# Leisure Luxuries and the Labor Supply of Young Men*

Mark Aguiar Mark Bils Kerwin Kofi Charles Erik Hurst

August 21, 2019

**Abstract**

We propose a methodology to measure quality improvements in leisure activities. The starting point is a leisure demand system that parallels that often estimated for consumer expenditures. By combining the estimated "leisure Engel curves" with detailed time diaries, we can infer how quality changed across leisure activities as well as the associated increase in the marginal return to leisure. We apply our method to evaluate the returns to leisure of younger men, ages 21 to 30. This demographic shifted their leisure sharply to video gaming and other recreational computer activities since 2004. Over the same period, these younger men exhibited a larger decline in work hours than older men or women. Using cross-region variation, we estimate that gaming/recreational computer use is distinctly a leisure luxury for younger men. We calculate that innovations to gaming/recreational computing shifted in younger men's labor supply at a given wage by 3.2 percent since 2004.

*We thank Shirley Yarin and Hyun Yeol Kim for outstanding research assistance. We are grateful to Bob Hall for detailed and constructive comments on an earlier draft. We also thank Thomas Crossley, Matt Gentzkow, Bob Hall, Patrick Kehoe, John Kennan, Pete Klenow, Alan Krueger, Hamish Low, Kevin Murphy, and Yona Rubinsteinfor helpful comments. Authors contact information: maguiar@princeton.edu, mark.bils@gmail.com, kerwin.charles@gmail.com, and erik.hurst@chicagobooth.edu.

# 1 Introduction

We propose a methodology to measure quality improvements in leisure activities and the associated increase in the marginal return to leisure. Using detailed time diaries collected by the American Time Use Surveys (ATUS), we estimate the quality improvement of recreational computing and gaming, an activity that we document has shown a large increase in popularity over the last fifteen years. We then ask whether technological progress in leisure activities affected the opportunity cost of work for various demographic groups, with particular focus on its impact for younger men. Younger men have exhibited the sharpest increase in time devoted to gaming, while also exhibiting a large relative decline in market work between the early 2000s and 2018.

Our approach begins with the premise that an individual's time allocation is driven by the relative quality of various activities. Thus time diaries provide a guide to the relative return to alternative leisure activities. All else equal, a trend away from one leisure activity towards another suggests that relative qualities changed between the activities or that preferences shifted to favor the latter activity. However, in practice all else is not equal. In particular, we document sharp upward trends in total leisure for some demographic groups, particularly younger men. This raises the question of whether some activities face different levels of diminishing returns. That is, it may be the case that recreational computing is the more elastic margin for additional leisure time, and hence the increase in computing does not reflect improved quality but rather a response to additional leisure time.

To solve this identification problem, we introduce a leisure demand system that parallels that typically considered for consumption expenditures. We estimate how various leisure activities respond to total leisure time, tracing out "leisure Engel curves." To estimate the demand system, we exploit region-industry-year variations in leisure, such as that caused by differential impact of the Great Recession across US states and sectors. The identifying assumption is that such cross state-industry variation in total leisure is not driven by differential changes in preferences or technologies across leisure activities, but rather by labor market shocks that are independent of changes in leisure technology. We find that gaming and recreational computing is distinctively a leisure luxury for younger men, but only a modest luxury activity for other groups. A one percent increase in leisure time is associated with about a 2.5 percent increase in recreational computing time for younger men, roughly one percentage point higher than the elasticity found for other demographic groups.

With the estimated demand system, we can address the elemental question of whether increased computer use and gaming simply reflected a response to working fewer hours due, say, to reduced labor demand, or was a response to improved quality. We resolve this by dividing the large increase in recreational computer use by younger men into a movement *along* a leisure Engel curve versus a *shift* in that curve due to improved quality. We judge the shift in technology for computer leisure relative to that for leisure devoted to sleeping and personal care, a technology we assume is fairly static. Our leisure Engel curves predict that computer recreation would have increased by 22.1 percent between 2004 and 2017 in response to younger men's total increase in leisure. Thus the bulk of the actual increase, 38.3 out of 60.4 percent, is attributed to better technology for computer leisure.

Our final step maps changes in leisure technology to the marginal return to leisure and, thereby, to the opportunity cost of market labor. We show that total leisure demand (and hence labor supply) is especially sensitive to innovations to technology for leisure luxuries. Leisure luxuries are activities that exhibit little diminishing returns to time and therefore display disproportionate responses to changes in total leisure time. This is particularly relevant given that recreational computing and gaming is a prominent example of a leisure luxury for younger men. We find that for a fixed market wage and marginal utility of consumption, improvement in gaming technology has shifted inward the labor supply curve of younger men by 3.2 percent. By contrast, we find that better computer technology had no effect on the labor supply of older men and only a small effect on that of women, results compatible with our finding that the activity is not a strong leisure luxury for either group.

Our application's focus on younger men is motivated in part by the sharp changes we see in time use for younger men, ages 21 to 30, during the 2000s. From Current Population Survey data, we document that the annual hours worked of younger men not in school are 10.9% lower in 2017 than they were in 2000. The comparable declines for younger women and older men (those aged 31-55) were 2.2% and 7.5%, respectively.[1]. Despite the improvements in the aggregate labor market after 2011, young men's annual hours worked have remained well below both their 2000 and 2007 levels. Most of the decline in annual hours worked for younger men (who are not in school) occurred on the extensive margin with 13.3% of them in 2018 reporting having worked zero weeks in the prior year. There are many potential reasons why hours worked of younger men have remained depressed relative to their early 2000 levels. For example, labor demand could have declined more for this group compared to other groups resulting in more young men being closer to their reservation wage. However, our analysis shows that an increase in their marginal value of leisure can be one contributing factor as to why young men are working less relative to older men and younger women.

While we focus on the impact of computer leisure on younger men since the early 2000's,

[1]This secular decline in market hours for younger men is sizable by historical standards. For comparison, consider the double-dip recession in the early 1980s: between 1979 and 1982, men ages 21-55 in the Current Population Surveys (CPS) decreased their hours worked by approximately 9%

our approach is more broadly applicable. For instance, in principal, one could estimate changes in the return to leisure stemming from past innovations such as the introduction of television or radio, if the relevant time-use data were available. Of course, how any leisure innovation translated to changes in observed labor market outcomes (like hours worked) will depend, not only on the impact of that innovation on labor supply, but also on how other contemporaneous forces affected labor demand.

Our focus on time allocation owes a natural debt to the seminal papers of Mincer (1962) and Becker (1965). They emphasize that labor supply is influenced by how time is allocated outside of market work—for instance, female labor force participation being affected by improved household technology. Our work complements that of Greenwood and Vandenbroucke (2008), Vandenbroucke (2009), and Kopecky (2011), who use a quantitative Beckerian model to show that declines in relative prices of leisure goods help to explain declining employment over the last century. We add to this literature by introducing and estimating a leisure demand system, showing that labor supply is most affected by technology for leisure luxuries, and illustrating how one can relate shifts in labor supply to changes in the allocation of time across leisure activities.

The paper is organized as follows: Section 2 presents our methodology including the leisure demand system; Section 3 examines changes in time use during the 2000s, emphasizing the sharp increase in computer and gaming time for younger men; Section 4 highlights our identification strategy and estimates the leisure Engel curves; Section 5 uses the demand system and trends in time allocations to infer changes in computer leisure technology and then quantifies the impact of these changes on the labor supply curves for different demographic groups; Section 6 highlights the robustness of our results to alternate parameterizations; Section 7 compares trends in self-reported well being for younger men to that for older men; and Section 8 concludes.

# 2 Leisure Luxuries and Labor Supply

We first derive a leisure demand system that maps total leisure into specific leisure activities. We show how shifts in the quality of leisure activities and, in turn, changes in the marginal return to total leisure, can be inferred from observed shifts in time allocations. That change in marginal return can then be linked to shifts in labor supply. This section develops the theoretical groundwork for the empirical estimation in Section 4 and the quantitative results of Sections 5 and 6. Given that our data reflect each individual's activities for a single day, we consider a static framework. Dynamic factors such as habit formation are natural theoretical extensions, but less amenable to empirical analysis given the nature of our dataset.

## 2.1 Preferences

Agents have preferences over a consumption good, $c$, and time spent on leisure activities $h_i$, $i = 1, ..., I$. We assume separability between consumption and leisure activities, writing utility as $U(c, v(h_1, ..., h_I; \boldsymbol{\theta}))$ where $v$ is an aggregator over leisure activities and $\boldsymbol{\theta} = \{\theta_1, ..., \theta_I\}$ is a vector of technology shifters. While not necessary for all results, for simplicity we impose strong separability between $c$ and $v$ by setting $U_{cv} = 0$.

We assume $v$ has the following functional form:

$$v(h_1, ..., h_I; \boldsymbol{\theta}) = \sum_{i=1}^{I} \frac{(\theta_i h_i)^{1-\frac{1}{\eta_i}}}{1 - \frac{1}{\eta_i}}. \tag{1}$$

The parameter $\eta_i > 0$ is activity specific and governs the diminishing returns associated with additional time spent on activity $i$. Increases in the technology parameter $\theta_i$ increase the utility associated with spending a given amount of time on activity $i$.

While each leisure activity enters with its specific elasticity $\eta_i$, the activities are assumed to be additively separable from one another (although the entire $v$ function may be raised to a power, which would be a feature of the overall utility function $U$). This assumption implies that the marginal value of allocating time to one leisure activity over another is not dependent on how leisure time is allocated across the remaining activities. As a robustness exercise, however, we explore the possibility that some leisure activities are substitutes with each other.

## 2.2 Leisure Engel Curves

The agent faces a wage $w$ in terms of the consumption good, and chooses how to allocate their time endowment (normalized to one) across the $I$ leisure activities and the labor market. If $N$ denotes market labor, the time constraint is $N + \sum_i h_i = 1$. We assume $N > 0$ is optimal and omit $N \geq 0$ as a constraint. As discussed below, however, much of the analysis carries over to an environment in which market labor is fixed or rationed. The functional form for $v$ requires $h_i > 0$ at an optimum.

Specifically, the agent's problem is:

$$\max_{c, h_1, ..., h_I} U(c, v(h_1, ..., h_I; \boldsymbol{\theta})) \tag{2}$$

subject to

$$c + \sum_{i=1}^{I} p_i \ \le \ w \left(1 - \sum_{i=1}^{I} h_i\right) + \ y, \tag{3}$$

where $y$ is initial wealth or non-labor income and $p_i$ is the price of technology bundle $\theta_i$. For the present, we treat $\boldsymbol{\theta}$ as parameters that must be purchased, but will later discuss the choice of $\boldsymbol{\theta}$. The problem as stated can be interpreted as the optimal allocation problem conditional on a vector $\boldsymbol{\theta}$, with a subsequent step of optimizing over the possible technology bundles.

Let $\lambda$ denote the multiplier on the budget constraint. The first-order conditions are:

$$U_c = \lambda \tag{4}$$

$$U_v v_i = \lambda w \text{ for } i = 1, ..., I, \tag{5}$$

where $v_i = \partial v / \partial h_i$, and similarly $U_c = \partial U / \partial c$ and $U_v = \partial U / \partial v$.

In the spirit of Browning et al. (1985), it is useful to analyze this problem in stages. In particular, let $\omega \equiv \lambda w$ denote the opportunity cost of time, which is the the marginal value of wealth times the wage. Given this price of time, the agent makes a labor-leisure decision subject to $H \equiv \sum_i h_i = 1 - N$. Given $H$, the agent allocates leisure time across individual activities, equating the marginal utilities.

More formally, let $\mu$ denote $U_v$ at the optimal allocation, which is the marginal return to increasing the leisure aggregate $v$. Rewriting (5), we have:

$$h_i = \theta_i^{\eta_i - 1} \mu^{\eta_i} \omega^{-\eta_i}. \tag{6}$$

For a given $\mu$, the elasticity of demand for activity $i$ with respect to the shadow price $\omega$ is $\eta_i$. Activities with relative high $\eta_i$ are the ones that are most sensitive to changes in the opportunity cost of time. All else equal, an increase in technology $\theta_i$ increases or decreases time allocated to the associated activity depending on whether $\eta_i \gtrless 1$. If a leisure activity becomes more enjoyable, whether one spends more or less time in that activity turns on the size of the elasticity, with one being the crucial threshold.

Summing over the various leisure activities, (6) implies:

$$H = \sum_i \theta_i^{\eta_i - 1} \mu^{\eta_i} \omega^{-\eta_i}. \tag{7}$$

By the envelope condition of the leisure allocation sub-problem, $\mu$ is pinned down by total leisure $H$, which in turn is determined by $\omega$. Equation (7) implicitly defines $H$ as a function of $\omega$ given $\boldsymbol{\theta}$. Thus, we can write $H(\omega, \boldsymbol{\theta})$ as the optimal choice of leisure given the shadow price of time $\omega$ and technology $\boldsymbol{\theta}$. Similarly, let $h_i(\omega, \boldsymbol{\theta})$ denote the demand for activity $i$ given by (6).

We can use equation (6) to trace out a "leisure Engel curve." Consider individuals with different $\omega$ but employing the same leisure technology vector $\boldsymbol{\theta}$. That is, individuals differ by wages or wealth that shift the shadow price of time. From (6) and (7), one obtains:

$$\frac{\partial \ln h_i}{\partial \ln \omega} = \frac{\eta_i}{\overline{\eta}} \frac{\partial \ln H}{\partial \ln \omega}, \tag{8}$$

where $\overline{\eta} \equiv \sum_j \eta_j s_j$ is the weighted average elasticity, and the weights are given by the share of leisure time devoted to each activity: $s_j \equiv h_j/H$.

Equation (8) will play an important role in our empirical work. As we look across agents with different values of time, we observe how time allocated across individual leisure activities varies with total leisure time. This elasticity is the activity's own price elasticity divided by the weighted average of all elasticities. Activities with a greater $\eta_i$ increase disproportionately with total leisure. That is, high $\eta_i$ activities are "leisure luxuries." Our notion of a leisure luxury parallels that of a consumption luxury (or superior) good in traditional consumption demand systems. Given its importance, we denote this elasticity by $\beta_i$:

$$\beta_i \equiv \frac{\eta_i}{\overline{\eta}}. \tag{9}$$

Our derivation of the leisure Engel curves does not hinge on how total hours of leisure $H$ are determined. If labor time were indivisible or rationed, we would treat $N$ as a parameter of the individual's problem. This would imply the constraint $\sum_i h_i \leq 1 - N$ be added to problem (2). Let $\omega$ be the multiplier on that constraint and the analysis goes through unchanged. The crucial assumption is that the shadow price of time is the same when choosing between alternative leisure activities, not whether the price of time is pinned down by the wage, labor market frictions, or the returns to home production.

## 2.3 Inferring Technological Progress

The agent's time allocation problem also sheds light on technological progress in leisure activities. Let $I$ denote the activity of interest, which in the empirical analysis will be recreational computer use. Let $j \neq I$ be a "reference activity." In the empirical implementation, we consider several alternatives as the reference. From the respective first-order conditions

(6):

$$\frac{\ln h_I}{\eta_I} - \frac{\ln h_j}{\eta_j} = \left(\frac{\eta_I - 1}{\eta_I}\right) \ln \theta_I - \left(\frac{\eta_j - 1}{\eta_j}\right) \ln \theta_j. \tag{10}$$

The fact that the common price of time, $\omega$, and the marginal utility of $v$, $\mu$, are differenced out implies that this equation holds independently of wages, non-labor income, and the levels of consumption and leisure. It exploits the fact that the returns to individual activities are equated at the margin.

Now consider how time allocation changes as technology changes. Differencing (10) gives:

$$\frac{\Delta \ln h_I}{\eta_I} - \frac{\Delta \ln h_j}{\eta_j} = \left(\frac{\eta_I - 1}{\eta_I}\right) \Delta \ln \theta_I - \left(\frac{\eta_j - 1}{\eta_j}\right) \Delta \ln \theta_j. \tag{11}$$

The left-hand side is the change in relative time allocation between activity $I$ and the reference activity $j$, normalized by the elasticities. The right-hand side captures the change in relative technologies.

Equations (8) and (11) play an important role in our empirical analysis. To gain intuition for how technology can be inferred from time allocation, consider shocks to the price of time $\omega$, such as due to job loss or consumption changes. The shift in relative time allocation between activities $I$ and $j$ will be determined by the relative Engel curve elasticities $\eta_I$ and $\eta_j$.[2] These are movements *along* the leisure Engel curves. Equation (11) shows that the change in how time is allocated to activity $I$ relative to $j$, in *excess* of that explained by the relative slopes of their respective Engel curves, reflects changes in relative technology. These are *shifts* in the Engel curves rather than movements along the curves. A goal of the empirical exercise is to separate movements along leisure Engel curves due to changes in leisure hours from shifts in technology.

An alternative approach to inferring technological change uses prices. Consider changes over time in $\theta_i$, and the decision of the agent to purchase the latest technology. In particular, suppose the agent can upgrade technology by $\Delta\theta_i$ by paying an additional $\Delta p_i$. The utility gain from a marginal improvement is $U_v \frac{\partial v_i}{\partial \theta_i} \Delta\theta_i$. The opportunity cost is $\lambda \Delta p_i$, where $\lambda$ is the shadow value of wealth. Using the first-order conditions, the agent prefers the marginal upgrade as long as:

$$\frac{\Delta\theta_i}{\theta_i} \geq \left(\frac{p_i}{w h_i}\right) \frac{\Delta p_i}{p_i}. \tag{12}$$

[2] The Engel Curve elasticities are $\beta_I$ and $\beta_j$. However, given that $\bar{\eta}$ is the same for all Engel curve estimates, the relative difference in two $\beta$'s is only determined by the relative difference in the $\eta$'s.

The term in parentheses reflects relative cost shares in producing the leisure activity; that is, the numerator is the cost of the technology and the denominator is the cost of the time input, priced at the market wage. For the marginal consumer, equation (12) will hold with equality. Equation (12) provides an alternative to measuring technological change. It does not exploit the time allocation decision, but uses the ability to substitute between time inputs and market inputs in the production of leisure. We explore both approaches in the empirical work below.

## 2.4 The Response of Labor Supply to Leisure Technology

The derivation of the Engel curve elasticities took the relative shadow price of time $\omega$ as a parameter and traced out the choice over individual leisure activities. We now return to the problem of choosing consumption and market hours.

Recall from (7) that the choice of leisure is pinned down by the opportunity cost of time $\omega = \lambda w$ and the technology vector $\boldsymbol{\theta}$. Let $\epsilon$ denote the absolute value of the Frisch elasticity of leisure $\epsilon \equiv -d\ln H/d\ln\omega$, keeping in mind that this elasticity holds constant the marginal value of income, $\lambda$. Implicitly differentiating (7) and using $\mu = U_v$, we have:

$$\frac{1}{\epsilon} = \frac{1}{\overline{\eta}} - \frac{\partial \ln U_v}{\partial \ln v}\frac{\partial \ln v}{\partial \ln H}. \tag{13}$$

The left-hand side is the inverse Frisch elasticity of leisure. The first term on the right-hand side is the inverse elasticity of the leisure aggregate $v$ with respect to $H$. The second term captures the elasticity of the marginal utility of leisure with respect to $H$. The role of $\overline{\eta}$ comes directly from the leisure demand system. If the agent devotes a high share of leisure time to leisure luxuries then, all else equal, $\overline{\eta}$ is larger and so is the Frisch elasticity. This reflects that leisure luxuries are elastic at the margin, and a small change in the opportunity cost of time induces a large shift in the amount of leisure time.[3]

The second term on the right side of (13) shows that the response of leisure depends not only on the curvature of the leisure aggregate $v$ (the first term, $1/\overline{\eta}$) but also on how $v$ enters the utility function $U(c, v)$. If, for example, $U(c, v) = u(c) + v$, then the final term on the right is zero and the Frisch elasticity of leisure is governed solely by $\overline{\eta}$. Intuitively, with this utility function, the labor supply response to the wage (governed by $\epsilon$) must be identical to the labor supply response to the marginal value of leisure (governed by $\overline{\eta}$). That is, labor

[3]There are close parallels to this result in the literature on consumption. In particular, Crossley and Low (2011) discuss the restrictions necessary for a constant elasticity of inter-temporal substitution of expenditures in a demand system involving multiple consumption goods. Browning and Crossley (2000) demonstrate the link between relative income elasticities and willingness to substitute inter-temporally. Both points have clear parallels in our treatment of labor supply with multiple leisure goods.

supply is dictated by the relative value of the wage to the marginal value of leisure. However, if $v$ enters $U$ via a concave function, then $\epsilon < \overline{\eta}$, as the additional concavity mitigates the response of leisure to a change in wage. Conversely if $v$ enters $U$ via a convex function, then $\epsilon > \overline{\eta}$, although the extent of convexity is bounded such that the sum on the right is positive.

To trace out the impact of a change in $\theta_i$ on $H$, we differentiate (7) and, using (13), rearrange to obtain:

$$\frac{\partial \ln H(\omega, \boldsymbol{\theta})}{\partial \ln \theta_i} = s_i \left(\epsilon \beta_i - 1\right). \tag{14}$$

The response of $H$ to a change in technology depends on the share of that activity in leisure, $s_i$; the Frisch elasticity, $\epsilon$; and the elasticity of the Engel curve, $\beta_i = \frac{\eta_i}{\overline{\eta}}$. The role of the share $s_i$ is intuitive. If the activity is only a small component of overall leisure, then improving its technology has a minimal impact on total leisure.

The Frisch elasticity enters for the same reason it governs the response to a wage change. The change in leisure technology shifts the relative return of leisure versus work, and the Frisch captures the sensitivity of leisure to that relative price. Note that the same force is relevant if we were to model labor as an extensive-margin choice. For example, if we consider a distribution of agents with heterogeneous wages and wealth, an increase in the return to leisure will sweep the marginal agents out of employment. The Frisch elasticity is then determined by the density of agents with reservations wages close to the market wage, as in Chang and Kim (2006).

Finally, the elasticity of the Engel curve, $\beta_i$, plays an important role in the response of leisure to technological changes. This elasticity captures the extent of diminishing returns to that activity relative to the overall elasticity. An activity with a high $\eta_i$ does not experience strong diminishing returns. Thus, total leisure must increase significantly in order to restore equality between the marginal return to leisure and the opportunity cost of time. The presence of $\beta_i$ indicates that the response of total leisure to technological change is particularly strong for improvements in a leisure luxury.

A related exercise yields how much the value of time needs to increase alongside the technological change to keep leisure constant. That is, implicitly differentiating $H(\omega, \boldsymbol{\theta}) = \bar{H}$ for some arbitrary constant $\bar{H}$, we obtain:

$$\left.\frac{d \ln \omega}{d \ln \theta_i}\right|_{\Delta H = 0} = s_i \left(\beta_i - \frac{1}{\epsilon}\right). \tag{15}$$

By definition of the Frisch elasticity, (15) is (14) normalized by $\epsilon$.

From equation (14), we can derive the response of labor supply to a change in technology:

$$\Delta \ln H|_{\Delta\omega=0} \approx s_i \left(\epsilon\beta_i - 1\right) \Delta \ln \theta_i. \tag{16}$$

This represents the change in leisure hours holding the wage fixed. Alternatively, the implied change in the price of time holding hours fixed is (16) normalized by $\epsilon$.

Combining (11) with (16), and assuming stable technology in the reference activity $j$, we obtain:

$$\Delta \ln H|_{\Delta\omega=0} = s_I \left[\frac{\epsilon\beta_I - 1}{\overline{\eta}\beta_I - 1}\right] \left(\Delta \ln h_I - \frac{\beta_I}{\beta_j}\Delta \ln h_j\right). \tag{17}$$

Or, if we measure the shift in labor supply in terms of prices rather than quantities:

$$\Delta \ln \omega|_{\Delta H=0} = s_I \left[\frac{\beta_I - \epsilon^{-1}}{\overline{\eta}\beta_I - 1}\right] \left(\Delta \ln h_I - \frac{\beta_I}{\beta_j}\Delta \ln h_j\right). \tag{18}$$

The alternative measure of technological progress (12) yields the following:

$$\Delta \ln H|_{\Delta\omega=0} \approx s_I \left(\epsilon\beta_I - 1\right) \left(\frac{p_I}{wh_I}\right) \Delta \ln p_I, \tag{19}$$

where $\Delta \ln p_I$ is the change in price across vintages of $\theta_I$. Comparing (17) and (19), we see that former requires a measure of $\overline{\eta}$, the average elasticity, while the latter requires a measure of the relative cost shares and the additional cost of new technology. We shall explore both approaches in the empirical analysis.

The framework presented in this section provides an empirical road map. In the next section, we summarize trends in time allocation for alternative demographic groups. We then take the leisure demand system of Section 2.2 to the data to estimate $\beta_i$ for alternative leisure activities. In Section 5 we use equation (11) and the empirical shift in time allocation to estimate the change in technology for recreational computer use and video games. We combine this with price data and use (12) to recover $\overline{\eta}$. The last step is to use (17) or (18) to quantify the impact of improved technology on labor supply.

# 3 Younger Men's Changing Composition of Time

In this section we document how younger men, and other demographic groups, have allocated their time since the early 2000's based on the time diaries of the American Time Use Survey (ATUS) from 2004 through 2017. The ATUS surveys a sample drawn from CPS respondents within a few months after their final CPS survey, collecting a 24-hour diary in which respondents record the previous day's activities in 15-minute intervals. The ATUS groups these activities into categories.[4] We restrict the sample to civilians ages 21 to 55. We further exclude full-time students who are less than age 25.[5] This mitigates any role for increased college attendance in the decline in work hours for younger men. We apply weights to the ATUS samples so that the educational distribution of ATUS respondents by age group and gender (e.g., young men, young women, older men, and older women) match the corresponding educational distribution in the March CPS for each time period.[6]

## 3.1 Trends in Broad Time Use Categories

We divide activities into six broad categories: market work, job search, home production, child care, education, and leisure.[7] Our classification of time use activities follows closely the classification used in Aguiar and Hurst (2007), Aguiar et al. (2013), and Boppart and Ngai (2017). Job search includes sending out resumes, job interviewing, and researching jobs. Home production includes doing household chores or maintenance, preparing meals, shopping, and caring for other adults. We separate child care from home production. Education refers to time spent on one's *own* education, such as attending courses or doing homework. Leisure consists of watching television and movies, recreational computing and video games, reading, playing sports, hobbies, etc. We discuss leisure in more detail in the next subsection. We treat a portion of eating, sleeping, and personal care (ESP) as leisure as these categories have both a biological and leisure component. To isolate the leisure component of ESP, we exclude 7 hours per day from total ESP time to account for the fact that a certain amount of sleeping, eating and personal is needed for survival.[8] Given this, each individual's time use across the six categories sums to a maximum of 17 hours per day or 119 hours per week.

Table 1 shows time use for younger and older men (Panel a) and younger and older women (Panel b). We report time use in weekly hours, multiplying the daily averages by 7.

[4]Each ATUS sample is uniformly distributed across days of week. Time spent traveling to or from an activity is always included in the activity's time. Though the ATUS starts in 2003, we begin our analysis with 2004, as there are small changes in the survey methodology between 2003 and 2004. The Data Appendix discusses in more detail our ATUS sample, as well as other data sets employed in the paper.

[5]Before 2013 the CPS, and therefore the ATUS, asked only those under age 25 about school attendance.

[6]It is well known that the ATUS does not match the educational distribution of the March CPS for sub-groups (Grossbard and Vernon (2015)). For example, in the ATUS 28.7% and 38.7% of women ages 21 to 30 have at least a bachelor's degree during the 2004-2007 and 2014-2017 periods, respectively. The comparable numbers in the March CPS for those periods are only 27.6% and 33.3%. Tables A1 and A2 in the online appendix detail ATUS time allocations by demographic group without the additional weighting.

[7]Some small categories like personal health care and unclassified time use are omitted from our analysis.

[8]Approximately 95 percent of respondents report 7 or more hours per day for ESP. We explored alternative adjustments (e.g., excluding 6 or 8 hours per day for biological ESP needs) and found our results were not sensitive to these changes.

To increase power we group data for 2004-2007 and for 2014-2017. The table reports average time for each category by time period as well as the change between the two periods.

Starting with the top panel, we see that younger men reduced their market work by 1.8 hours per week over this period, which corresponds to a nearly 5 percent decline. Comparing top and bottom rows of the panel, we see this decline in market hours was more than matched by an increase in leisure of 2.3 hours for younger men.[9] The remaining time activities display relatively small changes with younger men increasing time spent on job search and education and reducing their time on home production and child care. By comparison, older men reduced their weekly market work by a half an hour per week, while increasing their leisure by 0.6 hours per week. As we will further highlight using CPS data below, the decline in market work for young men during this period was much larger than the decline in worker for older men. Panel (b) shows patterns for women. Younger women had a smaller decline in market work, but a larger decline in home production and child care, than younger men. The decline in home production was also pronounced for older women. Comparing across all groups, younger men exhibited the largest gain in leisure.

To explore the robustness of the trends in market work by differing demographic groups, we use data on annual hours worked from the March CPS. An advantage of the March CPS over the ATUS is that market hours are reported based on the calendar year, rather than a snapshot from a single day.[10] The top panel of Figure 1 compares the percent change in log annual hours worked (relative to survey year 2000) for younger and older men. Between survey year 2000 and survey year 2018, younger men's hours have fallen by 10.9% while older men's hours have fallen by 7.5%. While annual hours for both groups have been increasing since 2011, they are still far below 2007 levels. The differential hours gap between younger and older men began widening prior to the start of the Great Recession, widened substantially during the Great Recession, and has remained large ever since. Comparing averages for years 2014-2017 to 2004-2007, the March CPS show a decline 140 hours per year (2.7 hours per week) for men ages 21-30, which is a somewhat steeper decline than seen in the ATUS. The relative difference in the decline in market hours between young and older men during this time period were similar in the ATUS and March CPS (1.4 hours per week vs. 1.0 hours per week).

Panel B of Figure 1 shows that much of the differential decline in annual hours worked between younger and older men is on the extensive margin. This panel measures the fraction

[9] Appendix Figure A1 displays the cross-sectional distribution of leisure time for younger men for the 2004-07 and 2014-17 sub-periods. The density displays a noticeable rightward shift over time.

[10] Our measure of annual hours worked in the March CPS is the respondent's report of their usual hours per week worked multiplied by the number of weeks they worked during the prior calendar year. As with the ATUS sample, we exclude full-time students ages less than 25 when using the March CPS sample.

Table 1: Broad Time Allocation During the 2000s

(a) Men, Age 21-55

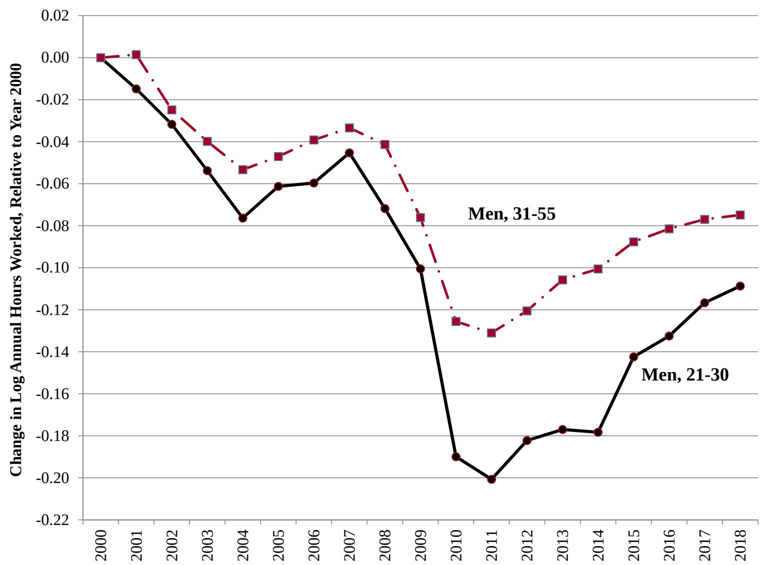
| | Age 21-30 | | | Age 31-55 | | |
|---|---|---|---|---|---|---|
| Activity | 2004-2007 | 2014-2017 | Change | 2004-2007 | 2014-2017 | Change |
| Market Work | 38.4 | 36.6 | -1.8 | 40.8 | 40.2 | -0.5 |
| Job Search | 0.3 | 0.8 | 0.5 | 0.3 | 0.4 | 0.1 |
| Home Production | 12.1 | 11.7 | -0.4 | 14.8 | 14.1 | -0.7 |
| Child Care | 2.8 | 2.2 | -0.6 | 3.6 | 4.1 | 0.5 |
| Education | 2.4 | 2.7 | 0.3 | 0.6 | 0.6 | 0.0 |
| Leisure | 61.1 | 63.4 | 2.3 | 57.1 | 57.7 | 0.6 |

(b) Women, Age 21-55

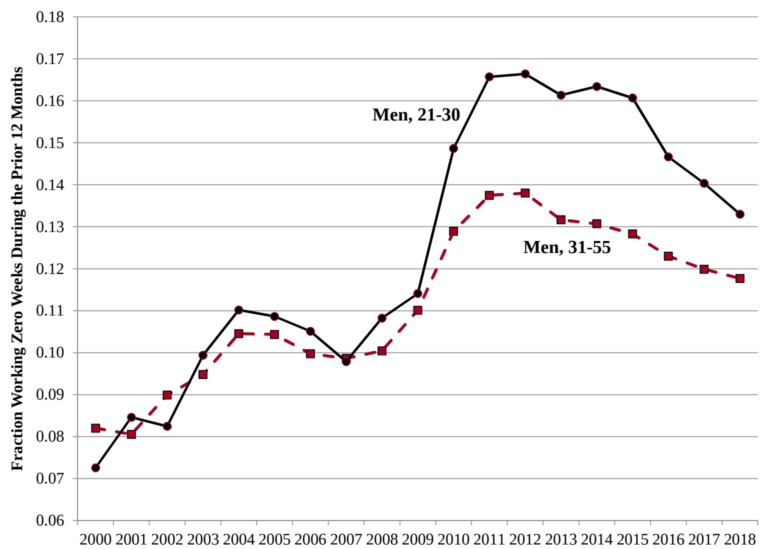
| | Age 21-30 | | | Age 31-55 | | |
|---|---|---|---|---|---|---|
| Activity | 2004-2007 | 2014-2017 | Change | 2004-2007 | 2014-2017 | Change |
| Market Work | 27.5 | 26.8 | -0.7 | 27.3 | 27.4 | 0.1 |
| Job Search | 0.2 | 0.3 | 0.1 | 0.2 | 0.2 | 0.0 |
| Home Production | 19.0 | 17.8 | -1.2 | 24.2 | 22.4 | -1.8 |
| Child Care | 10.0 | 8.6 | -1.4 | 7.3 | 7.8 | 0.4 |
| Education | 2.3 | 3.1 | 0.8 | 1.1 | 0.9 | -0.2 |
| Leisure | 58.5 | 60.0 | 1.6 | 56.2 | 57.5 | 1.3 |

Note: Table reports time spent on activities from the ATUS, expressed in units of hours per week. Data are pooled for 2004-2007 and 2014-2017 periods. An individual's total time endowment, after subtracting off 49 hours per week for biological sleeping, eating and personal care needs, is 119 hours per week. Data are weighted by ATUS survey weights adjusted to match the corresponding education distribution by year-demographic cell in the corresponding year's March CPS. See Appendix Table A1 for the same means using the original ATUS weights.

Figure 1: Differences in Hours Worked Between Younger and Older Men, March CPS




Panel A: Change in Log Annual Hours, Relative to 2000




Panel B: Fraction Worked Zero Weeks During Prior Year

Note: Panel A shows the change in log annual hours worked relative to year 2000 while panel B shows the shares who report working zero weeks during the prior year. Data for men ages 21-30 are shown in the solid lines while data for men ages 31-55 are shown in the dashed lines. Data are from the CPS March supplement. Full-time students ages less than 25 are excluded. The year refers to the year of the survey where hours are measured.

of respondents in each group that reports working zero weeks during the prior calendar year. For both older and younger men, between 7 and 8 percent reported working zero weeks during the prior year in 2000. The shares between the groups track each other up to 2009. After that, the share of younger men reporting working zero weeks during the prior year starts to diverge. Like with annual hours worked, the gap increased substantively during the Great Recession and has only modestly reversed as of 2018. Both panels of Figure 1 illustrate that hours worked of younger men have remain depressed relative to older men despite the gains made in aggregate labor market conditions during the last decade. Could part of this recent gap be driven by the increased marginal value of leisure for younger men relative to older men? We next turn to some descriptive evidence along these lines.

## 3.2 Trends in the Nature of Leisure

We now explore leisure at a more disaggregated activity level. Within total leisure, we distinguish the following five activities: recreational computer time; television and movie watching; socializing; discretionary eating, sleeping and personal care (ESP); and other leisure. Recreational computer time includes time spent on non-work email, playing computer games, browsing web sites, leisure time on smart phones, online chatting, and engaging in social media. We often highlight the video/computer game component of recreational computer.[11] Computer time for work or non-leisure activities (like paying bills or checking email) are captured by other time-use categories. Watching television and movies specifically includes watching on streaming platforms (like Netflix and YouTube), as well as traditional television and movies. Socializing includes entertaining or visiting friends and family, parties, dating, and participating in civic or religious activities. "Other leisure" includes all remaining leisure activities, such as reading, listening to music, exercising, and engaging in hobbies.

Table 2 shows the weekly hours spent by younger men in each leisure category. We see that the increase of 2.3 hours in weekly leisure hours for younger men is more than accounted for by an increase of 2.7 hours in their recreational computer time.[12] Furthermore, much of that increase took the form of increased video game playing (1.8 hours per week). The implied annual increase in computer leisure of 140 hours is a striking change for a time-

[11] The ATUS has a category of time use labeled "playing games." This includes video games, but also includes playing cards as well as traditional board games like checkers, Scrabble, etc. So we cannot distinguish playing Scrabble from video gaming. We document a very large increase in playing games during the 2000s by younger men. We equate this with an increase in video gaming. However, we realize that we may be identifying a Scrabble boom as opposed to a video game boom.

[12] Appendix Figure A2 displays the cross-sectional distribution of recreational computing time for younger men, conditional on spending a strictly positive amount of time. Similar to the leisure distribution presented in Figure A1, the distribution of computing time displays a prominent rightward shift between 2004-07 and 2014-17.

use category over a short span of time. For reference, annual hours women spend at home production fell by 520 hours over the last forty years (Aguiar and Hurst (2007)).

Eating, sleeping and personal care (ESP) also increased for young men during this time period by 1.7 hours per week. The marked increase in sleeping time is a feature of the ATUS data across all demographic groups during this time period (e.g., younger women, older men, and older women). This may be a real phenomenon or it may be an artifact of changes in the way sleep time is measured within the ATUS. The sleep time use category also includes sleeplessness and trying to fall to sleep.[13] For our procedure using ESP as a reference activity, any shift in preferences or technology that increases sleep time over the period will bias us away from finding a decrease in labor supply for young men from innovations in computer technology.[14] Given that the increase in recreational computer use and sleeping exceeded the total increase in leisure time, time spent in other leisure categories must have fallen. As seen from Table 2, younger men spent 1.6 hours less time watching TV/movies. The two other leisure categories – socializing and other leisure activities – exhibited small declines in time use as well (by about 0.2 and 0.3 hours per week, respectively).

Why did recreational computing display such explosive growth for younger men over this period? One major innovation in the mid 2000s was people moving their social interactions, especially gaming, online. Facebook, started in 2004, grew from 12 million users in 2006 to 360 million by 2009. A generation of video game consoles introduced in 2005 and 2006 allowed individuals to interact online. Massive multiplayer online games launched around the same time. For example, World of Warcraft, began in 2004, grew to 10 million monthly subscribers by 2010. Coupled with advances in graphics, these innovations fueled a large expansion of the video game industry. Nominal revenues of the video game industry increased by about 50 percent between 2006 and 2009 after being fairly flat for the prior five years.[15]

From Table 2, weekly leisure hours for younger men increased by 2.4 hours between 2004-07 and 2014-17. At the same time, there was a large increase, from 11.7 to 14.5 percent, in the share of younger men in the ATUS who are not employed. Because the non-employed exhibited nearly 30 hours more leisure on average in 2004-2007, the shift to fewer employed played a major role in the overall increase in average leisure. In Table 3 we look at leisure conditional on being employed. Unfortunately, since there is no panel dimensions to the ATUS, we are comparing different pools of employed across a period with a large decrease in employment. So it is important to keep in mind that the changes in average leisure

[13]For example, watching TV while trying to fall to sleep may be classified as either sleeping or TV watching.

[14]It is interesting to note that the systematic increase in sleeping time found in the ATUS is not present in other data sets. For example, Hou et al. (2018) finds no increase in sleep time for prime age individuals in the National Health and Nutrition Examination Survey (NHANES) between 2005 and 2014.

[15]Data are from the NPD group: vgsales.wikia.com/wiki/NDP_sales_figures.

Table 2: Leisure Activities for Men 21-30

| Activity | 2004-2007 | 2014-2017 | Change |
|---|---|---|---|
| Total Leisure | 61.1 | 63.4 | 2.3 |
| Recreational Computer | 3.3 | 6.1 | 2.7 |
| Video Game | 2.1 | 3.9 | 1.8 |
| ESP | 24.3 | 26.0 | 1.7 |
| TV/Movies/Netflix | 17.4 | 15.8 | -1.6 |
| Socializing | 7.8 | 7.6 | -0.2 |
| Other Leisure | 8.3 | 8.9 | -0.3 |

Note: Time spent on each activity expressed as hours per week. Leisure components sum to total leisure time. Video gaming is a subcomponent of total computer time. ESP refers to eating, sleeping and personal care net of 49 hours. The final column is the change in hours per week controlling. Data are weighted by ATUS survey weights adjusted to match the corresponding education distribution by year-demographic cell in the corresponding year's March CPS. See Appendix Table A2 for the same means using the original ATUS weights.

calculated for those employed will reflect compositional effects driven by the greater share not employed.

Turning to Table 3, we see that leisure for employed younger men *increased* by 2.3 weekly hours. Even among the employed, hours worked are falling during this time period. So, while much of the decline in market work overall for younger men was due to declines on the extensive margin, there were also intensive margin adjustments. What is interesting is that even among employed men, there is a substantial shift towards more recreational computer time over this period. The 1.9 hours per week increase in recreational computer time was again about the same magnitude as the increase in total leisure time.[16]

Below we infer changes in computer leisure technology from how individuals shifted leisure toward that activity, adjusting for changes in total leisure time. As a first look at the data, we sort individuals into bins based on hours of leisure their previous day. The bins are on the horizontal axis of Figure 2, where, for example, label 5 indicates individuals who spent five to six hours at leisure. For each leisure bin, we report average time spent at recreational computer use. The lighter bars in the figure depict the averages for younger

[16]While the non-employed have substantially more leisure time than the employed, they also display a particularly sizable shift in their recreational computing time from 5.4 hours per week in 2004-2007 to 12.0 hours per week in 2014-2017. The 12 hours per week spent on recreational computing time for the non-employed in 2014-2017 exceeds the time they spend socializing (6.8 hours per week) and other leisure activities (9.5 hours per week).

Table 3: Leisure Activities for Employed Men 21-30 (Hours per Week)

| Activity | 2004-2007 | 2014-2017 | Change |
|---|---|---|---|
| Total Leisure | 57.6 | 59.9 | 2.3 |
| Recreational Computer | 3.0 | 4.9 | 1.9 |
| Video Games | 1.9 | 3.2 | 1.3 |
| ESP | 23.5 | 24.7 | 1.3 |
| TV/Movies/Netflix | 16.0 | 14.6 | -1.4 |
| Socializing | 7.4 | 7.7 | 0.3 |
| Other Leisure | 7.6 | 7.8 | 0.2 |

Note: Components sum to total leisure time. Video gaming is a subcomponent of total computer time. ESP refers to eating, sleeping and personal care net of 49 hours per week. Data are weighted by ATUS survey weights adjusted to match the corresponding education distribution by year-demographic cell in the corresponding year's March CPS. See Appendix Table A3 for the same means using the original ATUS weights.

men for 2004-2007, while the darker bars depict those for 2014-2017. We see that computer leisure increased within essentially all leisure bins, but especially for high-leisure individuals.

Table 4 compares younger men's shift toward computing and gaming (top panel) to that for older men, younger women, and older women (bottom three panels). The table clearly shows that the increase in computer leisure in general, and its gaming component in particular, was a younger men's phenomenon. While younger men increased their computer leisure by 2.6 hours per week, the increases were only 0.0, 1.1, and 0.4 hours per week for older men, younger women, and older women, respectively. Younger women reported a modest increase in their recreational computer time; but, in contrast to younger men, only about one-third of that increase involved video games.

## 4 Estimating Leisure Engel Curves

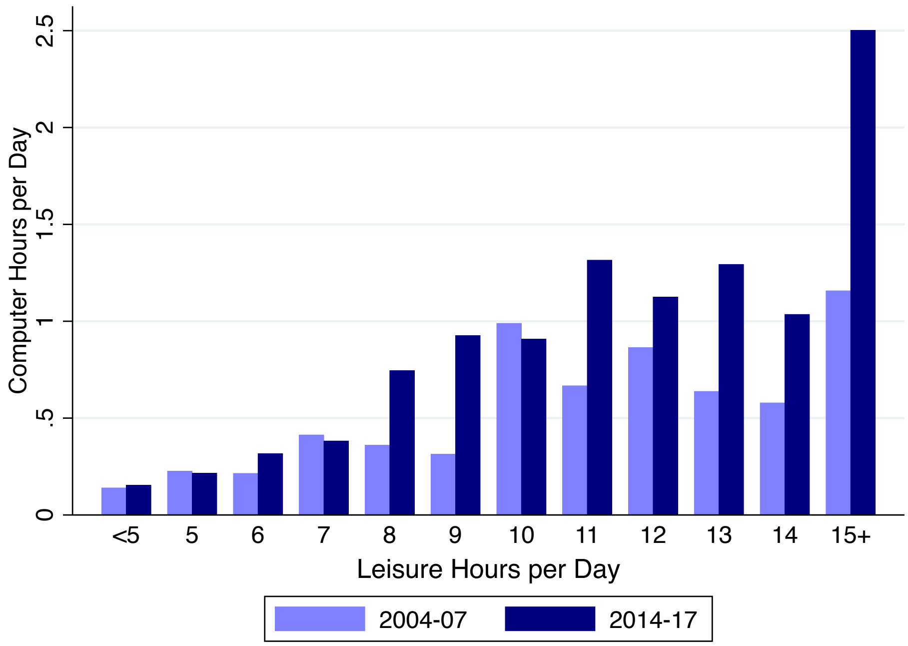
We now estimate the leisure demand system outlined in Section 2.2. The key targets are the Engel curve elasticities $\beta_i$. From estimates of the Engel curves, we will construct estimates of the primitives $\theta_i$ and $\eta_i$. In this section, we discuss in turn measurement error, functional forms, and identification. We then report our estimated Engel curve elasticities.

Table 4: Computer Leisure and Video Game By Age-Sex Groups

| | 2004-2007 | 2014-2017 | Change |
|---|---|---|---|
| | | Men 21-30 | |
| Total Leisure | 61.1 | 63.4 | 2.3 |
| Recreational Computer | 3.3 | 6.1 | 2.7 |
| Video Games | 2.1 | 3.9 | 1.8 |
| | | Men 31-55 | |
| Total Leisure | 57.1 | 57.7 | 0.6 |
| Recreational Computer | 2.1 | 2.1 | 0.0 |
| Video Games | 0.9 | 1.0 | 0.0 |
| | | Women 21-30 | |
| Total Leisure | 58.5 | 60.0 | 1.6 |
| Recreational Computer | 1.5 | 2.6 | 1.1 |
| Video Games | 0.8 | 1.2 | 0.4 |
| | | Women 31-55 | |
| Total Leisure | 56.2 | 57.5 | 1.3 |
| Recreational Computer | 1.6 | 2.0 | 0.4 |
| Video Games | 0.6 | 0.7 | 0.1 |

Note: Video game time is a subcomponent of computer leisure. Data are weighted by ATUS survey weights adjusted to match the corresponding education distribution by year-demographic cell in the corresponding year's March CPS. See Appendix Table A4 for the same means using the original ATUS weights.

Figure 2: Younger Men's Hours per Day of Computer Leisure by level of Total Leisure




Note: Figure shows average time spent on computer leisure (including video games) by individual's total leisure. Time use is expressed in hours per day. Except for first and last bins, leisure bins span one hour per day, with minimal value of each bin denoted.

## 4.1 Measurement Error

The major measurement challenge is that the time diaries are a single-day's snapshot, with zeros reported for most activities on that given day. Ideally, we would like data on an individual's typical allocation of leisure, which requires observations over multiple days or even weeks. The lack of such broader coverage makes our data especially prone to sampling error. A secondary concern is that measurement error in an individual activity will distort measured total leisure as well, given that total leisure is simply the sum of the individual activities. This generates an artificial correlation, a well known issue in estimating consumption demand systems.

To address both issues, we construct synthetic time diaries that average over similar types of individuals. Specifically, we form cells based on gender, age, educational attainment, industry, geographic region, and time period. Age is demarcated as in Section 3.1; namely, 21-30 and 31-55. Educational attainment is split by those with at least a bachelor's degree versus those with less than 16 years of schooling, omitting full time students throughout. Industry is reported as of the last CPS interview, typically a few months prior to the time diary. The CPS asks the industry of the current job or, if not currently employed, the industry of the last job held in the preceding 12 months.[17] Note that we include as a separate "industry" a missing industry code, which typically reflects those who have not had a job in the preceding 12 months.

For region, we first compute the change in each state's average leisure between 2004-07 and 2012-15 separately for each gender-age group. We then sort states into five roughly equally-populated groups based on the recorded change. Thus individuals in states with a large increase in leisure are grouped separately than those in states with a small increase (or decrease) in leisure.

The final cell characteristic is time period, where we use the four periods discussed in Section 3.1; namely, 2004-07, 2008-10, 2011-13 and 2014-17. Theoretically, this implies up to 2,240 cells in total – 560 for each sex-age group; but in practice, some cells contain no individuals. In estimating, we weight all cells by the sum of its individual members' weights and restrict attention to cells with at least 10 observations.

## 4.2 Specification

Our empirical specification builds on the consumption literature, most notably Deaton and Muellbauer's (1980) Almost Ideal Demand System (AIDS). Adapting AIDS to a leisure demand system, we posit that the share of time allocated to an activity is approximately linear in the log of total leisure time. We estimate:

$$s_{ikt} = \delta_{it} + \gamma_i \ln H_{kt} + \varepsilon_{ikt}, \tag{20}$$

where $s_{ikt} = h_{ikt}/H_{kt}$ is the share of total leisure $H_{kt}$ devoted to activity $i$ in period $t$ by demographic group $k$, while $\ln H_{kt}$ is log of that group's total leisure time. We include time-period fixed effects, $\delta_{it}$ in all specifications. As added controls, we consider fixed effects for education, region, and industry, respectively, across alternative specifications. Time-dependent shifters that influence the allocation of leisure time to activity $i$ are captured by $\delta_{it}$. In particular, $\delta_{it}$ controls for movements in technology $\theta_i$. We estimate (20) separately for each activity and allow all parameters to vary by age-gender groups.

[17]Specifically, we use PRMJIND1 in the ATUS-CPS file. The 13 industries are: 1) Agriculture, forestry, fishing, and hunting; 2) Mining; 3) Construction; 4) Manufacturing; 5) Wholesale and retail trade; 6) Transportation and utilities; 7) Information; 8) Financial activities; 9) Professional and business services; 10) Educational and health services; 11) Leisure and hospitality; 12) Other services; and 13) Public administration. The final CPS industry is Armed Forces, which is not present in our sample. We treat individuals without an industry code as the 14th industry.

From estimate $\hat{\gamma}_i$, we recover an estimate of $\beta_i = \partial \ln h_i / \partial \ln H$:

$$\hat{\beta}_i = 1 + \frac{\hat{\gamma}_i}{\bar{s}_i}, \tag{21}$$

where $\bar{s}_i$ is the average of activity $i$'s leisure share over the sample period, specific to each age-gender group.

## 4.3 Identification

To consistently estimate $\gamma_i$ from (20) requires that $H_{kt}$ is orthogonal to the error term. Recall that the activity-time fixed effect $\delta_{it}$ captures time-dependent shifts in tastes or technology that are uniform across cells.[18] Thus, our identifying assumption is that cell-specific tastes for a given leisure activity are uncorrelated with total leisure.

To flesh out our identification assumption, note that an ideal source of variation in a cell's relative leisure time would be forces such as differential employment opportunities due, say, to the Great Recession. This type of variation allows an accurate measure of how leisure is allocated across activities due to exogenous changes in total leisure, where by exogenous we mean independent of idiosyncratic tastes and technologies for a particular activity.

The construction of our cells is designed to isolate such variation. In particular, the 2000s saw large relative swings in employment across education groups, regions, and industries. These movements are plausibly unrelated to idiosyncratic shifts in the taste for particular leisure activities.[19] Thus, by grouping individuals in cells defined by education, industry, and region, not only minimizes measurement error, but also isolates a plausibly exogenous source of variation in total leisure.

The threat to identification arises if cells with especially high total leisure systematically have different tastes and technologies for an activity than cells with low levels of leisure. For example, suppose that cells with high leisure have a relative preference for recreational computing. In this case, we will over-estimate the Engel curve elasticity for computing and under-estimate the elasticities for other activities. Conversely, if high-leisure cells have a weaker taste for computing, we will under-estimate the Engel elasticity for that activity, and over-estimate the other activities' elasticities. To the extent our cells are broadly defined and

[18]In the case of computers and video games, the assumption of common technology seems justified, given the widespread and rapid diffusion of these technologies during the 2000s. According to the FCC, all MSAs had high speed internet as of 2000. We explored using regional variation in introducing broadband internet as a shift in the quality of recreational computing. However, since broadband had saturated the country by the start of our time use data, that leaves no regional or time-series variation to use as an instrument.

[19]This assumption is supported by evidence suggesting that much of the cross-state variation in market work during the 2000s was driven by industrial composition or housing markets. See, for example, Charles et al. (2016) and Mian and Sufi (2014).

designed to isolate variation due to labor market conditions, such a failure of orthogonality should not be a primary concern. To address concerns that the level of leisure may be correlated with demographic characteristics, we explore the robustness of the results to adding fixed effects for education, industry, and region. With these controls, the concern for orthogonality arises only if a differential correlation still remains after controlling for the average level of the leisure activity within that education, industry, or regional group.

### 4.4 Estimates

Table 5 reports our estimates of $\beta_i$ for younger men for each of the leisure activities reported in Table 2. We also break out video gaming from its broader computer category. All estimates are based on the AIDS specification, equation (20), and the implied $\hat{\beta}_i$ are obtained using (21). The first column is a baseline specification that includes time-period fixed effects. The second column adds education-group fixed effects; the third column further adds regional fixed effects; the final column adds fixed effects for the fourteen industry groups. Thus, by the final column, all variation is based on time series variation within the subgroups relative to the average cell effect and the aggregate time fixed effect. The standard errors for $\beta_i$ are bootstrapped.[20]

As seen from Table 5, computers and video games are leisure luxuries. Focusing on the results in Column 1, recreational computing has an Engel elasticity of 2.48, while the video games sub-component has an elasticity of 2.42. The estimates suggest that recreational computing and gaming is the most luxurious leisure activity for younger men. All other activities have elasticities close to or strictly less than 1. TV/Movie watching has an estimated leisure elasticity of 1.19. Other Leisure is neither a luxury nor necessity ($\hat{\beta}_i = 0.97$). Eating-sleeping-personal care is a leisure necessity ($\hat{\beta}_i = 0.76$), as is socializing ($\hat{\beta}_i = 0.46$).

The Engel curve elasticities are similar across specifications, save perhaps for the last column. Including industry fixed effects moves the estimated elasticities towards one. This largely reflects the impact of controlling for those without an industry code; that is, individuals who have been non-employed for at least twelve months. The fact that these individuals have disproportionately high leisure and devote relatively more time to computing implies that including their fixed effect "flattens" the estimated Engel curve. In terms of the calculation of equation (17), the shallower slope for recreational computing, relative to that for ESP, implies that less of the observed increase in recreational computing should be attributed to moving "along" its Engel curve, with more attributed to improvements in its technology. In

[20] Specifically, the bootstrap procedure repeatedly draws samples, estimates the AIDS coefficient $\gamma_i$ and the average share $\bar{s}_i$, and computes $\hat{\beta}_i$ using equation (21). The bootstrap is performed using the 160 replication weights provided by the ATUS.

Table 5: Leisure Engel Curves of Younger Men: $\hat{\beta}_i$

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Recreational Computer | 2.48 | 2.46 | 2.40 | 1.53 |
| | (0.42) | (0.40) | (0.42) | (0.38) |
| Video Games | 2.42 | 2.34 | 2.26 | 1.37 |
| | (0.43) | (0.42) | (0.43) | (0.48) |
| TV/Movies/Netflix | 1.19 | 1.10 | 1.13 | 1.18 |
| | (0.13) | (0.12) | (0.13) | (0.17) |
| Socializing | 0.46 | 0.51 | 0.40 | 0.70 |
| | (0.26) | (0.26) | (0.29) | (0.31) |
| ESP | 0.76 | 0.76 | 0.76 | 0.84 |
| | (0.10) | (0.10) | (0.11) | (0.13) |
| Other Leisure | 0.97 | 1.09 | 1.18 | 1.09 |
| | (0.23) | (0.21) | (0.20) | (0.26) |
| Fixed Effects: | | | | |
| Time Period | ✓ | ✓ | ✓ | ✓ |
| Education | | ✓ | ✓ | ✓ |
| Geographic | | | ✓ | ✓ |
| Industry | | | | ✓ |
| Number of Cells | 281 | 281 | 281 | 281 |
| Number of Individuals | 6,780 | 6,780 | 6,780 | 6,780 |

Note: Implied $\hat{\beta}_i$ using AIDS specification. An observation is a time-gender-age-education-industry-state group cell. Bootstrapped standard errors are in parentheses.

this sense, the estimates of Column 1 are more conservative than Column 4 for estimating the impact of this better leisure technology on labor supply.[21]

Table 6 reports the estimated Engel elasticities of computing and ESP for other demographic groups. The specification is that of Column 1 from Table 5. The implied elasticity for recreational computing is 1.40 for older men, 1.58 for younger women, and 1.48 for older women, all of which are smaller than that that estimated for younger men. However, it is worth noting that recreational computer use is a leisure luxury and ESP is a leisure necessity for all groups.

Figure 3 provides a visual sense of the data behind the estimation of the computer Engel curve for younger men. Specifically, it depicts a scatter plot of log recreational computer time against log total leisure. Each point represents a cell average. Circles depict $2004-2007$

[21] If we employ Column (4)'s estimates in our calculations, the implied shift in labor supply is -3.7%, compared to the -3.3% reported below.

Table 6: Engel Curve Estimates by Demographic Group

| | Men 31-55 | Women 21-30 | Women 31-55 |
|---|---|---|---|
| Recreational Computer | 1.44 | 1.81 | 1.43 |
| | (0.20) | (0.48) | (0.17) |
| ESP | 0.61 | 0.64 | 0.65 |
| | (0.04) | (0.09) | (0.04) |
| Number of Cells | 509 | 275 | 463 |
| Number of Individuals | 36,715 | 10,246 | 44,149 |

Note: Specification is that of Table 5 Column 1. Bootstrapped standard errors are in parentheses.

observations; triangles depict those for $2014 - 2017$. These patterns provide a sense of how we disentangle movements along an Engel curve from shifts driven by changes in $\theta_I$. A shift up in the leisure Engel curve reflects the increase in $\theta_I$ over time.

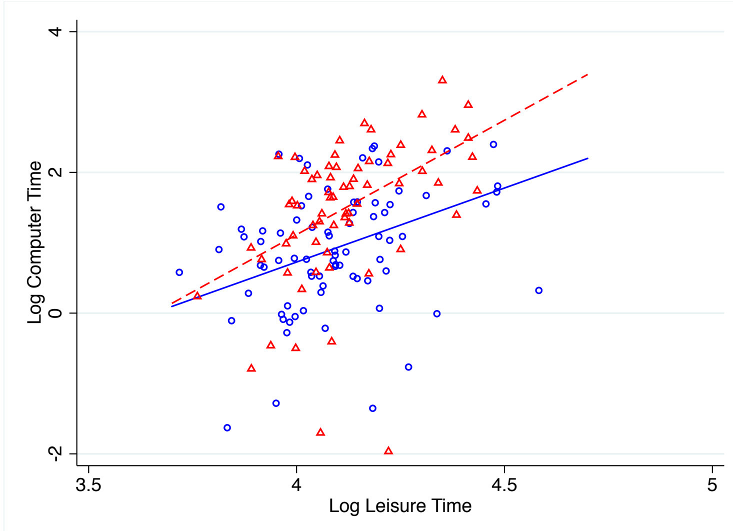
# 5 Leisure Luxuries and Labor Supply During the 2000s

We use time diaries in this section, together with the estimated leisure demand system, to infer technological progress for computer leisure. We then assess the impact of this change on labor supply.

## 5.1 Implied Technological Change from Time Use

With the estimates of $\hat{\beta}_i$ in hand, we can use time-series trends in time allocation to infer the rate of technological progress for gaming and computer leisure since the early 2000s. We begin with equation (11), which relates changes in time allocation to changes in technology. As noted in Section 2, changes in time allocations identify relative technology changes. For our baseline, we treat leisure eating/sleeping/personal care (ESP) as our reference activity. This assumes no technological or preference change for eating, sleeping or personal care during our sample period. In Section 6, we explore robustness of our results to alternate choices for a reference activity. Setting $\Delta\theta_{ESP} = 0$ in (11) and indicating activity $I$ as

Figure 3: Leisure Engel Curves for Computer Leisure: 2004-2007 vs. 2014-2017 [Need to update]




Note: Figure depicts a scatter plot of cell average leisure time (horizontal axis) and recreational computing and gaming (vertical axis), both in log hours per week. All cells are included regardless of size. The circles represent data from 2004-2007 and the triangles represent 2014-2017. The solid line is the weighted regression line for the earlier period and the dashed for the later period. The slopes with standard errors are 2.19 (0.55) and 3.25 (0.68), respectively.

recreational computer, we have:

$$(\eta_I - 1)\Delta \ln \theta_I = \Delta \ln h_I - \frac{\beta_I}{\beta_{ESP}} \Delta \ln h_{ESP}. \tag{22}$$

As reported in Table 2, younger men increased ESP time by 6.7 percent over the ATUS sample period. The estimates in Table 5 imply that $\hat{\beta}_I / \hat{\beta}_{ESP} = 3.3$. This implies that, absent any technological change, their computer time would increase by 22.1 percent. This is the term subtracted on the right-hand side of equation (22), and corresponds to the predicted movement *along* the Engel curve for computer leisure. However, computer time for younger men actually rose by 60.4 percent. We therefore estimate the change in $(\eta_I - 1)\Delta \ln \theta_I$ to be 38.3 percent (with standard error of 14.8 percent), or 2.9 percent per year.[22]

We can repeat this calculation for other demographic groups. For example, we estimate for younger women that $(\eta_I - 1)\Delta \ln \theta_I$ increased by 32.1 percent (standard error 12.5 percent), or 2.5 percent per year. The only group which does not show an increase in computer technology is older men. For this group, $(\eta_I - 1)\Delta \ln \theta_I = -8.2\%$ over the entire period, with a standard error of 7.3%. This reflects that time spent at recreational computing did

[22]We bootstrap our entire procedure to estimate the standard errors for our $(\eta_I - 1)\Delta \ln \theta_I$, using the ATUS replication weights.

not change for older men while ESP increased 3.2 percent.

## 5.2 Impact on Labor Supply from Technology Change

The preceding subsection used shifts in time allocation to document that there has been rapid progress in technology associated with recreational computer use and video games. The question we now address is how this affects the willingness to work. From Section 2.4, equation (17) maps shifts in time allocations into shifts in leisure demand, holding constant the wage and marginal utility of consumption.

In addition to our estimates of the $\beta$'s, $(\eta_I - 1)\Delta \ln \theta_I$, and time use data, we need two additional parameters to estimate how changes in leisure technology affect labor supply as given by (17). The first parameter is the Frisch elasticity of leisure, $\epsilon$. The second is the average leisure-activity elasticity $\overline{\eta}$. The two parameters are related, as seen from equation (13). As a benchmark, we assume $v$ enters linearly in $U$; that is, $\epsilon = \overline{\eta}$. In Section 6, we use price data and equation (19) to check the plausibility of the assumption $\epsilon = \overline{\eta}$, as well as to explore the robustness of our results to alternative choices of $\epsilon$ and $\overline{\eta}$.

We see from (17) that, if $\epsilon = \overline{\eta}$, the impact of technology on labor supply in terms of hours supplied at a given wage is independent of the level of $\epsilon$. Although a higher $\epsilon$ implies a greater response to a given shift in technology, a higher $\overline{\eta}$ also implies that a given change in time allocation reflects a smaller increase in technology. When $\epsilon = \overline{\eta}$, the two effects cancel exactly, making our estimates independent of the level of $\epsilon$.[23]

Table 7 reports estimates for the shift in the labor supply curve for our four demographic groups, fixing wages and the marginal value of a dollar. To move from shifts in leisure demand (equation 17) to labor supply, we scale by the ratio of average leisure to average non-leisure time for each demographic group, with these averages based on the 2004-2017 ATUS. That is, $\Delta \ln n \approx -\Delta \ln H * (H/(1-H))$.

To see how these estimates are constructed, consider younger men. Over the ATUS sample, the share of leisure devoted to computers ($s_I$) is 7.8 percent. As discussed in previous subsection, $\Delta \ln h_I - \frac{\beta_I}{\beta_{ESP}} \ln h_{ESP}$ is estimated at 38.3 percent. From equation (17) and setting $\epsilon = \bar{\eta}$, this implies a shift in leisure demand of 3.0 percent. Given that $H/(1-H)$ is 1.1, we have $\Delta \ln n = -3.3$ percent, which is the number reported in the table.

To put this shift in perspective, in the ATUS younger men exhibited an actual decline in market work between 2004 and 2017 of 4.5 percent (Table 1).[24] Thus the shift in labor

[23]If we consider the shift of labor supply in terms of the wage needed to induce a given level of hours (equation (18)), the level of $\epsilon$ matters, even if it equals $\overline{\eta}$. As a convenient benchmark, a Frisch of one implies the shift of labor supply is of the same magnitude whether measured in terms of wages or hours.

[24]For comparison the CPS data show a decline of about 8.0 percent over those years.

Table 7: Impact of $\Delta\theta_I$ on Labor Supply

| | Men 21-30 | Men 31-55 | Women 21-30 | Women 31-55 |
|---|---|---|---|---|
| $\Delta \ln N$ | -3.32% | 0.29% | -1.17% | -0.12% |
| | (1.29%) | (0.26%) | (0.48%) | (0.18%) |

Note: Table shows the shift in labor supply (wage constant) from $\Delta\theta_I$ for 2004-2007 to 2014-2017. Bootstrapped standard errors are in parentheses.

supply due to better computer technology is quantitatively sizable relative to the observed shift in hours. However, it is important to keep in mind that we are computing the change in desired hours at a *given wage*; how this shift translates into equilibrium wages versus market hours depends on the elasticity – and stability – of labor demand. Given that younger men are a fairly small demographic group, and are likely highly substitutable with other workers, it is reasonable to assume that a relative shift in labor supply of younger men primarily affects their hours rather than wages. However, regardless of that mapping into equilibrium hours versus wages, the implied shift in labor supply is sizable even in the context of the large observed decline in market hours.

A few other results are of note from Table 7. First, improved computer technology explains none of the decline in hours for older men. This stems from the facts that: (1) older men's share of time spent on computer activities is relatively small, and (2) they experienced essentially no increase in the time spent on computer activities during the 2000s relative to other leisure activities. These findings, coupled with the results for younger men in Row 1, suggest that increases in computer technology can explain much of the differential decline in hours worked for younger versus older men from 2004 to 2017. From the 2004 to 2017 ATUS, younger and older men experienced respective declines in market hours of 4.5 versus 1.5 percent.[25] If there were no differential labor demand shocks between younger and older men and if young men's labor demand was perfectly elastic, our estimates imply that all of the differential employment decline could be explained by younger men's increased valuation of leisure. Put another way, our estimates suggest that, absent the increase in computer technology, younger men would have exhibited a decline in market hours close to that of older men.

Second, we find that increased computer technology explains a shift in of the labor supply curve for younger women of 1.2 percent. This is only thirty-five percent of that for younger men. This reflects the lower share of leisure younger women allocate to recreational

[25]CPS data from 2004 to 2017 show a similar differential change of roughly 3.5 percentage points between the decline in annual hours of younger men versus older men.

computing, 3.6 percent, averaging over the period, versus 7.8 percent for younger men. However, the decline for women is still sizable in its own right. Younger women did experience a larger decline in hours worked compared to older women. Our estimates suggest that an increasing valuation of leisure due to improvements in recreational computer technology can also explain some of the differential decline in hours worked for younger women relative to older women.

# 6 Robustness

Our base specification assumes that $\epsilon = \bar{\eta}$, which implies that leisure activities enter the utility aggregator $U$ in an additive separable fashion. In this section we explore the plausibility of this assumption using price and expenditure data. We then examine the sensitivity of the results to alternative assumptions.

## 6.1 Estimating Technology Change from Prices and Expenditures

As discussed above, observed shifts in time allocation and the leisure Engel curves identify changes in technology up to the scaling parameter $\bar{\eta}$. Specifically, the leisure demand system allows us to measure $(\eta_I - 1)\Delta \ln \theta_I = (\bar{\eta}\beta_I - 1)\Delta \ln \theta_I$. To obtain a measure of $\bar{\eta}$, we need an independent measure of $\Delta \ln \theta_I$. We compute an estimate of $\Delta \ln \theta_I$ by using equation (12), assuming an interior solution, together with BLS price and expenditure data. The equation relates $\Delta \ln \theta_I$ to the difference in prices across technological vintages, $\Delta \ln p_I$, as well as the relative cost shares of goods ($p_I$) and time ($wh_I$) in the production of the leisure activity.

The relative prices of video games and equipment fell sharply during the 2000s. The BLS publishes a CPI for toys and games, which includes video games and equipment. The overall CPI increased 0.021 log points per year during the period of 2004-2015. Over the same period, the annual rate for toys and games equaled -0.057 log points. For post-2008, the BLS has provided us the relative weight by year for the non-gaming component of "toys and games" as well as the price series for that non-gaming component. From this, we can infer that the price of the gaming component declined -0.127 log points per year. That is an annual price decline of 14.8 percent relative to the overall CPI. The CPI for computers and peripherals declined similarly, by 13.3 percent per year *relative* to the overall CPI. The BLS designs the CPI to be quality adjusted; that is, the price series ideally reflects the change in price holding quality constant. If the entry price of new models/vintages tracked the overall CPI, then the annual relative decline in the category's CPI captures the relative price across introductions of newer vintages.[26] The log price difference across annual vintages then should reflect the rate of increase in the overall CPI relative to a CPI for computers, peripherals, and video games. We put this rate, perhaps conservatively, at 13.3 percent per year.

We showed in (12) that one can recover $\Delta \ln \theta_I$ based on the relative price change for computer leisure goods together with the cost share of goods in the activity. We take the marginal purchaser to be the average person in our sample. We deflate nominal quantities by the PCE deflator in 2009 dollars. Using the Consumer Expenditure Survey (CE), we break out expenditure on computers, video games, and peripherals. Reported expenditure on these goods in the CE averaged \$464 for 2004 to 2014 (in 2009 dollars), where we average over households with a member between the ages 21 and 55. Time spent on recreational computing for this period averaged 127 hours per year, where again we average over all respondents ages 21 to 55. From the CPS, the median real wage for the period for employed individuals ages 21 to 55 is \$17.9. Assuming a marginal tax rate of 25 percent, the after-tax wage is \$13.4. Using this as the opportunity cost of time, the time input into computers and gaming is \$1,711. Hence, an estimate of the goods-to-time cost ratio is 0.27. From equation (12), and a price decline of 13.3 percent per year, this implies annual technological progress for computers and video games of 3.6 percent a year.

As context for the 3.6 annual growth in computer and gaming technology, nominal expenditure on computers and peripherals by households with younger men increased at an annual rate of 8.6 percent (CE data). Deflating by the CPI price index for computers and peripherals, this represents a real increase of 20.2 percent *per annum*.[27] While all of the expenditure on computers and peripherals is not solely for leisure, it does provide a sense of the substantial increase in computer and gaming hardware in the typical household. This naturally should increase the return on the time spent computing and gaming, which is reflected in our estimated $\Delta \ln \theta_I$.

Comparing our $(\eta_I - 1)\Delta \ln \theta_I = 2.9$ percent per year number, obtained from the shifts in time allocation, to the $\Delta \ln \theta_I = 3.6$ percent per year from price data, yields an $\eta_I$ of 1.81. Using our estimated Engel curve $\hat{\beta}_I = 2.48$ and $\beta_I = \eta_I/\bar{\eta}$, we obtain $\bar{\eta} \approx 0.73$. Given this estimate, our benchmark assumption that $\epsilon = \bar{\eta}$ implies a leisure Frisch elasticity of 0.73. This calculation provides a sense of the magnitude of $\Delta \ln \theta_I$ from price and expenditure

[26]Tracking prices across vintages is complicated by the alternate varieties and features that are introduced with new models. For reference, the original Xbox was introduced in 2001 retailing for \$299.99. The next generation Xbox 360 arrived in 2005, with the "core" system selling for \$299.99 and the "bundle" for \$399.99. The Xbox One entered in 2013 at \$499.99, which included a Kinect sensor that sold separately for \$150.

[27]For the sample period 2012-2014, average nominal expenditure is \$571. The corresponding figure for 2004-2006 is \$288, representing an annual nominal growth rate of 8.6 percent. The decline in the CPI Price Index for computers and peripherals, also calculated as the difference in three-year averages, is 11.6 percent. Thus real expenditures increased at an annual rate of 20.2 percent.

data, and hence the scale parameter $\bar{\eta}$. Given the assumptions and data challenges involved, it should be viewed as a rough guide rather than a firm estimate. For this reason, in the next subsection we explore how our results vary with alternative values of $\bar{\eta}$ and $\epsilon$.

## 6.2 Sensitivity of Results to $\epsilon$ and $\bar{\eta}$

In Section 5.2, we assumed that $\epsilon = \bar{\eta}$. In doing so, we did not need to specify a specific value for either variable. However, the size of the induced shift in labor supply more generally depends on the values of $\epsilon$ and $\bar{\eta}$. Equation (17) indicates exactly how our benchmark result varies with alternative values of these two parameters, showing that the magnitude is scaled by the factor $\left[\frac{\epsilon\beta_I - 1}{\bar{\eta}\beta_I - 1}\right]$. Here we explore robustness of the implied impact on labor supply to varying both $\epsilon$ and $\bar{\eta}$.

There is an extensive literature estimating the Frisch labor supply elasticity. Recall that as leisure is roughly half the discretionary time in our framework, the leisure Frisch is approximately equal to the labor Frisch. Moreover, the relevant elasticity for our framework is the combination of the extensive and intensive margins. Hall (2009) surveys the literature estimating the *intensive* margin Frisch. He takes its value to be in the range of 0.7, with that choice especially influenced by Pistaferri (2003)'s estimate of 0.71. Chetty et al. (2013) similarly survey a number of estimates of the intensive margin Frisch and arrive at a somewhat smaller consensus value of 0.54. Chetty et al. (2013) also survey several quasi-experimental estimates of the extensive-margin Frisch elasticity. They put the extensive elasticity, at 0.32. Several authors have produced structural estimates of the Frisch elasticity at the extensive margin. These suggest modestly higher elasticities of about 0.4, or a little higher. (See Gourio and Noual (2009), Mustre-del-Río (2015), and Park (2017).) Based on this literature, we treat the *combined* Frisch, reflecting both the intensive and extensive responses, to be upwards of one. To err on the conservative side, we examine robustness to Frisch values of $\{0.5, 0.75, 1\}$. From the calculations in the last subsection, we arrived at 0.75 as a plausible value for $\bar{\eta}$, though with admittedly some uncertainty attached to that calculation. We consider the same range of values for $\bar{\eta}$ as taken for $\epsilon$, that is, $\{0.5, 0.75, 1.00\}$.

The implied change in labor supply of younger men due to changes in leisure technology is reported in Table 8 for these alternative values for parameters $\epsilon$ and $\bar{\eta}$. Recall that our benchmark sets $\epsilon = \bar{\eta}$. Hence, the diagonal of the table replicates our baseline estimate of a 3.3 percent decline in labor supply.

Fixing $\epsilon$, we see that an increase in $\bar{\eta}$ reduces the implied shift in labor supply. For example, holding $\epsilon$ constant at 0.75, the shift in labor supply ranges from $-11.9\%$ to $-1.9\%$ as $\bar{\eta}$ increases from 0.5 to 1. Recall from equation (13) that the Frisch elasticity can be

Table 8: Sensitivity of Labor Supply Shift to $\epsilon$ and $\bar{\eta}$

| | $\bar{\eta} = 0.50$ | $\bar{\eta} = 0.75$ | $\bar{\eta} = 1.00$ |
|---|---|---|---|
| $\epsilon = 0.50$ | -3.3% | -0.9% | -0.5% |
| $\epsilon = 0.75$ | -11.9% | -3.3% | -1.9% |
| $\epsilon = 1.00$ | -20.5% | -5.7% | -3.3% |

Note: Table shows the shift in labor supply (wage constant) for 2004-2007 to 2014-2017 for younger men due to $(\eta_I - 1)\Delta\theta_I$, displaying sensitivity of Table 7's result to alternate values of $\epsilon$ and $\bar{\eta}$.

decomposed into $\bar{\eta}$, the average elasticity within $v$, and the additional curvature due to the leisure aggregator $U$. As we hold $\epsilon$ constant and increase $\bar{\eta}$, we increase the curvature of $U$, which lowers the responsiveness of leisure to an increase in technology. Reading down a column, fixing $\bar{\eta}$, a higher Frisch elasticity increases the implied shift in labor supply. For example, fixing $\bar{\eta} = 0.75$, the implied shift in labor ranges from $-0.9\%$ to $-5.7\%$ as the Frisch elasticity varies between 0.5 and 1. While it is clear that the relative magnitude of $\epsilon$ to $\bar{\eta}$ plays an important role in the quantitative impact of computer and gaming technology on labor supply of younger men, for a wide range of these parameters the estimated impact remains quite substantial.

## 6.3 Differential Substitutability Across Leisure Categories

Specification (20) assumes additive separability across activity sub-utilities, which is consistent with the preferences assumed in equation (1). This implies that, conditional on $H$, time spent at activity $i$ offers no information on the relative returns to activities $j$ versus $k$ ($j, k \neq i$). Part of the motivation for this assumption is parsimony. But the other is empirical–we do not observe that individuals who allocate more time to computer leisure in turn skew the remainder of their leisure more or less towards any of the remaining categories.

Perhaps the most likely candidate for a close substitute to recreational computing and gaming is TV (which includes online streaming services). Suggestive of this is the fact that younger men's time spent watching TV has declined during our sample period. In this subsection, we perform two exercises to provide a sense of how closely substitutable these activities are.

The first exercise is to look directly at whether TV-watching and computing are correlated, conditional on available non-computing leisure time. Specifically, denote total non-computing leisure time by $\tilde{H} \equiv \sum_{i \neq \text{computing}} h_i$. By definition, this time is allocated to TV, socializing, ESP, and other leisure. We now explore whether this allocation differs depending on whether the individual spends more or less time in recreational computing. To this end, let $h_{Ikt}$ denote average time spent computing for demographic cell $k$ in time-period $t$, where cells and time periods are the same as in our benchmark analysis. Let $\tilde{s}_{ikt} = h_{ikt}/\tilde{H}_{kt}$ denote the share of non-computing leisure time devoted to activity $i \neq I$. We modify (20) and estimate the following demand-system for the younger men:

$$\tilde{s}_{ikt} = \tilde{\delta}_{it} + \tilde{\gamma}_i \ln \tilde{H}_{kt} + \tilde{\alpha}_i \ln h_{Ikt} + \tilde{\epsilon}_{ikt}, \tag{23}$$

where $\tilde{\delta}_{it}$ reflects that time fixed effects are included in all regressions. Note that, because the specification conditions on total non-computing leisure time, the $\tilde{\alpha}_i$'s must sum to zero across all non-computing leisure categories.

An important caveat relative to our benchmark analysis is that we are not attempting to recover a structural demand system elasticity. In particular, that would require the taste for activity $i$ (captured in $\tilde{\epsilon}_{ikt}$) being orthogonal to the taste for computing (reflected in $h_{Ikt}$). The regression instead is designed to answer whether in our sample, conditional on available time $\tilde{H}$, the propensity to allocate time towards computing tell us anything about the propensity to allocate time to alternative leisure activities. Below we discuss an instrument that will allow us to plausibly recover the exogenous impact of additional TV watching on computing.

Table 9 reports the estimated $\tilde{\gamma}_i$ and $\tilde{\alpha}_i$ for younger men in the first and second columns, respectively. The sample is the same as for Table 5. The first column indicates that TV and Other Leisure tend to have increasing shares as total non-computing leisure increases, while the shares of Socializing and ESP tend to decline. Our interest is in the estimates of $\tilde{\alpha}$ reported in the second column. Holding constant non-computing leisure, demographic cells that spend more time computing also spend a greater share of $\tilde{H}$ watching TV. Conversely, they tend to spend a lower share of remaining leisure on Eating, Sleeping, and Personal care. More precisely, the estimates imply that younger men that spend one more hour at computer leisure should be expected to spend about one more minute of the remaining leisure watching TV, and one fewer minutes at ESP. The two remaining leisure activities, Socializing and Other, have a negligible conditional correlation with computing.

The conditional correlations indicate that individuals that spend additional time computing skew their remaining leisure toward TV and not away from it. This is inconsistent with the proposition that computing simply replaces TV watching. It does not, however, rule out that the two are substitutes, as a possible positive correlation in tastes (for example, those who like computing also like TV) could be masking the negative relationship due to substitutability. To identify the latter, we need an exogenous shifter of time spent on a leisure activity that is independent of tastes for the remaining activities.

Table 9: Computing and
Alternative Leisure Activities

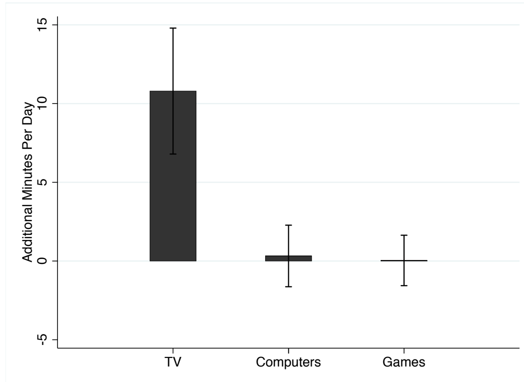
| | $\tilde{\gamma}_i$ | $\tilde{\alpha}_i$ |
|---|---|---|
| TV/Movies/Netflix | 0.055 | 0.015 |
| | (0.031) | (0.006) |
| Socializing | -0.068 | 0.002 |
| | (0.026) | (0.004) |
| ESP | -0.006 | -0.013 |
| | (0.034) | (0.005) |
| Other Leisure | 0.018 | -0.004 |
| | (0.027) | (0.004) |

Note: Sample is the same as Table 5. Standard errors are in parentheses.

Towards that goal, we exploit the fact that the timing of certain televised events increase the amount of time spent watching TV that is plausibly orthogonal to interest in recreational computing or gaming. Specifically, we create a dummy variable that takes the value one if the diary day coincides with one of the following key televised sporting events: the men's NCAA basketball tournament ("March Madness"); the Olympics; the playoffs of the NFL, NHL, and Major League Baseball; and the men's soccer World Cup. We regress time spent watching TV, computing, and gaming on the sporting event indicator variable plus day-of-the-week and month-of-the-year dummies. We do this for the full sample; the results are similar restricting to younger men, but very imprecisely estimated.

Figure 4 contains a bar graph indicating the magnitude of the coefficient on the sporting event dummy for each of the three activities, overlaid with the 95-confidence interval. TV watching increases by 10.8 minutes on days of major sporting telecasts, with a standard error of two minutes. The second bar indicates that computing marginally *increases* on those days as well, although the p-value is 0.75, making the increase indistinguishable from zero. The standard error is one minute, and hence we can reject a decrease in computing of more than two minutes. The third bar is the impact of televised sporting events on gaming. The point

Figure 4: Additional Time Spent during Major Sports Telecasts




Note: Each bar represents the coefficient from regressing the respective activity (in minutes per day) against a dummy variable indicating the diary day coincides with a major televised sporting event. Small lines indicate 95-percent confidence intervals. Additional controls include day-of-week and month-of-year dummies. The coefficient for TV is 10.8 with a standard error of 2.0; for computing it is 0.3 with a standard error of 1.0; and for gaming it is 0.04 with a standard error of 0.82.

estimate is 0.04, suggesting zero impact on gaming. We have also regressed computing and gaming on TV watching, instrumenting the latter with the timing of major televised sporting events. As suggested by Figure 4, the first-stage is strong, but there is no effect observed at the second stage.

The results presented in this subsection suggest there is little substitutability between computing and TV-watching at the daily frequency, and no reduced form correlation evidence at lower frequencies. Neither of these exercises support the idea that the increase in recreational computing is simply a consequence of being an especially close substitute for declining TV watching.

## 6.4 Alternative Reference Activity

One key assumption for our above analysis is the choice of a reference activity. In our baseline estimates we made a conservative choice and assumed that there was no change in technology or preferences for sleep during this period. A priori, this seems a plausible assumption. However, as discussed above, sleep time has increased sharply during this period for all demographic groups. The increase in sleep time may be an artifact of changes in the coding of peripheral sleep activities in the ATUS or it may reflect that $\theta_{ESP}$ is not equal to zero. As an additional robustness exercise we instead assume no technological change in the weighted average of all other leisure activities. This assumes that collectively, there was no technological change in other leisure activities during this time period. With this alternate assumption, our estimate of $(\eta_I - 1)\Delta \ln \theta_I$ is even higher than our baseline estimate at 60.2%

with a standard error of 12.6%. Given that our estimate of $\theta_I$ is more than 50% larger with this alternate normalization, the predicted shift in of the labor supply curve for young men is 5.2% under this alternative normalization.

# 7 Trends in Well-Being

Before concluding, we complement our demand system results with reported life satisfaction information from the General Social Survey (GSS). Despite declining employment and hours, younger men report increased happiness during the 2000s. This contrasts sharply with older men, whose satisfaction fell along with their relative earnings. We see the life satisfaction results as indirect evidence that younger men value their improved leisure options.

The GSS assesses attitudes and beliefs of US residents. It has consistently asked individuals: "Taken together, how would you say things are going these days – would you say that you are very happy, pretty happy, or not too happy?" We create an index that equals 1 if an individual reports being either "very happy" or "pretty happy," and equals 0 otherwise. As with the ATUS, we pool waves of the GSS index, given the survey's modest sample size.[28] We examine three time periods: 2001 to 2005, 2006 to 2010, and 2011 to 2015.

Table 10: Reported Happiness

| | Fraction Reporting "Very Happy" or "Pretty Happy" | | | | |
|---|---|---|---|---|---|
| | (1) Pooled 2001-2005 | (2) Pooled 2006-2010 | (3) Pooled 2011-2015 | Diff (3)-(1) | p-value of difference |
| Men, Ed = All, 21-30 | 0.839 (n=249) | 0.854 (n=507) | 0.892 (n=343) | 0.053 | 0.060 |
| Men, Ed = All, 31-55 | 0.886 (n=630) | 0.854 (n=1,528) | 0.847 (n=903) | -0.039 | 0.031 |
| Men, Ed < 16, 21-30 | 0.813 (n=193) | 0.828 (n=372) | 0.881 (n=244) | 0.068 | 0.048 |
| Men, Ed < 16, 31-55 | 0.883 (n=426) | 0.828 (n=1,043) | 0.813 (n=594) | -0.069 | 0.023 |

Note: Data from General Social Survey. See text for details.

Table 10 tracks happiness measures for younger versus older men. Looking at the first

[28]The survey is biannual and nationally representative. Each GSS wave has 2,000 to 4,000 respondents.

row, measured happiness for younger men actually increased by 5 percentage points since the early 2000s, from 84 to 89 percent, despite their sharp decline in employment. This stands in contrast to the pattern for older men (row 2), for whom measured happiness fell by 4 percentage points. In the early 2000s, older men reported being happier than did their younger counterparts. That relationship flipped by 2011-2015. The contrast is more striking restricting attention to those with less than a 4-year degree (rows 3 and 4). Younger men without a 4-year degree show a 7 percentage point increase in happiness, compared to a 7 percentage point decline among their older counterparts.

The decline in measured well being for older workers has been studied recently by Case and Deaton (2015). But we see that younger men actually experienced a rise, rather than decline, in measured happiness over the past 15 years. While by no means conclusive, these results are consistent with computer technology broadly, and video games in particular, increasing the value of leisure for younger workers. Consistent with this interpretation, Krueger (2017) compares the emotional experience of young men across various leisure activities by using ATUS self-reported well-being measures. He finds they report greater happiness when playing video games relative to watching TV. He also finds that video gaming is a social activity for younger men—70% of play involves interacting with others in person or virtually.

# 8 Conclusion

We develop a leisure demand system that parallels that typically considered for consumption expenditures. This allows us to estimate how leisure activities vary with one's total leisure time, generating activity-specific leisure Engel curves. Our framework also provides a means for assessing how much improvements in leisure technologies can affect individual's opportunity cost of labor. We show that such innovations are likely to reduce labor supply much more if they affect leisure luxuries. Estimating our leisure demand system based on leisure differences across time, states, industries, and education groups during the 2000s, we find that recreational computer, including video gaming, is a strong leisure luxury for younger men. We estimate that younger men respond to a 1 percent increase in total leisure by increasing recreational computer time by 2.5 percent. For other groups – younger women, older men, and older women – recreational computing is only modestly a leisure luxury.

Using our estimated leisure demand system, together with detailed time use data from the American Community Survey, we can identify the relative increase in computer and video game technology during the 2000s. As of 2017, men between the ages of 21 and 30 allocated 6.0 hours per week to recreational computer activities, 3.9 hours going specifically to video gaming. For these younger men recreational computer time increased by nearly 60 percent during the 2004-2017 period, while total leisure time increased by only 4 percent. Our estimated leisure demand system predicts that recreational computer time would have increased by 22 percent if younger men had remained on their original leisure Engel curve. We can attribute the much greater increase in younger men's computer time to a sizable improvement in technology for computer and video gaming, an improvement we would expect given CPI-measured declines in relative prices for computer and video games.

We estimate that technology growth for recreational computer activities, by increasing the marginal value of leisure, shifted in the labor supply curve of younger men by 3.2% (holding both the wage and the marginal utility of consumption fixed). We also estimate that technological growth in recreational computing shifted in the labor supply curve for younger women by about 1.3% and had no effect on the labor supply of older men and women. Annual hours worked for younger men have diverged sharply from that of older men during the last decade. Even though aggregate labor market conditions have improved in recent years, the gap in hours worked between younger and older men have persisted. Our findings suggest that the increased valuation of leisure for younger men could be one quantitatively important channel explaining why younger men's hours have declined relative to older men during the 2000s.

This paper's methodology for measuring the impact of technology changes for leisure on reservation wages could be used to analyze earlier leisure innovations, subject to available data. Whether improvements in leisure align empirically with reductions in market hours depends, of course, on how those leisure technology shifts happen to coincide with factors shifting labor demand. In periods where labor demand and reservations wages are both increasing (like during the 1970s and 1980s when the quality of television expanded rapidly), increases in leisure technology may not correspond with declines in employment. However, during the 2000s, market wage growth was declining, reflecting declining labor demand, while the reservation wage from advances in leisure technology was arguably increasing. For any individual, an increase in leisure technology is more likely to result in declining employment when the market wage is close to the reservation wage.

Finally, while our framework is static, innovations to computer and gaming leisure could have dynamic effects on labor supply if individuals develop a habit (or addiction) for such activities. Certainly individuals build "leisure capital" in the form of physical equipment, but especially human skills, that enhances enjoyment from leisure activities. Thus negative shocks to labor demand could persistently reduce labor supply via individuals first increasing their computer leisure, then developing a taste or skills for the activity. Such dynamic consideration may be a source of hysteresis in labor market conditions resulting from downturns, such as the Great Recession. We leave these considerations to future work.

# References


**Aguiar, Mark and Erik Hurst**, "Measuring Trends in Leisure: The Allocation of Time over Five Decades," *Quarterly Journal of Economics*, 2007, *122*, 969–1006.

_ , _ , **and Loukas Karabarbounis**, "Time Use during the Great Recession," *American Economic Review*, 2013, *103*, 1664–96.

**Becker, Gary**, "A Theory of the Allocation of Time," *Quarterly Journal of Economics*, 1965, *75*, 493–517.

**Boppart, Timo and Liwa Rachel Ngai**, "Rising Inequality and Trends in Leisure," *Center for Economic Policy Research Working Paper 12325*, 2017.

**Browning, Martin and Thomas Crossley**, "Luxuries are Easier to Postpone: A Proof," *Journal of Political Economy*, 2000, *108*, 1022–6.

_ , **Angus Deaton, and Margaret Irish**, "A Profitable Approach to Labor Supply and Commodity Demands over the Life-Cycle," *Econometrica*, 1985, *53*, 503–543.

**Case, Anne and Angus Deaton**, "Suicide, Age, and Wellbeing: An Empirical Investigation," *NBER Working Paper*, 2015, *21279.*

**Chang, Yongsung and Sung-Bin Kim**, "From Individual to Aggregate Labor Supply: A Quantitative Analysis based on a Heterogeneous-Agent Macroeconomy," *International Economic Review*, 2006, *47*, 1–27.

**Charles, Kerwin, Erik Hurst, and Matthew Notowidigdo**, "Housing Booms, Manufacturing Decline, and Labor Market Outcomes," *NBER Working Paper*, 2016, *18949.*

**Chetty, Raj, Adam Guren, Day Manoli, and Andrea Weber**, "Does Indivisible Labor Explain the Difference Between Micro and Macro Elasticities? A Meta-Analysis of Extensive Margin Elasticities," *NBER Macroeconomics Annual 2012*, 2013, *27.*

**Crossley, Thomas and Hamish Low**, "Is the Elasticity of Intertemporal Substitution Constant?," *Journal of the European Economic Association*, 2011, *9*, 87–105.

**Deaton, Angus and John Muellbauer**, "An Almost Ideal Demand System," *American Economic Review*, 1980, *70*, 312–326.

**Gourio, Francios and Pierre-Alexandre Noual**, "The Marginal Worker and the Aggregate Elasticity of Labor Supply," *working paper*, 2009.

**Greenwood, Jeremy and Guillaume Vandenbroucke**, "Hours Worked (Long-Run Trends)," in L.E. Blume and S.N. Durlauf, eds., *The New Palgrave Dictionary of Economics*, Palgrave, 2008, chapter Hours Worked (Long-Run Trends).

**Grossbard, Shoshana and Victoria Vernon**, "Common Law Marriage, Labor Supply, and Time Use: A Partial Explanation for Gender Convergence in Labor Supply," in Konstantinos Tatsiromos Polachek, Solomon and Klaus Zimmermann, eds., *Research in Labor Economics*, Vol. 41 01 2015, pp. 143–175.

**Hall, Robert**, "Reconciling Cyclical Movements in the Marginal Value of Time and the Marginal Product of Labor," *Journal of Political Economy*, 2009, *117*, 281–323.

**Hou, Y, X Liu, and J Liu**, "Trends In Self-reported Sleep Duration And Disturbance In The US General Population: NHANES 2005-2014," *Sleep*, 04 2018, *41*, A110–A110.

**Kopecky, Karen**, "The Trend in Retirement," *International Economic Review*, 2011, *52*, 287–316.

**Krueger, Alan**, "Where Have All the Workers Gone," *Brookings Papers on Economic Activity*, 2017, *Fall 2017.*

**Mian, Atif and Amir Sufi**, "What Explains the 2007-2009 Drop in Employment?," *Econometrica*, 2014, *82*, 2197–2223.

**Mincer, Jacob**, "Labor Force Participation of Married Women: A Study of Labor Supply," in "Aspects of Labor Economics," Princeton University Press, 1962.

**Mustre-del-Río, José**, "Wealth and Labor Supply Heterogeneity," *Review of Economic Dynamics*, 2015, *18*, 619–634.

**Park, Choonsung**, "Consumption, Reservation Wages, and Aggregate Labor Supply," *working paper*, 2017.

**Pistaferri, Luigi**, "Anticipated and Unanticipated Wage Changes, Wage Risk, and Intertemporal Labor Supply," *Journal of Labor Economics*, 2003, *21*, 729–54.

**Vandenbroucke, Guillaume**, "Trends in hours: The U.S. from 1900-1950," *Journal of Economic Dynamics & Control*, 2009, *33*, 237–249.

# Online Appendix for “Leisure Luxuries and the Labor Supply of Young Men”

## A1 Data Appendix

Our analysis primarily uses the American Time Use Survey. Here, we further detail our use of that data – including sample restrictions – as well as for the Current Population Survey, which we employ for supplemental statistics. We also use data from the General Social Survey and the BLS Price data. The main text discusses our use of these datasets.

### A1.1 American Time Use Survey (ATUS)

The bulk of our analysis is based on the 2004 to 2017 waves of the American Time Use Survey (ATUS). The ATUS is conducted by the U.S. Bureau of Labor Statistics (BLS), with individuals drawn from the exiting sample of the CPS. (We download the ATUS data directly from the BLS website.) Individuals are sampled approximately 3 months after completion of their final CPS survey. At the time of the ATUS, the BLS updates the respondent's employment and demographic information. The time-use data reflect a 24-hour diary where respondents report activities from the previous day broken by 15 minute intervals. Survey personnel then classify each activity to a specific one of over 400 detailed categories. We omit a few minor time categories, such as own health and a catch-all "uncategorized" activity.

The time diaries are designed to measure an individual's primary task. It measures secondary tasks less well. For example, consider someone who commutes for a half hour on the subway, reading a book during their commute. The survey will prompt the individual to only report the primary activity, which would likely be commuting. However, if the individual lists multiple activities as their primary activity, those activities get allocated an equal portion of that time interval. (Continuing the example, if someone reported both commuting and reading were primary activities, 15 minutes would get allocated to commuting and 15 minutes to reading.) This preserves that each individual's total reported time is 24 hours. So it is likely that the less primary of multi-tasking activities are underreported. This may be relevant to some recreational computer activities, like engaging in social media.

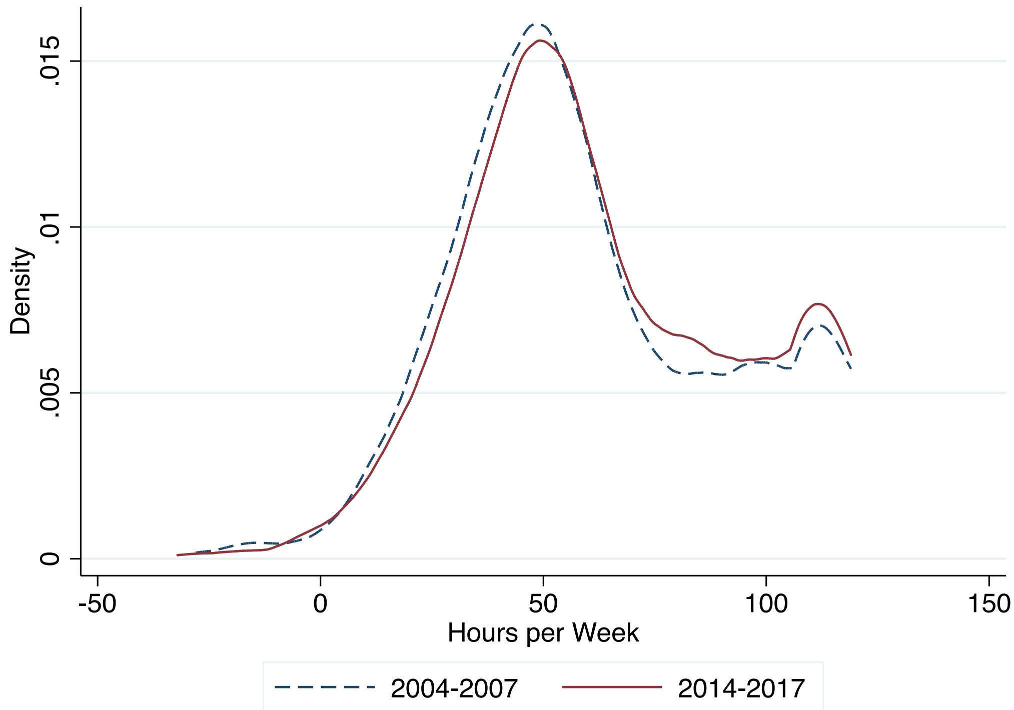
Time spent at market work in the ATUS differs from that reported in the CPS March supplements. The time diary includes commuting time. It also reflects time worked during one 24-hour period, rather than a recall estimate of hours worked in a “usual” week.

We restrict the sample to those ages 21 to 55. We exclude individuals in the military and full-time students ages 24 and under. Status as a full-time student is only consistently asked in the March Supplement for those ages 24 and under.

### A1.2 Current Population Survey (CPS)

We downloaded the 1977-2018 March Annual Social and Economic Supplements to the CPS directly from the IPUMS CPS website (https://cps.ipums.org/cps/index.shtml). We restrict the sample to ages 21 to 55, again excluding individuals in the military and full-time students

Figure A1: Distribution of Leisure Time for Young Men [Need to update]




Note: Figure shows kernel density of leisure time for younger men.

ages 24 and under. (Status as a full-time student is only consistently asked in the March Supplement for those 24 and under.)

Our CPS series focus on hours and employment. We define those who are employed as anyone who reports working last week (empstat = 10) and anyone who has a job but did not work last week (empstat = 12). Employment status is measured as of the survey. For example, respondents in the 2018 March Supplement report information about whether they were working in March of 2018. Hours worked are reported retrospectively. Survey respondents in year $t$ report (1) how many weeks worked during the prior calendar year and (2) the hours per week they usually worked during the prior year. We construct annual hours worked by multiplying weeks worked during the prior year by the usual weekly hours worked during the prior year. We also document the extent to which individuals did not work during the prior year. We define not working during the prior year as survey respondents who report working zero weeks during the prior year.

# A2 Additional Tables and Figures

In this section we report several tables and figures referenced in Section 3 of the text.

Table A1: Broad Time Allocation During the 2000s: Unadjusted ATUS Weights

(a) Men, Age 21-55

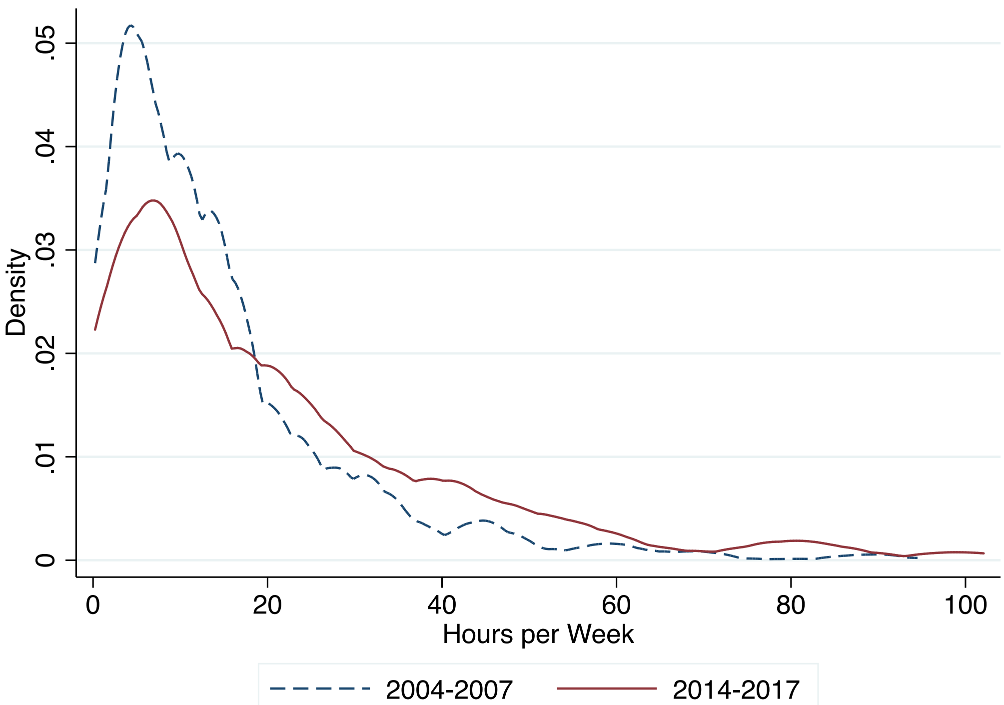
| | Age 21-30 | | | Age 31-55 | | |
|---|---|---|---|---|---|---|
| Activity | 2004-2007 | 2014-2017 | Change | 2004-2007 | 2014-2017 | Change |
| Market Work | 38.5 | 36.7 | -1.7 | 40.9 | 40.5 | -0.4 |
| Job Search | 0.3 | 0.8 | 0.5 | 0.3 | 0.4 | 0.1 |
| Home Production | 12.1 | 11.6 | -0.4 | 14.8 | 14.0 | -0.7 |
| Child Care | 2.8 | 2.1 | -0.7 | 3.6 | 4.1 | 0.5 |
| Education | 2.5 | 2.9 | 0.4 | 0.6 | 0.6 | 0.0 |
| Leisure | 61.0 | 63.3 | 2.3 | 57.0 | 57.5 | 0.5 |

(b) Women, Age 21-55

| | Age 21-30 | | | Age 31-55 | | |
|---|---|---|---|---|---|---|
| Activity | 2004-2007 | 2014-2017 | Change | 2004-2007 | 2014-2017 | Change |
| Market Work ” | 27.4 | 27.3 | -0.1 | 27.4 | 27.4 | 0.0 |
| Job Search | 0.2 | 0.3 | 0.1 | 0.2 | 0.2 | 0.0 |
| Home Production | 19.0 | 17.6 | -1.4 | 24.2 | 22.4 | -1.8 |
| Child Care | 9.9 | 8.3 | -1.7 | 7.4 | 7.8 | 0.5 |
| Education | 2.3 | 3.2 | 0.9 | 1.1 | 0.9 | -0.2 |
| Leisure | 58.5 | 59.9 | 1.4 | 56.1 | 57.4 | 1.3 |

Note: This table replicates Table 1 using the raw ATUS weights rather than those adjusted for educational attainment.

Figure A2: Distribution of Recreational Computing Time for Young Men [Need to update]




Note: Figure shows kernel density of recreational computing time for younger men conditional on strictly positive time. The share of younger men with zero computing time is 0.23 for the 2004-07 ATUS sample and 0.28 for the 2012-15 ATUS sample.

Table A2: Leisure Activities for Men 21-30: Unadjusted ATUS Weights

| Activity | 2004-2007 | 2014-2017 | Change |
|---|---|---|---|
| Total Leisure | 61.0 | 63.3 | 2.3 |
| Recreational Computer | 3.3 | 5.9 | 2.6 |
| Video Game | 2.0 | 3.8 | 1.8 |
| ESP | 24.3 | 25.9 | 1.6 |
| TV/Movies/Netflix | 17.3 | 15.6 | -1.7 |
| Socializing | 7.8 | 7.7 | -0.1 |
| Other Leisure | 8.3 | 8.2 | -0.1 |

Note: This table replicates Table 2 using the raw ATUS weights rather than those adjusted for educational attainment.

Table A3: Leisure Activities for Employed Men 21-30 (Hours per Week)

| Activity | 2004-2007 | 2014-2017 | Change |
|---|---|---|---|
| Total Leisure | 57.6 | 59.8 | 2.2 |
| Recreational Computer | 3.1 | 5.1 | 2.0 |
| Video Games | 1.9 | 3.2 | 1.3 |
| ESP | 23.4 | 24.6 | 1.2 |
| TV/Movies/Netflix | 15.9 | 14.5 | -1.4 |
| Socializing | 7.5 | 7.7 | 0.2 |
| Other Leisure | 7.7 | 7.9 | 0.2 |

Note: This table replicates Table 3 using the raw ATUS weights rather than those adjusted for educational attainment.

Table A4: Computer Leisure and Video Game By Age-Sex Groups

| | 2004-2007 | 2014-2017 | Change |
|---|---|---|---|
| | | Men 21-30 | |
| Total Leisure | 61.0 | 63.3 | 2.3 |
| Recreational Computer | 3.3 | 5.9 | 2.6 |
| Video Games | 2.0 | 3.8 | 1.8 |
| | | Men 31-55 | |
| Total Leisure | 57.0 | 57.5 | 0.5 |
| Recreational Computer | 2.1 | 2.1 | 0.0 |
| Video Games | 0.9 | 0.9 | 0.0 |
| | | Women 21-30 | |
| Total Leisure | 58.5 | 59.9 | 1.4 |
| Recreational Computer | 1.5 | 2.6 | 1.1 |
| Video Games | 0.8 | 1.3 | 0.5 |
| | | Women 31-55 | |
| Total Leisure | 56.1 | 57.4 | 1.3 |
| Recreational Computer | 1.6 | 2.0 | 0.3 |
| Video Games | 0.6 | 0.7 | 0.1 |

Note: This table replicates Table 4 using the raw ATUS weights rather than those adjusted for educational attainment.