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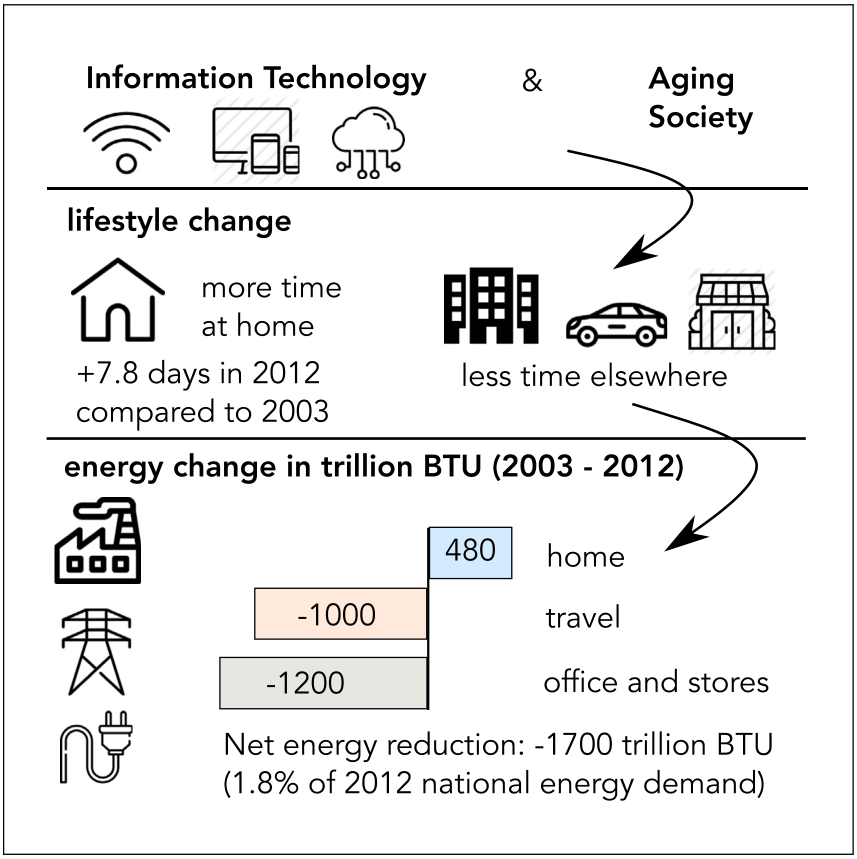
Changes in Time Use and Their Effect on Energy Consumption in the United States



This research aims to better understand lifestyle changes and the associated energy effects in the United States over the past decade. We find that Americans are increasingly spending more time at home and less time elsewhere. The lifestyle shift led to reduced energy consumption of 1,700 trillion BTU, 1.8% of 2012 national demand. This effect is not explicitly captured in current national energy models. The approach used has implications for prioritizing energy policies for governments and utilities.

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HIGHLIGHTS

Technology is enabling lifestyle shifts and influences energy use across sectors

Americans are spending more time at home: 8 more days in 2012 versus 2003

Additional time at home came from less time traveling and in offices/retail stores

1.8% of 2012 national energy demand was reduced due to activity tradeoffs

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Changes in Time Use and Their Effect on Energy Consumption in the United States

Ashok Sekar,[1,3,*] Eric Williams,[1,2] and Roger Chen[1,2]

SUMMARY

Lifestyles are changing due to information technology and other socio-technological trends. We study the energy effects induced by lifestyle shifts via trade-offs in time spent in performing activities. We use the American Time Use Survey to find changes in times performing different activities from 2003 to 2012. The results show that Americans are spending considerably more time at home (7.8 days more in 2012 compared with 2003). This increased home time is counterbalanced by decreased time spent traveling (1.2 days less in 2012 versus 2003) and in non-residential buildings (6.7 days less in 2012 versus 2003). Increased residential time is mainly due to increased work at home, video watching, and computer use. Decomposition analysis is then used to estimate effects on energy consumption, indicating that more time at home and less on travel and in non-residential buildings reduced national energy demand by 1,700 trillion BTU in 2012, 1.8% of the national total.

Context & Scale

Technological advancements and socio-economic trends are enabling rapid changes in lifestyle that influence energy use. This research tracks lifestyle changes in the United States through changes in times spent on different activities and measures the associated energy effects. We find that Americans are spending more time at home and correspondingly less time traveling and in offices and stores. We find that more time at home implies lower energy consumption due to reduced automobile travel and energy use in non-residential buildings. At the national scale, this research shows that time-based models would improve energy forecasts by capturing behavioral changes that current models fail to capture. Knowledge of such lifestyle trends can help prioritize energy efficiency policies of federal and state governments and utilities. For individuals, the research raises awareness of connections between lifestyle and energy use.

INTRODUCTION

Despite substantial improvements in energy efficiency, energy demand has increased around the world in the last several decades. In the United States total residential energy use increased 39% from 1975 to 2015, with a per capita decrease of 6%.[1] Over the same period, transportation energy use increased 52%, with a per capita increase of 3%. Mitigating consumption is a critical strategy to manage the societal challenges of energy, and many argue that improving efficiency is more economically effective than changing the energy supply (e.g., Refs.[2,3])

Mitigating energy use is supported by measuring and understanding it. Lifestyle and energy demand are integrally tied.[4,5] The rapid advancement of technology combined with evolving social, economic, and demographic factors influence lifestyle choices and thereby energy demand.[4,6] Information and communication technology (ICT) is one of the most important drivers of recent changes in lifestyle.

There are two main quantitative lenses for analyzing lifestyle. One lens characterizes spending to purchase goods and services. Which products are bought is important for energy use, e.g., the size of home or efficiency of a vehicle. Many nations conduct expenditure surveys, e.g., the Consumption Expenditure Survey in the United States,[7] which track trends in consumer purchases. From an energy perspective, there is a data infrastructure measuring trends in energy efficiency of vehicles and appliances.[8–10] There is a long history of work combining expenditure data with economic input-output models to characterize environmental implications of consumption patterns.[11–13]

Another lens through which to analyze lifestyle is time use, i.e., the activities people perform, for how long, and where. Many nations conduct regular surveys of time use;[14] for example, in the United States the Bureau of Labor Statistics (BLS) has conducted the American Time Use Survey (ATUS) annually for over a decade, querying more than 11,000 Americans each year on their daily schedule. Activity choices influence energy use over multiple sectors. For example, a person retiring no longer requires an office, and is likely to travel less and spend more time at home, affecting energy use in commercial, transport, and residential sectors, respectively. The importance of time-based analysis in modeling future energy demand was first explored by Schipper et al.,[5] who demonstrated that individual energy consumption could vary by up to 15% by changing the mix of activities, especially travel.

Most prior literature on time use and energy focuses on the residential sector. The literature is divisible into three broad areas. The first area is development of bottom-up time-resolved models of residential energy demand. Activities are linked to use of particular energy-consuming devices; for example, the energy consumption of a television scales with the time spent watching it. A number of researchers have developed activity-based energy models.[15–19] Others have combined time use data with dwelling characteristics and climate data to build more comprehensive energy demand models.[20–22] For a detailed review of the literature on time use-based techniques, readers can refer to work by Torriti.[23]

The second area investigates social practices to explain the dynamics of energy demand. Walker[24] provides a theoretical overview of three forms of temporality in energy demand—change, rhythm, and synchronicity—and their associated relationship with social practices. Torriti et al.[25,26] empirically quantified temporality of various social practices to assess activity flexibility for demand response. Anderson[27] explored the time dependence of laundry.

The third area measures energy rebound from the adoption of time-saving innovations. Using an empirical approach based on the theory of the allocation of time,[28–31] Brenčič and Young[32] quantified energy rebound due to the adoption of various household appliances.

Another direction of time use work extends modeling to account for the direct and indirect energy of an activity.[33] Direct energy is energy required for performing an activity. Indirect energy is energy used in the production of the goods and services necessary for the activity. Estimating indirect energy in lifestyle analysis typically involves combining expenditure survey data with environmentally extended economic input-output (EIO) models. Druckman et al.[34] used this approach to study the carbon implications of British adults' time use for the year 2004. Another study extended this methodology by adding decomposition analysis to measure the effect of lifestyle change on energy consumption in Finnish households between the years 1987 and 2009.[35]

Our research question is to understand how changes in time use, as influenced by socio-technological trends, affect energy use via tradeoffs between different sectors. For example, adoption of ICT implies more working, shopping, and consumption of entertainment at home, suggesting less time (and presumably energy use) for travel and in non-residential buildings. Recent data suggest that such tradeoffs may be occurring and important for energy use. Notably, vehicle miles per person in the United States increased steadily from 6,200 miles in 1975 to a peak of 10,100 miles in 2008, thereafter falling slowly to a level of 9,500 miles in 2014.[36] Less time in vehicles implies more time being spent elsewhere, presumably at home. While it is not yet

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clear to what degree travel is stabilizing versus decreasing, there appears to be a new regime starting from the early 2000s that breaks the steady increase of previous decades. While the new trajectory in vehicle use is promising, it is important to understand it in a larger context. The environmental impacts of telework, e-commerce, and other digital modes have been compared with their analog counterparts taking into account rebounds.[37–43] However, there is as yet no holistic retrospective examining how lifestyle changes are leading to shifts in energy consumption within and between sectors. Our focus is on the United States partly because it is a large country with significant energy demand and also because there is a large-scale time use survey, ATUS, whose micro-data are publicly available. Many other nations also conduct time use surveys,[44] although unlike ATUS they are not conducted yearly.

To address our research question, we develop a time use model that (1) accounts for 24 hr of activities, (2) finds tradeoffs in time spent in different locations, and (3) estimates the effect of time use changes in residential, transport, and non-residential building sectors. As in prior studies, such as that of Jalas and Juntunen,[35] we use annual time use survey to characterize trends in time spent on different activities. However, we must account for all 24 hr of activities. Tradeoffs emerge from the constraint of allocating time over a fixed 24 hr. There are many activity types accounted for by the surveys (e.g., 465 in ATUS), so understanding tradeoffs between activities requires some form of aggregation. Locations where activities take place is an important determinant of energy consumption and can be simplified into three categories: home, vehicle, and commercial/public buildings. Tradeoffs between time spent in these three types of location is an indicator of the lifestyle trends of interest.

We treat residential, transport, and commercial/public buildings as aggregate sectors as measured annually in US national statistics (Energy Information Administration) and estimate changes in direct energy use. Note that this aggregate approach retreats from specificity and scope developed in some prior models that link time use, expenditures, and energy consumption. For example, Jalas and Juntunen[35] characterize direct and indirect energy use for 14 distinct activities. Our aggregate treatment of direct energy use is a consequence of treating our particular research question. We only include direct energy, as our focus is on how consumers are changing their use of energy-using products, not their purchasing patterns. We treat energy use per time used in three aggregate sectors (residential, transport, and non-residential) because while one can detail energy consumption per time done for a subset of specific activities, e.g., kWh per hour television watched, it is not feasible to do so for all activities, which we would need for a 24-hr treatment. Also, the allocation of energy to particular in-home activities, e.g., stoves for cooking, requires annual or near-annual breakdowns of consumption per appliance, which is not available in the United States. Our contribution is thus not in detail of model coverage, but in a 24-hr treatment that enables examination of tradeoffs between activities.

Having set a goal and context for the work, we next specify the flow of the study. First, time use surveys are analyzed to determine trends in how Americans are spending their time. This is done via linear regression of total time use per day for separate activities such as working, sleeping, computer use, and socializing, over the years 2003–2012, a period chose to match the availability of energy and infrastructure data. We study the total United States population and separate subpopulations. Separating and analyzing the employed population, for example, controls for time use changes driven by economic cycles. We also consider segmented age groups to check for generational differences in lifestyle trends.

The second and more challenging part of the analysis is to relate changes in time use to shifts in energy consumption. We address this with a decomposition analysis of national energy consumption in residential buildings, transport, and commercial (and public) buildings. Decomposition analysis partitions an overall change in energy use into contributions from individual factors such as population, intensity, and others. Analysts have long used decomposition analysis to study the structural changes of national-level and sector-level energy consumption.[12,45–53] We add time use as an additional descriptor to other drivers of energy use, such as population, area (of buildings), and intensity.

The model accounts for how changes in time spent in different classes of buildings and vehicles affects energy use. The model does not account for interactions not mediated by time use, in particular the additional electricity consumption of data centers induced by residential demand for the Internet. Supply chains for changes in production associated with lifestyle changes are also not included, e.g., for consumer electronics. Future models could potentially account for such factors. Later in the article, we argue that the decomposition analysis based on time use captures important aspects of changes in energy use due to lifestyle changes.

The results detailed here show that time use changed significantly in the United States from 2003 to 2012, with people spending more time at home, while driving and spending time in commercial buildings correspondingly less. The model suggests that Americans are saving energy by spending more time at home. While energy use at home increased, this was accompanied by reduced driving (the most energy-intensive activity per minute) and operating fewer commercial buildings, primarily offices and retail outlets.

RESULTS

Trends and Status in Activity Times

To understand trends in activity times, using ATUS we derive a dataset describing total time for individual activities by year and analyze this using a linear regression model for each activity. The slope reflects the rate of change in activity time; the modeled value of total hours per day for the year 2003 is the intercept. Figure 1 shows results averaging all employed Americans including both weekends and weekdays. The employed population was chosen to control for economic up- and downturns. For ease of illustration, only selected activities with statistically significant changes (>95% confidence) are shown; therefore hours per day, on the right, totals 18.1 hr (out of a 24-hr possible total), representing 75% of a day. Regression output for the complete list of activities and various demographics categories can be found in Table S1. Non-residential locations are commercial and public buildings and outdoors, the last representing a very small portion of time spent on average.

To first discuss total time use, sleep and work are (unsurprisingly) the two activities with the highest values. Total work was 5 hr/day in 2003 (4.7 hr/day at the workplace, 0.3 hr at home), differing from the usual "8 hr/day" because weekends and part-time workers are included. Television, which includes watching videos on other devices, is the most popular other activity at 2.1 hr per day.

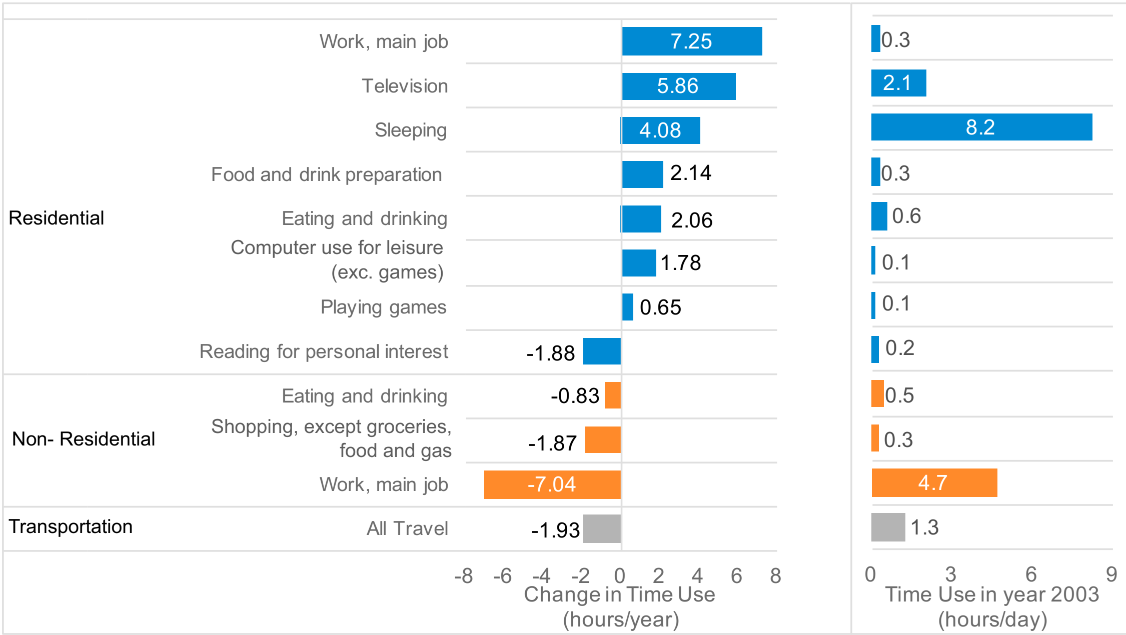

Figure 1. Annual Changes and 2003 Total Average Time Spent on Select Activities for the US Working Population from 2003 to 2012

Note that units are different for total time use (hr/day) and change in time use (hr/year). Non-residential locations are commercial and public buildings and outdoors.

To next discuss changes in time use, the results indicate considerable changes in lifestyle patterns over the decade. For example, a decrease in reading of 1.9 hr per year amounts to 19 hr less reading in 2012 compared with 2003. Considering that total reading hours/year started at 0.2 hr/day × 356 days/year = 73 hr per year, this is a 26% decrease in reading time. Most of the trends appear attributable to the adoption of ICT. Time spent on television watching and computer use increased. Time spent shopping on non-food/fuel items was 19 hr less in 2012 compared with 2003, presumably due to e-commerce. Note that this is consistent with total sales through the Internet growing more than 3-fold between the years 2005 and 2015.[54] Total work time is roughly constant, but there is a substantial shift of about 3 days from workplaces to home in 2012 versus 2003. This change is due to a combination of teleworking and more home-based work. Travel time was 0.8 days less in 2012 versus 2003. The decrease in travel time mirrors the reduction of total vehicle miles traveled per year in the United States.[55]

Trends and Status in Locations of Activities

Next, we analyze trends and state in which people spend their time (at home, in a vehicle, or in a commercial/public building) from 2003 to 2012. Location is important for energy use because increased/reduced time spent at home/in a vehicle or other building corresponds to increased/decreased energy use. As before, a regression model of total time per year yields a slope for the change in time use and intercept for modeled value in 2003. We consider both the aggregate populations and subpopulations of different work status and age. The Employed group consists of both full-time and part-time employees. Respondents not in the labor force consist of students, household members taking care of children, and others. Figure 2 shows the results.

The notable trend for all groups except >65-year-olds is a considerable increase in time spent at home, 5–33 hr per year, which corresponds to an astounding 5–14 days

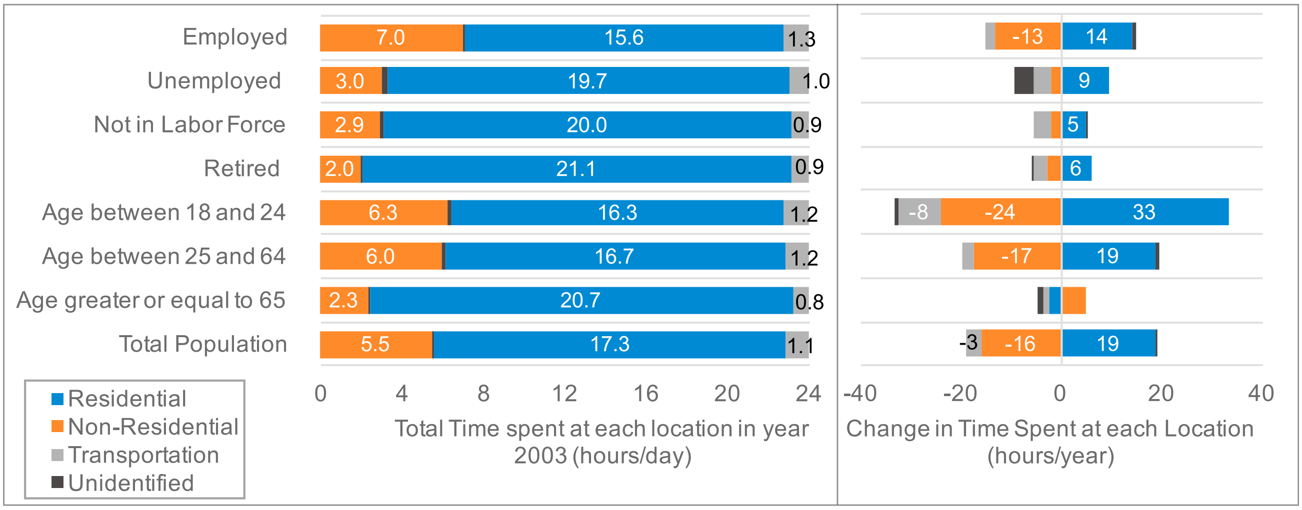

Figure 2. 2003 Total and Annual Changes in Average Time Spent by Location for Subpopulations and Total Populations in the United States, 2003–2012

"Unidentified" reflects data where survey respondents did not report locational information. Note that units are different for total time (hr/day) and change in time spent (hr/year). Non-residential locations are commercial and public buildings and outdoors.

more at home in 2012 compared with 2003. This additional time in residences comes at the expense of time spent traveling and in non-residential buildings. The population aged between 18 and 24 shows the most dramatic change, 14 additional days at home in 2012 compared with 2003, balanced by 4 days less traveling and 10 hr less time in non-residential buildings. Notably, for the population aged >65, time spent in residences decreased, with more time in non-residential buildings and traveling. This can be explained by another societal trend: more people of older age remaining in the workforce.[56] An aging society implies two relevant trends: an increased share of retired people in the population and an increased retirement age. Given a higher share of people older than 65 are participating in the workforce, this age group spends more time at work and correspondingly less time at home compared with previous years.

Lifestyle Effect on Energy Demand across Sectors

We next model shifts in energy consumption induced by time use changes using decomposition analysis. Details are discussed in Experimental Procedures, but to briefly summarize, decomposition analysis distributes a change in energy use to a number of explanatory factors, such as population, house size, and efficiency. We use national aggregate data for annual energy use in residential, transport, and non-residential sectors from 2003 to 2012.[55,57] Energy use and floor space in the non-residential building sector is taken from the Commercial Building Energy Consumption Survey (CBECS) and includes offices, retail stores, warehouses, restaurants, and public buildings such as schools.[10] The decomposition analysis allocates changes in energy use in each sector to a number of factors. For the residential sector the explanatory factors are population, house size, intensity, and time. For the non-residential sector the explanatory factors are population, building area, intensity (inverse of efficiency), and time. For the transport sector the explanatory factors are population, intensity (inverse of efficiency), and time use. National data sources are used for population and building area. Time use changes data represent the mean estimates for all Americans in Figure 2. The intensity effect is calculated as from the remainder after the other factors are estimated and can be interpreted as energy efficiency. To explore how accounting for time use changes results, the analysis was done including and not including it as

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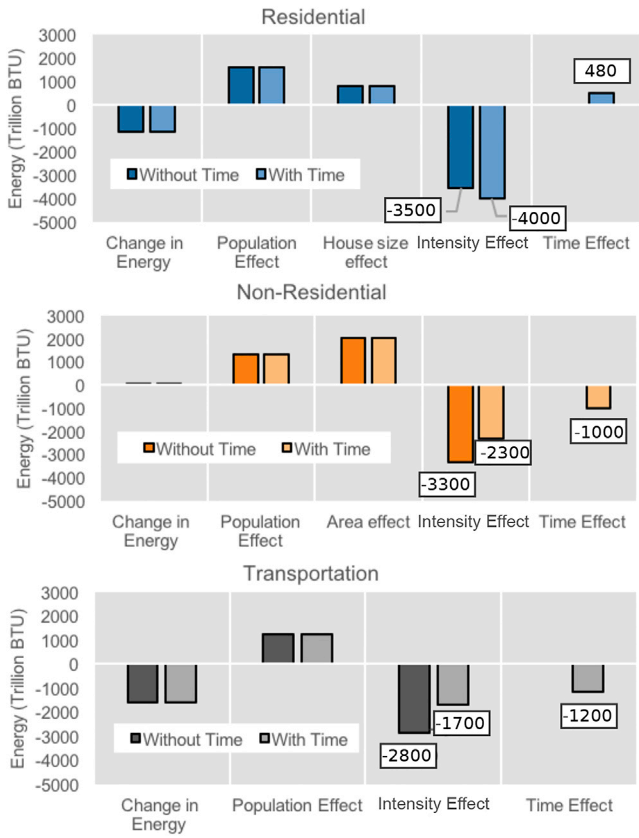

Figure 3. Decomposition of Energy Use Changes in Residential, Non-residential, and Transport Sectors Including and Not Including Time Use as Explanatory Factor

Data on energy use, population, and building area come from national sources. Time use changes data are from Figure 2 results. The intensity effect aggregates factors that are not included in the analysis including energy efficiency at home, weather, and so forth.

decomposition variable. Figure 3 shows the decomposition of the change in energy use in all the three sectors over the years 2003–2012.

Overall, energy consumption in the residential sector decreased by 1,160 trillion BTU from 2003 to 2012 (conversion factors are shown in Table 1). The decomposition expresses the 1,160 trillion BTU decrease as a sum of drivers, three increasing energy use (population, house size, time at home) and a fourth decreasing consumption (intensity or, equivalently, improved efficiency). Overall, efficiency improvements exceeded the combined effect of increased population, house area, and time at home. The increase of 7.8 hr in time spent in homes in 2012 versus 2003 translates to an increase in residential energy consumption of 480 trillion BTU.

Decomposition of drivers for the non-residential sector indicates that the reduction of time spent in non-residential buildings of 6.7 days in 2013 versus 2012 lowered energy consumption by 1,000 trillion BTU. Energy consumption in the transportation sector decreased by 1,600 trillion BTU. Higher population drove increases, more than compensated for by improved efficiency and decreased use of vehicles. Note that accounting for time effect affected the portion of energy change allocated to intensity (or efficiency); e.g., in the non-residential sector −3,300 trillion BTU without

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Table 1. Conversion Factors

1 BTU	1,055.06 J
1 kWh	3,412.14 BTU
1 BTU of delivered energy	3.14 BTU of primary energy

time use and −2,300 trillion with time use. This is relevant to future decomposition analyses of national energy trends.

Figure 4 summarizes the energy impact of respective sectors due to time use changes. The main result from the decomposition is that from 2003 to 2012 the energy change due to time effect is a net decrease of 1,700 trillion BTU in 2012, corresponding to 1.8% of national primary energy use that year. To paraphrase in colloquial terms, Americans are saving considerable energy by staying more at home.

The interpretation of net energy reduction of staying at home is that additional residential energy use is more than compensated for by reductions in transportation and non-commercial buildings. The reduction in transportation energy can be interpreted directly in terms of reduced VMT. The interpretation for non-residential buildings is complicated by different building types being aggregated into one sector. A plausible explanation is that energy use reductions in the operation of offices and retail stores exceeded the additional use of warehouses due to increased e-commerce. Verifying this is a challenge for future models, part of the larger issues of model caveats discussed in the next section.

Caveats

A full accounting of energy shifts induced by lifestyle changes is beyond the scope of the model. We first discuss the exclusion of indirect energy consumption from the model. Indirect energy use is tied to the manufacturing of goods, which in turn is driven by trends in purchases. While there are connections between the purchase and use of goods (e.g., more use of ICT goods relates to higher purchases), we suggest that the effects of purchase and use can reasonably be assessed separately. This said, accounting for both purchase and use of goods is a worthwhile goal and could be addressed following prior work combining expenditure survey and environmental economic input analysis.[33] In the United States, such an analysis would need to address the limitation that detailed benchmark EIO tables are only available for 1992, 1997, 2002, and 2007.

In assessing direct energy use, it is important to discuss the assumption that the current decomposition analysis framework relates time spent in an aggregated sector to energy consumption in that sector. For transportation, this relationship is straightforward as energy and time spent driving correlate closely. While there is a correlation between energy use and time spent in residential and non-residential sectors, the relationship is more complex. The energy use of appliances that are turned on and off based on home activities connect to time spent in residences, but the relationship between occupancy and heating and cooling energy use depends on the operation of thermostats. The commercial sector is diverse and has more complicated connections with lifestyles, but time spent in offices and retail stores reasonably connects to energy use.

Is it important to consider the cross-sector interaction of induced energy use in servers and networks due to more time spent at home using ICT. Estimates put the United States energy consumption of servers at 40 TWh in 2003 and 65 TWh

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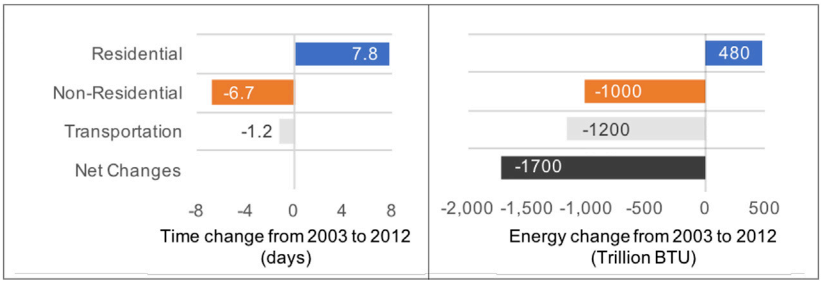

Figure 4. Changes in Time Spent in Locations for US Households (Total Population) and Effect on Energy Consumption in Different Sectors, 2003–2012

The net change is negative, −1,700 trillion BTU in 2012, due to savings in transportation and non-residential buildings exceeding the residential increase.

in 2012.[58] This corresponds to 410 and 665 trillion BTU, respectively. The growth in server energy use is thus 15% of the 1,700 trillion BTU of the time use-induced energy change from Figure 4. It is thus expected that inclusion of network operation induced by consumers would shift, but not dominate, energy changes induced by ICT lifestyles.

Here, energy change is modeled as a function of changes in population, area, energy intensity, and time. Note that energy intensity aggregates factors that are not included in the analysis, including energy efficiency at home, weather, and energy efficiency of energy generation. Expanding the model to include the contribution of these additional factors will not change the magnitude of time use factor. Since the objective of the paper is to understand the effect of time, an additional breakdown is left for future work.

Two limitations of the ATUS data are worth mentioning. First, ATUS does not record secondary activities, i.e., a person cooking and watching television reports only one activity during the survey.[59,60] This does not affect our main analysis, which is based on the location where an activity takes place, and location cannot be multi-tasked. Second, ATUS samples a population aged 15 years and older; however, we assume these time use changes as a measure for the entire population.

While there are model refinements and additions that could address the issues addressed above, we argue that our attempt here is a reasonable first-order estimate of the effect of time use tradeoffs on energy use across different sectors.

DISCUSSION

The results indicate rapid and substantial changes with regard to where Americans spend their time: almost 8 more days spent at home in 2012 compared with 2003. We postulate that use of ICT largely drives this change. Because lifestyle choices ultimately lead to decisions on allocating time in a fixed 24-hr day, any change in one direction necessarily induces changes elsewhere.

These shifts in time use in lifestyle plausibly induce interdependent changes in the energy consumption in multiple sectors. Our model, subject to the caveats above, suggests that Americans are saving energy by spending more time at home because the additional energy use at home is more than compensated for by savings in transport and non-commercial buildings.

Will these historical time and energy use trends continue into the future and for how long? We do not attempt forecasting in this work but offer a few thoughts on the question. Ownership of technologies saturates over time. Some equivalent endpoint for lifestyle changes induced by ICT could exist, but continuing improvements make crystallization of this saturation point difficult. There is also a question of co-evolution of ICT and energy infrastructures.[61] Up to today, progress for ICT has been far more rapid than the evolution of energy infrastructure. Infrastructure changes have lagged greatly. Changes are in progress, however; for example, the increasing ownership and use of smart thermostats are expected to increase the elasticity of energy consumption with time spent at home.

The apprehension of trends in energy demand should endeavor to capture interactions between lifestyle changes and use of energy technologies. Our results show non-trivial differences in shifts in energy use when including time use, so it can thus play an important role in future models. Especially with the advent of autonomous vehicles and increased access to a shared mode of travel activity, time use patterns can be expected to shift profoundly. A time use-based analysis would improve forecasts of energy demand.

What do our results imply for energy policy? One issue is shifting priorities for energy efficiency policies. The EPA Café standards for automobile efficiency are arguably the centerpiece of efficiency improvement efforts by the federal government. If, however, trends toward decreased vehicle use continue, compounded by car sharing, this reduces the energy savings according to improved vehicle efficiency. While spending time at home is, per minute, much less energy intensive than driving, people use an increasing portfolio of energy-consuming ICT devices to enhance their time at home.[62] Given these trends, additional emphasis on improving the efficiency of consumer electronics and home appliances might be warranted.

A second potential policy implication is the role time use could play in personalized plans for energy efficiency. Home energy audits, for example, account for a particular home's major appliances such as furnace or insulation but do not consider how the residents' lifestyle choices affect energy use and the effectiveness of different technology interventions. We have shown in prior work that, at least for televisions, heterogeneity in time use leads to large heterogeneity in energy consumption.[63] Accounting for behavioral heterogeneities, including time use, has potential to reveal a different set of benefit-cost profiles for energy interventions.

What are the gaps in measuring time use for energy management purposes and how might they be addressed? The results suggest that two megatrends, digital and aging society, play major roles in activity shifts. While the ATUS includes some questions on ICT-related activities, detailed information may not be available. For example, ATUS does not classify various activities performed when using a computer for leisure. Furthermore, as discussed in the caveats, ATUS does not record secondary activities. Therefore, future ATUS could include time use categories that provide improved information on ICT-related activities. The importance of the digital society for economic and social issues provides additional motivation for an increased focus on ICT-related activities. While surveys are the traditional tool to measure time use, ICTs present an opportunity for personalized and real-time measurement.[64] While adoption to date has emphasized personal health applications (e.g., FitBit), there are many untapped opportunities in the energy domain.

EXPERIMENTAL PROCEDURES

Summary

Time use trends are summarized for all Americans and subpopulations based on employment characteristics and age. We use a linear regression model to quantify changes in time use over 2003–2012. The average total time use for a given subpopulation (e.g., working Americans) is calculated for each year, and the value of the slope from the regression gives the range of increase or decrease in the total activity time. Observed energy trends between 2003 and 2012 are decomposed into time use and non-time use factors using a technique called Log Mean Divisia Index Method I (LMDI-I).[65] The non-time use factors include population trends, changes in building area, and energy intensity trends. The contribution of the factors to total energy use trends are compared within and across three sectors, namely residential, non-residential, and transportation. The sectors are defined based on activity location.

Data: American Time Use Survey

The ATUS informs how people allocate their time during a 24-hr day. ATUS is an annual survey conducted by the BLS since 2003. Respondents for the survey are 15 years and older. Annual participation in the survey exceeds 11,000 respondents each year. Only one household member is sampled per household. The survey is conducted using computer-assisted telephone interviewing whereby the participants respond on how they spent their time during the previous day, the location of their activity, and information about people they were with when performing the activity. Conducting the survey via a conversational interviewing style mediated by an expert is assumed to improve reporting accuracy. In addition to the activity information, ATUS also collects respondents' household level socio-economic data such as age, income, sex, race, marital status, education level, employment status, and many others. The ATUS web site provides more information about the survey.[66]

Information about activity location in ATUS enables categorization of activities into sectors (residential, non-residential, and transportation), enabling a sector-level analysis. Activities categorized as *Residential* include activities performed at the respondent's or someone else's home. Personal care activities such as sleeping and grooming oneself, which did not contain location data due to privacy concerns, were also categorized as *residential*. The *non-residential* sector comprises all activities performed in a commercial space such as the workplace, school, malls and grocery stores, and other outdoor spaces. The *transportation* sector includes travel in a personal vehicle (car, motorcycle, or truck) as a driver or passenger. Other travel modes such as walking, cycling, and public transportation were not included in this sector because our goal is to link automobile time use to energy use. The category *other* includes various travel modes not covered in the *transportation* sector, and activities for which location information was ambiguous and not specified.

Data for Decomposition Analysis: Energy and Floor Space

Data on population, area, and primary energy demand in each sector are obtained from public sources. The Energy Information Administration (EIA) provides data on primary energy consumption and building area for residential and non-residential sectors.[57] We use commercial sector energy consumption as the proxy for the non-residential sector. Note that despite its name, the commercial sector as defined by EIA includes public buildings such as schools. For the transportation sector, we use data from the Bureau of Transportation Statistics (BTS) on energy

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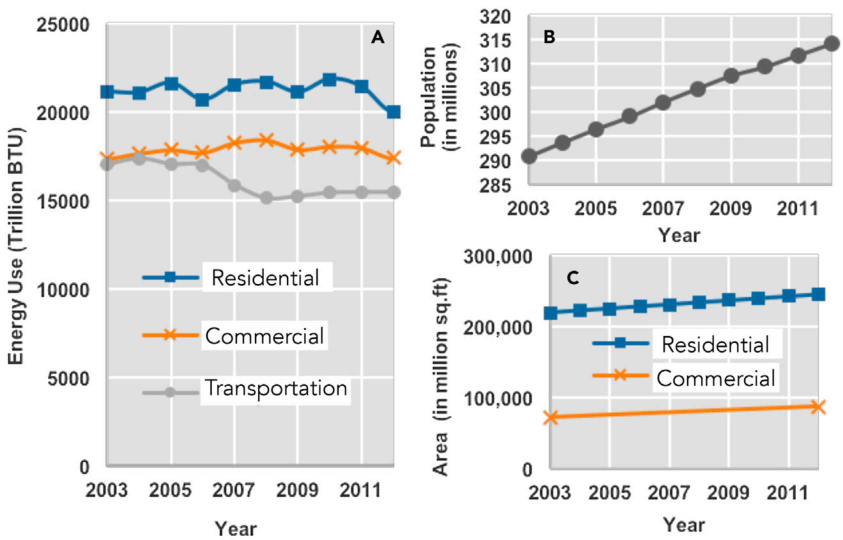

Figure 5. Input Data for the Decomposition Analysis, 2003–2012

(A) Sector-by-sector primary energy consumption.

(B) United States population.

(C) Occupied building areas in residential and commercial sectors.

Data sources: Bureau of Transportation Statistics,[55] Energy Information Administration,[57] US Census Bureau.[67]

consumption of personal vehicles, the "Light duty vehicles" category in their reports.[55] The Census Bureau provides population statistics.[67] Figures 5A–5C summarize data trends between the years 2003 and 2012. While ATUS data are available until 2015, due to unavailability of energy and floor space data in the commercial sector post 2012, we limit our study to between the years 2003 and 2012.

Decomposition Analysis

Decomposition analysis attributes changes in an aggregate indicator, e.g., energy demand, to contributions of underlying factors. For example, a decomposition of residential sector energy consumption may involve capturing three effects, namely activity, structure, and intensity effects. The activity effect captures the change in population in the household sector. The structure effect captures the change in the mix of activities within the sector by floor area per population, and the intensity effect captures the energy use per floor area. Decomposition analysis finds its basis in the index number theory that is used to study price and quantify effects on total consumption of goods.[68] It has been widely used in many fields including, but not limited to, energy, logistics, and emissions at various levels including sector, country, and global levels.[47,48,51,69–77]

There are many methods for decomposition, although all such methods can be classified into one of two techniques: the Laspeyres index and the Divisia index.[78] In Laspeyres index-based methods, the contribution of any factor to the change in an aggregate indicator is quantified by letting the factor in question change while holding all other factors constant. In other words, a factor's effect is calculated as a function of the factor's percentage change. For Divisia index-based methods, a factor's contribution is measured as a function of the factor's logarithmic change. Also, depending on how changes in aggregate indicators are measured, decomposition methods can be classified into additive or multiplicative decomposition. Additive techniques support decomposing the change measured as a difference. Multiplicative decomposition is used when change is measured as a ratio. Given n factors, the mathematical representation of an additive decomposition is shown in Equation 1.

$$\Delta E = E^{t_2} - E^{t_1} = \Delta V_1 + \Delta V_2 \ldots, \ \Delta V_n + V_{rsd} \qquad \text{(Equation 1)}$$

where ΔE is the change in aggregate indicator measured as the difference between two time periods t_1 and t_2. $\Delta V_1, \ \Delta V_2 \ldots, \ \Delta V_n$ are the underlying n factors changes and V_{rsd} is the residual. In the case of Divisia-based methods, factor effects are quantified using the formula $\Delta V_n = \sum_{i=1,2\ldots n} w_n \times \ln(V_n^t / V_n^0)$, where w_n is a weighting function that varies depending on the approach used.

In this paper, the LMDI-I, an additive decomposition technique, is used.[65] The basic form of LMDI-I is similar to Equation 1 explained above. The weighting used in this method is the logarithmic mean of the change in the aggregate indicator (E). Researchers recommend LMDI-I for general use because of its theoretical soundness, ease of use, and adaptability.[71,78] LMDI-I has the virtue of leaving no residuals, easing interpretation of factor effects. Furthermore, a direct and simple association exists between additive and multiplicative forms of the LMDI-I method. Therefore, researchers who conduct a meta-analysis and other review studies can easily translate additive forms to multiplicative or vice versa. Decision makers have widely used this method in various capacities. Ang et al.[79] report that LMDI techniques were used by government organizations from many countries including the United States, Canada, New Zealand, and Australia. Recently international organizations such as the International Energy Agency (IEA) have also adopted this technique.[53]

For residential and non-residential buildings, we decompose sector-wise energy changes into four factors: population, area, intensity, and time. For the transportation sector, we decompose energy changes into population, intensity, and time. The population is measured as the number of persons in national total. Time is the number of minutes spent in a given sector (residential, transportation, and non-residential). The area in residential and non-residential sectors is the total building area per capita. The intensity effect captures all the other changes not modeled explicitly for each sector, and the primary contributor to intensity is presumably efficiency upgrades. The intensity effect is measured as energy per unit area per time. Equations 2 and 3 capture our modeling framework.

$$\Delta E_k = \text{Population effect} + \text{Area effect} + \text{Intensity effect} + \text{Time effect} \qquad \text{(Equation 2)}$$

$$\Delta E_k^{\text{time use}} = \frac{\left(E_k^{t_2} - E_k^{t_1}\right)}{\ln\left(\dfrac{E_k^{t_2}}{E_k^{t_1}}\right)} \left[\ln\left(\frac{P^{t_2}}{P^{t_1}}\right) + \ln\left(\frac{\left(\dfrac{A_k}{P}\right)^{t_2}}{\left(\dfrac{A_k}{P}\right)^{t_1}}\right) + \ln\left(\frac{\left(\dfrac{E_k}{A_k \times T_k}\right)^{t_2}}{\left(\dfrac{E_k}{A_k \times T_k}\right)^{t_1}}\right) + \ln\left(\frac{T_k^{t_2}}{T_k^{t_1}}\right) \right], \qquad \text{(Equation 3)}$$

where ΔE_k is the change in energy consumption in each sector k, over the years 2003 (t_1) and 2012 (t_2). P is the United States national population and does not vary by sector, T is time spent in each sector, and A is the area of building space for residential and commercial sectors. In the transportation sector, time use in vehicles scales with vehicle miles traveled.

It is important to understand if accounting for time use gives qualitatively different results from prior studies that did not account for it. Therefore, two decomposition analyses are conducted for each sector with and without time use effect. In the case of decomposition without time effect, the intensity effects also comprise time use changes. The importance of time use is determined by comparing the intensity effect between the two versions.

SUPPLEMENTAL INFORMATION

Supplemental Information includes one table and can be found with this article online at https://doi.org/10.1016/j.joule.2018.01.003.

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AUTHOR CONTRIBUTIONS

A.S. conducted the work and contributed to the writing of the article. E.W. provided intellectual guidance in design and direction of the work and also contributed to writing the article. R.C. provided intellectual guidance in research design.

DECLARATION OF INTEREST

The authors declare no competing interests.

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