In Transit: Exploring Interactive Effects of Public Transportation on the Gender Leisure Gap

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ABSTRACT

There is a persistent gender commuting and gender leisure gap in the United States, with women making shorter commutes yet still having fewer minutes of daily leisure. Both lines of research point to a time crunch faced by women; however, the constructs have not been unified under the same analytical framework. This thesis investigates novel interactions between commuting, household support trips, public transportation, and leisure. Because a survey that collects both time-use diaries and detailed travel information does not exist, leisure values are imputed from pooled waves of the American Time Use Survey (ATUS) ranging from years 2015 to 2019 into the 2017 National Highway Transportation Survey (NHTS). This analysis targets full-time workers who are married or cohabiting. Results suggest that for each additional minute dedicated to either commuting or household support travel, leisure is reduced by roughly 45 seconds and 39 seconds, respectively. Women have 46 fewer minutes of leisure relative to men, even after controlling for differences in mobility and the presence of children. Otherwise, no statistically significant gender or racial effects were uncovered. Furthermore, even though commutes using public transportation take twice as long compared to private automobiles, leisure time did not differ between public transportation riders and private automobile drivers.

TABLE OF CONTENTS

LIST OF FIGURES

INTRODUCTION

In the United States, a persistent gender commuting gap exists–women commute shorter distances to work compared to men. These shorter commutes are considered deleterious for women because they represent limited economic mobility. Women tend to commute shorter distances to low-paying jobs, while men make longer commutes to higher-paying positions. Some theories explaining women's shorter commutes focus on occupational segregation: jobs in the "pink sector" offer relatively constant wages between different firms, hospitals, and schools within a commutable range and are more evenly distributed geographically. Lastly, the Household Responsibility Hypothesis (HRH) suggests that mothers are compelled to seek jobs closer to home due to the time constraints underpinned by an unequal sharing of household responsibilities, such as childcare.

The Great Generalization of women's mobility states that women make shorter commutes but perform more household support trips. Household support trips include trips to the grocery store, running household errands, or dropping children off at school. The great generalization presents a contradiction: although women commute shorter distances to work, they perform more household support trips and travel more miles overall compared to men.

The HRH points to a time crunch but lacks the tools to measure it. Time constraints and unequal sharing of household responsibilities squarely fall within the domain of leisure poverty research. Similar to income poverty, leisure poverty identifies individuals who do not have enough leisure to flourish as humans. Likewise, similar to the gender commuting gap, a persevering gender leisure gap also exists, with women having less leisure time relative to men.

Racial differences in mobility are also paramount. Throughout highway development in the United States, infrastructure projects intentionally routed highways through Black and Hispanic communities or along historic racial segregation boundaries, creating physical barriers to mobility in minority communities that persist to this day. Furthermore, theories explaining the gender commuting gap may not be relevant for minority communities, as Black and Hispanic individuals typically make long commutes to low-paying jobs. Additionally, minority communities are often underserved by public transportation.

Unequal access to public transportation is also a driver of mobility inequality. Generally, neighborhoods well served by public transportation have higher housing costs, and low-income families are forced to choose between lower-cost housing in the suburbs and spending more on transportation or allocating more financial resources towards housing and using public transportation. Furthermore, on average, public transportation commutes take twice as long as private automobiles. Therefore, minority mothers who use public transportation face the time crunch associated with motherhood along with long commutes to low-paying jobs. Black women endure the longest commutes overall and also confront the widest wage gap compared to white men.

Existing research primarily focuses on the interactions between gender and commuting, gender and household support travel, gender and leisure disparities, or race and commuting. However, each line of research is interconnected, not only with disparities in mobility and leisure but also with inequality in the labor market, particularly gender and racial wage gaps. Therefore, this thesis aims to unite these lines of research under a single analytical framework. For example, it is uncertain how long commutes impact leisure and whether the public transportation commuting time penalty directly translates into a leisure time penalty.

To accomplish this task, I impute leisure values from the American Time Use Survey (ATUS) into the National Household Survey (NHTS) and construct the following three hypotheses:

1. I expect public transportation riders will also face leisure deficits compared to individuals who drive private automobiles because public transportation commutes take twice as long as private automobile commutes. Furthermore, because I am focusing on full-time workers, I believe this group will be unable to compensate for the public transportation time penalty.
2. I predict women will have less leisure time relative to men after controlling for commuting, household support travel, and the usage of public transportation.

Furthermore, I expect heightened leisure deficits for full-time working mothers with young children who ride public transportation, as this subgroup faces the greatest time crunch overall and, therefore, should have the least ability to compensate for the public transportation time penalty.

3. I anticipate an additional leisure penalty for Black individuals who use public transportation, given their longer commute durations, mobility barriers, and discrimination in the labor market.

LITERATURE REVIEW

The Gender Commuting Gap

There is a gender commuting gap: on average, women's commutes are shorter, measured in both distance and time, compared to men (Pratt 1911; Hansson and Pratt 1990; Crane 2007; Kwan and Akar 2022). Unlike a wage gap, a commuting gap, as a measure of gender inequality, is not straightforward; commutes have both beneficial and deleterious attributes. Typically, commutes are viewed as an unpaid part of the workday and should be minimized.

Not only are long commutes unpaid labor, but they are also associated with higher levels of stress and fatigue, especially when combined with childcare responsibilities (Gimenez-Nadal and Molina 2019). Extremely long commutes, over 50 miles to work–100 miles round trip–represent a consistent and recurring stressful event, which for pregnant women, has been shown to greatly increase the risk of having low birth weight babies (Wang and Yang 2019). Additionally, environmental considerations are relevant, as longer commutes use more resources and emit more greenhouse gasses (Hanson 2010).

On the contrary, long commutes have one core benefit: long commutes represent increased mobility and greater access to higher-paying jobs in diverse occupations and careers. Therefore, women's shorter commutes represent less access to economic opportunities compared to men.

The finding that women make shorter commutes is strikingly persistent. A gender commuting gap was first noted during a 1907 investigation into the causes of traffic congestion in New York City (Pratt 1911). However, gender commuting differences, as a research question, mostly laid dormant in the US until Rosenbloom's call to action in 1978, which coincided with dual-earner households overtaking male-breadwinner as the most common household income structure (Rosenbloom 1978; Ruggles 2015).

In the fifty years following World War II, the percentage of women in the workforce nearly doubled, increasing from 31.1 percent in 1950 to a near-peak of 57.6 percent in 2000. After this tremendous gain, the percentage of women in the workforce has remained stable over the past twenty years. In 2023, 55.1 percent of women were in the workforce (U.S. Bureau of Labor Statistics 2023). From 1950 to 2000, the change in the gender composition of the workforce increased women's income and catalyzed a shift in the income and family structures of US households.

In the 1950s, most households had male-breadwinner income structures, where the male's income comprised the majority of the household income. By the 1980s, dual-earner households overtook male-breadwinners as the most common income structure. Dual-earner indicates that both the husband and the wife contribute to total household income. In 2010, most married couples, with or without children, were dual-earners (Ruggles 2015).

Unlike male-breadwinner households, where only the husband makes a commute to work, in dual-earner households, both spouses commute to work. Rosenbloom (1978) points out that this change in household income structure has infrastructure planning implications and asks whether higher-income, dual-earner households will continue to prefer single-family homes in the suburbs and long commutes to work or if they will opt for dense, urban neighborhoods with mixed land uses, shorter commutes, and more mobility options including walking, biking, and public transportation. Additionally, Rosenbloom (1978) questions if dual-earners will attempt to balance commute durations between partners or if one spouse will make a long commute while the other makes a short commute.

Taking up Rosenblooms's call to action, Hanson and Johnston (1985) compared one-way commute times between men and women using the 1977 Baltimore Travel Demand Dataset–a home interview survey of 787 workers in the Baltimore metro area with the unique attribute that home and work address were recorded along with sociodemographic characteristics including income. These data allowed Hanson and Johnston to uncover a gender-commuting gap–men commuted 28.8 minutes while women commuted 25.7 minutes–and they also explored why women's commutes are shorter.

Hanson and Johnston state that women make shorter commutes because of their lower income levels, explaining that both low-income men and women make statistically shorter commutes. However, women are concentrated in low-wage occupations–73 percent of women held a low-wage job compared to 34.9 percent of men–so occupational segregation is driving the gender commuting gap. Furthermore, within occupations, gender commuting gaps are negligible, as only male professionals and managers travel significantly further than female professionals. Two surprising findings from Hanson and Johnston (1985) are as follows: part-time and full-time workers commute similar lengths, and the presence of children or a spouse does not impact commute time or distance. These results run counter to "folklore" that mothers with young children work closer to home due to their increased childcare responsibilities and the prevalence of part-time employment among women.

Because Hanson and Johnston had access to survey participants' home and work addresses, they could also evaluate if predominantly female occupations are more evenly distributed in geographical space across the Baltimore metropolitan area. Hanson and Johnston compared a female-dominated occupation, administrative support, which is 75 percent female, to a male-dominated occupation, manufacturing, which is 71.5 percent male. After mapping each home and work location, the authors concluded that administrative support jobs are more uniformly distributed across the Baltimore metro area relative to manufacturing work locations. This finding supports the notion that administrative support roles are, on average, more convenient because they are located closer to women's homes.

Hanson and Johnston also considered transportation modes men and women use to commute to work. Female workers tended to rely more frequently on public transportation, resulting in shorter commute distances but longer commute times. Furthermore, additional support for the existence of a gender commuting gap is provided by Hanson and Pratt (1988). They also used a local transportation survey, which was collected in Worcester, Massachusetts. This analysis also found that women working full-time, on average, made significantly shorter commutes relative to men. However, one-way commute times for full-time workers were markedly lower–16.5 minutes for women and 20.5 minutes for men–compared to commuters in Baltimore.

Crane (2007), citing the need to examine the gender commuting gap over several time periods and the benefits of a sample representative of the entire US population, shows that the gender commuting gap is persistent through time using the American Housing Survey from 1985 to 2005. In each sample year–1985, 1995, and 2005–significant differences were found, measured in both minutes and miles, between the average commutes of men and women. In 2005, on average, men commuted 23.5 minutes (14.1 miles) and women only commuted 21.1 minutes (11.8 miles).

Additionally, Crane (2007) observes that average commutes, measured in both miles and minutes, increased throughout the twenty years for both genders. However, the commute distances and durations for women with children grew at a rate three times faster than those of their husbands, although the absolute difference remains great. Lastly, by 2005, women no longer relied on public transportation at a higher proportion compared to men, as public transit ridership dwindled nationally for both genders.

Recently, Kwan and Akar (2022), in their analysis of the National Household Transportation Survey, found that for married couples where both partners work full-time, the gender commuting gap persevered from 2001 through 2017. Married couples where both partners work full time are of particular interest because both partners balance the obligations of paid work and household responsibilities. Furthermore, partners are forced to negotiate residential locations and the corresponding commuting tradeoffs. As Sultana (2005) notes, dual-earner couples are assumed to be the household structure with the longest commutes due to having to meet the needs of both partners.

In 2017, on average, dual-earning men who worked full-time commuted 15.6 miles to work, compared to dual-earning, full-time working women who only commuted 12.9 miles. Exploring the determinants of the gender commuting gap, Kwan and Akar found that the presence of a child between the ages of 6 and 15 decreased commute distances for women but not for men. Lastly, when both partners ride public transit or take an active mode of transportation like walking or biking to work–the gender commuting gap vanishes.

Commutes occur in the built environment through geographical space, from a home to a work location. In the US, the majority of the population, 52 percent, live in the suburbs (AHS 2017). Suburbanization of US cities is not a new trend. In 1980, 40.1 percent of commutes began and ended in the suburbs. Meanwhile, what is typically considered prototypical commutes–commutes that begin in the suburbs and end in the central city–only accounted for 20.1 percent of all commutes (Pisarski 1987).

Between 1990 and 2000, the share of commutes that began and ended in the suburbs grew by 64 percent. Meanwhile, suburb-to-city center commutes (prototypical commutes) only grew by 14 percent. Commutes that both began and ended within the city center grew by just 3 percent, and city center-to-suburb commutes (reverse commutes) grew by 19 percent (Pisarski 2007). City center-to-suburb commutes, typically called reverse commutes, accounted for 15.4 percent of all commuting journeys in Boston in 2019. Historically, in Detroit, reverse commutes were so frequent that the city's population would drop during the workday (U.S. Census 2000). In general, as cities decentralized, commutes got longer, and commuting patterns increased in complexity.

The mode of transportation used for commuting is another important factor. In the United States, the majority of workers rely on private automobiles, with 76.4 percent driving alone to work in 2017. Additionally, 8.9 percent carpooled, while only 5 percent used public transportation. Walking was the mode of choice for 2.5 percent of Americans, and bicycling accounted for just half a percent of commutes (U.S. Census 2017). Clearly, the private automobile is the primary means of commuting for most Americans.

A connection between suburbanization and the gender commuting gap is that in the 1950s, during the planning and drafting of the US highway network, which culminated with the passage of the 1956 Federal Highway Act, most women were not in the paid workforce, and the majority of households had male breadwinner income structures (Ruggles 2015). Therefore, most households faced only one commute–the man commuting to work–when the nation's highways were developed.

A striking example is Interstate Highway 5, one of the United States' great mega highways paralleling the west coast, connecting Mexico to Canada, and crossing California, Oregon, and Washington (Engellenner 1979). Construction began in 1956 when the majority of households followed the male breadwinner model. By the time the highway was completed in 1979, dual-earner households (dual-commuter households) were on the cusp of becoming the most common household income structure (Ruggles 2015).

Suburbanization and highway development also had negative impacts on black communities, with highway projects intentionally routed through thriving black neighborhoods, displacing residents and businesses and creating physical barriers, which in the South were often built along historical segregation boundaries. For black communities, instead of enhancing mobility, highways served as physical barriers that impeded mobility throughout their neighborhoods (Karas 2015).

With the majority of the middle-class population living in the suburbs, retail and service jobs also moved from the central city to the suburbs; these dynamics left many black workers with long commutes to low-paying jobs. Although, on average, women have shorter commutes–black women have the longest commutes overall, followed by black men (Crane 2007). The mismatch between black workers living in the central city and making long commutes to low-paying jobs is often described by the spatial mismatch hypothesis, which states that long commutes result from racial inequality (Kain 2004).

Feminist geographers argue that the built environment reflects the society that built it (Kern 2021). Not only was the male-breadwinner the dominant household income structure from roughly 1950 to 1980, leaving most women out of the paid workforce but also, women could not legally take out private bank loans until 1974 (Rose 2023). Furthermore, racial segregation was legal in the US until 1964 (Act 1964). Together, these facts provide evidence that it was an outwardly sexist and racist society that shifted to the suburbs and made significant investments in highways. Therefore, it should be no surprise that women and black workers face commuting inequality–commuting long distances to low-paying jobs–as the built environment was not designed to achieve equitable mobility outcomes.

Aside from the feminist geography perspective, three primary mechanisms have been proposed to explain women's shorter commutes: the first mechanism is that women's lower wages do not justify long commutes (Madden 1981); the second mechanism is that jobs in the pink sector–nursing, teaching, and administrative support–are distributed more evenly in geographical space making pink sector jobs geographically closer to women's homes relative to other occupations (MacDonald 1999); and the third mechanism is the household responsibility hypothesis (HRH), which states that women, as the primary caregivers, are required to have shorter commute times due to their increased childcare and household duties. Therefore, women must select jobs closer to home to balance dual roles as employees and caregivers (Gimenez‐Nadal Molina 2016).

The mechanisms outlined above are all interrelated. Madden (1981) uses a utility maximization framework to examine the gender commuting gap, stating that optimal household work trip distances are a function of wages, housing prices, and socioeconomic characteristics. Therefore, higher wages and lower housing prices result in longer commutes. Furthermore, men and women work in different occupations, and the careers that primarily employ women–nursing, teaching, and administrative support, known as the "pink sectors"–offer a relatively constant wage rate between competing firms, schools, and hospitals, compared to occupations that primarily employ men. Consequently, women do not receive higher returns for longer commutes. On the contrary, highly skilled men have job opportunities that are far away from their homes but that are markedly more lucrative than competing offers in their local neighborhoods. This implies that men have job opportunities justifying long commutes, whereas similar prestigious job opportunities do not typically exist for most working women.

Madden (1981) implicates gender wage differentials as driving the gender commuting gap. However, Madden does not address factors driving the gender wage gap. As women surged into the labor force in the 1980s, a gender pay gap--women being paid less than men for equal work--became evident. Blau and Kahn (2017) explore changes in the gender wage gap over 40 years, from 1981 to 2011. In 1981, on average, women who worked full-time in non-farm occupations were paid 60 cents on the dollar relative to men. The wage gap has shrunk over time, with most of the convergence occurring in the 1980s. However, in 2011, women still earned only 80 cents on the dollar compared to men. Additionally, wage convergence has been slower at the very top of the wage distribution, a phenomenon often referred to as the “glass ceiling.” According to Madden (1981), it is these top-tier jobs that also justify long commute durations.

Historically, measurable factors contributing to the gender pay gap were differences in education, job tenure, and occupation. In 1981, women were less educated than men; but as of 2011, women, on average, have become more educated than men. For job tenure, in 1981, women, on average, had 7 fewer years of job experience. By 2011, the experience gap shrunk to 1.4 years (Blau and Kahn 2017). Lastly, the measurable factor that has not changed significantly since 1981 is the gender segregation of occupations–the pink sector still primarily employs women. In 2021, 88.9 percent of registered nurses were women, 80.5 percent of elementary school and middle school teachers were women, and roughly 97 percent of administrative support positions were held by women (BLS 2023).

Regression modeling using income data from 2010 shows that differences in occupation account for 32.9 percent of the gender wage gap, while differences in industry explain 7.6 percent. Additionally, 14.1 percent of the gender wage gap is explained by differences in job experience. Educational attainment, which now favors women, reduces the wage gap by -5.9 percent. Lastly, even though combined occupation and industry explain 40.5 percent of the gender wage gap, 38 percent of the wage gap remains unexplained. This indicates that a significant portion of the variation in wages is not accounted for by variables in the model, suggesting that excluded and difficult-to-measure factors, such as gender discrimination, may also strongly influence the gender wage gap (Blau and Kahn 2017).

Working women also experience a motherhood penalty in the job market. An inverse relationship exists between the number of children and a mother's wages–the more children mothers have, the less they get paid. Part of the reason for the reduction in mothers' pay is thought to be that since mothers may have to take time away from work to give birth and raise young children, firms view mothers as risky investments because they will require lengthy periods of paid time-off (maternity leave) and be less dedicated to their jobs. Furthermore, firms are also thought to believe that mothers prioritize their home responsibilities over work productivity (Blau and Kahn 2017).

Both laboratory and audit studies show that mothers are discriminated against in the job market. Participants in a controlled laboratory experiment penalized the resumes of mothers relative to fathers by decreasing the starting salary of mothers but increasing the starting salary of fathers. Audit studies also show that actual employers, outside of the laboratory, discriminate against women too. After submitting identical resumes, the only difference being an applicant's status as a mother or father, Correll, Benard, and Paik (2007) found that firms preferred to hire fathers over mothers.

In addition to the gender pay gap, there is also a racial pay gap. But unlike the gender pay gap, the racial pay gap has not decreased since 1979, when a black worker earned 80 cents on the dollar compared to what a white man earned. In 2016, black male workers only earned 70 cents on the dollar compared to white male workers. Similar to the gender wage gap, these differences are not accounted for by differences in age or experience but are primarily a function of unmeasured factors, such as racial discrimination, school quality, or access to jobs. Additionally, black workers are more likely to work part-time despite wanting to work more hours (Daly, Hobijn, and Pedtke 2017).

Black women are confronted with both racial and gender discrimination. There is a gender wage gap between men and women, and there is a racial wage gap between white men and workers of different ethnicities. Therefore, black women experience a double wage gap in the labor market–both gender and racial discrimination. In 2017, African American women made 63 cents on the dollar compared to white men working in the same occupation with similar levels of education (Holder 2020).

Both Madden's (1981) analysis of the gender commuting gap and recent research on the gender wage gap indicate that the gender segregation of occupations is an important factor. However, Madden does not account for gender discrimination. Given that a large portion of the gender wage gap remains unexplained and that resume studies point towards gender discrimination, while education and job tenure now have a limited role in explaining the wage gap, it is likely that gender and racial discrimination have a meaningful impact in determining wages and, therefore, commute durations.

Although occupation is an important factor in explaining wages, neither line of research sheds light on why women continue to choose careers in the pink sectors. Additionally, the most discriminated group, black women, have the longest commutes overall–often commuting long distances to low-paying jobs, which contradicts Madden's framework (Johnston-Anumonwo 2000).

The second mechanism proposed for women's shorter commutes is that jobs in the pink sector are better distributed in geographical space relative to male-dominated occupations like manufacturing, construction, or higher-level management roles, which are typically located in the central city. Given that the majority of the US population lives in the suburbs, an even distribution in geographical space indicates that jobs in the pink sector were also able to make the move to the suburbs. With the population shifting into the suburbs, healthcare centers and public schools must logically follow suit (MacDonald 1999).

The shifting of office parks to the suburbs is often described as spatial entrapment: motivated by cost savings, firms moved administrative support offices to where a ready supply of their ideal workers, educated white women, were already living. In doing so, firms were able to achieve cost savings by reducing turnover and allowing mothers to work more hours (MacDonald 1999; Hanson 1988).

Although it is generally accepted that jobs in the pink sector are more evenly distributed in geographical space, a robust study demonstrating this conclusively using GIS or other analytical techniques does not currently exist, as exact home and work addresses, especially for national samples, are typically masked to protect the privacy of survey respondents. Wheeler (1967) demonstrated that in Pittsburgh, occupational prestige correlated with longer commuting distances to work. Specifically, men employed as professionals and craftsmen tended to travel further to work compared to those in administrative support roles. However, a similar effect was not observed for women, as they tended to commute the same distances regardless of their occupation. As noted previously, Hanson and Johnston (1985) also found evidence that pink-sector occupations are generally located closer to residential centers. Additionally, Hanson (1988) concluded that administrative support jobs and manufacturing jobs were situated in different parts of the Worcester, Massachusetts metropolitan area.

The third proposed mechanism explaining women's shorter commutes is the household responsibility hypothesis (HRH). Household responsibilities are not shared equally between married spouses, with women taking on the majority of caregiving and household duties. Therefore, women's shorter commutes are a result of balancing roles as caregivers and employees, and women must select jobs that are located closer to their homes to fulfill both roles (Gimenez‐Nadal Molina 2016).

Several analyses support the HRH. Turner and Niemeier (1997) demonstrated that married men with children have the longest commutes, while married women with children have the shortest. Additionally, the presence of children significantly reduced the commute duration of married women but increased that of married men when earnings were held constant (McLafferty and Preston 1997).

Furthermore, Hanson and Pratt (1995) found that women who took a childbearing break from employment were much more likely to have a job in a pink-sector occupation and work closer to home. This indicates that it is the increased caregiving responsibilities that come with raising young children that motivate women to work closer to home. Fan (2017) states that women's commutes are only significantly shorter when parenthood and paid work outside the home interact and that single men and women commute similar distances. If gender commuting differences were solely a function of pink-sector occupations being more evenly distributed across geographical space, then single women without children should also have shorter commutes, as these occupations employ the majority of women in total.

According to Hanson (2010), women commuting shorter distances to work is only the first part of "The Great Generalization" of women's mobility (Hanson 2010). The second part of the great generalization is that women make more household support trips. Examples of such trips include grocery shopping, taking children to school and doctor visits, and running errands. Using data from the 2003–2010 American Time Use Survey (ATUS), Fan (2017) demonstrated that women with children spend significantly more time performing household support travel compared to men and women without children. When examining the intersection of gender and family structure, Fan also revealed that the greatest gender travel disparities are experienced by single mothers and mothers from dual-earning households. On average, both single mothers and dual-earning mothers spent 33 minutes each day performing household support travel, in contrast to single fathers (20 minutes) and fathers from dual-earning households (22 minutes). Even when women face similar time constraints to their spouses in dual-earning households, they still undertake more household responsibilities, as evidenced by household support trips. Furthermore, shorter commutes also afford mothers more time to engage in household support travel.

Regarding household support travel, McGuckin and Nakamoto (2005) illustrated using the 2005 NHTS that for full-time working couples with children, mothers are much more likely than fathers to include dropping children off at school as part of their commute to work. McGuckin and Nakamoto also found that trip chaining–combining commutes, grocery shopping, household errands, and trips to the gym in a single journey–increased for both genders by comparing the

1995 NHTS to the 2005 edition. However, men's trip chaining increased primarily due to making a stop for coffee on their way to work, dubbed "the Starbucks effect."

Leisure Poverty

Balancing roles as employees and mothers is not only a core feature of the HRH, but the same conflict is also central to time poverty research. Working mothers need shorter commutes because they face a time crunch, and their time budgets do not allow for long commutes. This time crunch not only limits working mothers' commute times and economic opportunities but also substantially reduces leisure time. Vickery (1977) pioneered research into time poverty, which examined how neglect of time poverty led to a downward bias in poverty estimates. The Levy Institute Measure of Time and Income Poverty (LIMTIP) recasts the Vickery framework to explicitly take into account intrahousehold disparities in the allocation of time between employment and household production responsibilities. Time deficits in Vickery and LIMTIP approaches are defined as deficits in household production. They assume a minimum leisure requirement in the calculation of time deficits (Zacharias 2023; Zacharias 2011)

Similar to time poverty, leisure poverty argues that leisure deficits–on their own–have detrimental consequences and identifies individuals and households who do not have enough leisure time to flourish as humans. Having leisure time is fundamental to well-being. Leisure allows for relaxation and the opportunity for physical and emotional healing. Leisure provides the space for reflection, self-improvement, and growth. Moreover, friendships and networks are developed during leisure in ways that cannot be replicated in the office (Coleman 1988).

Furthermore, leisure deficits are associated with detrimental physical, emotional, and cognitive impacts (Bittman 2002). Additionally, Kalenkoski and Hamrick (2013) found that leisure-poor individuals are less likely to spend time engaging in sports, exercise, walking, and biking. Moreover, feelings of not having enough time have been linked to increased incidence of hypertension and depressive symptoms (Roxburgh 2004; Yan et al. 2003)

Driving the gender leisure gap are differences in the time men and women commit to childcare and unpaid household production. Even though men and women have become more equal in labor force participation, childcare and unpaid household labor duties are not shared equally between the genders. In the 1990s, married men only performed one-third of the total household duties. The unequal sharing of household responsibilities leaves employed mothers with a double burden of time commitments. Mothers must perform the majority of unpaid household labor while balancing time committed to being an employee. On average, married men have 27 more minutes of leisure time every day relative to married women. This amounts to 164 hours of leisure time each year–the equivalent of four weeks of paid vacation (Bianchi et al. 2000). Men and women also experience leisure time differently. Not only do men have more leisure time, they also have more "pure" leisure time, where leisure activities do not run concurrently with supervisory child care. As the primary caregiver, boundaries between household responsibilities and leisure are blurred for women, as leisure activities are much more likely to be interrupted by childcare responsibilities (Bittman and Wajcman 2000).

A clear illustration of these dynamics is presented by Bittman and Wajcman (2000). They compared "total work," which is the combination of paid labor and unpaid household duties between men and women. Bittman and Wajcman found that men do roughly two more hours of total work weekly because of their increased number of hours in the paid workforce. However, if supervisory childcare is included in the definition of total work, the result flips, and women perform two more hours of total work weekly.

The finding that the presence of children in the household significantly reduces leisure time for married women but not for married men supports the notion that men and women experience leisure time differently (Mattingly and Bianchi 2003). Mattingly and Bianchi (2003) also found that mothers' pure leisure time is more likely to be interrupted by childcare and household responsibilities compared to fathers'.

There are relatively few time-use studies specific to the US using a leisure poverty framework. Kalenkoski, Hamrick, and Andrews (2011) explore setting relative time poverty thresholds using data from the 2003 through 2006 American Time Use Survey (ATUS). Although the authors found that the presence of children reduces leisure, the analysis does not consider gender or marriage status. Additionally, Zilanawala (2013) investigated the relationship between leisure time and relationship status for full-time working mothers. Surprisingly, leisure time did not differ significantly between single, married, or cohabiting mothers. It is assumed by some that full-time working single mothers have the highest rate of leisure poverty because they do not have a partner to share childcare and household responsibilities with (Zilanawala 2013).

The HRH states that mothers must reduce their commute durations to fulfill their household responsibilities. Because mothers are balancing roles as caregivers and employees, their time budgets do not allow for long commutes. Meanwhile, investigations into gender leisure differences show that mothers, relative to fathers, have less leisure time, pointing towards the unequal sharing of household responsibilities as the root cause. It is clear that even with shorter commutes, mothers still face leisure deficits, indicating that heightened household responsibilities cannot be compensated for through shorter commutes alone.

As described above, there are competing mechanisms and debates regarding the root cause of women's shorter commutes and fewer minutes of leisure time. Regardless of which mechanisms might be at play in determining the length of a commute–such as spatial entrapment, spatial mismatch, or the HRH–or the magnitude of gender differences in commute durations or time dedicated to childcare or household responsibilities, the paramount concern is leisure deficits. It is the lack of leisure that leads to detrimental biological and cognitive outcomes.

Mode of Transportation Matters

Examining commute times and leisure outcomes for working mothers and fathers is not enough; the mode of transportation parents use to get to work is also extremely important. Taking public transportation to work has been shown to double commuting times, raising the question: is riding public transportation a luxury for individuals with excess time, such as men without children, or does the doubling of trip durations directly reduce leisure (Crane 2007)? Additionally, the public transportation time penalty could be compensated for in other ways, such as purchasing prepared meals, hiring house cleaners, or utilizing other household services, as riding public transit is significantly cheaper than owning a private automobile.

Another mechanism by which individuals could offset the time penalty associated with riding public transportation is by working during their commute, a feature that is observationally prominent on commuter rail, as commuter rail is associated with longer commutes and provides a relatively comfortable environment. However, the impact of working while commuting, or how effectively individuals are able to work while commuting, is unexplored.

In a similar vein, Jachimowicz et al. (2016) conducted a field experiment where they asked individuals to engage in "goal-directed prospecting" during their commutes. Some examples of goal-directed prospecting include planning out the workday, contemplating schedule conflicts, and identifying immediate and tangible daily goals. Jachimowicz et al. found that individuals who engage in goal-directed prospecting find commuting to be less stressful. Although Jachimowicz et al. did not make comparisons between individuals who drive private automobiles and those who commute by public transit, it is reasonable to believe that riding public transportation, as it does not require active engagement in a similar fashion to driving a car, provides an environment that is more conducive to goal-directed prospecting.

Even though the US is a car-centric society, many reasons exist to focus on the interaction between public transportation and leisure time. One of the most obvious motivations is that when public transportation is heavily utilized by urban populations, it is robustly more sustainable than private automobile travel. Public transportation moves people in dense urban environments more efficiently, uses fewer natural resources, and produces fewer greenhouse gasses compared to private automobiles (Hanson 2010).

Young people in the US are also driving less, as driver’s license rates continue to trend lower for Millennials and Generation Z (Federal Highway Administration 2021). Part of the reason driver’s license rates are falling is the increasing cost of owning a car. Not only is car ownership typically financed, resulting in monthly car payments, but it also includes expenses such as gas, insurance, routine maintenance, and repairs. The roadside service provider AAA estimates that the cost of car ownership is $10,728 per year (AAA 2022). Foregoing car ownership can provide significant financial savings for households and individuals.

According to an Urban Land Institute Poll, 80 percent of millennials say that public transportation is “very important” when considering where to live and work (Urban Land Institute 2015). Additionally, 33 percent of millennials say they will never live in the suburbs. Furthermore, driving trips per capita are falling among millennials while biking, walking, and transit trips are all increasing. Lastly, living near quality public transportation comes at a premium, as home and rent prices within 0.5 miles of public transportation rose faster compared to neighborhoods located further away (Shankar et al. 2019). Together, the above findings support the notion that demand for public transportation is increasing.

The combined costs of commuting and housing also disproportionately impact the working poor, with poor households spending 32.4 percent of their income on housing and commuting expenses combined, compared to only 25 percent for non-poor households (Roberto 2008). Poor households also have fewer choices when it comes to choosing where to live. A common trade-off is between affordable rent and long commutes, as housing near employment centers and quality public transportation is typically unaffordable for the working poor. Therefore, the working poor face mobility constraints due to housing and car ownership costs. Furthermore, when the working poor rely on public transportation, they are subjected to longer trips. Additionally, since the working poor have less income to purchase household services, such as childcare, prepared meals, and house cleaning, they could also be more at risk of experiencing leisure deficits, which may be exacerbated by using public transportation.

Significant financial investments in public transportation infrastructure have already been approved. Build Back Better is the Biden administration’s framework for infrastructure investment in the US and has been touted as a “once-in-a-generation investment in our nation’s infrastructure,” with $39 billion aimed at investments in public transportation (Fact Sheet: The Bipartisan Infrastructure Deal). Increasing public transportation access in disadvantaged communities is a core policy initiative.

Exploring the interactions between public transportation and leisure provides a framework for evaluating the effectiveness of public transportation investments. Equitable and efficient public transportation must appeal not only to the wallet (financial savings) but also to the watch (time savings). Merely having the option of riding public transportation isn't a replacement for effective public transportation that can compete with the trip durations of private automobiles measured in time.

Decentralized cities, enabled by private automobiles, exhibit increasing commute times year over year (Crane 2007; Kwon and Akar 2022). Due to the physical space that cars occupy, both on the road and when parked, societies that revolve around private automobiles are inherently decentralized (Shoup 2021). There is no reason to think that commute times would be reduced if the US moved from 76.4 percent of workers commuting by car to 100 percent or if cities became even more decentralized. Reducing commute times requires urban environments with mixed land uses, which is a city design that is achieved through public transportation.

Decentralized cities and reliance on private automobiles also contribute to the time crunch faced by mothers. Although women typically have shorter commutes, they often perform more household support trips, such as transporting their children to school, sports, and community events, which often require lengthy drives. By law, children cannot drive a car until they are 16 years old. Therefore, suburban youth often cannot navigate their neighborhoods by themselves until they reach this age, as safe biking routes are limited, and the distances are often too far to walk (Lubitow, Rainer, and Bassett 2017).

In many communities, the availability of safe and equitable public transportation, along with encouragement for active modes of travel, would provide a means for youths and teens to navigate the city independently, thereby reducing the mobility burden on their parents. Additionally, journeys on public transportation are associated with less stress and allow parents to engage with their children in more meaningful ways compared to private automobile trips (Smith 2017).

The primary aim of this study is to investigate how using public transportation impacts leisure time for couples–married or cohabiting–men and women who work full-time. Given the literature on gender differences in travel behavior and available leisure time that has been reviewed thus far, a valid framework must include gender, race, mode of transportation, and the presence of children, in addition to commute and household support trip durations.

Fan (2017) is the only framework that combines both commuting and household support trips, along with the relationship status and the presence of children in their analysis of gender travel behavior in the US. Furthermore, Fan also measures travel times, the relevant target variable for joining the gender commuting gap and leisure poverty frameworks. However, Fan does not use a leisure poverty framework and only compares gender differences in time allocated to commuting and household support travel. Additionally, Fan did not include modes of transportation or race in their analysis.

Other studies like Kalenkoski, Hamrick, and Andrews (2011) and Zilanawala (2013) invoke a leisure poverty framework in the US context but do not include commute or household support trips in their analyses. Hu (2020) looks at the interaction of commute duration, race, and household structure in the U.S. but only examines commutes made by private automobiles and does not explore how commute durations impact leisure. Lastly, I choose to examine married or cohabiting couples only, as these household structures must negotiate between partners' household duties, residential locations, commuting durations, and amounts of time allocated to household support travel. To my knowledge, I am the first to investigate how commutes and household support trips impact leisure. I also include a third novel variable by examining how public transportation impacts leisure. With these analytical goals in mind, I form the following three hypotheses:

(1) I expect that public transportation riders will also face leisure deficits, on average, when compared to individuals who drive private automobiles because public transportation commutes take twice as long as private automobile commutes. Furthermore, because I am focusing on full-time workers, I believe this group will not be able to compensate for the public transportation time penalty.
(2) I predict women will have less leisure time relative to men after controlling for commuting, household support travel, and the usage of public transportation. Furthermore, I expect heightened leisure deficits for full-time working mothers with

young children who ride public transportation, as this subgroup faces the greatest time crunch overall and, therefore, should have the least ability to compensate for the public transportation time penalty.

(3) I anticipate an additional leisure penalty for Black individuals who use public transportation, given their longer commute durations, mobility barriers, and discrimination in the labor market.

METHODOLOGY

Empirical Strategy and Data Sources

The primary aim of this analysis is to assess how using public transportation to commute or perform household support trips influences leisure time. Unfortunately, no survey currently exists that collects both time-use diaries and travel diaries simultaneously. In the United States, the American Time Use Survey (ATUS) is the most comprehensive time-use survey. In addition to recording conventional time-use variables, like minutes engaged in work, childcare, and leisure, ATUS diaries also capture minutes allocated to travel and the purpose of each trip. However, the ATUS does not collect data on the mode of transportation used to perform trips, rendering it unsuitable for evaluating how different modes of transportation impact leisure time.

For transportation data, the National Household Transportation Survey (NHTS) is the most robust national travel survey and includes information on the modes of transportation used to perform trips. Accordingly, given the NHTS's focus on travel, it does not collect information on leisure. Therefore, to examine the relationship between leisure and mode of transportation, leisure values are imputed from ATUS time diaries into NHTS travel diaries.

Furthermore, to account for the inherent uncertainty in imputed leisure values, I adopt a multiple imputation (MI) method and generate five imputed values for each NHTS record (Enders 2022). After the imputation procedure is complete, an analytical regression model is fit on each set of imputations, and the coefficients and standard errors from each separate regression model are pooled together according to Rubin's Rules. Lastly, the pooled results are evaluated to measure the impact of using public transportation on leisure time.

As discussed above, two surveys are used in this analysis: the ATUS and the NHTS. The ATUS is a federally administered, representative, annual, cross-sectional survey evaluating how Americans divide their time among daily activities. Survey respondents are randomly selected from a subset of individuals who completed the Community Population Survey (CPS). The ATUS implements a time-diary data collection strategy. The time diary begins at 4 AM on the assigned day and continues until 4 AM the next day. After completing the time diary, respondents are interviewed by an interviewer who codes written diaries into standardized time-use variables. Only one person per household, age 15 or older, completes a time diary. Although there is only a single time-use diary per household, demographic information is collected for all household members. Therefore, the presence of children, spouses, and unmarried partners can be determined, allowing household composition to be included in the analysis (BLS 2017).

The ATUS uses a multi-tiered coding scheme. The major category code represents the highest level of aggregation. For example, ATUS major category code 02 constitutes time committed to household activities. Furthermore, major category 02 (household activities) can be decomposed into specific chores (activities). Activity codes represent the lowest level of aggregation available in the ATUS. For instance, ATUS activity code 020102 accounts for the time dedicated to the specific "household activity" (major category code: 02) of doing laundry.

In addition to category and activity codes, select secondary activities are also coded in the ATUS. In this analysis, the secondary activity of interest is secondary childcare, which is interpreted as supervisory childcare. For example, the primary activities of socializing, relaxing, and enjoying leisure (ATUS major code: 12) can be performed concurrently with supervisory child care. Data were extracted from the IPUMS American Time Use Survey Data Extract Builder (Flood, Sayer, and Backman 2023). The sample was restricted to time diaries from 2015, 2016, 2017, 2018, and 2019. Before applying any restrictions, the sample includes 50,649 time diaries.

Next, I discuss the second survey used in this analysis, the NHTS. Administered by the Federal Highway Administration, the NHTS is the main source for evaluating national-level travel behavior in the United States. Since 2000, NHTS surveys have been conducted in 2001, 2009, and 2017. Recently, a 2022 edition of the NHTS was released. Unfortunately, the 2022 release collected markedly fewer travel diaries relative to previous years. For example, in 2022, only 190 bus commutes were recorded, relative to 2017, which logged 1,757 bus commutes. Therefore, the 2022 NHTS did not collect enough travel diaries to meaningfully evaluate the impacts of public transportation. Consequently, the 2017 edition of the NHTS was selected for this analysis.

The NHTS is a direct stratified sample that collects information on daily travel behavior using a travel diary that begins at 4 a.m. and ends at 4 a.m. the following day, aligning with the data collection time window used for the ATUS. After completing the travel diary, participants have seven days to submit their diaries by using a web portal or through a phone interview. However, in contrast to the ATUS, a travel diary is completed for each household member five and older. The key distinction arising from the different diary collection strategies is that when analyzing diaries from the ATUS, time negotiations between spouses cannot be directly examined because there is only a single time diary per household. However, using the NHTS, tradeoffs between partners, like one partner making a long commute while the other makes a short commute, can be examined because each spouse completes a separate travel diary.

The NHTS provides datasets aggregated at the household, person, and trip levels. This analysis used all datasets to construct the analytical dataset employed for alignment and imputation. The NHTS uses a straightforward, single-tiered coding structure. For instance, trip purposes are categorized into nineteen broad categories, such as work, exercise, healthcare visits, and purchasing goods. Additionally, trip duration is calculated by subtracting the trip end time from the start time. Most importantly, the NHTS provides sufficient information on the mode of travel, distinguishing between private automobiles, public buses, subway, light rail, walking, and biking for both commutes to work and household support trips. In total, travel diaries were collected for

264,234 individuals.[1] Data are available for download directly from the NHTS website (Federal Highway Administration 2017).

How and when to apply survey weights is another important consideration when working with survey data. ATUS survey participants are randomly assigned a specific day to complete their time diary. The ATUS is intentionally designed so that weekdays and weekends are sampled at the same rate. This means that even though during a typical week there are five work days (Monday through Friday) and only two weekend days (Saturday and Sunday), an equal number of time diaries were collected for the two groups–weekday and weekend. As a result, the ATUS survey weights primarily focus on adjusting for the oversampling of weekends.

Households participating in the NHTS are also randomly assigned a specific day to complete their travel diaries. However, in contrast to the ATUS, survey dates are assigned to ensure that each day of the week is sampled equally. Likewise, the NHTS uses a standard weighting scheme, where each weight corresponds to the number of individuals in the total population represented by an observation. Therefore, survey weights from both the ATUS and NHTS are incorporated into the imputation model. (Flood, Sayer, and Backman 2023; Federal Highway Administration 2017).

After imputing leisure values into the NHTS dataset, survey "person" weights and replicate weights are incorporated into the analytical model. These weights help to account for sampling imperfections and ensure that the estimates produced are accurate and representative of the population. Both sets of weights are needed to produce accurate estimates, unbiased standard errors, and meaningful statistical inference.

Lastly, several filters are used to target demographics that experience the greatest time crunch and would be most affected by the time penalty associated with riding public transportation for both commuting and household support travel. Only married or cohabiting couples who work full-time, are between the ages of 18 and 64, and live in an MSA of 1 million or more residents are considered. For both the ATUS and NHTS, an individual is considered to be a full-time

[1] Records are from 129,696 households, including add-ons

worker if they usually work at least 35 hours a week. Including singles and single parents in the analysis was initially considered; however, after applying the above restrictions, in the NHTS, the sample size of single parents is limited to only 107 single fathers and 272 single mothers. These sample sizes are too small to impute leisure values accurately. Hence, this analysis focuses only on married or cohabiting couples.

Virtually every recorded public transportation trip occurred in an MSA with a population of one million or more. As a result, this analysis focuses exclusively on urban residents. Additionally, only respondents who logged a two-way commute of at least one minute but not more than four hours are included.

Lastly, for the NHTS, only individuals who commuted or performed household support travel using either a private automobile or public transportation are included in the analysis. Furthermore, individuals are not allowed to mix modes of transportation, allowing the direct comparison of individuals who exclusively use public transportation to those who exclusively drive private automobiles when commuting or performing household support travel. This restriction has a minor impact as, for example, it is rare for individuals to take the subway to work and then drive home, or vice versa. However, for all other travel purposes, such as travel related to leisure activities, any mode of transportation is acceptable, including walking and biking.

After applying these filters, the ATUS sample is reduced to 3,457 observations, and the NHTS sample is limited to 24,809 observations.

Calculating Leisure Time

There are many ways to measure leisure time. One strategy is to consider leisure to be the time left over after the day's necessary tasks have been completed, often referred to as a residual measure of leisure. Calculating residual leisure time uses a two-step process. First, committed time is calculated. Second, committed time is subtracted from the total number of minutes in a day, as shown in Equation 1.

$$(1) \qquad Leisure\,Time = 1440 - Comitted\,Time$$

In the time-use literature, frequently used terms include "contracted time," "committed time," and "necessary time." These terms delineate the differences between employment, unpaid household production, and the time required for basic biological necessities like sleep. In this analysis, each component is bundled under the umbrella term "committed time," as the focus is on the residual: leisure time.

This comparison of leisure measures begins with, and subsequently adds to, the residual leisure measure formulated by Kalenkoski, Hamrick, and Andrews (2011). Accordingly, the baseline leisure time calculation is the residual after accounting for minutes dedicated to personal care (major code: 01), household activities (major code: 02), caring for household members (major code: 03), and work (major code: 05) as shown in Equation 2.

$$\begin{aligned}(2) \qquad Leisure\,Time = 1440 - (&Personal\,Care + Household\,Activities \\ &+ Caring\,for\,Household\,Members \\ &+ Employment)\end{aligned}$$

The formulation by Kalenkoski, Hamrick, and Andrews (2011) of committed time excludes care for non-household members (major code: 04), arguing it is a discretionary activity. Regardless if caring for non-household members is discretionary or not, the formulation excludes childcare provided by grandparents, in-laws, and siblings, which are important and common sources of childcare. Therefore, the first addition to the formulation is to include the time allocated to providing care to children and adults who are not household members.

$$\begin{aligned}(3) \qquad Leisure\,Time = 1440 - (&Personal\,Care + Household\,Activities \\ &+ Caring\,for\,Household\,Members \\ &+ Work \\ &+ Caring\,for\,NonHousehold\,Members)\end{aligned}$$

Folbre (2005) calls attention to the value of supervisory childcare. Supervisory childcare (labeled secondary childcare in the ATUS) occurs when a person is providing supervision for a child under age 13 while simultaneously doing another task, for example, keeping an eye on a toddler while watching TV. Hence, an adult can be engaged in a leisure activity and provide supervisory childcare at the same time. For this analysis, our focus is solely on instances where supervisory childcare overlaps with a primary leisure activity, considering it as a constraint on leisure time. Therefore, to prevent the double counting of time allocated to committed activities, supervisory childcare is only included in the leisure time calculation when it occurs simultaneously with a leisure activity.

(4)
$$\begin{aligned} Leisure\ Time \ = \ 1440 - (&Personal\ Care + Household\ Activities \\ &+ Caring\ for\ Household\ Members \\ &+ Work \\ &+ Caring\ for\ NonHousehold\ Members \\ &+ \ Supervisory\ Childcare) \end{aligned}$$

According to Mattingly and Bianchi (2003), "pure free time" is leisure time that occurs without the responsibility of supervisory childcare and is fundamentally different from leisure time that is constrained by supervisory childcare. Additionally, Mattingly and Bianchi (2003) found that men have more pure free time. Thus, this analysis adopts the pure free time definition of leisure time.

An alternative to using a residual measure of leisure is to formulate leisure time based on activities (Han, Meyer, and Sullivan 2020). For example, this approach involves examining time dedicated explicitly to activities such as watching TV, playing sports, reading, playing video games, etc. In contrast to the residual measure of leisure, which aims to define what is not leisure time--such as paid labor, unpaid labor, and child care–the activities-based approach has the opposite goal; it seeks to define what constitutes leisure and directly examines it. In this analysis, the activities-based measure of leisure analysis defines leisure as time spent socializing, relaxing (major code 120000), and engaging in sports, exercise, and recreation (major code 130000), as shown in Equation 5.

$$(5) \qquad Leisure\ Time = Socializing + Relaxing + Sports + Exercise + Recreation$$

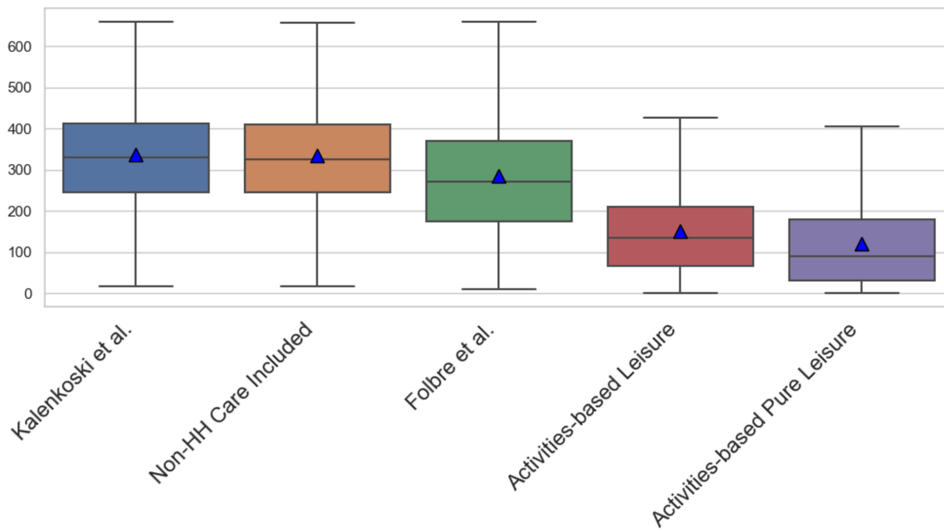
The residual measure of leisure time is much more inclusive, as it includes every element that is in the activities-based measure of leisure, but it also includes several activity categories that the activities-based measure does not. For example, the residual-based measure includes activities such as education, religious and spiritual activities, phone calls, consumer purchases, government and civic obligations, and volunteer activities as leisure time. While education, religious activities, and volunteering contain elements of socializing and personal growth, each activity category also has its drawbacks in terms of rest, relaxation, recovery, and health and well-being. For example, education could range from a painting class at the local community center to a series of evening accounting classes with the sole purpose of increasing an individual's earning potential. Similarly, all phone calls are denoted as leisure using residual measures, regardless of whether the phone call is with a friend or a lawyer. Lastly, in some instances, volunteering can have positive social outcomes, but it can also be viewed as unpaid labor.

The last consideration in this comparison of leisure time measurements, and specifically the activities-based measure of leisure, due to the same motivations outlined above, I am only considering pure leisure activities. This means that I am, again, excluding leisure activities that occur simultaneously with supervisory child care, as shown in Equation 6.

$$(6) \qquad Leisure\ Time = Pure\ Socializing + Pure\ Relaxing + Pure\ Sports + Pure\ Exercise + Pure\ Recreation$$

Figure 1 compares the six formulations of leisure discussed above using boxplots. Mean leisure times, indicated by the blue triangles, are only slightly reduced when minutes dedicated to caring for non-household members are included in the calculation. Kalenkoski, Hamrick, and Andrews' (2011) formulation yields a mean leisure value of 337.4 minutes, while the calculation incorporating care for non-household members minimally reduces the mean leisure time by 2.2 minutes, resulting in a mean value of 335.2 minutes. However, including time dedicated to supervisory childcare is crucial. This addition, as demonstrated in the calculation by Folbre et al., decreases the mean leisure value by 53.1 minutes, bringing mean leisure to 284.3 minutes. The activities-based measure of leisure, titled "Activities-based Leisure," shows a markedly lower mean leisure value of 151.1 daily minutes of leisure. Lastly, the activities-based pure leisure measure demonstrates the lowest average leisure time, which is 119.6 minutes.

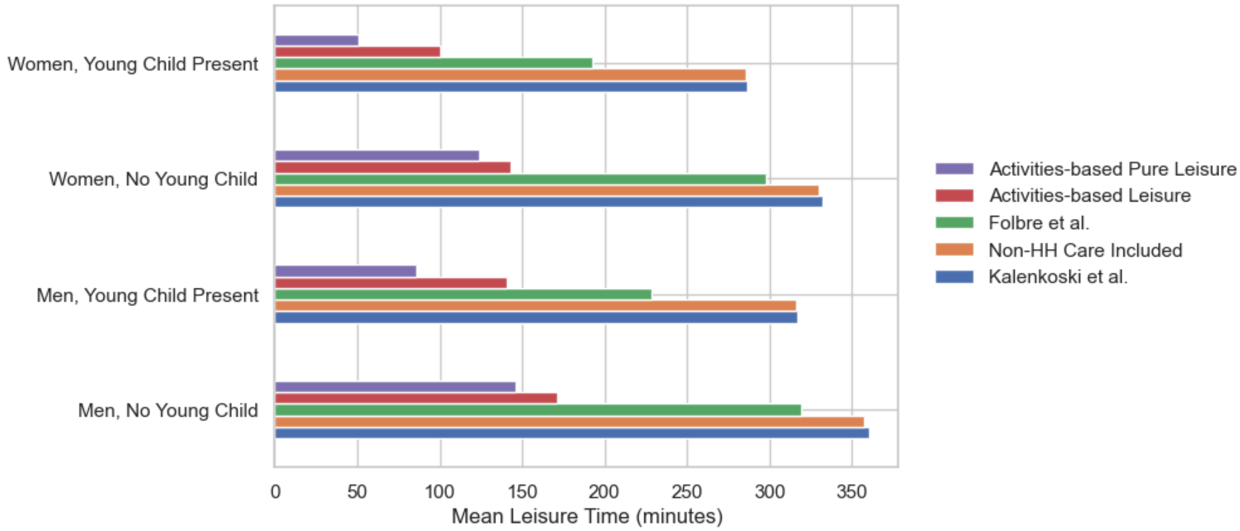
Figure 1. Comparing Leisure Equations



Source: Author's calculations; ATUS donor sample used for imputation, 3,457 observations.

Together, these figures highlight the importance of selecting an appropriate measure of leisure. In this analysis, our objective is to gauge leisure inequality concerning activities most associated with rest, relaxation, and well-being. Furthermore, residual leisure measures may lack clarity as discrepancies in leisure could stem from one group receiving more education or spending more time volunteering. Additionally, guided by Mattingly and Bianchi (2003), including only pure free time is crucial when assessing gender differences in leisure time. Therefore, the activities-based pure leisure measure is used in this analysis.

Figure 2. Comparing Leisure Equations at the Intersection of Gender and Children



Source: Author's calculations; ATUS donor sample used for imputation, 3,457 observations.

Imputation Model

In this thesis, Multiple Imputation (MI), along with Predictive Mean Matching (PMM), is used to impute leisure time values from the ATUS time diaries into the NHTS travel diaries. This imputation methodology consists of four key steps. First, a regression model is fit on the ATUS data–the complete cases–as each observation from the ATUS has a leisure time value calculated from each survey respondent's time use diary. Second, the same regression model is then used to predict leisure time values for each observation in the NHTS–the incomplete cases. Third, for each observation in the NHTS, the predicted leisure time value is used as a reference point to find the five closest donor candidates from the ATUS dataset. To determine the five closest candidates, the predictive mean matching metric, which incorporates both numeric and categorical variables into the distance calculation, is used (Van Buuren and Groothuis-Oudshoorn 2011).

After determining the five closest candidates, the fourth step is to randomly select one of the five donor candidates. The initial leisure time value (derived from the donor's ATUS time diary) from the randomly selected ATUS donor is imputed into the corresponding NHTS travel diary. One advantage of PMM is that it only inputs real leisure values that were observed in the ATUS, thus eliminating the possibility of the model imputing negative leisure values, leisure values exceeding 24 hours, or leisure values that did not occur (Van Buuren and Groothuis-Oudshoorn 2011).

The steps outlined above comprise the key attributes of performing a single set of imputations using PMM. However, to appropriately capture uncertainty in the predicted leisure values due to the random draw component and because the regression model does not explain all of the variation in leisure time, five sets of imputations are conducted. Performing multiple sets of imputations (MI) recognizes that there are several possible leisure values, each with its own level of uncertainty, which cannot be captured using only a single set of imputations. Several papers have explored the optimal number of imputations to perform and found that there is "little to no benefit" in generating more than five sets of imputations (Schafer and Olsen 1998). Hence, five sets of imputations are performed in this analysis.

Gender is paramount in this analysis; therefore, donor selection was run separately for men and women, ensuring that female recipients only receive leisure time values from female donors and that male recipients only receive leisure time values from male donors. The regression model used in tandem with MI and PMM to impute leisure values is presented below in Equation 7. The weighted means for the numeric variables from the ATUS–leisure, commute time, household support trips, and age–used in the imputation model are presented in Table A1. The mean coefficient values from the regression models for both men and women are presented in Table A2. The rows of Table A2 represent the variables used in the regression model, while the columns represent the mean coefficient values from each imputation model for both men and women. Additionally, a term ID is also present for each variable.

(7) leisure ~ commute time
+ household support travel
+ child present 0 through 5
+ child present 6 through 12
+ child present 13 through 17
+ race
+ age

+ education

+ household income

+ homeown

+ commute time * race

+ commute time * homeown

+ commute time * household income

+ commute time * child present 0 through 5

+ commute time * child present 6 through 12

+ commute time * child present 13 through 17

+ household support travel * race

+ household support travel * homeown

+ household support travel * household income

+ household support travel * child present 0 through 5

+ household support travel * child present 6 through 12

+ household support travel * child present 13 through 17

The purpose of the imputation regression model (Equation 7) used in tandem with MI and PMM is to produce accurate imputations, not statistical inference. Therefore, at this stage in the analysis, only the magnitude of the coefficients is relevant. In regards to reducing leisure, Table A2 shows that the presence of children between the ages of 0 through 5 (see: term 4) and ages 6 through 12 (see: term 5) are the most impactful variables, with children between the ages of 6 and 12 reducing leisure slightly more than children between the ages of 0 and 5. For example, the presence of a young child reduces fathers' leisure by -81.5 minutes and mothers' leisure by -77 minutes, relative to couples without a young child in their household. Meanwhile, a child between the ages of 6 and 12 reduces leisure by -95.5 minutes for fathers and -90 minutes for mothers, compared to couples without a young child in their home.

One surprising result is that teenagers (see: term 6) only reduce leisure time for fathers, as fathers' leisure is reduced by -9.7 minutes relative to coupled men without a teenager in their home; however, comparatively, mothers' leisure increases by 37.7 minutes when a teenager is present in the household. However, women still have less leisure overall. The intercept (see: term

1) compares the average leisure difference between men and women, as both groups were modeled separately. On average, women have -29.8 fewer minutes of leisure relative to men.

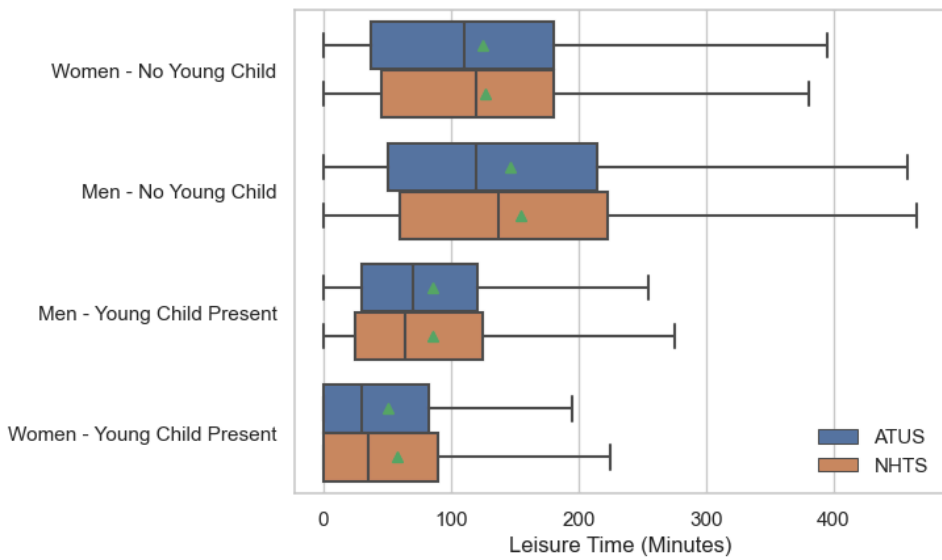
Time dedicated to commuting (see: term 2) and performing household support travel (see: term 3) reduces leisure time more for women compared to men. For each additional minute dedicated to commuting, women's leisure is reduced by -1.2 minutes, compared to men who only experience a leisure reduction of -36 seconds. A similar pattern holds for household support trips, although not as strong, as each additional minute dedicated to commuting only reduces leisure by -48 seconds for women and -35 seconds for men.

The imputation model also shows that parents with children 12 and younger experience an additional leisure boost as they dedicate more time to commuting (see: terms 23 and 24), regardless of gender. However, for mothers, the interaction between commuting and the presence of a teenager (see: term 25) reduces mothers' leisure by -29 seconds, but for fathers, the impact is negligible. The interaction between the presence of children and household support travel follows a similar trend (see: terms 32, 33, and 34).

Next, to assess the quality of the imputed leisure values between the ATUS and the NHTS, I compare the mean leisure values, along with the percent change, between the two surveys for the core variables in the imputation model. These comparisons are presented in Table A3. The general guideline is that mean values should not differ by more than 15 percent between surveys. Every variable in the imputation model adheres to this guideline. Overall, the imputations are quite accurate, with the largest mismatch only reaching 7.9 percent for households that earn "Less than 50k." Furthermore, the average deviation between imputed and actual values across all variables is only 1 percent.

To further evaluate the imputation quality, box plots are constructed (see: Figure 3) to assess imputed leisure values at the intersection of gender and the presence of a young child in the household. In each group, the body of the box plot, representing the dispersion of leisure time from the 25th to the 75th percentile, shows a high degree of overlap. Going past simple mean comparisons, these boxplots indicate that the distribution of imputed leisure times closely resembles the original distributions from the ATUS. Furthermore, the middle bands represent median values, while the green triangles represent mean values. Most importantly, the relationship between gender, children, and leisure time is transferred from the ATUS to the NHTS--women with young children have the least amount of leisure time, followed by fathers with young children, then women without young children, and lastly, men without young children.

Figure 3. Comparing Key Interactions Between Gender and Parenthood



Source: Author's calculations. ATUS donor sample used for imputation, 3,457 observations. NHTS sample used with the analytical model, 24,809 observations.

The last quality assurance step involves confirming that both surveys sample from the same underlying population. Given that both surveys are intended to be representative national samples, it is reasonable to expect alignment between the ATUS and NHTS. Table A4 validates this assumption using alignment tables to compare counts and proportions of every variable used in the imputation model across both surveys. Again, alignment is considered satisfactory if the proportions differ by no more than 15 percent. Every level of each categorical variable adheres to this standard. The largest mismatch is found for individuals with a "High school education or less," reaching 11.3 percent. Overall, the average alignment between the two surveys equals 2.9 percent.

DISCUSSION OF RESULTS

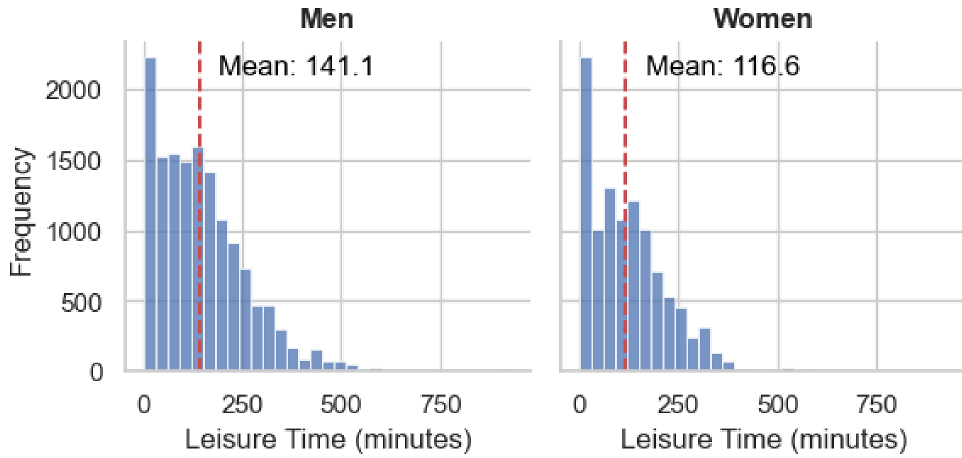
Descriptive Analysis

Both surveys recorded gender as a binary, male or female, selection. Following Hanson (2010), at least two views of gender are always circulating: gender as a social construct and gender as a biological characteristic. The two views are in direct conflict–one view suggests gender can be fluid, and the other is that gender is a fixed biological characteristic. It is impossible to know which definition of gender the survey respondent is using when completing either the ATUS or the NHTS; this ambiguity makes binary gender groupings messy, potentially misrepresenting some proportion of the sample. Despite this, binary gender variables still hold some meaning. Regarding the NHTS, binary gender groupings are the only measure of gender that is available.

The dependent variable in this analysis is leisure time. Figure 4 displays a histogram with the bin width set to thirty, illustrating that the most frequent leisure times for both men and women fall within the range of 0 to 30 minutes. Furthermore, although the distributions are skewed to the right, the mean values for both groups lie within the third most common bin. Additionally, I observed a statistically significant gender leisure gap of 24.5 minutes, confirmed using a t-test. Figure 3 and all subsequent figures in this section are constructed using imputed leisure values and the corresponding variables from the NHTS. Likewise, leisure values from the first set of imputations were selected for these visualizations.

Aguiar and Hurst (2007) found that in 2003, using the ATUS, that men enjoyed an average of 37.6 weekly hours of leisure, while only women had 33.8 weekly hours--a gap of 3.8 hours favoring men. The leisure gap reported in Aguiar and Hurst was calculated using a residual measure of leisure, with a sample that included part-time and full-time workers. In contrast, this analysis focuses specifically on individuals who are employed full-time. Converting the daily leisure gap of 24.5 minutes from this analysis to weekly hours reveals that full-time working women have 2.9 fewer hours of leisure compared to full-time working men. These results are also consistent with those of Mattingly and Bianchi (2003), who reported that women have less pure free time, as I am also using a pure free time measure of leisure.

Figure 4: Comparing Leisure Time By Gender



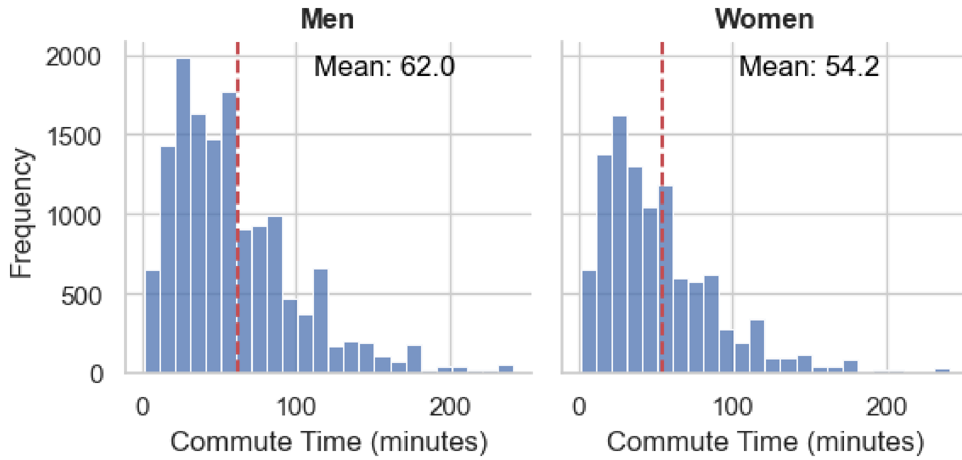
Source: Author's calculations. NHTS sample used with the analytical model, 24,809 observations.

Next, I describe the three novel variables employed in this analysis to explain leisure time: commute time, time dedicated to household support trips, and the dummy variable indicating if individuals used public transportation for their commute to work or while performing household support travel.

In accordance with the long line of research demonstrating the persistence of the gender commuting gap, including Kwon and Akar (2022), which showed a gender commuting gap between dual earners using data from the 2017 NHTS, I also found an average gender commuting gap between married or cohabiting men and women who work full-time. However, unlike Kwon and Akar, the gap is measured in commute time instead of distance. Women commute 7.8 fewer minutes round trip, confirmed as statistically significant using a t-test.

Furthermore, Figure 5 evaluates the distribution of commute times between men and women. Commute times display a similar distribution between genders, which is slightly skewed to the right. In Figure 5, the bin width is set to 10 minutes. For men, a mean commute time of 62 minutes falls within the second most frequent bin, while for women, a mean value of 54.2 falls into the fourth most common bin.

Figure 5. Comparing Commute Time By Gender



Source: Author's calculations. NHTS sample used with the analytical model, 24,809 observations.

The NHTS not only documents actual commute minutes but also goes a step further by asking respondents about their typical one-way commute times without traffic. The advantage of using the typical one-way commute time is that it provides data for markedly more individuals. Even if a full-time worker did not commute on the day they completed their travel diary, they still reported their typical commute time. This becomes particularly crucial when examining the impacts of public transportation, as public transportation riders are a subgroup that suffers from small sample sizes. Consequently, in the NHTS, if actual commute time was recorded in the travel diary, it was used as the individual's commute time. However, if a travel diary commute time was absent, the typical one-way commute was doubled to emulate a round trip, ensuring consistency with the ATUS time-use diaries.[2]

The second novel variable used to explore the relationship between mobility and leisure time is Household Support Trips. In this analysis, the main goal of the Household Support Trips variable is to capture travel time that corresponds to unpaid committed activities, such as grocery shopping and running household errands. Household support travel is a notable variable because, like leisure time and the gender commuting gap, findings from Fan (2017) and McGucking and Nakomoto (2005) outline that mothers make more household support trips compared to fathers. Fan (2017) used data from the 2003 to 2010 ATUS and found that women spend more time on average performing household support travel. Furthermore, McGucking and Nakomoto (2005)

[2] The same strategy was used when selecting records to include in the sample.

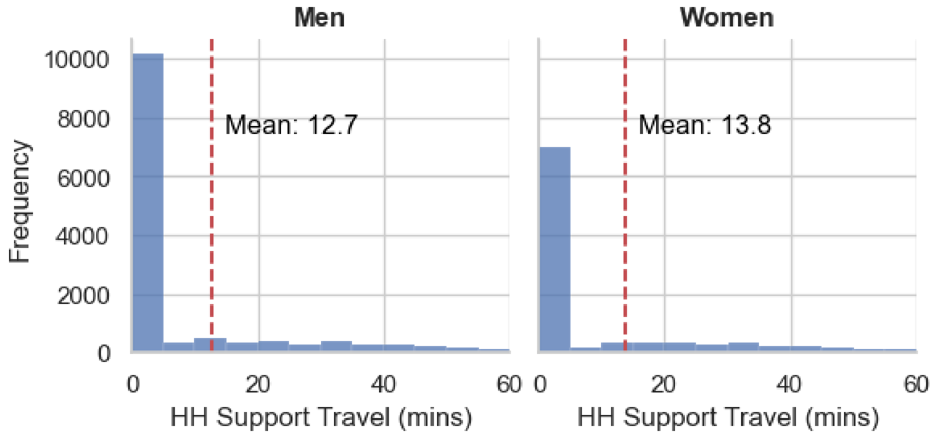
found that full-time working women are more likely to include shopping trips on their return trip back home from work.

To illustrate how minutes dedicated to household support travel are calculated, consider the following example: if a survey respondent goes grocery shopping after work, the minutes dedicated to travel from their work location to the grocery store are attributed to household support travel. If, after completing their grocery shopping, the respondent then heads to a yoga class instead of returning straight home, only the trip from work to the grocery store would be classified as household support travel. The trip from the grocery store to the yoga studio would be coded as travel related to exercise; similarly, the trip from the yoga studio back home would also be classified as travel related to exercise.

Figure 6, a histogram with the bin width set to 5 minutes, compares the time dedicated to household support travel between men and women. The most striking feature of Figure 6 is that most individuals, who are, once again, full-time workers, did not make a household support trip. Specifically, 69.9 percent of men did not perform a household support trip, and 67.1 percent of women did not allocate any time to household support travel. This indicates that combining commutes and household support travel on work days is relatively uncommon, as roughly only 30 percent of individuals do so.

Figure 6 also shows that, on average, women dedicate 1.1 more minutes to household support travel compared to men. Although a difference of roughly a minute may not be practically meaningful, the mean difference is statistically significant using a t-test. Thus far, I have confirmed that a gender leisure gap, gender commuting gap, and gender household support travel gap are all present for full-time workers in the NHTS. Next, I present the third novel variable in this analysis, the public transportation dummy variable.

Figure 6. Comparing Household Support Travel By Gender



Source: Author's calculations. NHTS sample used with the analytical model, 24,809 observations.

In this thesis, the public transportation dummy variable is composed of the following modes of transportation: public buses, subway or light rail, paratransit, and commuter rail. Furthermore, cars, vans, pick-up trucks, motorcycles, and SUVs are all considered private automobiles. Therefore, this analysis excludes individuals who bike, walk, take the ferry, golf carts, or segway scooters to work or when performing household support travel.

This analysis aims to compare individuals who commute or perform household support travel exclusively using public transportation to those who exclusively commute or perform household support travel using private automobiles. For all other trips, such as travel related to leisure activities, any mode of transportation is acceptable. If an individual uses public transportation for either a commute or a household support trip, they are considered a public transportation rider. However, in the analytical sample, only 15 household support trips were performed using public transportation. Therefore, the public transportation dummy variable mostly represents individuals who commute to work using public transportation.

Table A5 provides counts of private automobile drivers and public transportation riders, along with the percentage of public transportation users within each group, as determined by the levels of each categorical variable. Overall, only 5 percent of individuals in the analytical sample used public transportation. Men and women rode public transportation at similar rates. Asian individuals rode transit more than any other racial category, topping out at 11.7 percent.

Regarding income, high-income individuals rode transit more than low-income individuals–8 percent compared to 4.5 percent. Additionally, individuals with a graduate degree rode transit more than individuals with a high school education or less–9.9 percent compared to 2.8 percent, respectively.

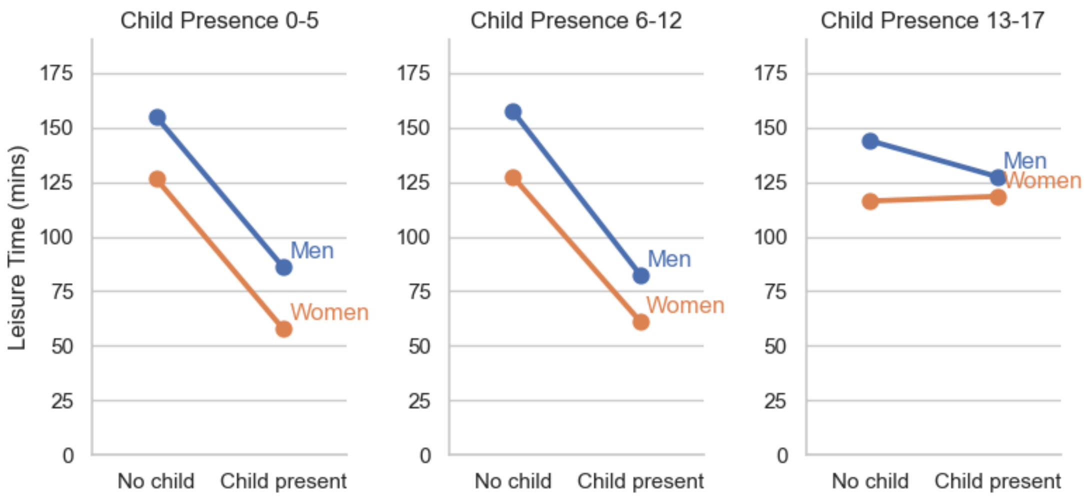
Several studies show that the presence of children has a dramatic effect on leisure, commute durations, and the amount of time allocated to household support travel. Kalenkoski, Hamrick, and Andrews (2011) found that households with children have the highest rates of leisure poverty, noting that each additional child reduces an adult's leisure time by 35 minutes. However, Kalenkoski, Hamrick, and Andrews did not consider gender in their analysis. Zilanawala (2013) extends Kalenkoski, Hamrick, and Andrews' analysis by including gender in their leisure poverty framework. Zilanawala found that women with children have the highest rates of leisure poverty, with 40 percent of mothers classified as leisure poor based on a relative measure of leisure poverty.

In my analysis, I construct the variable "Child present 0 through 5" indicating if a child between the ages of 0 and 5 years old is present in the household. "Child present 0 through 5" is also selected as the definition of a "young child" in this analysis because at six years old, most children in the US begin full-time schooling (NCES 2017). Furthermore, Sayer and Bianchi et al. (2004) report that children who have not yet started school (preschoolers) require more attention and care, creating a time constraint that mothers disproportionately shoulder.

Two additional variables, "Child present 6 through 12" and "Child present 13 through 17," have been constructed to cover the entire age range of household children. At ages 6 through 12, most US children are in school full-time but still require more parental supervision than older children. Lastly, teenagers, ages 13 through 17, are expected to require the least amount of parental care.

Collectively, these variables encompass the entire age range of household children. In analyses not shown here, the child counts for each age range were examined instead of child presence. The majority of variation in leisure time occurs when individuals move from having zero children to having one child in a specific age range. Additionally, sample sizes become exceedingly small as most households only have one child in each age range, and it is extremely rare for households to have more than two children in a specific age category.

Figure 7. Comparing Mean Leisure by the Presence of Children and Gender



Source: Author's calculations. NHTS sample used with the analytical model, 24,809 observations. The label "No child" represents households without a child between the ages referenced in the corresponding plot title.

Figure 7 compares mean leisure times across each child age category. Additionally, mean leisure times are also compared between men and women and between couples with or without children. Regardless of the age or presence of children, women consistently have less leisure time compared to men across all household structures. Furthermore, the drop in leisure time observed as couples move from having no children to having a child between the ages of 0 and 5 or 6 and 12 is quite similar. Specifically, for women, the magnitude of the reduction in leisure differs by less than three minutes between the two groups–a 68.8 minute drop vs. a 66.1 minute drop, respectively. Lastly, relative to younger children, teenagers have a minimal impact on leisure time.

In this analysis, only individuals living with a spouse or unmarried partner are considered. Living with a spouse or unmarried partner implies a negotiation between partners. These negotiations include discussions about who provides childcare, performs household chores, where to live, or which partner makes a lengthy commute. On the contrary, singles, both with and without children, do not have an analogous negotiation in their daily lives.

The level of household responsibilities is also typically determined by marital or cohabiting status and the number and age of children (Fan 2017; Molina 2016). As outlined previously, the unequal sharing of household responsibilities plays a central role in the gender commuting gap and the gender leisure gap. Specific to marriage status, McLafferty (1997) found that the gender gap in time allocated to performing household responsibilities widens with marriage. Furthermore, Fan (2017) states that women still have more household responsibilities, even in dual-earner households.

Additionally, Zilanawala found that regardless of whether a mother is single, married, or cohabiting, their leisure poverty rates remain unchanged. This indicates that another adult in the household is not alleviating a proportionate amount of the household duties. However, because the leisure poverty calculation is based on a relative metric, average leisure time still differs between single mothers and mothers with an additional partner in the household, with married or cohabiting couples having two more hours of leisure time compared to single mothers. No difference was found between married or cohabiting couples in Zilanawala (2013), providing justification for grouping married and cohabiting individuals together, as is done in this analysis.

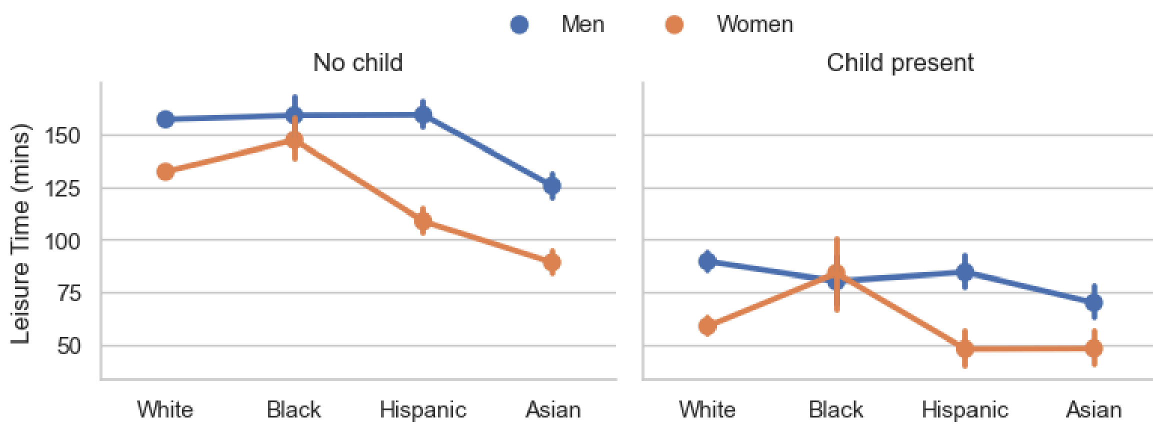
In this thesis, the variable "race" reports the ethnicity of the survey respondent. Potential values for the constructed race variable are “White,” “Black,” "Hispanic," and "Asian."[3] White represents individuals who identify as non-Hispanic white. Black represents individuals who identify as non-Hispanic black. Hispanic indicates that a survey respondent reported their ethnicity as Hispanic. Lastly, the ethnicity “Asian” records non-Hispanics who reported their race as Asian.

Figure 8 compares mean leisure times between each race category, conditioned on gender. On average, White men, Black men, and Hispanic men all have similar amounts of leisure. Furthermore, the largest gender leisure gap is between Hispanic men and women without children. The leisure gap between White men and women remains mostly unchanged by the presence of a young child. Notably, Black women with young children are the only group where

[3] A residual group of 82 survey respondents, not belonging to any of the race categories listed, were dropped from the analysis.

women have slightly more leisure time compared to men. However, this group suffers from small sample sizes.

Figure 8. Comparing Mean Leisure by Race and Gender

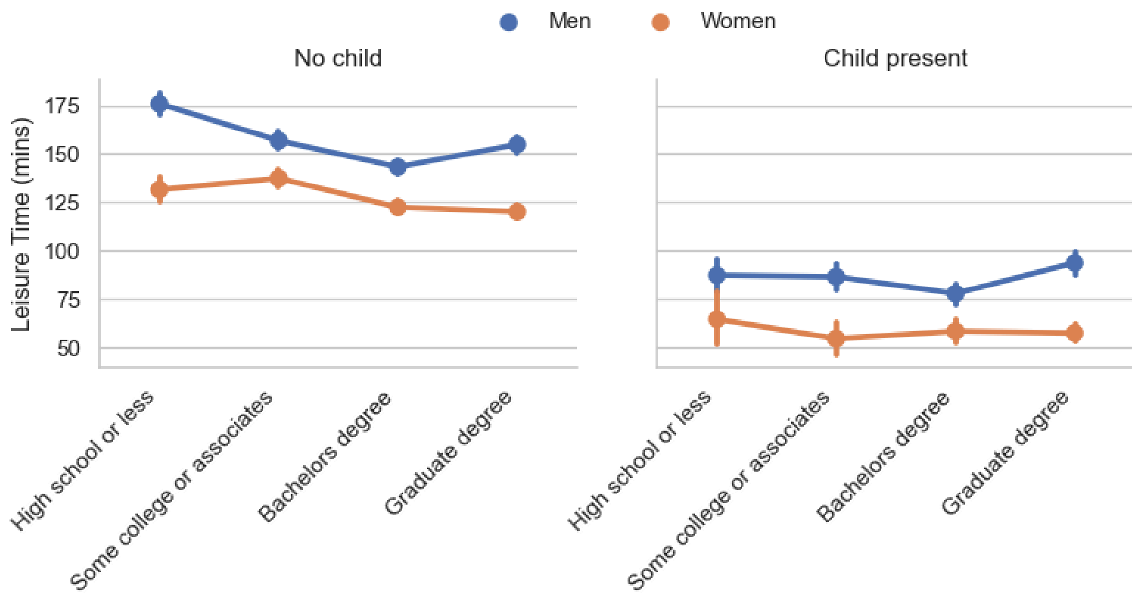


Source: Author's calculations. NHTS sample used with the analytical model, 24,809 observations.

In this thesis, the variable education categorizes an individual's educational attainment into four tiers, ranging from "High school or less" to "Graduate degree." The gender leisure gap is most pronounced among couples who have a high school education or less, as shown in Figure 9. Additionally, a sizable gender gap exists between individuals with a graduate degree, regardless of the presence of a young child. Lastly, irrespective of education level or parental responsibilities, men tend to enjoy more leisure time compared to women.

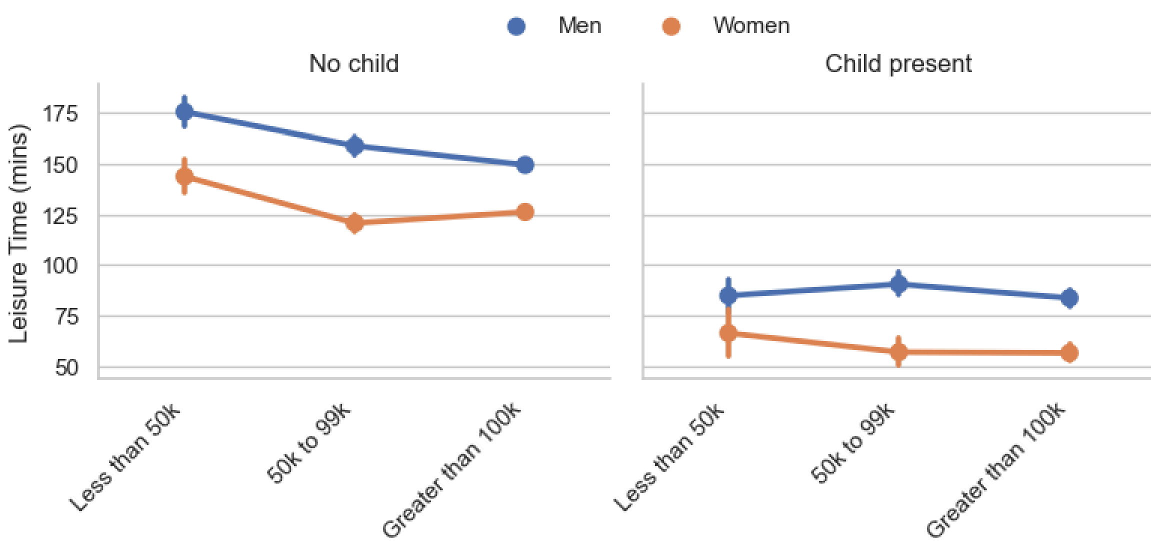
In my analysis, the variable household income categorizes a household's financial status into three tiers, ranging from less than $50,000 to greater than $100,000. Figure 10 contrasts household incomes with mean leisure times across genders. The most striking outcome is that high-income households, making more than 100k a year, do not consistently have more leisure time compared to lower-income households. However, gender leisure gaps are most pronounced among middle-income households, regardless of whether they have children. These results align with those of Kalenkoski, Hamrick, and Andrews (2011), who also found that income is unrelated to leisure.

Figure 9. Comparing Mean Leisure by Education and Gender



Source: Author’s calculations. NHTS sample used with the analytical model, 24,809 observations.

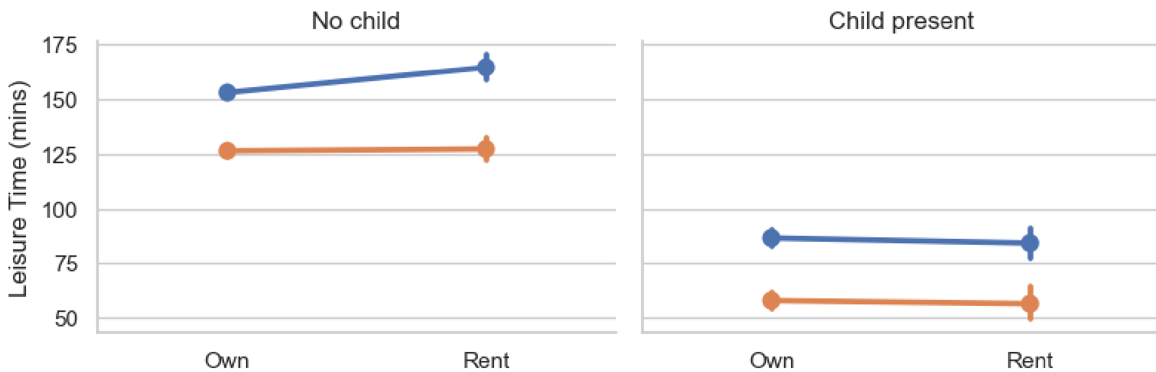
Figure 10. Comparing Mean Leisure by Household Income and Gender



Source: Author’s calculations. NHTS sample used with the analytical model, 24,809 observations.

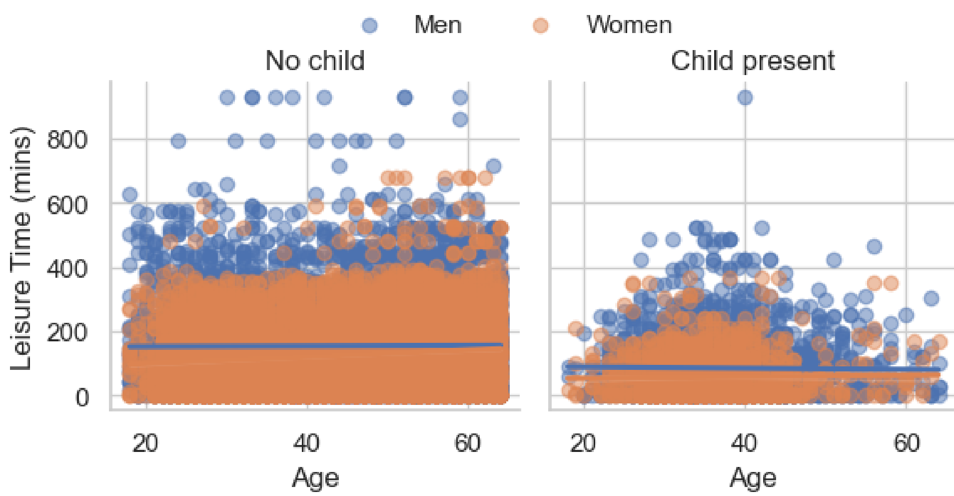
In this thesis, the variable homeownership is also a control variable and captures the differences between renters and owners. Generally, renters are linked with living in densely populated urban centers. As a result, renters should have greater access to key destinations such as employment centers and shopping districts and improved access to public transportation. Conversely, homeowners are associated with suburban living and longer commute times. Nevertheless, Figure 11 shows that, regarding homeownership status conditional on gender, the impact on leisure remains relatively minimal. However, men who rent and do not have children have the most leisure.

Figure 11. Comparing Mean Leisure by Homeownership and Gender



Source: Author's calculations. NHTS sample used with the analytical model, 24,809 observations.

Figure 12. Evaluating the Relationship Between Age, Gender, and Leisure



Source: Author's calculations. NHTS sample used with the analytical model, 24,809 observations.

In my analysis, the variable age is a control variable that represents the ages of the survey respondents as an integer. Amongst full-time working adults, ages 18 through 64, Figure 12 shows that leisure time tends to increase with age for individuals without children. However, for parents, leisure time peaks around the age of 40 and younger, and older parents have less leisure time. There are disparities in the daily experiences related to mobility and economic opportunities between younger and older full-time workers. For example, older workers may occupy senior leadership roles that allow for a flexible schedule and more vacation time. Furthermore, older workers may have more difficulty utilizing public transportation, especially if a lengthy walk is required to get to the bus stop or train station. The variable age attempts to capture these differences across the working population.

Analytical Model

The main research question in this thesis asks how riding public transportation impacts leisure time. To address this research question, leisure values were imputed from the ATUS into the NHTS. Furthermore, five sets of imputations were performed to account for uncertainty in the imputed variable: leisure time. However, during the imputation procedure, only the magnitudes of the coefficients from the regression model were evaluated. Now, in the analytical model, both the magnitude and statistical significance of each variable must be examined.

To maintain consistency with the regression model used during the imputation procedure, the analytical regression model retains the same formula, with the exception that it includes a dummy variable indicating if an individual used public transportation for commuting or household support travel. Additionally, for the analytical model, men and women are combined into the same model. This analytical regression model is presented below in Equation 8.

$$
\begin{aligned}
(8) \qquad \text{leisure} \sim\ & \text{gender} \\
& + \text{commute time} \\
& + \text{household support travel} \\
& + \text{transport mode} \\
& + \text{child present 0 through 5} \\
& + \text{child present 6 through 12} \\
& + \text{child present 13 through 17} \\
& + \text{race} \\
& + \text{age} \\
& + \text{education}
\end{aligned}
$$

+ household income

+ homeown

+ gender * child present 0 through 5

+ gender * child present 6 through 12

+ gender * child present 13 through 17

+ commute time * gender

+ commute time * race

+ commute time * homeown

+ commute time * household income

+ commute time * child present 0 through 5

+ commute time * child present 6 through 12

+ commute time * child present 13 through 17

+ household support travel * gender

+ household support travel * race

+ household support travel * homeown

+ household support travel * household income

+ household support travel * child present 0 through 5

+ household support travel * child present 6 through 12

+ household support travel * child present 13 through 17

+ transport mode * gender

+ transport mode * homeown

+ transport mode * household income

+ transport mode * child present 0 through 5

+ transport mode * child present 6 through 12

+ transport mode * child present 13 through 17

+ transport mode * commute time

+ transport mode * household support travel

Furthermore, to appropriately account for uncertainty in the imputed leisure values, the analytical model is fit on all five sets of imputations, and then the estimates and standard errors from each distinct model are pooled according to Rubin's Rules (RR). As a high-level overview, RR consists of three core steps. First, RR averages the coefficient estimates across each of the five models. RR also accounts for variance both within each regression model and between each regression model. Second, for within-model variance, the sum of the squared standard errors for each model is averaged. Third, the between-model variance is measured by comparing the parameter estimates from each model to the pooled averages and squaring the difference (Enders 2022).

The NHTS also includes person weights and replicate weights. Person weights serve as standard survey weights, enabling population-level estimates and addressing non-responses and sampling stratification. Additionally, the NHTS provides sets of replicate weights, which are essential for calculating unbiased variance estimates. Replicate weights allow a single sample to simulate multiple samples, providing more informed estimates of standard errors while preserving all details of the survey design (NHTS 2017). Therefore, alongside fitting the analytical model for each of the five sets of imputations, person weights and replicate weights are also incorporated into each model.

The formula for the analytical model, presented in Equation 8, differs from Equation 7 only in its inclusion of a dummy variable indicating if an individual used public transportation, along with men and women being included in the same model. Additionally, pertinent interaction terms between riding public transportation and other independent variables are also included. Table A6 provides the pooled estimates, standard errors, and corresponding p-values for all of the variables in the analytical model.

Now, to evaluate the results from the analytical model, I will address the core hypotheses outlined in the literature review, beginning with the first hypothesis: I anticipate that individuals who use public transportation will experience leisure deficits compared to those who drive private automobiles. This expectation arises from the fact that public transportation commutes typically take twice as long as commutes by private automobile. Moreover, since my analysis focuses on full-time workers, I hypothesize that this group will be unable to offset the time penalty associated with using public transportation.

Addressing the first hypothesis directly: is there a leisure time penalty for riding public transportation? Riding public transportation does not impact leisure time, all else held equal, as indicated by the variable "Public transit" (see: term 5 in Table A6), which is not statistically significant, suggesting that riding public transportation on its own does not reduce leisure time. Furthermore, the magnitude of the coefficient is small, with public transit riders only having -1.2 fewer minutes of leisure. However, the link between riding public transportation and leisure time is complex.

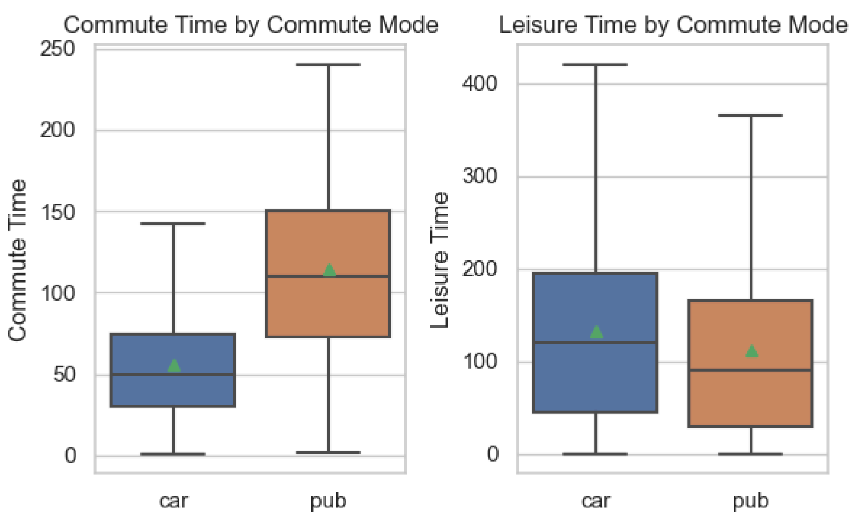
"Commute time" (term 3) and time allocated to "Household support travel" (term 4) are both statistically significant and reduce leisure time, all else held equal. The coefficient for commute time is -0.75, indicating that for a 1-hour round trip commute, daily leisure time would be reduced by -45.2 minutes. Furthermore, the coefficient for household support travel is -0.65, suggesting that allocating one-hour to household support travel reduces daily leisure time by -38.9 minutes. Therefore, commute time and household support travel reduce leisure time, controlling for socioeconomic factors and mode of transportation. However, the relationship is not one-to-one.

To examine the combined effects of public transportation, commuting, and time allocated to household support travel, I evaluate the interaction terms "Public transit * Commute time" (term 52) and "Public transit * Household support travel" (term 53). "Public transit * Commute time" (term 52) has a small coefficient and is not statistically significant. However, the coefficient for "Public transit * Household support travel" (term 53) is also small but it is, in fact, statistically significant, indicating that individuals who use public transportation can offset a small portion of the household support travel leisure penalty.

This analysis is the first to investigate the relationship between commuting time, time allocated to household support travel, and leisure, confirming the intuition that time dedicated to commuting and household support travel reduces leisure. For every additional minute dedicated to either commuting or household support travel, leisure time is reduced by roughly 45 seconds and 39 seconds, respectively. Additionally, I go one step further and control for the impacts of riding public transportation. Contrary to my expectations, riding public transportation does not reduce leisure time, all else held equal. As shown in Figure 13, unconditional average commute times are doubled for individuals who ride public transit, but the average leisure gap, comparatively, is small. Furthermore, a comparison of conditional means shows that public transit riders have, on average, -19.2 fewer minutes of leisure time.

There are reasons to believe that individuals who ride public transportation are, in fact, able to offset the time penalty associated with riding public transit. For example, riding public transportation allows individuals to work while commuting; however, the impact of working while commuting, or how effectively individuals are able to work while commuting, is unexplored. Jachimowicz et al. (2016) showed, using a field experiment, that individuals who engage in goal-directed prospecting during their commutes find commuting to be less stressful. Although Jachimowicz et al. did not make comparisons between individuals who drive private automobiles and those who commute by public transit, it is reasonable to believe that riding public transportation, as it does not require active cognitive engagement in a similar fashion to driving a car, provides an environment that is more conducive to goal-directed prospecting. Furthermore, being able to plan out the day's activities during the commute could lead to greater productivity and more available time for leisure activities.

Figure 13. Comparing Commuting and Leisure By Mode: Car vs. Public Transit



Source: Author’s calculations. NHTS sample used with the analytical model, 24,809 observations.

Additionally, individuals who ride public transportation walk more relative to private automobile drivers (Saelens et al. 2014). Furthermore, the more minutes allocated to walking during daily activities, the more likely individuals are to stick with their exercise and fitness goals (Strava 2021). This finding is relevant because I am using an activities-based measure of leisure, which directly measures minutes dedicated to exercise. Therefore, even though individuals who use public transportation spend more time on their commutes, they are still more physically active compared to people who drive private automobiles to work.

Now for my second hypothesis, I predict women will have less leisure time relative to men after controlling for commuting, household support travel, and the usage of public transportation. Furthermore, I expect heightened leisure deficits for full-time working mothers with young children who ride public transportation, as this subgroup faces the greatest time crunch overall and, therefore, should have the least ability to compensate for the public transportation time penalty. As outlined when discussing the first hypothesis, time dedicated to commuting and households or travel reduces leisure; however, there are reasons to believe that the effects of commuting could be different for women and mothers.

Some of these reasons include women making shorter commutes compared to men, but women also allocate more time to household support travel (Fan 2017; Kwon and Akar 2022). Additionally, mothers have less leisure time compared to fathers, and lengthy commutes do not financially reward women like they do men (Zilanawala 2013; Madden 1981). Lastly, public transportation does not effectively serve mothers, as public transportation in the US does not typically have adequate space for strollers or groceries. Additionally, women cite safety concerns when riding public transportation due to the unreliability of public transit services, inadequate lighting at bus stops and train stations, and persistent overcrowding (Lubitow, Rainer, and Bassett 2017).

Notably, in my analytical model which controls for commute time, household support travel, mode of transportation, and uses an activities-based measurement of pure leisure, I find that women have -45.7 fewer minutes of leisure time relative to men, all else held equal (see: term 2 in Table A6). This finding is statistically significant, practically meaningful, and novel, as the model presented in Equation 8 is the first to unify commuting, household support travel, mode of transportation, and leisure within one framework.

Next, I examine if commutes impact women’s leisure time differently than men's by examining the interaction term "Women * Commute time" (see: term 22 in Table A6). This interaction term has a positive coefficient but it is not statistically significant, indicating that long commutes do not impact women any differently than they do men. On the contrary, allocating time to household support travel does impact men and women differently, as indicated by the interaction term "Women * Household support travel" (see: term 32 in Table A6), which is positive and statistically significant. This interaction term indicates that women are able to offset a small portion of the overall household support travel leisure penalty. Therefore, if women allocate one hour to performing household support travel, their leisure time is reduced by -21.5 minutes, compared to men whose leisure is reduced by -38.9 minutes.

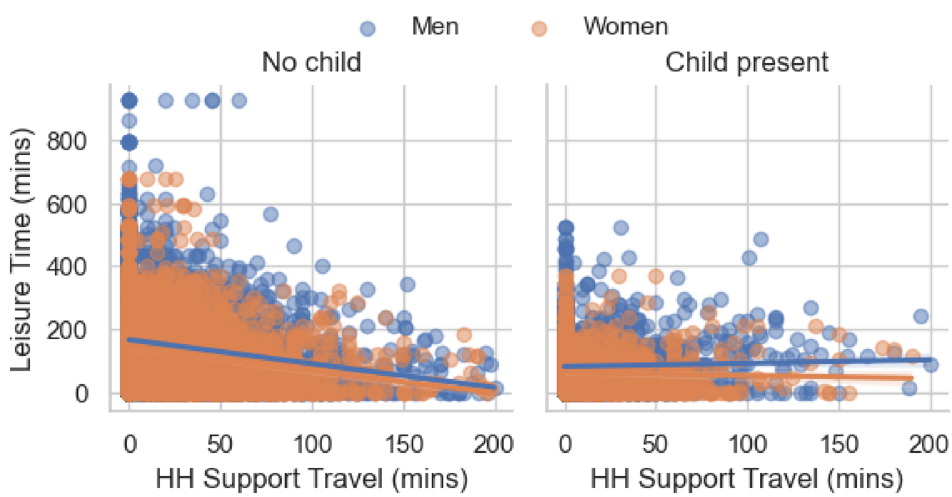
Women, in comparison to men, allocate more time on average to household support travel, are more likely to drop their kids off at school on the way to work, and are more likely to pick up groceries on the way home from work (Fan 2017; McGuckin and Nakamoto 2005). Perhaps women's increased general mobility presents more opportunities to socialize, build networks, or incorporate a workout into the trip chain.

On the other hand, Figure 14 depicts relatively similar trends for men and women as they allocate more time to household support travel, regardless of the presence of children. Furthermore, Figure 14 illustrates that it is primarily men who do not engage in any household support travel that comprise the outlier leisure values, thereby driving the negative relationship between household support travel and leisure for men. In contrast, women, even when they do not perform any household support travel, are not able to achieve these extreme levels of leisure.

Addressing specifically whether women incur a leisure penalty when riding public transportation relative to men, the interaction term "Public transit * Women" (see: term 42 in Table A6) is evaluated. This interaction term has a positive coefficient, but it is not statistically significant, indicating that there are no statistically significant gendered effects of riding public transportation in relation to a leisure penalty. Next, I explore the impact of children and investigate whether parents, compared to individuals without children, experience an additional time penalty as they allocate more time to commuting or household support travel.

The presence of children, commuting, and household support travel have a counterintuitive effect on leisure time. The following interaction terms between commuting, household support travel, and the presence of children are all positive and statistically significant at the 0.5 level: "Child 0 through 5 present * Commute time" (see: term 29 in Table A6), "Child 6 through 12 present * Commute time" (see: term 30 in Table A6), "Child 0 through 5 present * Household support travel" (see: term 39 in Table A6), "Child 6 through 12 present * Household support travel (see: 40 in Table A6)."

Figure 14. Comparing the Relationship Between Household Support Travel, Leisure, and Gender

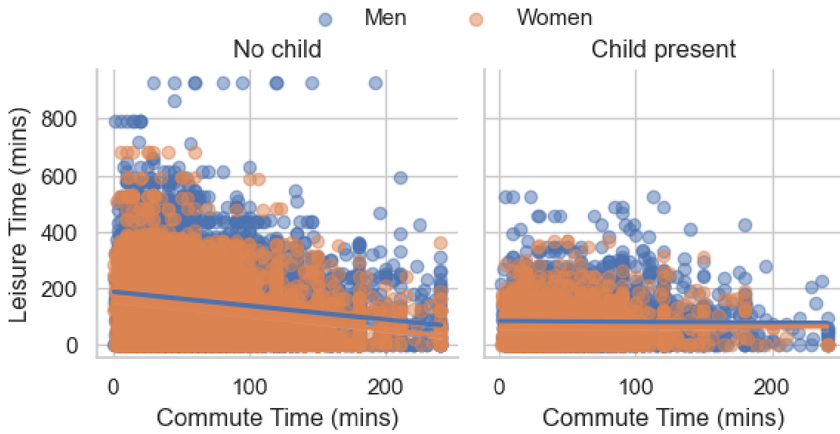


Source: Author’s calculations. NHTS sample used with the analytical model, 24,809 observations.

The combination of these interaction terms indicates that parents, regardless of gender, who have longer commutes and allocate more time to household support travel, can offset a portion of the leisure penalty associated with parenthood. However, it is noteworthy that the leisure penalty associated with the presence of young children is the largest of any term included in the model. For instance, parents with a child between the ages of 0 and 5 have -93.4 fewer minutes of leisure time relative to couples without a young child in the household. Therefore, these interaction terms have minimal impacts on overall leisure for parents.

Again, Figures 14 and Figure 15 provide some guidance as to what might be driving the relationship between commuting, household support travel, and a smaller leisure penalty at the margin for parents. For household support travel (Figure 14), couples without children exhibit a negative relationship between household support travel and leisure time. Individuals without children and who make short commutes (or household support trips) are able to maximize their leisure time. On the contrary, for couples with a young child, the relationship is flat, indicating that when parents make short commutes (or household support trips), their leisure changes very little.

Figure 15. Comparing the Relationship Between Commute Time, Leisure, and Gender

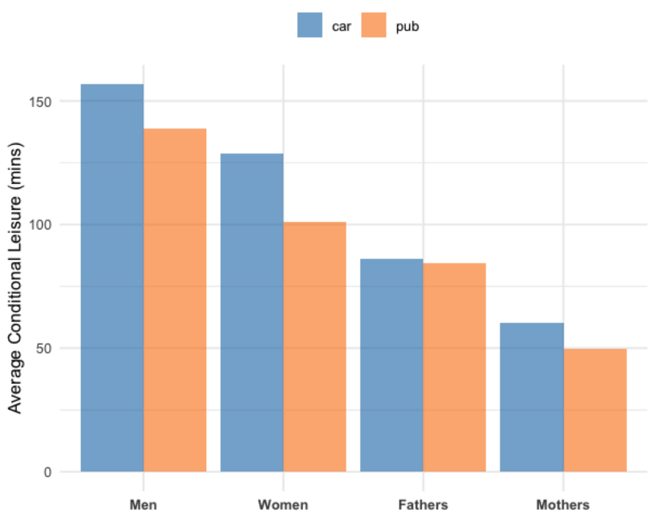


Source: Author's calculations. NHTS sample used with the analytical model, 24,809 observations.

Moving on, I evaluate if riding public transportation has a specific leisure penalty for parents with young children by examining the interaction terms between riding public transportation and the presence of children. The interaction between riding public transportation and the presence of a young child in the household–"Public transit * Child 0 through 5 present" (see: term 49 in Table A6)–has a negative coefficient, suggesting that riding public transportation could penalize individuals in ways different from those who drive private automobiles, but this term is not statistically significant. Similarly, the interaction between riding public transportation and having a child between the ages of 6 and 12 in the household–"Public transit * Child 6 through 12 present" (term 46)–also has a negative coefficient and is not statistically significant. Conversely, parents who ride public transportation and have a teenager in the household, represented by the interaction term "Public transit * Child 13 through 17 present" (see: term 47 in Table A6), have a positive coefficient. However, this interaction is, again, not statistically significant. Therefore, the presence of children does not impact leisure for parents who ride public transportation, nor is there a statistically significant gender-specific effect when women ride public transportation.

To address if mothers, relative to fathers, have less leisure time, the interaction terms between gender and the presence of children are paramount. However, I find that the presence of children does not impact women any differently than men, all else held equal, because all the interaction terms are statistically insignificant (see: terms 19 through 21 in Table A6). The incremental effect of being a mother does not worsen the gender leisure penalty.

Figure 16. Conditional Means by Gender, Parenthood, and Public Transit Usage



Source: Author's calculations. NHTS sample used with the analytical model, 24,809 observations.

Finally, for hypothesis two, I address whether mothers who ride public transportation have less total leisure time than fathers by comparing conditional means. Conditional means take into account the magnitude of each regression coefficient but not its statistical significance. Women, as noted previously, have -45.7 fewer minutes of leisure relative to fathers, all else held equal (see: term 2 in Table A6). The interaction terms between gender and the presence of children are not statistically significant. Furthermore, the incremental gendered leisure impacts of commuting, household support travel, and riding public transit are minimal. However, a comparison of conditional means, as presented in Figure 16, shows that mothers who ride public transportation experience a greater leisure penalty relative to fathers. When fathers ride public transit, their average leisure only drops by 1.5 minutes, but for mothers, their leisure is reduced by 10.6 minutes. Lastly, mothers who ride transit have the least amount of leisure overall.

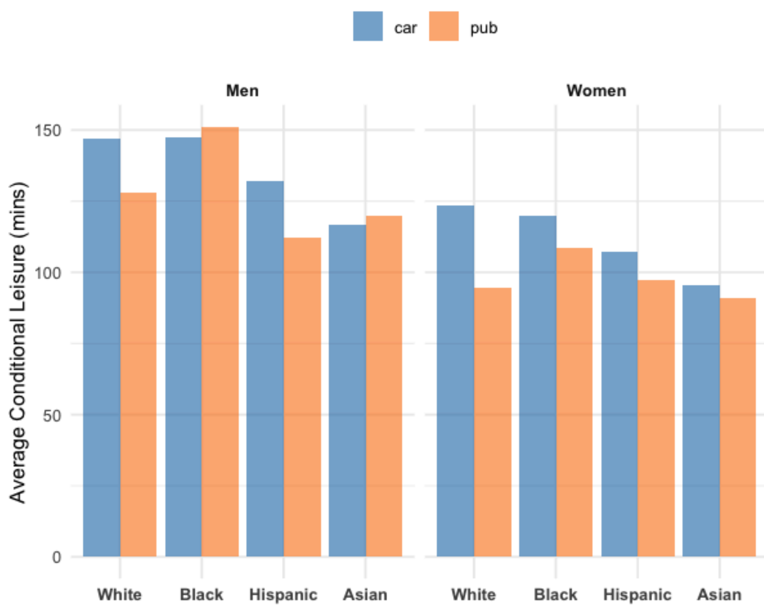
For my final hypothesis, I anticipate an additional leisure penalty for Black and Hispanic individuals who use public transportation, given their longer commute durations, mobility barriers, and discrimination in the labor market. To address Hypothesis 3, the variable race plays a crucial role. Daily leisure time does not differ between Black, Hispanic, and White individuals, as indicated by their corresponding variables of the same name (see: terms 9, 10, and 11 in Table A6), with White individuals serving as the reference variable. None of these variables are statistically significant, indicating that individuals in each racial category have similar amounts of leisure. However, Asian individuals do have significantly less leisure time compared to White individuals, as individuals who identify as Asian have -47.4 fewer minutes of leisure time compared to White respondents (see: term 9 in Table A6).

To explore the relationship between commute time and leisure across racial groups, I analyze the interactions between commute time and race. Again, for Black and Hispanic individuals, there are no racial-specific effects in regards to commuting (see: terms 24 and 25 in Table A6). The interaction between race and commuting is positive and statistically significant for Asian individuals (term 23) but does not offset the overall leisure penalty experience by Asian respondents. Regarding household support travel, the interaction terms between Race and Household support travel are not statistically significant for Black and Asian individuals (terms 33 and 34). However, Hispanic individuals receive a small leisure boost as they allocate more time to household support travel (see: term 35 in Table A6).

All of the interaction terms between Race and Public Transit are small and are not statistically significant, indicating that there is no race-specific penalty for riding public transportation. Several factors could obscure the detection of a meaningful link between race and public transportation. The first factor is that, relative to private automobiles, there are very few trips performed using public transportation, comprising only five percent of the analytical sample. Additionally, because the dependent variable in the analytical model is an imputed value, the impact of riding public transportation on leisure time would need to be quite strong, perhaps on the same scale as the presence of children or gender, to persist through the pooling of model results.

Lastly, because the NHTS only provides data at the MSA level, mobility inequality is difficult to detect. Preston and McLafferty (2018) showed in New York City that it is minority communities located in the inner ring that experience the greatest commuting inequality, and the inequality diminishes for individuals who live in the central city or the suburbs. The geographic regions (MSAs) provided in the NHTS are not detailed enough to detect similar impacts.

Figure 17. Conditional Means by Gender, Race, and Public Transit Usage



Source: Author's calculations. NHTS sample used with the analytical model, 24,809 observations.

Figure 17 presents the conditional means for each race category, gender, and the usage of public transportation. Overall, Asian women who ride public transportation have the least amount of leisure, with only 91 minutes of leisure on average. White women who ride public transportation have 94.7 minutes of leisure on average and also have the widest leisure gap between private automobile drivers and public transportation riders–a leisure gap of 28.7 minutes. These results indicate that there is often a leisure penalty for individuals who ride public transportation, driven by public transit rides taking twice as long as car trips. However, there are no statistically significant, incremental, race-specific coefficients rejecting my third hypothesis.

CONCLUSION

This thesis demonstrates that allocating increasing amounts of time to commuting or performing household support travel directly reduces leisure. For every minute dedicated to either commuting or household support travel, leisure is reduced by roughly 45 seconds and 39 seconds, respectively. Although both forms of travel reduce leisure, the tradeoff is not one-to-one.

This analysis also confirms a gender leisure gap, utilizing a model that unifies commuting, household support travel, and mode of transportation into one framework–the first of its kind. I find that women have nearly 46 fewer minutes of leisure compared to men. This leisure gap is a reflection of patriarchy and the unequal allocation of paid and unpaid work between men and women. Partnered men who work full-time are able to combine commutes with leisure activities, such as going to the gym or heading to a happy hour after work, more easily than partnered women who work full-time.

Women having less leisure time compared to men, and the finding that commuting and household support travel directly reduce leisure, have important implications for the Household Responsibility Hypothesis (HRH). Specifically, there is a statistically significant and practically meaningful gender leisure gap, and long commutes will exacerbate the leisure divide. Therefore, women are compelled to accept jobs closer to home because they lack sufficient leisure to accept employment that requires long commutes.

No statistically significant links were found between riding public transportation and leisure. Riding public transportation is a challenging behavior to measure in a society built around private automobiles, as only 5 percent of the analytical sample made a trip using public transportation. Furthermore, because a single survey that captures detailed travel information and leisure activities does not exist, leisure values were imputed from the ATUS into the NHTS. Due to the inherent uncertainty of imputations, an impact must be quite large to persist through model pooling, which is difficult to achieve with small sample sizes.

To effectively evaluate the impact of public transit on leisure time, national-level survey data should be complemented with qualitative interviews and field studies. Interviews capture individual perspectives that are not represented in survey responses, while field studies can offer real-time observations into how individuals allocate their time and engage in leisure activities while using public transit.

In a country where commute times have been increasing year over year, the finding that commute time directly reduces leisure has further important implications. Keynes did not follow his prediction of a 15-hour work week with a subsequent prediction that we would be spending the other 25 hours commuting (Keynes 1930). Decreasing driver's license rates and survey results show that young adults are driving less and are demanding better public transportation. Recently, large infrastructure projects like Biden's Build Back Better have also allocated significant financial resources to improving public transportation. But it is not enough to simply add public transportation where it did not exist before. Public transportation must compete with the travel times of private automobiles if widespread adoption is going to be achieved. This analysis shows that even households earning less than $50,000 still only use public transit for 4.5 percent of all commutes, even when private automobile ownership costs roughly $10,000 a year, 20 percent of total household income. Clearly, to households and individuals, it is the watch (time savings) and not the wallet (financial savings) that is paramount.

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APPENDIX

Table A1. Weighted Means for Numeric Variables

	Men (weighted mean) (minutes)	Women (weighted mean) (minutes)
Leisure	137.4	112.1
Commute Time	60.9	48.3
Household Support Trips	13.3	21.7
Age	43.3	42.5

Table A2. Mean Regression Coefficients From Each Set of Imputations

Term ID		Women (mean)	Men (mean)
1	(Intercept)	188.26	218.01
2	Commute time	-1.13	-0.53
3	Household support travel	-0.51	-0.49
	Children present (reference: No child)		
4	Child 0 through 5 present	-81.47	-93.72
5	Child 6 through 12 present	-83.07	-88.17
6	Child 13 through 17 present	17.80	-18.07
	Race (Reference: White)		
7	Asian	-46.23	-47.48
8	Black	-2.23	-5.10
9	Hispanic	-13.98	-11.03
10	Age (years)	0.50	0.22
	Education (Reference: < High school)		
11	Bachelor's degree	-9.08	-23.55
12	Graduate degree	-6.98	-14.35
13	Some college or associates	2.57	-17.19
	Household Income (reference: < 50k)		
14	50k to 99k	-27.11	23.46
15	Greater than 100k	-38.59	4.23

	Home ownership status (reference: Own)		
16	Rent	0.93	19.04
	*Race * Commute time (reference: White)*		
17	Commute time * Asian	0.17	0.46
18	Commute time * Black	0.22	0.17
19	Commute time * Hispanic	-0.01	0.00
	*Home ownership status * Commute time (reference: Own)*		
20	Rent * Commute time	0.03	-0.14
	*Household income * Commute time (reference: < 50k)*		
21	50k to 99k * Commute time	0.48	-0.29
22	Greater than 100k * Commute time	0.70	-0.04
	*Children present * Commute time (reference: No child)*		
23	Child 0 through 5 present * Commute time	0.48	0.41
24	Child 6 through 12 present * Commute time	0.35	0.35
25	Child 13 through 17 present * Commute time	-0.25	-0.01
	*Race * Household support travel (reference: White)*		
26	Asian * Household support travel	0.25	0.23
27	Black * Household support travel	0.11	-0.04
28	Hispanic * Household support travel	0.17	0.23
	*Homeown * Household support travel (reference: Own)*		
29	Rent * Household support travel	-0.13	-0.16
	*Household income * Household support travel (reference: < 50k)*		
30	Household income 50k to 99k * Household support travel	0.02	-0.54
31	Household income > than 100k * Household support travel	0.18	-0.28
	*Children present * Household support travel (reference: No child)*		
32	Child 0 through 5 present * Household support travel	0.24	0.58
33	Child 6 through 12 present * Household support travel	0.30	0.47

34	Child 13 through 17 present * Household support travel	-0.24	0.33

Table A3. Mean Leisure Comparisons Between the ATUS and Values Imputed in the NHTS

	ATUS leisure (mins) (weighted mean)	NHTS leisure (mins) (weighted mean)	% Deviation
Gender			
Men	137.4	133.5	-2.8
Women	112.1	112.1	0
Child 0 through 5 present			
Child present	72.8	76.0	4.4
No child	143.3	140.0	-2.3
Child 6 through 12 present			
Child present	76	72.8	-4.2
No child	148.5	142.1	-4.3
Child 13 through 17 present			
Child present	120.6	123.3	2.2
No child	130.2	126.0	-3.2
Race			
Asian	96.2	96.4	0.2
Black	136.6	129.0	-5.6
Hispanic	119.7	119.1	-0.5
White	134.2	130.9	-2.5
Age			
Lower-quintile (18-35)	121.5	121.9	0.3
Middle-lower quantile (35-45)	105.8	104.9	-0.9
Middle-upper quintile (45-54)	132.5	133.7	0.9
Upper-quintile (54-64)	167	156.0	-6.6
Education			
Bachelor's degree	124.5	120.5	-3.2
Graduate degree	117.5	118.6	0.9
High school or less	139.2	139.2	0

Some college or associates	129	129.4	0.3
Household income			
50k to 99k	130.8	122.7	-6.2
Greater than 100k	125.3	122.7	-2.1
Less than 50k	129.7	140.0	7.9
Homeown			
Own	128.1	124.8	-2.6
Rent	128.1	127.2	-0.7

Table A4. Comparing Alignment Between the ATUS and the NHTS

	ATUS (unweighted n)	NHTS (unweighted n)	ATUS (weighted %)	NHTS (weighted %)	Difference (absolute)
Gender					
Men	2,169	14,444	63.2	62.5	0.7
Women	1,288	10,365	36.8	37.5	0.7
Child 0 through 5 present					
Child present	986	4,394	21.5	22.7	1.2
No child	2,471	20,415	78.5	77.3	1.2
Child 6 through 12 present					
Child present	1,231	4,804	28.1	24	4.1
No child	2,226	20,005	71.9	76	4.1
Child 13 through 17 present					
Child present	808	4,022	21.9	19	2.9
No child	2,649	20,787	78.1	81	2.9
Race					
Asian	334	2,293	8.3	8.3	0
Black	340	1,430	10.8	9.7	1.1
Hispanic	677	3,036	22	19.8	2.2
White	2,106	18,050	58.9	62.2	3.3
Age					
Lower-quintile (18-35)	907	6,638	29.5	33.4	3.9

Middle-lower quantile (35-45)	1,157	6,149	28.2	28.2	0
Middle-upper quintile (45-54)	799	6,060	23.8	21.1	2.7
Upper-quintile (54-64)	594	5,962	18.5	17.3	1.2
Education					
Bachelor's degree	1,090	8,094	30.4	30.5	0.1
Graduate degree	858	7,264	21	26.6	5.6
High school or less	751	3,407	28.6	17.3	11.3
Some college or associates	758	6,044	19.9	25.6	5.7
Household income					
50k to 99k	1,135	7,096	34.7	31	3.7
Greater than 100k	1,654	14,927	44.8	53	8.2
Less than 50k	668	2,786	20.5	16.1	4.4
Homeown					
Own	2,584	20,365	71.9	73.1	1.2
Rent	873	4,444	28.1	26.9	1.2

Table A5. Comparing Public Transit Ridership Across Categorical Variables

	Car (unweighted n)	Public Transit (unweighted n)	Public Transit (weighted %)
Gender			
Men	13,840	604	6.2
Women	9,909	456	6.9
Child 0 through 5 present			
Child present	4,213	181	5.7
No child	19,536	879	6.7
Child 6 through 12 present			
Child present	4,638	166	4.4
No child	19,111	894	7.1
Child 13 through 17 present			
Child present	3,884	138	5.3
No child	19,865	922	6.7
Race			

Asian	2,127	166	11.7
Black	1,353	77	7.4
Hispanic	2,925	111	4.7
White	17,344	706	6.2
Age			
Lower-quintile (18-35)	6,290	348	7.5
Middle-lower quantile (35-45)	5,893	256	6.2
Middle-upper quintile (45-54)	5,829	231	5.7
Upper-quintile (54-64)	5,737	225	5.8
Education			
Bachelor's degree	7,672	422	7.8
Graduate degree	6,831	433	9.9
High school or less	3,347	60	2.8
Some college or associates	5,899	145	3.9
Household income			
50k to 99k	6,890	206	4.5
Greater than 100k	14,173	754	8.0
Less than 50k	2,686	100	5.2
Homeown			
Own	19,618	747	5.3
Rent	4,131	313	9.6

Table A6. Analytical Model Regression Results for Leisure (minutes)

Term ID		estimate	std. error	p-value	
1	Intercept	230.41	16.57	0.00	**
	Gender (reference: Men)				
2	Women	-45.67	8.77	0.00	**
3	Commute time (minutes)	-0.75	0.24	0.02	**
4	Household support travel (minutes)	-0.65	0.34	0.10	*
	Transportation mode (reference: Car)				
5	Public transit	-1.21	25.72	0.96	
	Children present (reference: No child)				
6	Child 0 through 5 present	-93.40	15.13	0.00	**
7	Child 6 through12 present	-88.92	12.62	0.00	**
8	Child 13 through 17 present	-12.27	13.12	0.37	
	Race (reference: White)				
9	Asian	-47.44	14.43	0.01	**
10	Black	-5.27	20.64	0.81	
11	Hispanic	-18.17	17.15	0.33	
12	Age (years)	0.22	0.29	0.47	
	Education (Reference: < High school)				
13	Bachelor's degree	-17.97	9.81	0.11	
14	Graduate degree	-14.27	8.06	0.11	
15	Some college or associates	-11.73	8.21	0.19	
	Household Income (reference: < 50k)				
16	50k to 99k	6.19	22.11	0.79	
17	> 100k	-10.54	21.45	0.64	
	Home ownership status (reference: Own)				

18	Rent	13.39	8.33	0.12	
	*Gender * Children present (reference: Men, No child)*				
19	Women * Child 0 through 5 present	8.18	16.42	0.64	
20	Women * Child 6 through 12 present	3.23	9.60	0.74	
21	Women * Child 13 through 17 present	21.12	14.90	0.20	
	Commute time interactions				
	*Gender * Commute time (reference: Men)*				
22	Women * Commute time	0.07	0.14	0.64	
	*Race * Commute time (reference: White)*				
23	Commute time * Asian	0.43	0.20	0.07	*
24	Commute time * Black	0.16	0.27	0.57	
25	Commute time * Hispanic	0.06	0.20	0.76	
	*Home ownership status * Commute time (reference: Own)*				
26	Rent * Commute time	-0.09	0.08	0.27	
	*Household income * Commute time (reference: < 50k)*				
27	50k to 99k * Commute time	-0.07	0.24	0.78	
28	> 100k * Commute time	0.15	0.23	0.55	
	*Child present * Commute time (reference: No child)*				
29	Child 0 through 5 present * Commute time	0.46	0.15	0.02	**
30	Child 6 through 12 present * Commute time	0.39	0.13	0.03	**
31	Child 13 through 17 present * Commute time	-0.06	0.16	0.71	
	Household support travel interactions				
	*Gender * Household support travel (reference: Men)*				
32	Women * Household support travel	0.29	0.11	0.02	**
	*Race * Household support travel (reference: White)*				

33	Asian * Household support travel	0.14	0.19	0.49	
34	Black * Household support travel	-0.01	0.18	0.94	
35	Hispanic * Household support travel	0.30	0.12	0.03	**
	*Homeown * Household support travel (reference: Own)*				
36	Rent * Household support travel	-0.25	0.18	0.20	
	*Household income * Household support travel (reference: > 50k)*				
37	50k to 99k * Household support travel	-0.30	0.34	0.43	
38	> 100k * Household support travel	-0.12	0.29	0.69	
	*Children present * Household support travel (reference: No child)*				
39	Child 0 through 5 present * Household support travel	0.51	0.15	0.01	**
40	Child 6 through 12 present * Household support travel	0.49	0.19	0.04	**
41	Child 13 through 17 present * Household support travel	0.10	0.15	0.50	
	Transportation mode interactions				
	*Transportation mode * Gender (reference: Car, Men)*				
42	Public transit * Women	-11.48	14.49	0.44	
	*Transportation mode * Race (reference: Car, White)*				
43	Public transit * Asian	-3.00	23.12	0.90	
44	Public transit * Black	2.61	21.39	0.90	
45	Public transit * Hispanic	-1.03	33.57	0.98	
	*Transportation mode * Homeown (reference: Car, Own)*				
46	Public transit * Rent	-3.99	12.21	0.75	
	*Transportation mode * Household income (reference: Car, < 50K)*				
47	Public transit * 50k to 99k	7.25	31.39	0.82	

48	Public transit * > 100k	5.39	22.33	0.81	
	*Transportation mode * Children present (reference: Car, No child)*				
49	Public transit * Child 0 through 5 present	-15.69	16.17	0.35	
50	Public transit * Child 6 through 12 present	-2.41	18.87	0.90	
51	Public transit * Child 13 through 17 present	2.49	22.69	0.91	
	*Transportation mode * Commute time (reference: Car)*				
52	Public transit * Commute time	0.07	0.12	0.53	
	*Transportation mode * Household support travel (reference: Car)*				
53	Public transit * Household support travel	0.21	0.12	0.08	*

* statistically significant at the 0.1 level

** statistically significant at the 0.05 level