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Examining inequality in the time cost of waiting

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Time spent waiting for services represents unproductive time lost while fulfilling needs. We use time diary data from the nationally representative American Time Use Survey to estimate the difference between high- and low-income people in time spent waiting for basic services. Relative to high-income people, low-income people are one percentage point more likely to wait on an average day, are three percentage points more likely to wait when using services, spend an additional minute waiting for services on a typical day and spend 12 more minutes waiting when waiting occurs. The unconditional gap in waiting time suggests low-income people spend at least six more hours per year waiting for services than high-income people. The income gap in waiting time cannot be explained by differences in family obligations, demographics, education, work time or travel time. Further, high-income Black people experience the same higher average wait times as low-income people regardless of race.

Autonomy over the allocation of one's time—to care for oneself and one's family, to work for pay and to engage in leisure—is essential to well-being and flourishing. Yet previous research suggests that the degree of this autonomy is unequal among groups in society in ways that enforce and reproduce social inequality[1,2]. In this study, we examine time spent waiting for services, an unproductive activity in which individuals lose autonomy of their time use, and document substantial inequality between high- and low-income people in the time they spend waiting for services.

'Time inequality', or inequality in the autonomy over one's time, is important to understand as it reflects differences in how society values people's time on the basis of race/ethnicity, class or gender, and it has direct consequences for well-being, especially when paired with other disadvantages, such as income poverty. For example, delays in receiving medical care result in worse health outcomes, waiting in long lines reduces individuals' ability to vote, and dealing with prolonged bureaucratic processes to receive government benefits reduces both other productive or enjoyable time and programme participation. Closely related is research on 'time poverty', which is defined differently by different authors, but is generally related to having insufficient time for rest and leisure, after accounting for necessary and committed time, such as paid and unpaid labour[3–7].

Time inequality also likely serves as a mechanism for other observed inequities. Researchers have documented the ways in which time is an important social determinant of health[8], and thus time inequality likely contributes to observed health inequality. Time is needed for physical-health-promoting activities, such as exercise, sleep, preventative care and making healthy food choices[9], as well as mental-health-promoting activities, such as maintaining social relationships, caring for loved ones and managing stress[2]. Additionally, both income and time scarcity are related to reduced physical activity and less healthy diets[10]. And generally, a lack of time is linked to stress and illness; in fact, the signal that one's time matters less because of one's social positioning may have its own psychological 'weathering' effect on health[2]. Time inequality likely also contributes to income inequality, since spending time in necessary but unproductive activities (that is, waiting for goods and services) may take away time spent in paid work.

Social patterning in time autonomy and scarcity results from a number of mechanisms. First, higher-income jobs often come with more job flexibility than lower-income ones[11]. Thus, higher-income employees are more likely to have the ability to, for example, take a long lunch break or paid leave to accommodate a doctor's appointment or a parent–teacher conference. A lower-income employee is less likely to have paid leave or any flexibility over their break time and may have to

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take an entire day off work to accommodate necessary appointments. Relatedly, pay structures—salary versus hourly pay—are correlated with income and dictate the opportunity cost of taking time off work for such appointments. Higher-income, salaried workers suffer no economic cost from attending an appointment during work hours, whereas lower-income, hourly workers lose out on earnings. Since women and people of colour are more likely to be employed in less flexible, hourly jobs, this also has implications for gender and racial time inequality[12].

Higher-income people also have the ability to pay for convenience in ways lower-income people cannot afford[13]. In other words, money allows one to pay for time. This broad observation may manifest in ways that produce relatively small time savings, such as ordering a grocery delivery and avoiding bargain hunting, or very large ones, such as paying for elder care for an aging parent instead of providing it oneself.

Additionally, people in more disadvantaged social positions are more likely to interact with the government more frequently and in more burdensome ways than more advantaged people[14]. For instance, receipt of means-tested benefits, such as Medicaid, the Supplemental Nutrition Assistance Program, Temporary Assistance for Needy Families, housing assistance or childcare subsidies, often carries a high administrative burden: substantial time spent on paperwork, in government office waiting rooms and on the phone dealing with bureaucracy[15]. Failing to shoulder this burden can mean the loss of access to needed support. Further, administrative burdens across various domains, including the social safety net, immigration and voting, have been used to 'normalize and facilitate racially disparate outcomes from public organizations that promise fair and equal treatment'[16]. For example, in the 2016 US presidential election, residents of entirely Black neighbourhoods waited nearly 30% longer to vote than residents of entirely White neighbourhoods. They were also 74% more likely to spend more than 30 minutes at their polling place[17]. Other research has shown similar disparities in voting wait times[18].

Racism and class discrimination are at the root of other sources of time inequality as well, as discussed by Gee and colleagues (2019)[2]. For example, evidence from a field experiment finds that middle-class mental-healthcare seekers were offered appointments from psychotherapists at nearly three times the rate of their working-class counterparts[19]. Further, among middle-class help-seekers, Black seekers were less likely than White seekers to be offered an appointment[19]. This suggests it may take considerably more time for working-class and Black individuals to find necessary mental healthcare because of the bias of practitioners. Another example comes from the housing market: research has documented that Black-sounding callers took twice as long to find an apartment compared to White-sounding callers[20]. As a final example, research has found that race, having Medicaid or no insurance, and living in a low-education community are among the predictors of a longer wait time for breast surgery among breast cancer patients[21].

Lower-income people are also less likely to have efficient access to efficient goods and services. For example, Medicaid patients have reduced access to care compared to privately insured patients[22] and longer doctor's waiting room times, largely due to the number and types of practices and providers that accept Medicaid insurance, given its reimbursement rate is generally lower than that of private insurance[23].

Neighbourhoods also matter: they play an important role in shaping intergenerational poverty and the children of families who move to lower-poverty neighbourhoods experience substantially better economic outcomes in adulthood[24,25]. Access to reliable and high-quality services likely serves as one mechanism through which neighbourhoods affect poverty. Lower-income and racial-minority neighbourhoods are more likely to be located in food deserts—areas where people have limited access to a variety of healthy and affordable food[26]—thus requiring residents spend more time finding transportation and travelling to buy their groceries or rely on less healthy but nearby alternatives[27]. While research on the systematic differences in the location of food outlets has received the most attention in the literature, other work has demonstrated that retail patterns more generally vary by neighbourhood income: high-poverty neighbourhoods have lower retail employment density for supermarkets, drug stores, food services and laundry[28]. Other work has shown that banking deserts—areas without access to a physical bank branch—are more likely to be poorer and have a higher proportion of Black and Hispanic residents[29,30].

Time inequality due to differences in the built environment and neighbourhood characteristics is further exacerbated by transportation inequality. Access to an automobile plays an important role in the economic outcomes of low-income households, yet low-income and racial-minority households are less likely to own a reliable car compared to higher-income and White households[31–33]. Public transit plays an important role in increasing less advantaged groups' access to goods, services and jobs, but bus and subway riders have less control over departure, arrival and travel times and locations, resulting in more time wasted during the day.

Finally, in addition to these structural factors, at least some portion of differences in individuals' allocation of time may also represent individual choice or reflect individuals' assessments of the value of their time, which may vary by socioeconomic status (SES). For example, research has documented an increase in leisure time since 1985—a time of stagnating wages for lower-educated workers—among men without a high school degree and a decrease among men who have completed college[34]. Growth in the allocation of time to leisure may be a response to the lower cost of non-labour time for non-college-educated men, given their declining wages. However, allocating more time to leisure may instead reflect a compensation for qualitative differences in leisure time by income, which makes the relative importance of individual allocation decisions and responsiveness to social factors less clear even in the context of leisure time, an activity characterized by autonomy[35].

One useful way to investigate this broad issue of time inequality is by studying time spent waiting for goods and services. We argue that because most people would rather not wait than wait for a service, waiting time represents a loss of autonomy over one's time. Waiting is generally unproductive and often unpleasant, and takes time away from life-enhancing endeavours such as paid work, time with family, health-related activities and leisure time. In his seminal work on the subject, Schwartz concludes that 'waiting is patterned on the distribution of power in a social system', and, more generally, that 'far from being a coincidental by-product of power, then, control of time comes into view as one of its essential properties[36].' Others have similarly documented the ways in which time is used as an instrument of power and resistance, particularly in the field of sociology[37–39].

Just as in research on time inequality generally, research across academic disciplines suggests likely disparities in time spent waiting for goods and services by SES, race and ethnicity, and gender. For example, people who have a lower income or are part of a racial-minority group are more likely to live in neighbourhoods with more limited access to grocery stores, drug stores, laundries and banks[28–30], and Medicaid recipients wait longer to see a healthcare provider[23]. Having low income also limits individuals' ability to pay for convenient, time-saving services[13] and increases individuals' interaction with burdensome government bureaucracies[15,16]. Yet, with some notable exceptions using an ethnographic approach[40,41], empirical work on this social patterning of waiting is lacking.

In this paper, we begin to fill this gap in the literature by providing descriptive evidence from 17 years of nationally representative time diary data of differences in time spent waiting by SES, race/ethnicity, gender and the intersections of these characteristics. In doing so, we hope to shed more light on a less-studied aspect of inequality and inform policies and practices that enhance time autonomy for all people.

We find that low-income people spend an additional minute waiting for services (that is, shopping; medical care or educational services for themselves, household children and adults, and non-household children and adults; household services; legal services; financial services; government services; and personal care services), on a typical day—or six additional hours per year—relative to high-income people. Broadly speaking, on a typical day, the average American is unlikely to wait for services. However, relative to their high-income peers, low-income people are one percentage point more likely to wait on any given day and three percentage points more likely to wait when consuming services. Moreover, when waiting occurs, low-income people spend about 45 minutes waiting for services on average, while high-income Americans only spend about 29 minutes waiting. An income gap is also observed in time spent waiting for medical care and shopping. These gaps shrink but remain practically significant after controlling for a host of demographic characteristics, and likely understate the true extent of this disparity, given that high-income people are more likely to avoid waiting entirely. Additionally, we find large disparities by race for Black people: while wealthier White, Asian and Hispanic people all face less waiting time than their low-income, same-race/ethnicity peers, wealthier Black people wait as long as or longer than lower-income Black people and wealthy non-Black people.

Our analysis offers two primary contributions to the literature on inequality. First, our use of time diary data tied to detailed household information allows us to provide a large-scale confirmation of the socioeconomic gap in time spent waiting for common and necessary services. Moreover, the data enable us to investigate the role of household, transit, race/ethnicity, gender and schedule flexibility in the income-based gap in waiting time. Second, our analysis raises an important aspect of income inequality for further research and policy attention—unproductive waiting time. We posit that income-based gaps in time spent waiting for basic services capture a symptom of structural inequalities that likely reinforces economic inequality through unevenly distributed lost productivity and well-being.

Results

Main effects

We begin with a look at the SES gaps in (1) the probability that a person waits at all on a typical day, (2) the probability that a person waits for services on a typical day, conditional on using some services (s), (3) the time a person spends waiting for services on an typical day, unconditional on waiting some time, and (4) the time a person spends waiting for services on a typical day, conditional on waiting some time.

Table 1 presents linear probability model (LPM) and ordinary least squares (OLS) estimates from a number of simple models, described in detail in Methods, focusing on the parameter of interest—the SES gap in each dependent variable. Columns (2) through (6) add potential moderators. Panel A, column (1) shows that on a typical day, a low-income person is one percentage point more likely to spend some time waiting than a high-income person. Panel B, column (1) shows that on a typical day when some services are used, a low-income person is about three percentage points more likely to wait for services compared to a higher-income person. Panel C, column (1) indicates that a randomly selected low-income person spends about one more minute waiting for services each day compared to a high-income person. And finally, panel D, column (1) indicates that on diary days when people spend some time waiting for services, people at the bottom of the income distribution spend 12 more minutes waiting for services than do people at the top.

At the population level, as shown in panel C, on a typical day selected at random, low-income people spend an additional minute waiting for services and only about 38% of the gap can be accounted for by controlling for observable differences (that is, employment, family characteristics, demographics, travel time and location factors) between high- and low-income people. Our results suggest that in an average year, a low-income person will spend at least six more hours waiting for services than a high-income person. About 3.75 of these hours might be attributable to observable differences in the habits and characteristics of these two groups, while income alone explains about 37% of the annual difference in waiting time.

This likely reflects a conservative estimate of the annual gap in time spent waiting due to the downward bias of excess zero time when aggregating single-day time diaries for non-routine behaviours (see Supplementary Information Section A for a brief discussion of estimating long-run time aggregates from time diary data). Indeed, the gap in waiting time among those who spend some time waiting provides a means to consider different points in the distribution of waiting time. For instance, for a high-income and a low-income person who wait for a service at least once per week, the low-income person can anticipate spending about ten more hours waiting per year. Even an otherwise identical low-income person with a weekly wait would spend five more hours waiting for services each year than a high-income person in the same state. The loss of nearly an entire work day to additional waiting time for basic services each year underscores the extent of the inequality low-income households face in quality of life daily.

While the population estimate of the income gap in time spent waiting on a typical day provides a baseline understanding of inequality in access to services in the US, our focus lies primarily in the inequality in autonomy over one's time. As discussed in the introduction, at least some share of waiting time reflects individuals' decisions to wait at all for a service and might also reflect personal assessments of their valuation of their time. However, once waiting occurs, the length of time spent waiting captures factors outside of the waiter's control. If, conditional on spending some time waiting, low- and high-income people spent similar amounts of time waiting for services, we might conclude that the daily gap is a consequence primarily of individual decisions on whether to wait. In panel D, we present estimates of the amount of time spent waiting conditional on spending some time waiting during the diary day to assess inequality in the autonomy Americans have over their time when consuming needed services. As we show, even among waiters, low-income people spend more time waiting for services than their high-income counterparts.

One possible explanation for these discrepancies is that high-income people live in denser cities where they may have more service options for both public and commercial services. Column (2) controls for living in an MSA, which includes the largest cities in the US and their adjacent communities. Of course, MSAs include a wide geographic area and services differ systematically by neighbourhood. Another possibility is that quality service options cluster in neighbourhoods farther from low-income people or the reliance on public transit means low-income people schedule slack time in their appointments to account for unreliable transportation schedules. Column (3) also controls for waiting time associated with time spent travelling to use services. Differences between low- and high-income people in time spent travelling to use services and selection of living in an MSA lead to an understatement of income-based differences in exposure to waiting and overall waiting time differences, but explain only about 7% of the SES gap in time spent waiting among waiters.

In column (4), we add controls for time spent working during the diary day. Generally, low-income workers have less control over their work hours and less flexibility in their work schedules. As a result, some of the gap in waiting for services might be driven by high earners' ability to schedule service appointments during the day or when they are not working to receive services during non-peak hours. After accounting for time spent working on the diary day, the SES gap in total wait time decreases to 0.79 minutes, and the gap in wait time among those who wait decreases by about 25%, but a substantial gap still remains. As shown in column (5), even after adding controls for education, unemployment status, race, gender, age, marital status and household children, SES-based gaps shrink but remain statistically significant; among those who wait, low-income people spend

Table 1 | OLS estimates of SES gap in waiting time, weighted

		(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Likelihood of any waiting ($Pr(T>0)$)							
Income ≥US$150,000		(Omitted)					
Income ≤US$20,000	b	0.01	0.02	0.01	0.01	0.01	0.00
	se	0.00	0.00	0.00	0.00	0.00	0.00
	p	<0.001	<0.001	<0.001	<0.001	<0.001	0.066
	ci	0.0,0.0	0.0,0.0	0.0,0.0	0.0,0.0	0.0,0.0	−0.0,0.0
Adjusted R^2		0.01	0.05	0.05	0.05	0.05	0.04
Observations		210,586	210,586	210,586	210,586	210,586	210,586
Panel B. Likelihood of any waiting ($Pr(T>0\|S>0)$)							
Income ≤US$20,000	b	0.03	0.03	0.02	0.02	0.01	0.01
	se	0.00	0.00	0.00	0.00	0.00	0.00
	p	<0.001	<0.001	<0.001	<0.001	<0.001	0.01
	ci	0.02,0.03	0.02,0.04	0.01,0.03	0.01,0.03	0.01,0.02	0.00,0.01
Adjusted R^2		0.01	0.03	0.04	0.04	0.04	0.04
Observations		107,749	107,749	107,749	107,749	107,749	107,749
Panel C. Waiting time (T)							
Income ≤US$20,000	b	0.99	1.21	0.79	0.89	0.65	0.37
	se	0.16	0.16	0.15	0.15	0.15	0.09
	p	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
	ci	0.7,1.3	0.9,1.5	0.5,1.1	0.6,1.2	0.3,1.0	0.2,0.6
Adjusted R^2		0.00	0.02	0.02	0.02	0.02	0.02
Observations		210,586	210,586	210,586	210,586	210,586	210,586
Panel D. Waiting time ($T\|T>0$)							
Income ≤US$20,000	b	12.11	11.26	8.59	10.80	7.34	5.83
	se	2.76	2.84	2.68	2.65	2.76	2.16
	p	<0.001	<0.001	0.002	<0.001	0.010	0.010
	ci	6.6,17.6	5.5,17.0	3.2,14.0	5.5,16.1	1.8,12.9	1.5,10.2
Adjusted R^2		0.01	0.02	0.03	0.03	0.04	0.03
Observations		8,363	8,363	8,363	8,363	8,363	8,363
Controls for time trends		✓	✓	✓	✓	✓	✓
Controls for MSA			✓	✓	✓	✓	✓
Controls for travel time			✓	✓	✓	✓	✓
Controls for work time				✓	✓	✓	✓
Controls for family					✓	✓	✓
Controls for demos and edu.						✓	✓
Controls for state FE							✓

Note: Robust standard errors clustered at the state level. Demos, demographics; edu., education; income, household income; MSA, metropolitan statistical area; S, services; T, time; b, coefficient; se, standard error; p, *p*-value; ci, 95% confidence interval; FE, fixed effects. Panel A presents LPM estimates of the likelihood of spending any time waiting on a given day. Panel B presents LPM estimates of the likelihood of spending no time waiting on days in which respondents use some services. Panel C presents OLS estimates of time spent waiting. Panel D presents OLS estimates of time spent waiting on days waiting occurred.

more than seven additional minutes waiting for services relative to the wait time of their high-income peers. See Supplementary Information Section B for our analysis of the role of gender and income on waiting time. Finally, the gaps remain after accounting for state-specific patterns in waiting time, though exposure to any waiting on a given day shrinks to about 0.3 percentage points and becomes only marginally significant.

In Supplementary Tables 3 through 6, we show the coefficients for all income levels estimated from the three models presented in Table 1. Supplementary Figures 4 through 7 present the marginal effects of all income brackets from the same models to provide a visual presentation of the variation in waiting time across income levels. Supplementary Table 7 replicates the analysis examining differences in wait times among waiters and restricts the sample to observations that reported non-zero time spent using services included in our waiting time measure to remove respondents reporting zero wait time due to not engaging with services on the diary day. Again, the results are consistent. Finally, Supplementary Table 8 replicates the results from the LPM presented in Supplementary Table 6 with logistic regressions to account for the binary nature of the outcome. The results are strikingly similar.

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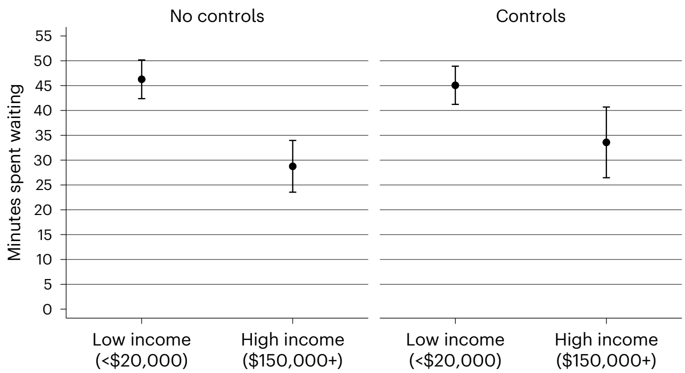

Fig. 1 | Marginal effect of income on time spent waiting for medical services for self or HH child (in minutes; $T \mid T > 0$; weighted). Note: Marginal effects from OLS regressions shown. Caps represent 95% confidence intervals (CI). No controls includes only controls for day of week, month and year time trends. Controls accounts for travel and work time, being in an MSA, being unemployed and family controls. Weighted using Bureau of Labor Statistics (BLS)-provided weights. HH, household. Low income, no controls (mean 46.28, $P < 0.001$, CI 42.38–50.17); high income, no controls (mean 28.75, $P < 0.001$, CI 23.55–33.96). Low income, controls (mean 45.06, $P < 0.001$, CI 41.22–48.91); high income, no controls (mean 33.58, $P < 0.001$, CI 26.46–40.69). $n = 832$.

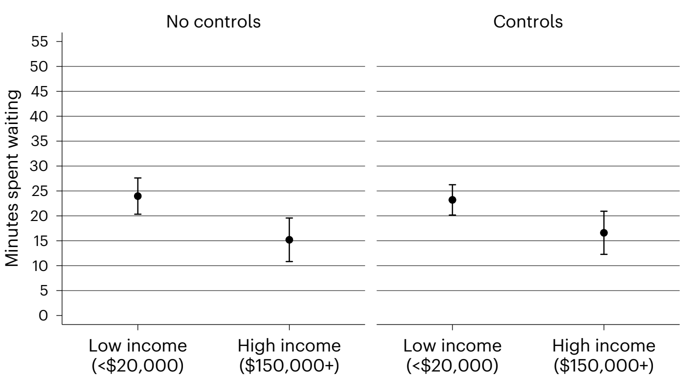

Fig. 2 | Marginal effect of income on time spent waiting while shopping (in minutes; $T \mid T > 0$; weighted). Note: Marginal effects from OLS regressions shown. Caps represent 95% CI. No controls includes only controls for day of week, month and year time trends. Controls accounts for travel and work time, being in an MSA, being unemployed and family controls. Weighted using BLS-provided weights. Low income, no controls (mean 23.97, $P < 0.001$, CI 20.33–27.61); high income, no controls (mean 15.20, $P < 0.001$, CI 10.83–19.57). Low income, controls (mean 23.21, $P < 0.001$, CI 20.16–26.25); high income, no controls (mean 16.60, $P < 0.001$, CI 12.27–20.93). $n = 274$.

Waiting for specific services

We have focused our analysis on total time spent waiting for any basic services, including services less commonly observed on an average diary day, such as legal or government services. Two of the services most commonly used (and, in fact, often impossible to avoid) and most commonly associated with waiting time are medical services and shopping (including grocery shopping). Given the importance of access to medical care and shopping in daily life, a waiting gap for these services provides insight into inequality in quality of life when meeting basic needs in a typical day. We restrict the sample to diary days with non-zero waiting time for these two basic services to examine whether the SES gap persists.

Figure 1 presents the marginal effects of SES on total time spent waiting for medical services among people who spent some time waiting for medical care for themselves or their children. As the figure shows, accounting only for time trends, low-income people spend significantly more time waiting for medical services. On an average day when both a high- and low-income person wait for medical care, the poorer person waits an average of 46.28 minutes while the wealthier person waits an average of 28.75 minutes – a 38% difference in time spent unproductively waiting to be seen. Even after controlling for family characteristics, employment status, travel time associated with medical care and time spent working, wealthy people spend considerably less time waiting for medical care on average (45.06 minutes versus 33.58 minutes).

Figure 2 presents the same analysis for time spent waiting while shopping. As with waiting for all services and waiting for medical care, among shoppers kept waiting for some amount of time, low-income people wait longer on average. Accounting for only year, month and day of week effects, low-income people spend about 24 minutes waiting while shopping, including for basic necessities like groceries, while wealthier people face an average wait of 15 minutes when they have to wait. Differences between high- and low-income people in travel time, work time, family characteristics and unemployment status only account for about two minutes of the nearly-nine-minute gap in average time spent waiting while shopping for goods.

Even small differences in average wait time add up throughout the year. A low-income household with a regular need for medical care that involves two appointments a month—such as seeing a doctor or picking up a prescription for household members themselves or their children—can expect to spend nearly five additional hours per year in waiting rooms compared to a high-income person. Similarly, a low-income household that shops for goods three times a week with some waiting time can expect to spend 16 additional hours per year standing in line at shops and grocers' in comparison to people in the wealthiest households.

Race and ethnicity differences in waiting by SES

As discussed further above, we might also expect to see differences in wait time by race and ethnicity for a number of reasons, including a legacy of housing discrimination that has sorted Black people into underserved communities with overburdened services, ongoing racism in access to high-quality medical services, and increased contact with burdensome government processes, among others. In Supplementary Figure 8, we present differences in wait times by race and ethnicity with and without adjusting for SES, as race structures SES in a racially stratified society and differences in wait times by race and ethnicity are likely a product of these downstream SES differences as well as the more direct effect of racism[42–44]. These estimates, however, mask important nuance regarding the intersection of race/ethnicity and class. For instance, since race/ethnicity is more observable than class, the class-based benefits of reduced waiting times might differ across racial and ethnic groups. Thus, we focus our analysis on differences in both the likelihood to be kept waiting and time spent waiting for services by race/ethnicity and class simultaneously.

Figure 3 depicts the probability that someone using basic services had to wait for services separately by race/ethnicity and SES. Two results emerge from the patterns in Fig. 3. First, for White and Black Americans, class seems to play a larger role in determining the likelihood of waiting for services than race. Low-income White and Black Americans are both more likely to wait when seeking services than their wealthier same-race peers (see Supplementary Table 9 for regression output). Second, for Hispanic and Asian Americans, race/ethnicity seems more salient. Both low- and high-income Hispanic Americans share a higher likelihood of waiting for services than White Americans in the same income bracket. That is, Hispanic Americans do not seem to receive the same drop in their exposure to waiting that comes with

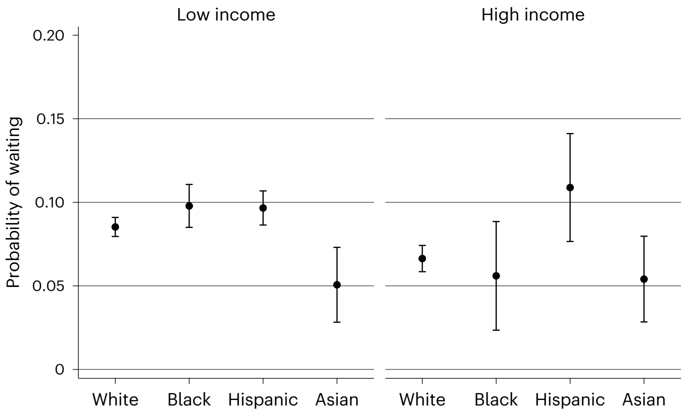

Fig. 3 | Marginal effect of income on probability of any waiting for services by race and ethnicity, with controls (weighted). Note: Marginal effects from OLS regressions shown. Caps represent 95% CI. Includes controls for day of week, month and year time trends, travel and work time, whether respondent lives in an MSA, unemployment status and family controls. Weighted using BLS-provided weights. Low income: White (mean 0.09, $P < 0.001$, CI 0.08–0.09), Black (mean 0.10, $P < 0.001$, CI 0.08–0.11), Hispanic (mean 0.10, $P < 0.001$, CI 0.09–0.11), Asian (mean 0.05, $P < 0.001$, CI 0.03–0.07). High income: White (mean 0.07, $P < 0.001$, CI 0.06–0.07), Black (mean 0.06, $P = 0.001$, CI 0.02–0.09), Hispanic (mean 0.11, $P < 0.001$, CI 0.08–0.14), Asian (mean 0.05, $P < 0.001$, CI 0.03–0.08). $n = 22{,}252$ for low-income sample and $n = 8{,}298$ for high-income sample.

wealth that White and Black Americans receive. On the other hand, Asian Americans are the least likely to experience any waiting for services regardless of income.

However, examining time spent waiting for services when waiting occurs illustrates a different link between race/ethnicity and time spent waiting. Figure 4 displays the average time spent waiting separately by race/ethnicity and SES. As the figure indicates, wealthier White, Asian and Hispanic people all face significantly less waiting time when waiting for services than their less-well-off same-race/ethnicity peers. However, when wealthier Black people wait for services, they wait as long as or longer than lower-income Black people. Moreover, the difference in time spent waiting for services between wealthy Black people and wealthy non-Black people is statistically significant. For instance, while wealthier White people face an average wait time of 28 minutes, wealthier Black people face a 54-minute average wait time (see Supplementary Table 9 for regression output).

Time of day differences in waiting by SES

Schedule flexibility presents another avenue through which inequity in time spent waiting might operate. As discussed above, high-income workers often have more autonomy in their professional lives and face fewer penalties for or barriers to taking time off work during the workweek to manage personal matters. Work schedule autonomy might allow for optimizing appointment scheduling during non-peak hours when many others must work. Intuitively, if schedule autonomy drives the income gap in waiting time, we anticipate wait times during high-demand hours—before and after the workday—to be distributed evenly between high- and low-income people. In the case of similar wait times during peak hours, an overall gap in waiting time could be driven by high-income individuals scheduling services in off-peak hours and not due to differential treatment or differential service quality. We break the time of day into morning (5 a.m. to 10:59 a.m.), lunchtime (11 a.m. to 1:59 p.m.), afternoon (2 p.m. to 5:59 p.m.) and evening (6 p.m. to midnight).

Figure 5 presents the estimated average time spent waiting for services by income and time of day on weekdays. Notably, during the week, when waiting for services, low-income people spend much more time waiting in the mornings and evenings than their wealthier peers who are also waiting for services. For instance, in the morning, a low-income person can expect to spend nearly double the amount of time waiting for services than a wealthier person (50 minutes versus 26 minutes). In the evening, the SES gap in time spent waiting is more than double (37 minutes versus 15). Meanwhile, as Supplementary Figure 11 shows, low-income people face a longer wait time at every time of day on the weekends. See also Supplementary Figure 12 for LPM estimates of the likelihood of facing any waiting time at each time of day. The results show a similar pattern.

The results suggest that while schedule autonomy may play a role (low-income workers are indeed more likely to be waiting before work in the mornings), they do not fully explain the SES gap in time spent waiting. For instance, even in the mornings and evenings, when demand for services might be highest, wealthier people face shorter waits. Similarly, our supplemental analysis shows that on the weekends, wealthier people face shorter waits at any time of day. Moreover, the gaps reflect a troubling inequality—low-income people lose more of their non-work time in the mornings and evenings, time which could be spent in leisure or with family, to unproductively waiting for basic services. Instead of rejuvenating on weekends or after work hours, low-income people have more of their time wasted trying to take care of basic needs. The patterns suggest the waiting-time gap is unlikely to be explained entirely by schedule autonomy and is instead a function of other inequalities, such as inequity in neighbourhood services or in public services provided to low-income people.

Discussion and conclusion

In summary, we find that when spending some amount of time pursuing basic services, high-income people are slightly more likely to avoid waiting entirely and, on average, people at the bottom of the income distribution spend about one more minute per day—or about six hours per year—waiting for services than people at the top. Our results suggest that low-income households receiving slower services than their high-income peers represents a conservative estimate of between US$3.6 billion and US$9.3 billion in lost productivity nationally each year. We estimate this range using a US$25 per hour wage rate and the implied hourly wage of annual earnings of US$20,000 per year (US$9.61 per hour). About 24% of US adults, or 61.99 million people, fall into this income bracket. We use this to estimate the value of six hours at this wage rate and multiply it by the affected population to derive the estimated national cost.

This gap shrinks but remains a statistically significant and practically meaningful 2.25 hours per year—representing between US$1.3 billion and US$3.5 billion in lost national productivity—after controlling for education, unemployment status, race/ethnicity, gender, age, marital status and household children, waiting time associated with time spent travelling to use services, work hours and state-fixed effects. Put differently, of the observed six additional hours per year low-income Americans spend waiting for services, only about 3.75 of those hours can be attributed to other observed differences between high- and low-income Americans. We also show evidence suggesting that while work schedule autonomy likely plays a role in this gap, it does not fully explain it. A known limitation of time diary data from single days is that the short time horizon leads to an overstatement of zero time spent in non-routine behaviours, thereby creating a downward bias in estimates of long-run time spent on such non-routine behaviours. We discuss this in Supplementary Information Section A and present annual estimates derived from different assumptions about service consumption habits to estimate the waiting time burden facing subgroups of low- and high-income Americans that may vary in their service consumption habits and likelihood of waiting.

More importantly for understanding inequality in autonomy over time allocation, conditional on spending some time waiting for

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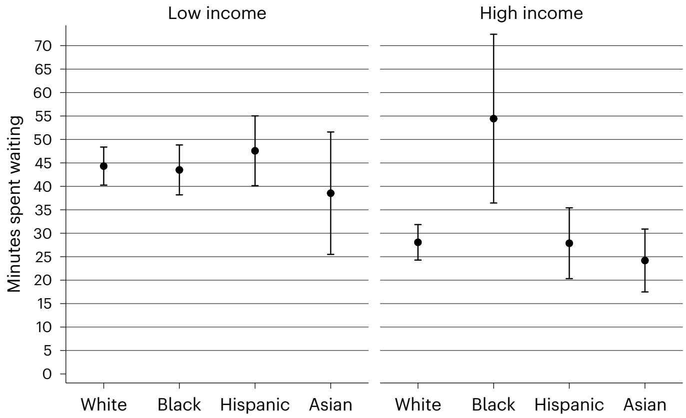

Fig. 4 | Marginal effect of income on time spent waiting for services by race and ethnicity, with controls (in minutes; $T | T > 0$; weighted). Note: Marginal effects from OLS regressions shown. Caps represent 95% CI. Includes controls for day of week, month and year time trends, travel and work time, whether respondent lives in an MSA, unemployment status, and family controls. Weighted using BLS-provided weights. Low income: White (mean 44.32, $P < 0.001$, CI 40.27–48.38), Black (mean 43.51, $P < 0.001$, CI 38.19–48.83), Hispanic (mean 47.58, $P < 0.001$, CI 40.14–55.03), Asian (mean 38.54, $P < 0.001$, CI 25.49–51.59). High-income: White (mean 28.07, $P < 0.001$, CI 24.29–31.85), Black (mean 54.45, $P < 0.001$, CI 36.46–72.44), Hispanic (mean 27.87, $P < 0.001$, CI 20.32–35.42), Asian (mean 24.19, $P < 0.001$, CI 17.49–30.89). $n = 2,020$ for low-income sample and $n = 531$ for high-income sample.

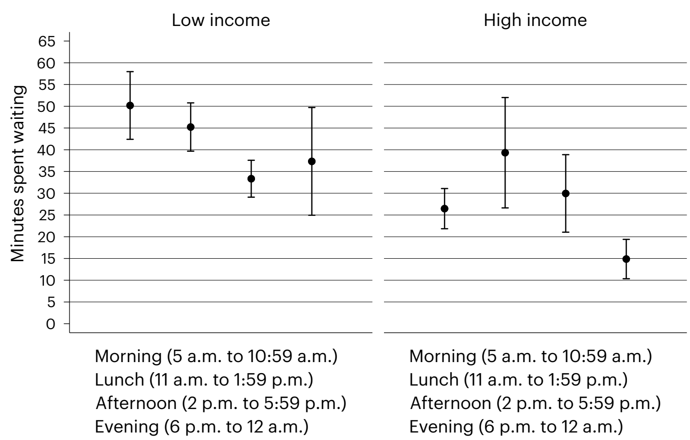

Fig. 5 | Marginal effect of income on time spent waiting for services by time of day, weekdays (in minutes; $T | T > 0$; weighted). Note: Marginal effects from LPM regressions shown. Caps represent 95% CI. Includes only controls for month and year time trends. Monday through Friday are considered weekdays. Weighted using BLS-provided weights. Low income: morning (mean 50.19, $P < 0.001$, CI 42.40–57.97), lunch (mean 45.23, $P < 0.001$, CI 39.67–50.78), afternoon (mean 33.34, $P < 0.001$, CI 29.10–37.59), evening (mean 37.33, $P < 0.001$, CI 24.95–49.72). High income: morning (mean 26.46, $P < 0.001$, CI 21.84–31.08), lunch (mean 39.32, $P < 0.001$, CI 26.63–52.02), afternoon (mean 29.96, $P < 0.001$, CI 21.05–38.87), evening (mean 14.88, $P < 0.001$, CI 10.35–19.40). $n = 1,484$ for low-income sample and $n = 276$ for high-income sample.

services, we find low-income Americans face longer wait times. On a day when some waiting occurs, low-income Americans spend 12 more minutes waiting for services than their high-income counterparts. After accounting for observable differences between high- and low-income Americans and state-fixed effects, a 5.8 minute gap in waiting times remains. The differences become even more stark when focusing on two essential activities: obtaining medical care and shopping. On an average day when both a high- and a low-income person wait for medical care, the poorer person waits an average of 18 minutes longer to receive that care. Given recent evidence about the link between racial disparities in hospital waiting times and racial disparities in mortality[45], this gap in time spent waiting for medical services is particularly troubling. Among shoppers kept waiting for some amount of time, low-income people wait about nine minutes longer.

Even beyond exacerbating inequity, the waiting gap carries two important policy considerations. First, wait times might alter behaviour. If medical service appointments take more time, low-income households may put off seeking medical help until health problems become severe and more costly to ameliorate, especially if low-income households face less schedule flexibility. When grocery shopping involves burdensome wait times, low-income households may consume more processed foods to reduce their number of trips to the store, possibly leading to less healthy eating choices. Second, income-based gains in waiting time during a typical waiting spell for services suggests different service quality availability in neighbourhoods where low- and high-income people live.

Our analysis of differences in the likelihood of waiting by race/ethnicity reveal that low-income White and Black Americans are both more likely to wait when seeking services than their wealthier same-race peers, which suggests that for these groups SES plays a more prominent role than race in whether or not a person can avoid waiting altogether. This is not the case for Hispanic Americans, who are more likely to wait for services than White Americans in the same income bracket. Asian Americans are the least likely to wait for goods and services, regardless of income. However, when analysing gaps in time spent waiting for services among people who wait at all, we find that while wealthier White, Asian and Hispanic people all face less waiting time than their low-income, same-race/ethnicity peers, wealthier Black people wait as long as or longer than lower-income Black people and wealthy non-Black people.

Together, these analyses suggest a few patterns in the roles of race/ethnicity and SES in waiting for services. Wealthier Black people might be less subject to waiting on the extensive margin because income allows some people to seek more high-quality services or pursue strategies that avoid waiting entirely (for example, online retail for shopping or paying for someone else to wait in their place). However, when waiting does occur, a higher income buys reduced wait times only for non-Black people. This finding mirrors existing research in other areas, such as patterns of health inequalities[44]. When seeking basic services, Black Americans face a double disadvantage due to historic and current discrimination: they are more likely to be poor and therefore subject to higher wait times driven by SES inequality and Black Americans experience higher average wait times independent of income. That even wealthier Black Americans do not see lower wait times could be a function of systematic discrimination in treatment, a symptom of Black communities receiving less financial support, leaving services overburdened and under-resourced, or a combination of both discriminatory treatment and structural disadvantage.

Our results underscore an inequity in how society values the time of people from the poorest households. The income gap in waiting time we document reflects a difference between rich and poor Americans in autonomy, productive time left available each day, and daily quality of life. Moreover, the gap cannot be explained by transit, working time, education or family circumstances, which points to the possibility that neighbourhood quality differences leave poor Americans with less access to quality, efficient services in trying to meet their daily needs. The difference in treatment when seeking basic services represents a pernicious inequality in the daily lives of the rich and poor. Beyond the economic effects of imposed unproductive time, additional time waiting for basic services makes predictable daily schedules more difficult, leading to stress and creating spillovers into the quality of time spent in other activities[41]. There are a number of policy and management responses—big and small—that might be considered to help mitigate this particular manifestation of inequality.

First, building schedule flexibility into everyday, necessary institutions would increase access for poor and low-income families[41]. For example, longer daycare hours and expanded, free afterschool programming would immediately increase low-income parents' discretionary time by allowing less congested drop-off and pick-up times and more accommodation for shift work that may not align with a typical, nine-to-five work schedule. Similarly, medical clinics could adopt more flexible and predictable appointment scheduling aimed at both reducing wait times and accommodating a wider range of work schedules.

Second, Medicaid could be reformed to increase the number of healthcare providers who accept Medicaid-covered patients. Currently, the combination of Medicaid providing lower reimbursement rates than private insurance and the lack of a mandate for providers to accept Medicaid makes doctors less likely to accept Medicaid than other types of insurance. As mentioned above, research shows that differences in wait times for medical care between higher- and lower-income people is largely driven by differences in the types of practices and providers that accept Medicaid, and is larger in states with lower Medicaid reimbursement rates[23]. This suggests that Medicaid patients in states with higher reimbursement rates have more access to high-quality or less-overburdened practices and providers, and offers a simple and direct way to reduce the income-based gap in waiting for medical services we document in our analysis.

Third, labour and employment policy changes might be another avenue to reduce the SES gap in waiting time through two primary avenues. First, policy changes that provide more autonomy and predictability in work schedules for low-income and hourly workers could help provide needed flexibility to optimize service appointments, creating smoother demand for services throughout the day for providers and reducing wait times for low-income households. Fair workweek laws, which provide workers with the right to advance notice of their work schedule, compensation for schedule changes, and the right to request scheduling accommodations, have recently been enacted in five major cities and the state of Oregon in an attempt to reduce the propensity for hourly work to be 'on-call' and unpredictable week to week[46]. Expanding such laws can provide low-income workers the work schedule flexibility available to high-income workers, and preliminary evidence suggests employers may also benefit from increased productivity[47]. Second, policies that reduce poverty and economic inequality will likely reduce time inequality as well. Simply increasing household income, through policies such as refundable child tax credits, the Earned Income Tax Credit and minimum wage laws may reduce the time burden of poverty, leaving more productive time available for contributing to society and personal well-being.

Fourth, more equitable investment in neighbourhoods, especially neighbourhoods of colour, and public transit may help reduce the SES gap in time spent waiting for services. To the extent that waiting times reflect inefficient or low-quality service, increasing the number of options in a small geographic space can induce service improvements and provide additional options for surplus demand. As noted previously, low-income people and people of colour often face limited options for both retail and financial services[26–29]. Facing such thin competition in low-income neighbourhoods, businesses may both understaff to reduce costs and face excess demand—a combination that likely feeds long wait times. The relative lack of options for services forces low-income people to choose between spending more time travelling to higher-quality services elsewhere and spending more time waiting for services locally. Reducing neighbourhood segregation by race and class and investing more heavily in basic services in communities of colour could help provide the competition necessary to both improve service and reduce excess demand for services.

Finally, while our analysis focuses on waiting spells when waiting occurs to minimize the influence of individual choice on our estimates of the SES gap in waiting time, individual choices may still explain part of the gap in time spent waiting for services. Indeed, we document an SES gap at the extensive margin of waiting, suggesting wealthier individuals select out of waiting at a higher rate. Thus, at least part of the SES gap in waiting time may be attributable to time allocation differences driven by the higher opportunity cost of waiting time faced by high earners. To the extent that income itself drives the allocation of time to less productive activities, such as accepting longer waiting times, our results point to otherwise unmeasured benefits from employment-based cash transfer benefits (for example, the Earned Income Tax Credit) and other wage-enhancing policies, as reducing income inequality would also mechanically reduce time spent unproductively waiting for services or shift demand to more efficient services without long waiting times.

Our work also suggests directions for future research. First, future work should continue to investigate the behavioural changes that are likely differentially induced by these wait disparities. Such work could help reveal how time and waiting inequalities work as mechanisms for other observed inequalities, such as health outcomes. Future work examining how exogenous exposure to waiting in grocery stores changes purchasing patterns or whether exposure to waiting in medical clinics alters how long patients delay scheduling an appointment would help illuminate some of the most important potential consequences of the waiting gap we document in our analysis.

Second, while valuable, the ATUS has several limitations that likely bias our estimates downward. In other words, we are likely underestimating the true time gaps in time spent waiting for services. Further, because the ATUS captures respondents' time on one particular day, it is not well suited to measure differences in time spent waiting for less-common but important activities, such as applying for social safety net benefits or voting. Future work should use other data sources or collect data on time use and waiting time for specific activities. Relatedly, the ATUS comes from the United States; however, several countries (for example, Australia, Canada, Germany, Japan, Korea, New Zealand, South Africa and the United Kingdom) also collect time diary data from representative samples. International comparisons of the SES gap in waiting time could provide valuable insights regarding the societal, economic and cultural differences that shape waiting time.

Third, while our analyses shed some light on some potential mechanisms underlying these differences—such as work schedules—they must be paired with existing and future qualitative work to more fully understand these experiences. For example, an ethnographic study of low-income mothers in Chicago emphasizes the lack of control these mothers reported over their time[41]. As the authors note, 'If low-income working mothers could not make the health department's office hours for their children's immunization, they could not opt to use private physicians. They also could not choose to use flex-time options on their jobs to stay home to nurse sick children. Instead, these mothers risked lost wages, valuable work hours, and even job security by giving priority to inevitable family crises.' The authors also describe the extra hours these mothers built in to their daily commutes to accommodate public transit wait times. Such qualitative insights can help researchers and policy-makers identify the particular levers through which low-income people's time can be better respected in daily life.

Finally, this work might inspire research questions in a number of social science fields. For example, public administration scholars might analyse whether socioeconomic or racial representation among public sector employees reduces wait times or the impact of government efficiency on the gap between the real and nominal value of public subsidies. Political scientists might consider the effects of time spent waiting on public opinion of government and subsequent voting and civic participation behaviours. Economists might consider the productivity costs and relative economic value of time suggested by our estimated wait time gap, the influence of market competition on wait times and the use of waiting times to consider inequality in the price of consumption. In short, the descriptive inequities in wait times we observe here reflect a broad array of social, political and economic forces that warrant continued study.

Methods

Data

Ethics approval was not required for this analysis of publicly available data. Data were collected by the United States Bureau of Labor Statistics, which obtained informed consent of all participants. We investigate the socioeconomic gap in time spent waiting for services using data from the ATUS, which collects retrospective time diary data from a nationally representative subsample drawn from respondents to the Census Bureau's Community Population Survey (CPS) each year. When completing the time diaries, one respondent aged 15 or older per household reports their activities during the previous 24 hours. When collecting time diary data, interviewers use a computer-assisted interview system that begins by prompting respondents to report what they were doing at 4 a.m. Interviewers then ask respondents how long they did the activity. The interviewers then move to the time block at the end of the activity and repeat the inquiries. Three features of the ATUS make the data appropriate for the purposes of our analysis. First, time diaries do not direct respondent attention to any particular activity, thereby reducing the potential biases of framing, interpretation, social desirability or recall common in conventional survey data[48]. Second, the ATUS links respondents to rich CPS data regarding their household characteristics, demographics, education and SES, which allow us to compare time-use patterns in an average day across people in different economic circumstances. Finally, the ATUS includes waiting time associated with various activities separately from time spent in said activity.

Dependent variable

We focus our analysis on the average amount of time spent waiting for common services, in minutes, in a typical 24-hour period. We estimate this using the total minutes spent waiting for services on the diary day recorded by the ATUS. We argue that waiting is a useful measure of time inequality because it does not, in and of itself, provide utility or increase productivity. Thus, unlike differences in leisure time, which provide utility and which some have argued reflect a choice that systematically varies by SES, time spent waiting is more likely to reflect structural constraints on one's time[34]. Most people—regardless of SES—would choose to receive a good or service without a wait. Moreover, we cannot readily distinguish differences between zero waiting time due to choice versus zero waiting time attributable to efficient service provision. Given this data limitation and in accordance with our interest in time inequality rather than individual choices in time use, we focus our analysis on the gap in waiting time conditional on non-zero time spent waiting.

We include time spent on waiting associated with shopping; medical care for the respondent, household children and adults, and non-household children and adults; household services (for example, maintenance, lawn services, etc.); legal services; financial services; educational services for the respondent or household and non-household children; government services; and personal care services (for example, salons, barbers, etc.). We take the sum of time spent waiting on common services in a 24-hour period as our primary outcome of interest. We complement our analysis with an examination of time spent waiting on medical services for respondents and their household children and time spent on waiting associated with shopping, two core services for which inequality in waiting time suggests inequality in treatment and access to quality services or inequality in neighbourhood conditions.

Independent variables

Our primary independent construct of interest is household income. The CPS collects self-reported annual household income for each respondent and provides a categorical measure of household income that is top-coded at an annual household income of US$150,000 or more per year. For our main analysis, we use a seven-category measure of household income that ranges from US$20,000 or less to US$150,000 or more in annual income. For the purposes of our analysis, we define 'low income' as households with income of US$20,000 or less and 'high income' using the top-coded category of US$150,000 or more. The federal poverty line for an individual in 2021 in the continental US is US$12,880 with an additional US$4,540 for each additional person in the household. In 2003, the poverty line for a family of four was US$18,400 in the 48 contiguous states and the District of Columbia. See https://aspe.hhs.gov/poverty-guidelines for more detail. In Supplementary Information Section F, we impute household income using data from the Annual Social and Economic Survey of the CPS to estimate our model using quantiles of income relative to the federal poverty line by household size.

Of course, other factors might systematically differ by both income and the factors that contribute to time spent waiting for services. For instance, transit or hours spent working might contribute to the socioeconomic gap in wait time. Fortunately, in addition to providing time spent working throughout the day, the ATUS includes separate measures of travel time associated with specific activities, including the activities for which respondents wait. The ATUS associates travel time according to the activity performed immediately following the travel. For instance, if a person stops at a shop on the way to work, travel to the shop is coded as 'travel associated with shopping' and the travel from the shop to work is coded as 'travel associated with working'. While the coding rule adopted by the ATUS carries potentially substantial implications for estimating commute times to and from work[49], estimates measuring travel time for specific activities besides work is not meaningfully influenced by the ATUS coding rule[50]. We measure travel time as the sum of all time spent on travel associated with the activities included in our measure of waiting time. This includes travel associated with personal care services, household services, caring for household members, caring for non-household members, education, childcare services, financial services, legal services, medical services, shopping and government services.

We also include measures for family composition, demographics, education and an indicator for whether the respondent is unemployed. We measure family composition with an indicator for whether the respondent is married, whether the respondent has a child of two years old or younger in their household, and the number of children aged 17 or under in the household. We capture education with mutually exclusive indicators for whether the respondent's highest educational attainment is less than a high school diploma, a high school diploma, some college, or a four-year college degree or more. Finally, demographics include gender (male or female), race/ethnicity (Black, White, Asian/Pacific Islander, Hispanic, Native American, multiple races, and other race) and age. Demographic and family factors might shape the probability that a person needs to engage in some activities associated with wait times or might shape where a person lives and the mix of service quality in their neighbourhood.

Finally, we also include a measure for whether someone lives in the MSA of a major city. People living in denser cities may have more options available nearby for services; however, denser cities may also increase wait time due to higher demand for services. We summarize the ATUS sample, both overall and separately by household income, in Supplementary Information Section C.

Empirical methods

We aim to descriptively investigate the size of income-based gaps in time spent waiting for necessary and common services, as well as some of the potential explanations for these gaps. We adopt a straightforward linear model of waiting time (Y) of person i:

$$Y_i = \alpha + \beta \mathrm{SES}_i + \gamma \mathrm{X}_i + \tau + \varepsilon_i \quad (1)$$

where **SES** represents socioeconomic status measured with indicators for each category of household income described previously; **X** represents a vector of controls for demographics, education, family composition, unemployment status, MSA status, and travel and work time; and τ represents day of week, month and year time trends. In equation (1), β represents our parameter of interest and captures the difference in waiting time experienced by high- and low-income households after accounting for differences in observable characteristics and time trends in waiting time. Important for our purposes, as various **X** enter the model, the resulting change in β provides insights regarding how much of the SES gap in time spent waiting can be attributed to other factors that differ by SES. Finally, we estimate three augmentations of equation (1). In one extension, we add state-fixed effects to account for possible variation in SES gaps in waiting time driven by unobserved state-specific, time-invariant attributes. In another, we replace time spent waiting with a binary indicator equal to 1 if the respondent spent any time waiting during the diary day. In a third, we replace time spent waiting with a binary indicator equal to 1 if the respondent spent no time waiting on a diary day in which they reported spending some time using services. Using indicators for any time waiting and the likelihood of no waiting when using services allows us to examine the SES gap on the extensive margin of waiting in addition to comparing total time spent waiting.

We estimate equation (1) using OLS with standard errors clustered at the state level and take that as our preferred estimate for ease of inference. See Supplementary Table 13 for average partial effects estimated using Tobit regression models to account for the left censored nature of time data and the 'pile-up' at zero. Earlier work shows that OLS is more robust to Type II errors than count models, even with a pile-up at zero[51]. Similarly, evidence also shows OLS is more robust than Tobit when the measurement error is attributable to the sampling of days inherent to time diary data[52]. Supplementary Tables 14 and 15 report the average partial effects of Type I Tobit, two-limit Tobit and Poisson regression to demonstrate robustness of choice of estimator. We weight all regressions using BLS-provided sampling weights that account for the unequal sampling probability of subgroups, days and months of time diaries. We conduct all analyses in the study using Stata17.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

The ATUS data used in our analysis is publicly available and the multi-year microdata files used in our analysis can be found at https://www.bls.gov/tus/datafiles-0319.htm. The poverty thresholds used in the imputation-based robustness check in Supplemental Information can be found at https://www.census.gov/data/tables/time-series/demo/income-poverty/historical-poverty-thresholds.html. The Annual Social and Economic Supplement to the Current Population Survey (also used in the imputation-based robustness check in Supplemental Information can be found at IPUMS (https://cps.ipums.org/cps/).

Code availability

Data files and the Stata17.do file for replicating the analysis is available on GitHub at https://github.com/stevebholt/waiting-time.

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Data collection	No software was used; publicly available data.
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The ATUS data used in our analysis is publicly available and the multi-year microdata files used in our analysis can be found at https://www.bls.gov/tus/datafiles0319.htm. The poverty thresholds used in the imputation-based robustness check in the Supplemental Information can be found at https://www.census.gov/data/tables/timeseries/demo/income-poverty/historical-poverty-thresholds.html.

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Population characteristics	See below
Recruitment	Participants are randomly sampled from the nationally representative Current Population Survey (CPS). They are recruited with mailers in English and Spanish after participation in the CPS. The mailers include the date of the interview, a brochure with frequently asked questions and, for minors, explanations about the study to parents.
Ethics oversight	Ethics approval was not required for this analysis of publicly available data. Data were collected by the United States Bureau of Labor Statistics, which obtained informed consent of all participants.

Note that full information on the approval of the study protocol must also be provided in the manuscript.

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Study description	The study analyzes a nationally representative repeated cross-section of time diary data collected in the U.S. using OLS regression analysis.
Research sample	The American Time Use Survey (ATUS) collects 24-hr retrospective time diary data from a nationally representative sample of the U.S. The data is collected from different respondents annually and we use data from 2003 to 2019. The dataset was chosen to generate nationally representative time use estimates.
Sampling strategy	The sample is a stratified random sample that is stratified in three stages - at the state level, by household characteristics (race, presence and age of children, number of adults in the household) with an oversample of Black respondents and respondents with children (corrected by weights), and finally the diary respondent is randomly selected from within households (above the age of 15).
Data collection	The data is collected by the Bureau of Labor Statistics via phone interviews with trained interviewers using a computer assisted prompting system (CATI). Interviewers enter retrospective diary data for how the respondent spent each 15 minute interval of the previous 24-hrs (from 4 a.m to 4 a.m.). The diary data is then coded by 2 coders with a 3 reviewer settling disagreements. The authors of this manuscript did not collect the data.
Timing	The sample is for each year is collected throughout the year with subsamples collected each month. Households from the sample are randomly selected for month, week, and day-of-week subsamples of time diary data collection.
Data exclusions	Some analyses restricts the sample to diary days in which waiting occurred, as waiting is the primary phenomena of interest to the study. Unless otherwise indicated for subgroup and subsample analyses, all cases were used. Sample sizes vary by analysis and are provided for all analyses in the manuscript.
Non-participation	The response rates vary by year in the ATUS; however, response rates have declined annually over time. In 2003 the response rate was 57.8% while in 2019 the response rate had declined to 42%.
Randomization	Covariates were controlled using regression analysis.

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