Down the Rabbit Hole: Habit Formation in Internet Use among Unemployed Workers

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Abstract

This paper tests for the presence of habit formation in leisure-related internet use (LIU) using weekly time-diary data from a panel of unemployed workers. I show that a simple model of time allocation can be used to derive a relationship between the strength of habit formation and the autocorrelation of the growth rate of LIU. Estimating the model, I find robust evidence of habit formation in LIU. In contrast, I find no evidence of habit formation in any of a variety of offline leisure activities in the data, including reading, writing, exercising, relaxing or watching television.

Keywords: Habit formation; internet use; screen time; unemployment
JEL Classification: J64, C82, B22

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1 Introduction

We spend a large—and growing—amount of time online. In 2018, the average person spent four hours online each day, more than twice as much as in 2010. This increase was driven entirely by time spent on a mobile device, which has quadrupled since 2010 and now accounts for over 75% of online time.[1] The activities we engage in online appear to be, in important respects, different from other forms of leisure: The World Health Organization lists digital gaming alongside gambling as an official addictive disorder in the International Classification of Diseases;[2] a recent neurological study showed that sharing information about oneself on social media can have a chemical effect on the brain similar to that of addictive substances;[3] and in its podcast "Rabbit Hole," the New York Times chronicles how YouTube's algorithms facilitate immersive viewing patterns that can result in political radicalization.[4] Taken together, these observations lead naturally to a simple question: Is internet use habit forming? While there is growing interest in this question among social scientists, existing evidence is typically either anecdotal, based on associational cross-sectional analysis, or limited to an experimental setting.[5]

This paper provides causal evidence on habit formation in leisure-related internet use (LIU) based on observational data.[6] To do so, I consider the time allocation problem of an unemployed worker in the presence of a potentially habit-forming leisure activity, and show that the worker's first-order condition implies an equation that can be taken to the data to test for the presence of habit formation. I estimate the model using high-frequency time-diary data from a panel of unemployed workers, exploiting the panel structure of the data to overcome possible endogeneity. The results provide robust and statistically significant evidence of a modest degree of habit formation in LIU. By contrast, when I estimate the model on other categories of *offline* leisure in the data—reading, writing, exercising, watching television and relaxing—I find no evidence of habit formation. These results suggest that internet use is fundamentally different from other forms of leisure and, in view of the rapid increase in LIU over the past ten years, highlight the importance of further research into the behavioral underpinnings of how we use the internet.

The paper is organized as follows: Section 2 lays out the model and derives an estimating equation, Section 3 describes the data and estimation, Section 4 reports the results and Section 5 concludes.

2 Model

Consider the problem of an unemployed worker choosing how much time to spend online using a computer, smart phone, tablet, etc. for leisure—that is, choosing LIU. Suppose that time can be allocated either to LIU or to stochastically evolving time commitments (e.g. errands, household chores, repairs, etc.) that can be transferred intertemporally but must eventually be completed.

Formally, in each period t, unemployed worker i chooses LIU, denoted by $l_{i,t}$, to maximize

[1] Zenith Media, 2019.

[2] https://www.who.int/news-room/q-a-detail/addictive-behaviours-gaming-disorder.

[3] Tamir and Mitchell (2012).

[4] https://www.nytimes.com/column/rabbit-hole.

[5] For interesting recent evidence in an experimental setting, see Allcott et al. (2021).

[6] LIU includes any time on a connected device that is not used for work or work-related activities such as searching for a job. See Section 3 for a formal definition.

$$E_t\left[\sum_{d=0}^{D}\beta^d u(\tilde{l}_{i,t+d};\xi_{i,t+d})\right] \tag{1}$$

where $\xi_{i,t+d}$ is a taste shock to LIU and

$$\tilde{l}_{i,t+d} \equiv l_{i,t+d} - \rho l_{i,t+d-1} \tag{2}$$

is habit-adjusted LIU where ρ governs the strength of habit formation. Optimization is subject to three constraints,

$$l_{i,t} \leq T \tag{3}$$

$$l_{i,t} + \tau_{i,t} \leq T + b_{i,t} - b_{i,t-1} \tag{4}$$

$$b_{i,D} \leq 0 \tag{5}$$

where T denotes the total time available in a period, $\tau_{i,t} \geq 0$ denotes an idiosyncratic time commitment shock in period t which detracts from the total time available for leisure, and $b_{i,t}$ denotes "borrowed" time in period t. The constraint in (3) represents the fact that workers cannot enjoy more leisure than there is time in the day, the constraint in (4) reflects the observation that individuals can both "save" and "borrow" leisure in a manner largely analogous to consumption,[7] and the constraint in (5) reflects the fact that all time commitments must eventually be completed. The model is thus similar in many respects to familiar models of consumption habit formation, such as those considered by Dynan (2000) and Deaton (1992).[8]

Suppressing dependence of the utility function on the shock $\xi_{i,t}$, the first-order condition for the optimal choice of LIU is thus:

$$u'(\tilde{l}_{i,t}) - \rho\beta E_t\left\{u'(\tilde{l}_{i,t+1})\right\} - \Gamma_{i,t} = \beta E_t\left\{u'(\tilde{l}_{i,t+1}) - \rho\beta u'(\tilde{l}_{i,t+2}) - \Gamma_{i,t+1}\right\}. \tag{6}$$

I maintain two assumptions throughout the analysis: First, I assume separability of LIU from other possible arguments in the felicity function, such as consumption and other types of leisure. This assumption has a frequently invoked analog in the consumption-habit literature, which typically assumes separability of the felicity function in various types of consumption goods (and implicitly leisure) in order to estimate models using data on, e.g., food expenditures. Second, I assume that the time constraint in (3) is slack, so that the multipliers associated with (4) are zero: $\Gamma_{i,t} = \Gamma_{i,t+1} = 0$. This assumption is justified on the grounds that the sample described in Section 3 consists of unemployed workers for whom a time constraint is unlikely to bind.[9]

Under these assumptions, we can follow Hayashi (1985), who shows (in the context of a model of

[7] To illustrate this point, consider a decision to vacuum on a Saturday instead of on a relatively busy Monday: This can be viewed either as saving leisure (from the vantage of Saturday) or as borrowing leisure (from the vantage of Monday).

[8] There is a rich literature on habit formation in a range of other activities including, e.g., voting (Fujiwara et al. (2016)), exercise (Royer et al. (2015)) and water conservation (Bernedo et al. (2014)).

[9] In the data, the 99^{th} percentile of time spent on the category of leisure I define as LIU is seven hours. See Section 3 for details.

consumption habit formation) that when D is large, (6) simplifies to

$$E_t\Big\{\beta\frac{u'(\tilde{l}_{i,t+1})}{u'(\tilde{l}_{i,t})}\Big\} = 1. \tag{7}$$

which implies

$$\beta\frac{u'(\tilde{l}_{i,t})}{u'(\tilde{l}_{i,t-1})} = 1 + \epsilon_{i,t} \tag{8}$$

where $\epsilon_{i,t}$ is the individual's forecast error, reflecting innovations to the "permanent" level of time available for leisure. Such shocks might include losing a job or unexpectedly having to take care of an aging parent, etc. Rational expectations imply $E_{t-1}[\epsilon_{i,t}] = 0$ and that $\epsilon_{i,t}$ is serially uncorrelated.

Assuming the felicity function is isoelastic and of the form $u(\tilde{l}_{i,t};\xi_{i,t}) = \xi_{i,t}\frac{\tilde{l}_{i,t}^{1-\sigma}}{1-\sigma}$, (8) becomes

$$\beta\frac{\xi_{i,t}}{\xi_{i,t-1}}\left[\frac{\tilde{l}_{i,t}}{\tilde{l}_{i,t-1}}\right]^{-\sigma} = 1 + \epsilon_{i,t}. \tag{9}$$

Taking the natural logarithm and using (2), we obtain

$$\Delta\ln(l_{i,t} - \rho l_{i,t-1}) = \frac{\beta}{\sigma} + \frac{1}{\sigma}\Delta\ln(\xi_{i,t}) - \frac{1}{\sigma}\ln(1+\epsilon_{i,t}). \tag{10}$$

Finally, following Muellbauer (1988), I approximate $\Delta\ln(l_{i,t} - \rho l_{i,t-1})$ with $\Delta\ln(l_{i,t}) - \rho\Delta\ln(l_{i,t-1})$, which allows (10) to be written as

$$\Delta\ln(l_{i,t}) = \gamma_0 + \rho\Delta\ln(l_{i,t-1}) + \gamma_1\Delta\ln(\xi_{i,t}) + e_{i,t}. \tag{11}$$

where $\gamma_0 \equiv \beta/\sigma$ and $\gamma_1 \equiv \frac{1}{\sigma}$ are constants. This equation provides a direct test for the presence of habit formation in LIU: A finding of $\rho > 0$ indicates the presence of habit formation, while $\rho = 0$ indicates the absence of habit formation.[10] Note also that this formulation allows for arbitrary person-specific effects in the marginal utility of LIU, which are implicitly differenced out of (11).

3 Data and Estimation

3.1 Data

I estimate (11) on a panel of unemployed workers from the Survey of Unemployed Workers in New Jersey (SUWNJ). The SUWNJ is a weekly survey of unemployment insurance benefit recipients in New Jersey beginning in the fall of 2009 and continuing through early 2010. The survey covers 6,025 unemployed job seekers for up to 24 weeks for a total of 39,201 weekly interviews. Importantly, the survey contains a detailed time diary component in which respondents were asked to provide an hour-by-hour account of the preceding day, selecting up to two choices from 21 activity categories for each hour. See Krueger and Mueller (2011) for a comprehensive description of methodology.

[10] A negative coefficient would be be suggestive of durability in the leisure services provided by LIU.

The SUWNJ is uniquely well-suited to studying habit formation in LIU for two principal reasons: First, the time-diary component of the SUWNJ provides a relatively granular window into the various types of leisure activities that individuals engage in during unemployment, and thus allows testing for the presence of habit formation in LIU as well as other categories of leisure. The granularity of the activity categories and the fact that individuals can select multiple activities in a given hour also reduce the likelihood of significant measurement error in the constructed measure of LIU. Second, the high frequency of interviews reduces the likelihood of bias due to time averaging that arises when respondents' decision interval is short relative to the observation interval.[11]

3.2 Measuring LIU

I construct a measure of LIU using six of the 21 activity categories from which individuals select: "Using the Computer/Internet/Email" (CIE), "Watching TV" (TV), "On the phone" (Phone), "Working" (Work), "Searching for a job" (Search), "Attending job training program" (Training), "Preparing for/taking course" (Course). For any hour of the day $\tau \in \{7\text{am}, 8\text{am},..., 10\text{pm}\}$, let $a_{\tau,1}$ denote the first activity reported and let $a_{\tau,2}$ denote the second activity reported. Without loss of generality, order activities such that CIE is always the first activity if selected. Then I define LIU as

$$\text{LIU} \equiv \sum_{\tau=7\text{am}}^{10\text{pm}} \begin{cases} 60 & \text{if } a_{\tau,1} = \text{CIE} \quad \& \quad a_{\tau,2} \in \{\text{CIE , TV , Phone , }\cdot\} \\ 30 & \text{if } a_{\tau,1} = \text{CIE} \quad \& \quad a_{\tau,2} \notin \{\text{Work , Search , Training , Course}\} \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

where '·' indicates non-response. I thus attribute a full hour to LIU if an individual is using a computer or the internet and possibly also using a phone (e.g. using a smart phone) or watching TV (e.g. watching Netflix on a laptop); half an hour if an individual reports using a computer or the internet and another activity other than activities related to finding a job or working (reflecting reporting patterns for individuals who switch activities in the middle of an hour); and no time otherwise. This precise formulation of LIU is not essential so long as CIE is included—I return to this point below. See Appendix A for further details on data construction. Based on this construction, the average (median) worker in the sample spends 68 minutes (30 minutes) each day on LIU.[12]

3.3 Empirical strategy

In the presence of unobserved preference shocks on the right-hand side of (11), the resulting composite error term, $(\gamma_1 \Delta \ln(\xi_{i,t}) + e_{i,t})$, will be correlated with the lagged dependent variable, $\Delta \ln(l_{i,t-1})$. Accordingly, I estimate (11) using several instrumenting strategies proposed in the dynamic panel literature. First, I consider the parsimonious approach of Anderson and Hsiao (1981): Instrumenting $\Delta \ln(l_{i,t-1})$ with a twice-lagged level $(\ln(l_{i,t-2}))$ and with a twice-lagged difference $(\Delta \ln(l_{i,t-2}))$. Second, to improve efficiency by exploiting the full set of available internal instruments, I also estimate the model using the Arellano-Bond difference GMM estimator.[13]

To further alleviate concerns of endogeneity, I consider specifications that include as regressors jobless duration and indicators for the day of the week and entry cohort, as well as dummies for sex, age,

[11] This problem was first pointed out by Working (1960) and is endemic in the literature estimating consumption habit models, which typically uses quarterly or even annual data.

[12] This is broadly in line with data from Zenith Media discussed in the Introduction, according to which the average person spent 85 minutes per day online 2010.

[13] See Arellano and Bond (1991) and Holtz-Eakin and Rosen (1988).

education level, the number of children, marital status, savings and entry cohort. These variables will both help to account for shifts in marginal utility as well as potential differences across individuals in time discount factors that appear implicitly in (11).[14] I also include weekly time dummies to control for the possibility of aggregate shocks that could lead to inconsistent estimates.

4 Results

4.1 Leisure-related internet use

Table 1 reports results for the model estimated on a sample of respondents between the ages of 20 and 50. The first three columns correspond to a baseline specification with only a lagged-dependent variable on the right-hand side, the second three to a specification that adds duration and dummies for time, day-of-week and cohort, and the third to a full specification that adds demographic controls. Within each of these three specifications, AH(D) and AH(L) denote the Anderson-Hsiao 2SLS instrumenting strategy with differenced and level instruments, respectively, and GMM denotes the Arellano-Bond difference GMM estimator.

The first row of Table 1 reports the coefficient on the lagged growth rate of LIU, ρ, indicating the extent of habit formation in the data. Across specifications, the coefficient is positive, modest in magnitude, and significant at the 5% level—and at the 1% level in some of the more saturated specifications. To put the magnitude of these numbers in perspective, note that in the presence of habit formation ($\rho > 0$), a one-time $g\%$ shock to the growth rate of LIU—say, due to job loss—will result in the *long-run level* of LIU asymptoting towards a value that is approximately $g \times \left(\frac{\rho}{1-\rho}\right)\%$ greater than it would be in the absence of habit formation ($\rho = 0$). Concretely, under the range of parameter estimates in Table 1, this implies that a shock that doubles time spent on LIU will eventually result in individuals permanently spending between 10% and 20% more time online than they otherwise would.

Comfortingly, we observe no evidence of second-order serial correlation in the residuals as indicated by the Arellano-Bond tests, suggesting that measurement error and time averaging are not significant problems and thus that the twice-lagged instruments are valid. In the GMM specification, we observe a marginally significant Sargan test statistic but cannot reject the null that the over-identifying restrictions are valid using the Hansen test, which should be preferred because it is robust to heteroskedasticity and serial correlation.

These results are robust to various combinations of controls as well as various definitions of LIU. For example, including reading in the set of second activities that yield a full hour of LIU in (12), or excluding phone use from this set of activities, yields similar results. What appears to be essential is inclusion of CIE and exclusion of work and search-related activities. On the other hand, as the age window expands to include older individuals, the results become weaker and less significant, whereas—so long as the sample remains sufficiently large—the same is not true of restricting the sample to younger individuals, in which case the results continue to hold. A possible explanation for this observation is that older individuals, who have spent larger fractions of their lives without internet access, are less susceptible to the underlying habit-forming nature of LIU than younger individuals who have had internet access for most if not all of their lives.

[14] The consumption habit literature typically assumes the discount factor is constant over time and across households.

Table 1: Habit formation in leisure-related internet use

	Baseline			Simple controls			Full controls		
	AH(D)	AH(L)	GMM	AH(D)	AH(L)	GMM	AH(D)	AH(L)	GMM
Habit (ρ)	0.14**	0.07**	0.07**	0.15***	0.07**	0.07**	0.14***	0.07**	0.07**
	(0.05)	(0.03)	(0.03)	(0.05)	(0.03)	(0.03)	(0.05)	(0.03)	(0.03)
Duration				-0.00	-0.01**	-0.01**	-0.08	-0.05	-0.02
				(0.01)	(0.01)	(0.01)	(0.05)	(0.04)	(0.04)
Weekend				-0.04	-0.05**	-0.03	-0.04	-0.05**	-0.03
				(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Female							-0.15*	0.02	0.03
							(0.09)	(0.06)	(0.07)
30-39							0.05	0.07	0.10
							(0.15)	(0.12)	(0.12)
40-49							0.04	-0.04	-0.01
							(0.14)	(0.12)	(0.13)
Constant	-0.07*	-0.08**	-0.10***	-0.01	0.26	0.16	1.09	0.60	0.39
	(0.04)	(0.04)	(0.03)	(0.47)	(0.23)	(0.23)	(0.93)	(0.40)	(0.40)
Dummies:									
Time				×	×	×	×	×	×
Educ.							×	×	×
Kids							×	×	×
Mar. status							×	×	×
Savings							×	×	×
AB test: AR1†	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AB test: AR2†	0.28	0.48	0.54	0.30	0.56	0.58	0.36	0.60	0.62
Sargan test‡			0.09			0.07			0.07
Hansen test‡			0.66			0.46			0.43
Observations	3922	5906	5906	3922	5906	5906	3922	5906	5906

† p-values reported; H_0: No order-i autocorrelation in first-differenced errors.

‡ p-values reported; H_0: Restrictions are valid.

Robust standard errors in parentheses.

Source: Survey of Unemployed Workers in New Jersey

Notes: Regressions use survey weights. Standard errors are robust and clustered at the individual level. Sample consists of all respondents ages 20-50. AH(L): Anderson-Hsiao estimator with twice-lagged level IV; AH(D): Anderson-Hsiao estimator with twice-lagged differenced IV; GMM: Arellano-Bond Difference GMM estimator.

4.2 Other forms of leisure

An important advantage of the SUWNJ is that it provides information not only on internet use, but also on time devoted to other types of leisure. This allows us to test whether the habit formation observed in LIU in Table 1 is also a feature of other types of leisure, or unique to internet use. To this end, Table 2 estimates (11) replacing LIU with four common types of leisure: (i) reading/writing, (ii) TV (offline), (iii) exercise and (iv) relaxing. In each case, I define the time use variable used in the regression so as to exclude time spent on the activity that is work-related and exclude time also spent on the internet: For example, reading excludes time spent reading for a course (work-related) or reading online (internet use), etc.[15] All specifications include the full set of controls.

Table 2: Habit formation in other leisure activities

	LIU		Reading		TV (offline)		Exercise		Relaxing	
	AH(D)	GMM	AH(D)	GMM	AH(D)	GMM	AH(D)	GMM	AH(D)	GMM
Habit (ρ)	0.14***	0.07**	-0.04	0.08	-0.02	-0.04	0.05	0.05	0.06	0.05
	(0.05)	(0.03)	(0.08)	(0.05)	(0.06)	(0.04)	(0.07)	(0.04)	(0.07)	(0.04)
Full controls	×	×	×	×	×	×	×	×	×	×
Observations	3922	5906	3922	5906	3922	5906	3922	5906	3922	5906

Robust standard errors in parentheses.

Source: Survey of Unemployed Workers in New Jersey

Notes: Regressions use survey weights. Standard errors are robust and clustered at the individual level. Sample consists of all respondents ages 20-50.

Across these four common categories of leisure, I find no evidence of habit formation in any specification. The same is true of the Anderson-Hsiao estimator using level instruments and in the less-saturated specifications not reported in Table 2. These results are important for at least three reasons: First, they suggest that there is something fundamentally different about LIU relative to other, more traditional, categories of leisure. Second, they suggest that the results in Table 1 are not due to some mechanical feature of the data or estimation procedure rather than the presence of true habit formation. Finally, they emphasize that it is not screen time, but rather *online* screen time, that is important: Specifically, the third group of columns—TV (offline)—highlight that watching TV offline does not seem to be habit forming in the way that online screen time is. Indeed, the point estimates here are negative, albeit statistically insignificant. On the other hand, in some cases *not* excluding episodes in which an individual might also be online can lead to significantly positive point estimates. All of this points directly to a central role for the internet in habit formation.

5 Conclusion

This paper tests for the presence of habit formation in various types of leisure, including LIU, using high-frequency time-diary data from a panel of unemployed workers surveyed between 2009 and 2010. The results illustrate a stark contrast between two types of leisure: Time spent online is characterized by a modest but robustly significant degree of habit formation, whereas time spent offline is not. That internet use has increased so dramatically over the past decade—and the related improvements in predictive algorithms, digital marketing and media quality—should both highlight the importance of these results and spur further research into the behavioral underpinnings of how we use the internet.

[15]See Appendix A for details on data construction.

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Appendices

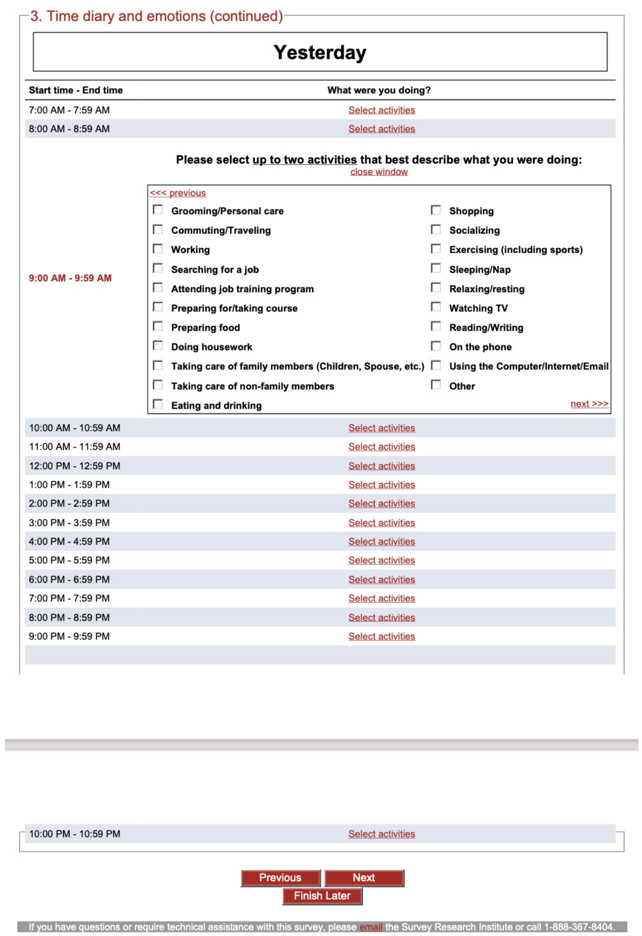
A Data construction

This appendix describes the time diary component of the SUWNJ and provides further details on construction of time-use variables used for the empirical analysis.

A.1 Time diary data

Each weekly survey of the SUWNJ asked respondents to complete a time diary, accounting for their activities between 7am and 11pm on the previous day. Figure 1 contains a graphic of what respondents would see in this section of the survey.[16]

Figure 1: Survey of Unemployed Workers in New Jersey: Time Diary



Respondents thus had a total of 21 activities from which to choose. For each hour of the time diary, respondents were able to choose up to two activities describing what they were doing.

[16]Complete survey data and documentation may be obtained from: https://dss.princeton.edu/catalog/resource1350.

A.2 Variable construction

To construct the time use measures used in the empirical analysis, I process the time diary data in a manner similar to the approach described in Krueger and Mueller (2011). Specifically, for each week in which an individual completed the survey, I compute the total number of missing episodes (that is, hour-long segments of the day in which there are no recorded activities). I then drop all observations in which there are more than two such missing episodes. The remaining observations comprise the sample of time diary entries used in the empirical analysis. Because of the presence of zeros in the time diary data, I approximate $\ln(x)$ with $\ln(1+x)$. Results are robust to the exclusion of zeros.

The "offline" time use variables used in the empirical analysis in Table 2 are generally computed in a manner analogous to the method used to compute LIU, as described in the body of the text. Specifically, for any unaltered leisure activity in the survey, L (e.g. "On the phone" in Figure 1), following the ordering convention described in the body of the text, I define the offline time use analog used in the empirical analysis, $\mathrm{L}^{\text{Offline}}$, as:

$$\mathrm{L}^{\text{Offline}} \equiv \sum_{\tau=7\text{am}}^{10\text{pm}} \begin{cases} 60 & \text{if } a_{\tau,1} = \mathrm{L} \;\;\&\;\; a_{\tau,2} \in \{\mathrm{L}\ ,\ \cdot\} \\ 30 & \text{if } a_{\tau,1} = \mathrm{L} \;\;\&\;\; a_{\tau,2} \notin \{\text{Work}\ ,\ \text{Search}\ ,\ \text{Training}\ ,\ \text{Course}\} \;\;\&\;\; a_{\tau,2} \notin \{\text{CIE}\} \\ 0 & \text{otherwise} \end{cases}$$

where the second and third conditions in the second row are intended to restrict the measure to offline leisure activities as desired.

Note that this approach of attributing 0, 30 or 60 minutes to a particular activity at a particular time based on the two reported activities for that time is similar to the approach used in Krueger and Mueller (2011).

A.3 Summary statistics

Table 3 reports summary statistics for the constructed time-use variables described in the body of the paper.

Table 3: Summary statistics for constructed time-use variables

	Mean	Std. Dev.	Min.	P_{25}	P_{50}	P_{75}	Max.
LIU	67.9	90.8	0	0	30	120	840
TV (offline)	92.1	98.0	0	0	60	120	960
Reading	19.1	46.9	0	0	0	0	840
Exercise	15.9	38.4	0	0	0	0	540
Relaxing	35.7	53.7	0	0	0	60	660

Source: Survey of Unemployed Workers in New Jersey

Notes: All times are reported in minutes per day. Sample consists of all respondents ages 20-50.