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Notching for free: Do cyclists reveal the opportunity cost of time?☆

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ABSTRACT

We estimate time-for-money tradeoffs for cyclists by exploiting revealed behavior in response to a bikesharing program's discontinuous, "notched" pricing structure. The cost of a bicycle trip increases from \$0 to \$1 after 30 min. We observe cyclists adding time to their trip by checking-in at an intermediate station along their route to avoid the price, thus revealing their value of saving time (VST) cycling. Estimates of the VST for cycling are close to the minimum wage or roughly 20% of hourly wages implied by median incomes. These estimates are smaller than comparable estimates for automobiles, likely driven by leisure benefits of cycling. Although bicycle commuters exhibit somewhat larger VSTs, our results across user type, time, and route-specific characteristics are relatively homogeneous, suggesting a more fundamental time–money tradeoff. Additionally, we estimate small changes along extensive margins in response to a large price increase, but changes along intensive margins are virtually nonexistent.

1. Introduction

Time is a fundamental economic constraint. Becker (1965) operationalized time-allocation decisions as a function of forgone earnings: in essence, the opportunity cost of time is equal to the shadow value on money income. DeSerpa (1971) generalized this model to allow different activities to possess different values of time, providing a consistent framework to evaluate how individuals trade off money for time spent in a specific activity.

The value of time – or, more concretely, the value of saving time (VST) – is a critical input into both transportation policy and nonmarket valuation methods that rely on travel costs. One of the largest automobile externalities is the external cost of traffic congestion (Parry et al., 2007), thus reducing time spent in traffic is often the largest economic benefit of improvements in transportation infrastructure. On the other hand, time spent traveling to recreational sites is typically the largest cost associated with a recreational trip (Phaneuf and Smith, 2005), which can then be used to value environmental quality changes. For example, the opportunity cost of time was a primary feature of the value of lost recreational benefits from the Deep Water Horizon oil spill (Deepwater Horizon Natural Resource Damage Assessment Trustees, 2016). Although the theory of time allocation decisions is well-established, there remain unsettled empirical questions about the value of time for specific purposes (utilitarian vs. recreational),[1] for different modes of transit, and for differences arising from methodological approaches (e.g., stated vs. revealed preference).

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[1] Throughout the manuscript, we use "utilitarian" to mean a trip that provides productive benefits such as commuting.

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In this paper, we estimate revealed values of saving time for cyclists on an intensive margin in contrast to much of the literature that relies a combination of stated and revealed preference data using discrete-choice frameworks. Much of this literature focuses on time–money tradeoffs identified through motorists' preferences for free travel on congested routes vs. priced, free-flowing travel on toll roads or express lanes either using stated preference surveys that present hypothetical scenarios, revealed decisions based on observed route choice, or a combination of both (Small et al., 2005; Fezzi et al., 2014; Lew and Larson, 2005; Bockstael et al., 1987; Feather and Shaw, 1999).[2] In contrast, we leverage observed cyclist behavior in response to a "notched", nonlinear pricing structure that introduces a discontinuity in the cost of a trip beyond 30 min. This setting is unique in that the discontinuous price threshold provides a direct price for time spent commuting and recreating via bicycle. In response to this nonlinear incentive, we identify cyclists who re-dock their bicycle midway through their trip to reset their trip's duration, thus avoiding the price but adding a time cost to their trip—a phenomenon colloquially referred to as "daisychaining". By comparing the duration of daisychained trips to counterfactual direct trips on similar routes, we estimate a time-for-money trade off in a way that is consistent with DeSerpa (1971), which provides a framework to estimate activity-specific values of time and allows individuals to gain utility directly from time spent in a given activity. These features are important because cyclists likely use bikesharing programs for utilitarian and recreational purposes. We explore this heterogeneity directly via cyclist type, temporal heterogeneity, and observable route characteristics that are suggestive of a given trip's purpose.[3]

We uncover several key results. First, we estimate that cyclists spend 7–9 min daisychaining to avoid a discontinuous price increase of $1 in our preferred specifications. These estimated time expenditures are robust to controlling for unobserved heterogeneity at the route and cyclist level, and they are estimated on a matched sample that accounts for the nonrepresentativeness of daisychained trips. Second, there is intuitive heterogeneity in this response based on observable characteristics: routes, users, and time periods associated with leisurely trips generally exhibit greater time expenditures, while routes, users, and time periods that are associated with utilitarian trips exhibit smaller time expenditures daisychaining. Although this heterogeneity aligns with predictions from our conceptual framework and general intuition, the gap in time expenditures for leisure vs. commuting trips is relatively narrow.

Using these estimated time expenditures, we measure cyclists' revealed value of saving time at approximately $6–9 per hour. This estimate is approximately 13%–25% of local wage rates, depending on different measures of income. This value of time saved is small relative to official US Department of Transportation (DOT) guidance (U.S. Department of Transportation, 2014), which suggests valuing time saved cycling at 100% of the wage rate. The measure used in DOT guidance, however, presumes that time spent on a bicycle provides discomfort and should be valued similarly to time spent waiting outside for (or standing inside of) a bus. These values are intended to capture the disutility of commuting. In this paper, we argue that cycling provides enjoyment benefits, resulting in a lower VST than alternative modes of transit. Our estimates are also small relative to recent revealed preference estimates from the transportation literature. Wolff (2014) finds that drivers' speed choice in response to fuel costs reveal an estimate around 50% of the prevailing wage; Fezzi et al. (2014) find estimates closer to 75% of the wage rate for drivers choosing to use toll roads en route to the beach; and Goldszmidt et al. (2020) find estimates equal to 100% the median wage from a large-scale experiment with a ridesharing company that experimentally varies wait times for consumers. Our estimates are considerably smaller than most in this literature, which can be explained by the fact that cyclists bicycle because it provides greater utility than driving. Time spent commuting on a bicycle is valued more strongly than time spent commuting in a vehicle, which, sensibly, translates to lower values of *saving* time for cyclists. Further, many cyclists use bikesharing programs as leisure or as an input to a leisurely activity (Chan and Wichman, 2020).[4] Although perhaps counterintuitive, the smaller values of saving time on a bicycle that we estimate are supportive of policies that increase commuting and recreational cycling opportunities because they are inclusive of the enjoyment cyclists receive when cycling. Specifically, because the VST for cycling is a fraction of estimated VSTs for other modes of transit, this suggests that cyclists would be willing to spend comparatively more time cycling than driving a car, waiting for an Uber, or standing on a bus for a similar trip purpose.

Our primary time-expenditure estimates for cyclists vary by whether a bikeshare user is a "registered" or "casual" user, by day-of-week and hour-of-day, and by route characteristics (such as proximity to parks, bicycle lanes, transit stops, and commercial building density). The strongest aspect of heterogeneity we find is that registered users on weekday mornings add the least amount of time to their trips to avoid the price increase, which translates to a larger value of time saved. This behavior accords with findings from Bento et al. (2020) who focus on the value of urgency, driven by scheduling constraints, and Buchholz et al. (2020) who find that values of time revealed through a ride-hailing service are slightly larger during work hours. Even for these cyclists who are likely commuting to work, their estimated VST is roughly 1/3 the wage rate. What is more surprising in these results is the degree of homogeneity in VSTs across user type and trip purpose. Across the spectrum of implied utilitarian and recreational trips, our estimated value of time is approximately equal to the minimum wage and around 20% of the prevailing hourly wage inferred from median incomes.

Additionally, we exploit a 400% increase in the price of a trip beyond 30 min, from $1 to $5, to explore price responsiveness of cyclists along extensive and intensive margins. We estimate a modest increase in the proportion of trips daisychained (extensive

[2] Value of time estimates from stated preference studies are generally smaller than those arising from revealed preference data (Small, 2012).

[3] Throughout, we use the term "route" to refer to a unique origin–destination pair because that is what we observe in the data. We do not observe the specific streets and paths cyclists use between start and end stations.

[4] Although, in theory, pure leisure would exhibit a value of saving time equal to zero because recreators are willing to spend more than the minimum amount of time engaging in that activity, we exploit a discontinuous price of leisure that allows the behavior of leisure cyclists to reveal their value of time savings directly.

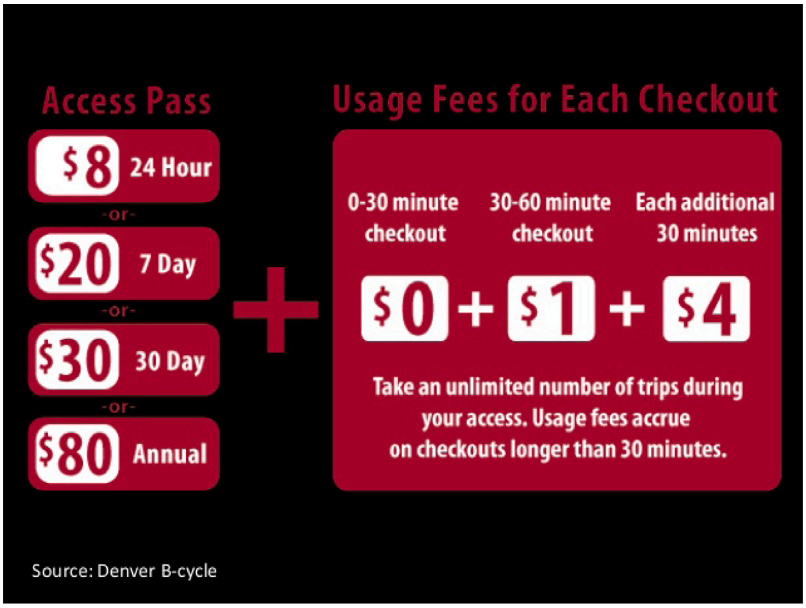

Fig. 1. Example of Denver B-cycle's pricing structure in the beginning of our sample.

margin), which is concentrated among casual users, weekend trips, and routes with more park area and lower transaction costs for daisychaining. Along an intensive margin, however, we estimate no change in the duration of daisychained trips or the speed of daisychained trips (relative to direct trips) in response to the price increase. We find additional suggestive evidence that cyclists with more familiarity of the bikeshare system (regular users on weekdays) might ride slightly faster on direct trips to avoid the price increase. The lack of price responsiveness on the intensive margin is likely driven by the fact that many intermediate stations exist along routes, so cyclists need not expend more than 7–9 min to avoid the price, regardless of its level. Alternative behavioral explanations for this price inelasticity include reference dependence focused on the free segment of the trip or responsiveness to quantity thresholds and not price levels.

Overall, this paper make several contributions. We provide the first revealed preference estimate of how cyclists trade off time for money, which is an important input to transportation policy decisions, especially as those policies aim to reduce automobile externalities by shifting drivers to active modes of transit. Second, we contribute to the broader revealed preference literature on valuing time for both commuting and leisure purposes by exploiting a nonlinear pricing structure that affects both types of bikeshare usage. By leveraging user, time, and route characteristics, we shed light on how time–money tradeoffs are affected by the purpose of the trip within the same sample for a novel mode of transit. Lastly, we document extensive margin changes in response to a large price change, but find virtually no responsiveness along intensive margins.

In what follows, we provide background on bikesharing, in general, and on the cyclists' behavior that we leverage to reveal time-for-money tradeoffs, in particular. We then situate this behavior in a conceptual framework that motivates our empirical approach. Discussion of our data, empirics, and a discussion of our results follows.

1.1. Background and empirical setting

We focus on a docked bikesharing program in which members can use bicycles from stations in public places and return them to other stations when their ride is complete. Docked bikesharing programs require members to purchase a membership for a specified time period (e.g., one day, three days, one month, and one year). Members use a key or credit card to unlock a bicycle at any station, and they can return it to an empty dock at a station near their end destination. Generally, the marginal cost of a trip completed within a given amount of time (typically 30 min) is zero, while trips that last longer than that are priced according to an increasing, tiered price schedule. An example of this pricing structure for the bikesharing program studied in this paper – Denver B-cycle – is shown in Fig. 1.

Bikesharing programs are intended to encourage short-to-medium distance trips and to provide recreational opportunities. These systems often complement existing public transit, providing an alternative to walking to and from a major transit center (Pucher and Buehler, 2005). Shaheen (2012) notes several potential private and public benefits of bikesharing: increased mobility, consumer transportation cost savings, reduced transportation infrastructure costs, reduced traffic congestion (Hamilton and Wichman, 2017), reduced fuel use, increased use of public transit (Martin and Shaheen, 2014), public health improvements, and greater environmental awareness.

Table 1
B-cycle membership and usage fees.

Dates effective	Membership costs (one-time)				Usage fees (per trip)		
	24-h	7-day	30-day	Annual	[0–30 min.]	(30–60 min.]	Each add'l 30 min.
Jan. 2012–Dec. 2014	8	20	30	80	0	1	4
Jan. 2015–Sep. 2015	9	N/A	15	90	0	1	4
Oct. 2015–Dec. 2015	9	N/A	15	90	0	5	5
Jan. 2016–Feb. 2016	9	N/A	15	N/A	0	5	5
Mar. 2017–Dec. 2017	9	N/A	15	95	0	5	5

Notes: All amounts are nominal U.S. Dollars. B-cycle offered an "Annual Plus" membership, beginning in Jan. 2015, that allowed registered members to receive an allotment of 60-min free per trip. We drop annual plus members from our sample. Annual memberships were discontinued in favor of Annual Plus memberships in Jan. 2016. Annual memberships purchased prior to Jan. 2016, however, were still valid throughout 2016. Annual memberships were offered again starting in March of 2017.

In our empirical application, we focus on cyclists' decisions within a bikesharing program that reveal their marginal rate of substitution of time for money. Specifically, users of Denver's bikesharing program can borrow shared bicycles in the B-cycle program from any station in Denver and deposit them at any other station in the network. B-cycle's two-part pricing structure includes a fixed membership cost, which provide access to the program's bicycles for an allotted time period, as well as per-trip costs that are priced nonlinearly. Bicycle trips that take fewer than 30 min are free, whereas trips that last more than 30 min are charged a positive price. As shown in Table 1, this additional cost was \$1 for trips lasting longer than 30 min. B-cycle increased this rate to \$5 on October 1, 2015.

One strategy cyclists use to avoid the discontinuous price increase is to temporarily dock the bicycle at an intermediate station to reset the 30-min clock. This strategy – colloquially referred to as "daisychaining" – adds time to the total trip duration that can be compared to the money cost savings. In this paper, we identify daisychained trips to understand how cyclists trade off time for money. In Fig. 2, we show a map of the most commonly daisychained trip in our sample. This trip begins in downtown Denver (point A), moves southeast following Cherry Creek, along which runs a bicycle path, enters Washington Park where the bike is temporarily "re-docked" at a station on its southeastern corner, and continues south to terminate nearby the University of Denver (point C). According to Google Maps directions, the route is 6.7 miles and projected to take 43 min via bicycle. There are a few noteworthy things about this trip. First, if the trip were taken from point A to point C directly, the user would likely exceed the free 30 min. Second, there was re-docking opportunity at point B along the route.[5] Third, there are distinct observable features of the trip that notionally inform its purpose: the trip originates downtown, near Union Station (with multiple transit options) and points of interest (e.g., a Major League Baseball stadium and the Museum of Contemporary Art Denver), it follows a recreational, protected bike path along a creek and dissects a public park, and terminates near a university. Fourth, and critically, the intermediate stop along the route (at point B) is located more than 80% of the distance to the final destination. The most likely rationale for stopping at point B is to avoid the discontinuous price increase for trips that last more than 30 min.

We rely on cyclists' responses to the nonlinear pricing structure they face, which resembles nonlinear tax codes and increasing-block rates for water and electricity use. There is a vast literature that focuses on responses to kinks in budget constraints driven by nonlinearites in tax rates (e.g., Le Maire and Schjerning, 2013; Saez, 2010; Bastani and Selin, 2014) and water/energy prices (e.g., Ito, 2014; Wichman, 2014). Because the bikesharing rate structure increases the total cost of a trip beyond some threshold, our setting more closely resembles a price *notch* that introduces a discontinuity in consumer budget sets (e.g., Slemrod, 2013; Kleven and Waseem, 2013; Kopczuk and Slemrod, 2003). Despite this commonality, the behavior we observe will not result in typical "bunching" behavior on the favorable side of tax/price thresholds because cyclists may split a direct 35 min trip into two 20-min trips. This "splitting" behavior has been identified at the corporate level, in which larger companies split into multiple smaller companies to avoid tax liability (Onji, 2009), but has not been explored in a consumer behavior or transportation setting.

By observing bicycle trips that demonstrate behavior like the trip in Fig. 2, we exploit this margin of adjustment to estimate how much time cyclists spend avoiding the nonlinear increase in the cost of their trip. This revealed preference time-for-money tradeoff can be used to evaluate how individuals' value time saved during their bicycle trip, and we use this tradeoff to discuss the implications of the value of time spent recreating vs. commuting on a bicycle (and how that might differ from commuting in a vehicle). To emphasize this tradeoff, imagine that the cost of the direct trip from A to C is \$1 in Fig. 2, but a cyclist can re-dock their bicycle at station B to avoid the \$1 cost. If the cyclist spends an additional 3 min finding the intermediate station B, docking the bicycle, and getting back onto their route, the implied value of saved time would be calculated as \$1 / (3 min/60 min) = \$20 per hour. While intuitively appealing, this time–money tradeoff has roots in a classic model of time allocation decisions, described in more detail below. Notably, our approach allows for a within-sample comparison of the opportunity cost of time across commuting and recreational trips for cyclists. We estimate this time–money tradeoff directly by uncovering evidence of daisychaining and, because the cost of a trip beyond 30 min changes exogenously within our sample, we can estimate behavioral changes in response to changes in price.

[5] Google Maps predicts that the bicycle trip time between Point A and B is 35 min, although Google Maps bicycle trips assume a constant speed of approximately 10 miles-per-hour regardless of conditions, traffic lights, weather, and so forth; this constant speed assumption may not be accurate for all cyclists or trips.

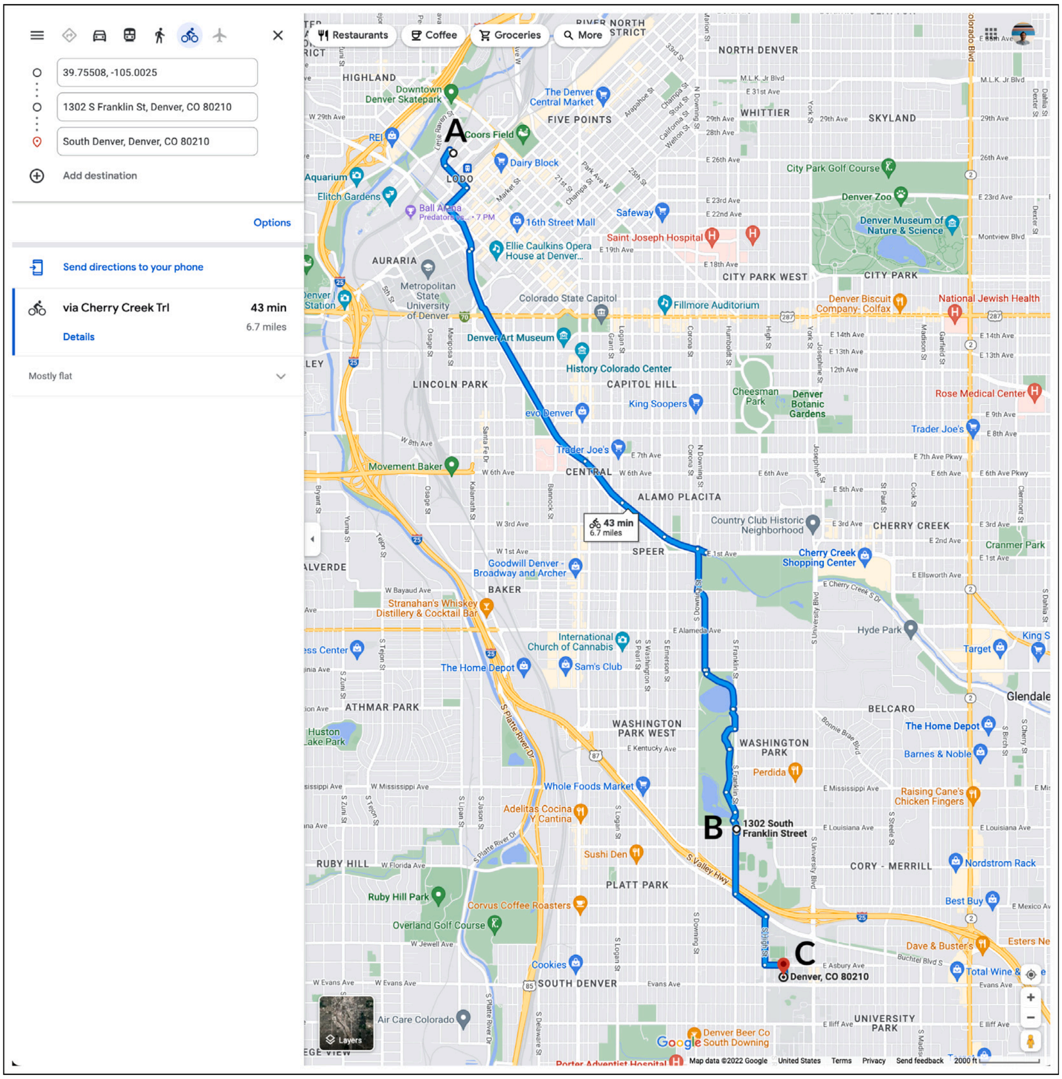

Fig. 2. Map of daisychained route. Notes: Map of most frequently daisychained route in sample. Point A represents the start station, point C is the end station, and point B is the intermediate docking station.
Source: Google Maps screenshot.

2. Valuing time

We adopt a conceptual framework that follows DeSerpa (1971) to set the stage for our empirical approach. The DeSerpa (1971) framework generalizes the canonical Becker, 1965 model of time allocation, but has seen few empirical applications in transportation or recreation outside of Jara-Díaz et al. (2008) and Fezzi et al. (2014). We adopt it here because, as we will show, it embeds several relevant features for cycling as a joint mode of transportation and recreation. Consider a set of commodities $X = (X_1, \ldots, X_n; T_1, \ldots, T_n)$, where X_i represents consumption goods and T_i represents the amount of time allocated to the ith good. The consumer's preferences are represented by a well-behaved utility function, $U(X)$, and they receive a fixed positive amount of money income (Y), which they spend all of on consumption goods in the present period. As a result, total expenditures equal money income:

$$Y = \sum_{i=1}^{n} P_i X_i. \tag{1}$$

Similarly, the individual receives a fixed time endowment, which is allocated to each specific use:

$$\bar{T} = \sum_{i=1}^{n} T_i. \tag{2}$$

We assume that consumption of goods requires a minimum amount of time expenditure associated with that good. These relationships can be represented by the time consumption constraint:

$$T_i \geq a_i X_i \text{ for } i = 1, \dots, n, \tag{3}$$

where each a_i is the minimum amount of time required to consume one unit of X_i.

The consumer maximizes utility subject to their budget constraint (Eq. (1)), time resource constraint (Eq. (2)), and the n time consumption constraints (Eq. (3)), expressed by the following Lagrangian:

$$L = U(X) + \lambda(Y - \sum_{i=1}^{n} P_i X_i) + \mu(\bar{T} - \sum_{i=1}^{n} T_i) + \kappa_i(T_i - a_i X_i) \tag{4}$$

where $\kappa_i \geq 0$ and $\mu, \lambda > 0$. Maximizing Eq. (4) results in the following equilbrium conditions:

$$\frac{\partial U}{\partial X_i} = \lambda P_i + \kappa_i a_i, \forall i \tag{5}$$

$$\frac{\partial U}{\partial T_i} = \mu - \kappa_i, \forall i \tag{6}$$

$$\kappa_i(T_i - a_i \kappa_i) = 0, \forall i \tag{7}$$

where λ is the marginal utility of money; μ is the marginal utility of time; and κ_i is the marginal utility of time spent in a given activity (i.e., the shadow value of relaxing the ith time consumption constraint). The ratio μ/λ is the marginal rate of substitution between time *as a resource* and money. Dividing Eq. (6) through by λ provides a measure of the marginal rate of substitution of T_i – that is, time *as a commodity* – for money, or:

$$\frac{\partial U/\partial T_i}{\lambda} = \frac{\mu}{\lambda} - \frac{\kappa_i}{\lambda}, \forall i. \tag{8}$$

In other words, Eq. (8) represents the value of time associated with consumption of a particular good (e.g., time spent driving to the movie theater or time spent cooking dinner). Importantly, the value of time as a resource is only equivalent to the value of time as a commodity if the time constraint does not bind (i.e., $\kappa_i = 0$). This nonbinding constraint has implications for valuing leisure time, which is described more below.

2.1. The value of saving time

Although Eq. (8) is useful conceptually, we often want to know how individuals value time saved, which is especially relevant for transportation where the primary benefits of a congestion mitigation project might be shorter commutes or where access to toll roads may permit quicker access to a recreational site. The value of saving time (VST) in a specific activity is equivalent to relaxing one of the time consumption constraints for a given i. As a result, κ_i can be interpreted as the marginal utility of saving time and κ_i/λ can be interpreted as the value of saving time in a given activity. We can represent the value of saving time consuming a given X_i as the difference between the value of time in an alternative use and the value of time in any particular use:

$$\text{Value of saving time (VST) consuming } X_i = \frac{\mu}{\lambda} - \frac{\partial U/\partial T_i}{\lambda} = \frac{\kappa_i}{\lambda}, \forall i \tag{9}$$

From this, we see that the quantity κ_i/λ is an empirically useful value of time savings because both the money budget constraint (Eq. (1)) and the time consumption constraint (Eq. (3)) can be incremented, revealing the shadow prices λ and κ_i. Contrarily, the time constraint (Eq. (2)) is fixed and, thus, empirically unhelpful.

2.2. Leisure, commuting, and leisurely commuting

A unique aspect of our analysis is that cycling can be a mode of commuting, a form of recreation, or both simultaneously. Typically, researchers focus on estimating either commuting/congestion costs (e.g., Anderson, 2014; Small et al., 2005; Bento et al., 2020) or travel time to a recreational site (e.g., Bockstael et al., 1987; McConnell and Strand, 1981; Feather and Shaw, 1999; Fezzi et al., 2014). In our sample, cyclists are likely commuters as well as recreational cyclists. For cyclists as commuters, the value of saving travel time can largely be treated analogously to that of automobile drivers. Generally commuters want to minimize time spent commuting such that the time consumption constraints are binding (i.e., $\kappa_i > 0$). We suspect many cyclists enjoy cycling as a mode of transportation, however. Typically, automobile commuting provides little pleasure or even disutility (e.g., the frustration of being stuck in traffic) such that the marginal utility of time spent commuting ($\partial U/\partial T_i$) is zero or negative. The greater individuals dislike commuting, the greater the value of reducing travel time in Eq. (9) since $\lambda > 0$. Because time spent commuting enters the utility function directly and individuals might enjoy cycling for its effect on health, well-being, or the environment (Heinen et al., 2010), it is possible that the marginal utility of additional time spent commuting via bicycle *lowers* the value of time savings.[6] In

[6] It is worth noting that the DeSerpa (1971) framework, which permits individuals to gain utility from time spent commuting via bicycle, is more germane to our setting than the canonical Becker, 1965 model in which individuals gain utility from time only through its use as an input to the production of consumption commodities.

other words, it is easy to argue that the shadow value, κ_i, is greater for cycling than it is for driving. This observation suggests that estimates of the value of time savings on a bicycle commute may be smaller than equivalent estimates on other modes of transit. Of course, this effect is theoretically ambiguous and it is possible that bicycle commuting generates disutility through channels of increased risk of injury and fatality (Fernández-Heredia et al., 2014).[7]

Beyond commuting, individuals may use the bicycle-sharing program for purely recreational purposes (e.g., Chan and Wichman, 2020), which poses a challenge in interpreting the value of time savings in this framework. Specifically for consumption of time spent recreating – which is distinct from time saved traveling to a recreational site – the time-consumption constraints in Eq. (3) will be nonbinding. This slackness occurs because the recreator spends more time engaged in the recreational activity than the bare minimum. As a result the first-order conditions for the individual's optimal choice of time and goods must be evaluated with $\kappa_i = 0$, which implies that the value of time *as a resource* (μ/λ) and the value of time *as a commodity* coincide. The intuition for this result is that the value of time "on site" has the highest possible value so saving time in this activity is worth nothing.

In our application, we contend that cyclists use bikesharing programs for some combination of recreation and commuting, which we call "leisurely commuting". In the example presented in Fig. 2, the trip serves a utilitarian purpose (getting from point A to C) but also provides leisure opportunities via cycling through parks. As a result, bikeshare usage can be conceptualized as leisurely commuting as opposed to pure recreation. In other words, leisure cycling is complementary to a broader utilitarian purpose (e.g., recreationalists likely choose to bicycle because it provides transportation to a park, movie, museum, etc.). On the other hand, commuters likely choose to bicycle because it is pleasant or more convenient than alternative transportation options. As a result, cycling is often not the end-goal for leisurely commuters and hence the time consumption constraint will bind for bikeshare users (i.e., $\kappa_i > 0$). The factors discussed above suggest that there is a continuum of leisure–commuting cycling opportunities, which will be reflected with large κ_i reflecting primarily commuters (and hence a large VST) and small κ_i for primarily recreators (and hence a small VST).

This insight stems directly from the DeSerpa (1971) framework, although we are aware of no study that explores and quantifies the notion that transportation can provide leisure benefits and that leisure time can provide transportation benefits. The usual cases are ones in which reducing travel time to a recreational opportunity reveals the value of that recreational opportunity, which is germane to most settings in which travel time is the largest cost associated with recreation, or reducing travel time to work, for example, by focusing on road choice or wait time for a ridesharing service. The empirical goal in this paper is to use observed decisions to identify κ_i/λ for cyclists and, specifically, to estimate how this value of time varies based on the purpose of the trip.

2.3. The choice to daisychain and the price of time

We now adapt this approach to our empirical setting in which an individual faces a simple decision, conditional on wanting to get from point A to point B on a bicycle. For a trip greater than 30 min, they can choose to pay the positive price or, as described in the previous section, they can bear some time cost via daisychaining to avoid paying that price. To formalize, let $U_{n,j}$ represent the nth individual's utility from a trip on route j:

$$U_{n,j} = \theta_j + \lambda_n c_{n,j} + \kappa_n t_{n,j} + \varepsilon_{n,j} \tag{10}$$

where θ_j are attributes of route j (where a "route" is defined as a unique start and end point combination), $c_{n,j}$ is n's money cost of trip j with marginal utility λ_n, $t_{n,j}$ is n's time cost of a trip along route j with marginal utility κ_n, and $\varepsilon_{n,j}$ is the residual capturing all unobserved attributes of the route or individual.

Let superscripts D and ND represent a trip that was daisychained or not daisychained, respectively. An individual will choose to daisychain if $U^D_{n,j} \geq U^{ND}_{n,j}$, or, equivalently:

$$\Delta U_{n,j} = U^D_{n,j} - U^{ND}_{n,j} = \lambda_n (c^D_{n,j} - c^{ND}_{n,j}) + \kappa_n (t^D_{n,j} - t^{ND}_{n,j}) \geq 0. \tag{11}$$

To arrive at this relationship, we assume that marginal utilities are linear and constant, which is reasonable for small changes in trip time and costs, and that the differences in residual unobserved terms (i.e., $\varepsilon^D_{n,j} - \varepsilon^{ND}_{n,j}$) are negligible. This latter point is reflective of our empirical approach because (a) we compare trips with the same start and end destination, (b) many daisychained trips occur on the same streets and paths as direct trips, and (c) we partial out these differences with route and person fixed effects in our empirical models described in Section 4. It is also possible that individuals will exert more effort on a direct trip to avoid the discontinuous price increase, but that would be captured by Eq. (11) in the time difference $t^D_{n,j} - t^{ND}_{n,j}$. We explore this margin of choice empirically.

After imposing that $t^D_{n,j} > t^{ND}_{n,j}$ – a safe assumption given that daisychained trips are at least as long in distance than similar direct trips – and rearranging, the relationship in Eq. (11) can be represented as

$$\frac{\kappa_n}{\lambda_n} \geq \frac{(c^{ND}_{n,j} - c^D_{n,j})}{(t^D_{n,j} - t^{ND}_{n,j})}. \tag{12}$$

From Eq. (12), we arrive at a useful result that informs our empirics. The ratio κ_n/λ_n is the opportunity cost of time spent cycling, or the value of saving time, that is analogous to the DeSerpa (1971) framework. That is, the ratio in Eq. (12) is the empirical analog of

[7] Additionally, from a policy perspective, it is helpful to note that if the VST for bicycling is smaller than the VST for driving, then policies that shift commuters from cars to bicycles without adding disproportionate time costs may be welfare improving from a purely private perspective because it would imply that the value of time spent on a bicycle is greater than time spent in a car.

the value of time saved cycling that corresponds to its theoretical representation in Eq. (9) above. For the marginal cyclist, Eq. (12) is satisfied with equality since marginal utilities will be equalized in equilibrium; i.e., $\partial U_{n,j}/\partial t_{i,j} = \kappa_n$ and $\partial U_{n,j}/\partial c_{n,j} = \lambda_n$ and, hence, $\left[\partial U_{n,j}/\partial t_{i,j}\right] / \left[\partial U_{n,j}/\partial c_{n,j}\right] = \kappa_n/\lambda_n$. A lower bound for this ratio of marginal utilities can be expressed by the marginal rate of substitution of money for time expressed on the right-hand side of the inequality in Eq. (12), which is simply the dollar cost savings of daisychaining divided by the additional time spent daisychaining. For example, if daisychaining saved $1 but required an additional trip of 10 min, then the ratio of $1 to 10 min provides a lower bound estimate of the "price" of time equal to $6 per hour. If we observe an individual choosing to daisychain (thus revealing that $U^D_{n,j} \geq U^{ND}_{n,j}$), we can compare their trip time and cost savings relative to a non-daisychained counterfactual trip on the same route, which will reveal an estimate of the value of time savings directly.[8]

Several researchers specify something akin to Eq. (10), and then proceed to estimate marginal utilities in a random utility framework where individuals are observed to choose one route relative to alternatives with different costs and travel times (e.g., Fezzi et al., 2014; Jara-Díaz et al., 2008; Small et al., 2005). Instead, we use cyclists' revealed choices to isolate the marginal rate of substitution of time for money on a fixed cycling route. By virtue of this isolation, we can construct estimates of the structural relationship of marginal utilities in Eqs. (9) and (12) along an intensive margin with very few empirical restrictions. Only a measurement of the time difference and associated money cost savings between daisychaining are required. By virtue of the "notched" pricing structure for bikesharing, we have an discontinuous price change that informs the numerator on the right-hand side of Eq. (12). Our empirical approach seeks to estimate the time cost savings, which serves as the quantity used in the denominator on the right-hand side of Eq. (12).

2.4. Extensive and intensive margins

Eqs. (11) and (12) demonstrate how cyclists will response to changes in the cost of a trip. In our empirics, we first leverage the nonlinear rate structure to estimate the additional time cyclists spend daisy chaining ($t^D_{n,j} - t^{ND}_{n,j}$) to avoid the price increase that discontinuously changes the cost of a trip ($c^{ND}_{n,j} - c^D_{n,j}$). The ratio of these two quantities provides a measure of the value of saving time cycling. Second, we exploit an exogenous price change that increases $c^{ND}_{n,j} - c^D_{n,j}$, which we hypothesize will increase the overall number of daisychained trips as daisychaining becomes more attractive. This is the extensive margin we seek to measure. With larger potential cost savings from daisychaining, we also expect the time spent daisychaining to increase to keep the ratio in Eq. (11) constant; this is the intensive margin response to the price change.

3. Data

3.1. Primary bikeshare data

We use publicly available trip and station data from Denver B-cycle (henceforth, "B-cycle") to analyze the patterns of bikeshare users.[9] B-cycle began in 2010 and had approximately 90 stations with more than 700 bicycles throughout Denver, Colorado, as of the end of 2017. For each trip taken, we observe the start and end destination and their geographic coordinates; the start and end time of the trip, providing its duration; a unique subscriber ID; and an indicator for whether the user is a registered (annual) member or casual (sub-annual) member. We contend that registered users are more likely to be regular users of the bikesharing system, possess greater awareness of the locations of bikeshare stations, and more likely to use the bikesharing system for routine transportation (such as commuting or running errands). Casual users, on the other hand, purchase bicycle trips à la carte and, thus, are more likely to use the bikesharing system on a whim, possess less knowledge of the location of stations, and use the bikesharing system for more recreational trips. In practice, however, both registered and casual users could use the bikesharing system for utilitarian and recreational trips. For each route, defined by its start and end locations, we construct an estimate of time needed to bike the route and the distance of the optimal route using the Google Maps Directions API.[10]

8 We can additionally use this framework to shed light on whether cyclists are "pure" recreators with a slack time consumption constraint. In Eq. (11), we note that $\kappa_i = 0$ would result in perfectly inelastic demand for cycling trips or, more concretely, that cyclists would spend an inordinate amount of time daisychaining for very small changes in the cost of a trip. We thus view this as an empirical question in which we would only observe cyclists daisychaining if their cost of doing so is worth their time, thus revealing the ratio in Eq. (12). Evidence of daisychaining, or price responsiveness more generally, provides support that the time consumption constraint is binding (i.e., that $\kappa_i > 0$).

9 Denver B-cycle provided publicly available trip data on their website (https://denver.bcycle.com/). In January 2020, the Denver B-cycle program was dissolved and is no longer in operation. Denver B-cycle provided us with information on retired stations and other helpful information about the data via email.

10 We present simple summary statistics. in Appendix Table A.1. Mean trip time for trips in our full sample (n = 1,044,971) in 2013–2017 was 15.01 min, with a standard deviation of 15.77 and a median of 10. For registered users (n = 745,259), the mean is 10.56 with a standard deviation of 9.13 and median of 8. For casual users (n = 299,712), the mean is 26.07 with standard deviation of 9.13 and a median of 20.

3.2. Price information

Details on B-cycle's rates are presented in Fig. 1 and Table 1. At the beginning of 2015, fixed costs for the daily and annual passes increased (from $8 to $9 and $80 to $90, respectively), which should not affect marginal decisions that alter trip times or the proportion of daisychain trips.[11] In October of 2015, B-cycle increased the overage charges for the cost of a trip (see Table 1). Prior to October 2015, the first overage charge (i.e., for trips that last more than 30 min) was $1, and each half hour afterwards was $4. Beginning in October 2015, the first overage charge was $5, and $5 for every 30 additional minutes. In all cases, the first 30 min of trip time were free. Within this analysis, we analyze both "pre-Oct. 2015" observations and "post-Oct. 2015" observations. Our initial results are drawn from the pre-Oct. 2015 sample. To assess the price responsiveness of cyclists, we use the 400% increase in the price between pre- and post-Oct. 2015 to estimate whether and how cyclists respond on extensive and intensive margins.

3.3. Daisychaining data construction and evidence

To identify what we define as daisychaining (i.e., splitting a trip into multiple segments by re-docking the bicycle at an intermediate station), we use B-cycle trip data from January 2013 through December 2017, inclusive.[12] We use the subscriber ID to isolate each member's trips, sorting from oldest to newest, and we flag pairs where the second trip began three minutes or less after the first trip ended. We are then able to combine each group of two or more consecutive trips into one multi-segment trip, and calculate the aggregate trip time, starting station, and ultimate ending station.[13] To identify trips during which the user stopped at an intermediate station between their true start and end destination, we include other restrictions to eliminate observations that might confound our modeling approach: (i) we eliminate round trips, where a user's start and end destination are identical; (ii) we eliminate trips over 150 min, because they are often caused by failure to dock the bike properly; (iii) we eliminate daisychain trips where one or more segments exceeded 65 min; and (iv) we remove daisychain trips if the two segments went in opposing directions.[14]

After imposing these restrictions, we identify 21,891 daisychain trips taken by 2915 registered and 10,204 casual users within the universe of trips between 2013 and 2017. Approximately 29 percent of all registered users had daisychained at least once, as well as nine percent of casual users.

We are interested in whether there is lumpiness or bunching in the distribution of daisychain trip time to provide evidence that the price discontinuity at 30 min influences behavior. As a graphical example, we present two alternative distributions of trip times in response to a notched pricing structure in Fig. 3. The solid blue line represents a counterfactual in which the consumer has no ability to manipulate her trip time. The dashed black line represents cumulative trip durations from daisychaining. As shown, the density moves smoothly through the discontinuity in the price schedule, and displays bunching on the *less* favorable side of the threshold because cyclists can link multiple shorter trips get from their starting destination to their end destination. We expect that cyclists who expect their trip to take, say, 35 min might re-dock their bicycle after 20 or 25 min to avoid the price notch, which adds time to their cumulative trip duration, thus generating the daisyching distribution in Fig. 3. The difference in these two illustrative densities allows us to understand how cyclists trade-off time for cost savings and our empirical approach seeks to measure the difference in trip times stemming from this behavior.

To generate this distribution in our data, we append individual trips that meet our criteria for a daisychain trip and plot the resulting distribution in Fig. 4. In this figure, we observe a set of trips that displays more concentrated mass around the 30-min threshold. For casual users, the distribution is roughly symmetric, peaking between 35 and 40 min. There appears to be a small discontinuity in the distribution at the 30-min mark, although this distribution is relatively noisy. The distribution for registered users is more irregular. There is substantially more mass below the 30-min notch and a relatively smooth change across the notch point. Between 35 and 40 min, however, there is a dramatic drop in the density, which provides suggestive evidence that consumers are daisychaining trips that would have come close to exceeding the 30-min threshold if ridden directly. The smoother distribution for casual users suggests less precision in the ability to sort around the 30-min threshold as well as more slack time constraints, which comports with our characterization of causal users. Overall, these distributions do suggest differences in behavior for registered and casual users that are broadly consistent with utilitarian and recreational trips, respectively. Unlike other settings with notched, nonlinear incentives (e.g., Kleven and Waseem, 2013; Kopczuk and Slemrod, 2003), we do not expect to see bunching immediately before a threshold because there is a continuum of intermediate stations available to daisychain.

[11] At the same time, B-cycle introduced an "Annual Plus Membership", which allowed 60 min of free ride time instead of 30. The price difference between this membership and the annual membership that only provides 30 min free per trip was $10. Significant migration to the annual plus membership would change the distribution of annual member trip times and reduce split trips. Because of these differential incentives, we remove Annual Plus members from our analysis. In the calendar year of 2016, annual memberships were no longer available for purchase. Thus, we only observe registered users in our sample in 2016 if they had purchased an annual membership in 2015. Marginal trip costs change for all users simultaneously regardless of when the membership was purchased.

[12] 2013 was the first year that a unique subscriber ID was provided in the trip data.

[13] For our analysis, we only use two-segment daisychains, although we identified a small number of trips with three or more segments.

[14] We identify trips where the first segment and second segment point in opposing directions using the bearing (angle from North) of each trip. If the linear direction for the second segment is larger than 135 degrees from the linear direction from the first segment, we drop the entire trip from our sample.

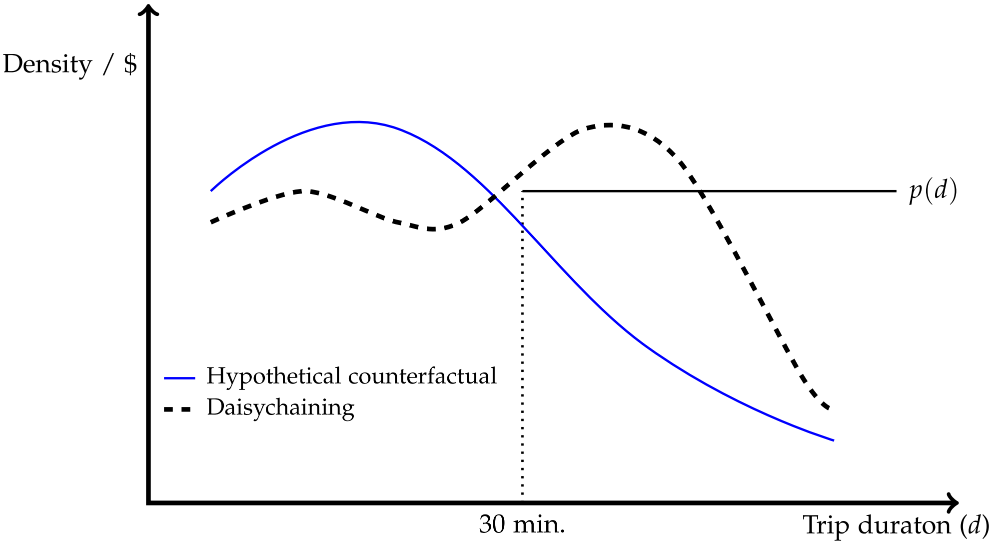

Fig. 3. Stylized densities for alternative models of consumer behavior in response to a notched price schedule, $p(d)$.

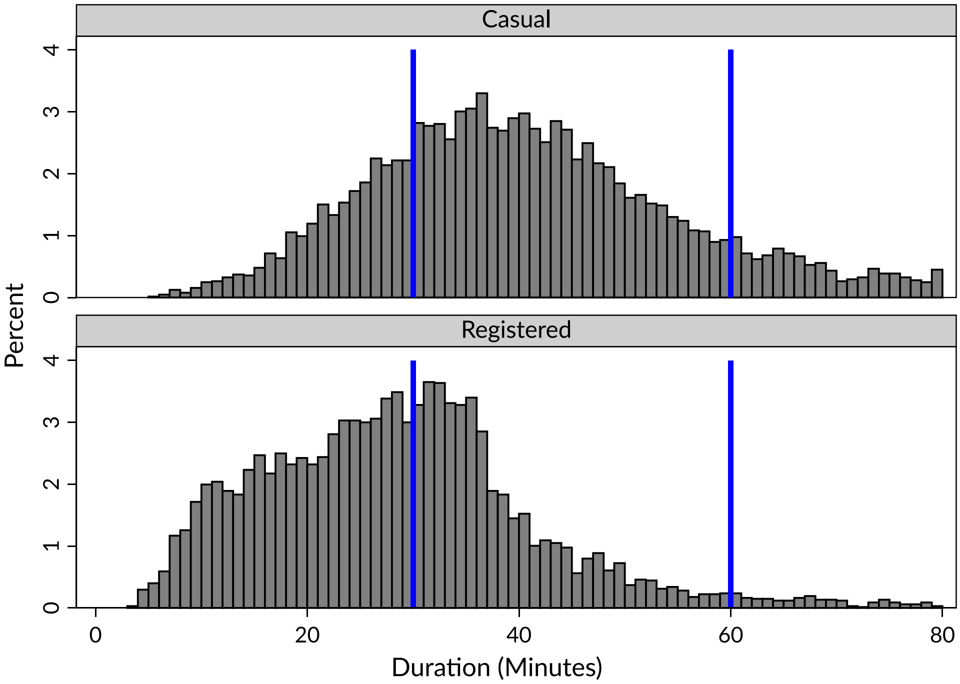

Fig. 4. Distributions of cumulative daisychain trip time by member type. Each distribution is truncated at 80 min. All observations are pre-Oct. 2015 price change.

3.4. Station, route, and weather data

In addition to trip data, we gather additional static information on route characteristics from Open Street Map. For each start and end station, we find the number of light rail stations, number of bus stops, and the number of residential and commercial buildings, which we use to construct a measure of residential or commercial building density, within a 0.5 km buffer. Additionally, we draw a straight line between every combination of start and end stations and calculate a 0.5 km buffer around that line, resulting in a "hot dog"-shaped route buffer that captures the likely path that a cyclist takes between start and end destinations. From this, we determine the park area that intersects with this buffer and the distance of protected cycleways (we specifically choose "cycleways" because they are usually separated bike lanes and greenways, although it is possible that some on-street bike lanes also use this

Table 2
Mean trip time statistics by user-time groups and daisychain vs. direct trips for raw and matched samples.

Panel A: Trip time statistics for full sample						
	Mean (Daisy = 1)	Obs.	Mean (Daisy = 0)	Obs.	Diff.	Std. Error
Registered, Weekday	26.98	4530	9.98	413,166	−17.0***	0.13
Registered, Weekend	41.31	3382	25.46	103,572	−15.9***	0.40
Casual, Weekday	30.62	2275	12.77	88,438	−17.8***	0.23
Casual, Weekend	41.53	3268	27.45	87,831	−14.1***	0.42
Panel B: Trip time statistics for matched sample						
	Mean (Daisy = 1)	Obs.	Mean (Daisy = 0)	Obs.	Diff.	Std. Error
Registered, Weekday	26.77	4436	18.65	4436	−8.12***	0.27
Registered, Weekend	41.30	3380	31.38	3380	−9.92***	0.48
Casual, Weekday	30.59	2273	20.36	2273	−10.2***	0.39
Casual, Weekend	41.52	3267	32.28	3267	−9.24***	0.50

Notes: Trip time means and differences (Direct-Daisychain). Trip time statistics for the matched sample presents results from 1:1 Mahalanobis covariate matching without replacement with calipers equal to 1 SD. All observations are pre-Oct. 2015 price change. $*$, $**$, and $***$ represent statistical significance at the 10, 5, and, 1 percent level.

geotag). We additionally count the number of bikeshare stations within this buffer to gauge the quantity of potential stations that could be used to daisychain. We use this information as proxies for the purpose of a trip. If a trip originates or terminates nearby a rail station, then it is likely that this trip is primarily for transportation. If a trip occurs on a route that has a lot of park area or cycleways, we expect this trip to be primarily recreational. Summary statistics for these variables are presented in Table A.2 in the appendix. We also present a map of stations and these additional transit/urban characteristics in Figure A.1 in the appendix.

In addition, we obtain historical, hourly weather data from for the city of Denver. We include temperature, precipitation, windspeed, and humidity as measures that likely influence the decision to bicycle.

4. Empirical strategy

In our empirical approach, we have two primary goals. First, we measure the additional time cyclists add to their trip via daisychaining to avoid the discontinuous price increase. Then, we estimate changes on extensive and intensive margins in response to changes in the price level for trips beyond 30 min.

Two identification challenges arise in this context. First, if daisychain trips are not representative of all bikeshare trips, then sample selection will bias our estimates of the time elasticity of daisychaining. Second, because the cost of a trip is a function of trip duration, the choice to daisychain is made concurrently with the trip duration. If there is some unobserved component of choice that affects both the extensive margin (whether to daisychain) and the intensive margin (duration of the trip), then any econometric estimate of consumers' time expenditure will be biased.

We approach each of these empirical concerns as follows. First, we adopt a covariate matching algorithm to construct an observationally similar comparison sample before estimating our regressions. This strategy, by balancing "treated" (i.e., daisychain) and "comparison" (i.e., direct) trips on observable characteristics of the route and user, effectively eliminates the selection-on-observables concern and reduces model dependence (Ho et al., 2007). In addition, by including individual-specific fixed effects, we remove time-invariant characteristics associated with a user's propensity to daisychain (including, e.g., their income, ability, and risk preferences). Alternatively, by including route-specific fixed effects, we are able to eliminate attributes that comprise the geography and characteristics of a route. As such, our preferred estimates come from regression specifications on our matched sample with varying fixed effects, described in more detail below.

4.1. Matching to construct counterfactual densities

Trips that are likely to be daisychained are not representative of all direct trips. For example, a short trip that is expected to take less than 10 min does not serve as a good counterfactual for a trip that is likely to exceed 30 min. This fact is borne out in the data by a simple comparison of means for direct and daisychain routes, indicating that daisychain trips are between 14 and 18 min longer in duration and 1.2–1.9 miles longer in distance (see Panel A of Table 2). This estimate almost certainly is biased upward by sample selection. The proper comparison is the time difference between daisychain trips and direct trips that are of similar distances, on similar routes, during similar times, and so forth. We contend that for trips along similar dimensions in our observed covariates, any omitted variables that affect the propensity to daisychain are also balanced. We use covariate matching methods to construct a balanced comparison group.

Specifically, following the approach of Ferraro and Miranda (2017), we use one-to-one Mahalanobis covariate matching without replacement with calipers (equal to one standard deviation) to reweight our comparison sample. That is, for each daisychain observation in our data set, we search for a direct route that is within the caliper width for each variable using the Mahalanobis distance metric. If a daisychain trip does not have a match within the caliper width, it is dropped from our sample. We use our matching algorithm to construct frequency weights that are passed on to our regressions described below. The covariates used for matching are: start station latitude and longitude, end station latitude and longitude, month of sample, and hour of day.

Rather than matching on categorical variables, we implement our matching algorithm for subsets of our full data set, including: (i) whether the trip was taken by a casual or registered user, (ii) whether the trip was taken on a weekday or weekend, and (iii) whether the trip was taken before the October 2015 rate change. We present balance tables and matching diagnostics that demonstrate our balancing approach is valid for each of our relevant time periods in the online appendix (Tables B.1–B.4).[15] In Panel B of Table 2 we present trip time differences on our matched sample. From these statistics, we see that the unconditional average trip time of daisychained routes is 8–10 min longer than observationally similar direct routes.

In Fig. 5, we present k-densities for trip time between daisychain and direct routes on our matched sample. These densities illustrate our primary identification strategy. Because all daisychain and direct trips are matched to be similar along observable route characteristics – and thus, by assumption, balanced on unobservable characteristics that may affect the decision to daisychain – the matched distribution of direct trips provides a proper, observed counterfactual density for daisychain trips. As shown in Fig. 5, we contend that the distribution of daisychain trips (solid gray line) would look exactly like the weighted distribution of direct trips (dashed red line) in the absence of a price discontinuity at 30 min. These figures reveal substantially more mass on the unfavorable side of the price discontinuity for daisychain trips than that of direct trips. Such sorting around the discontinuity is enabled by the alternative to paying the discontinuous price by splitting one trip into two smaller trips.

4.2. Estimating time expenditures of daisychaining

In our empirical approach, we first estimate the additional time that cyclists spend avoiding the discontinuous price increase for trips beyond 30 min before Oct. 2015.[16] To do so, we estimate variants of the following equation:

$$\text{Trip Time}_{ijt} = \alpha_{(0|i|j)} + \beta 1[\text{Daisy}_{ijt}] + \gamma_1 W_t + \gamma_2 R_j + \lambda_t + \varepsilon_{ijt} \tag{13}$$

where Trip Time_{ijt} is the elapsed duration of a trip in minutes for subscriber i, on route j, at time t. $1[\text{Daisy}]_{ijt}$ is a dummy variable equal to one if the trip is identified as a daisychain trip rather than a direct trip. R_j is a vector of route-specific controls that are fixed over time at the route-level, including the route's distance. W_t is a vector of hourly weather conditions, including temperature and its square, whether it is raining, humidity, and windspeed. λ_t is a set of hour-of-day and month-of-sample fixed effects. We estimate variants of this equation on both unmatched and matched samples.

We adopt the somewhat unusual notation $\alpha_{(0|i|t)}$ to represent alternative fixed effects specifications. Our simplest specification uses a common intercept, α_0. We also estimate a specification using subscriber fixed effects (α_i). For this specification, we identify β by observing variation in the choice to daisychain within a given subscriber. The notion here is that for similar routes we observe a single bicyclist multiple times—sometimes they take a direct route and sometimes they daisychain, and the difference in trip time conditional on other covariates is our estimate of β. The subscriber-level fixed effects control for time-invariant individual characteristics such as income, cycling speed, ability, preferences for risk, and so forth. Inclusion of subscriber fixed effects are valuable because we do not have detailed individual-level data on subscribers. If certain types of users are more prone to daisychain due, for example, to low opportunity costs of time, then cross-sectional comparisons of cyclists' time spent daisychaining may be biased. Subscriber fixed effects help alleviate this concern. The primary limitation of this approach, however, is that we have relatively few repeated observations for casual users, thus coefficient estimates are driven primarily by cyclists who daisychain frequently. Additionally subscriber fixed effects rely on variation across routes, which may have different attributes that may be more or less complementary to daisychaining (e.g., availability of intermediate stations).

Our preferred specification controls for route-level fixed effects (α_j). In this specification, we identify our parameter of interest by fixing the route (i.e., traveling from point A to point B) and observing multiple cyclists using the same start and end stations, but some cyclists daisychain by splitting their trip into two segments and some cyclists ride directly from start to end. With route fixed effects, variation in the choice to daisychain across individuals provides an estimate of the additional time it takes to daisychain controlling for time-invariant route-specific attributes such as scenery, bicycle infrastructure along the route, locations of employment, common trip patterns for specific neighborhood, and so forth. In this specification, trip times along a given route are compared to the set of all other trips along that same route. Inclusion of route fixed effects thus fixes the route attributes and allows coefficients to be identified off of residual variation trip time from different users. In this specification, β is our estimate of the time cost associated with daisychaining, relative to a direct counterfactual route, thus providing an empirical estimate of (the negative of) the numerator in Eq. (12).

Further, we examine heterogeneity by user groups that likely possess different knowledge of the bikesharing infrastructure. We estimate each of our econometric specifications using subsamples of registered (i.e., annual) and casual (i.e., sub-annual) members. We contend that registered users will have better knowledge of where intermediate stations are located and they will be representative of cyclists who use B-cycle for regular commuting. Casual users, on the other hand, are more likely to be tourists with less knowledge of urban infrastructure and different constraints on their time. To segment our sample further along these dimensions, we analyze differences between weekday and weekend travel for each user type.[17] In our regression framework, we

[15] Each of our matching covariates is nearly perfectly balanced on all measures. To provide an illustration that our matching algorithm is adequate, we present k-densities for both unweighted and weighted samples for each primary covariate for each of our user-time combinations before and after the rate change in Figures B.1–B.4 in the online appendix.

[16] Trips than take fewer than 30 min are free, whereas trips that exceed 30 min cost $1.

[17] In some additional specifications, we estimate time-of-day heterogeneity within each of these user–time groups to explore the importance of temporally distinct values of time.

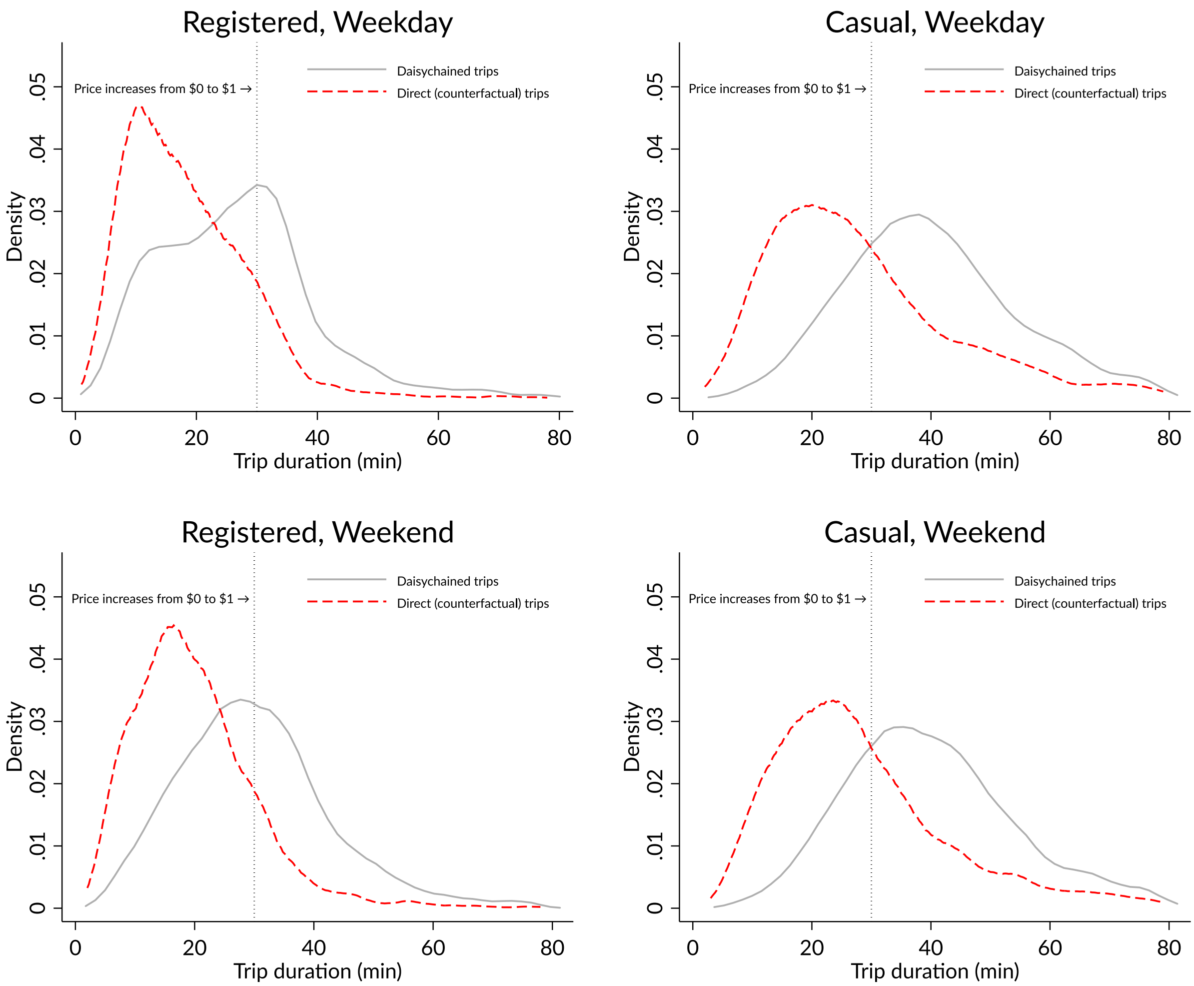

Fig. 5. Distributions of trip duration for daisychained and direct (counterfactual) trips. Note: Daisychained trips can avoid the price increase at 30 min by re-docking their bicycle at an intermediate station along their route, adding time to the duration of the trip. Each panel presents k-density distributions on matched sample for each of our user–time combinations. Solid gray line represents the distribution of daisychained trips and dashed red line represents the distribution of direct trips along similar routes, which serve as an appropriate counterfactual distribution. The difference in the distributions reveals sorting around the discontinuous price threshold at 30 min (vertical gray line). Matched sample is generated using 1:1 Mahalanobis matching without replacement for key variables. All observations are pre-Oct. 2015 price change.

estimate Eq. (13) on four distinct user–time groups: registered users on weekdays, casual users on weekdays, registered users on weekends, and casual users on weekends.

In addition to our user–time heterogeneity, we explore how route characteristics affect our estimates of β. To do so, we estimate the following equation,

$$\text{Trip Time}_{ijt} = \alpha_j + \beta 1[\text{Daisy}_{ijt}] + \sum_k \beta_k \left(1[\text{Daisy}_{ijt}] \times X_j^k \right) + \sum_k \nu^k X_j^k + \gamma_1 W_t + \lambda_t + \varepsilon_{ijt} \tag{14}$$

where we include a set of route-specific variables (X_j^k) interacted with our indicator for whether the route was daisychained. Because the route characteristics are time-invariant, the coefficients on these interactive terms are identified through their interaction with time-varying daisychain decisions in specifications with route fixed effects. In X_j^k we include the following variables: park area along the route (in square miles per route mile), protected cycletracks along the route (in miles per route mile), the number of bikeshare stations along the route, whether the trip started or ended within 0.5 km of a rail station, the number of bus stops within 0.5 km of the start or end station, and commercial and residential building density at the start station. We demean each of these variables for the regression sample to make interpretation easier. We estimate this specification for our full sample, but include controls for user type and weekday in the regression.

4.3. Estimating price responsiveness

Next, we explore the impact of a rate change that increased the cost of a trip beyond 30 min by 400%. We exploit an exogenous change in rate structure on October 1st, 2015, that increased overage fees from \$1 to \$5. We estimate how this price change affects cyclist behavior in several ways in an attempt to capture both extensive and intensive margin decisions.

4.3.1. Extensive margin

Recall that the choice to daisychain in Eq. (11) is governed both by the additional time it would take to daisychain and the cost savings of doing so. The rate change from \$1 to \$5 affects the cost savings of daisychaining. As a result, we estimate the extent to which this rate change affects the quantity of trips daisychained. We do this by collapsing our trip data to the route (j)-by-week (w) level and then estimating the following equation:

$$Y_{jwt} = \alpha_j + \delta 1[\text{Post}_t] + \pi W_{wt} + \theta_{wt} + \varepsilon_{jwt}. \tag{15}$$

In this specification, $1[\text{Post}_t]$ is an indicator for time periods after the rate change that occurred on Oct. 1, 2015. W_{wt} captures the same weather variables as in Eq. (13), but collapsed to their weekly averages. In θ_{wt}, we include both week-of-year and year fixed effects. We estimate this specification with route fixed effects (α_j). With these controls and fixed effects, our primary coefficient of interest (δ) can be interpreted as the route-level average weekly change of our outcome variable after controlling for common weekly effects across weeks of the year and years of the sample. In an additional specification, we include a set of interactions between $1[\text{Post}_t]$ and the same demeaned route-level characteristics (X_j^k) used in Eq. (14) to probe the route characteristics that may drive responsiveness to the price change.

We include several outcome variables in Y_{ijt} to probe the extensive margin in multiple ways. First, we use $sinh^{-1}(\text{No. trips}_{jwt})$ to capture the effect of the rate change on the aggregate quantity of trips taken along each route. This quantity is transformed using the inverse hyperbolic sine, which retains zero-valued observations and permits interpretation of $\hat{\delta}$ as a semielasticity (Bellemare and Wichman, 2020). Additionally, we use $sinh^{-1}(\text{No. daisy}_{jwt})$ to capture the change in the quantity of daisychained trips along each route under the hypothesis that more users will choose to daisychain trips as a result of the price increase. Lastly, we use the proportion of daisychained trips at the route level as our final outcome, which recognizes that the ratio of daisychained to direct trips on a given route is potentially more informative than aggregate quantities alone.[18]

To visualize how cyclists' behavior changes in response to the rate change, we also estimate an event study regression based on Eq. (15). In this specification, instead of a common $1[\text{Post}_t]$ variable, we substitute a dummy variable for each weekly increment before and after the rate change, for 30 weeks before and after. Formally, if w indexes weeks and the rate change occurs at $w = 0$, we include dummy variables for: $1[w < -30]$, $1[w = -30]$, …, $1[w = -2]$, $1[w = 0]$, $1[w = 1]$, …, $1[w = 30]$, $1[w > 30]$. Inclusion of this set of indicators estimates the average change in outcomes for each week preceding and succeeding the rate change relative to the omitted week immediately before the rate change ($w = -1$). All observations beyond 30 weeks from the rate change are grouped into a common bin.

4.3.2. Intensive margin

Conditional on choosing to daisychain, individuals should be willing to spend more time daisychaining when they receive a larger cost-savings from doing so according to Eqs. (11) and (12). We return to our specification in Eq. (13) to estimate cyclists' intensive margin adjustments in response to the price change. Specifically, we estimate:

$$\text{Trip Time}_{ijt} = \alpha_{(i|j)} + \beta_1 1[\text{Daisy}_{ijt}] + \beta_2 1[\text{Daisy}_{ijt}] \times 1[\text{Post}_t] + \gamma_1 W_t + \gamma_2 R_j + \lambda_t + \varepsilon_{ijt} \tag{16}$$

where all variables are defined similarly to Eq. (13) although we now estimate this equation on our full sample (including observations after Oct. 2015), and we include a $1[\text{Post}_t]$ dummy variable capturing these "post-rate change" trips. As a result, we are interested in the $\hat{\beta}_2$ coefficient, which can be interpreted as the additional time spent daisychaining after the rate change (from \$1 to \$5) went into effect. We estimate Eq. (16) with both user and route fixed effects and we do so using our matched sample. Lastly, we estimate the exact specification in Eq. (16), but with average speed for each trip (in miles per hour) as our dependent variable.[19] We examine changes in speed as an additional margin on which cyclists can react to the rate change.

[18] Importantly, for our weekly extensive margin analysis, we do not incorporate our matched sample because we are primarily interested in changes in aggregate quantities of trips at the route level. Because our matching approach effectively chooses a 1:1 sample of counterfactual direct trips that appear observationally similar to daisychained trips, the number of direct and daisychained trips is equal. As a result, the proportion of daisychained-to-direct trips would be 0.5 exactly and would not permit us to explore how changes in quantities evolve in response to the rate change.

[19] Because we do not observe the exact streets that each trip uses, we calculate speed using observed trip time and route distance returned by the cycling directions from the route's start station to end station (incorporating the intermediate station for daisychained trips) from Google Maps.

Table 3
Regression results for trip time on full and matched samples.

	Weekday		Weekend	
Panel A: OLS on full sample				
	Registered	Casual	Registered	Casual
1[Daisy]	8.51***	10.81***	10.20***	9.73***
	(0.47)	(0.39)	(0.35)	(0.41)
Observations	401 851	103 054	86 140	86 968
Adjusted R^2	0.30	0.09	0.30	0.08
Panel B: OLS on matched sample				
	Weekday		Weekend	
	Registered	Casual	Registered	Casual
1[Daisy]	7.96***	9.52***	9.62***	8.78***
	(0.33)	(0.56)	(0.40)	(0.57)
Observations	8478	6518	4299	6225
Adjusted R^2	0.35	0.15	0.32	0.14
Panel C: Subscriber fixed effects on matched sample				
	Weekday		Weekend	
	Registered	Casual	Registered	Casual
1[Daisy]	6.81***	11.42***	8.76***	13.55***
	(0.40)	(1.12)	(0.54)	(1.20)
Observations	7315	1976	3237	1683
Adjusted R^2	0.53	0.53	0.48	0.48
Panel D: Route fixed effects on matched sample				
	Weekday		Weekend	
	Registered	Casual	Registered	Casual
1[Daisy]	7.34***	9.37***	8.98***	8.25***
	(0.36)	(0.69)	(0.52)	(0.68)
Observations	7342	5350	3177	5149
Adjusted R^2	0.51	0.31	0.49	0.34

Notes: Dependent variable in each model is trip time (in minutes). All observations are pre-Oct. 2015 price change. All regressions include controls for weather, year-by-month fixed effects, and hour-of-day fixed effects. All regressions except those with route fixed effects include route distance. Panel A presents results estimated on the full, unmatched sample. Panel B presents results estimated on the matched sample. Panel B presents results estimated with subscriber fixed effects on the matched sample. Panel C presents results estimated with route fixed effects on the matched sample. Matched sample is constructed using 1:1 Mahalanobis matching without replacement with calipers equal to 1 SD. Standard errors clustered at the route level are presented in parentheses in Panels A, B, and D. Standard errors clustered at the subscriber level are presented in parentheses in Panel C. *, **, and *** represent statistical significance at the 10, 5, and, 1 percent level.

5. Results and discussion

5.1. Empirical results on the time cost of daisychaining

Our first empirical goal is to estimate the additional time spent daisychaining for a trip relative to an otherwise identical trip.[20] In our first naïve model, we regress trip time on a binary variable for whether the trip was a daisychain trip, an estimate of trip distance returned by Google Maps' API as a control, and a suite of weather variables that vary by hour. We estimate these regressions on each of our four user-time groups. We report robust standard errors, clustered at the route level in all specifications. In Panel A of Table 3, we show that results from a simple regression improves the precision of our estimates for the coefficient on Daisy relative to the comparison of means in Table 2, but the point estimates remain largely unchanged—daisychain trips for registered users on weekdays take approximately 8.5 min longer than direct trips, and this coefficient is larger (approximately 9.7–10.8 min) for weekend trips or trips taken by casual users. This pattern of coefficients is preserved when we estimate the same specification on our matched sample in Panel B. The weighted estimates are similar to those of the unweighted sample. We suspect that some sample-selection bias is present in our most rudimentary models, but the change in coefficients is small. P-values for a test of equality across specifications via stacked regression are 0.345, 0.058, 0.268, and 0.174, suggesting that across unmatched (Panel

[20] We construct a simple lower bound using expected bicycle trip time estimates returned from Google Maps. Using the B-cycle data, we create a variable equal to the difference between a Google time estimate for a direct trip and the sum of the time estimate for the two segments that make up a daisychain route for all observed trips in our raw data. The median and mean of this variables are 2.5 and 3.2 min, respectively. We expect this estimate to be an underestimate of the true time expenditure because Google uses a constant speed for cycling trips and these durations do not necessarily reflect the time cost of getting into and out of the flow of traffic, docking the bicycle, etc.

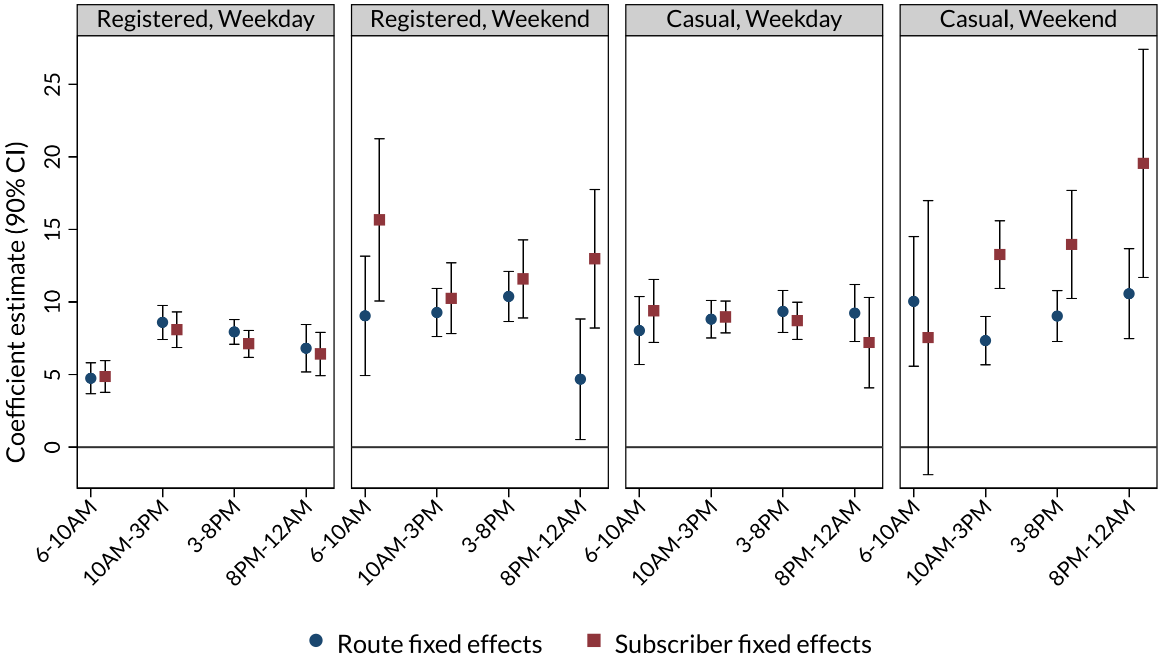

Fig. 6. Estimates for additional time spent daisychaining by time-of-day.

A) and matched (Panel B) samples, the only statistically significant difference in time-spent daisychaining is for casual users on weekdays. Pairwise tests of significance for coefficients within each user-time combination are presented in Table A.3.

Additionally in Table 3, we apply panel data estimators to our matched sample to explore the possibility that unobservable, time-invariant characteristics of users or routes affect the likelihood to daisychain. In Panels C and D, we control for subscriber-specific and route-specific unobserved heterogeneity, respectively. Specifications with subscriber fixed effects (Panel C) exhibit larger coefficients for casual users, with larger estimates of variance, than in Panels A and B and in specifications with route fixed effects (Panel D). The larger variance is likely due to fewer repeated observations within each casual subscriber. In models with route fixed effects in Panel D, coefficients on 1[Daisy] for registered users on weekdays are smaller than on weekends (7.3 min vs. 9.0 min); the same statistic for casual users is 9.4 and 8.3 min for both weekdays and weekends although the confidence intervals of these estimates overlap. Are these time costs reasonable? We suspect that adding a potentially off-route intermediate stop, re-docking the bicycle, and returning to the original destination could easily add upwards of 10 min to a trip.

Comparing the two sets of results in Table 3 suggests that our matching approach reduces model dependence (Ho et al., 2007) (i.e., the matching algorithm makes our regression sample less sensitive to the regression specification) to the point where different model specifications and identification assumptions do not have a qualitatively important impact on our estimated parameters. Most of these estimates within user–time groups are statistically similar under conventional standards (see Table A.3 for statistical tests across specifications). Our preferred estimates are those with route fixed effects (Panel D) primarily because they are estimated with precision and they rely on the most sensible variation in the available data. That is, the route fixed effects rely on variation in trip times on a given route, leveraging cross-sectional variation in cyclists' trips, whereas subscriber fixed effects control for cyclist-specific heterogeneity while identifying coefficients by variation across routes. This within-cyclist variation is particularly limited for casual users who do not contribute many repeated observations. Despite these differences, the results from both specifications are largely in agreement.

Using our specifications with subscriber and route fixed effects, we explore how our estimates of time expenditures vary throughout the day. We decompose our average effects for each user-time group by interacting 1[Daisy] with indicators for trips taken during the morning, afternoon, evening, and night. By doing so, we hope to further isolate commuting behavior from recreational behavior. In Fig. 6, we observe a relatively consistent pattern: morning periods tend to have smaller point estimates, especially for register users on weekdays, than the relatively homogeneous estimates at other times of the day.[21] These estimates are smallest for registered users on weekdays, which accords with the notion that these are most likely commuters who value more strongly a prompt arrival at their workplace. The coefficients for this group are smaller than all other coefficients for registered-weekday trips. Although other user–time groups display similar intra-day patterns, the coefficients are not estimated precisely enough to reveal statistical differences. Estimates based on subscriber fixed effects tend to be larger, particularly for casual users

[21] We present regression coefficients for these specifications in the online appendix, in Tables A.4 and A.5.

Table 4
Regression results for time spent daisychaining interacted with station and route characteristics.

Panel A: Route fixed effects on matched sample								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1[Daisy]	8.55***	8.51***	8.54***	8.53***	8.53***	8.53***	8.52***	8.52***
	(0.26)	(0.26)	(0.26)	(0.26)	(0.26)	(0.26)	(0.26)	(0.25)
... × Park area (sq. mi./route mi.)	−4.11***							−6.04***
	(1.16)							(1.23)
... × Cycleway (mi./route mi.)		0.55**						0.74***
		(0.23)						(0.25)
... × No. bike stations/10			−0.14***					−0.18***
			(0.04)					(0.04)
... × 1[Rail station]				−0.02				−0.67
				(0.53)				(0.66)
... × No. bus stops/10					0.14			0.20
					(0.13)			(0.15)
... × Comm. density						0.03		−0.01
						(0.02)		(0.02)
... × Res. density							−0.01**	−0.01
							(0.00)	(0.00)
Observations	24 297	24 297	24 297	24 297	24 297	24 297	24 297	24 297
Adjusted R^2	0.39	0.39	0.39	0.39	0.39	0.39	0.39	0.40
Panel B: Subscriber fixed effects on matched sample								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1[Daisy]	8.99***	8.92***	8.80***	8.94***	8.86***	8.98***	8.98***	8.46***
	(0.34)	(0.33)	(0.31)	(0.33)	(0.33)	(0.34)	(0.34)	(0.30)
... × Park area (sq. mi./route mi.)	0.32							−1.38
	(1.16)							(1.20)
... × Cycleway (mi./route mi.)		−0.08						0.19
		(0.18)						(0.20)
... × No. bike stations/10			−0.19***					−0.20***
			(0.04)					(0.04)
... × 1[Rail station]				−2.07***				−1.36**
				(0.57)				(0.61)
... × No. bus stops/10					−0.19			0.16
					(0.12)			(0.13)
... × Comm. density						−0.00		−0.00
						(0.02)		(0.02)
... × Res. density							0.00	−0.00
							(0.00)	(0.00)
Observations	15 503	15 503	15 503	15 503	15 503	15 503	15 503	15 503
Adjusted R^2	0.48	0.49	0.49	0.48	0.49	0.48	0.48	0.52

Notes: Dependent variable in each model is trip time (in minutes). All observations are pre-Oct. 2015 price change. All regressions include controls for weather, subscriber and weekday controls, year-by-month fixed effects, and hour-of-day fixed effects. All interacted variables are demeaned. Base effects for interacted terms in Panel B are estimated, but omitted from this table. Matched sample is constructed using 1:1 Mahalanobis matching without replacement with calipers equal to 1 SD. Standard errors clustered at the route level are presented in parentheses. *, **, and *** represent statistical significance at the 10, 5, and, 1 percent level.

on weekends. We suspect that these estimates are biased upward by potential positive correlation between daisychaining and route characteristics that are conducive to daisychaining (e.g., longer routes and routes with more intermediate stations). Moreover, these estimates are based on limited within-cyclist variation within a given time period. Both explanations provide more confidence in the specifications with route fixed effects.

In addition to user–time heterogeneity, we explore how station- and route-specific heterogeneity affects the time cost associated with daisychaining. In Table 4, we present regression results in which we interact our indicator for whether a trip was daisychained with demeaned route- or station-specific variables. We present results for specifications that include route fixed effects (Panel A) and subscriber fixed effects (Panel B). In the first seven columns, we add each measure of heterogeneity individually, culminating in a specification that includes all measures of heterogeneity in column (8). We also estimate the "full" specification in the final column for each of our user–time groups. Results for those regressions are in Appendix Tables A.6 and A.7.

For park area along the route, the interaction coefficient is negative and significant for route fixed effects reducing daisychain trip time by 6 min for every square-mile increase in park area per route mile (in column (8)).[22] This result is surprising as we expected that routes near parks would constitute leisurely trips for which time might be less constrained. This result could be explained by the fact that the largest parks in our sample tend to be concentrated near residential neighborhoods, such that we are picking

[22] For context, the standard deviation of park area is 0.2, so a one SD increase in park area would result in a $0.2 \times -6.04 \approx -1.2$ min change in daisychained trip time.

up daisychained routes for commuters. Or, it is possible that bike lanes might be concentrated near parks because of fewer space constraints, resulting in more unimpeded bicycle routes and more obvious intermediate docking opportunities. In Tables A.6 and A.7, we find that this negative effect is driven primarily by weekday trips taken by both registered and casual users. With subscriber fixed effects, however, this coefficient is not statistically different from zero. Taken jointly, this result suggests that park area does not provide a good measure of leisure opportunities.

Next, we estimate a positive interactive effect between time spent daisychaining and the distance of cycleways along the route when using route fixed effects. In column (8) of Table 4, Panel A, a one standard deviation increase in cycleways results in a $0.74 \times 1.3 \approx 0.96$ min increase in daisychain trip time. This effect is primarily driven by registered users on weekends (as shown in Table A.6). When estimated with subscriber fixed effects, however, we find a null effect in Panel B. So, we find some weak evidence that leisurely opportunities provided by cycleways increase daisychain trip time. Of course, these cycleways may also serve as commuting routes.

We also explore the role of bikeshare stations along the route as a measure of how costly daisychaining might be. We find intuitive results. For routes with more bikeshare stations, the time cost of daisychaining is smaller by about 0.2 min for every 10 additional bikeshare stations. If a route has many intermediate stations, a cyclist may not have to go far out of their way to re-dock their bike. This coefficient is also primarily driven by registered users on weekdays (as shown in Tables A.6 and A.7), which suggests that daisychainers who are likely commuters tend to daisychain for less time on routes with many re-docking opportunities.

Next, we consider the effects of alternative transportation options – whether there is a light rail station or the quantity of bus stops – within 0.5 km of the start or end station of the route. We estimate that the presence of a rail station reduces the time spent daisychaining by 0.67 to 1.36 min with route and subscriber fixed effects, respectively, although only the latter is significant. The interacted coefficient for routes with a greater number of bus stops is small and insignificant in both specifications. These results are consistent with the idea that commuters who ride light rail and use bicycles for "last mile" transit have tighter time constraints and are thus willing to spend less time daisychaining. Finally, we also include commercial and residential building density proximate to the start station to explore the role of common areas of work and residence. We find largely inconsequential results for both of these density variables.

Overall, these results suggest some heterogeneity based on route type that corresponds with leisure vs. commuter behavior in sensible ways. Taken jointly with our user–time heterogeneity in Table 3, we find that routes or cyclists that are more likely to be commuters (i.e., registered users on weekdays or cyclists on routes that start/end proximate to a rail station) add less time to their trip to daisychain. The route heterogeneity provides some justification for our results that interpret registered users on weekdays as likely commuters, as well, since most of the heterogeneity in Table 4 associated with utilitarian trips is driven by these users. On the other hand, cyclists who are more likely to be recreationalists (i.e., weekend cyclists or cyclists on separated bike trails) add more time to their trip to daisychain. Despite this heterogeneity, the differences in trip time expenditures across user–time groups and based on route characteristics is relatively small and, in many cases, these differences are statistically similar.

5.2. Price responsiveness along extensive margins

We now turn to our analysis of the price change on October 1, 2015. On this date, the price of a trip beyond 30 min increased by 400%, from $1 to $5. Because of this large increase in costs, our conceptual framework suggests that daisychaining should become more attractive. To explore this question we collapse our data to the route–week level, as described in Section 4.3.1. We first present estimates from an event study based on Eq. (15) in Fig. 7. In this figure, we show changes in the proportion of trips daisychained by week before/after the price change for each of our user–time groups.[23] For weeks preceding the rate change, changes in the proportion of trips daisychained remained generally constant and centered at zero. For registered users (both on weekdays and weekends), we see little change in the trend of the proportion of trips daisychained after the price increase. For casual users on weekdays, there is a notable increase in the proportion of trips daisychained after the rate change. For casual users on weekends, there appears to be a small increase in the average proportion of trips daisychained after the rate change, although these effects are noisy and they are difficult to draw any conclusions visually.

Turning to our primary estimation of Eq. (15), we can estimate the effect of the rate change with more precision. We present these results in Table 5 for several outcome variables. Because the price change increases the cost of all bikeshare trips beyond 30 min from $1 to $5, we expect that the quantity of aggregate bikeshare trips will decrease and/or shift more trips towards daisychaining to avoid the price increase. In Panel A, we present the effect of the rate change on the inverse hyperbolic sine of total number of trips. All coefficients are negative, but only the effect for casual users on weekdays (a 3.4% reduction) and registered users on weekends (a 1.6% reduction) are statistically significant. Neither registered users on weekdays or casual users on weekends reduce the total quantity of trips in reaction to the rate change. In Panel B, we present the same quantities, but for number of daisychained trips. All coefficients are positive, although this effect is not significant for registered users on weekdays. For the other user–time groups, we estimate an average 0.7–1.6% increase in the quantity of daisychained trips. It appears that the rate change decreased the total quantity of trips and increased the quantity of daisychained trips by a modest amount, with some heterogeneity in the effect across user groups.

[23] In appendix Figure A.2 we present the same figure, but with $\sinh^{-1}$(No. daisychained trips), which provides corroborating results.

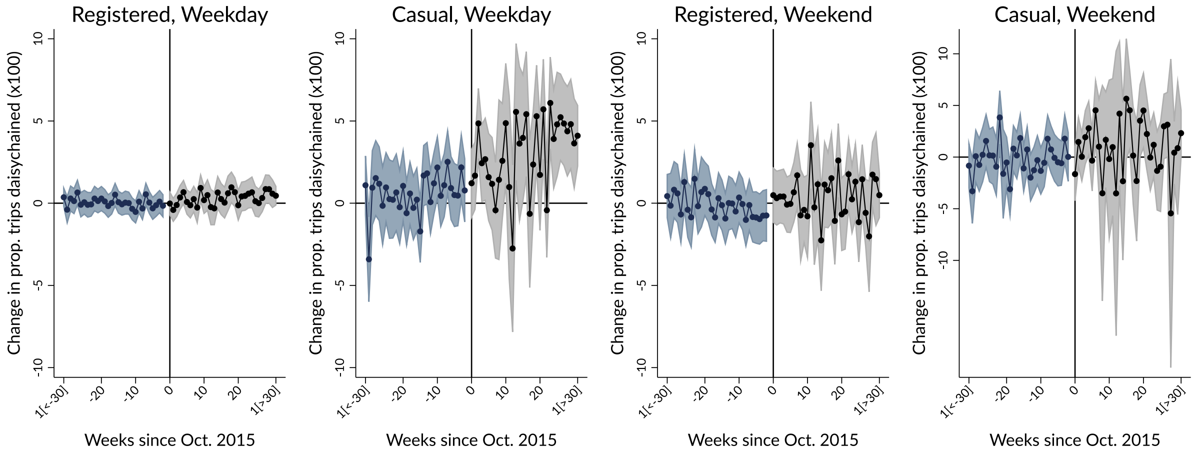

Fig. 7. Weekly event study for proportion of trips daisychained. Notes: Each figure is estimated as a separate regression. The outcome variable is the weekly proportion of daisychained trips along each route. The end points (i.e., time periods before/after 30 weeks) in the figure are all observations before/after the event window collapsed into a single bin. All regressions include weather controls, route fixed effects, week-of-year and year fixed effects.

In Panel C, we present results using the ratio of daisychained trips to total trips as our outcome variable.[24] Here, we see similar results to changes in the quantity of daisychained trips. For registered users on weekdays, there is no statistical change, but for all other user groups, we estimate a 0.5 to 1.4 percentage point change in the quantity of daisychained trips. This estimate is our preferred estimate of the extensive margin response to the price change, which shows that although the total quantity of trips went down, the proportion of trips daisychained increased for most of the user–time groups. This effect is a modest increase the proportion of trips daisychained for all user–time groups except for registered users on weekdays.

In Panel D of Table 5, we interact our 1[Post] variable with station and route characteristics to explore which types of routes see the largest changes in the proportion of daisychained trips. We find evidence that park area heterogeneity increases the proportion of daisychained trips. We also find that routes with greater cycleway length per mile have a smaller increase in the proportion of daisychained trips. In other words, proportionally more daisychained trips originate on routes with fewer cycleways after the rate change. This result suggests that more utilitarian-focused routes experience a larger increase in daisychained trips. Routes with many intermediate stations experience a proportionally larger increase in daisychained trips, and this effect is strongest for casual users. This interactive effect suggests that cyclists are daisychaining more trips on routes with more intermediate stations after the price change, which is intuitive. Further, we estimate the routes that originate or terminate nearby rail stations see no statistical change in the proportion of daisychained trips after the rate change and we see a smaller increase for routes that have more bus stops. Lastly, there is evidence that greater commercial building density is associated with a relatively smaller increase in daisychained trips.

To summarize, we observe a relatively small increase in the proportion of daisychained trips in response to the price increase, which largely comes from casual users and weekend trips. Some drivers of heterogeneity in this responsiveness suggest that routes that are more recreational and have low-cost opportunities for daisychaining (e.g., with more park area and more intermediate bikeshare stations) increase the proportion of daisychained trips. Interestingly, we see a relatively smaller increase in the proportion of daisychained trips for routes with more cycleways and bus stops and no relative change for routes proximate to rail stations. There are two issues with these route-heterogeneity results: many of the route characteristics may be positively correlated (e.g., more bikeshare stations might be sited on routes with more park area) and there is not a decisive division of characteristics across recreational/utilitarian purposes (e.g., routes along cycleways may be conducive to commuting and recreational purposes).

5.3. Price responsiveness along intensive margins

Finally, we explore consumer behavior in response to price increase on the intensive margin. Specifically, we ask: conditional on the choice to daisychain, did the price increase the time spent daisychaining? Eq. (12) in our conceptual framework suggests that cyclists should extend their daisychain trip time to keep the ratio of the marginal value of time in a given activity and the marginal value of money constant. The results for our intensive margin specifications, in which we regress trip time on an indicator for whether the trip was daisy multiplied by an indicator for time periods in the post-rate change period are presented in Table 6.

In the first two panels of Table 6, we present our preferred specifications on our matched sample using subscriber (Panel A) and route (Panel B) fixed effects. Our estimates on the baseline indicator for daisychaining are nearly identical to that of Table 3. The additional time spent daisychaining in response to the price increase is revealed through the interaction, 1[Daisy] × 1[Post]. Across

[24] The average proportion of trips daisychained at the route–week level for each of our user–time groups before the rate change is: 1.3%, 5.7%. 2.5%, and 6.2% for a sample average of 3.0%.

Table 5
Price responsiveness on the extensive margin.

Panel A: $sinh^{-1}$(No. trips) at week–route level				
	Weekday		Weekend	
	Registered	Casual	Registered	Casual
1[Post]	−0.008	−0.034***	−0.016**	−0.007
	(0.008)	(0.008)	(0.006)	(0.009)
Observations	276 302	96 757	90 203	78 600
Adjusted R^2	0.361	0.077	0.085	0.058
Panel B: $sinh^{-1}$(No. daisychained trips) at week–route level				
	Weekday		Weekend	
	Registered	Casual	Registered	Casual
1[Post]	0.001	0.016***	0.007**	0.012**
	(0.001)	(0.005)	(0.003)	(0.006)
Observations	276 302	96 757	90 203	78 600
Adjusted R^2	0.145	0.070	0.140	0.070
Panel C: Proportion trips daisychained (×100) at week–route level				
	Weekday		Weekend	
	Registered	Casual	Registered	Casual
1[Post]	0.083	1.388***	0.528*	1.054**
	(0.113)	(0.451)	(0.282)	(0.507)
Observations	276 302	96 757	90 203	78 600
Adjusted R^2	0.160	0.086	0.151	0.086
Panel D: Proportion trips daisychained (×100) at week–route level with interactions				
	Weekday		Weekend	
	Registered	Casual	Registered	Casual
1[Post]	0.105	1.492***	0.547*	1.248**
	(0.115)	(0.452)	(0.286)	(0.510)
... × Park area (sq. mi./mile)	0.814**	0.809	1.209*	1.826**
	(0.366)	(0.526)	(0.645)	(0.767)
... × Cycleway (1000 ft/mile)	−0.086***	−0.255***	−0.165***	−0.297***
	(0.033)	(0.067)	(0.061)	(0.080)
... × No. bike stations/10	0.046***	0.276***	0.008	0.355***
	(0.016)	(0.035)	(0.035)	(0.037)
... × 1[Rail station]	−0.251	0.146	0.458	−0.258
	(0.158)	(0.437)	(0.343)	(0.537)
... × No. bus stops/10	0.002	−0.201**	−0.172**	−0.383***
	(0.030)	(0.082)	(0.074)	(0.090)
... × Res. density (start)	−0.000	0.003	−0.000	0.002
	(0.001)	(0.003)	(0.002)	(0.003)
... × Comm. density (start)	−0.005	−0.055***	0.015	−0.043**
	(0.007)	(0.017)	(0.014)	(0.019)
Observations	276 302	96 757	90 203	78 600
Adjusted R^2	0.160	0.088	0.151	0.089

Notes: All variables are collapsed to the week–route level and include weather controls, a weekly linear time trend, week-of-year fixed effects, and year fixed effects. All interacted variables in Panel D are demeaned. Standard errors are clustered at the route level. *, **, and *** represent statistical significance at the 10, 5, and, 1 percent level.

all user–time groups and both fixed effects specifications, all estimates are economically small and statistically insignificant. These results suggest that cyclists do not alter their behavior by spending more time going out of their way in response to a 400% increase in price. In addition, we reproduce our primary results from Section 5.1 restricted to post-Oct. 2015 time periods in the appendix in Tables A.8, A.9, and A.10. Because of their similarity to the same results in the pre-Oct. 2015 period, these results provide additional corroborative evidence that time–money trade offs do not change meaningfully in the post-Oct. 2015 time periods.

An alternative response to the price increase along an intensive margin is that cyclists could increase the speed at which they ride on direct routes. We explore this directly in Panels C and D, in which we substitute average speed in for our dependent variable.[25] The results suggest two findings. First, daisychained trips are, on average, around 2 mph slower in our baseline estimates, and

[25] Formally, average speed is defined as cycling distance (in miles) returned by Google Maps' API between start and end stations (including the distance to an intermediate station for daisychained trips) divided by trip time (in hours).

Table 6
Price responsiveness on the intensive margin.

Panel A: Trip time with subscriber fixed effects				
	Weekday		Weekend	
	Registered	Casual	Registered	Casual
1[Daisy]	6.79***	11.53***	8.96***	13.52***
	(0.39)	(1.09)	(0.51)	(1.15)
1[Daisy] × 1[Post]	−0.24	0.53	−0.55	0.36
	(0.54)	(1.33)	(0.77)	(1.47)
Observations	10 769	3797	4722	3357
Adjusted R^2	0.52	0.53	0.51	0.54
Panel B: Trip time with route fixed effects				
	Weekday		Weekend	
	Registered	Casual	Registered	Casual
1[Daisy]	7.30***	9.39***	8.94***	8.17***
	(0.35)	(0.64)	(0.50)	(0.64)
1[Daisy] × 1[Post]	0.19	0.62	0.69	0.71
	(0.49)	(0.84)	(0.83)	(0.90)
Observations	10 970	10 788	4760	10 330
Adjusted R^2	0.49	0.29	0.48	0.30
Panel C: Trip speed (mph) with subscriber fixed effects				
	Weekday		Weekend	
	Registered	Casual	Registered	Casual
1[Daisy]	−2.04***	−1.51***	−2.18***	−1.63***
	(0.10)	(0.17)	(0.13)	(0.18)
1[Daisy] × 1[Post]	−0.24	0.10	0.06	0.08
	(0.16)	(0.23)	(0.20)	(0.25)
Observations	10 769	3797	4722	3357
Adjusted R^2	0.46	0.52	0.43	0.55
Panel D: Trip speed (mph) with route fixed effects				
	Weekday		Weekend	
	Registered	Casual	Registered	Casual
1[Daisy]	−2.38***	−1.78***	−2.42***	−1.59***
	(0.08)	(0.07)	(0.10)	(0.07)
1[Daisy] × 1[Post]	−0.18	−0.11	−0.25	−0.07
	(0.12)	(0.09)	(0.18)	(0.10)
Observations	10 970	10 788	4760	10 330
Adjusted R^2	0.61	0.51	0.56	0.55

Notes: Dependent variable in Panels A and B is trip time (in minutes). Dependent variable in Panels C and D is speed (in miles per hour). 1[Post] equals 1 for time periods after Oct. 1, 2015. All regressions include controls for weather, year-by-month fixed effects, and hour-of-day fixed effects. All regressions are estimated on a matched sample that is constructed using 1:1 Mahalanobis matching without replacement with calipers equal to 1 SD. Standard errors clustered at the route level are presented in parentheses. *, **, and *** represent statistical significance at the 10, 5, and, 1 percent level.

this result is consistent across our user–time groups. This finding is not particularly surprising: if a trip has an intermediate station directly along the taken route, simply taking time to re-dock the bike will decrease average speed for that trip.[26]

Our second finding is that for all user–time groups, we estimate no change in speed in the post-Oct. 2015 period. For registered users on weekdays, we estimate a small but insignificant decrease (a 0.2 mph reduction) in speed for daisychained trips in the post-Oct. 2015 period, widening the difference in speeds between direct and daisychained trips. These results are consistent with the results focused on trip time: there is no evidence of an intensive margin change in speed either by non-daisychainers biking faster or daisychainers biking slower to avoid the price increase.

In the online appendix, we repeat this exercise for routes that are projected to take 20–40 min to isolate the behavior of cyclists that likely anticipate facing the price increase. These results (presented in Table A.12) generally suggest slightly smaller baseline time expenditures and show that registered users on weekdays do increase their daisychained trip time by approximately 2 min in the post-Oct. 2015 increase periods. This increase in trip time is met with a concomitant decrease in daisychained trip speeds relative to direct trips after the price change. So, for registered users on weekdays, we do see some adjustment along the intensive margin for a narrower set of trips.

[26] For a 30-min direct trip, a 2 mph speed difference implies that daisychained trips, which are on average 0.26–0.40 miles longer within our matched sample, would take 7.8 to 12.0 min longer, which is consistent with the results in Panel A.

Table 7
Income statistics.

	Median HH income		% HHs less than $35K		Minimum wage	
	2012	2014	2012	2014	2012	2014
United States	$52,970	$53,657	28.1	26.4	$7.03	$7.25
Colorado	$58,532	$61,303	24.2	21.6	$7.41	$8
Denver	$63,366	$66,870	–	–	$7.41	$8
B-cycle annual members	$99,214	–	9.7	5.5	–	–
B-cycle casual users	–	–	12.6	18.3	–	–

Notes: All dollar figures are in 2014 adjusted USD. % Households with income less than $35,000 is based on nominal amounts. Median household income is estimated using the table on page 7 of the Denver B-cycle Member demographics report, 2012 (https://denver.bcycle.com/docs/librariesprovider34/default-document-library/denver-b-cycle-demography_2011--2012.pdf?sfvrsn=2). The percent of households with income under $35,000 comes from page 8 of the 2010-14 report (https://denver.bcycle.com/docs/librariesprovider34/default-document-library/denver-b-cycle-demography_2010--2014.pdf?sfvrsn=2). Household median incomes for the United States, Colorado, and Denver metro area come from http://www.deptofnumbers.com/income/colorado/denver/. Estimates of the percent of households with income less than $35,000 were constructed using the 1-year ACS samples, which can be downloaded from https://usa.ipums.org/usa. Minimum wage adjusted to 2014 USD.

6. Discussion

In our empirical analysis, we have uncovered several key results. First, in our preferreed specifications, we find that cyclists spend roughly 7–10 min daisychaining to avoid the discontinuous price increase of $1. Second, there is some degree of heterogeneity in this response based on observable characteristics. Routes, users, and time periods that suggest leisurely trips generally exhibit greater time expenditures via daisychaining, whereas routes, users, and time periods that suggest utilitarian trips exhibit smaller time expenditures daisychaining. Third, although this heterogeneity aligns with predictions from our conceptual framework and general intuition, the gap in time expenditures for leisure vs. commuting trips is relatively narrow. Fourth, in response to a 400% increase in the price of a trip beyond 30 min, we estimate a modest increase in the proportion of trips daisychained (extensive margin), which is concentrated among casual users, on weekends, on routes that have more intermediate docking stations and are nearby more park area. Fifth, along an intensive margin, we see virtually no change in the duration or speed of daisychained trips, relative to direct trips, in response to the price increase. In the following discussion, we situate these findings in our conceptual framework that we use to provide an estimate of the price of time and we reconcile the (lack of) observed cyclist behavior in response to the large price change.

6.1. Implications for the value of travel time

In official federal guidance on using value of travel time savings estimates in economic analyses (U.S. Department of Transportation, 2014), the only direct guidance for bicycling states: "Personal time spent...bicycling, should be evaluated at 100 percent of hourly income, with a range of 80 to 120 percent to reflect uncertainty" [pp. 13]. This value is intended to capture the discomfort or disutility of commuting and is interpreted similarly to time spent on waiting for, or standing in, a bus. The value used for cycling is not, to our knowledge, informed by any empirical evidence. The same guidance suggests presenting the VST using the median hourly income, constructed as median household income for a given geographic region divided by the number of working hours in a year: 2080. In a 2012 member survey, B-cycle members reported annual household income ($99,000 in 2012) approximately one-half larger than that of Denver residents ($67,000 in 2014). This estimate suggests that our sample of bikeshare users is skewed towards relatively wealthy individuals. Demographic surveys reach the same conclusion: bikeshare users are more likely to be male, younger, white, and wealthier than the population in the same urban area.[27] We present relevant income statistics for our application – median household income for residents in the U.S., Colorado, Denver, and for B-cycle members – in Table 7.

How do our estimates translate to an estimate of consumers' value of time saved? Recall that our conceptual framework allows us to translate our time cost estimates from daisychaining into an estimate of the value of time saved cycling. Eq. (12) shows that the ratio of cost savings from daisychaining ($c_{n,j}^{ND} - c_{n,j}^{D}$) to time savings from daisychaining ($t_{n,j}^{D} - t_{n,j}^{ND}$) provides a lower bound for κ_n/λ_n, which is the ratio of the marginal utility of time spent cycling and the marginal utility of money. The nonlinear pricing structure provides a discrete change in the cost of a trip beyond 30 min equal to $1 before the Oct. 2015 rate change, which enters the numerator. Our estimate of the additional time spent daisychaining, $\hat{\beta}$ from Eq. (13), provides our denominator for Eq. (12). As a result, our estimate of the value of cycling time saved, in dollars per hour, is given by $\$1/(\hat{\beta}/60\text{ min.})$.

In Table 8, we present implied VST estimates for various estimates of $\hat{\beta}$ representing user–time heterogeneity and time-of-day heterogeneity along with 95 percent confidence intervals in square brackets. Our primary VST estimates vary from $6.40–$8.18 per hour for our four "baseline" user-time combinations prior to Oct. 2015. These estimates are approximately the level of the minimum wage, ranging from 13.5%–17.2% of the B-cycle members' implied hourly wage, and 19.9%–25.4% of the average implied hourly

[27] See, e.g., the 2015 Demography of Users report for Denver B-cycle: https://web.archive.org/web/20200201192434/https://www.denverbcycle.com/company.

Table 8
Implied estimates of cyclists' opportunity cost of time ($/hour).

	Baseline	Time-of-day			
		6–10 AM	10 AM–3 PM	3 PM–8 PM	8 PM–12 AM
Registered, Weekday	8.18	12.62	6.97	7.55	8.79
	[7.39, 8.97]	[9.25, 15.99]	[5.84, 8.10]	[6.59, 8.50]	[6.29, 11.30]
	(17.1%)	(26.5%)	(14.6%)	(15.8%)	(18.4%)
	{25.4%}	{39.3%}	{21.7%}	{23.5%}	{27.3%}
Registered, Weekend	6.40	6.62	6.46	5.77	12.79
	[5.48, 7.33]	[3.04, 10.21]	[5.08, 7.83]	[4.63, 6.92]	[−0.70, 26.28]
	(13.4%)	(13.9%)	(13.5%)	(12.1%)	(26.8%)
	{19.9%}	{20.6%}	{20.1%}	{18.0%}	{39.8%}
Casual, Weekday	6.68	7.46	6.79	6.41	6.49
	[5.92, 7.43]	[4.88, 10.04]	[5.61, 7.98]	[5.24, 7.58]	[4.85, 8.13]
	(14.0%)	(15.6%)	(14.2%)	(13.4%)	(13.6%)
	{20.8%}	{23.2%}	{21.1%}	{19.9%}	{20.2%}
Casual, Weekend	7.27	5.97	8.16	6.63	5.67
	[6.09, 8.45]	[2.82, 9.12]	[5.95, 10.37]	[5.11, 8.16]	[3.69, 7.65]
	(15.2%)	(12.5%)	(17.1%)	(13.9%)	(11.9%)
	{22.6%}	{18.6%}	{25.4%}	{20.6%}	{17.6%}

Notes: Primary statistics presented are value time saved cycling (VST) estimates in dollars per hour. 95% confidence intervals are presented in brackets. All VDT estimates and confidence intervals are drawn from regression specifications with route fixed effects. VDT is calculated as $\$1/(\hat{\beta}/60 \text{ min.})$, where $\hat{\beta}$ is our estimated coefficient on Daisy and $1 is the notch price for trips beyond 30 min. All dollar values are in 2014 adjusted USD. In parentheses, we present the VST as a percentage of Denver B-cycle users hourly wage, calculated as median household income ($99,214)/2080 h per year = $47.69 per hour. In curly braces, we present the VST as a percentage of Denver median household income ($63,366)/2080 h per year = $32.15 per hour.

wage for the City of Denver.[28] Further, our time-of-day results suggest some which is consistent with heterogeneity in the VST for recreational vs. commuting purposes. Registered users on weekday mornings, who are most likely commuters, reveal a value of $12.62 per hour, or 26.5%–39.3% of the hourly wage.[29] Our results suggest that casual users on weekend nights, in contrast, value time saved cycling at only 11.9%–17.6% of the hourly wage.

Although this user–time heterogeneity in the VST is sensible, Fig. 8 reveals that these estimates, in large part, are quite similar when placed in a broader context. Most VST estimates are centered around (or below) Denver's minimum wage ($8/hour in 2014). The notable exception is registered users on weekday mornings who exhibit a larger VST. Another exception is registered users on weekend nights, but this estimate is too imprecise to draw any conclusions from. So, the primary takeaways from this figure are: (a) the VST revealed from daisychaining behavior is relatively stable across user types, day of week, and hour of day; and (b) the VST estimated for cyclists is demonstrably smaller than most empirical estimates of the VST in other contexts, primarily for motorists in commuting and recreational contexts. Taken directly, these results suggest that official federal guidance may overestimate the VST for cycling, in some cases by a factor of seven.

Why is the VST for cyclists so low? First, we argue in Section 2 that the VST for cyclists will likely be smaller than that of drivers for at least two reasons. One rationale is that even for commuting, cyclists likely choose to ride a bicycle because it provides some level of enjoyment or health benefits. As a result, cyclists value each minute on a bicycle more than they do sitting in a car, which leads to a lower value of saving time on a bicycle, which is what we estimate. Recall that, conceptually, the value of time saved is the difference between the value of time in an alternative use (which is fixed across all uses of time) and the value of time spent in any particular use (see Eq. (9)). If individuals value time spent cycling more than driving, for example, then we should expect a low VST because we are substracting a larger value (i.e., the monetized marginal utility of cycling). Additionally, we contend that many cyclists use the bikesharing program, at least in part, for leisure. There is good reason to believe that leisure time is valued more strongly than commuting time because the opportunity cost of leisure is higher than utilitarian purposes. Again, this translates to a lower value of time savings for cycling.

Second, we reiterate that our conceptual framework identifies a lower bound of the true ratio of marginal utilities in Eq. (12). Although this ratio exactly identifies the VST for marginal cyclists, what we measure in our empirical framework is likely a weighted average of marginal and inframarginal cyclists. In the Appendix Table A.11, we produce our baseline results for a subsample of trips that are expected to take between 20 and 40 min. Because we isolate trips right around the 30-min price increase, we believe these trips are more likely to be marginal. Estimates of $\hat{\beta}$ are 1–2 min smaller than our full sample, which translates to VSTs ranging from $8.1–13.4 per hour. These estimates are larger, but still fairly small in general.

In terms of policy implications, a small value of time saving for cyclists can provide justification for policies that encourage mode-switching from automobile trips to bicycle trips because time spent cycling is valued more strongly than time spent driving,

[28] We use two measures of median household income to benchmark our estimates of $\hat{\beta}$ to local wage rates. We use reported B-cycle user income from 2012, which is $99,214 as reported in Table 7. We also use median household income for the City of Denver, which is $63,366 in 2012. Annual income is divided by 2080 working hours in the year to provide an implied hourly wage.

[29] Statistics from Denver B-cycle's 2012 Member survey show that 43.6% of annual members use their membership for commuting to or from work.

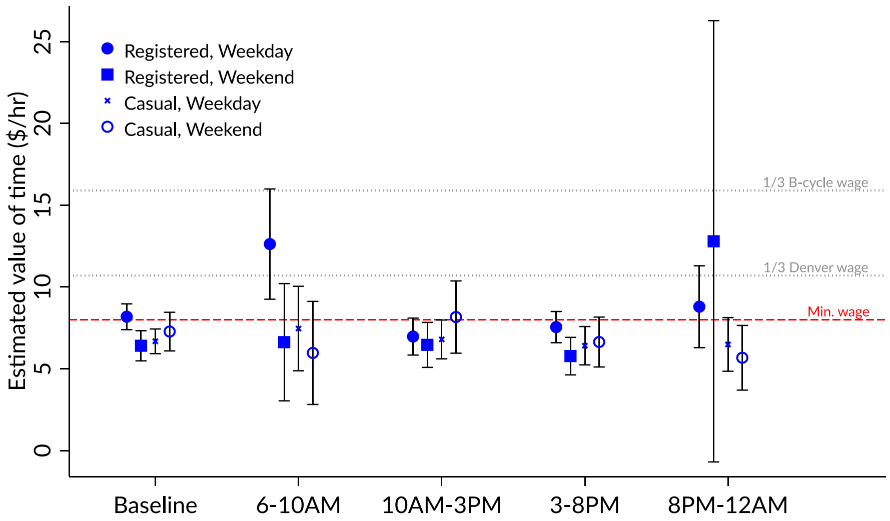

Fig. 8. Implied estimates of cyclist's value of time saved cycling for different user–time combinations. Notes: All value of time saved estimates are based on regressions that include route fixed effects and include controls for weather, year-by-month fixed effects, and hour-of-day fixed effects. All regressions are estimated on a matched sample that is constructed using 1:1 Mahalanobis matching without replacement with calipers equal to 1 SD. Standard errors are clustered at the route level and confidence intervals are calculated with the delta method.

in addition to differences in external costs of the two modes. As a thought experiment, imagine a policy that converts an automobile driver with a 30-min commute to a cyclist with a 60-min commute. Suppose further that the VST for driving is 100% of the wage rate, while the VST for cycling is 25% of the wage rate. Commute times have doubled for the cyclist, but because they value their time cycling four times as much that of driving, they have been made better off. Suppose even further that the policy induces enough drivers to commute via bicycle such that it reduces traffic congestion (e.g., as demonstrated by Hamilton and Wichman, 2017), which may lower commute times for remaining drivers in the short run, generating additional benefits. From this, it is apparent that low VSTs for cyclists can reveal important tradeoffs that are necessary for characterizing the benefits and costs of public investments in transportation infrastructure or policies that induce mode-switching towards bicycling. Research that directly compares the value of time saved cycling to other modes of transit would be valuable for a complete welfare analysis.

6.2. Reconciling price responsiveness

We believe our estimates of the VST based on the discontinuous price increase for trips beyond 30 min are valuable for revealing how cyclists trade off time for money. That said, we must reckon with the fact that we observe only a modest change in behavior in response to a 400% increase in price in Oct. 2015. Overall, we find that the price change operates primarily on an extensive margin for daisychaining (Table 5). The most intuitive response we observed is an increase in the proportion of daisychained trips, coming primarily from casual users, on weekends, and on routes that have lower transaction costs for daisychaining. We see smaller increases in the proportion of daisychained trips for registered users on weekends and no change on weekdays.[30]

Cyclists' response to the price change on the intensive margin is more puzzling. With a greater financial benefit for daisychaining, we hypothesized that cyclists would go further out of their way to avoid the larger price for trips beyond 30 min or, perhaps, cycle faster on direct trips to avoid the price. But, we find consistent and robust evidence that cyclists do not add time to their daisychained trips and there is no evidence that trip speed diverges between direct and daisychained trips (Table 6). Because the cost savings from daisychaining are $5 rather than $1, our finding no price responsiveness on an intensive margin leads to even smaller estimates of the VST.

There are several reasons why we might observe this behavior; the most likely explanation is mechanical. The B-cycle bikeshare network is fairly dense, with many intermediate stations available on longer routes. As noted in Table A.2, the median route in our sample has 14 additional stations within 0.5 km of a straight line connected to the start and end points of the trip. So, if a cyclist could daisychain a trip in 7–9 min prior to the price change, there is no reason why that same cyclist on the same or a similar route could not daisychain for the same amount of time. We would expect more trips to be daisychained, and we do see evidence of that extensive margin change in Table 5, as described previously.

Additionally, we see that some cyclists might react to the price change along a different intensive margin: speed. For registered users on weekdays, we see a small divergence in the speed of daisychained vs. direct trips: the gap in speed increases by an average

[30] One rationale for why we do not see more movement on the extensive margin is that B-cycle introduced a new, "Annual Plus" membership option that provided 60 min of free trip time in January 2016 (see Fig. 1 for more discussion). Migration from annual memberships upon expiration to "Annual Plus" memberships could explain the relatively small effect for registered users.

of 0.2–0.3 mph in periods after the price change. This margin of adjustment is relatively small, and unlikely to explain the pervasive nonresponse to price.

Behavioral considerations could also drive this price inelasticity. De Borger and Fosgerau (2008) and Hess et al. (2008) suggest that reference dependence might reconcile differences in willingness-to-pay and willingness-to-accept for travel-time reductions. In our scenario, we contend that the ‘‘free’’ segment of the rate structure might serve as a reference point and place an unobserved shadow premium on the free segment of the trip, such that we do not observe the full, perceived change in price. This ‘‘zero-price effect’’ concept is similar in spirit to research on pricing of health care premiums (Douven et al., 2017).

An alternative explanation is an information failure. Relative to other papers in this literature that exploit variation in highway tolls (Small et al., 2005; Fezzi et al., 2014), gasoline prices (Wolff, 2014), or speed limits (Ashenfelter and Greenstone, 2004), which tend to be salient signals, our application relies on a somewhat unintuitive price structure. In other contexts with opaque, nonlinear prices, research has found that consumers use heuristics to make consumption decisions (e.g., Chetty et al., 2009; Kahn and Wolak, 2013; Grubb, 2014; Ito, 2014; Sallee, 2014; Sexton, 2015; Wichman, 2017). Consumers may recognize that for trips beyond the notch threshold a positive price will be charged, but they may not know the precise level of that price. Thus, consumers might be responding to the more salient quantity threshold rather than the price itself. When the price changes from \$1 to \$5, cyclists might internalize the quantity as the more salient signal and not respond to the change in price.

6.3. Caveats

Naturally, our estimates are subject to several caveats. Our analysis is an evaluation of a single bicycle-sharing program composed of relatively high-income users. Other bikesharing programs, however, comprise similarly select populations, so our sample is likely representative of behavior in other programs. More specifically, nearly all U.S.-based bikesharing programs, and many more globally, have similar rate structures to the one analyzed here. One also might contend that even within our select sample, we analyze a distinct set of trips that are not representative of overall bikeshare user behavior. While this is true, we believe the consistency in our time expenditures across user–time groups and across route vs. fixed effects specifications suggests a more fundamental time–money tradeoff for cyclists.

Our identification strategy relies upon the assumption that conditional on observable characteristics any unobservable components that affect the choice to daisychain are balanced. One threat to this strategy is that a short trip, in distance, may embed other characteristics associated with daisychaining that are not balanced but, in principle, unobservable. For example, a one-mile direct route may not be a good counterfactual for a daisychain trip with the same start and end destinations if there are potential recreational, sightseeing benefits nearby. That is, a direct route would be shorter than a meandering daisychain trip on the same route, which would bias our coefficient estimates away from zero. In Table A.13, we re-run our primary models for different trip distance subsamples. Our results are robust to this stratification. We additionally re-estimate our primary regressions on a subsample that focuses on trips that are expected to take 20–40 min. These results, presented in Tables A.11 and A.12, suggest slightly smaller additional time from daisychaining, which would result in slightly larger VSTs, but our primary conclusions would remain.

There are two additional confounding factors that could alter the interpretation of our results: redocking a bicycle mid-trip because of a mechanical failure and falsely assigning daisychain status to a trip when there was actually a brief layover at an intermediate destination. For the former, we cannot identify this relationship statistically and it is possible that we are partially attributing the daisychain response to cyclists going out of their way to swap their bicycle for a better one. Second, because we identify daisychain trips as trips that are checked-in and checked-out of the same stations within 3 min, we may be misattributing daisychaining behavior to a productive task. Perhaps, for the sake of example, cyclists dock their bicycle on their way to a dinner party to purchase a bottle of wine. We cannot rule out this behavior, but it seems unlikely that such short intermediate stops are representative of all bikeshare trips in our sample. Further, Fig. 5 reveals some suggestive sorting around the 30-min price notch, which lends credence to the fact that cyclists are responding to the discontinuous price change.

7. Concluding remarks

Overall, we provide evidence of time-for-money tradeoffs among a novel class of consumers – cyclists – by exploiting a nonlinear pricing structure for bikesharing. Cyclists spend an additional 7–9 min checking in their bicycle at an intermediate station to avoid a \$1 increase in the cost of their trip. There is some heterogeneity in this time cost that correlates with whether the trip's purpose is utilitarian or recreational. Likely commuters add the least amount of time to their trip, but the range of heterogeneous time expenditures is relatively narrow. These estimates translate to values of time 13%–25% of the prevailing wage or approximately the level of the minimum wage. These low values of time savings reflect the degree to which cyclists, unlike drivers, enjoy time spent on a bicycle. Our findings suggest that official federal guidance overstates the value of saving time for cyclists because it fails to account for the leisure benefits of cycling. Cycling is fundamentally different than time spent driving or waiting for a bus because of the comparative utility gains cyclists derive from their trip. Our analysis provides evidence that time spent cycling is potentially much more valuable than time spent on alternative modes of transit. Additionally, we find modest increases to a large increase in the price of a trip on the extensive margin, but virtually no price responsiveness on intensive margins.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jeem.2023.102817.

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