Leisure Luxuries and the Labor Supply of Young Men*

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Abstract

We explore the declining market hours of younger men, ages 21-30, over the last fifteen years. Young men experienced a larger decline in work hours than older men or women. Over the same period, time-use data show that young men distinctly shifted their leisure to video gaming and other recreational computer activities. We propose a methodology to answer whether improved leisure technology played a role in reducing young men's labor supply. The starting point is a leisure demand system that parallels that often estimated for consumption expenditures. We show that total leisure demand is much more affected by innovations to leisure luxuries, that is, activities that display a high response to one's total leisure time. We estimate that gaming/recreational computer use is distinctly a leisure luxury for young men. Moreover, we calculate that innovations to gaming/recreational computing can justify on the order of half the increase in leisure for young men over the past fifteen years, and between 20 and 40 percent of their decline in market hours.

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1 Introduction

Between 2000 and 2015, market hours worked fell by 12 percent for younger men ages 21-30, compared to a decline of just over 8 percent for men ages 31-55. These declines started prior to the Great Recession, accelerated sharply during the recession, and have rebounded only modestly since.[1] We use a variety of data sources to document that the hours decline was particularly pronounced for younger men. These trends are robust to including schooling as a form of employment. Not only have hours fallen, but there is a large and growing segment of this population that appears detached from the labor market: 15 percent of younger men, excluding full-time students, worked *zero* weeks over the prior year as of 2016. The comparable number in 2000 was only 8 percent.

In this paper, we explore the decline in market work of younger men. An obvious candidate is a decline in the demand for their labor which would result in a corresponding reduction in their real wages. There is growing evidence that declining demand for manufacturing and routine employment has contributed to the secular decline in employment rates for less educated workers during the 2000s.[2] However, we document that real wages of younger men closely track those of their older counterparts during the 2000 to 2015 period. This suggests that the greater decline in younger men's hours is not readily explained by a differential decline in labor demand for younger versus older men.

We go in a different direction. We ask if innovations to leisure technology, specifically to recreational computer and gaming, reduced the labor supply of younger men. Our focus is propelled by the sharp changes we see in time use for young men during the 2000s. Comparing data from the American Time Use Survey (ATUS) for recent years (2012-2015) to eight years prior (2004-2007), we see that: (a) the drop in market hours for young men was mirrored by a roughly equivalent increase in leisure hours, and (b) increased time spent in gaming and computer leisure for younger men, 1.9 hours per week, comprises three quarters of that increase in leisure of 2.5 hours per week. Younger men increased their recreational computer use and video gaming by nearly 50 percent over this short period. Non-employed young men now average 10 hours a week in recreational computer time, sixty percent of that spent playing video games. This exceeds their time spent on home production or non-computer related socializing with friends. Older prime age men and women allocate much less time to computer and gaming and displayed little upward trend in these activities.

An elemental question is whether increased computer use and gaming contributed to the rise in younger men's leisure and the corresponding decline in their market hours, or simply

[1] Data, described fully below, are from the March CPS and exclude full time students.

[2] See, for example, Autor et al. (2013) and Charles et al. (2016a, 2016b).

reflected their response to working fewer hours due, say, to reduced labor demand. To identify these channels we introduce a leisure demand system that parallels that typically considered for consumption expenditures. In particular, we estimate how alternative leisure activities vary with total leisure time, generating "leisure Engel curves." Our estimation exploits state-year variations in leisure, such as caused by differential impact of the Great Recession across US states. The key identifying assumption is that variations in total leisure at the state level are not driven by differential preferences or technologies across leisure activities during the 2000s. We estimate that gaming and recreational computer use is distinctively a "leisure luxury" for younger men, but not for other demographic groups. In particular, a one percent increase in leisure time is associated with a more than 2 percent increase in time spent playing video games for younger men. Watching TV has an elasticity slightly above one, making it a modest luxury for younger men, while all other leisure activities have elasticities less than or equal to one for younger men. This implies that any marginal increase in leisure for younger men will be disproportionately devoted to computers and gaming.

With the estimated leisure demand system in hand, we can quantify the change over time in the marginal return to leisure based on how leisure's allocation across activities has shifted. Specifically, we decompose the large increase in recreational computer use between 2004 and 2015 into a movement along the leisure Engel curve due to additional leisure time, and the shift of the expansion path due to technological improvement in computer and video games relative to other leisure goods. From this decomposition, we infer how much the marginal return to leisure increased over time due to improved computer and video gaming technology. We also document that the implied relative increase in leisure technology from our demand system for computer and video game leisure activities is consistent with the relative price decline for computer and video game goods found in BLS price data.

We then use our framework to calculate how better computer and video game technology affected younger men's labor supply. This impact depends on how reduced earnings affects consumption. We consider two scenarios. If individuals are "hand-to-mouth," so consumption equals labor earnings, we calculate that improvements in computer leisure sufficiently increased leisure, holding wage fixed, to explain one third of the increase in reported leisure for younger men, rationalizing 20 percent of their observed decline in market hours. Alternatively, if consumption is held constant, which in our framework holds the marginal value of a dollar constant, then the effects are considerably larger. We then calculate that better computer and gaming options explain two-thirds of the observed increase in leisure for younger men, and forty percent of their decline in their market hours. Additionally, we find that increased computer and video game technology can explain upwards of three-quarters of the differential decline in hours between younger and older men during the 2000s.

The assumption that consumption is held constant turns out to be consistent with several pieces of data. More generally, a natural question is how these younger men support themselves given their large decline earnings. We document that 67 percent of non-employed younger men lived with a parent or close relative in 2015, compared to 46 percent in 2000. The importance of cohabitation with a parent has been emphasized in the business-cycle context by Kaplan (2012) and Dyrda et al. (2012). We document that it is also relevant for the longer-run decline in employment of younger men. While government transfers are not large for younger men, family transfers are substantial. To get a sense of the value of such transfers, we measure the consumption of younger men using the Panel Study of Income Dynamics. Specifically, we compare expenditures for households that contain younger men to expenditures for all households, scaled appropriately for household size. By this measure, we see little, if any, decline in the relative consumption of younger men since 2000.

Our narrative emphasizes the impact on labor supply of expanded leisure opportunities. An alternative is that younger men face diminished market opportunities. One avenue to gauge how younger men perceive their fortunes is to use survey data on happiness. In this spirit, we complement the patterns in hours, wages, and consumption with data on life satisfaction from the General Social Survey. We find that younger men reported increased happiness during the 2000s, despite stagnant wages, declining employment rates and increased propensity to live with parents/relatives. These patterns contrast sharply with those for older men, whose satisfaction clearly fell, tracking their declines in employment. We take these results as suggesting a role for improved leisure options for younger men.

Our focus on time allocation owes a natural debt to the seminal papers of Mincer (1962) and Becker (1965), which emphasize that labor supply is influenced by how time is allocated outside of market work. We introduce the concept that some non-market activities are leisure luxuries, which display little diminishing returns. Because recreational computer use and video gaming is such a leisure luxury for younger men, we should expect improvements in its technology to bring forth large increases in its time allocation.

Our work complements that of Greenwood and Vandenbroucke (2008), Vandenbroucke (2009), and Kopecky (2011), who use a quantitative Beckerian model to show that declining relative prices of leisure goods can help explain employment declines over the last century. We augment this approach by considering a leisure demand system and exploring how the allocation of time across leisure activities may also be relevant for labor supply. We show that it is key for labor supply whether innovations affect leisure luxuries or leisure necessities.[3]

There is, of course, a large literature on the decline in U.S. employment rates during

[3]This distinction for leisure's response parallels that consumption's inter-temporal elasticity hinges on the share of goods with little curvature in consumption, emphasized by Browning and Crossley (2000).

the Great Recession. A separate literature has focused on what forces might explain longer-term employment declines during the 2000s.[4] Collectively, these papers provide evidence – often by exploiting cross-region variation – that declining labor demand has been the predominant factor for depressed wages and employment rates, with the effects concentrated among prime-age less-educated workers. Our work complements this literature by providing a labor-supply force for the sustained decline in hours worked driven by changes in leisure technology. Because younger men are predicted to respond more to these innovations, our work also helps explain why their hours declined more than for older men and women.

The paper is organized as follows: Section 2 documents declines in employment, hours and wages for younger men and other demographic groups; Section 3 examines changes in time use during the 2000s, emphasizing the dramatic increase in computer and video game time for younger men; Section 4 presents our methodology including the leisure demand system; Section 5 estimates the leisure Engel curves; Section 6 uses the demand system and changes in time allocation to infer changes in leisure technology; Section 7 quantifies the shift in leisure and labor supply curves for different demographic groups during the 2000s; Section 8 documents patterns in cohabitation, consumption, and self-reported well being for younger men; and Section 9 concludes.

2 Background Labor Market Trends

In this section, we document labor market changes for younger men compared to other demographic groups during the 2000s. Our primary data for trends in employment, hours, and wages are the March Current Population Survey (CPS).[5] We restrict the sample to civilians ages 21 to 55. We further exclude full-time students who are less than age 25.[6] This restriction mitigates the possibility that the decline in work hours we see for younger men is driven by increased college attendance. We focus on two age groups: ages 21-30 (younger) and ages 31-55 (older). Given the age bracket and the fact we drop full time students, the vast majority of the younger men sample (25 percent) has less than a bachelor's degree in educational attainment. The small sample of more educated younger men introduces a fair amount of sampling error, particularly in the small time-use survey used later in the paper. We therefore focus in the text on all younger men as our benchmark as well as report

[4]See Autor et al. (2003), Moffit (2012), Autor and Dorn (2013), Autor et al. (2013), Hall (2014), Charles et al. (forthcoming), Charles et al. (2016), and Acemoglu et al. (2016). The Council of Economic Advisors' 2016 Economic Report of the President discusses longer term trends in male labor force participation.

[5]A Data Appendix accompanies the paper, providing greater discussion of all data sets, including yearly sample sizes. Throughout the paper, we weight observations by the relevant survey's sampling weight.

[6]Between 1986 and 2012, the CPS asked only those under age 25 about school attendance. Starting in 2013, it began asking older respondents as well.

results for the sub-sample with less than a college degree. The results for more educated respondents are reported in the appendix.

2.1 Employment and Hours Worked

Figure 1 reports work for younger and older men since 2000 using data from the March CPS. Panel (a) reports the log change in annual hours since 2000.[7] Panel (b) reports employment rates at the time of the March CPS survey. Annual hours decline over this period for both younger and older men. However, the decline is relatively severe for younger men. The separation begins to appear in the mid-2000s, accelerates during the Great Recession, and then fails to close completely after the recession. Similarly in Panel (b), the employment rate of younger men displays a sharper downward trend since 2000. From 2000 to 2016, the employment rate for younger men fell by 8 percentage points, compared to 4 percentage points for older men. In the appendix, we show trends back to 1986, documenting that the differences in market work between younger and older men is a post-2000 phenomenon.

Table 1 Panel (a) reports the level of annual hours worked for men and women at four points over the last 15 years. Panel (b) reports the same for those with less than a college degree. From 2000 to 2015, annual hours worked by younger men declined by 203 hours (12 log points) while the decline for OM was 163 hours (8 log points). The relative decline of younger men versus older men is starker when we restrict attention to less educated men (Panel (b)). Younger less educated men experienced a 242 hour per year decline in market work between 2000 and 2015 (a 14.4 log point decline). Table 1 also indicates that both younger and older women experienced a decline in market work during the 2000s. However, the declines were approximately one-third to one-half of their male counterparts. Younger men in general and less educated younger men in particular experienced by far the largest decline in hours worked during the 2000s relative to other sex-age-skill groups.

We document similar patterns in the Census and American Community Surveys (ACS) in Appendix Table A1. Beyond confirming the results above from the CPS, these data allow us to explore robustness to excluding all full-time students, including those more than 25 years old. Our results are not affected by excluding these older students, as one might expect, given that full-time students are a small fraction of those ages 26-30.[8]

[7] For year t, annual hours are computed from year $t+1$'s March survey response regarding the previous calendar year's weeks worked times the response regarding usual hours worked per week the previous year.

[8] Appendix Table A2 shows trends in younger mens hours by race. While levels differ, these trends are nearly identical for blacks and whites. There we also examine separately younger men living in center cities, in an MSA, but outside its center city, and those not in an MSA. While all groups experienced declines in hours worked, the declines were much larger for those outside of center cities, including rural areas. In 2000 younger men in center cities worked many fewer hours than those in other areas. But, by 2015, hours are actually quite similar across the three locations. We view the patterns in Table 1 as broad-based.

Table 1: Annual Market Hours Worked

(a) All Education

Year	Men 21-30	Men 31-55	Women 21-30	Women 31-55
2000	1,829	2,050	1,407	1,452
2007	1,728	1,964	1,355	1,429
2010	1,519	1,796	1,218	1,351
2015	1,626	1,887	1,312	1,398
Change 2000-15	-203	-163	-95	-54
Log Change 2000-25 ($\times$100)	-11.8	-8.2	-7.0	-3.8

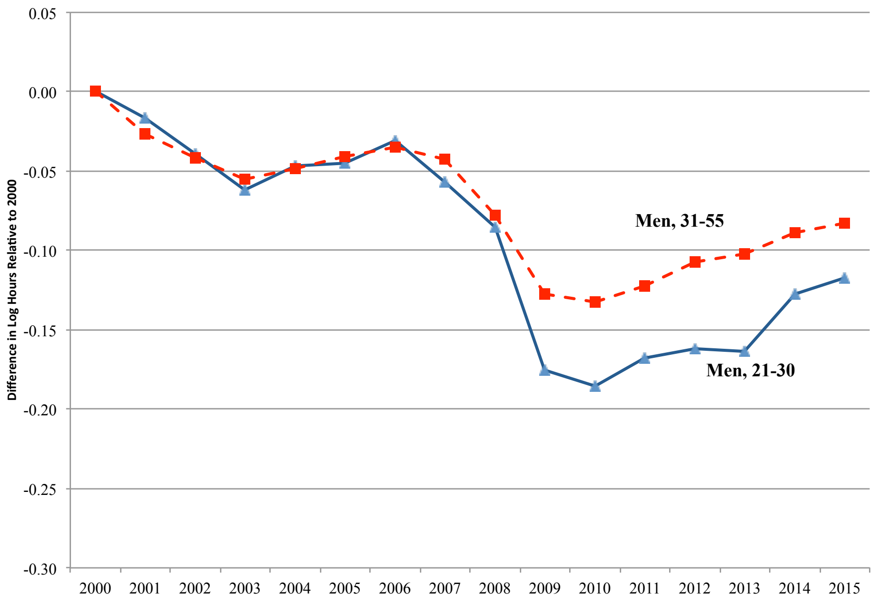
(b) Education < 16

Year	Men 21-30	Men 31-55	Women 21-30	Women 31-55
2000	1,801	1,953	1,311	1,397
2007	1,691	1,859	1,227	1,346
2010	1,436	1,658	1,080	1,241
2015	1,559	1,763	1,167	1,258
Change 2000-15	-242	-190	-144	-139
Log Change 2000-25 ($\times$100)	-14.4	-10.2	-11.7	-10.5

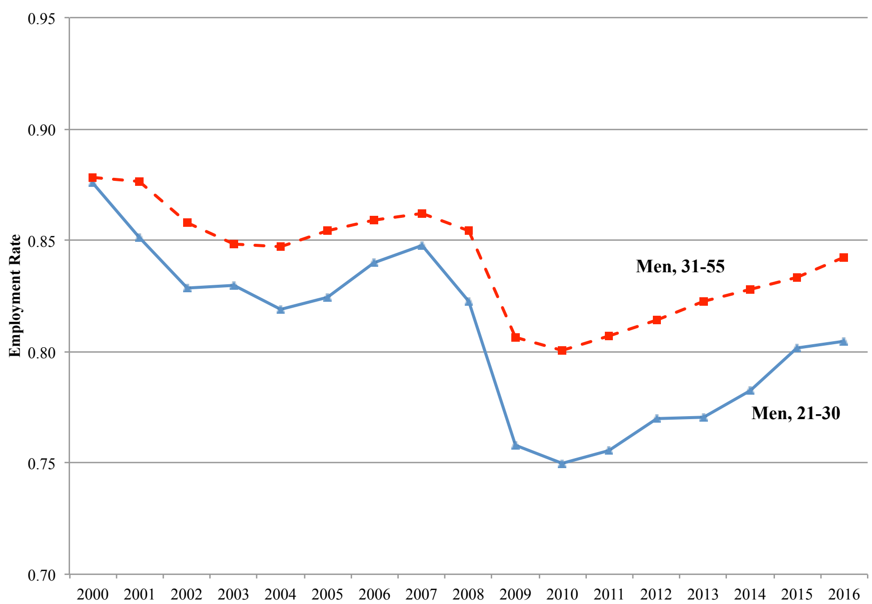
Note: Data are from the March CPS. Annual hours equal last year's weeks worked multiplied by usual weekly hours. Year t hours refer to hours worked by year $t+1$ respondents. Full-time students less than age 25 are excluded.

Figure 1: Market Hours

(a) Log Annual Hours (Index)



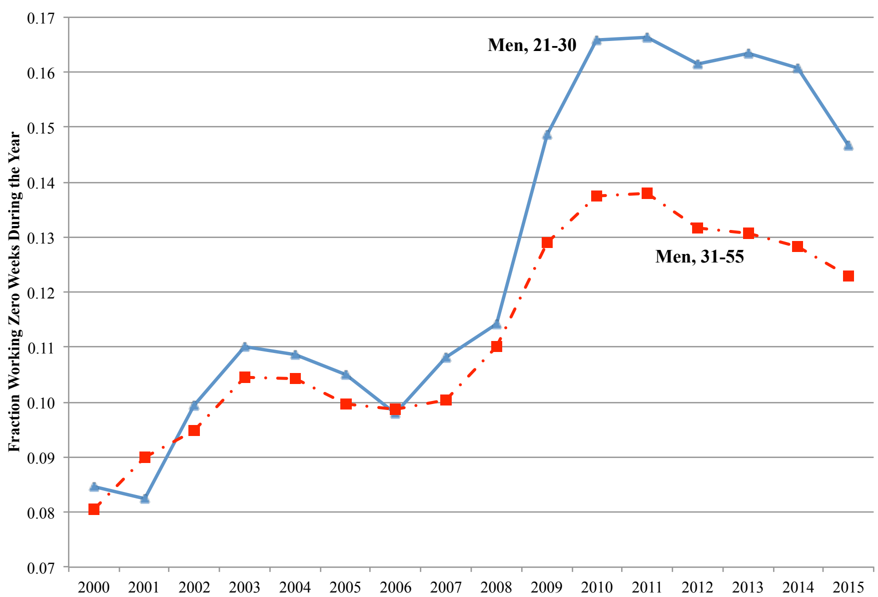
(b) Employment Rates



Note: Data are from CPS March supplements. Full-time students less than age 25 are excluded. Panel (a) shows log hours relative to year 2000 for men ages 31-55 (squares) and ages 21-30 (triangles). Annual hours equal last year's weeks worked multiplied by usual hours worked per week. The point for year t on the horizontal axis corresponds to responses from March $t + 1$ report of previous year's hours. Panel (b) depicts employment rates at the time of the March survey for the year indicated on the horizontal axis.

We conclude this subsection with Figure 2, which plots the fraction of younger and older men who worked *zero* weeks over the year. This provides perspective on the extent that men of differing ages remain persistently non-employed. Our sample continues to exclude full-time students ages less than 25. The fraction reporting zero weeks worked is roughly similar at 8 percent across age groups in 2000. (In the appendix we show this similarity extends back to 1985.) The fraction not working increased considerably during the 2000s for both groups. But it is much more dramatic for younger men. The fraction of younger men not working the entire year began increasing prior to the Great Recession, accelerated during the Great Recession, and has only modestly recovered. As of 2015, the fraction of younger men not working the entire year was nearly 15 percent. As seen in the corresponding appendix figure, such divergences has not been a feature of prior recessions.

Figure 2: Fraction of Men With Zero Weeks Worked Over Prior Year by Age, March CPS



Note: The figure shows the shares of men ages 31-55 (squares) and men ages 21-30 (triangles) who report working zero weeks during the prior year. Data are from the CPS March supplement. Full-time students ages less than 25 are excluded.

2.2 Real Wages

In this subsection we document how real wages evolved in conjunction with the declines in younger men's hours reported above. We construct wages for year t based on year $t+1$ March CPS data by dividing labor income for the prior year by the prior year's annual hours. We deflate this series by the June CPI-U. Wages are computed for those in our CPS sample that report positive earnings. After imposing this restriction, we trim the top and bottom one percent of the wage distribution in each year.

Figure 3 reports the log difference in real wages since 2000. Panel (a) is the full sample of men, while Panel (b) restricts attention to those with less than 16 years of schooling. Real wages decline over this period in all cases. However, unlike market hours, the decline for younger men tracks that of older men closely, particularly for less educated men. One caveat is that our wage series is constructed from repeated cross sections. It is well known that changes in composition of the workforce over time can bias trends in such series. In the appendix we explore a number of alternatives to address this challenge.[9] These adjustments suggest a larger decline in real wages since 2000, but still indicate no difference in wage trends between younger and older men.

The declines in hours and wages documented in this section presumably reflect a combination of factors. Many authors have highlighted a role for declining labor demand.[10] The sharper decline in relative hours of younger men, given a similar decline in their real wages, suggests a role also for younger men's labor supply, either in terms of a high responsiveness to wage changes or shifts in their willingness to work. Understanding the determinants and evolution of younger men's labor supply over the past fifteen years is the focus of the paper.

3 The Changing Composition of Leisure

As a first step to understanding the labor-leisure decision, we document how younger men, and other demographic groups, allocate their non-market time. We do so using the time diaries of the American Time Use Survey (ATUS) from 2004 through 2015.[11] Our ATUS sample is discussed in detail in the Data Appendix. Briefly, the ATUS draws a sample from CPS respondents and surveys them within a few months after the final CPS survey, collecting a 24-hour time diary in which the respondent records the previous day's activities in 15-minute increments. These activities are categorized into detailed activity codes by the ATUS. Our ATUS sample restrictions are the same as for the CPS sample used in the previous section; in particular, we exclude full-time students less than age 25.

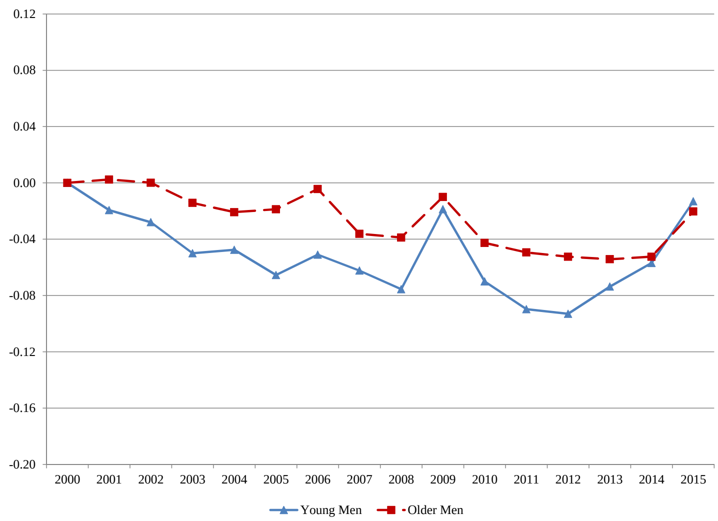
[9] In particular, we adjust wages for demographic changes in composition. We also construct an index that imputes wages for non-employed individuals using the 33rd percentile of the wage distribution for their demographic group.

[10] Examples include Autor et al. 2013 and Charles et al. (2016a, 2016b).

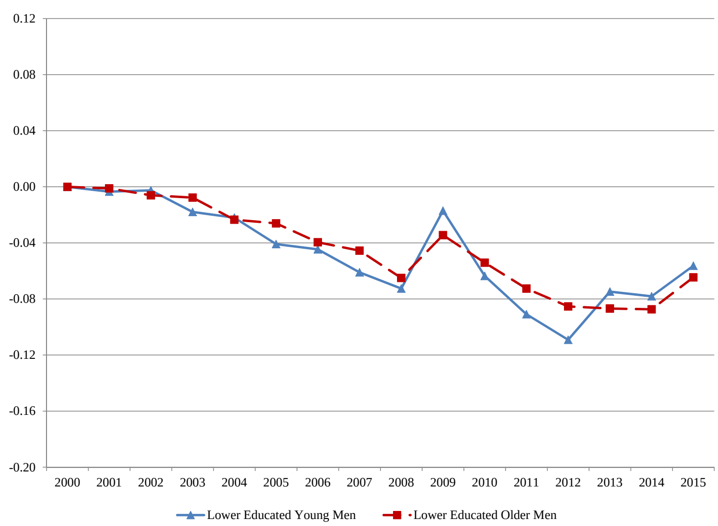
[11] Though the ATUS starts in 2003, we begin our analysis with 2004, as there are small changes in the survey methodology between 2003 and 2004.

Figure 3: Hourly Real Wage Index for Men By Age, March CPS

(a) All Men



(b) Men Ed<16



Note: Figure shows hourly real wage indices for younger men (squares) and older men (triangles). Hourly wages equal annual earnings divided by annual hours worked, both over prior year. Wages are deflated by the June CPI-U. We convert the series to an index, setting year 2000 values to 0, with later years log deviations from year 2000 values. Data are from the CPS March supplement. Sample includes all individuals with positive earnings during the prior year.

3.1 Trends in Broad Time Use Categories

We begin by aggregating activities into six broad categories: market work, job search, home production, child care, education, and leisure. Job search includes such activities as sending out resumes, job interviewing, researching jobs, or looking for jobs in the paper or the Internet. Home production includes time doing household chores, preparing meals, shopping, doing home or vehicle maintenance, and caring for other adults. We record child care separately from home production. Education refers to time spent on one's *own* education, such as time attending courses, or doing related homework. Leisure consists of watching television and movies, recreational computing and video games, reading, playing sports, hobbies, etc. We discuss leisure in more detail in the next subsection. We include a sub-set of time spent on eating, sleeping, and personal care (ESP) in leisure. In particular, we treat 7 hours per day as non-discretionary ESP, and the residual as leisure. Approximately 95 percent of respondents, ages 21 to 55, report 7 or more hours per day for ESP. We explored alternatives (such as subtracting 6, 8 or 9 hours per day) and found no sensitivity to this choice. Transportation time spent traveling to or from an activity is always included in the activity's time.[12] We report time use in "hours per week" by multiplying the daily average by 7.

Table 2 shows changes in time use for men (Panel a) and women (Panel b). We report both the full sample as well as those without a college degree. To increase power we group together data for 2004-2007 and for 2012-2015, and report differences across the two pooled time periods. Starting with the first two columns of the top panel, we see that younger men and older men reduced their market work, respectively, by 2.7 and 1.1 hours per week. Multiplying by 52 weeks to obtain an annualized measure, the ATUS indicates that younger men reduced labor hours 83 hours per week more than older men, a difference that is slightly larger than that obtained from the CPS.

Comparing the top and bottom row of Table 2 Panel (a) indicates that the declines in market hours are nearly identical to the increases in the associated leisure time for both younger and older men. The remaining activities reveal small changes that approximately net out to zero. In particular, the relative decline in labor hours for younger men is matched by a relative increase in leisure, a differential increase on the order of 1.3 hours per week, or nearly 70 hours per year. The results for less educated men (final two columns) paint a similar picture, although the differential between younger and older men is slightly smaller in magnitude.

Panel (b) shows the patterns for women. Comparing to Panel (a), younger women had a smaller decline in market work but a larger decline in home production than younger

[12] Other than the 7 hours per day for non-discretionary ESP, we also omit a few additional small categories such as own health care and catch-all "uncategorized" activity code.

Table 2: Changes in Time Allocation

(a) Men

	All		Education < 16	
Change 2004-2015 (Hours per Week)	21-30	31-55	21-30	31-55
Market Work	-2.7	-1.1	-2.7	-2.0
Job Search	0.4	0.1	0.3	0.2
Home Production	-0.6	-0.9	-0.8	-0.3
Child Care	-0.4	0.4	-0.1	0.4
Education	0.7	0.0	0.8	0.0
Leisure	2.5	1.2	2.5	1.6

(b) Women

	All		Education < 16	
Change 2004-2015 (Hours per Week)	21-30	31-55	21-30	31-55
Market Work	-0.5	-0.5	-2.2	-0.9
Job Search	0.1	0.1	0.2	0.1
Home Production	-1.4	-1.8	-1.5	-1.8
Child Care	-1.2	0.2	0.0	0.1
Education	0.6	-0.1	0.7	-0.1
Leisure	1.6	1.9	1.9	2.3

Note: Table reports the difference in average time allocation between the pooled 2004-2007 and the pooled 2012-2015 waves of the ATUS for each demographic group. Differences are expressed in hours per week.

men. On net, younger women experienced a smaller increase in leisure than younger men. The decline in home production for women during this periods reflects a well known trend that dates back at least a half century (see Aguiar and Hurst (2007)). The decline in home production was even more pronounced for older women, generating a larger increase in leisure than younger women or older men. Comparing across all demographic groups, younger men systematically have the largest gain in leisure over the sample period.

3.2 Trends in the Nature of Leisure

We now explore leisure at a more disaggregated activity level. Within total leisure, we distinguish the following five activities: recreational computer time; television and moving watching; socializing; discretionary eating, sleeping and personal care (ESP); and other leisure. Recreational computer time includes time spent on non-work email, playing computer games, surfing or browsing web sites, leisure time on smart phones, online chatting, engaging in social media and unspecified computer use for leisure. We often highlight the video/computer game component of recreational computer time.[13] Computer time for work or non-leisure activities (like paying bills or checking email) are embedded in other time-use categories (like household management). Watching television and movies includes not only watching traditional television and movie platforms, but also streaming platforms like Netflix or youtube. Socializing includes entertaining or visiting friends and family, going to parties, hanging out with friends, dating, and participating in civic or religious activities. "Other leisure" includes all remaining leisure activities, such as reading, relaxing, listening to music, going to the theater, exercising, playing sports, and engaging in hobbies.

Table 3 shows hours per week spent in each leisure category by younger men. The top row is the total leisure reported in the bottom row of Table 2, reporting both the averages per period as well as the change from that table. We can see the increase in leisure of 2.5 hours for all younger men is predominantly accounted for by a 1.9 hour increase in recreational computer time. The pattern is similar when we restrict attention to less educated younger men. Recreational computing and video gaming represents 76 percent of the total leisure increase for all younger men, and 80 percent for less educated younger men. Most of this increase in computer time for younger men took the form of increased video game playing (roughly 1.5 hours per week). The complement of this result, is that other leisure categories changed very little, despite the large increase in total leisure. For example, younger men

[13]The ATUS has a category of time use labeled "playing games". This includes video games, but also includes playing cards as well as traditional board games like checkers, Scrabble, etc. So we cannot distinguish playing the Scrabble board game from video gaming. We document below that there was a very large increase in playing games during the 2000s, especially for 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.

did not spend significantly more time watching TV or movies, socializing, or at other leisure activities. The only other leisure category that recored a substantial increase in levels is eating, sleeping, and personal care, although in percentage terms the increase is quite modest.

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

	Ed=All			Ed<16		
Activity	2004-2007	2012-2015	Change	2004-2007	2012-2015	Change
Total Leisure	61.1	63.6	2.5	61.9	64.5	2.5
ESP	24.3	24.9	0.6	24.2	25.3	1.1
Recreational Computer	3.3	5.2	1.9	3.5	5.5	2.0
Video Game	2.0	3.4	1.4	2.3	3.8	1.5
TV/Movies/Netflix	17.3	17.2	-0.1	18.5	18.0	-0.5
Socializing	7.8	8.0	0.2	7.8	8.0	0.2
Other Leisure	8.3	8.2	-0.1	8.0	7.7	-0.3

Note: Table shows average weekly hours spent at leisure activities for men ages 21-30 (left panel) and men ages 21-30 with less than a bachelors degree (right panel). These components sum to total leisure time. The first column of each panel pools the 2004-2007 waves of the ATUS. The second pools waves 2012-2015. Video gaming is a subcomponent of total computer time. ESP refers to residual eating, sleeping and personal care.

Table 4 reports leisure patterns for younger men by employment status. Employed younger men experienced a 1.9 hour-per-week increase in leisure over our sample period. Nearly 70 percent of this is accounted for by increased recreational computer time, with the bulk of that increase spent playing video games. Not surprisingly, the the non-employed have substantially more leisure. However, conditional on on-employment, leisure hours actually fell since 2004. This partly reflects a composition shift in the pool of non-employed, as non-employment now constitutes a much bigger share of younger men. As seen in the last row of Table 4, the non-employed in 2012-2015 were much more likely to allocate time to both education and job search. These increases exactly offset the decline in leisure time. Nevertheless, despite the overall decline in leisure time for non-employed younger men during the 2000s, time spent on recreational computers (video games) increased for this group by 4.2 (2.4) hours per week. It is also worth noting that in 2012-2015 non-employment young men spent nearly 10 hours per week on recreational computer activities. This exceeds both the amount of time they spend socializing on non-computer activities and the amount of time they spend on other leisure categories (exercise and sport, hobbies, relaxing, etc.).

The above average time spend on recreational computer activities for non-working younger

Table 4: Leisure Activities for Men 21-30 (Hours per Week): By Employment Status

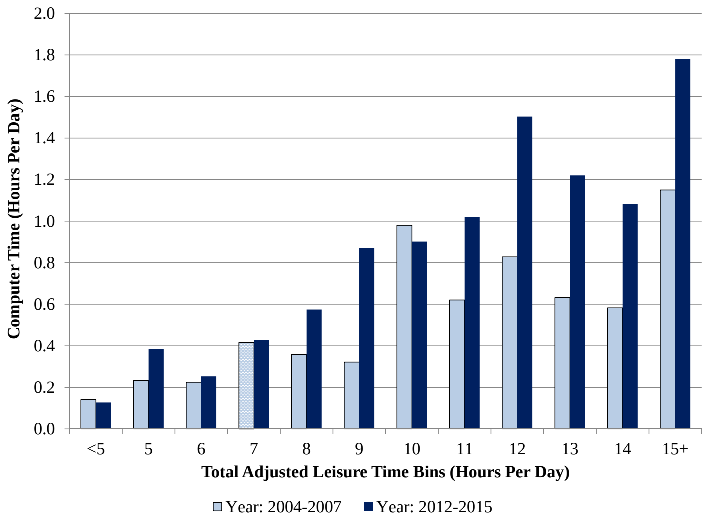
	Employed			Non-Employed		
Activity	2004-2007	2012-2015	Change	2004-2007	2012-2015	Change
Total Leisure	57.8	59.7	1.9	86.6	82.3	-4.3
ESP	23.6	23.9	0.3	30.1	29.9	-0.2
Recreational Computer	3.0	4.3	1.3	5.5	9.7	4.2
Video Game	1.9	2.9	1.0	3.5	5.9	2.4
TV/Movies/Netflix	16.0	15.5	-0.5	27.6	25.1	-2.5
Socializing	7.5	7.8	0.3	10.6	8.9	-1.7
Other Leisure	7.7	8.1	0.4	12.9	8.7	-4.2
Job Search and Education	1.9	1.9	0.0	9.6	14.0	4.4

Note: Table shows average hours spent per week across leisure activities for younger men by employment status. Components sum to total leisure time. The first column of each panel pools data for the 2004-2007 waves of the ATUS. The second pools waves 2012-2015. Video gaming is a subcomponent of total computer time. ESP refers to residual eating, sleeping and personal care.

men masks a large amount of heterogeneity. For example, in 2004-2007 only 30 percent of non-working younger men reported spending time on recreational computer time. The comparable number for 2012-2015 was 40 percent. Conditional on spending time on recreational computer activities, non-working younger men reported spending 2.6 and 3.4 *hours per day* in the 2004-2007 and 2012-2015 periods, respectively. During the 2012-2015 period, 11 percent of non-working younger men spent more than 4 hours per day while 7.5 percent and 4 percent spent more than 5 and 6 hours per day. For some younger men, their primary activity during the day was spending time on the computer.

To infer relative changes in computer leisure technology below we will exploit the fact that individuals are shifting their leisure time toward computer activities holding constant their total leisure time. As a first look at the data, we sort individuals into bins based on the amount of leisure enjoyed in the previous day. The bins are on the horizontal axis of Figure 4, where, for example, the label 5 indicates that the individuals in the bin spent five to six hours the previous day on leisure. For ease of presentation the units are hours per day rather than week. For each leisure bin, we average the amount of time allocated to recreational computer use across individuals within the bin. The bars in the figure depict the averages for younger men for the periods 2004-2007 (lighter bars) and 2012-2015 (darker bars). The figure indicates that computer time has increased systematically within each leisure bin over

Figure 4: Younger Men's Hours per Day of Computer Leisure by level of Total Leisure



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

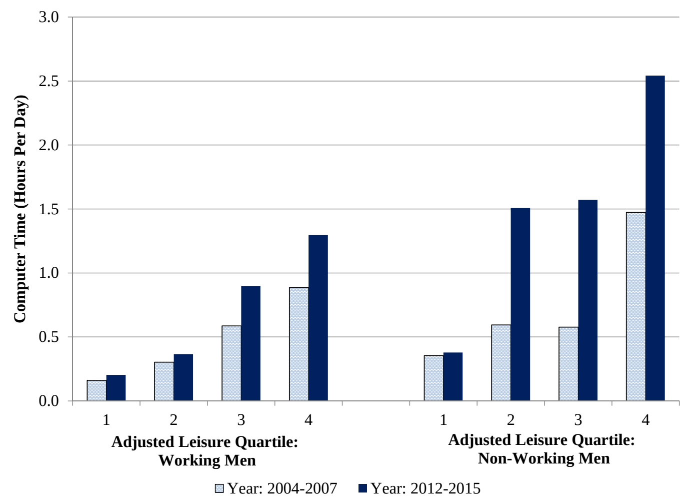
the last fifteen years. Moreover, the increase has been particularly strong for high-leisure individuals. For example, younger men with 9 to 10 hours of leisure per day tripled computer time between 2004 and 2015, from 0.3 to 0.9 hours per day.

Individual differences in total leisure largely reflect differences in market work. Figure 5 conditions on employment status. For this figure, we sort younger men into bins defined by the quartile thresholds of the 2004-2007 distribution (for each employment status), using the same bin thresholds for both periods.[14] The higher leisure quartiles for working younger men are disproportionately skewed towards individuals whose time diary day fell on a weekend. Figure 5 shows that computer time increased for both employed and non-employed younger men, holding constant total leisure, and the increase was particularly pronounced for non-employed younger men.

Table 5 compares younger men's shift toward computing and gaming to that for other demographic groups. The top panel reports total leisure, computer leisure, and video game time for younger men for 2012-2015 versus 2004-2007. The lower panels show the same for older men, younger women, and older women. The table clearly shows that increase in computer leisure in general, and the gaming component in particular, was a younger men's

[14]The specific quartile thresholds in hours per day are $[0, 5.8), [5.8, 8.3), [8.3, 12.9), [12.9, 24]$ for employed younger men and $[0, 9.7), [9.7, 12.9), [12.9, 16.3), [16.3, 24]$ for non-employed younger men.

Figure 5: Younger Men's Hours per Day of Computer Leisure by Leisure Quartile



Note: Figure shows average time spent on computer leisure (including video games) by total leisure quartile. Results shown separately by employment status–leisure quartiles are defined separately for working and non-working men. Quartile thresholds are defined by the 2004-2007 distribution for both periods. For working men the 25th, 50th, and 75th percentiles are 5.8, 8.3, and 12.9 hours per day. For non-working men, these are respectively 9.7, 12.9, and 16.3.

phenomenon. While younger men increased their computer leisure by 1.9 hours per week, the increases were only 0.1, 0.7, and 0.5 hours per week for older men, younger women, and older women, respectively. Women reported a modest increase in their recreational computer time, but, in contrast to younger men, zero of that increase involved video games.

4 Leisure Luxuries and Labor Supply

In this section we derive a leisure demand system that maps total leisure into specific leisure activities. We show how observations on changing time allocations can be used to infer shifts in the quality of leisure activities in general and changes in the marginal return to total leisure in particular. The change in the marginal return can then be linked to shifts in labor supply. This section develops the theoretical groundwork for the empirical estimation in Section 5 and the quantitative results of Sections 6 and 7.

Table 5: Computer Leisure and Video Game By Age-Sex-Skill Groups, ATUS

	(1) Pooled 2004-2007	(2) Pooled 2012-2015	(3) Diff (2)-(1)
	Men 21-30, Ed=All		
Total Leisure	61.1	63.6	2.5
Recreational Computer	3.3	5.2	1.9
Video Games	2.0	3.4	1.4
	Men 31-55, Ed=All		
Total Leisure	57.0	58.1	1.1
Total Recreational Computer	2.1	2.2	0.1
Video Games	0.9	0.8	-0.1
	Women 21-30, Ed=All		
Total Leisure	58.4	60.0	1.6
Total Recreational Computer	1.5	2.2	0.7
Video Games	0.8	0.8	0.0
	Women 31-55, Ed=All		
Total Leisure	56.1	58.0	1.9
Total Recreational Computer	1.6	2.1	0.5
Video Games	0.6	0.7	0.1

Note: Table shows average hours spent per week in computer leisure and video gaming across age-sex-skill groups. The first column reflects ATUS waves 2004 to 2007, the second 2012-2015. Video game time is a subcomponent of computer leisure.

4.1 Preferences

Agents have preferences over a numeraire consumption good, c, and time spent on leisure activities h_i, $i = 1, ..., I$. We assume weak separability between consumption and leisure activities. Utility can therefore be written $U(c, \tilde{v}(h_1, ..., h_I; \boldsymbol{\theta}))$, where $\tilde{v}$ is an aggregator over leisure activities and $\boldsymbol{\theta} = \{\theta_1, ..., \theta_I\}$ is a vector of technology shifters.

We assume $\tilde{v}$ has the following functional form:

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

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

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 $\tilde{v}$ function may be raised to a power, which would be a feature of the overall utility function U). This assumption implies that the marginal value of allocating time to one leisure activity is not dependent on how leisure time is allocated across the other activities. We provide some empirical support for this assumption in Section 5.

4.2 Leisure Engel Curves

Given the separability assumption, we can solve the agent's problem in two stages. In the "first" stage, the agent chooses c, allocates a unit of time between leisure time H and market labor $1 - H$, and purchases a technology bundle $\boldsymbol{\theta}$. In the "second" stage, the agent allocates H across the I activities. Working backwards, we consider the second stage budgeting problem in this subsection and then return to the first stage in the next.

The second stage problem is:

$$v(H; \boldsymbol{\theta}) \equiv \max_{\{h_i\}_{i=1}^{I}} \tilde{v}(h_1, ..., h_I; \boldsymbol{\theta})$$
$$\text{subject to}$$
$$\sum_i h_i \leq H.$$

Let μ denote the multiplier on the total leisure constraint. The first-order conditions are:

$$\theta_i^{1-\frac{1}{\eta_i}} h_i^{-\frac{1}{\eta_i}} = \mu. \tag{2}$$

The parameter η_i is the elasticity of activity i with respect to the shadow value of leisure time, μ.

Taking (2) and imposing the time constraint, which holds with equality, we have:

$$H = \sum_i \theta_i^{\eta_i - 1} \mu^{-\eta_i}. \tag{3}$$

Given H, there is a unique positive solution μ to (3). The envelope condition implies that $v'(H; \boldsymbol{\theta}) \equiv \partial v / \partial H = \mu$, and v is strictly concave in H.

A focus of our empirical work is how marginal leisure time is allocated across activities. The leisure Engel curve for activity i traces out how h_i varies with total leisure time, H. This is directly analogous to traditional expenditure Engel curves. Define β_i as the elasticity of h_i with respect to H, holding constant $\boldsymbol{\theta}$. The first-order conditions imply:

$$\beta_i \equiv \left. \frac{d \ln h_i}{d \ln H} \right|_{\boldsymbol{\theta}} = \frac{\eta_i}{\bar{\eta}}, \tag{4}$$

where $\bar{\eta} \equiv \sum_i s_i \eta_i$ is a weighted average of elasticities η_i, with weights $s_i = h_i / H$ given by activity i's share of total leisure time. For convenience, we write s_i, β_i, and $\bar{\eta}$ without explicitly indicating that they depend on H and $\boldsymbol{\theta}$. The reader should keep in mind that they are not parameters but outcomes of the agent's optimization and, save for the knife-edge case of identical $\eta_i = \eta, \forall i$, will vary with the state variables.

From equation (4), the elasticity of h_i with respect to H is the activity's own elasticity with respect to $v'(H; \boldsymbol{\theta})$ divided by the weighted average of all elasticities. 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 the notion of a consumption luxury good in traditional models of consumption demand systems.

With the leisure Engel curves, we can link shifts in time spent across activities to an implied change in the marginal utility of total leisure. Let I denote the activity of interest, which in the empirical analysis will be recreational computer use and video games. 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 (2), we have:

$$\ln \theta_I^{1 - \frac{1}{\eta_I}} - \ln \theta_j^{1 - \frac{1}{\eta_j}} = \frac{\ln h_I}{\eta_I} - \frac{\ln h_j}{\ln \eta_j} = \eta_I^{-1} \left(\ln h_I - \frac{\beta_I}{\beta_j} \ln h_j \right), \tag{5}$$

where the second equality uses the definition of β from equation (4).

Now consider two allocations $(H, \boldsymbol{\theta})$, with associated (h_j, h_I). Differencing (5) across the two allocations, we have:

$$\Delta \ln \theta_I^{1-\frac{1}{\eta_I}} - \Delta \ln \theta_j^{1-\frac{1}{\eta_j}} = \eta_I^{-1} \left(\Delta \ln h_I - \frac{\beta_I}{\beta_j} \Delta \ln h_j \right). \tag{6}$$

Note that $\beta_I/\beta_j = \eta_I/\eta_j$ does not depend on H or $\boldsymbol{\theta}$ and so is held constant.

Equation (6) will play an important role in our empirical analysis. To gain intuition for how technology can be inferred from time allocations, consider the term in parentheses on the far right of equation (6). This term is $\Delta \ln h_I$, minus the percent change in h_I that one would predict based solely on how time spent on activity j has changed, assuming technologies were constant. Any deviation is then attributed to changes in technology. In particular, suppose we observe data that indicates a change from (h_j, h_I) to (h'_j, h'_I). This change can be partially due to total leisure moving from H to H'. That component represents relative movements along the activities' leisure Engel curves, with the relative movement captured by the difference in slope parameters β_I and β_j. Any residual movement represents a relative shift in the leisure Engel curves–that relative shift in Engel curves reveals the movements in θ_I versus that in θ_j. Hence, given knowledge of the leisure Engel curves, we can attribute the changing patterns of time use between movements along Engel curves and changes in technology. With this procedure, in Section 6 we will use our estimated β_i (from Section 5) and observed shifts in time allocation (from Section 3) to measure the relative increase in technology for computers and video games.

4.3 The Labor-Leisure and Technology Decision

We now consider the allocation of time between work and total leisure. For simplicity, we do so in a static setting in which the agent faces a wage rate w and an endowment of non-labor income y.

We model the choice over $\boldsymbol{\theta}$ as follows. For each activity i, the agent faces a menu of $\theta_i \in [0, \overline{\theta}_i]$ with a price schedule $p_i(\theta_i)$. Specifically, by paying $p_i(\theta_i)$, the agent purchases a bundle of inputs that yield a technology parameter θ_i. We assume p_i is weakly increasing, differentiable, and weakly convex. For computers and video games, a natural interpretation is that the bundles are combinations of consoles and games of a particular vintage. Consumers have the option of purchasing the state-of-the-art package at $p_i(\bar{\theta}_i)$, or a previous year's vintage at a cheaper price. Technological progress is viewed as an increase in $\bar{\theta}_i$. Denote the choice set for the vector of technologies $\boldsymbol{\Theta} \equiv \Pi_i[0, \bar{\theta}_i]$. The individual's problem is then:

$$\max_{c, H \in [0,1], \boldsymbol{\theta} \in \boldsymbol{\Theta}} U(c, v(H; \boldsymbol{\theta})) \tag{P}$$
$$\text{subject to}$$
$$c + \sum_i p_i(\theta_i) \leq w(1 - H) + y.$$

For the choice of θ_i, the necessary condition for an interior optimum is:

$$U_v \frac{\partial v}{\partial \theta_i} = p_i'(\theta_i) U_c.$$

For $\theta_i = \bar{\theta}_i$, the equal sign is replaced with $\geq$. Conversely, for $\theta_i = 0$, the equal sign is replaced with $\leq$.

It is convenient to define the elasticity of price with respect to quality:

$$\phi_i(\theta_i) \equiv \frac{d \ln p_i(\theta_i)}{d \ln \theta_i}.$$

Assuming H is interior (which we shall do throughout), we can use the properties of $v(H; \boldsymbol{\theta})$ described in the previous subsection and the first-order conditions for H and c to write the first-order condition for an interior θ_i as:

$$\phi_i(\theta_i) = \frac{w h_i}{p_i(\theta_i)}. \tag{7}$$

This says that a higher sensitivity of price to quality induces the agent to shift the cost of activity i towards time and away from the market input.

A necessary optimality condition for interior H and c is:

$$U_v v'(H; \boldsymbol{\theta}) = w U_c, \tag{8}$$

which is our version of the familiar consumption-leisure tradeoff. The Frisch elasticity of leisure is the elasticity of leisure with respect to the wage holding constant the marginal utility of consumption (and $\boldsymbol{\theta}$):

$$\epsilon \equiv -\frac{d \ln H}{d \ln w}\bigg|_{U_c, \boldsymbol{\theta}}. \tag{9}$$

This elasticity depends on the sensitivity of U_v as well as $v'(H; \boldsymbol{\theta})$ to movements in H. From

(2), we have

$$\left.\frac{d\ln v'(H;\boldsymbol{\theta})}{d\ln H}\right|_{\boldsymbol{\theta}} = -\frac{1}{\eta_i}\frac{d\ln h_i}{d\ln H} = -\frac{\beta_i}{\eta_i} = -\frac{1}{\bar{\eta}}.$$

Let $\sigma \equiv -\frac{d\ln U_v}{d\ln H}$. Differentiating (8) yields the following:

$$\frac{1}{\epsilon} = \frac{1}{\bar{\eta}} + \sigma. \tag{10}$$

Thus the Frisch elasticity reflects both the average curvature over individual leisure activities ($\bar{\eta}^{-1}$) and the curvature over the leisure bundle (σ). As noted above, $\bar{\eta}$ varies with H, and hence the Frisch elasticity is not a constant structural parameter.[15] In particular, as H increases, the shares devoted to high-η luxuries increase, which from (10) raises the Frisch elasticity of leisure for a given σ.

4.4 Leisure Technology and Labor Supply

We now consider the impact of technology on labor supply. In particular, we are interested in how an improvement in θ_I influences the choice of H. As θ_I is a choice variable, one natural interpretation of the comparative static is an increase in the technological frontier, $\bar{\theta}_I$. For agents up against that constraint, introduction of better technology will be reflected in a higher θ_I. More generally, we can think of comparative statics in p_I, such that an agent chooses a higher θ_I. We then use the static labor-leisure condition (8) to trace out the associated shift in H.

One caveat for our comparative static is that we hold θ_i, $i \neq I$, constant. That is, we abstract from the effect of changes in θ_I on the choice of technology for competing leisure activities. Within the context of the model, this is consistent with the agent being strictly constrained by the frontier in those activities. In practice, it seems reasonable that better computing and gaming technology will have only second order consequences for technology choices for other activities. We ignore any such potential cross effects to facilitate both exposition and empirical implementation.

As equation (8) depends on consumption as well as leisure, we need to take a stand on how the agent finances the additional leisure and new technology. We explore two extremes. We first assume U_c remains constant, with any loss in labor earnings offset by an increase

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

in non-labor income – that is, the individual is perfectly insured. This requires that y shifts with θ_I to exactly offset labor earnings and changes in the cost of technology. Secondly, we assume that consumption falls one-to-one with labor earnings.

In the former case, with the marginal utility of consumption insulated, we differentiate (8) to obtain:

$$\left.\frac{d \ln H}{d \ln \theta_I}\right|_{U_c} = s_I \left[\epsilon \beta_I - 1\right]. \tag{11}$$

Thus the impact of a shift in technology is pinned down by the share of time allocated to the activity, the slope of its Engel curve, and the Frisch elasticity of leisure. Note that the more luxurious the activity, that is, the higher the β, the more elastic the response to technological changes. This reflects that leisure luxuries are subject to relatively minimal diminishing returns.[16]

If the agent is not compensated for foregone earnings, the impact on leisure will be mitigated by the income effect. In particular, suppose $\Delta c = -w\Delta H$. We refer to this scenario as "hand-to-mouth" as movements in earnings are reflected one-to-one in consumption.[17] We assume strong separability for this comparative static; that is, $U_{cv} = 0$. Let ρ be the intertemporal elasticity of consumption, $\rho = -U_c/(U_{cc}c)$, and differentiating (8) yields:

$$\left.\frac{d \ln H}{d \ln \theta_I}\right|_{\Delta c = -w\Delta H} = \frac{\left.\frac{d \ln H}{d \ln \theta_I}\right|_{U_c}}{1 + \frac{\epsilon}{\rho}\left(\frac{H}{1-H}\right)\left(\frac{w(1-H)}{c}\right)}. \tag{12}$$

Thus, relative to (11), the sensitivity of leisure to θ is scaled down by the income effect, which depends on the ratio of the curvature parameters ρ and ϵ, as well as the ratio of leisure to work and the ratio of labor income to consumption.

The framework provides a guide to interpret the decline in labor hours in the context of the changing allocation of leisure time. In particular, we can use (6) to map shifts in time allocation into changes in technology and (11) or (12) to trace the impact on leisure demand. We do so assuming that $\Delta\theta_i = 0$ for $i \neq I$; that is, we assume technology in other leisure

[16] The response of technological improvement will be negative for $\epsilon\beta_i < 1$. For example, technological improvement in a leisure necessity such as sleep would result in less time allocated to sleep (and hence leisure time in total).

[17] More generally, $\Delta c = -w\Delta H - \Delta p_I$, where Δp_I is the change in cost due to the upgrade in technology. Including this effect involves subtracting $\gamma(p_I/c)(\Delta p_I/p_I)$ from the numerator of (12). This adjustment is likely to be small. The first term in parentheses is the share of consumption expenditures devoted to gaming. The second is the change in cost as new vintages enter the market. If new vintages enter at a constant price, and then become discounted over time, which is not too far from the case in practice, the final term is zero.

activities is fixed. From (11), we have:

$$\begin{aligned}\Delta \ln H|_{U_c} &\approx \frac{d\ln H}{d\ln\theta_I}\Delta\ln\theta_I \\ &= s_I\left[\frac{\epsilon\beta_I-1}{\bar{\eta}\beta_I-1}\right]\left(\Delta\ln h_I-\frac{\beta_I}{\beta_j}\Delta\ln h_j\right) \end{aligned} \tag{13}$$

The hand-to-mouth calculation is scaled down by dividing by the denominator of (12).

These expressions map time allocation decisions into the shift in the leisure-demand schedule; that is, the change in leisure due to technological change for a given real wage. As a guide to empirical implementation, note that the term in parenthesis on the right-hand side of (13) can be measured using time diaries and an estimated leisure demand system (that is, estimates of β_i). Similarly, s_I is the share of leisure time devoted to computers and video gaming, which is reported in Table 3. The numerator in the square brackets involves the Frisch elasticity of leisure ϵ. This parameter is widely studied in the literature.

Finally, the denominator in the bracketed term in (13) includes $\bar{\eta}\beta_I=\eta_I$, the elasticity parameter for activity I. The allocation of leisure *across* activities for a given H depends only on the relative magnitude of η_i; that is, the decision is governed by $\eta_i/\bar{\eta}$, and thus invariant to an increase in scale. This is why estimation of the demand system can recover $\beta_i=\eta_i/\bar{\eta}$, but not η_i itself. However, the mapping of changes in leisure technology into changes in leisure demand depends on the scale of η_I. Recall from (10) that a given Frisch elasticity ϵ reflects curvature over the leisure bundle (σ) as well as the average curvature over individual activities ($\bar{\eta}$). The source of curvature is important in determining how elastically total leisure responds to technological change in an individual activity. That is, from (13), the relative size of ϵ and $\bar{\eta}$ determines the sensitivity of leisure demand to changes in θ_I. The model provides guidance on how to use prices to pin down the scale of η_I.

In particular, consider an agent who is indifferent between two vintages of technology sold at a point in time, given the prevailing price difference. That is, the agent is at an interior optimum characterized by (7). Let $\Delta\ln\theta_I$ denote the log difference in technology across the two vintages and $\Delta\ln p_I$ denote the associated price difference. Using $\phi(\theta_I)\approx\Delta\ln p_I/\Delta\ln\theta_I$, equation (7) implies:

$$\Delta\ln\theta_I\approx\left(\frac{p_I}{wh_I}\right)\Delta\ln p_I. \tag{14}$$

The term on the right is the relative cost shares for the marginal purchaser of the new vintage multiplied times the price differential across the vintages. Thus data on prices and the relative cost shares provides an estimate of technological progress. Equation (6), setting

$\Delta\theta_j = 0$ for the reference activity, implies

$$(\eta_I - 1)\Delta \ln \theta_I = \Delta \ln h_I - \frac{\beta_I}{\beta_j}\Delta \ln h_j. \tag{15}$$

Using (14) and (15), along with data on time allocation and estimates of β_i, we can obtain a measure of technological change as well as the parameter η_I (and hence $\bar{\eta} = \eta_I/\beta_I$).

The framework presented in this section provides an empirical roadmap. In the next section, we take the leisure demand system of Section 4.2 to the data and estimate β_i for the leisure activities discussed in Section 4. In Section 6 we use equation (15) 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 (14) to recover $\bar{\eta}$. The last step is to use (13) to quantify the impact of improved technology on labor supply.

5 Estimating Leisure Engel Curves

In this section, we estimate the leisure demand system outlined in Section 4.2. Specifically, we estimate the second-stage budgeting problem. We defer the first-stage labor-leisure choice until Section 7. Given that the η_i's may differ across demographic groups, we estimate our demand systems separately for various age-gender combinations. In the discussion below, we suppress the notation indicating that preference parameters are group specific.

We estimate the demand system using the ATUS time diaries. There are two econometric concerns we need to address. First, the time diaries are a single-day snapshot of time allocation. Ideally, we would like data on individuals' typical allocation of leisure, which requires observations over multiple days (or perhaps weeks). In that sense, our data are measured with error as many individuals report zero time on a given activity during the prior day. Second, at the individual level, there is the potential that preferences for a given activity correlate with an individual's total leisure time. For example, it may be that individuals with a strong taste for computer use also have a strong taste for total leisure.

To help address both these issues, we group ATUS respondents into time-state-demographic cells, averaging across individuals within each cell. Demographic cells are defined by age (21-30 and 31-55) and gender. Time is divided into three four-year periods: 2004-2007, 2008-2011, and 2012-2015. We group years, as the number of individuals in a demographic cell can be quite small for small states in a given year. Grouping similar individuals helps with the measurement problem from seeing one's time use for just a single day. Grouping observations at the state-time level also helps with identification. Our key identifying assumption is that fluctuations in labor market conditions during the 2004-2015 period at the state level were not driven by differential changes in preferences or technology for leisure activities that are state specific. For example, we assume that the increase in leisure in Nevada relative to Texas during the 2000s was not driven by people in Nevada experiencing a greater increase in leisure preference or leisure technology than did people in Texas.[18]

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

$$s_{ikt} = \alpha_{ik} + \delta_{it} + \gamma_i \ln H_{kt} + \varepsilon_{ikt}, \tag{16}$$

where $s_{ikt} = h_{ikt}/H_{kt}$ is the share of total leisure H_{kt} devoted to activity i in period t and state k; α_{ik} and δ_{it} are state and time fixed effects; and $\ln H_{kt}$ is log of total state leisure time. From the estimate $\hat{\gamma}_i$, we recover an estimate of $\beta_i = d \ln h_i / d \ln H$:

$$\hat{\beta}_i = 1 + \frac{\hat{\gamma}_i}{\bar{s}_i}, \tag{17}$$

where $\bar{s}_i$ is the share devoted to activity i averaged across the three time periods and fifty states. A leisure luxury is defined as $\gamma_i > 0$, which implies $\beta_i > 1$.

To consistently estimate γ_i, we require that H_{kt} is orthogonal to the residual term. The residual term captures idiosyncratic state level tastes for particular leisure activities conditional on total state leisure time and state and time fixed effects. The state fixed effect captures permanent taste differences across states. We assume that the technological frontier is uniform across states in a time period; and we assume that the average technology within a state-time-demographic cell is at the frontier. Movements in this frontier are then captured by the time fixed effects.[19] Thus, our identifying assumption is that time varying idiosyncratic tastes for individual leisure activities at the state-demographic group level are uncorrelated with time varying trends in total leisure at the state-demographic group level.[20]

[18] This assumption is supported by considerable evidence suggesting that much of the cross-state variation in market work (leisure) during the 2000s was driven by industrial composition or housing markets. See, for example, Charles et al. 2016 and Mian and Sufi 2013.

[19] In the case of computers and video games, the assumption of common technology seems justifiable, given the widespread and rapid diffusion of these technologies during the 2000s. According to reports from the FCC, all MSAs had individuals with high speed internet as of 2000.

[20] As a robustness exercise, in Appendix Table A3 we stratify states by their trends in hours worked for older men from 2004-2007 to 2012-2015. State declines in older men's hours presumably reflected labor demand, not the gaming preferences, or technologies, affecting younger men. We show that the states where older men's market hours most declined exhibited a 5 percent greater increase in total leisure for younger men. But younger men's time spent at computer leisure in these states increased 10 to 11 percent faster–suggesting computer leisure is a leisure luxury for younger men. The implied Engel curve for younger men

When estimating (16), each observation is a state-time cell, with each cell observation weighted by the number of individuals it represents. The estimation is conducted for each activity separably. Our primary focus are estimates of (16) for younger men. But we also present results for older men, and for both younger and older women.

Table 6 reports our estimates of γ_i and the implied β_i for younger men. Our leisure activities are those reported in Table 3: Recreational computer, TV/movies, socializing, (adjusted) eating-sleeping-personal care, and other leisure. We also break out video gaming from its broader computer category. The first column includes time fixed effects, while the second includes both time and state fixed effects. The third column reports the implied β_i using (17) and the first column's estimate $\hat{\gamma}_i$. The standard errors for β_i are bootstrapped by repeatedly drawing samples, estimating γ_i and $\bar{s}_i$, and computing $\hat{\beta}_i$ using equation (17). The final column reports the log-log specification for comparison:[21]

$$\ln h_{ikt} = \delta_{it} + \beta_i \ln H_{kt} + \varepsilon_{ikt}. \tag{18}$$

As seen from Table 6, computers and video games are leisure luxuries. Focusing on the results in Column 1 and the associated β_i (Column 3), the $\hat{\gamma}_i$ for Recreational Computer, 0.08, implies a $\hat{\beta}_i$ of 2.11. Estimated purely for video gaming yields an elasticity of 2.43. The estimates suggest that video game time is the most luxurious leisure activity for younger men. TV/Movie watching has an estimated leisure elasticity of 1.32. No other activities have elasticities clearly above 1. Eating-sleeping-personal care is a leisure necessity ($\hat{\beta}_i = 0.58$), while socializing and other leisure are neither a luxury nor necessity.

The estimates of γ_i are similar between Columns 1 (no state fixed effects) and Column 2 (with state fixed effects), suggesting that differing tastes for activities across states do not bias our estimated elasticities. However, the estimates with state fixed effects, which reflect only within-state fluctuations, have larger standard errors. The final column indicates that the estimated slopes of the log-log specification track those obtained from the AIDS specification quite closely.

Table 7 shows estimated $\hat{\gamma}_I$, and implied $\hat{\beta}_I$, for recreational computer use for other demographic groups. From Column 1, the implied elasticity for computers is 2.03 for less-educated younger men, nearly the same as the 2.11 estimated for all younger men. However, estimates for other demographic groups differ markedly from less-educated younger men. Younger men with a college degree (Column 2) have an estimated elasticity of 0.95, older men (Column 3) 0.50, and younger and older women (Columns 4 and 5) elasticities a little

from this exercise is actually quite close to our benchmark estimate from the text.

[21]With the log-log specification some small time-use categories in small states equal zero, and so are dropped from the regression.

Table 6: Leisure Engel Curves of Younger Men

	AIDS Specification			Log-Linear Specification
	$\hat{\gamma}_i$	$\hat{\gamma}_i$	Implied $\hat{\beta}_i$	$\hat{\beta}_i$
Recreational Computer	0.08	0.12	2.11	2.00
	(0.03)	(0.04)	(0.39)	(0.38)
Video Games	0.07	0.12	2.44	2.40
	(0.03)	(0.03)	(0,57)	(0.56)
TV/Movies/Netflix	0.09	0.06	1.32	1.33
	(0.06)	(0.07)	(0.22)	(0.13)
Socializing	0.002	0.03	1.02	1.15
	(0.03)	(0.04)	(0.24)	(0.26)
ESP	-0.17	-0.22	0.58	0.54
	(0.08)	(0.10)	(0.21)	(0.11)
Other Leisure	-0.004	0.001	0.97	0.81
	(0.03)	(0.03)	(0.21)	(0.34)
Time Fixed Effects	Yes	Yes	Yes	Yes
State Fixed Effects	No	Yes	No	No
Number of Obs.	150	150	150	(†)

Note: The first two columns show results regressing each activity's share of leisure time on log total leisure–with each row a separate regression. In the last column log of time at each activity is regressed on log of total leisure. Each observation is a state-year cell. Data are aggregated within periods: 2004-2007, 2008-2011, and 2012-2015. State observations are weighted by its number of individual observations. Standard errors, clustered at the state level, are in parentheses. The third column includes the implied $\hat{\beta}_i$ using estimates from the first columns. Standard errors for this column are bootstrapped. See text for details.
†: Number of observations in log-linear specification vary across activities due to zero time spent on some activities for some state-time cells.

less than 1. Recreational computer, including gaming, is a leisure luxury for younger men, especially those without a college degree, but not for other demographic groups.[22]

Figure 6 offers a visual of the estimation of β_I for computer leisure for younger men. It provides a scatter plot of log recreational computer time against log total leisure. Each point represents a state average. Circles depict $2004-2007$ observations; triangles depict those for

[22]We considered a number of additional robustness checks on the estimated Engel curve for Computer leisure. For example, we re-estimated (16) allowing γ_I to vary across time periods. An F-test that the coefficient is the same across the three time-periods has a p-value of x.x. We also found no impact on $\hat{\beta}_I$ from including higher order terms in total log leisure.

Table 7: Computer Leisure Engel Curve Estimates by Demographic Group

	Men 21-30 Ed<16	Men 21-30 Ed $\geq$ 16	Men 31-55 Ed: All	Women 21-30 Ed: All	Women 31-55 Ed: All
Recreational Computer ($\hat{\gamma}_i$)	0.08	-0.004	-0.02	-0.01	-0.004
	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)
Implied $\hat{\beta}_i$	2.03	0.95	0.50	0.77	0.88
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	No	No	No	No	No
Number of Obs.	150	150	150	150	150

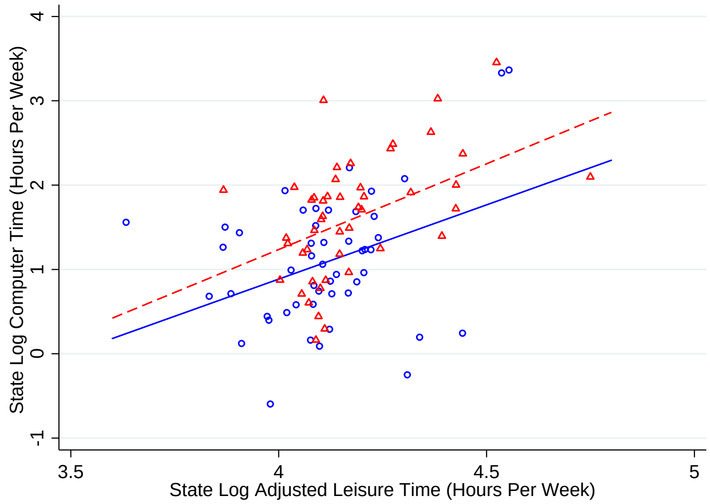
Note: Table shows results by different sex-skill-age groups of regressing the share of leisure time spent on recreational computer activities on the log of total leisure for that group. Each observation is a state-year cell. Data are aggregated within periods: 2004-2007, 2008-2011, and 2012-2015. State observations are weighted by its number of individual observations. Standard errors, clustered at the state level, are in parentheses.

$2012-2015$. The two fitted lines yield elasticities of 1.76 and 2.03 respectively for the earlier and later periods. A test that the slopes are equal has p-value x.x; so the hypothesis that time allocated to recreational computer shifted up proportionally across states cannot be rejected. This figure clearly shows a shift upwards of the leisure Engel curve for young men during the 2000s. These patters will underlie the intuition for our estimates of increasing θ_I during this period.

As a final robustness check on our leisure demand system, we re-visit the assumption of additive separability across different activity sub-utilities (Equation 1). This implies that conditional on H, the amount of time spent in activity i offers no information on the relative returns to activities j versus k ($j, k \neq i$). To explore if this is consistent with the data, we ask whether time spent at computer leisure predicts how remaining leisure is divided across the other activities. Specifically, we group the younger men, using their individual ATUS time diaries for 2004 to 2015, into three groups based on time spent at computer leisure (h_I) the prior day: $h_I = 0$, $h_I \in (0, 2$ hours/day$]$, and $h_I > 2$ hours/day. Denote these groups by $n = 0, 1, 2$, respectively. The first group comprises roughly 70 percent of the sample, while the latter two each comprise about 15 percent. For each group we compute $h_{in}/(H_n - h_{In})$ for i = TV/movies, socializing, adjusted ESP, and other leisure–that is, shares of non-computer leisure time devoted to each alternative leisure activity.[23] Panel (a) of Figure 7

[23] h_{in} is the average time spent on activity i for group n, H_n is the average leisure time for group n, and

Figure 6: Leisure Engel Curves for Computer Leisure: 2004-2007 vs. 2012-2015



Note: Figure shows estimated computer leisure Engel curves for 2004-2007 (circles and solid line) and 2012-2015 (triangles and dashed line) for younger men. The horizontal axis displays each state's log of total leisure separately by time period, while vertical axis does same for its log of computer time. Each period includes about 48 states with strictly positive computer leisure. The lines represent the fitted regressions by time period, with each state weighted by its underlying number of observations. The slope and intercept associated with the 2004-2007 data, with standard errors, are 1.76 (0.67) and -6.15 (2.78). For 2012-2015 these are 2.03 (0.91) and -6.90 (3.75).

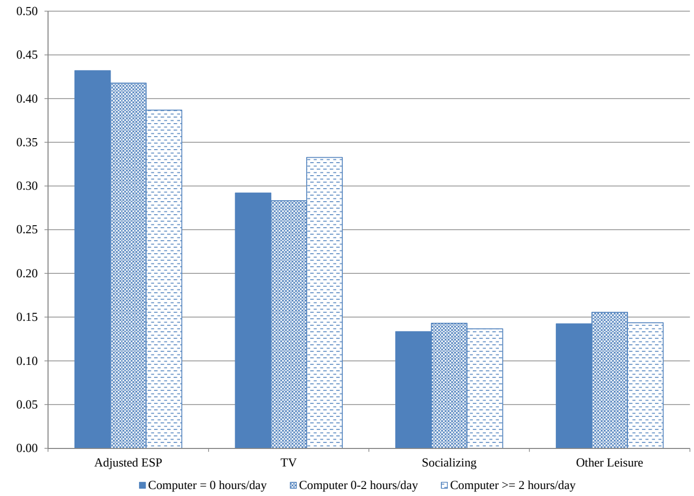
reports the mean shares for each group. Panel (b) accounts for the fact that groups with greater computer use also have greater total leisure. Given the estimates for the leisure Engel curves above, those groups should allocate a greater share of their remaining leisure to watching TV/Movies and less to eating, sleeping and personal care. Panel B controls for the differences in total leisure.[24] Both panels indicate that there is no systematic difference in how non-computer leisure is allocated across those who spend no time, some time, and a great deal of time at computer leisure. This is consistent with our assumption of separability between computer and other leisure activities.

h_{In} is average computer time for group n.

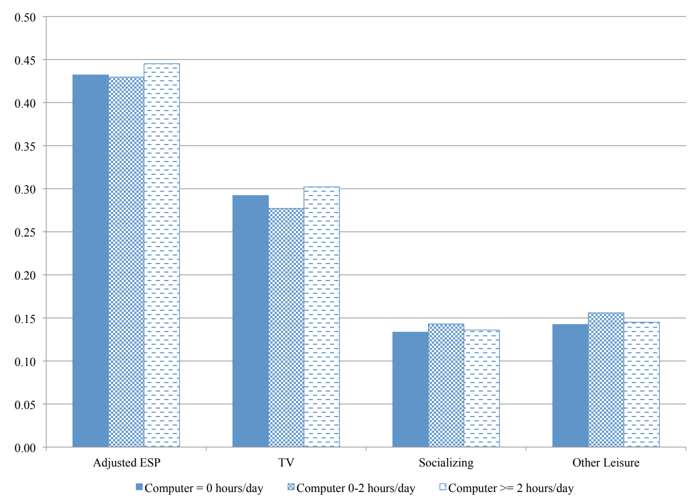
[24]Specifically, we estimate the AIDS specification using non-computer leisure time ($\ln[H_{kt} - h_{Ikt}]$) as our independent variable and the associated share in each alternative activity ($h_{ikt}/(H_{kt} - h_{Ikt})$) as the dependent variable (using the same time-state source of variation as our benchmark). Let $\hat{b}_i$ denote the estimated coefficients. Then $\hat{b}_i\,[\ln(H_n - h_{In}) - \ln(H_0 - h_{I0}]$ is the predicted difference in shares based on the estimated Engel curves. We subtract this from the shares reported in Panel (a) and report the results in Panel (b). Note that if differences in time allocation line up on the Engel curves, the three columns in Panel B will be the same height for each activity.

Figure 7: How Non-Computer Leisure is Allocated to Other Categories, Younger Men

(a) Raw Data



(b) Engel Curve Adjusted



Note: Figure shows shares of non-computer leisure allocated to other leisure activities. Data pool the 2004-2015 ATUS. The sample excludes full-time students, ages less than 25. We stratify by three groups: younger men who spent zero time on computer leisure the prior day, those who spent 2 hours or less, and those who spent more than 2 hours. The top panel shows the raw data. The bottom panel adjusts shares for differences in total leisure across the groups using each activity's estimated leisure Engel curve as described in footnote 24.

6 Technological Change and Prices

In this section, we use time diaries and the model developed above to infer technological progress in recreational computing and video games. We then relate these to the path of prices for the associated market goods.

6.1 Implied Technological Change from Time Use

With the estimated β_i, we can use time allocation data to infer the rate of technological progress for gaming and computer leisure since the early 2000s. We begin with equation (6), which relates changes in time allocation to changes in technology. As noted in Section 4, changes in time allocations identify relative technology changes. We proceed by assuming a reference activity that has a constant level of technology. We explore the robustness of this assumption by varying the reference activity. Setting $\Delta\theta_j = 0$ in (6), we have:

$$(\eta_I - 1)\Delta \ln \theta_I = \Delta \ln h_I - \frac{\beta_I}{\beta_j}\Delta \ln h_j. \tag{19}$$

For our benchmark reference activity we use a share weighted average of the activities other than computer leisure. In particular, let

$$\Lambda \equiv \sum_{i \neq I} \frac{s_i}{1 - s_I}\left(\frac{\beta_I}{\beta_i}\right)\Delta \ln h_i. \tag{20}$$

Λ can be computed from the time use data, which provide the s_i's and h_i's, given the estimates $\widehat{\beta}_i$'s. While our baseline assumption is that there has been no technological or preference change *on average* for other leisure activities during the 2000s, we also explore robustness to using only ESP as a reference category. This assumes no technological or preference change for eating, sleeping or personal care during our sample period.

Using (19), our $\hat{\beta}$'s for younger men, and the relevant time use data for younger men, we estimate that $(\eta_I - 1)\Delta \ln \theta_I$ for younger men during the 2004-2015 period was 42.7 percent (with a standard error of 11.6 percent), or 5.3 percent per year.[25] Our estimate changes little if we use only ESP as our reference group. Under that specification, our $(\eta_I - 1)\Delta \ln \theta_I$ is 37.4 percent (with a standard error of 14.7 percent).

[25]We bootstrap our entire procedure to estimate the standard errors for our $\Delta \ln \widehat{\theta}_I$. We start by sampling the raw ATUS with replacement to compute time use statistics by state-year cells. After estimating β_i's, we employ those estimates together With the time use statistics to compute $(\eta_I - 1)\Delta \ln \theta_I$. We replicate the procedure 500 times.

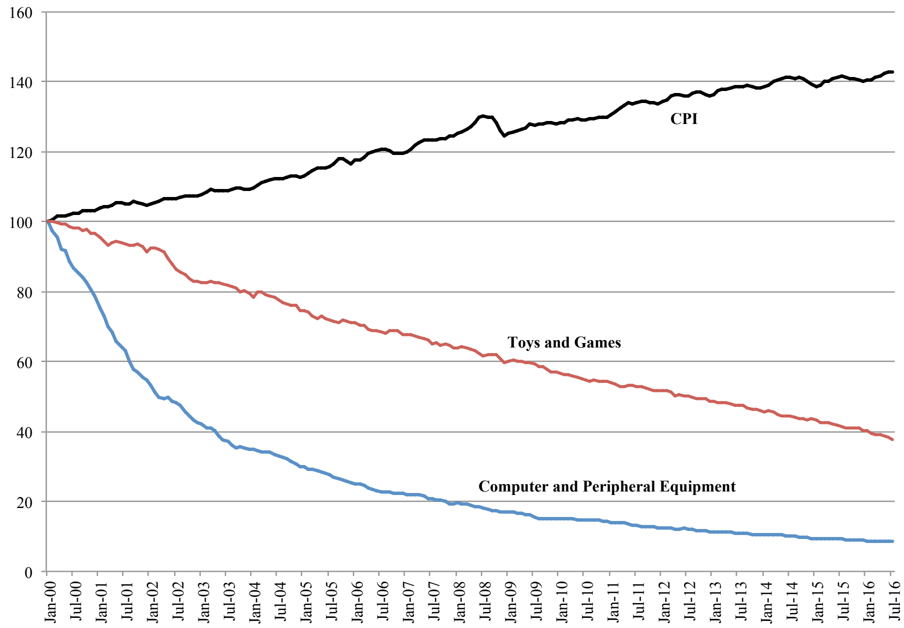
6.2 Implied Technological Change from Prices

Consistent with an increase in implied technology, quality-adjusted prices for computers and video games have fallen steadily during our sample period. Figure 8 show that the price of computer goods and video games fell sharply relative to the full CPI during the 2000s. Specifically, the figure plots the price series for the overall Consumer Price Index (CPI); the price series for toys and games, which includes video games; and the price series for computers and peripheral equipment. All data are from the Bureau of Labor Statistics (BLS) and normalized to be 100 in January 2000. The overall CPI averaged an increase of 0.021 log points per year during this period. The corresponding annual change for toys and computers was -0.059 and -0.149 log points per year, respectively. Thus the relative price decline of toys and computers was -0.08 and -.17 log points per year, respectively. For the post-2008 period, the BLS has provided us the relative weight by year for the "toys" component of "toys and games" as well as the price series for toys. From this, we can infer that the price of the "games" component declined -0.127 log points per year, or a relative price decline of approximately 15 percent, which is not too far from the relative price decline of computers.

We can use our model to assess whether our estimates of $\Delta \ln \theta_I$ are consistent with relative price movements for computer and video games during the 2000s. The BLS designs the price series 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 tracks the overall CPI, then the annual relative decline in the category's CPI captures the relative price across vintages at the time the newer model is introduced. Therefore, the log price difference across annual vintages is approximately 15 percent.

Using the results of Section 4.4, we can map this price differential into a rate of technology change. Recall from (14) that a measure of $\Delta \ln \theta_I$ can be recovered from relative prices and relative cost shares. We take the marginal purchaser to be the average person in our sample. In the ATUS sample of those age 21-55, both men and women, the average time devoted to recreational computer use and video games for 2004-2015 is 2.37 hours per week, or 123 hours per year. The median wage in the CPS is $21.80 in 2010 dollars. Assuming a marginal tax rate of 25 percent, the after tax wage is $16.35. Using this as the opportunity cost of time, the time input into computers and gaming is $2,011. For the goods share, the BLS Consumer Expenditure Survey indicates spending on all audio and visual equipment (including game consoles as well as televisions, stereos etc.) averages roughly $1,000 per household [number from all audio and visual equipment. needs to be updated]. If we assume half of this is spent on recreational computers and video games, then a reasonable estimate of the goods-to-time ratio of cost shares is 0.25. From equation (14), and a price decline of 15 percent per year,

Figure 8: Prices



Note: Price series from BLS.

this implies annual technological progress for computers and video games of 3.8 percent a year.

Comparing our $(\eta_I - 1)\Delta \ln \theta_I = 5.3$ percent per year number obtained from time allocation to the $\Delta \ln \theta_I = 3.8$ percent per year from price data, we obtain $\eta_I \approx 2.4$. Using the fact that $\hat{\beta}_I = 2.11$ and $\beta_I = \eta_I/\bar{\eta}$, we obtain $\bar{\eta} \approx 1.1$. If the leisure Frisch elasticity is approximately 0.7 to 1.0, which is the typical range estimated in the data, then this suggests that $\bar{\eta}$ is not very different from the Frisch elasticity.[26] From equation (10), this implies that $\sigma \approx 0$, or $U_{vv} \approx 0$. In this case, diminishing returns to leisure activities are governed completely by η_i, and $\partial^2 U/\partial h_i \partial h_j = 0$ for $i \neq j$. That is, leisure activities are neither substitutes nor complements in utility.

7 Leisure Luxuries and Labor Supply During the 2000s

The preceding sections found, based on shifts in time allocation as well as from price data, that there has been rapid progress in technology associated with recreational computer use and video games. The question we now address is how much this has affected labor supply

[26] Note that our leisure measure excludes 49 hours/week for non-discretionary sleep and personal care. According to Table 3, adjusted leisure is roughly 50 percent of discretionary time. Hence, our leisure elasticity is comparable to the labor elasticity, which is typically estimated to be between 0.5 and 1.

of younger men. From Section 4.4, equation (13) maps shifts in time allocations into shifts in leisure demand, holding constant the wage and marginal utility of consumption. The alternative mapping, under which declines in labor earnings generate equivalent declines in consumption, are given by taking this U_c constant prediction and dividing by the denominator of equation (12). To quantify this income effect, note that $\epsilon(H/(1-H))$ is simply the Frisch elasticity of labor, which equals the Frisch elasticity of leisure times the ratio of leisure to non-leisure time.[27] We assume the Frisch elasticty of labor is equal to the inter-temporal elasticity of substitution in consumption, $\epsilon = \rho$. The final term in the denominator of (12) is the ratio of labor income to consumption. We make a hand-to-mouth assumption and take this to be one. Therefore, the denominator is 2, and accounting for consumption changes reduces the U_c-constant effect on leisure by one half.

We report results for all demographic groups, using their respective time allocations and $\widehat{\beta}_i$'s.[28] For an easier comparison to the changes in market hours, we translate our shift in leisure to a shift in market labor using $\Delta \ln n \approx -\Delta \ln H * (H/(1-H))$, where the ratio of leisure to non-leisure time is taken from the ATUS data for each demographic group.

Table 8 shows our estimates of the shift in the labor supply curve. The first two columns use all other leisure activities when computing Λ, while the last two use eating, sleeping, and personal care as the reference activity. Bootstrapped standard errors are reported in parentheses.[29] The first and third columns labeled "Hand-to-Mouth" assume $c = w(1-H)$, while the second and fourth columns hold the marginal utility of consumption constant.

To help interpret the results, consider column 2 of Table 8 for younger men. This column computes the labor supply response for the $\Delta\hat{\theta}_I$ assuming that younger men are fully insured. Breaking it down, over the entire 2004-2015 period, s_I for younger men was 7.2 percent. $H/(1-H)$ for younger men during this period was 1.09. $\Delta \ln h_I$ and Λ were 0.461 and 0.033, respectively. Multiplying 0.072 by (0.461-0.033) by -1.09 generates the -3.38 percent entry in column 2 of row 1. If agent's are hand-to-mouth, this effect is discounted by one-half (Column 1). For columns 3 and 4 we use ESP as the reference group to normalize θ_I yielding the corresponding $\beta_j/\beta_I \Delta \ln h_j$ of 0.087 (as opposed to 0.033). Across our various

[27] Technically, this is the elasticity of non-leisure time. In the data, non-leisure time is split between market work and home production (including child care, education, etc.). We assume that changes to leisure at the margin do not alter the share of non-leisure time devoted to market work. That is, additional leisure time is drawn from market work and home production proportionally. Thus a one percent decrease in non-leisure time is associated with a one percent decrease in both market work and home production.

[28] Technically, $\bar{\eta}$ will not be constant across demographic groups given the difference in the share of leisure time spent on each activity. We find these changes to be quantitatively small, and hence hold $\bar{\eta}$ constant across demographic cells for ease of exposition.

[29] To compute standard errors, we bootstrap the entire procedure. Specifically, we recompute the s_i's, the H_i's, the β_i's and the $\Delta \ln h_i$'s for each draw of our ATUS sample. With these inputs, we calculate $\Delta \ln n$. We draw 1000 samples with replacement when computing the standard errors.

Table 8: Impact of $\Delta\theta_I$ on Labor Supply

	Reference Activity: All other leisure activities		Reference Activity: ESP	
	Hand-to-Mouth	Full Insurance	Hand-to-Mouth	Full Insurance
Men 21-30	-1.69%	-3.38%	-1.48%	-2.95%
	(0.4%)	(0.9%)	(0.5%)	(1.1%)
Men 31-55	-0.07%	-0.15%	-0.03%	-0.06%
	(0.1%)	(0.2%)	(0.1%)	(0.3%)
Women 21-30	-0.56%	-1.13%	-0.47%	-0.94%
	(0.3%)	(0.5%)	(0.3%)	(0.5%)
Women 31-55	-0.37%	-0.73%	-0.24%	-0.48%
	(%)	(%)	(%)	(%)

Note: Table shows the shift in labor supply (wage constant) from $\Delta\widehat{\theta}_I$ for 2004-2007 to 2012-2015. It is calculated under: (a) one-to-one response of consumption to earnings (hand-to-mouth), (b) consumption fully insured. The first two columns treat all non-computer activities as the reference activity in computing θ_I, the latter two uses just eating, sleeping, and personal care. Bootstrapped standard errors are in parentheses.

specifications, we estimate that the increase in computer leisure technology reduced labor supply for younger men by between 1.4 percent and 3.4 percent.

To put this shift in perspective, younger men within the ATUS experienced an actual decline in market work between 2004 and 2015 of 7.2 percent. Thus the shift in labor supply due to computer technology is roughly 23 to 47 percent of the observed decline in hours for younger men. Keep in mind that our labor supply shifts holds the wage constant. How this shift translates into equilibrium wages versus market hours depends on the elasticity of labor demand. Given that younger men are a relatively small demographic group, and are likely highly substitutable with other workers, a reasonable assumption is that the relative shift in labor supply of younger men primarily affects hours rather than wages. Regardless of the mapping into equilibrium hours versus wages, the data indicate that the shift in labor supply is sizable given the context of the observed decline in market hours. The alternative estimate, which uses ESP as the reference activity, suggests that increased leisure technology shifts labor supply by 21 percent to 41 percent of the observed decline in market work for younger men during the 2004-2015 period.

A few other results are of note from Table 8. First, improved computer technology explains essentially none of the decline in hours for older men. This stems from the facts that: (1) older men's share of time spent on computer activities is relatively small, and (2) they experienced little increase in the time spent on computer activities during the 2000s. Our framework anticipates the latter fact, since we estimate computer leisure to be a leisure necessity for older men. These findings, coupled with the results for younger men in Row 1, suggest that increases in computer technology explain one-third to three-quarters of the greater decline in hours worked for younger, versus older, men from 2004 to 2015.[30] Here, again, improved computer technology explains a greater share of the phenomenon to the extent younger men's consumption is insured. Second, increased computer technology also explains a modest reduction in the labor supply of younger women, who also a considerable increase in computer time during the 2000s. As discussed above, most of this increase was in non-video game computer activities. The decline in market hours for younger women during the 2000s, roughly 2 percent, was considerably smaller than for younger men. So the shift in labor supply for younger women from better computer technology, while modest, still explains 20 percent to 45 percent of that decline in market work.

[30]From 2004 to 2015, based on the ATUS, younger and older men experienced respective declines in market hours of about 7 versus 3 percent.

Table 9: Fraction of younger Living With Parent or Close Relative

	Men 21-30		Women 21-30	
	All	Ed<16	All	Ed<16
2000	0.23	0.34	0.20	0.22
2007	0.27	0.39	0.26	0.28
2010	0.31	0.44	0.29	0.32
2015	0.35	0.49	0.34	0.38
Change 2000-15	0.12	0.15	0.14	0.16

Note: Table shows the fraction of men and women ages 21-30 cohabitating with their parents/step-parents or other close relatives (siblings, grandparents, etc.). Data are from the American Community Survey.

8 Younger Men's Consumption and Well Being

We find that the impact of innovations to recreational computer use on labor supply of younger men depends on how well their consumption is insulated, if they sacrifice earnings for gaming. In this section, we show that younger individuals - particularly younger men - receive substantial inter-family transfers when they do not work.

8.1 Trends in Cohabitation and Consumption

Table 9 documents cohabitation patterns of younger men and women during the 2000s using data from the 2000 Census and the 2001-2015 American Community Surveys (ACS).[31] The first column shows the trend in younger men living in a household where their parent, step-parent, or other close relative (sibling, grandparent, uncle, aunt) is the household head. The second column repeats the finding for less educated younger men. In 2000, 23 percent of all younger men and 34 percent of less educated younger men lived with a close relative. By 2015, 35 of all younger men, and 49 percent of those with less education, lived with a close relative, with most of these trends from an increase in living with one's parent. Columns 3 and 4 show the patterns for younger women. Younger women are less likely to live with parents, but experienced a similar upward trend during the 2000s as did younger men.

Table 10 shows the cohabitation patterns for younger men by employment status. The

[31] The 2000 Census and subsequent ACS surveys contain a set questions that are comparable over time. Each respondent is asked their relationship to the household head. A household head is the person (or persons) that owns or rents the housing unit. Our Census/ACS samples, like those from CPS and ATUS above, exclude full-time students ages 25 or less. We also exclude those individuals residing in group quarters.

top panel pools data from 2000 to 2003, while the bottom panel does so for 2012-2015. Columns 1 and 2 show patterns for working versus non-working younger men. Columns 3 and 4 repeat the patterns, but just for less educated younger men. We summarize the key takeaways. (1) Non-employed younger men are much more likely, 80 percent more likely, to live with Parents/relatives. In 2012-2015, 67 percent of those not working lived with a parent or close relative, with only 12 percent living on their own. (2) Secondly, there has been a dramatic increase in living with parents and other close relatives in the 2000's. Between the two panels (periods differing by only 8 years on average), there was nearly a 50 percent increase in the rate of living with Parents/relatives, both for employed and for not employed younger men. In the early 2000s, 26 percent of employed and 46 percent of non-employed younger men lived with a parent or close relative. By 2012-2015, those shares were 37 percent and 67 percent. We also see little difference in cohabitation propensities, conditional on work status, between all younger men and less educated young men.

By 2012-2015, looking at the bottom panel, bottom row of Table 10, only 12 percent of non-working younger men are married, or live with a partner. A similarly small fraction report living in a household with a child. The fact these younger men are neither married nor have children in the household suggests that government programs are not a major factor for their lack of labor market attachment. younger single men without children do not receive welfare programs like SNAP. Their lack of work experience means many do not receive unemployment benefits. Disability take-up is also rare for this age group. Thus parents and other relatives are the more likely source for support (including housing) for non-employed young men, thereby helping them to maintain consumption despite not working.

Younger men living on their own may still receive support from their parents. To examine this, we use biannual surveys from the Panel Study of Income Dynamics (PSID) for 2001 to 2013. From the PSID it is possible to see transfers in the form of help from relatives, beyond the important component of living with them. We highlight a few takeaways.[32] First, for younger men that do not live with relatives, help from relatives is still fairly common, with about 20 percent of households reporting such help. But these transfers are typically small, averaging (including zeros) only 1.5 percent of those households' average earnings. Second, as anticipated by the discussion above, government transfers are reasonably small for households headed by younger men. Government transfers (e.g., unemployment benefits, SSI benefits) averaged 2.9 percent of household earnings for these households, while tax credits (EITC, child credits, etc.) averaged another 1.9 percent. Finally, the PSID data shows that government transfers are much more important for households where younger men live with

[32] A fuller description of our PSID sample can be found in the Data Appendix. As with other data sets, we exclude full-time students ages less than 25.

Table 10: Cohabitation Patterns by Employment Status: Men 21-30

(a) Pooled 2000-2003 Census/American Community Survey Data

	All Men 21-30		Education < 16	
Living Status	Employed	Non-Employed	Employed	Non-Employed
Head: Single	0.25	0.19	0.22	0.17
Head: Live with Spouse/Partner	0.41	0.26	0.40	0.26
Not Head: Live with Parent/Close Rel.	0.26	0.46	0.29	0.49
Not Head: Live with Others	0.09	0.08	0.09	0.08

(b) Pooled 2012-2015 Census/American Community Survey Data

	All Men 21-30		Education < 16	
Living Status	Employed	Non-Employed	Employed	Non-Employed
Head, Single	0.23	0.12	0.20	0.11
Head, Live with Spouse/Partner	0.28	0.12	0.27	0.12
Not Head: Live with Parent/Close Rel.	0.37	0.67	0.42	0.69
Not Head: Live with Others	0.12	0.09	0.12	0.08

Note: Table shows the fraction of younger men in each cohabiting arrangement by employment status. Data are from the American Community Survey (ACS). Sample excludes full-time students ages 25 or less. We classify as a household head anyone who is reported as being the household head, the spouse of the household head, or the unmarried domestic partner of the household head. (Household head in ACS refers to the individual that owns or rents the housing unit.) Panel A pools 2000 to 2003 ACS, while panel B pools 2012 to 2015.

parents or other relatives. Across the seven PSID waves, government transfers and credits represented 15.7 percent of average earnings for these households. These transfers have increased substantially with time. By the 2013 survey (calendar year 2012) transfers/credits equaled 22.1 percent of average household earnings for households that include younger men. The government payments presumably contribute toward spending by the younger men in these households, even if they are not the direct beneficiary.[33]

In Appendix Table 4, we track expenditures in households with younger men, versus those with older men, using PSID expenditure measures. Given their differential trends in hours worked documented above, we examine whether they display different trends in consumption. The analysis is imperfect, in that expenditures are measured at the household level while our analysis on employment and hours concerns individuals. We take the standard approach of deflating household expenditures by a measure of household scale (equivalence units), cognizant that this imposes the assumption that expenditures are split equally between the parent and the dependent. The PSID data indicate that younger men's consumption, adjusted for household size, does not decline relative to households containing older men. In particular, households containing a younger man experienced a decline in after-tax income of 6.6 percent between 2000 and 2012, but recorded less than a one percent decline in consumption. Households containing men age 31-55 experienced a smaller decline in income but a larger decline in expenditure. [34] While mapping of household expenditure to individual consumption is problematic, we view the consumption data as reinforcing the cohabitation trends as evidence that parents and close relatives are providing significant consumption insurance to younger men during the 2000s.

8.2 Trends in Well-Being

Before concluding, we turn to data from the General Social Survey (GSS) to examine trends in reported life satisfaction for younger men relative to other groups. The GSS assesses attitudes and beliefs of US residents. The GSS has consistently asked individuals the following question: "Taken together, how would you say things are going these days – would you say that you are very happy, pretty happy, or not too happy?" We create a happiness index that takes the value of 1 if individuals report that they are either "very happy" or "pretty happy," and takes value 0 otherwise. As with the ATUS, we pool waves of the GSS index

[33]Easily the most important government payment for these households, both in level and trend growth, are social security benefits. For these payments the younger men are unlikely to be the direct recipient.

[34]Restricting attention to less educated men, households with younger and older men reported the same decline in income (10 percent) and roughly similar declines in consumption.

over time, given the survey's modest sample size.[35] We examine three time periods: 2001 to 2005, 2006 to 2010, and 2011 to 2015.

Table 11: Reported Happiness

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

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

Table 11 tracks the trends in happiness for younger versus older men, first for all education groups, then excluding those with 4 or more years of college. Jumping to the third row, the happiness of younger non-college men actually increased by 7 percentage points since the early 2000s, from 81 to 88 percent. So, in conjunction with a steep decline in their employment, reported satisfaction has increased for these younger men. (This increase is statistically significant at the 5 percent level.) Among non-college younger men, both the employed and non-employed exhibit increases in happiness.[36] This pattern stands in stark contrast to that for older workers. The last row of Table 11 documents that happiness fell sharply for non-college older men since the early 2000s. This group experienced a large decline in work hours as well. In the early 2000s, non-college older men reported being happier than did their younger counterparts. That relationship flipped by 2011 to 2015. The deterioration of measures of well being for older workers has been studied recently by Case and Deaton (2015). Table 11 adds to this literature showing, by contrast, that younger men experienced a rise, rather than decline, in measured happiness over the past 15 years.

[35] The survey is biannual and designed to be nationally representative. Each wave of the GSS has between 2,000 and 4,000 respondents.

[36] Over the same period, reported happiness of younger men and women with bachelors degrees remained roughly constant. Again, this occurred despite falling employment rates for both groups.

While by no means conclusive, these results are consistent with computer technology broadly, and video games in particular, increasing the value of leisure for younger workers. Put differently, we should suspect forces, beyond reduced demand for their labor services, have affected the choices and well-being of younger non-college men, as reduced demand for one's labor should be no source of cheer.

9 Conclusion

In this paper 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 labor supply. We show that such innovations are likely to reduce labor supply much more if they affect leisure luxuries. Estimating our leisure demand system using cross-state variations during the 2000s, we find that recreational computer activities in general, and video gaming especially, are strong leisure luxuries for younger men. We estimate that younger men respond to a 1 percent increase in total leisure by increasing recreational computer time by 2.1 percent. For other groups - younger women, older men and older women - recreational computer is not a leisure luxury.

Using our estimated leisure demand system, together with detailed time use data from the American Community Survey, we can identify the relative increase in computer and video game technology during the 2000s. As of 2015, men between the ages of 21 and 30 allocated 5.2 hours per week to recreational computer activities, 3.4 hours going specifically to video gaming. For younger men recreational computer time increased by 45 percent during the 2004-2015 period, while total leisure time increased by only 4 percent. Our estimated leisure demands predict that recreational computer would have increased by 8 percent if younger men had remained on their original leisure Engel curve. We can attribute the much greater increase in younger men's computer time to a sizable improvement in technology for computer and video gaming, an improvement we would expect given CPI-measured declines in relative prices for computer and video games.

We estimate that technology growth for recreational computer activities, by increasing the marginal value of leisure, accounts for 20 to 40 percent of the decline in market work for younger men during the 2000s. Based on CPS data, men ages 21-30 reduced their market work hours by 12 percent from 2000 to 2015, whereas the decline was only 8 percent for men ages 31-55. Our estimates suggest that technology growth for computer and gaming leisure can explain as much as three-quarters of that 4 percent greater decline for younger men.

We estimate that improved computer and gaming technology also explains a small decline in market work for younger women, but had no impact for older men and women.

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

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Appendix [Under Construction]

A1 Data Appendix

TBA

A2 Trends in Market Hours: Additional Tables and Figures

Appendix Table A1 shows similar patterns to those reported in Section 2 using data from the 2000 U.S. Census and the 2001-2015 American Community Surveys (ACS). The U.S. Census and ACS asks comparable questions for large cross sections of U.S. residents pertaining to demographics, family composition and labor market experiences. The Census and ACS data tracks full time school enrollment consistently during the 2000-2015 period for all individuals not just those under the age of 25. Therefore, using the Census/ACS data allows us to explore the robustness of our results to excluding all full time students as opposed to just full time students under the age of 25. Panel A of Appendix Table A1 is analogous to Table **??** but with the Census/ACS data imposing similar sample restrictions as with the CPS data. In particular, panel A excludes only full time students under the age of 25.[37] The CPS and Census/ACS data compare well in terms of annual hours worked in all years. There are two exceptions. First, similar to what others have documented in the literature, annual hours works in the 2000 CPS exceed hours worked in the 2000 Census.[38] Despite the differences in levels of hours worked in 2000, the relative changes in annual hours across sex-age-education groups are very similar. LEYM had the largest decline in annual hours worked during the 2000s. Moreover, the annual hours of LEYM decreased by 63 hours per year more than less educated older men during the 2000-2015 period. This is nearly identical to the patterns shown in Table **??**. Also similar to Table **??** is the fact that both young and older higher educated men had nearly the same decline in annual hours worked during the 2000s. Second, the Census/ACS data show only a small difference in the trend in hours worked during the 2000s between younger and older higher educated women. The difference was much larger in the CPS data.

Panel B of Table Appendix Table A1 explores the robustness of our results to excluding from our sample full time students over the age of 25. The patterns between Panel A and Panel B are nearly identical. Less educated younger men declined their market work hours

[37]To fascilitate comparison with the CPS, we also exclude those individuals residing in group quarters for our Census/ACS analysis. We impose this restriction throughout the rest of the paper any time we use the Census/ACS data.

[38]It is well documented that employment rates in the 2000 Census are much lower than employment rates in the 2000 CPS. See, for example, Clark et al. (2003). This depresses annual hours worked in the 2000 ACS relative to the CPS. Additional differences occur between the CPS and Census/ACS hours worked measures given the different sampling frame and different way that hours worked are asked. For example, the Census/ACS ask about hours worked during the prior 12 months as opposed to the prior calendar year. Given this difference, when using the Census/ACS data, we designate year t hours as coming from year t respondents. The fact that the timing between the two data sets are not exact will also cause the hours worked measures to differ slightly.

by about 172 hours per year when all full time students are excluded. The comparable number where only full time students under 25 were excluded was 183 hours per year. This robustness exercise shows that the extent to which we cannot exclude all full time students in the CPS is not substantively affecting our conclusions about trends in market work for younger men relative to older men during the 2000s.

Finally, the patterns we document in Section 2 are robust for many other demographic groups. For example, the decline in hours worked for younger black men and younger native born white men during the 2000-2015 period in the CPS was 12.4 percent and 12.6 percent, respectively. Appendix Figure A1 is analogous to Figure 2 except the trends are shown for younger black men and younger native born white men. While the fraction of younger black men not working for the entire year is persistently higher than the fraction of younger white men not working for the entire year, the time series trends are very similar between the two groups. For example, the fraction of native born whites who did not work the prior year was only 5 percent in 1993. As of 2015, that number is roughly 13 percent. Although not shown, we also explored the patterns based on whether the younger men lived in center cities, suburbs, or rural areas. The declines were roughly similar for black and white men across all three of these location types. These results show that the declines in hours worked for younger men were broad based hitting both blacks and whites regardless of whether they were living in urban or rural areas.

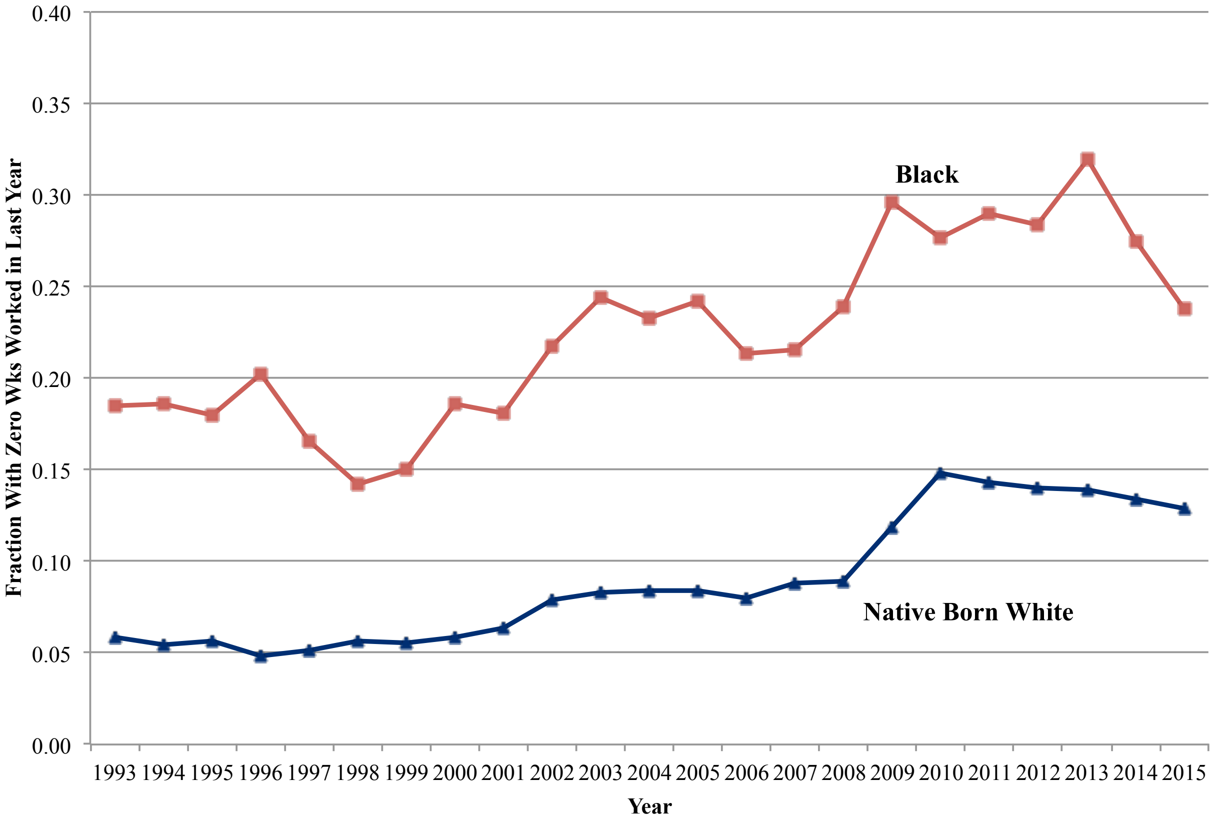
A3 Trends in Real Wages: Demographic Adjustments and Imputationd

In Appendix Figures A2 and A3 we explore the potential role of selection in biasing the conclusions from Figure 3. We detail these procedures in depth in the Data Appendix that accompanies the paper. Briefly, in Appendix Figure A2 we adjust the real wage trends for the changing nature of the demographic composition of the workforce over time. In particular, we define demographic cells in each year based on four education groups (less than high school, high school, some college, and a bachelors degree or more) and seven five-year age groups (21-25, 26-30, etc.). We then compute the average real wage within each demographic cell within each year. To compute the time series of wages for both younger and older men, we hold the demographic composition fixed at year 2000 levels. In Appendix Figure A3 we go one step further. In addition to holding the demographic weights of the sample fixed at 2000 levels, we also attempt to impute the wages for those with no wage observation. Our imputation procedure assumes that those with no wage observation were drawn from the bottom part of the wage distribution for those with wages in their respective demographic cell.[39]

There are two important results from Appendix Figures A2 and A3. First, the decline in wages between 2000 and 2015 for all groups is much larger with these adjustments. This is not surprising given that those who left the labor force during the 2000s tended to come

[39]Specifically, we assign the individuals with non-positive wages the wage of the 33rd percentile of those with positive wages within their respective demographic cell. For this analysis, our sample sizes are larger because we do not exclude those with zero or negative wages. See the Data Appendix for additional details.

Figure A1: Fraction of younger Men Who Report Working Zero Weeks During Year By Race, March CPS

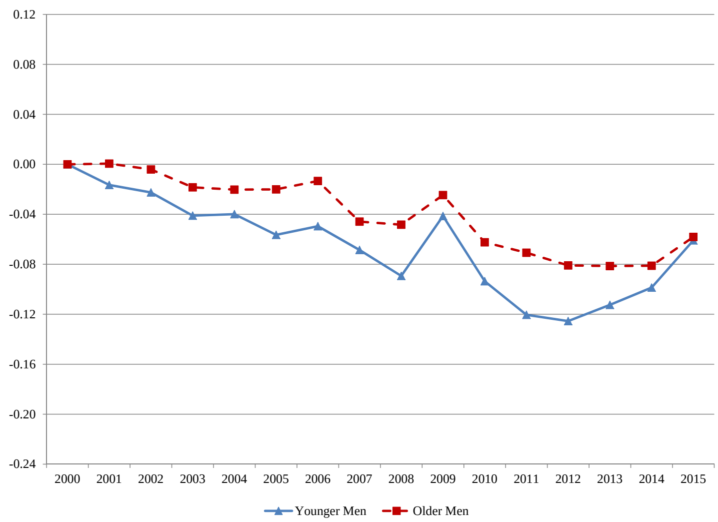


Note: Figure shows the share of men aged 21-30 who report working zero weeks during the prior year, by race. We show the series for individuals who report their race as black (squares) and for individuals who report their race as white and who report being born in the United States (triangles). Data from the March supplement of the Current Population Survey. Individuals reporting attending school full time are dropped from the sample. See text for additional details.

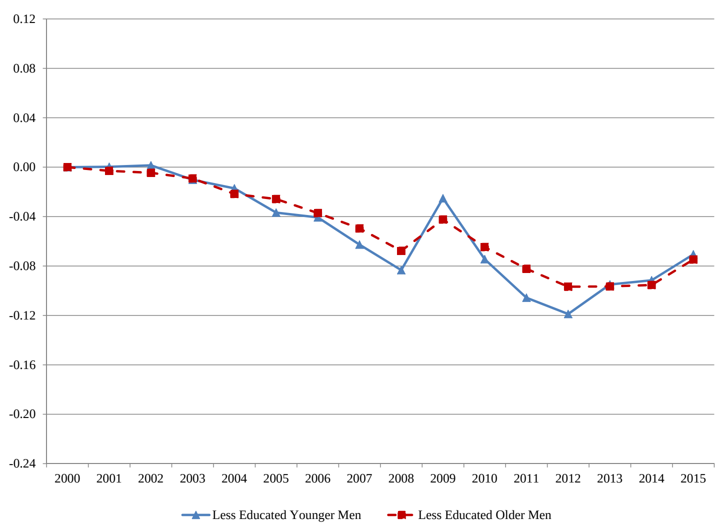
from demographic groups with lower average wages. For example, with no adjustments at all (Figure 3), less educated men experienced wage declines between 2000 and 2015 of about 10 percent. Adjusting for the changing demographic composition of the work force over time (Appendix Figure A2) and imputing the wages for those with non-positive wages (Appendix Figure A3) resulted in mean wage declines for less educated men of roughly 11 percent and 13 percent, respectively, during this time period. Second, and most importantly, with the demographic adjustments our main conclusion from Figure 3 persist. In particular, the decline in wages between younger men and older men during the 2000s is identical regardless of our treatment for selection. While accounting for selection may be important for how much wages fell during the 2000s, it does not seem to be important at all for our point that the relative wage declines of younger men and older men were very similar despite the large differences in hours worked between the groups.

Figure A2: Demographically Adjusted Hourly Real Wage for Men By Age, March CPS

(a) All Men



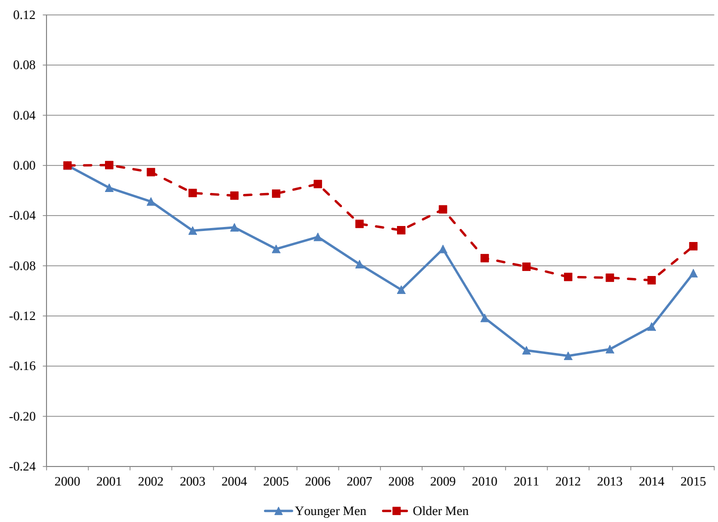
(b) Men Ed <16



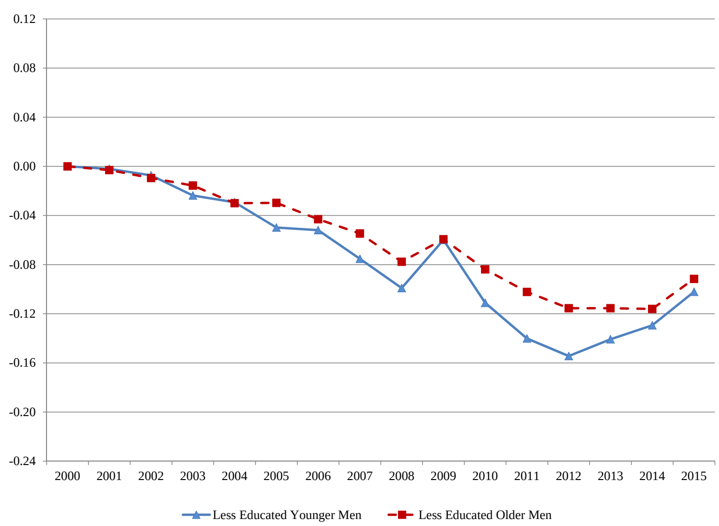
Note: Figure shows hourly real wage index for younger men (triangles) and older men (squares). Hourly wages are reported as annual earnings last year divided by annual hours worked last year. We demographically adjust the wage series by defining cells based on age and education. We compute wages within each cell within each year. We then hold the cell weights fixed at year 2000 levels. The procedure holds the demographic composition fixed over the sample period. See text for additional details. We deflate wages using the June CPI-U. We convert the series to an index by setting year 2000 values to 0. All other years are log deviations from year 2000 values. Data from the March supplement of the Current Population Survey.

Figure A3: Demographically Adjusted Hourly Real Wage Index for Men By Age with Imputations for those with Missing Wages, March CPS

(a) All Men



(b) Men Ed <16



Note: Figure shows hourly real wage index for younger men (squares) and older men (triangles). Hourly wages are reported as annual earnings last year divided by annual hours worked last year. We demographically adjust the wage series by defining cells based on age and education. We compute wages within each cell within each year. We then hold the cell weights fixed at year 2000 levels. The procedure holds the demographic composition fixed over the sample period. In addition, we set the wages of those with no wage observation to the 33rd percentile of their respective demographic cell. The imputation crudely accounts for the potential for those who are not working to be selected from the lower part of the wage distribution. See text for additional details. We deflate wages using the June CPI-U. We convert the series to an index by setting year 2000 values to 0. All other years are log deviations from year 2000 values. Data from the March supplement of the Current Population Survey.

Table A1: Annual Hours Worked During the 2000s By Age-Sex-Education Groups, ACS Data

(a) Excludes Full Time Students Whose Age 24

	Men Ed<16		Men Ed≥16		Women Ed<16		Women Ed≥16	
	21-30	31-55	21-30	31-55	21-30	31-55	21-30	31-55
2000	1,749	1,884	1,937	2,197	1,231	1,314	1,630	1,560
2007	1,712	1,849	1,913	2,169	1,196	1,309	1,638	1,563
2010	1,478	1,665	1,817	2,109	1,116	1,248	1,624	1,579
2015	1,567	1,764	1,859	2,125	1,176	1,253	1,663	1,630
Change 2000-15	-183	-120	-78	-73	-55	-61	33	70
Pct Change 2000-15	-11.0%	-6.6%	-4.1%	-3.4%	-4.5%	-4.8%	2.0%	4.4%

(b) Excludes Full Time Students Whose Age 24

	Men Ed<16		Men Ed≥16		Women Ed<16		Women Ed≥16	
	21-30	31-55	21-30	31-55	21-30	31-55	21-30	31-55
2000	1,760	1,888	2,013	2,216	1,230	1,314	1,665	1,562
2007	1,732	1,855	2,002	2,189	1,195	1,310	1,692	1,564
2010	1,499	1,675	1,916	2,129	1,116	1,253	1,681	1,585
2015	1,589	1,770	1,950	2,142	1,178	1,254	1,722	1,634
Change 2000-15	-172	-118	-63	-74	-52	-60	57	72
Pct Change 2000-15	-10.3%	-6.5%	-3.2%	-3.4%	-4.3%	-4.7%	3.4%	4.6%

Note: Table shows annual hours worked from the 2000, 2007, 2010, and 2015 ACS. Annual hours are calculated by multiplying self-reported weeks worked over the last 12 months by self-reported usual hours worked per week. Given the structure of the ACS, respondents in year t report hours worked during the prior 12 months. We designate the response by respondents in survey year t as referring to hours worked in t. Sample in Panel A excludes individuals under the age of 24 (inclusive) who report being full time students. Sample in Panel B excludes all individuals who report being full time students (regardless of age). See text for additional details.

A4 PSID Consumption Measures

To continue our analysis of the potential insurance parents provide to their children (both employed and non-employed) we also examine consumption for younger men based on data from the PSID. These data measure non-durable and service expenditures at the household level, while our analysis on employment and hours concerns individuals. We take a standard approach by deflating household expenditures by a measure of household scale (equivalence units). We set this scale equal to $\sqrt{n}$, where n denotes number of household members.[40] Note that we treat all household members symmetrically. Thus, in a household with a working prime-age adult plus a non-employed younger man, we would allocate an equal amount of consumption to both. To the extent that the expenditure of such households are geared towards the parents, we will overestimate consumption of these younger men.

In Table A2 we report the growth rate in average expenditure for all households that include younger men ages 21 to 30. For comparison, we report the same for households that include men ages 31 to 55. These sets overlap to the extent younger and older men are coresidents. Our measure of consumption includes expenditures on housing (either rent or imputed rental equivalence for owners, and utilities), food (both for consuming at home and away), transportation (gasoline, public transit), heath, and education. These are the NIPA-defined nondurable and service categories reported consistently within the 2001-2013 PSID samples.[41] The table also reports the growth in household after-tax income for each subgroup. Before-tax income reflects PSID responses, while household taxes are calculated using NBER TAXSIM. Both income and expenditures are deflated by each household's equivalence scale, discussed above, and the GDP deflator.

Looking at the first two column's of Table A2, we see that households with younger men displayed only a slight decline in real expenditure, 0.7 percent, despite displaying a decline in household income of 6.6 percent. The table compares results for younger and older men. We see that households with younger men displayed a 4.8 higher growth in consumption than households with older men, despite displaying 2.6 percent lower growth in income. The last column of Table A2 reports growth in expenditures for households with LEYM members versus households with men aged 31 to 55, also with less than four years of college. Again we see a slightly higher growth rate in expenditures, by 1.9 percent for LEYM, while household income growth looks the same across the two groups. Repeating, it is important to recognize that the increase in cohabiting with parents we document in Table 10 can act to raise the growth rates in household income and expenditures shown in Table 6. To the extent these "kept" younger men consume less than proportionately from household expenditures, Table A2 will exaggerate younger men's consumption growth since 2000. With this important caveat, we see this evidence, and especially that on increased cohabiting, as suggesting that younger men have insulated their consumption, at least partially, from the full force of any earnings loss.

[40] The square-root scaling factor has been adopted in recent OECD studies, for instance www.oecd.org/social/inequality.htm.

[41] Rental equivalence is imputed based on owner's reported value of home. This mapping is estimated from the BLS Consumer Expenditure Survey, which contains reponses on rental equivalence as well as value of home.

Table A2: Household Size Adjusted Real Consumption and Income Growth from 2000 to 2012, PSID

	Men: All Ed		Men: Ed<16	
	After-tax Income Growth	Consumption Growth	After-tax Income Growth	Consumption Growth
Households w/ Men 21-30	-6.6%	-0.7%	-10.0%	-4.8%
Households w/ Men 31-55	-3.9%	-5.5%	-10.0%	-6.7%
Difference	-2.6ppt	4.8ppt	-0.04ppt	1.9ppt

Note: Data reflect 2001 and 2013 PSID surveys, corresponding to calendar years 2000 and 2012. Series are deflated by household-specific equivalence scale and the GDP deflator. The household equivalent scale is equal to square root of number of household members. After-tax income is calculated by netting taxes from the before-tax income reported in the PSID, where taxes are calculated using NBER TAXSIM. The consumption measure reflects expenditures reported on rent, or imputed rental equivalence for owners, utilities, food, transportation (gasoline, public transit), heath, and education.

A5 Alternative Engel Curve Estimation

In this appendix, we explore two additional identification strategies for demand system estimation. First, we use state level movements in the employment of men 41-55 as a proxy for state level changes in leisure of younger men. The identification assumption here is that relative state-level changes in θ for computer use are not correlated with relative shifts in labor supply or labor demand across states for 41-55 year old men. As shown in the prior section, middle-age men allocate little time to either (non-work) computer usage or video games. Instead, we are assuming that cross state variation in the employment of middle-age men is being driven by local labor demand shifts.[42] By isolating state-specific movements in total leisure time for younger men that project on their state's movements in employment of older men, we are isolating changes in leisure for younger men that are driven by changing local labor demand conditions.

Second, we focus purely on relative shifts in total leisure between non-college and college younger men over time, and ask how these changes map to differential changes in computer use. The assumption here is that the preferences and technology of non-college men and college men are the same, at least with respect to computer and gaming leisure, so that changes in θ affect the two groups equally. Therefore, how the non-college group's computer time increases, vis a vis that for the college group, as its relative total leisure increases can identify the leisure Engel curve for computer usage.

Panel (a) of Table A3 implements our first alternate identification strategy. Using data from the 2007 and 2010 March CPS, we pool men ages of 41 to 55 by their state of residence each year. We then compute average hours worked for this group by state for both 2007 and 2010. We segment states into three groups based on the percentage change in work

[42] Beraja et al. (2016), Charles et al. (2016), and Mian and Sufi (2014) all conclude that declines in labor demand explain cross region variation in employment during the Great Recession.

Table A3: Cross-State Variation Based on Employment Decline of Older Men

	Large Hour Decline for Men 31-55		Small Hour Decline for Men 31-55	
	Log Average Leisure Time Men 21-30	Log Average Computer Time Men 21-30	Log Average Leisure Time Men 21-30	Log Average Computer Time Men 21-30
2004-2007	4.104	1.074	4.122	1.347
2011-2014	4.161	1.679	4.127	1.864
Difference	0.057	0.605	0.005	0.499

Note: Alternate estimates of the recreational computer time Engel Curve for younger men. See text for details.

hours for 41-55 year old men during the 2007-2010 period of the Great Recession. The "high-declining work hours" states include the 17 states with the largest hours decline for older men, while the"low-declining work hours" states are the 17 states with the smallest hours decline for these men.[43] We next compute pre-recession versus post-recession leisure and computer time use for all men aged 21-30 (from the ATUS), stratifying by these same three state groupings. We can then relate state differences in the growth in younger men's total leisure and computer use on how work hours declined for older men.

There are four columns in the top panel of Table A3. The first two columns refer to states with large hours decline for older men, while the third and fourth refer to states with small hours declines. The first and third rows show (log of) average leisure for younger men within each state grouping, while the second and fourth rows show (log of) their average computer time. (Rows also reflect time periods for measuring time use.) States where hours declined most for older men are also the states where leisure time of younger men most increased. Leisure time increased by 7 percent for younger men in states with steep declines in work hours for older workers, but by only 2 percent for states with slightest declines in work hours. Computer time increased by 59 percent and 47 percent, respectively, for younger men in the two state groupings. From this, we can compute the implied β, computer time's elasticity with respect to total leisure, to equal 2.6.[44] This is close to our baseline estimate for β of 2.15 from Table 6.

[43] Although not shown, this segmentation of states also strongly predicts hours declines across states for younger men. This is arguably consistent with most cross-state variation in hours for LEYM being driven by differential declines in labor demand.

[44] This reflects the differential change in computer time of 12 percent (from 0.59 minus 0.47) relative to the differential in total leisure time of 5 percent (from 0.07 minus 0.02).