12 shows the results graphically. Perhaps not surprisingly, since computer use for leisure is a component of the major leisure category, computer use for leisure has the largest effect on other leisure. Each minute spent engaged in computer leisure represents almost 0.3 minutes less of doing some other type of leisure. Online leisure appears to have a relatively large effect on time spent at work as well, with each minute of online leisure correlated with about 0.27 minutes less time working. Each minute of online leisure is also correlated with 0.12 minutes of personal care. Most other activities also show a negative, though much smaller, correlation with online leisure.

Travel time, too, is negatively correlated with online leisure time. Avoided

11. The full regression results are in an online appendix at http://www.nber.org/data-appendix/c13001/appendix-tables.pdf.

Table 2.3 **Estimated crowd-out effects of computer leisure on major categories**

Leisure (excluding computer)	–0.293***
	(22.34)
Work activities	–0.268***
	(19.38)
Personal care (including sleep)	–0.121***
	(12.36)
Travel	–0.0969***
	(17.36)
Household activities	–0.0667***
	(7.149)
Education	–0.0574***
	(8.560)
Sports	–0.0397***
	(9.17)
Helping household members	–0.0368***
	(7.589)
Eating and drinking	–0.0254***
	(6.991)
Helping nonhousehold members	–0.0232***
	(6.763)
Religion	–0.0146***
	(5.758)
Unknown	–0.0141***
	(4.080)
Volunteer	–0.0120***
	(3.503)
Professional care and services	–0.00360*
	(1.896)
Household services	–0.00129
	(1.583)
Government and civic obligations	–0.000177
	(0.303)
Consumer purchases	0.00368
	(1.025)
Phone calls	0.0134***
	(7.433)

Note: Equation (3) shows the variables included in each regression. Full regression results in appendix at http://www.nber.org/data-appendix/c13001/appendix-tables.pdf.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

* Significant at the 10 percent level.

travel time is generally considered a benefit, suggesting at least one area where the trade-off yields clear net benefits.

Phone calls are positively correlated with online leisure time, although the magnitude is small. It is conceivable that this result reflects identifying the type of person who tends to Skype. Calls made using Skype or similar VoIP services would likely be recorded as online leisure rather than phone calls

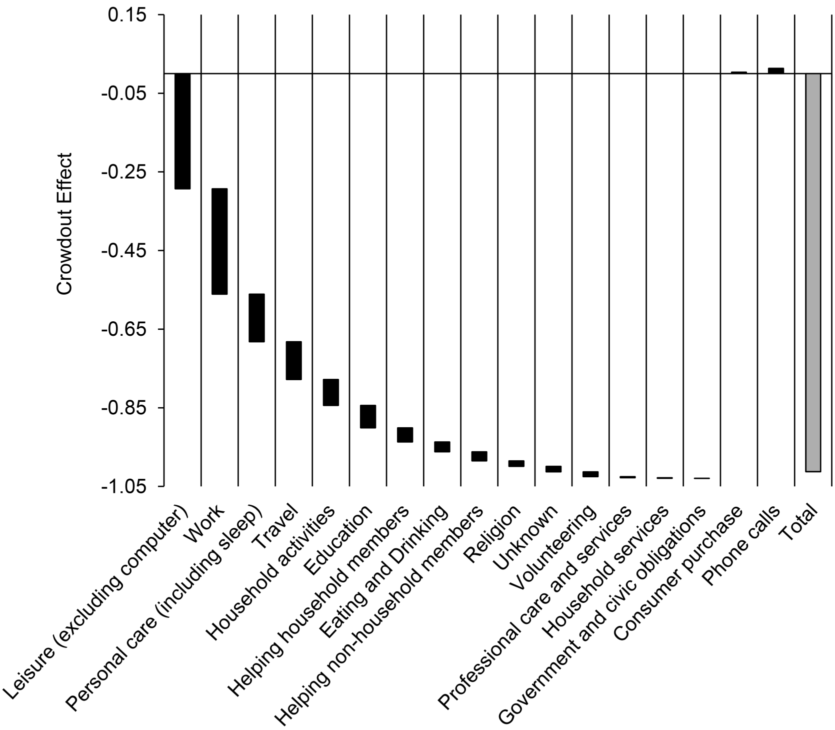

Fig. 2.12 Estimated crowd-out effects of online leisure on major categories

since phone calls are specifically time spent "talking on the telephone."[12] If people who are inclined to talk on the phone are also inclined to Skype, then perhaps the correlation is picking up like-minded people.

The analysis above controls for demographics, but any crowd-out (or crowd-in) effects may differ by those demographics, as well. Table 2.4 shows the abridged regression results by demographic group.

Men and women show few differences in terms of crowd-out effects, except for time spent helping household members. While online leisure time is not statistically significantly correlated with helping household members for men, each minute of online leisure is associated with 0.08 fewer minutes helping household members for women. This result, however, is at least partly because women spend more than 50 percent more time helping household members than men do.

Among race, black people show the biggest crowd-out correlation between online and other leisure, while Hispanic people show the smallest crowding out. Black, white, and Hispanic people show similar levels of crowding out

12. See http://www.bls.gov/tus/tu2011coderules.pdf, p.47.

Table 2.4 **Crowd-out effect on selected major categories by demographics**

Demographic	Leisure (other than online)	Work	Travel	Household activities	Education	Helping household members
Men	–0.307***	–0.258***	–0.0638***	–0.0668***	–0.0620***	–0.00833
Women	–0.283***	–0.264***	–0.0554***	–0.0642***	–0.0555***	–0.0724***
White	–0.274***	–0.273***	–0.0680***	–0.0732***	–0.0546***	–0.0418***
Black	–0.394***	–0.308***	–0.00453	–0.0348	–0.0450**	0.00511
Asian	–0.305***	–0.151**	–0.0589***	0.00178	–0.227***	–0.0195
Hispanic	–0.230***	–0.275***	–0.0590***	–0.174***	0.0177	–0.0709***
<$10k	–0.399***	–0.125***	–0.0180	–0.0686**	–0.0817***	–0.0175
$10k–$19k	–0.410***	–0.124***	–0.0255*	–0.151***	–0.0335	–0.0398***
$20k–$29k	–0.395***	–0.254***	–0.0287**	–0.0345	–0.0307*	–0.0581***
$30k–$49k	–0.218***	–0.297***	–0.0658***	–0.0997***	–0.0425***	–0.0282**
$50k–$74k	–0.267***	–0.262***	–0.0746***	–0.0725***	–0.0733***	–0.0482***
$75k–$99k	–0.209***	–0.383***	–0.0934***	–0.0134	–0.0892***	–0.0220*
$100k–$149k	–0.291***	–0.254***	–0.0600***	–0.0781***	–0.129***	–0.0186
$150k +	–0.220***	–0.297***	–0.0713***	–0.0229	–0.0774***	–0.00642
Age 15–19	–0.390***	–0.0871***	–0.0526***	–0.0377**	–0.295***	–0.00295
Age 20–24	–0.178***	–0.231***	–0.0651***	–0.0304	–0.118***	–0.0363*
Age 25–29	–0.223***	–0.326***	–0.0332*	–0.100***	–0.107***	–0.0268
Age 30–34	–0.209***	–0.375***	–0.0754***	–0.0906***	–0.0776***	–0.0887***
Age 35–39	–0.151***	–0.375***	–0.0722***	–0.0605**	–0.0255**	–0.0488**
Age 40–44	–0.221***	–0.331***	–0.0485***	–0.0531	–0.0314***	0.00239
Age 45–49	–0.233***	–0.315***	–0.0604***	–0.0934***	–0.0206*	–0.0156
Age 50–54	–0.268***	–0.326***	–0.0721***	–0.0436	–0.0155	–0.00327
Age 55–59	–0.282***	–0.294***	–0.0803***	–0.0837**	–0.00132	–0.00695
Age 60–64	–0.308***	–0.296***	–0.0793***	–0.0834**	0.000424	0.00246
Age 65–69	–0.412***	–0.146***	–0.0640***	–0.0877*	–0.00597	–0.00429
Age 70+	–0.471***	–0.0347*	–0.0464***	–0.134***	0.000160	–0.00708

Note: Each cell shows the coefficient on the "computer use for leisure" variable and its statistical significance in a regression in which the column heading is the dependent variable and regression includes only the observations in the group represented by the row heading. Thus, the table shows a single coefficient from each of 156 separate regressions. Each regression includes variables shown in equation (3). Full results available upon request.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

on work, with Asians showing the smallest crowding out of work. Asians, however, show the most crowding out of online time on education, with each minute of online leisure correlated with 0.23 fewer minutes engaged in educational activities.

Perhaps the most striking result is how the correlation between online time and education differs by age. Figure 2.13 shows this information graphically. Among people age fifteen to nineteen, each minute of online leisure is correlated with 0.3 fewer minutes engaged in educational activities. The magni-

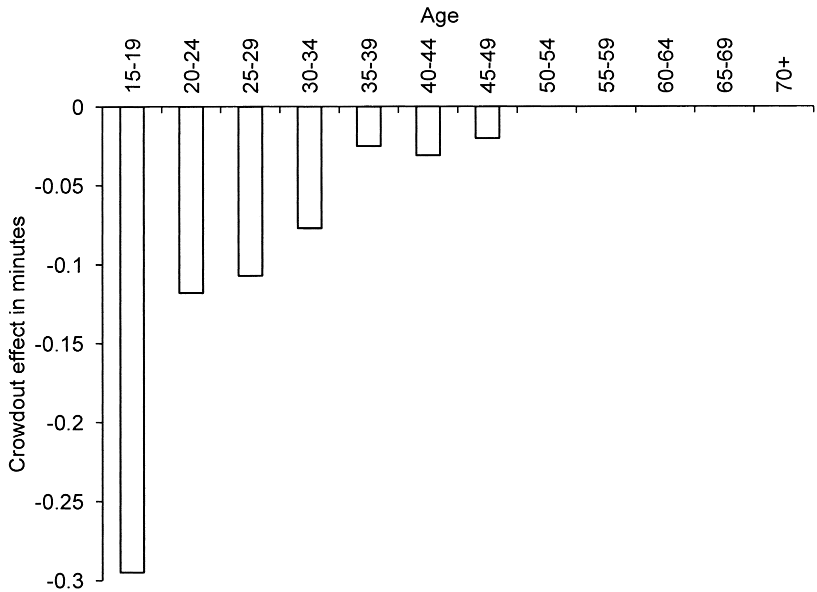

Fig. 2.13 Crowd-out effect on education by age

tude of the crowd-out correlation decreases quickly with age: 0.12 minutes for ages twenty to twenty-four, 0.03 minutes for ages forty-five to fifty-nine, and no statistically significant correlation beyond age fifty.

To some extent, the decreasing magnitude of the correlation with age has to do with the simple fact that the amount of time spent engaged in educational activities decreases sharply with age—much more sharply than the time spent in online leisure activities. This relationship, however, does not change markedly when estimating elasticities rather than levels: among the youngest group, each percent increase in time spent online is correlated with 0.06 percent less time spent in educational activities. The correlation becomes generally smaller in magnitude with age and statistically insignificant by age forty-five.

2.4.2 Activity Subcategories

As discussed above, each major category includes multiple subcategories (and even more sub-subcategories). To get a better idea of which specific activities online leisure might crowd out, I now estimate a set of similar regressions with the largest subcomponents of leisure as the dependent variable. Table 2.5 shows the coefficient its statistical significance for the online leisure variable for each regression.[13]

Online leisure has the strongest (in magnitude) negative correlation with

13. The full regression results are in the online appendix at http://www.nber.org/data-appendix/c13001/appendix-tables.pdf.

Table 2.5 Abridged regression results of online leisure on other types of leisure

Activities	Crowd out
TV and movies (nonreligious)	–0.12*** (–10.39)
Socializing and communicating	–0.054*** (–9.121)
Relaxing and thinking	–0.037*** (–8.286)
Parties	–0.016*** (–5.923)
Attending cultural events/institutions	–0.010*** (–4.069)
Listening to the radio	–0.0044*** (–3.637)
TV and movies (religious)	–0.0004 (–0.628)
Other leisure	–0.0003 (–0.591)
Waiting associated with leisure	–0.0002 (–0.855)
Smoking/drugs	0.0002 (0.357)
Writing	0.0005 (0.918)
Listening to music (not radio)	0.0021 (1.538)
Hobbies	0.0036** (1.994)

Note: Each entry shows the coefficient (and *t*-statistic) on the variable representing time engaged in online leisure in a regression in which the dependent variable is the row heading. Each regression includes the variables shown in equation (3). The *t*-statistics are in parentheses.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

watching TV and movies. Each minute of online leisure is associated with 0.12 minutes less of watching video. Note that this result does not speak to the question of whether over-the-top (OTT) video like Netflix complements or substitutes for traditional TV.[14] Watching video online in any form—

14. How OTT affects traditional TV is, of course, an important question that will affect the video delivery industry. Israel and Katz (2010) argue that Nielsen surveys and other data suggest online video complements traditional video because people watch online video to "catch up with programming or if the TV itself is unavailable." Other data suggest the two are not complements. Subscription TV services lost a record number of subscribers in the second quarter of 2011 with estimates of the loss ranging from 380,000 to 450,000 (http://www.usatoday.com/money/media/2011–08–10–cable-satellite_n.htm). Liebowitz and Zentner (2012) examine econometrically the relationship between Internet penetration and TV watching, using data from 1997 to 2003. They find a small negative correlation between the two, suggesting that online video was substituting for TV watching, at least among younger people.

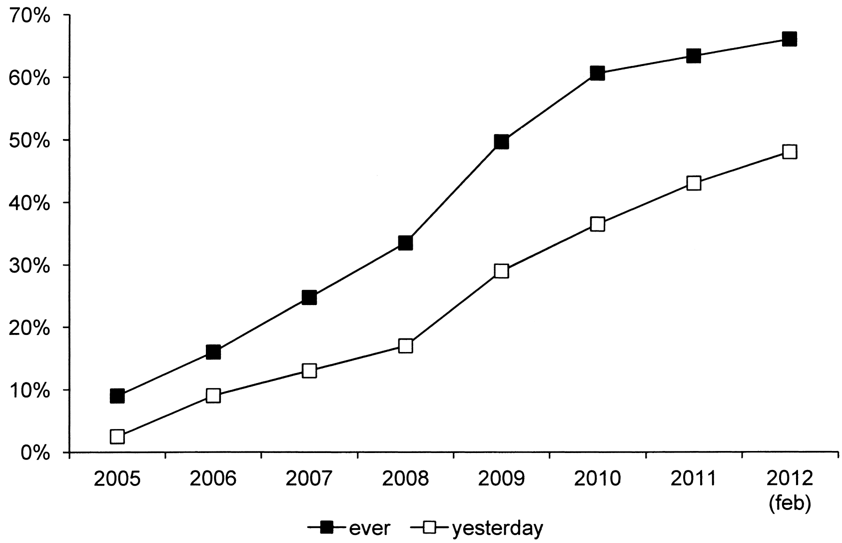

Fig. 2.14 Share of Internet users who use social networking sites
Source: Pew Internet and American Life Project. http://www.pewinternet.org/Static-Pages/Trend-Data-(Adults)/Usage-Over-Time.aspx.

including YouTube and Netflix—is coded as watching video, not computer leisure time. Thus, these results suggest that online activities not captured by the 2003-era list of leisure activities have a crowding-out effect on TV viewing. Given that Americans spend 2.75 hours per day watching TV (according to ATUS; more according to Nielsen), the crowd-out effect is small.

Nevertheless, the crowd-out effect on video suggests that the net effect of the Internet is less time watching all forms of video. If this result holds true, it means not only that OTT video competes with traditional video but that they are competing over a shrinking share of Americans' time.

The next-largest effect is on socializing and communicating. Each minute of online leisure time is correlated with 0.05 minutes less socializing in more traditional ways. Social media has become among the most popular online activities. Survey data from the Pew Internet and American Life Project show that by 2012 nearly 70 percent of all Internet users had engaged in social media online and almost half had done so the day prior to being surveyed. (figure 2.14). Given the ubiquity of social media, it is not surprising that scholars in various fields have investigated whether social networking strengthened or weakened other social ties, though there does not appear to be consensus on the answer.[15]

Previous studies have asked whether online social networking might crowd out other activities. Early studies, primarily during dial-up days, were incon-

15. See, for example, Wellman et al. (2001) and Valenzuela, Park, and Kee (2009).

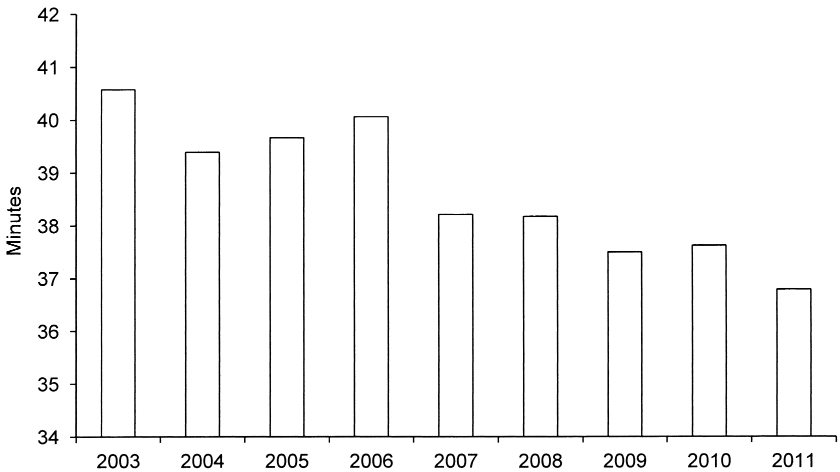

Fig. 2.15 Minutes per day spent socializing offline
Source: Derived from ATUS.

clusive (Wellman et al. 2001, 439), though the relevance of that research to today's activities is questionable, given the changes in the Internet, its ubiquity, and the growing variety of social networking applications. My results suggest a small crowding-out effect of online leisure on offline socializing. Data from the ATUS show generally declining levels of offline socializing since 2003 (figure 2.15).

My results also suggest that other offline leisure activities that involve interacting with other people are crowded out by online leisure: attending parties and cultural events and going to museums are all negatively correlated with online leisure. In short, these results based on ATUS data suggest that a cost of online activity is less time spent with other people.

Listening to the radio is also negatively and statistically significantly correlated, but the magnitude of the effect is quite small. Given the way the ATUS is coded, one might expect that if time spent listening to the radio is negatively correlated with online leisure that time spent listening to music but not on the radio would be positively correlated, not because listening to online streaming music would show up in the online leisure variable, but because people likely to engage in online leisure may also be likely to listen to streaming media. The coefficient is positive, but is not statistically significant.

Online leisure is statistically and positively correlated with one category of leisure, hobbies, although the magnitude is small. Each minute of online leisure is correlated with 0.004 minutes of doing hobbies. However, considering Americans spend, on average, only about two minutes a day on hobbies, the effect is not as small as it might seem based on the coefficient alone. A possible explanation for this effect is that the Internet has given people a way to find and interact with others who share their particular hobby interests. Similarly, the Internet is awash with instructional videos, product manuals, and other ways to get information about hobbies, and it is therefore not surprising to find a correlation between time spent doing hobbies and time online.

2.5 Conclusions

The amount of leisure time we spend online is increasing steadily as is the variety of activities available to do online. Translating this time into increased economic surplus is difficult, not just because many of these activities require no monetary payments, but because many online activities represent activities we already did but in a different form, and even brand new activities like social media come at the expense of activities we no longer do. Estimates of the value of online time that do not take these factors into account will overestimate the incremental economic surplus created by the Internet.

This chapter does not estimate the net change in surplus, but uses data from the American Time Use Survey to estimate the extent to which new online activities crowd out other, offline, activities. I find that online leisure does crowd out other activities. In particular, some incremental online leisure comes primarily from offline leisure, work time, and sleep. Online time is also correlated with less time traveling, which should count as a benefit. Online leisure is also associated with less time engaged in educational activities, especially among younger people. The crowd-out effect is sufficiently large that understanding the true economic effects of the Internet must take them into account.

This research is a small step forward in understanding the economic effects of the Internet. The data clearly show that time spent and the share of the population engaged in online leisure is increasing. The analyses suggest that new online activities come at least partly at the expense of less time doing other activities. Much, however, remains yet to be understood. While I control for a large number of relevant factors in the analyses, the relationships between online and offline time are correlations, meaning we cannot say definitively that an incremental minute translates into a tenth-of-a-minute less sleep. Perhaps, instead, when people suffer from bouts of insomnia they take to the Internet, either to look for insomnia cures or other ways of passing a sleepless night. Nevertheless, the analysis shows that online activities, even when free from monetary transactions, are not free from opportunity cost.

A next research step may be estimating the increase in economic surplus from new online activities net of the activities they replace, à la Robert Fogel's analyses of the true net economic effects of railroads. While such work is challenging, such an effort may be a worthwhile endeavor to counter much of the poorly informed hyperbole that routinely emanates from policymakers.

Appendix

Full Regression Results

See appendix tables 1 and 2 at http://www.nber.org/data-appendix/c13001/appendix-tables.pdf.

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Comment Chris Forman

It was a pleasure for me to read and comment on this chapter, which highlights an important set of issues and also presents some interesting statistics using a data set that has not frequently been employed by the digitization community. Increasingly, researchers have access to fine-grained data that allow us to make precise statements about behavior online. This has allowed us to make advances in a great many areas related to economic activity that has been digitized, which are reflected in many of the other chapters in this volume. However, there have generally not been similar advances in data that allow us to measure behavior online and offline simultaneously. As a result, we know comparatively little about how our behavior online influences our behavior offline. This is particularly true for offline behavior that is not monetized and for which we have little means other than surveys to track what people are doing. It is therefore difficult to observe, for example, how use of online social platforms such as Facebook influence offline social interactions.

The chapter uses the American Time Use Survey (ATUS), a data set that was started in 2003 and that provides national estimates of how Americans spend their time. After documenting American time use online and offline, the main analysis of the chapter then examines how time spent on computer leisure—the chapter's primary measure of online activity—"crowds out" time spent offline. The ATUS is a repeated cross section, so the identification approach uses cross-sectional variation with time controls. There are an impressive array of regressions that study the association between computer leisure time and a wide variety of offline activities such as work, personal care, and travel, and leisure categories such as watching TV and movies, socializing and communicating, and relaxing and thinking. A nice feature

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