Leisure Luxuries and the Labor Supply of Young Men

Mark Aguiar

Princeton University

Mark Bils

University of Rochester

Kerwin Kofi Charles

Yale University

Erik Hurst

University of Chicago

We propose a methodology exploiting time diary data and "leisure Engel curves" to infer quality changes across leisure activities and measure the effects on the marginal return to leisure. We study leisure returns for men aged 21–30, who have shifted leisure toward video gaming and recreational computing and have had larger market work hour declines than older men or women since 2004. We show that recreational computing is distinctly a leisure luxury for younger men. By increasing the value of time, innovations to this leisure technology have lowered young men's work hours by 2%, or much of their work hours decline compared to older men's.

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, Patrick Kehoe, John Kennan, Pete Klenow, Alan Krueger, Hamish Low, Kevin Murphy, and Yona Rubinstein for helpful comments. Data are provided as supplementary material online.

Electronically published December 18, 2020
[*Journal of Political Economy*, 2021, vol. 129, no. 2]

I. 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 past 15 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, aged 21–30, have exhibited a clear decline in market work, both absolutely and relative to other demographic groups, since the early 2000s. Over the same period, younger men have also exhibited a much sharper increase in time devoted to gaming and computer leisure. In fact, their increase in time devoted to computer leisure constitutes more than 100% of the magnitude of either their total increase in leisure or their decline in market hours.

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 toward 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 an upward trend in total leisure for all demographic groups, but especially for younger men. This raises the question of whether activities differ in terms of their diminishing returns. If so, it may be that recreational computing has a more elastic margin for adding leisure time and hence that the increase in computing partly reflects a response to additional leisure time rather than its improved quality.

We confront this identification problem by introducing 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 driven not 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 1% increase in leisure time is associated with about a 2.5% increase in recreational computing time for younger men, roughly 1 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 leisure was a response to working fewer hours—as a result, say, of reduced labor demand—or a response to improved quality. Comparing the years 2004–7 to 2014–17, younger men increased their recreational computer use by 60%. The increase, 2.7 hours per week, is 7% of average hours of market work. We divide that increase 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 that we assume is fairly static. Our leisure Engel curves predict that computer recreation should have increased 22% between 2004 and 2017 in response to younger men's total increase in leisure. So the bulk of its actual increase, 38% out of 60%, is attributed to better technology for computer leisure.

While this precise estimate rests on our estimated leisure demand system, we see it as indubitable that an important part of the increase in younger men's computer leisure since 2004 reflects a shift in demand toward that activity above and beyond that induced by the increase in younger men's total leisure. This is clear from the ATUS time diaries, as younger men's time spent on recreational computing increased more than their increase in total leisure time (including computers). That is, the time devoted to all other leisure activities actually declined, even though total leisure time increased. This would be consistent with stable leisure Engel curves only if the sum of all other leisure activities is inferior (with respect to total leisure time). Not only is that counterintuitive, it is also inconsistent with the estimates presented below that all broad subcategories of leisure are normal activities, for which time spent on that activity increases with total leisure.

Our final step maps changes in leisure technology to the marginal return to leisure and thereby to labor supply. 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, improved computer leisure technology increased younger men's marginal value of time by 2.5%. By contrast, we find that better computer technology caused no reduction in labor supply for older men and a much smaller negative effect for women, results compatible with our finding that the activity is not a strong leisure luxury for either group. Under reasonable Frisch elasticities, at both the intensive and extensive margins, the shift in labor supply for younger men from improved computer leisure maps to a decrease in market hours of 2.2% since 2004, all else equal. That constitutes nearly half of the decline in market work exhibited by younger men in the ATUS between 2004 and 2017 and nearly three-quarters of their differential decline in labor hours relative to older men.[1]

To be clear, we are not suggesting that leisure technology explains the decline in younger men's hours during the Great Recession. The unemployment rate for men ages 16 and over shot up by 5 percentage points, from 5.4% to 10.4%, from 2007–8 to 2009–10. The ATUS shows a corresponding drop in market hours for younger men of nearly 4 hours per week, or about 10%, while computer leisure increased by a full hour. Nonetheless, applied to that episode our methodology attributes only a small fraction of the decline in younger men's hours to improvements in leisure technology, with almost all attributable to other factors, such as a decline in labor demand. More generally, our approach in no way excludes the influence of labor demand or other labor supply factors on younger men's hours. Moffitt (2012), Binder and Bound (2019), and Abraham and Kearney (2020) each address several potential factors, including an increased role of intrafamily transfers.[2]

While we focus on the impact of computer leisure on younger men since the early 2000s, 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, if the relevant time-use data were available. Of course, how any leisure innovation translated to changes in observed labor market outcomes (such as 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 past century. We add to this literature by introducing and estimating a leisure demand system, showing that labor supply is most affected by technology for

[1] Below we document that market hours declined for younger men in the broader Current Population Survey (CPS) data, by 10.9% in annual hours from 2000 to 2017. The comparable declines for younger women and older men (aged 31–55) were 2.2% and 7.5%, respectively. Despite improvements in the labor market after 2011, younger men's hours have remained below both their 2000 and 2007 levels.

[2] Our working paper, Aguiar et al. (2017), also finds that budgets for younger men have become increasing detached from their labor earnings, especially via a much higher tendency to live with older relatives.

leisure luxuries and illustrating how one can relate shifts in labor supply to changes in the allocation of time across leisure activities. We show that technological change can affect labor supply, a complement to the large literature on technology's impact on labor demand.

The paper is organized as follows: section II presents our methodology, including the leisure demand system; section III examines changes in time use during the 2000s, emphasizing the sharp increase in computer and gaming time for younger men; section IV highlights our identification strategy and estimates the leisure Engel curves; section V uses the demand system and trends in time allocations to infer changes in computer leisure technology, then quantifies its impact on the labor supply curves for different demographic groups; section VI highlights the robustness of our results to alternate parameterizations; and section VII concludes.

II. 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 IV and the quantitative results of sections V and VI.

A. *Preferences*

Agents have preferences over a consumption good, c, and time spent on I leisure activities $\boldsymbol{h} = \{h_1, \dots, h_I\}$. We assume weak separability between consumption and leisure activities, writing utility as $U(c, v(\boldsymbol{h}; \boldsymbol{\theta}, \boldsymbol{\xi}))$ where v is an aggregator over leisure activities, $\boldsymbol{\theta} = \{\theta_1, \dots, \theta_I\}$ is a vector of technology shifters, and $\boldsymbol{\xi} = (\xi_1, \dots, \xi_I)$ are idiosyncratic preferences over activities.[3] We assume that U is strictly increasing and twice differentiable in (c, v) and that preferences are strictly concave in c and $\boldsymbol{h}$.

Letting i index activities and k index individuals, we assume that v has the following functional form:

$$v(\boldsymbol{h}_k; \boldsymbol{\theta}, \boldsymbol{\xi}_k) = \sum_{i=1}^{I} \frac{(\theta_i \xi_{ik} h_{ik})^{1-(1/\eta_i)}}{1 - (1/\eta_i)}. \tag{1}$$

The parameter $\eta_i > 0$ is activity specific and governs the diminishing returns associated with additional time spent on activity i. Increases in the

[3] Absent weak separability, there are wealth effects on how an individual allocates a given total leisure across activities. While idiosyncratic differences in wealth are not problematic for our estimates, a trend in mean wealth for a group of interest will confound our estimate of technology if weak separability is violated.

technology parameter θ_i increase the utility for a given amount of time spent on activity i. The preference shifter ξ_{ik} shifts utility in a manner identical to technology. The distinction we draw between θ_i and ξ_{ik} is that θ_i is common across individuals and varies over time. Conversely, ξ_{ik} is independently and identically distributed across individuals and is drawn from a distribution that is stable over time. Hence, a shift in the mean over time of the preference for a particular activity will be treated as a change in technology.

While each leisure activity enters with its specific elasticity η_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 implies that the marginal value of allocating time to one leisure activity over another does not depend on how leisure is allocated across the remaining activities. As a robustness exercise, however, we explore the possibility that some leisure activities are substitutes for each other.

Our approach assumes time separability in the utility over leisure. It is an extremely interesting question whether specific leisure activities are "habit-forming." Unfortunately, our data do not allow us to shed light on this question, and hence we abstract from it. In section VII, we discuss additional considerations that could arise in a life-cycle setting.

B. *Leisure Engel Curves*

We normalize the agent's time endowment to one, which it allocates across the I leisure activities and market labor. Let N denote the amount of time devoted to market work and w the wage in terms of the consumption good. Much of what follows is robust to alternative assumptions about how labor is chosen. To be more precise, we restrict the choice of N to lie in a set $\mathcal{N} \subset [0, 1]$. An unrestricted choice set is $\mathcal{N} = [0, 1]$; a purely extensive choice has $\mathcal{N} = \{0, \bar{n}\}$ for some $\bar{n} \in (0, 1]$; and a combination extensive/intensive choice set is $\mathcal{N} = \{0, [\underline{n}, 1]\}$ for some minimum hours $\underline{n}$. Shifts in "labor demand" are reflected in comparative statics with respect to w and the choice set for N. We defer discussion of labor choice to section II.E.

We consider the decision over consumption and time allocation in a given period. Let λ denote the marginal value of wealth, which can be derived from the multiplier on the individual's lifetime resource constraint (with or without financial market frictions). The analysis is done for a fixed λ.[4] For the present, we treat $\boldsymbol{\theta}$ as parameters, but we discuss

[4] Where this assumption restricts the analysis is by holding λ fixed as we vary the level of leisure technology. If λ does adjust, it would imply an additional wealth effect on labor-leisure decisions familiar from other contexts, such as from changes in nonlabor income.

below the choice of $\boldsymbol{\theta}$ and incorporate the cost of technology. The problem 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.

Conditional on λ, $\boldsymbol{\theta}$, and $\boldsymbol{\xi}$ (as well as w and $\mathcal{N}$), the agent's problem is[5]

$$\max_{c,\{h_i\},N}\{U(c, v(\boldsymbol{h}; \boldsymbol{\theta}, \boldsymbol{\xi})) + \lambda(wN - c)\}, \tag{2}$$

subject to

$$\sum_{i=1}^{I} h_i + N \leq 1, \quad N \in \mathcal{N}.$$

The first-order condition for c is $U_c = \lambda$. With additive separability, we can invert this to write $c = C(\lambda)$, where C is the inverse of U_c. Consumption can then be considered a parameter in what follows. If $U_{cv} \neq 0$, then $c = C(\lambda, v(\boldsymbol{h}; \boldsymbol{\theta}, \boldsymbol{\xi}))$, where $\boldsymbol{h}$ is the optimal allocation.

Letting ω denote the multiplier on the time endowment, the first-order condition for activity i is

$$U_v v_i = \omega \quad \text{for } i = 1, \dots, I, \tag{3}$$

where $v_i = \partial v / \partial h_i$. Condition (3) states that the agent equates the marginal value of an activity to the opportunity cost. Note that U_v is constant across activities. Let $\hat{\omega} \equiv \omega / U_v$ denote the normalized price of time, where U_v is evaluated at the optimal allocation. The normalized multiplier $\hat{\omega}$ is sufficient to determine the relative shares of each activity.

In particular, weak separability allows us to consider the subproblem of allocating a fixed amount of time H across I activities:

$$\mathrm{v}(H; \boldsymbol{\theta}, \boldsymbol{\xi}) \equiv \max_{\{h_i\}} v(h_1, \dots, h_I; \boldsymbol{\theta}, \boldsymbol{\xi}), \quad \text{subject to } \sum_i h_i \leq H. \tag{4}$$

The link between the subproblem and the agent's original problem is $\mathrm{v}_H = \hat{\omega}$. In the spirit of Browning, Deaton, and Irish (1985), we can derive "demand curves" for leisure activities, given "price" $\hat{\omega}$. Rewriting equation (3) and using equation (1), we have

$$h_i = (\theta_i \xi_i)^{\eta_i - 1} \hat{\omega}^{-\eta_i}. \tag{5}$$

The elasticity of demand for activity i with respect to the normalized shadow price $\hat{\omega}$ is η_i. Activities with relatively high η_i are those most sensitive to changes in the opportunity cost of time. All else equal, an increase

[5] Note that the functional form for v requires $h_i > 0$ at an optimum; hence, we omit $h_i \geq 0$ as a constraint.

in technology θ_i (or preference shifter ξ_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, equation (5) implies

$$H = \sum_i h_i = \sum_i (\theta_i \xi_i)^{\eta_i - 1} \hat{\omega}^{-\eta_i}. \tag{6}$$

For each $(\boldsymbol{\theta}, \boldsymbol{\xi})$, there is a strictly monotonic mapping between H and $\hat{\omega} = \mathrm{v}_H(H; \boldsymbol{\theta}, \boldsymbol{\xi})$, which simply reflects the convexity of subproblem (4). Differentiating equation (6) implies

$$\frac{\partial \ln \mathrm{v}_H}{\partial \ln H} = \frac{-1}{\sum_i s_i \eta_i} = \frac{-1}{\bar{\eta}}, \tag{7}$$

where $s_i = h_i / H$ is the share of leisure time devoted to activity i and $\bar{\eta} \equiv \Sigma_i s_i \eta_i$ is the share-weighted average of the individual elasticities. Similarly, we have

$$\frac{\partial \ln \mathrm{v}_H}{\partial \theta_i} = \frac{\partial \ln \mathrm{v}_H}{\partial \xi_i} = \frac{s_i(\eta_i - 1)}{\bar{\eta}}. \tag{8}$$

For a given H, an increase in technology is associated with a change in the marginal value of time, depending on the share s_i devoted to that activity and the extent to which $\eta_i \lessgtr 1$.

We can use equations (5) and (7) to trace out a "leisure Engel curve." In particular,

$$\frac{\partial \ln h_i}{\partial \ln H} = \frac{\partial \ln h_i}{\partial \ln \mathrm{v}_H} \frac{\partial \ln \mathrm{v}_H}{\partial \ln H} = \frac{\eta_i}{\bar{\eta}}. \tag{9}$$

As H varies, for a given $(\boldsymbol{\theta}, \boldsymbol{\xi})$, each activity adjusts with an elasticity $\eta_i / \bar{\eta}$. This equals the activity's own price elasticity divided by the weighted average of all elasticities. Equation (9) plays a key role in our empirical work. Activities with a greater η_i increase disproportionately with total leisure. That is, high-η_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 β_i:

$$\beta_i \equiv \frac{\eta_i}{\bar{\eta}}. \tag{10}$$

Note that our derivation of the leisure Engel curves does not hinge on how total hours of leisure H are determined. In particular, labor could be chosen optimally or rationed. The crucial assumption is that the shadow price of time is the same when choosing between alternative leisure activities, not how the price of time is pinned down by the wage, labor market frictions, and the marginal value of wealth λ. We return to this point when we discuss the empirical identification and estimation of β_i.

C. *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. 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 (eq. [5]) and suppressing idiosyncratic preference terms,[6]

$$\frac{\ln h_i}{\eta_i} - \frac{\ln h_j}{\eta_j} = \left(\frac{\eta_i - 1}{\eta_i}\right) \ln\theta_i - \left(\frac{\eta_j - 1}{\eta_j}\right) \ln\theta_j. \tag{11}$$

Because the common price of time, $\hat{\omega}$, differences out, this equation holds independently of wages, nonlabor 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 equation (11) gives

$$\frac{\Delta \ln h_i}{\eta_i} - \frac{\Delta \ln h_j}{\eta_j} = \left(\frac{\eta_i - 1}{\eta_i}\right)\Delta \ln\theta_i - \left(\frac{\eta_j - 1}{\eta_j}\right)\Delta \ln\theta_j. \tag{12}$$

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. Under the assumption that the technology for the reference activity j is stable over time, we can use equation (12) and $\eta_i = \beta_i\bar{\eta}$ to write

$$\Delta \ln\theta_i = \frac{1}{\beta_i\bar{\eta} - 1}\left(\Delta \ln h_i - \frac{\beta_i}{\beta_j}\Delta \ln h_j\right). \tag{13}$$

Equations (9) and (13) play an important role in our empirical analysis. To gain intuition, consider figure 1*A*, which displays the leisure Engel curve for activity i. The vertical axis is log time devoted to activity i, and the horizontal axis is log total leisure time. Suppose that we observe a movement from point A to point C. Total leisure has increased, as has time devoted to activity i. The movement from point A to point B is along

[6] For an individual k, the right-hand side of the expression also includes $(\eta_i - 1)/(\eta_i)\ln \xi_{ik} - (\eta_j - 1)/\eta_j \ln \xi_{jk}$. Anticipating averaging over individuals and differencing across time, we suppress this term in what follows.

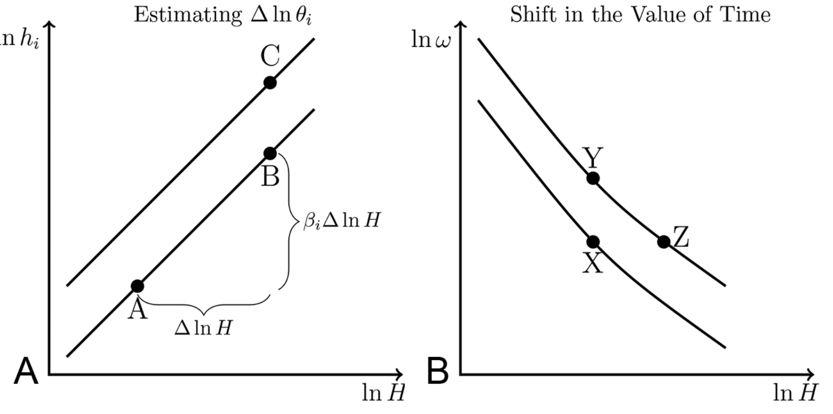

FIG. 1.—Inferring technology and leisure demand. Panel *A* depicts a heuristic leisure Engel curve for activity *i*. The movement from A to B represents a movement along the Engel curve. The remaining change in ln h_i represents forces other than the change in total leisure, namely, $\Delta \ln \theta_i$. Panel *B* traces out the first-order condition for total leisure. The vertical axis is the log shadow value of time, which equals the marginal utility of leisure at an optimum. The horizontal axis is log total leisure. The slope of this curve is $-1/\epsilon$. The movement from X to Y represents a shift in the marginal value of leisure due to a change in θ at a constant H. The movement from X to Z is the increase in H that would reduce ω to its original value at X. How much of technology's change is ultimately absorbed through changes in ω versus total leisure depends on the extent to which individuals adjust market labor in response to the relative price of work versus leisure; that is, the labor supply elasticity.

the initial leisure Engel curve. The residual increase in h_i from B to C, in excess of that predicted by the slope of the Engel curve, represents a shift in the Engel curve. A goal of the empirical exercise is to separate movements along leisure Engel curves due to changes in total leisure from shifts due to leisure technology.[7]

D. *Technology and the Shadow Value of Time*

Here we consider how shifts in leisure technology affect the shadow value of time ω. This is used in the next subsection to derive how labor supply changes with technology.

At an optimum, we have $U(c, v(\boldsymbol{h}; \boldsymbol{\theta}, \boldsymbol{\xi}) = U(c, \mathrm{v}(H; \boldsymbol{\theta}, \boldsymbol{\xi}))$, where v is defined by equation (4) and $c = C(\lambda, \mathrm{v}(H; \boldsymbol{\theta}, \boldsymbol{\xi}))$ is given by inverting

[7] The diagram uses total leisure as the reference against which we measure the change in h_i. However, movements in H could partly reflect technology changes for activities other than i. Hence, in practice we want a reference activity j that is unlikely to have experienced a large shift in technology—our benchmark in the empirical analysis is eating, sleeping, and personal care. We can then compare activity i to j from eq. (13) to recover the implied change in i's technology.

$U_c = \lambda$. Replacing $v(\boldsymbol{h}; \cdot)$ with $\mathrm{v}(H; \cdot)$ and c with $C(\lambda, \mathrm{v}(H; \cdot))$, we can rewrite equation (3) as a function of H and parameters:

$$U_v \mathrm{v}_H = \omega. \tag{14}$$

Fixing $\boldsymbol{\theta}$, the first-order condition traces out a mapping between ω and H. This is depicted in figure 1B. Concavity implies that this relationship is downward sloping. From the individual's problem, ω is a function of the state variables λ, $\boldsymbol{\theta}$, and $\boldsymbol{\xi}$ (plus w and $\mathcal{N}$), and this condition relates these states to leisure H. With some abuse of notation, we can think of equation (14) as defining a function $\omega(H; \boldsymbol{\theta}, \boldsymbol{\xi})$ that maps leisure and technology/preferences into the shadow value of leisure time. The value of this step is for discussing how technology affects the gap between the market wage and the shadow value of time at a given labor supply; this is purely expositional, as equation (14) implies that the shadow value of time is equivalent to the marginal utility of leisure at an optimum, so we use the terms interchangeably.

Differentiating equation (14), we obtain

$$\begin{aligned} \frac{\partial \ln \omega}{\partial \ln \theta_i} &= \left(\frac{U_{vv} - U_{cv}^2/U_{cc}}{U_v}\right)\mathrm{v}_{\theta_i}\theta_i + \frac{\partial \ln \mathrm{v}_H}{\partial \ln \theta_i} \\ &= \left(\frac{U_{vv} - U_{cv}^2/U_{cc}}{U_v}\right) s_i \mathrm{v}_H H + \frac{s_i(\eta_i - 1)}{\bar{\eta}}, \end{aligned} \tag{15}$$

where the second line uses $s_i \mathrm{v}_H H = \mathrm{v}_{\theta_i}\theta_i$ as well as equation (8). The first term captures the curvature U has over the leisure aggregate v. The second term is how v_H responds to a change in technology i.

To get a better sense of the first term, fix $(\boldsymbol{\theta}, \boldsymbol{\xi})$, and consider how H must change with ω to maintain equation (14). In particular, define

$$\epsilon \equiv -\frac{\partial \ln H}{\partial \ln \omega} \tag{16}$$

such that equation (14) holds. The slope of the line depicted in figure 1B is therefore $-1/\epsilon$. Concavity of U requires $\epsilon > 0$. If the labor choice is interior, then ω equals λw (see sec. II.E), and ϵ is the Frisch elasticity of leisure with respect to the wage. More generally, we take ϵ to be a measure of the curvature of utility with respect to leisure time. The benefit of this is that we have empirical measures of ϵ, both when labor is at an interior optimum and in other contexts. These are discussed in section IV. Differentiating equation (14), we obtain

$$-\left(\frac{U_{vv} - U_{cv}^2/U_{cc}}{U_v}\right)\mathrm{v}_H H = \frac{1}{\epsilon} - \frac{1}{\bar{\eta}}. \tag{17}$$

Combining this with equation (15), we have

$$\frac{\partial \ln \omega}{\partial \ln \theta_i} = \frac{s_i(\beta_i \epsilon - 1)}{\epsilon}, \tag{18}$$

where we recall that $\beta_i \equiv \eta_i/\bar{\eta}$.

Equation (18) states how the shadow value of leisure time responds to a change in technology for activity i conditional on H. The larger the share of activity i in total leisure, the more the price responds to a change in the associated technology. The formula $\beta_i = \eta_i/\bar{\eta}$ captures the relative elasticity of utility from activity i. A larger η_i implies that a small change in θ_i has a larger impact on the marginal utility of leisure. However, this is tempered by ϵ. For a given $\bar{\eta}$, equation (17) indicates that a small ϵ implies that U has significant curvature over H. Indeed, if ϵ is small enough ($\epsilon < 1/\beta_i$), then an improvement in leisure technology actually lowers the marginal value of leisure, as the increase in v lowers U_v more than v_i increases.

Collecting results, we combine the elasticity (eq. [15]) with the implied shift in technology (eq. [13]) to obtain

$$\Delta \ln \omega \approx \frac{\partial \ln \omega}{\partial \ln \theta_i} \Delta \ln \theta_i = \frac{s_i}{\epsilon}\left[\frac{\beta_i \epsilon - 1}{\beta_i \bar{\eta} - 1}\right]\left(\Delta \ln h_i - \frac{\beta_i}{\beta_j} \Delta \ln h_j\right). \tag{19}$$

In terms of figure 1*B*, the expression in equation (19) represents the vertical shift from point X to point Y. That is, at a given amount of leisure H, the observed change in technology increases the marginal value of leisure time. The individual then has incentive to adjust H in response. How much adjustment is done through changes in H depends on labor market elasticities, which is the topic of the next subsection.

E. The Response of Labor Supply to Leisure Technology

The preceding derivation of the Engel curve elasticities focused on choices over leisure activities, given total leisure H. We now return to the problem of choosing market hours in problem (2). What connects the two is how technology shifts the shadow cost of time, ω, which is specified in equation (18). As the decision of whether and how much to work balances the market wage against the opportunity cost of time, there is a mapping between the technologically induced change to ω and an equivalent change in market wages (or reservation wages). With this mapping in hand, the impact on market labor hours can be recovered from the equivalent change in wages, combined with estimates of labor supply elasticities. This subsection walks through this. As before, we hold the marginal value of wealth λ constant, and thus the appropriate labor supply elasticity is the Frisch elasticity.[8]

[8] Given the λ-constant response of labor, the total effect (including wealth effects) can be recovered with an estimate of how lifetime resources change and the wealth elasticity of labor supply.

The case when market hours are at an interior optimum is straightforward. Let $\mathcal{N} = [0, 1]$ in the individual's problem (2). The first-order condition for N is

$$U_v \mathrm{v}_H = \omega = \lambda w. \tag{20}$$

That is, the shadow price of time is equal to the market wage times the marginal value of income. In order to keep labor constant after an increase in technology, a worker requires a market wage that is higher in proportion to the implied increase in ω. Alternatively, we can say that the induced change in ω has the same effect on labor as a decline in wage of the same magnitude. To see this, use the fact that $\ln \omega(H; \boldsymbol{\theta}, \boldsymbol{\xi}) - \ln w$ is constant, and differentiate to obtain

$$-\frac{\partial \ln H}{\partial \ln w} = -\frac{\partial \ln H}{\partial \ln \omega} = \epsilon.$$

That is, the responses to the market wage and to the shadow value of time (at constant $\boldsymbol{\theta}$) are both governed by the Frisch elasticity of leisure ϵ. Thus, when labor is interior, we have

$$\frac{d \ln H}{d \ln \theta_i} = -\frac{\partial \ln \omega / \partial \ln \theta_i}{\partial \ln \omega / \partial \ln H} = \epsilon \frac{\partial \ln \omega}{\partial \ln \theta_i} = s_i(\beta_i \epsilon - 1), \tag{21}$$

where the last equality uses equation (18). In terms of figure 1*B*, equation (21) represents the horizontal shift from point X to point Z. Because ω is pinned down by the wage in this case, an individual fully adjusts at the labor/leisure margin to bring marginal utility of leisure back to its initial value.

Recall that ϵ is the elasticity of leisure with respect to the shadow value of time. As $N = 1 - H$, we can define the elasticity of labor at the intensive margin as $\varphi_{\mathrm{In}} = -(H/1 - H)\epsilon$. We can rewrite equation (21) as

$$\frac{d \ln N}{d \ln \theta_i} = -\varphi_{\mathrm{In}} \frac{\partial \ln \omega}{\partial \ln \theta_i} = -\left(\frac{\varphi_{\mathrm{In}}}{\epsilon}\right) s_i(\beta_i \epsilon - 1). \tag{22}$$

It is useful to separate φ_{In} from ϵ, as the former can depend on labor market frictions (which are being suppressed here) and the latter depends only on preferences. In the current frictionless benchmark, the ratio $\varphi_{\mathrm{In}}/\epsilon$ is simply N/H.

Alternatively, suppose that labor is chosen at the extensive margin, $\mathcal{N} = \{0, \bar{n}\}$. For simplicity, we assume $U_{cv} = 0$ (additive separability) in order to hold consumption fixed across the employment options (recalling that U_c is constant at λ). The utility value of the earnings from working is $\lambda w \bar{n}$. The cost in terms of leisure is $\Delta U \equiv U(c, \mathrm{v}(1, \boldsymbol{\theta}, \xi) - U(c, \mathrm{v}(1 - \bar{n}, \boldsymbol{\theta}, \xi))$, where c satisfies $U_c = \lambda$. An individual chooses employment if $\lambda w \bar{n} \geq \Delta U$ and nonemployment otherwise. We can define their reservation wage w^{R} as

$$w^{\mathrm{R}} = \frac{\Delta U}{\lambda \bar{n}}. \tag{23}$$

This expression shows that the impact of technology on ΔU can be mapped into an equivalent change in the reservation wage.

Taking a second-order approximation of ΔU around $H = 1 - \bar{n}$, we obtain

$$\begin{aligned} \Delta U &\approx U_v \mathrm{v}_H \bar{n} + \frac{1}{2}(U_{vv}\mathrm{v}_H^2 + U_{\mathrm{v}}\mathrm{v}_{HH})\bar{n}^2 \\ &= \omega\left(1 - \frac{1}{2\epsilon}\frac{\bar{n}}{1-\bar{n}}\right)\bar{n}, \end{aligned} \tag{24}$$

where the second line uses $\omega = U_v \mathrm{v}_H$ and ϵ's presence reflects its role in equation (17). Recall that $1/\epsilon > 0$ is a measure of the concavity of U over leisure time.

Combining, we have

$$\ln w^{\mathrm{R}} = \ln \omega + \ln\left(1 - \frac{1}{2\epsilon}\frac{\bar{n}}{1-\bar{n}}\right) - \ln \lambda. \tag{25}$$

For a given ϵ, we have that a 1% increase in ω corresponds to an equivalent increase in the reservation wage. Without further assumptions on U, we cannot evaluate how ϵ responds to technology. One straightforward case is when $\epsilon = \bar{\eta} = \Sigma_j s_j \eta_j$, that is, $U_{vv} = 0$. An increase in technology for activity i will raise s_i if $\eta_i > 1$ and correspondingly lower the shares on other activities. Hence, technology improvements in relatively high-η_i activities will raise $\bar{\eta}$ and hence increase ϵ. From equation (25), this further increases the reservation wage.

Take a set of individuals facing a common market wage w. The fraction employed is $E = \Pr(\ln w^{\mathrm{R}} \leq \ln w) = F(\ln w)$, where F is the cumulative distribution function of reservation wages across the individuals. The extensive-margin Frisch elasticity is $\varphi_{\mathrm{Ex}} \equiv d \ln E / d \ln w = f(\ln w)/F(\ln w)$, where $f = F'$. An increase in leisure technology that increases each individual's reservation wage by a factor δ is equivalent to a decline in the market wage by the same factor. We then have

$$\frac{d \ln E}{d \ln \theta_i} = -\varphi_{\mathrm{Ex}} \frac{\partial w^{\mathrm{R}}}{\partial \ln \theta_i} = -\epsilon_E \frac{\partial \ln \omega}{\partial \ln \theta_i} = -\left(\frac{\varphi_{\mathrm{Ex}}}{\epsilon}\right) s_i(\beta_i \epsilon - 1), \tag{26}$$

with the caveat on the middle equality that we are holding ϵ constant with respect to θ_i in equation (25). This is similar to the interior case (eq. [22]), but scaling is by the ratio of the extensive employment Frisch to ϵ, rather than by the intensive hours Frisch relative to ϵ. In terms of figure 1, the inframarginal agents fully absorb the technology change in a higher shadow value of leisure and do not adjust H. The marginal agents adjust H discretely. The aggregate response of employment hours is the share of the latter agents times $\bar{n}$.

Total hours are $\bar{N} = E \times N$, the product of the fraction employed and hours conditional on employment. The total response of hours reflects adjustments at both the extensive and intensive margins, as dictated by the sum of the intensive and extensive elasticities:

$$\begin{aligned}\frac{d\ln\bar{N}}{d\ln\theta_i} = \frac{d\ln(E\times N)}{d\ln\theta_i} &= -(\varphi_{\mathrm{Ex}} + \varphi_{\mathrm{In}})\frac{\partial\ln\omega}{\partial\ln\theta_i} \\ &= -\left(\frac{\varphi_{\mathrm{Ex}} + \varphi_{\mathrm{In}}}{\epsilon}\right)s_i(\beta_i\epsilon - 1).\end{aligned} \tag{27}$$

The change in total labor is the change in the price of time ω, given by equation (19), times the Frisch elasticity of labor supply $\varphi_{\mathrm{Ex}} + \varphi_{\mathrm{In}}$. Combining results, we obtain

$$\begin{aligned}\Delta\ln\bar{N} &= -(\varphi_{\mathrm{Ex}} + \varphi_{\mathrm{In}})\Delta\ln\omega \\ &= -(\varphi_{\mathrm{Ex}} + \varphi_{\mathrm{In}})\frac{\partial\ln\omega}{\partial\ln\theta_i}\Delta\ln\theta_i \\ &= -\left(\frac{\varphi_{\mathrm{Ex}} + \varphi_{\mathrm{In}}}{\epsilon}\right)s_i\left(\frac{\beta_i\epsilon - 1}{\beta_i\bar{\eta} - 1}\right)\left(\Delta\ln h_i - \frac{\beta_i}{\beta_j}\Delta\ln h_j\right).\end{aligned} \tag{28}$$

The main takeaway from this exercise is that the impact of improvements in leisure technology affects labor decisions in a manner similar to a change in the market wage. The key task is then to empirically estimate the change in ω due to innovations in leisure technology, as roadmapped above. Standard estimates of labor supply elasticities can then translate these into associated changes in hours worked.

F. The Choice of Technology

So far we have assumed a given technology bundle $\boldsymbol{\theta}$ and solved the associated subproblem of time allocation. In this subsection, we consider the trade-off a consumer faces in choosing θ_i. Consider changes over time in θ_i from the decision of individuals to purchase the latest technology. Let p_i denote the price to engage technology bundle θ_i for activity i. In particular, suppose that one can upgrade technology by $\Delta\theta_i$ by paying an additional Δp_i. The cost of such a purchase in terms of utility is $\lambda\Delta p_i$. The value, to a first order, is $U_v v_{\theta_i}\Delta\theta_i$.[9]

Using the fact that $v_{\theta_i}\theta_i = v_i h_i$, we can rewrite the gain as $U_v v_i h_i \Delta\theta_i/\theta_i = \omega h_i \Delta\theta_i/\theta_i$. The agent prefers the marginal upgrade as long as

[9] Recalling that v also depends on H, the first-order effect implicitly assumes that H is either at an interior optimum (and an envelope condition applies) or is held constant.

$$\frac{\Delta\theta_i}{\theta_i} \geq \frac{\lambda p_i}{\omega h_i}\frac{\Delta p_i}{p_i}. \tag{29}$$

On the left is the percentage increase in technology. On the right, the first fraction 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. For an indifferent consumer, equation (29) will hold with equality.

Equation (29) provides an alternative for 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. To map into observables, we assume that $\omega = \lambda w$, that is, that labor is at an interior optimum. In this case, the relative cost shares are p_i/wh_i, the cost of technology divided by the cost of the time input priced at the market wage. This independent measure of technological change can be combined with equation (13) to obtain a sense of the magnitude of $\bar{\eta}$.

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 II.B to the data to estimate β_i for alternative leisure activities. In section V, we use equation (13) 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 equation (29) to recover $\bar{\eta}$. The last step is to use equation (28) to quantify the impact of improved technology on labor supply.

III. 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 2000s, on the basis of the time diaries of the 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.[10] We restrict the sample to civilians aged 21–55. We exclude full-time students who are less than age 25—before 2013, the CPS, and therefore the ATUS, asked only those under age 25

[10] The ATUS surveys are distributed equally over weeks of the year. Within weeks, each weekday contributes 10% of the raw ATUS sample, with each weekend day contributing 25%; but we employ ATUS weights that achieve an equal weighting across days of the week. Time spent traveling to or from an activity is included in each 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. Section A1 of the appendix discusses in more detail our ATUS sample as well as other data sets employed in the paper.

about school attendance. 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 distributions 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.[11]

A. *Trends in Broad Time-Use Categories*

We divide activities into six broad categories: market work, job search, home production, child care, education, and leisure.[12] Our classification of time-use activities follows closely the classification used in Aguiar and Hurst (2007b), Aguiar, Hurst, and Karabarbounis (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, and so on. 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 a 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 ESP is needed for survival.[13] 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. To increase power, we group data for 2004–7 and for 2014–17. The table reports average time for each category by time period as well as the change between the two periods.

Starting panel A, we see that younger men reduced their market work by 1.8 hours per week over this period, which corresponds to a nearly 5%

[11] It is well known that the ATUS does not match the educational distribution of the March CPS for subgroups (Grossbard and Vernon 2015). For example, in the ATUS, 28.7% and 38.7% of women aged 21–30 have at least a bachelor's degree during the 2004–7 and 2014–17 periods, respectively. The comparable numbers in the March CPS for those periods are only 27.6% and 33.3%. Tables A1 and A2 detail ATUS time allocations by demographic group without the additional weighting.

[12] Some small categories, such as personal health care and unclassified time use, are omitted from our analysis.

[13] Approximately 95% 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 that our results were not sensitive to these changes.

TABLE 1
Broad Time Allocation during the 2000s

Activity	Age 21–30 2004–7	Age 21–30 2014–17	Age 21–30 Change	Age 31–55 2004–7	Age 31–55 2014–17	Age 31–55 Change
	A. Men Aged 21−55					
Market work	38.4	36.6	−1.8 (1.0)	40.8	40.2	−.5 (.5)
Job search	.3	.8	.5 (.1)	.3	.4	.10 (.05)
Home production	12.1	11.7	−.4 (.5)	14.8	14.1	−.7 (.2)
Child care	2.8	2.2	−.6 (.2)	3.6	4.1	.5 (.1)
Education	2.4	2.7	.3 (.4)	.6	.6	.002 (.075)
Leisure	61.1	63.4	2.3 (.9)	57.1	57.7	.6 (.4)
	B. Women Aged 21–55					
Market work	27.5	26.8	−.7 (.8)	27.3	27.4	.1 (.4)
Job search	.2	.3	.1 (.1)	.2	.2	.04 (.03)
Home production	19.0	17.8	−1.2 (.4)	24.2	22.4	−1.8 (.3)
Child care	10.0	8.6	−1.4 (.4)	7.3	7.8	.4 (.2)
Education	2.3	3.1	.8 (.3)	1.1	.9	−.2 (.1)
Leisure	58.5	60.0	1.6 (.7)	56.2	57.5	1.3 (.3)

Note.—Table reports time spent on activities from the ATUS, expressed in units of hours per week. Data are pooled for the 2004–7 and 2014–17 periods. An individual's total time endowment, after subtracting 49 hours per week for biological sleeping, eating, and personal care needs, is 119 hours per week. Data are weighted by ATUS weights adjusted to match the corresponding education distribution by year-demographic cell in the corresponding year's March CPS. See table A1 for the same means using the original ATUS weights. The standard errors of the changes between 2004–7 and 2014–17 are reported in parentheses.

decline. Comparing the top and bottom rows of the panel, we see that this decline in market hours was more than matched by an increase in leisure of 2.3 hours for younger men.[14] The remaining 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 further highlight using CPS data below, the decline in market work for younger men during this period was considerably larger than the decline in work 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. 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

[14] Figure A1 (figs. A1, A2 are available online) displays the cross-sectional distributions of leisure time for younger men for the 2004–7 and 2014–17 subperiods. The density displays a noticeable rightward shift over time.

CPS. An advantage of the March CPS over the ATUS is that market hours are reported on basis of the calendar year, rather than a snapshot from a single day.[15] Figure 2*A* 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 fell by 10.9%, while older men's fell by 7.5%. The differential hours gap between younger and older men began widening before the start of the Great Recession, then widened substantially during the Great Recession. While annual hours for both groups have been increasing since 2011, they are still well below 2007 levels, especially for younger men. Comparing averages for the years 2014–17 to the 2004–7 averages, the March CPS shows a decline of 140 hours per year (2.7 hours per week) for men aged 21–30, which is a somewhat steeper decline than is seen in the ATUS. The relative differences in the decline in market hours between younger and older men during this time period were similar in the ATUS and the March CPS (1.4 hours per week vs. 1.0 hours per week).

Figure 2*B* 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 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% 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. As with annual hours worked, the gap increased substantively during the Great Recession and has only modestly reversed as of 2018. Both panels of figure 2 illustrate that younger men's hours worked have declined since 2000 relative to older men's despite the gains made in the aggregate labor market since the Great Recession.

The brunt of the Great Recession's decline, and the subsequent partial rebound, in younger men's hours obviously reflects cyclicality of labor demand. But we ask whether part of the longer-term decline in their hours, especially compared to older men's, might reflect trend increases in younger men's marginal value for leisure. We next turn to some descriptive evidence along these lines.

B. *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 ESP,

[15] 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 aged less than 25 when using the March CPS sample.

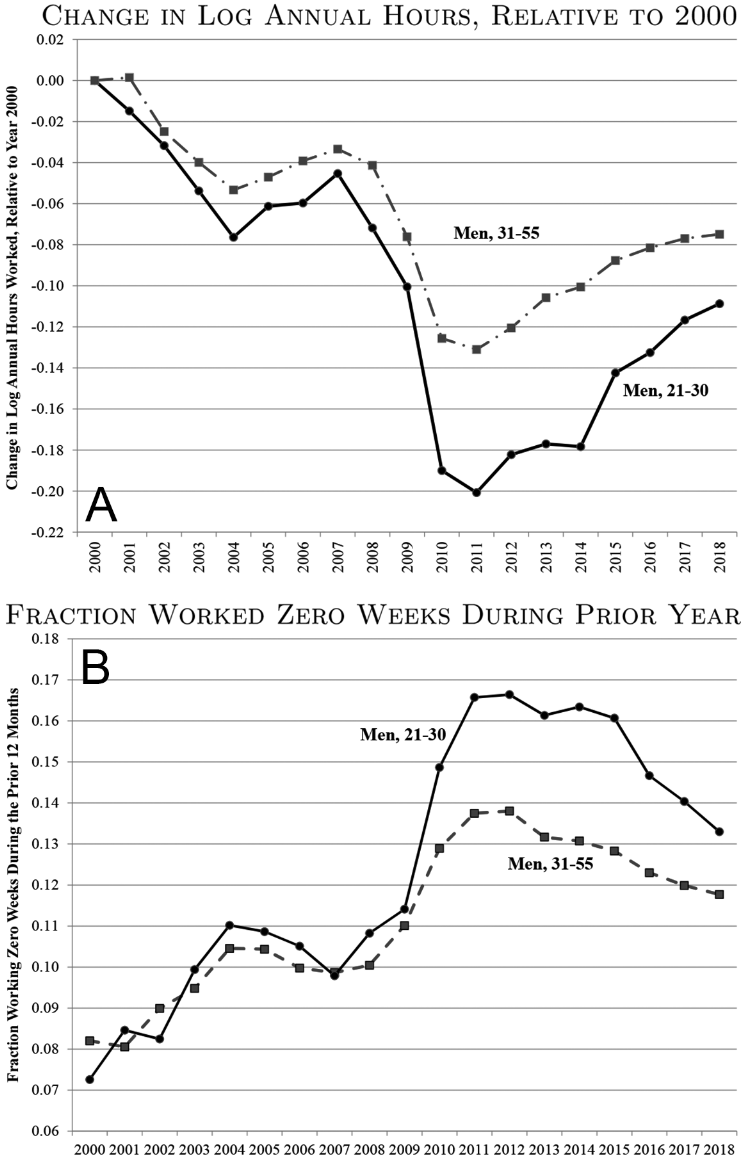

Fig. 2.—Differences in hours worked between younger and older men, March CPS. *A* shows log annual hours worked relative to year 2000, while *B* shows the shares working zero weeks during the prior year. Data for men aged 21–30 are shown with solid lines, those for men aged 31–55 with dashed lines. Data are from the CPS March supplement, excluding full-time students aged less than 25. Standard errors for the points in *A* are all in the ranges 0.007–0.008 for younger men and 0.003–0.004 for older men. For *B*, standard errors for the points are all in the ranges 0.003–0.004 for younger men and 0.0015–0.0020 for older men. A color version of this figure is available online.

and other leisure. Recreational computer time includes time spent on nonwork 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 time.[16] Computer time for work or nonleisure activities (such as paying bills or checking email) are captured by other time-use categories. Watching television and movies specifically includes watching on streaming platforms (such as 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 for younger men is more than accounted for by an increase of 2.7 hours in their recreational computer time.[17] 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-use category over a short span of time. For reference, annual hours women spend on home production fell by 520 hours over the past 40 years (Aguiar and Hurst 2007b).

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 is possibly an artifact of how sleep time is measured within the ATUS.[18] 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.[19] Given that the increase in recreational

[16] 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 such as 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.

[17] This increase in recreational computing reflected sizable increases in both the fraction of young men engaging in the activity on a given day, from 23% to 30%, and average time spent, conditional on engaging. Figure A2 displays the cross-sectional distribution of recreational computing time for younger men, conditional on spending strictly positive time. It displays a prominent rightward shift between 2004–7 and 2014–17.

[18] The sleep time-use category includes sleeplessness and trying to fall to sleep. So watching TV while trying to fall to sleep may be classified as either sleeping or TV watching.

[19] 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, Liu, and Liu (2018) find no increase in sleep time for prime-age individuals in the National Health and Nutrition Examination Survey between 2005 and 2014.

TABLE 2
Leisure Activities for Men 21–30

Activity	2004–7	2014–17	Change
Total leisure	61.1	63.4	2.3 (.9)
Recreational computing	3.3	6.1	2.7 (.4)
Video game	2.1	3.9	1.8 (.3)
ESP	24.3	26.0	1.7 (.6)
TV/movies/Netflix	17.4	15.8	−1.6 (.5)
Socializing	7.8	7.6	−.2 (.4)
Other leisure	8.3	8.0	−.3 (.4)

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 shows the change in hours per week. Data are weighted by ATUS weights adjusted to match the corresponding education distribution by year-demographic cell in the corresponding year's March CPS. See table A2 for the same means using the original ATUS weights. The standard errors of the changes between 2004–7 and 2014–17 are reported in parentheses.

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, begun 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% between 2006 and 2009, after being fairly flat for the prior five years.[20] Much of the increase in computer leisure technology occurred directly before the start of the Great Recession.

From table 2, weekly leisure hours for younger men increased by 2.3 hours between 2004–7 and 2014–17. At the same time, there was a large increase, from 11.7% to 14.5%, in the share of younger men in the ATUS who were not employed. Because the nonemployed exhibited nearly 30 hours more leisure on average in 2004–7, the shift to fewer employed played a role in the overall increase in average leisure. In table 3, we look at leisure conditional on being employed. Unfortunately, since

[20] Data are from the NPD Group: vgsales.wikia.com/wiki/NPD_sales_figures.

TABLE 3
LEISURE ACTIVITIES FOR EMPLOYED MEN 21–30 (HOURS PER WEEK)

Activity	2004–7	2014–17	Change
Total leisure	57.6	59.9	2.3 (.9)
Recreational computing	3.0	4.9	1.9 (.3)
Video games	1.9	3.2	1.3 (.3)
ESP	23.5	24.7	1.3 (.6)
TV/movies/Netflix	16.0	14.6	−1.4 (.5)
Socializing	7.4	7.7	.3 (.4)
Other leisure	7.6	7.8	.2 (.4)

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 weights adjusted to match the corresponding education distribution by year-demographic cell in the corresponding year's March CPS. See table A3 for the same means using the original ATUS weights. The standard errors of the changes between 2004–7 and 2014–17 are reported in parentheses.

there is no panel dimension to the ATUS, we are comparing different pools of employed across a period with a large decrease in employment. So one should keep in mind that the changes in average leisure calculated for those employed will reflect compositional effects driven by the smaller share employed.

Turning to table 3, we see that leisure for employed younger men still increased by 2.3 weekly hours. Even among the employed, hours worked were 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 was a substantial shift toward more recreational computer time over this period. The 1.9 hours per week increase in recreational computer time was again of about the same magnitude as the increase in total leisure time.[21]

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 3, where, for example, the label "5" indicates individuals who spent 5–6 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 men for 2004–7, while the darker bars depict those for 2014–17. We see that computer leisure increased within essentially all leisure bins, but especially for high-leisure individuals.

[21] While the nonemployed had substantially more leisure time than the employed, they also displayed a particularly sizable shift in their recreational computing time, from 5.4 hours per week in 2004–7 to 12.0 hours per week in 2014–17. The 12 hours per week spent on recreational computing time for the nonemployed in 2014–17 exceeded the time they spend socializing (6.8 hours per week) and in other leisure activities (9.5 hours per week).

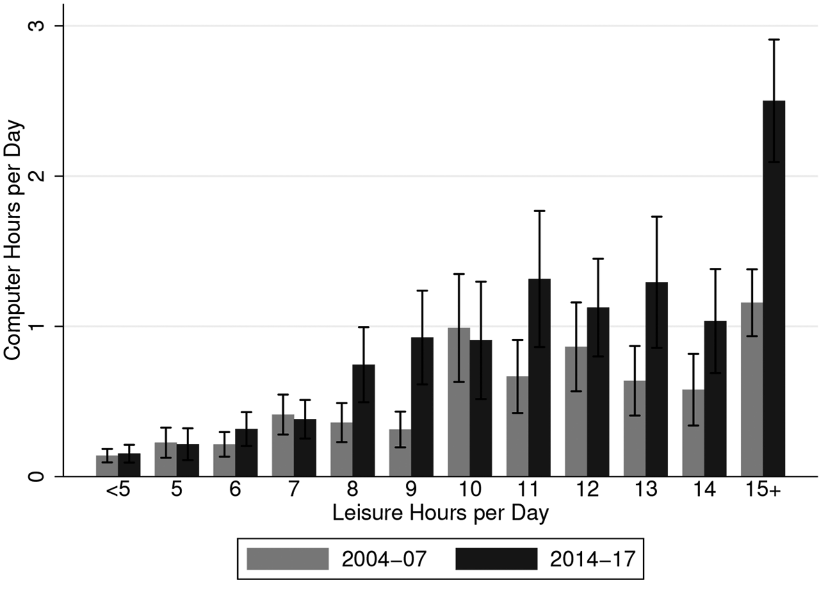

Fig. 3.—Younger men's hours per day of computer leisure by level of total leisure. Average time spent on computer leisure (including video games) by individual's total leisure. Time use is expressed in hours per day. Except for first and last bins, leisure bins span one hour per day, with minimal value of each bin denoted. 95% confidence intervals are also depicted. A color version of this figure is available online.

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 2.7 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.

IV. Estimating Leisure Engel Curves

We now estimate the leisure demand system outlined in section II.B. The key targets are the Engel curve elasticities β_i. From estimates of the Engel curves, we construct estimates of the primitives θ_i and η_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-GENDER GROUPS

	2004–7	2014–17	Change
		Men 21–30	
Total leisure	61.1	63.4	2.3 (.9)
Recreational computing	3.3	6.1	2.7 (.4)
Video games	2.1	3.9	1.8 (.3)
		Men 31–55	
Total leisure	57.1	57.7	.6 (.4)
Recreational computing	2.1	2.1	−.01 (.10)
Video games	.9	1.0	.05 (.07)
		Women 21–30	
Total leisure	58.5	60.0	1.6 (.7)
Recreational computing	1.5	2.6	1.1 (.2)
Video games	.8	1.2	.4 (.1)
		Women 31–55	
Total leisure	56.2	57.5	1.3 (.3)
Recreational computing	1.6	2.0	.4 (.1)
Video games	.6	.7	.14 (.05)

NOTE.—Video game time is a subcomponent of computer leisure. Data are weighted by ATUS weights adjusted to match the corresponding education distribution by year-demographic cell in the corresponding year's March CPS. See table A3 for the same means using the original ATUS weights. The standard errors of the changes between 2004–7 and 2014–17 are reported in parentheses.

A. 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 III.A, 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 before the time diary. The CPS asks the industry of the current job or, if not currently employed, that of the last job held in the preceding 12 months.[22] 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 each state's change in average leisure from 2004–7 to 2014–17 by 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 from those in states with a small increase (or decrease) in leisure. This grouping allows for sizable variations in leisure across regions over time, even in specifications that allow for region-specific fixed effects.

The final cell characteristic is time period, where we use the four periods discussed in section III.A, namely, 2004–7, 2008–10, 2011–13, and 2014–17. Theoretically, this implies up to 2,240 cells in total—560 for each gender-age group; but in practice, some cells contain no individuals. In estimating, we weight all cells by the sum of their individual members' weights and restrict attention to cells with at least 10 observations.

B. *Specification*

Our empirical specification builds on the consumption literature, most notably Deaton and Muellbauer's (1980) Almost Ideal Demand System (AIDS). Using equation (5) and $\hat{\omega} = \mathrm{v}_H$, we can write the share of time devoted to activity i by synthetic cell k at time t:

$$s_{ikt} = \frac{(\theta_{it}\xi_{ikt})^{\eta_i - 1}\mathrm{v}_H^{-\eta_i}(H_{kt}, \boldsymbol{\theta}_t, \boldsymbol{\xi}_{kt})}{H_{ikt}}.$$

Taking a first-order expansion around $(\bar{H}, \bar{\boldsymbol{\theta}}, \bar{\boldsymbol{\xi}})$ with associated shares $\{\bar{s}_j\}$ yields

$$s_{ikt} \approx \bar{s}_i + (\eta_i - 1)\bar{s}_i(\hat{\theta}_{it} + \hat{\xi}_{ikt}) - \bar{s}_i(1 + \beta_i)\hat{H}_{kt} - \beta_i\bar{s}_i\sum_{j=1}^{I}\bar{s}_j(\eta_j - 1)(\hat{\theta}_{jt} + \hat{\xi}_{jkt}). \tag{30}$$

A "hat" indicates log deviation from the point of approximation. We use $\eta_i \partial \ln \mathrm{v}_H / \partial \ln H = \beta_i$.

[22] 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 fourteenth industry.

Let

$$\delta_{it} \equiv \bar{s}_i\left[(\eta_i - 1)\hat{\theta}_{it} - \beta_i\sum_j \bar{s}_j(\eta_j - 1)\hat{\theta}_{j,t} - (1 + \beta_i)\ln \bar{H}\right]$$

denote the activity-time–specific elements that are common across cells k. In particular, it captures the state of technology i relative to a weighted average of the other activities' technologies. Let

$$\varepsilon_{ikt} \equiv \bar{s}_i\left[(\eta_i - 1)\hat{\xi}_{ikt} - \beta_i\sum_j \bar{s}_j(\eta_j - 1)\hat{\xi}_{jkt}\right]$$

denote the relative preference cell k has for activity i over a weighted average of all other activities. We can decompose ε_{ikt} into a group-specific component, $\alpha_{n,t}$, plus a residual, u_{ikt}, where $n = 1, \ldots, N$ indexes N groups based on education, industry, and region. We can then rewrite equation (30) as

$$s_{ikt} = \delta_{it} + \sum_n \alpha_{n,t}D_{k,n} + \gamma_i \ln H_{kt} + u_{ikt}, \tag{31}$$

where $\gamma_i = \bar{s}_i(\beta_i - 1)$ and $D_{k,n} = 1$ if k is in group n and zero otherwise.

We estimate equation (31) separately for each activity and allow all parameters to vary by age-gender groups. From estimate $\hat{\gamma}_i$, we recover an estimate of β_i:

$$\hat{\beta}_i = 1 + \frac{\hat{\gamma}_i}{\bar{s}_i}, \tag{32}$$

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

In table A5 (tables A1–A7 are available online), we also report results for a log-log specification, which yields nearly identical β_i estimates. In the appendix (available online), we also consider a nonlinear specification that allows for an added impact due to the square of a cell's log of total leisure. Results are given in table A7, which shows that implications including the quadratic term are similar to those from our base specification.[23]

C. *Identification*

To consistently estimate γ_i from equation (31) requires that H_{kt} be orthogonal to the error term. Recall that the activity-time fixed effect δ_{it} captures time-dependent shifts in tastes or technology that are uniform

[23] In particular, the nonlinear specification generates similar estimates for the growth in computer leisure technology and for its impact on labor supply.

across cells.[24] Thus, our identifying assumption is that cell-specific relative 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 as a result of exogenous changes in total leisure, where by *exogenous* we mean independent of idiosyncratic tastes and technologies for a particular activity. But, more generally, any variation in leisure driven by relative labor demands satisfies validity, even as would many factors that affect labor supply, such as differential wealth effects across cells. The construction of our cells is designed to isolate such variation. In particular, the 2000s saw large relative fluctuations in employment across education groups, regions, and industries. These movements are plausibly unrelated to idiosyncratic shifts in the taste for particular leisure activities.[25] Thus, 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.

In short, our identification rests on assuming that, conditional on a vector of time and possibly other fixed effects, differences in leisure across cells are driven by either "labor demand" (e.g., wages) or activity-independent "labor supply" shocks that do not differentially favor one activity over another (e.g., wealth effects plus weak separability). The threat to identification arises if cells with especially high total leisure systematically have different relative 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 overestimate the Engel curve elasticity for computing and underestimate the elasticities for other activities. By overestimating computing's Engel slope, we would underestimate how much computer leisure improved—see figure 1—and underestimate its impact on younger men's labor supply. Conversely, if high-leisure cells have a weaker taste for computing, we will underestimate the Engel elasticity for that activity, resulting in an overestimate of the impact on labor supply from improvements in computing. To the extent that our cells are broadly defined and

[24] 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 Federal Communications Commission, all metropolitan statistical areas 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.

[25] 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, e.g., Charles, Hurst, and Notowidigdo (2017) 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. For instance, consider introducing fixed effects for education groups. Without these effects, the threat to identification is from schooling groups differing in tastes for computing activity. With these effects, the threat arises only if relative variation in leisure over time across the schooling groups is related to changing relative preferences for computing.

D. *Estimates*

Table 5 reports our estimates of β_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 (31), and the implied $\hat{\beta}_i$ are obtained with equation (32). Column 1 is for a baseline specification that includes time-period fixed effects. Column 2 adds education-group fixed effects, column 3

TABLE 5
LEISURE ENGEL CURVES OF YOUNGER MEN: $\hat{\beta}_i$

	(1)	(2)	(3)	(4)
Recreational computing	2.48	2.46	2.40	1.53
	(.42)	(.40)	(.42)	(.38)
Video games	2.42	2.34	2.26	1.37
	(.43)	(.42)	(.43)	(.48)
TV/movies/Netflix	1.19	1.10	1.13	1.18
	(.13)	(.12)	(.13)	(.17)
Socializing	.46	.51	.40	.70
	(.26)	(.26)	(.29)	(.31)
ESP	.76	.76	.76	.84
	(.10)	(.10)	(.11)	(.13)
Other leisure	.97	1.09	1.18	1.09
	(.23)	(.21)	(.20)	(.26)
Fixed effects:				
Time period	X	X	X	X
Education		X	X	X
Geographic			X	X
Industry				X
No. of cells	281	281	281	281
No. 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.

further adds regional fixed effects, and column 4 adds fixed effects for the 14 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 β_i are bootstrapped.[26]

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 subcomponent 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 a necessity ($\hat{\beta}_i = 0.97$). ESP 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 for column 4. Adding fixed effects for schooling and region produces extremely similar elasticities. This implies that the extra leisure for younger men without a college degree or, on average, in certain regions is allocated toward computer leisure so as to nearly fit on our estimated Engel curve. Column 4 also includes industry fixed effects. For this specification, the identifying assumption is that variations over time in leisure for individuals grouped by schooling, region, and industry do not reflect variations in preference for a specific leisure activity. Including industry fixed effects moves the estimated elasticities toward 1. This largely reflects the impact of controlling for those without an industry code; that is, those who have been nonemployed for at least 12 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 (28), 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 this sense, the estimates of column 1 are more conservative than those of column 4 for estimating the impact of this better leisure technology on labor supply.[27]

Table 6 reports the estimated Engel elasticities of computing and ESP for other 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

[26] Specifically, the bootstrap procedure repeatedly draws samples, estimates the AIDS coefficient γ_i and the average share $\bar{s}_i$, and computes $\hat{\beta}_i$, using eq. (32). The bootstrap is performed with the 160 replication weights provided by the ATUS.

[27] If we employ the estimates from col. 4 in our calculations, the implied increase in the marginal value of time, ω, is 3.1%, compared to the 2.5% reported below.

TABLE 6
ENGEL CURVE ESTIMATES BY DEMOGRAPHIC GROUP

	Men 31–55	Women 21–30	Women 31–55
Recreational computing	1.44	1.81	1.43
	(.20)	(.48)	(.17)
ESP	.61	.64	.65
	(.04)	(.09)	(.04)
No. of cells	509	275	463
No. of individuals	36,715	10,246	44,149

NOTE.—Specification is that of table 5, col. 1. Bootstrapped standard errors are in parentheses.

than that estimated for younger men. However, it is worth noting that recreational computer use is a leisure luxury and ESP a leisure necessity for all groups.

Figure 4 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

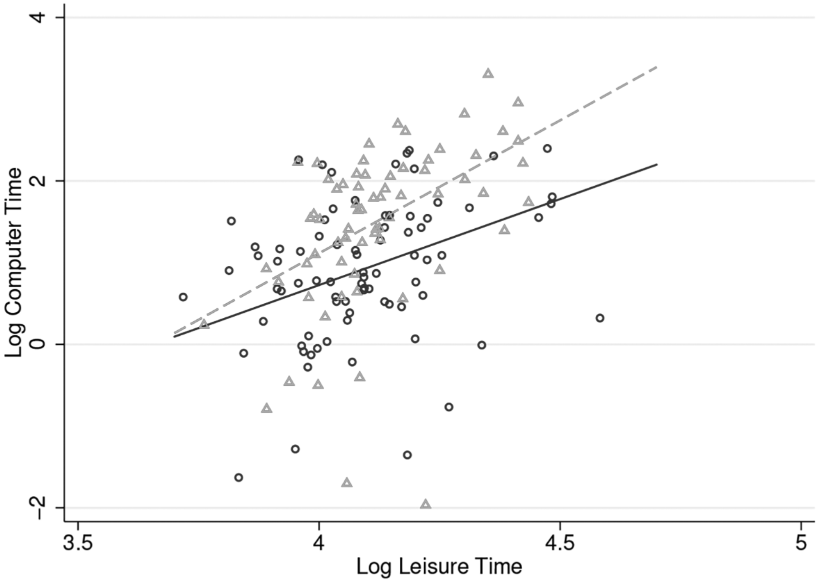

FIG. 4.—Leisure Engel curves for computer leisure: 2004–7 versus 2014–17. Figure depicts a scatter plot of cell average leisure time (horizontal axis) and recreational computing and gaming (vertical axis), both in log hours per week. The circles represent data from 2004–7, while triangles represent 2014–17. The solid line is the weighted regression line for the earlier period and the dashed line that for the later period. The slopes (standard errors) are 2.10 (0.52) and 3.25 (0.65), respectively. A color version of this figure is available online.

point represents a cell average. Circles depict 2004–7 observations; triangles depict those for 2014–17. These patterns provide a sense of how we disentangle movements along an Engel curve from shifts driven by changes in θ_I. A shift up in the leisure Engel curve reflects the increase in θ_I over time.

V. 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 the marginal value of leisure and the shift in labor supply.

A. *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 (12), which relates changes in time allocation to changes in technology. As noted in section II, changes in time allocation identify relative technology changes. For our baseline, we treat leisure ESP as our reference activity. This assumes no technological or aggregate preference change for eating, sleeping, or personal care during our sample period. In section VI, we explore robustness of our results to alternate choices for a reference activity. Setting $\Delta\theta_{\text{ESP}} = 0$ in equation (12) and indicating activity I as recreational computing, we have

$$(\eta_I - 1)\Delta \ln \theta_I = \Delta \ln h_I - \frac{\beta_I}{\beta_{\text{ESP}}}\Delta \ln h_{\text{ESP}}. \tag{33}$$

As reported in table 2, younger men increased ESP time by 6.7% over the ATUS sample period. The estimates in table 5 give $\hat{\beta}_I/\hat{\beta}_{\text{ESP}} = 3.3$. This implies that, absent any technological change, their computer time would increase by 22.1%. This is the term subtracted on the right-hand side of equation (13), and it corresponds to the predicted movement along the Engel curve for computer leisure. However, computer time for younger men actually rose by 60.4%. We therefore estimate the change in $(\eta_I - 1)\Delta \ln \theta_I$ to be 38.3% (with standard error of 14.8%), or 2.9% per year.[28]

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

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

TABLE 7
IMPACT OF $\Delta\theta_l$ ON $\ln\omega$ AND LABOR SUPPLY (%)

	Men 21–30	Men 31–55	Women 21–30	Women 31–55
$(1-\eta_l)\Delta\ln\theta_l$	38.3	−8.2	32.1	3.8
	(14.8)	(7.3)	(12.5)	(5.9)
$\Delta\ln\omega$	2.5	−.3	1.0	.1
	(1.0)	(.2)	(.4)	(.2)
$\Delta\ln N$	−2.2	.2	−.8	−.1
	(.9)	(.2)	(.4)	(.1)

NOTE.—Shift in labor supply (wage constant) from $\Delta\theta_l$ for 2004–7 to 2014–17. Bootstrapped standard errors are in parentheses.

32.1% (standard error 12.5%), or 2.5% per year. The only group that does not show an increase in computer technology is older men. For this group, $(\eta_l - 1)\Delta\ln\theta_l = -8.2\ \%$ over the entire period, with a standard error of 7.3%. This reflects that time spent at recreational computing did not change for older men, while ESP increased 3.2%. The estimated change in technology for each demographic group is reported in the first row of table 7.

B. Labor and Leisure Elasticities

The mapping between changes in leisure technology and labor supply is given in equation (27). The demand system estimates and time diaries provide a measure of changes in leisure's marginal return. To map this into changes in hours worked, we need estimates of several elasticities.

The preference parameter ϵ defined by equation (16) captures the curvature of utility over leisure, as seen in equation (17). In particular, it captures the sensitivity of leisure to a change in the shadow value of time. As noted in section II.E, if labor can costlessly adjust at the intensive margin, then this parameter equals the intensive Frisch elasticity of labor supply scaled by the ratio of leisure to labor. However, it is not clear that labor hours can be freely adjusted at the margin or that the wage is invariant to one's choice of hours. An alternative approach is to exploit the fact that work is the complement of leisure (and nondiscretionary time) and hence includes nonmarket work (home production, shopping, etc.). Using a data set on shopping effort and prices, Aguiar and Hurst (2007a) estimate the shadow value of time over the life cycle.[29] In figure 5*A*, we reproduce the life-cycle path of the value of time implied by the returns to price

[29] Aguiar and Hurst (2007a) contains the detailed methodology. In short, the value of time is computed in two steps. First, the responsiveness of price to shopping intensity is estimated using a Nielsen Homescan data set. Second, the monetary return to shopping is the estimated price elasticity times the size of the shopping bundle. The life-cycle profile of the marginal return to shopping then provides a measure of the marginal value of time.

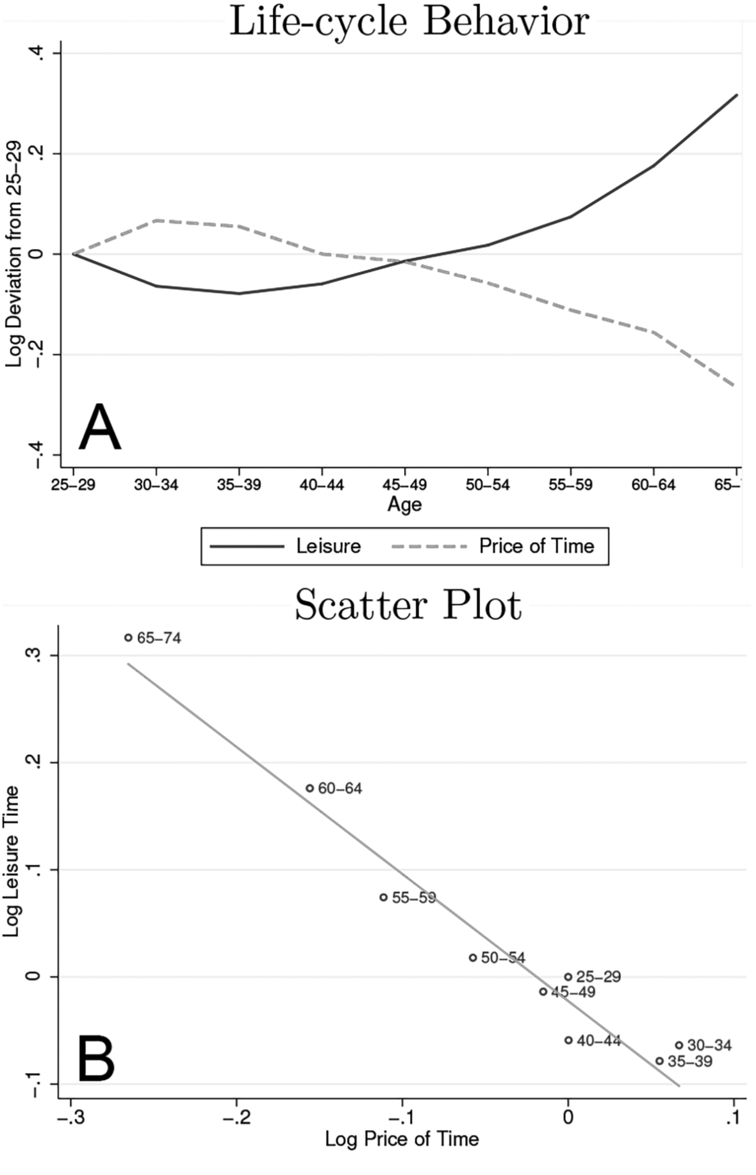

FIG. 5.—Leisure and the price of time. *A* plots the life-cycle profile of log average leisure time in deviations from ages 25–29 (solid line) and reproduces the life-cycle profile of the shadow cost of time from fig. 4 of Aguiar and Hurst (2007a; dashed line). *B* is a scatter plot version of the data from *A*, specifically, log average leisure time for each age range plotted against the log value of time (again normalizing age 25–29 to zero). A color version of this figure is available online.

search (fig. 4 in Aguiar and Hurst 2007a). In the same figure, we plot leisure time over the life cycle, using the ATUS sample.[30] The two series have a strong negative correlation. In figure 5*B*, we plot log leisure time against the log price of time for each age bin, normalizing ages 25–29 to zero. The uniformly negative relationship is striking, given that the two series were constructed using very different data sets: the value of time uses Nielsen Homescan, and leisure uses the ATUS. However, as an economic outcome it is not surprising, given that the market return to work peaks in middle age and then declines through retirement.

A regression of log leisure on the log shadow value of time yields an estimated elasticity ϵ of 1.19, with standard error 0.1. This implies a larger Frisch elasticity of labor supply on the intensive margin than is typically estimated, which likely reflects that fewer frictions are present in substituting between leisure and nonmarket work than between leisure and market work. For example, if workers face a curvature in their wage schedule as a function of hours worked (see, e.g., Bick, Blandin, and Rogerson 2020), then the estimated Frisch elasticity of labor will be lower than the underlying preference parameter.

A change in the return to leisure shifts the work-leisure trade-off in the identical manner as a change of the opposite sign in the market return to work. Hence, we can build on the vast empirical literature that estimates the responsiveness of labor, at both the extensive and intensive margins, to wage changes. 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's (2003) 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 larger elasticities of about 0.4 or a little higher. See, for example, Gourio and Noual (2009), Mustre-del-Río (2015), and Park (2020). On the basis of this literature, for our benchmark we take the combined Frisch to be Chetty's more conservative 0.86. In a robustness exercise reported in section VI, we explore alternative values.

C. Impact on Labor Supply from Technology Change

The results in section V.A use shifts in time allocation to document that there has been rapid progress in technology associated with recreational

[30] For this exercise, we extend the ATUS sample to span ages 25–74. Aside from this, the sample selection criteria are the same as in sec. III.

computer use and video games. The question we now address is how this affects the willingness to work. From section II.E, equation (28) maps shifts in time allocations into shifts in labor supply.

In addition to our estimates of the βs, $(\eta_I - 1)\Delta \ln \theta_I$, and the elasticities $\{\epsilon, \varphi_{\mathrm{In}}, \varphi_{\mathrm{Ex}}\}$, we need the average leisure-activity elasticity $\bar{\eta}$. The parameter $\bar{\eta}$ is related to ϵ, as seen from equation (17). As a benchmark, we assume that v enters linearly in U; that is, $\epsilon = \bar{\eta}$. Thus, in equation (28), the second ratio in the third line is set to 1. In section VI, we use price data and equation (29) to check the plausibility of assuming $\epsilon = \bar{\eta}$, as well as to explore the robustness of our results to alternative choices of ϵ and $\bar{\eta}$.

The second row of table 7 reports the implied shift in the marginal value of leisure, holding H constant. This is the vertical shift (point X to point Y) in figure 1 and is computed using equation (19). For younger men, the shift in the marginal return to leisure is 2.5%. The only other demographic group that experienced a notable increase in its return to leisure is younger women. In fact, the estimated technological improvement for younger women is similar to that for younger men. The smaller response in the value of leisure for younger women versus younger men reflects that their share of leisure devoted to computing/gaming is smaller: 3.6% for younger women, versus 7.8% for younger men.

The final row of table 7 reports the implied response of market hours to the change in the value of time. This is the second-row quantity times the combined Frisch of 0.86. For younger men, the implied decline in hours worked is 2.2%. 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% (table 1). Thus, the shift in labor supply due to better computer technology is quantitatively sizable relative to the observed shift in hours.[31]

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 fact that not only do older men spend relatively little time on computer activities but they also exhibited no increase in that time relative to other leisure activities during the 2000s. These findings, coupled with the results for younger men in the first row, 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 2004–17 ATUS, younger and older men experienced respective declines

[31] To illustrate that our methodology does not mechanically map changes in hours worked to leisure technology, we applied it to the sharp decline in younger men's market hours from 2007–8 to 2009–10 during the Great Recession. Over that short span, the unemployment rate for men aged 16 and above went from 5.4% to 10.4%, while, from the ATUS, market hours for younger men fell by nearly 4 hours per week, or about 10%, and computer leisure increased by an hour. Our approach would attribute only about a tenth of that decline in hours to improved computer leisure. So the overwhelming share remains to be attributed to a fall in labor demand, or perhaps other factors affecting labor supply.

in market hours of 4.5% and 1.5%.[32] If younger men's labor demand is perfectly elastic, then our estimates imply that nearly three-quarters of that differential hours decline can 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 within 1 percentage point of that of older men. Second, we find that increased computer technology explains a shift in of the labor supply curve for younger women of nearly 1%. This is only a third of that for younger men, reflecting the lower importance of computing/gaming in the leisure bundle of younger women. However, the decline for younger women is still notable in its own right.

VI. Robustness

Our base specification assumes that $\epsilon = \bar{\eta}$, which implies that leisure activities enter the utility aggregator U in an additively separable fashion. In this section, we explore the plausibility of this assumption, using price and expenditure data for computer leisure. We proceed to examine the sensitivity of the results to alternative choices for parameters ϵ and $\bar{\eta}$, explore our separability assumption for computing and television, and test robustness to the choice reference activity.

A. *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 $\bar{\eta}$ that is independent of ϵ, we need an independent measure of $\Delta\ln \theta_I$. We compute an estimate of $\Delta\ln \theta_I$ by using equation (29), assuming an interior solution, together with BLS (Bureau of Labor Statistics) 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 (consumer price index) for toys and games, which includes video games and equipment. The overall CPI increased 0.021 log points per year during the period of 2004–15. 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

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

for the nongaming component of "toys and games" as well as the price series for that nongaming 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% relative to the overall CPI. The CPI for computers and peripherals declined similarly, by 13.3% 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.[33] 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% per year.

We showed in equation (29) that one can recover $\Delta \ln \theta_I$ on the basis of 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 personal consumption expenditure 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 2004–14 (in 2009 dollars), where we average over households with a member between the ages of 21 and 55. Time spent on recreational computing for this period averaged 127 hours per year, where again we average over all respondents aged 21–55. From the CPS, the median real wage for the period for employed individuals aged 21–55 is $17.9. Assuming a marginal tax rate of 25%, 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 (29) and a price decline of 13.3% per year, this implies annual technological progress for computers and video games of 3.6% 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% (CE data). Deflating by the CPI for computers and peripherals, this represents a real increase of 20.2% per annum.[34] While all of the expenditure on

[33] 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.

[34] For the sample period 2012–14, average nominal expenditure is $571. The corresponding figure for 2004–6 is $288, representing an annual nominal growth rate of 8.6%. The decline in the CPI for computers and peripherals, also calculated as the difference in 3-year averages, is 11.6%. Thus, real expenditures increased at an annual rate of 20.2%.

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 $(\eta_I - 1)\Delta\ln\theta_I = 2.9\%$ per year number, obtained from the shifts in time allocation, to the $\Delta\ln\theta_I = 3.6\%$ per year from price data yields an η_I of 1.81. Using our estimated Engel curve $\hat{\beta}_I = 2.48$ and $\beta_I = \eta_I/\bar{\eta}$, we obtain $\bar{\eta} \approx 0.73$. This calculation provides a sense of the magnitude of $\Delta\ln\theta_I$ from price and expenditure 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 ϵ.

B. *Sensitivity of Results to ϵ and $\bar{\eta}$*

In section V.C, we assumed that $\epsilon = \bar{\eta}$. Equation (28) indicates exactly how our benchmark result varies with alternative values of these two parameters, showing that the magnitude is scaled by the factor $(\epsilon\beta_I - 1)/(\bar{\eta}\beta_I - 1)$ as well as by the ratio of the labor Frisch to ϵ. Here we explore robustness of the implied impact on labor supply to varying both ϵ and $\bar{\eta}$.

Specifically, we allow both $\bar{\eta}$ and ϵ to take values in {0.73, 1.0, 1.19}. The lowest number is the estimate of $\bar{\eta}$ discussed in the preceding subsection. The upper bound is the estimate of ϵ discussed in section V.B. The additional value 1.0 rounds out our robustness exercise.

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 ϵ and $\bar{\eta}$. Recall that our benchmark sets $\epsilon = \bar{\eta} = 1.19$. Hence, the bottom-right corner of the table replicates our baseline estimate of a 2.2% decline in labor supply.

Fixing ϵ, we see that an increase in $\bar{\eta}$ reduces the implied shift in labor supply. For example, with ϵ held constant at 1.19, the decline in labor supply ranges from −5.2% to −2.2% as $\bar{\eta}$ increases from 0.73 to 1.19. Recall from equation (17) that the total elasticity of leisure to ω can be decomposed into $\bar{\eta}$, the average elasticity within v, and the additional curvature

TABLE 8
Sensitivity of Labor Supply Shift to ϵ and $\bar{\eta}$ (%)

ϵ	$\bar{\eta} = .73$	$\bar{\eta} = 1.0$	$\bar{\eta} = 1.19$
.73	−3.5	−1.9	−1.5
1.0	−4.7	−2.6	−2.0
1.19	−5.2	−2.9	−2.2

Note.—Decline in labor supply from 2004–7 to 2014–17 for younger men due to $(\eta_I - 1)\Delta\theta_I$, displaying sensitivity of table 7 results to alternate values of ϵ and $\bar{\eta}$.

due to the leisure aggregator U. As we hold ϵ 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, with $\bar{\eta}$ fixed, a higher elasticity increases the implied decline in labor supply. For example, with $\bar{\eta}$ fixed at 0.73, the implied decline in labor ranges from −3.5% to −5.2% as ϵ varies between 0.73 and 1.19. While it is clear that the relative magnitude of ϵ 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.

C. *Differential Substitutability across Leisure Categories*

Specification (31) assumes additive separability across activity subutilities, 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 ($j, k \neq i$). This assumption is motivated partly by parsimony but also by the data. Younger men who allocate more time to computer leisure do not, in turn, skew the rest of their leisure more or less toward any of the remaining categories, as we discuss just below.

Perhaps the most likely candidate for a close substitute for 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 noncomputing leisure time. Specifically, denote total noncomputing 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 noncomputing leisure time devoted to activity $i \neq I$. We modify specification (31) and estimate the following demand system for the younger men:

$$\tilde{s}_{ikt} = \tilde{\delta}_{it} + \tilde{\gamma}_i \ln \tilde{H}_{kt} + \tilde{\alpha}_i \ln h_{Ikt} + \tilde{\epsilon}_{ikt}, \quad (34)$$

where $\tilde{\delta}_{it}$ reflects that time fixed effects are included in all regressions. Note that, because the specification conditions on total noncomputing leisure time, the $\tilde{\alpha}_i$ must sum to zero across all noncomputing 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 that the taste for activity i (captured in $\tilde{\epsilon}_{ikt}$) be 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 toward computing tells 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 noncomputing 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 noncomputing 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 ESP. More precisely, the estimates imply that younger men who spend one more hour at computer leisure should be expected to spend about one more minute of the remaining leisure watching TV and one less minute at ESP. The two remaining leisure activities, socializing and other, have a negligible conditional correlation with computing.

The conditional correlations indicate that individuals who spend additional time computing skew their remaining leisure toward TV, 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 (e.g., those who like computing also like TV) could be masking the negative relationship because of 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	.055	.015
	(.031)	(.006)
Socializing	−.068	.002
	(.026)	(.004)
ESP	−.006	−.013
	(.034)	(.005)
Other leisure	.018	−.004
	(.027)	(.004)

Note.—Sample is the same as in table 5. Standard errors are in parentheses.

Toward that goal, we exploit the fact that the timing of certain televised events increases 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 (National Collegiate Athletic Association) basketball tournament ("March Madness"); the Olympics; the playoffs of the National Football League, National Hockey League, 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 when restricted to younger men, but very imprecisely estimated.

Figure 6 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 2 minutes. The second bar indicates that computing marginally increases on those days as well, although the *p*-value is .75, making the increase indistinguishable from zero. The standard error is 1 minute, and hence we can reject a

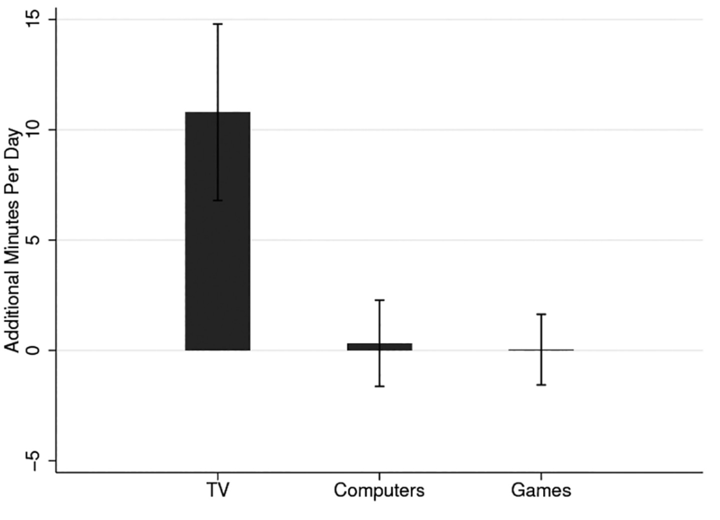

Fig. 6.—Additional time spent during major sports telecasts. Each bar represents the coefficient from regressing the respective activity (in minutes per day) against a dummy variable indicating that the diary day coincides with a major televised sporting event. Small lines indicate 95% confidence intervals. 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; that for computing is 0.3, with a standard error of 1.0; and that for gaming is 0.04, with a standard error of 0.82

decrease in computing of more than 2 minutes. The third bar shows the impact of televised sporting events on gaming. The point 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 6, the first stage is strong, but there is no effect observed at the second stage.

The results presented in this subsection suggest that 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 supports the idea that the increase in recreational computing is simply a consequence of being an especially close substitute for declining TV watching.

D. *Alternative Reference Activity*

One key assumption for our above analysis is the choice of a reference activity. Our baseline estimates assume no change in technology or preferences for sleep during this period. A priori, this seems plausible. However, as discussed above, sleep time has increased 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 $\Delta\ln\theta_{\mathrm{ESP}}$ 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 θ_I is more than 50% larger with this alternate normalization, the predicted shift inward of the labor supply curve for young men is 3.4% under this alternative.

VII. 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 on the basis of leisure differences across time, states, industries, and education groups during the 2000s, we find that recreational computing, including video gaming, is a strong leisure luxury for younger men. We estimate that younger men respond to a 1%

increase in total leisure by increasing recreational computer time by 2.5%. 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 changes in time-use allocations from the ATUS, we identify the relative increase in computer and video game technology during the 2000s. For men of ages 21–30, recreational computer time increased by 60% during the 2004–17 period, while their total leisure time increased by 4%. Our estimated leisure demand system predicts that recreational computer time would have increased by 22% if younger men had remained on their initial leisure Engel curve. So we can attribute much of the increase in younger men's computer time to rapid 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 computing increased the reservation wages of younger men by 2.5%, holding their marginal utility of consumption fixed. By contrast, we estimate that these innovations increased younger women's reservation wages by 1.0% and had little effect for older men and women. Hours worked for younger men have declined absolutely and relative to those for older men and women since the early 2000s. For reasonable Frisch elasticities of labor supply, we estimate that an increase in value of leisure due to improved recreational computing explains nearly half of younger men's hours decline of 4.5% from 2004 to 2017 and nearly three-quarters of their decline relative to older men.

This paper's methodology for measuring the impact of technology changes for leisure 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 reservation wages are both increasing—say, during the 1970s and 1980s when the quality of television expanded rapidly—increases in leisure technology may not correspond to declines in employment. However, during the 2000s market wage growth was slow, while advances in leisure technology appear to have been rapid. Improved leisure technology clearly matters more for employment if a number of workers have wages close to their reservation wages.

Finally, we highlight that our framework is static. Embedding the problem in a life-cycle setting will introduce several considerations. If leisure is separable over time, then our leisure demand framework carries over to a multiperiod setting. However, if individuals develop a habit/addiction to gaming and computer activities, then innovations to computer and gaming leisure could have dynamic effects on labor supply. Certainly, individuals build "leisure capital" in the form of physical equipment, but especially human skills, that enhance enjoyment from leisure activities. A downturn in labor demand, such as during the Great Recession, may then create hysteresis in the labor market as individuals first increase computer leisure and then develop their taste or skill for the activity. If individuals anticipate the skills/addiction derived from gaming and other computer leisure, then this will also alter leisure choices, as the consumer must weigh an activity's impact on their leisure capital as well as its flow benefits. We have held an individual's marginal value of wealth, λ, constant with respect to leisure choices. If greater computer leisure by younger individuals does lead to considerably lower lifetime labor supply and earnings, then it becomes especially pertinent to endogenize the marginal value of wealth. This should act to somewhat lessen the impact of leisure technology on hours worked.

References

Abraham, Katharine G., and Melissa S. Kearney. 2020. "Explaining the Decline in the US Employment-to-Population Ratio: A Review of the Evidence." *J. Econ. Literature* 58 (3): 585–643.

Aguiar, Mark, Mark Bils, Kerwin Kofi Charles, and Erik Hurst. 2017. "Leisure Luxuries and the Labor Supply of Young Men." Working Paper no. 23552 (June), NBER, Cambridge, MA.

Aguiar, Mark, and Erik Hurst. 2007a. "Life-Cycle Prices and Production." *A.E.R.* 97 (5): 1533–59.

———. 2007b. "Measuring Trends in Leisure: The Allocation of Time over Five Decades." *Q.J.E.* 122 (3): 969–1006.

Aguiar, Mark, Erik Hurst, and Loukas Karabarbounis. 2013. "Time Use during the Great Recession." *A.E.R.* 103 (5): 1664–96.

Becker, Gary S. 1965. "A Theory of the Allocation of Time." *Econ. J.* 75 (299): 493–517.

Bick, Alexander, Adam Blandin, and Richard Rogerson. 2020. "Hours and Wages." Working Paper no. 26722 (January), NBER, Cambridge, MA.

Binder, Ariel J., and John Bound. 2019. "The Declining Labor Market Prospects of Less-Educated Men." *J. Econ. Perspectives* 33 (2): 163–90.

Boppart, Timo, and Liwa Rachel Ngai. 2017. "Rising Inequality and Trends in Leisure." CEPR Discussion Paper no. 12325 (September), Center Econ. Policy Res., London.

Browning, Martin, Angus Deaton, and Margaret Irish. 1985. "A Profitable Approach to Labor Supply and Commodity Demands over the Life-Cycle." *Econometrica* 53 (3): 503–43.

Charles, Kerwin Kofi, Erik Hurst, and Matthew Notowidigdo. 2017. "Housing Booms, Manufacturing Decline, and Labor Market Outcomes." Working Paper no. 18949 (April), NBER, Cambridge, MA.

Chetty, Raj, Adam Guren, Day Manoli, and Andrea Weber. 2013. "Does Indivisible Labor Explain the Difference between Micro and Macro Elasticities? A Meta-Analysis of Extensive Margin Elasticities." *NBER Macroeconomics Ann.* 27:1–56.

Deaton, Angus, and John Muellbauer. 1980. "An Almost Ideal Demand System." *A.E.R.* 70 (3): 312–26.

Gourio, François, and Pierre-Alexandre Noual. 2009. "The Marginal Worker and the Aggregate Elasticity of Labor Supply." Manuscript.

Greenwood, Jeremy, and Guillaume Vandenbroucke. 2008. "Hours Worked (Long-Run Trends)." In *The New Palgrave Dictionary of Economics*, 2nd ed., edited by Lawrence E. Blume and Steven N. Durlauf. London: Palgrave Macmillan.

Grossbard, Shoshana, and Victoria Vernon. 2015. "Common Law Marriage, Labor Supply, and Time Use: A Partial Explanation for Gender Convergence in Labor Supply." In *Gender Convergence in the Labor Market*, edited by Solomon Polachek, Konstantinos Tatsiromos, and Klaus Zimmermann. *Res. Labor Econ.* 41:143–75.

Hall, Robert E. 2009. "Reconciling Cyclical Movements in the Marginal Value of Time and the Marginal Product of Labor." *J.P.E.* 117 (2): 281–323.

Hou, Y., X. Liu, and J. Liu. 2018. "Trends In Self-Reported Sleep Duration and Disturbance in the US General Population: NHANES 2005–2014." *Sleep* 41 (suppl. 1): A110.

Kopecky, Karen A. 2011. "The Trend in Retirement." *Internat. Econ. Rev.* 52 (2): 287–316.

Mian, Atif, and Amir Sufi. 2014. "What Explains the 2007–2009 Drop in Employment?" *Econometrica* 82 (6): 2197–223.

Mincer, Jacob. 1962. "Labor Force Participation of Married Women: A Study of Labor Supply." In *Aspects of Labor Economics*, 63–105. Princeton, NJ: Princeton Univ. Press (for NBER).

Moffitt, Robert A. 2012. "The US Employment-Population Reversal in the 2000s: Facts and Explanations." *Brookings Papers Econ. Activity* 2012 (Fall): 201–64.

Mustre-del-Río, José. 2015. "Wealth and Labor Supply Heterogeneity." *Rev. Econ. Dynamics* 18 (3): 619–34.

Park, Choonsung. 2020. "Consumption, Reservation Wages, and Aggregate Labor Supply." *Rev. Econ. Dynamics* 37:54–80.

Pistaferri, Luigi. 2003. "Anticipated and Unanticipated Wage Changes, Wage Risk, and Intertemporal Labor Supply." *J. Labor Econ.* 21 (3): 729–54.

Vandenbroucke, Guillaume. 2009. "Trends in Hours: The U.S. from 1900 to 1950." *J. Econ. Dynamics and Control* 33 (1): 237–49.