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Public transit generates new physical activity: Evidence from individual GPS and accelerometer data before and after light rail construction in a neighborhood of Salt Lake City, Utah, USA

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Abstract

Poor health outcomes from insufficient physical activity (PA) are a persistent public health issue. Public transit is often promoted for positive influence on PA. Although there is cross-sectional evidence that transit users have higher PA levels, this may be coincidental or shifted from activities such as recreational walking. We use a quasi-experimental design to test if light rail transit (LRT) generated new PA in a neighborhood of Salt Lake City, Utah, USA. Participants ($n=536$) wore Global Positioning System (GPS) receivers and accelerometers before (2012) and after (2013) LRT construction. We test within-person differences in individuals' PA time based on changes in transit usage pre- versus post-intervention. We map transit-related PA to detect spatial clustering of PA around the new transit stops. We analyze within-person differences in PA time based on daily transit use and estimate the effect of daily transit use on PA time controlling for socio-demographic variables. Results suggest that transit use directly generates new PA that is not shifted from other PA. This supports the public health benefits from new high quality public transit such as LRT.

Keywords

Physical activity; Public transit; Quasi-experiment; Global positioning system; Accelerometer

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1. Introduction

Insufficient physical activity (PA) and consequent poor health outcomes such as obesity, diabetes, heart disease and some cancers are persistent public health issues in the United States and elsewhere (United States Department of Health and Human Services, 2008). Public transit can promote PA because riders often use active transportation modes such as walking and biking to access and egress the system (Brown and Werner, 2007). There is evidence that public transit users are more physically active and experience better health outcomes such as healthier body mass indices (BMIs) than non-transit users (Besser and Dannenberg, 2005; Brown and Werner, 2009; Lachapelle and Frank, 2009; Lachapelle et al., 2011; Rissel et al., 2012).

Despite evidence that public transit users have higher levels of PA than non-transit users, it is unclear whether public transit generates *new* PA. Cross-sectional analysis of transit use and PA cannot easily disentangle confounding effects such as neighborhood density, mixed land uses and other unobserved factors to determine how much of observed PA directly relates to public transit, independent from other types of utilitarian or recreational PA. It is also possible that public transit users may shift PA from other activities, meaning that public transit redistributes one's daily PA rather than generating new PA (Christian, 2012; Saelens et al., 2014).

This paper addresses the question of whether public transit generates PA through a quasi-experimental study of participants' PA before and after construction of a light rail transit (LRT) line in a neighborhood of Salt Lake City, Utah, USA. Participants ($n=536$) wore Global Positioning System (GPS) receivers and accelerometers for a minimum of ten hours per day for at least three days before the construction of the LRT line (2012). Participants wore the equipment again approximately one year later, after the construction of the LRT (2013). The combination of GPS and accelerometer data allows the identification of travel mode (walk, bike, car, bus, light rail) and bouts of transit-related PA and non-transit-related PA for individuals.

We performed three types of analysis. First, we tested for within-person differences in PA time based on changes in transit use between 2012 and 2013. Second, we mapped and analyzed the geographic distribution of transit-related PA in 2012 and 2013. Third, we compared descriptively the daily PA time for non-transit users, transit users on days they use transit and transit users on days they do not use transit. We also tested for within-person differences in PA time for transit users on days they use transit versus days they do not use transit, and estimated linear mixed effects models to assess the effect of transit use on total daily PA while controlling for socio-demographic variables. Results suggest that the LRT line generated new transit-related PA that did not diminish existing non-transit-related PA. These results support the positive public health benefits from new public transit services such as LRT.

2. Background

2.1. PA and health outcomes

Physical activity has health benefits, including weight control and the lower risk of multiple health problems, such as obesity, heart disease, diabetes, and some cancers (United States Department of Health and Human Services, 2008). Walking is especially popular, with over half of adults in the U.S. reporting walking on the 2010 National Health Interview Survey (Berrigan et al., 2012). However, despite these benefits, few adults achieve sufficient levels of physical activity according to objective measures of physical activity (Troiano et al., 2008).

2.2. Public transit and PA

Evidence suggests that public transit users have higher overall PA than non-public transit users. Data from the National Household Travel Survey suggests that residents are more likely to walk to transit in areas with rail systems than in areas without rail (Freeland et al., 2013). A review of past studies that typically relied on self-reported PA and cross-sectional data demonstrated that between 8 and 33 min a day of PA may be attributable to transit use. Based on travel diary reports, Montreal residents using commuter trains reported between 35 and 41 min of additional walking, depending on whether there was walking between transfer stops (Wasfi et al., 2013), a figure consistent with more recent studies (Ferdinand et al., 2012).

Although suggestive, the evidence for public transit generating new PA is not conclusive. One possible explanation for higher overall PA among transit users is *confounding effects*. Public transit – especially LRT – tends to be provided in neighborhoods that have high residential density and mixed uses. Because density and mixed uses correlate with walking and biking, higher overall PA levels associated with public transit may be coincidental (Saelens et al., 2014). The possibility of *substitution effects* also weakens the argument for LRT as a public health intervention. Substitution occurs when new public transit users shift existing PA from other utilitarian or recreational activities, or when transit riders reduce other forms of PA on days when they ride transit (Saelens et al., 2014). In many cities, public transport requires more time than equivalent trips by automobile. Because individuals have limited amounts of discretionary time (i.e., flexible time outside of work, household maintenance and other obligations), higher levels of transit-related PA may come at the expense of other, non-transit-related PA. There is some empirical evidence to suggest that individuals with longer commutes engage in less recreational physical activity (Christian, 2012). The possibilities of confounding effects and substitution mean that aggregate and cross-sectional analysis cannot easily determine if transit generates new PA, that is, PA directly related to public transit that is not shifted from other activities. Required are individual-level, longitudinal studies that analyze the relationship between public transit and PA, with objective data on where transit-related PA occurs.

Saelens et al. (2014) attempt to resolve confounding and substitution effects in an individual-level study of public transit and PA using accelerometer, GPS and travel log data collected in 2008–2009 in King County, Washington, USA. They divide participants into

transit users and non-transit users, with transit user defined as having at least one day of transit use according to a self-reported travel log. They also divide transit users' observation periods into transit and non-transit days, with a transit day being any day with at least one observed transit use episode, based on travel diaries. Their main hypotheses are: (i) transit users are more physically active than nonusers and this increased activity is directly associated with transit use (i.e., no confounding); (ii) transit users' increased physical activity on days with transit use is not associated with a decrease in other PA during those days (i.e., no substitution). Saelens et al. (2014) find that transit users had more daily overall PA than non-transit users, but these groups did not differ with respect to non-transit-related walking or non-walking PA. Transit users also had higher PA levels only on transit days, and the most frequent transit users had more walking time than least frequent transit users. These results demonstrate that transit users are more physically active than non-transit users. A lack of difference in PA levels between non-transit users and transit users on non-transit days suggests that walking to and from transit directly accounts for the higher levels of PA found among transit users. There is little evidence of PA substitution: transit-related walking appears to be new PA added to existing PA among transit users.

The study by Saelens et al. (2014) is individual-level but cross-sectional rather than longitudinal. Brown et al. (2015) conduct a quasi-experimental study of PA before and after the construction of an LRT line in a neighborhood of Salt Lake City, Utah, USA. Adult participants wore accelerometers and GPS loggers for approximately one week during pre-construction (2012) and post-construction (2013) of a Complete Street intervention involving a new LRT line, improved sidewalks, and a bike path. Observations of the same participants before and after intervention allow direct evidence of the effects of new public transit service and Complete Streets on individuals' PA levels. Results indicate that, compared to those who never rode transit, new riders (who rode transit in the Complete Streets corridor in 2013 but not 2012) had significantly higher PA levels and more PA time while former riders (who rode transit in 2012 but not 2013) had lower PA and less PA time. In addition, new riders experienced a small but significant loss in body mass index (BMI) levels while former riders experienced a significant gain in BMI levels between 2012 and 2013.

The results reported by Brown et al. (2015) suggested beneficial changes in PA and BMI for new transit riders and detrimental changes for former transit riders. This paper extends their analysis to assess whether observed PA changes are new PA, independent of possible confounding factors and replacement of preexisting PA.

2.3. Research hypotheses

Table 1 summarizes our research hypotheses about changes in PA relative to changes in transit behavior after construction of a LRT line. The claim that public transit generates new PA means that observed PA changes directly relate to changes in public transit use (no confounding factors) with no compensating changes in other types of PA (no substitution). This implies that before and after an intervention such as construction of a new LRT line, we should see specific PA changes based on changed transit behavior. Participants who *Never* used transit in both pre- and post-intervention should have no change in their total PA

because there should be no change in other factors that can change demand for PA. People who used transit pre-intervention and *Continued* using transit post-intervention again should not have any change in PA unless it is due to changes in transit-related PA (e.g., different walking distances to stops after the intervention): non-transit factors should not cause these changes. *New* transit users who did not use transit pre-intervention but did use it post-intervention should have a direct effect indicated by an increase in transit-related PA but no corresponding decrease in non-transit PA if there is no substitution of other PA for transit-related PA. (New users may have an increase in other PA: e.g., taking LRT to work leads to walking at lunch rather than driving.) *Former* users who rode transit pre-intervention but did not ride transit post-intervention should have a direct decrease in transit-related PA but should not have an increase in non-transit-related PA from substituting the extra free time for other types of PA.

The spatial distribution of PA and the daily PA time of transit users can also provide evidence supporting a claim that public transit generates new PA. If an intervention such as new LRT line directly generates PA, we should also see spatial clustering of transit-related PA in proximity to the new LRT stops in the post-intervention time period. The spatial distribution of PA can shed light on the relative impacts of LRT versus bus transit: the mode with higher impact on PA should see stronger clustering of PA in proximity to its stops. Analysis of the daily PA of transit users on days they use transit versus days they do not use transit may also identify possible substitution effects at the individual-level.

3. Methods

3.1. Study area

Fig. 1 provides a map of the study area in Salt Lake City, Utah, USA. The anticipated construction of an LRT line and Complete Street rehabilitation in this neighborhood allowed a quasi-experimental design where we track PA time for the same neighborhood residents before and after this intervention. The construction and rehabilitation includes a new LRT line, five new residential LRT stops along the new line extension (and a 6th non-residential LRT stop at the Salt Lake International Airport; this stop is not included on the map), a bike path and improved sidewalks. The LRT line opened April 2013. Fig. 1 also indicates the locations of existing LRT stops (in the southeast portion of the map) and changes in bus stops between 2012 (pre-intervention) and 2013 (post-intervention). As Fig. 1 indicates, most of the changes in bus stops were along the Complete Streets/LRT corridor, with few changes outside that corridor.

3.2. Data collection

We recruited participants, typically using door-to-door canvassing, who lived within 2 km of the intervention, were over 18, could walk at least a few blocks, intended to stay in the neighborhood 1 year, were not pregnant and spoke either Spanish or English. Participants completed attitudinal surveys, had height and weight measures taken, and were fitted with accelerometers (Actigraph GT3X+) and GPS data recorders (GlobalSat DG-100) by trained research assistants. Participants wore the accelerometers and GPS devices for approximately one week during the pre-intervention and post-intervention periods. Valid data for a

participant requires a minimum of 10 h of accelerometer data for at least three days (Troost et al., 2005). We designed the data collection to occur during the non-winter seasons: pre-intervention data collection occurred between March and December 2012 and post-intervention data collection occurred between May and November 2013 (early December 2012 was an extension of the pre-intervention data collection period to take advantage of unusually warm weather, with average highs 47 °F instead of the usual 40). We checked for seasonality effects in the data and did not find significant influence on any measures of activity.

We recruited $n=939$ participants for the 2012 data collection wave; of these participants, $n=614$ completed the 2013 data collection wave. Most of the attrition between 2012 and 2013 was due to participants moving residences ($n=283$, verified as movers or did not respond to 8 or more phone and in-person contact attempts), rather than refusals ($n=34$), or ineligibility ($n=8$). Of the $n=614$ who completed both data collection waves, $n=536$ had complete GPS data for both periods and are consequently included in the analysis. Complete GPS data means meeting the minimum accelerometer requirements described above and having GPS points detected during valid accelerometer wear. Reasons for not having complete GPS data include failures to wear, recharge, or turn on the equipment properly, equipment failure or spending time indoors where GPS signals do not penetrate. The $n=78$ participants dropped from the analysis due to incomplete GPS wear were more likely to be female and have larger households compared to the $n=536$ with valid data, but did not differ from the complete GPS sample with respect to ethnicity, employment, number of children in the household, access to a car, marital status or years of residency in the home (Brown et al. (2015)).

The complete sample of $n=536$ participants is 51% female and 25% Hispanic. The average participant lived in their home 7.5 years, but 25% lived in their home only one year. 68% of the participants in the sample were employed at the time. 24% of the participants completed high school while 37% are college graduates. Median household income in the sample is USD\$30,000–40,000.

3.3. Data pre-processing

A custom web application and GIS-based *Trip Identification and Analysis System* (TIAS) (Westat, Inc.) supported the accelerometer and GPS data pre-processing. The web application uploads and fuses accelerometer and GPS data using time stamps. The web application also allows map-based prompted recall of selected PA bouts by participants during post-wear interviews (Brown et al. (2014)). TIAS provides a toolkit and a map-based user interface for processing the device data for identifying trips and travel modes to distinguish between transit-related PA and non-transit-related PA. The Appendix describes the data pre-processing in more detail.

3.4. Analysis and measures

Following Saelens et al. (2014), we define *physical activity* (PA) as a bout with a minimum duration of five minutes with a minimum of 1000 accelerometer counts per minute (cpm). This threshold encompasses light to moderate PA (LMPA) that corresponds with transit-

related walking. It is a lower threshold than the moderate to vigorous PA (MVPA) levels typically associated with health benefits (United States Department of Health and Human Services, 2008). For comparison, Table 2 reports average LMPA and MVPA time, based on all MVPA minutes exceeding 2020 cpm. We analyze MVPA and health-related outcomes of participants in (Brown et al. (2015)).

Total PA (PA-Total) is PA regardless of its relationship with public transit. *Transit-related PA* (PA-Transit) is a PA within a trip that contains a segment with bus, commuter rail or LRT use. *Non-transit PA* (PA-Other) is PA that does not occur within a trip with a public transit segment, such as walking the dog. PA-Other includes indoor PA that meets the accelerometer threshold (e.g., running on a treadmill). By definition, PA-Total is the sum of PA-Transit and PA-Other.

The first analysis is based on transit user groups. We test for differences between 2012 and 2013 in PA-Total, PA-Transit and PA-Other time among participations based on their change in public transit user status. We define a *public transit user* as a participant who rode bus, commuter rail or LRT at least once during their GPS/accelerometer wear time in either data collection wave. We divide participants into four groups based on their change in public transit use between 2012 and 2013:

1. *Never*: Not a public transit user in 2012 and 2013
2. *Continued*: A public transit user in 2012 and 2013
3. *New*: Not a public transit user in 2012 but a user 2013
4. *Former*: Public transit user in 2012 but not 2013

We standardize PA time as average minutes per ten hours of device wear due to varying lengths of wear periods among participants. Tests revealed that wear time was not significantly different across the four groups in 2012 but was in 2013. Post hoc Tukey tests showed that in 2013, New riders had more wear time than Never riders (94 h versus 85 h of wear, respectively; $p = 0.05$). We assumed both groups had sufficient wear time to detect transit ridership given the minimum wear time threshold required for inclusion in the study (Brown et al. (2015)).

We also map and analyze the geographic distribution of PA-Transit in 2012 and 2013. This allows comparison of the effects of bus versus LRT on PA by examining where PA-Transit clusters spatially. It allows assessment of changes in the spatial distribution of PA-Transit pre- and post-intervention to examine if the spatial clusters changed due to the new LRT line. We map GPS points associated with PA-Transit using the point density tool in ArcMap (ESRI, Inc.), aggregating the points into raster cells of 50 m resolution and smoothing the distribution using a neighborhood size of three cells. We categorize these maps using four levels of GPS point density: (i) high density; (ii) moderate density; (iii) low density; (iv) no GPS points. The high density category corresponds to the top 10% of the cells with respect to GPS point density (not including cells with no GPS points). The moderate density category includes cells with the top 25% with respect to GPS point density, exclusive of the high density category. The low density category includes the remaining cells that contained

any GPS points. We also calculate a local Moran's I spatial autocorrelation statistic on the GPS point data to identify spatial clusters of high activity locations.

A third analysis focuses on transit users and tests for within-person differences in PA-Total, PA-Transit and PA-Other time based on daily transit use. Following Saelens et al. (2014), we define a *transit day* as a standard 24 h period with an observed transit use, and a *non-transit day* as a day with no transit use. In this analysis, we standardize PA time as average minutes per day. An increase in PA-Total but no corresponding decrease in PA-Other on transit days relative to non-transit days is consistent with public transit directly generating new PA (no confounding or substitution). We test for these differences in both 2012 and 2013. To isolate the influence of transit days on PA, we used paired *t*-tests to test changes over time and mixed effects models for the combined data that included transit and non-transit days. The unit of analysis is the participant day-level: we tested whether transit days related to PA-Total, controlling for gender, Hispanic ethnicity, employment status, weight status, college graduate, and household income.

4. Results

4.1. Analysis within transit group

In this section, we analyze within-person differences in the different types of PA time based on changes in transit use between 2012 and 2013. Table 2 provides context for these differences by reporting PA time for the groups using two definitions: (i) the LMPA definition used in our analyses (Saelens et al., 2014), and; (ii) the MVPA definition typically associated with health benefits (United States Department of Health and Human Services, 2008).

Table 3 summarizes changes over time (year 2013–2012) for individuals within the four transit user groups on three measures: PA-Total, PA-Transit and PA-Other time. Table 3 entries include point estimates of the time difference (top; expressed in minutes per ten hours of device wear), a 95% confidence interval (middle) and the *p*-value for a paired *t*-test of individual differences between 2012 and 2013.

Table 3 indicates that the two groups that did not change their public transit use between 2012 and 2013 (the Never and Continued groups) had no significant changes in PA-Total (the Continued riders has a slight, non-significant drop in PA-Transit; the Never riders have no PA-Transit by definition). However, the two groups that changed their public transit behavior between 2012 and 2013 had significant changes in their PA-Total, more specifically, a decrease for Former riders and an increase for the New riders. (These are significant at $\alpha=0.10$ but differences are consistent with our directional hypotheses for these groups.). These changes correspond with significant changes in PA-Transit: an increase for New riders and a decrease for Former riders. New riders experienced an average increase of 5.27 min of PA-Total per ten hours of device wear time, including an increase of 3.46 min of PA-Transit. Conversely, Former riders experienced an average decrease of 5.54 min of PA-Total, including an average decrease of 2.34 min of PA-Transit. Neither the New nor Former riders had significant changes in PA-Other between 2012 and 2013. Although

Former riders had an average decrease in PA-Other of 3.20 min of PA-Other per ten hours of device wear time, this change was not significant due to a high variance.

Results in Table 3 are consistent with the pattern one would expect if there no confounding or substitution effects in the relationship between transit and PA. Participants who did not change their public transit behavior from 2012 to 2012 had no significant changes in total PA and non-transit-related PA time. New riders had significant increases in total PA time due to significant increases in transit-related PA time without correspondingly decreases in non-transit-related PA time. Former riders had significant decreases in total PA time due to decreases in transit-related PA without corresponding increases in non-transit-related PA time.

4.2. Spatial analysis

Table 3 suggests changes in PA-Transit drive changes in PA between the pre-intervention and post-intervention time periods. We now compare the spatial distribution of PA-Transit in 2012 and 2013. Fig. 2 is a map of the spatial distribution of PA-Transit for all transit groups based on GPS point density in 2012 and 2013. Both maps also illustrate activity clusters based on a local Moran I 's spatial autocorrelation statistic ($p < 0.05$).

Fig. 2 shows that LRT has stronger influence on PA-Transit than bus. In 2012, prior to the construction of the new LRT line, clusters of moderate to high PA-Transit tend to associate with existing LRT stops in the eastern portion of the study area rather than bus stops. Several of these clusters extend along the street network corridors feeding into the LRT stops: this is evidence of walking to access the LRT system prior to expansion in the study area. There are some weaker PA-Transit clusters proximal to bus stops along West Temple and also bus stops south of the West Temple corridor. But overall the PA-Transit spatial clusters focus mainly on the existing LRT stops rather than bus stops.

The spatial distribution of PA-Transit in 2013 indicates that construction of the LRT has intensified the pattern of spatial clustering near LRT stops. The PA-Transit clusters focused on existing LRT stops in 2012 are more intense in 2013, with higher concentrations of high activity locations, suggesting a synergistic effect from the new LRT line. The two modest PA-Transit clusters on West Temple associated with bus stops in 2012 have LRT stops after 2013: their associated PA-Transit clusters are stronger (higher concentration of high activity locations) and more spatially extensive, extending along street network corridors that feed pedestrians into the new LRT stops. There is a potential LRT-related cluster to the north of the new rail line, suggesting multiple participants walked to the LRT stop to its south. Similarly, the growth of a PA-Transit cluster near bus stops in the southwest portion of the study may be associated with a bus to LRT connection. Intercept interviews would be needed to verify these possibilities.

Figs. 3 and 4 further assess the observed changes in Fig. 2 by decomposing the changes in the spatial distribution of PA-Transit by transit group. Fig. 3 maps the distributions of PA-Transit for the Continued group in 2012 and 2013. Fig. 3 indicates that the new LRT line created a shift in PA-Transit from existing to new LRT stops among these transit users. An apparent consequence is some of the Continued group walking shorter distances to access

LRT. In particular, compare the distribution of moderate and high PA-Transit locations along N 600 W and W North Temple leading to existing LRT stops in 2012 to 2013. In 2013, the spatial pattern of PA-Transit in these locations is contracted and focused on the new LRT stops. This suggests that new LRT service can lead to existing transit users having lower PA-Transit due to the improved accessibility of the system. However, Table 3 suggests that this decrease is modest and offset by increased PA-Transit by New transit users.

Fig. 4 maps the distributions for the Former group in 2012 and the New group in 2013. As Fig. 4 indicates, the Former group corresponds to a relatively modest amount of PA-Transit time lost after the intervention, focused on existing LRT stops in the eastern portion of the study area. Fig. 4 also indicates that much of the gained PA-Transit from New users focuses on the new LRT stops along the West Temple corridor as well as the streets that feed these stops. Also, some of the existing LRT stops in the eastern portion of the study area also experienced increases in PA-Transit from New users. This supports the direct impact of LRT on PA: both new and existing LRT stations generate PA-Transit from New transit users after the intervention.

4.3. Day-level analysis

We now examine average PA time for non-transit users, transit users on transit days and transit users on non-transit days (Saelens et al., 2014). We also test within-person differences in PA among transit users on transit days versus non-transit days. This allows more direct analysis of possible confounding and substitution effects by examining day to day PA changes for individuals based on their daily transit use. We also estimate the effect of a transit day on transit users' total daily PA using linear mixed effects models.

Table 4 provides results from 2012 while Table 5 provides results from 2013. The left section of both tables provides group means of PA-Total, PA-Transit and PA-Other, including the point estimate and a 95% confidence interval. Also included is PA for non-transit users as a benchmark. The right section of the table provides individual-level differences in PA-Total and PA-Other for transit users on transit days relative to non-transit days and *p*-values for a paired *t*-test.

Table 4 suggests that, prior to the new LRT line, transit users had higher levels of PA than non-transit users. As a group, non-transit users are physically active an average of 5 min per day. In contrast, transit users are physically active 11 min per day during non-transit days and 20 min per day on transit days, with PA-Transit accounting for over half of the PA on transit days. A paired *t*-test of within-person differences for transit users on transit days versus non-transit days indicates that PA-Total is greater on transit days versus non-transit days, but PA-Other is not different. Table 5 indicates a similar pattern in the post-intervention time period: non-transit users are physically active an average of 6 min per day while transit users are physically active 10 min per day during non-transit days and 20 min per day on transit days, with PA-Transit accounting for the majority of PA on transit days. The difference in PA-Other between transit and non-transit days is still not statistically significant in 2013.

The results of the day-level analysis in Tables 4 and 5 support conclusions from the transit group analysis that confounding and substitution effects are not occurring. Transit users are more physically active than non-transit users and this increased activity can be directly associated with transit use. Also, transit users' increased physical activity on transit days is not associated with a decrease in non-transit related PA.

We estimated linear mixed effects models to test the effect of transit use on total daily PA, controlling for gender, Hispanic ethnicity, employment status, weight status, college graduate, and household income. In 2012, when controlling for socio-demographic variables, a transit use day results in about 9.9 min of additional PA ($p < .0001$), whereas in 2013 it results in about 11.1 additional PA minutes per day ($p < .0001$). Assessing the two years together, the average increase of PA on a transit day is 10.6 min ($p < .0001$). The demographic variables were not significant in any of the models, supporting the direct effect of transit use on PA.

5. Conclusion

This paper addresses the question of whether public transit generates PA through an individual-level quasi-experimental study of participants' PA before and after construction of a light rail transit (LRT) line in a neighborhood of Salt Lake City, Utah, USA. Participants wore Global Positioning System (GPS) receivers and accelerometers pre- and post-LRT intervention. Using these data, we examined participants' allocation of time in transit-related PA and other (non-transit related) PA in the pre- versus post-intervention periods in three ways: (i) differences in PA times based on changes in public transit behavior pre- versus post-intervention; (ii) the spatial distribution of PA pre- and post-intervention, and; (iii) PA time for transit users based on their daily use of public transit. We focus on two conditions that must occur for the claim that public transit generates new PA to hold: (i) no confounding effects: changes in PA relate directly to public transit with no other apparent factors; (ii) no substitution of transit-related PA for other, non-transit-related PA.

The results in this paper provide strong support for the hypothesis that public transit generates new PA, especially LRT relative to bus public transit. Based on analysis of changed public transit behavior pre- versus post-intervention, PA generated by the public transit is directly related to the intervention with no confounding factors and no substitution for other activities. Based on the spatial distribution of PA, LRT has stronger influence on PA than bus public transit, and the new LRT line strengthened this spatial concentration of PA in proximity to LRT stops. Based on analysis of the day to day PA of transit users versus non-transit users, transit users have more PA time than non-transit users, and this can be related directly to transit use with no substitution for other PA. Demographic, employment, weight, education and household income variables had no influence on this relationship.

Our results also compare favorably with other studies examining the relationships between public transit use and PA. We find that public transit users spend approximately 20 min per day in PA on days they use transit and 10 min per day on days they do not use transit, compared with approximately 5–6 min per day in PA for non-transit users. In comparison, analysis of 2001 National Household Travel Survey data by Besser and Dannenberg (2005)

and Edwards (2008) find (respectively) that public transit users report a median of 19 min per day walking to and from public transit, with an average of 8 min more PA time than non-transit users. Lachapelle and Frank (2009) find that public transit users in Seattle and Baltimore achieved 4–8 more moderate minutes per day than non-transit users based on reported transit ridership and GIS measures of distance to transit stops. Saelens et al. (2014) find that transit users in Seattle achieve 2–15 more daily minutes of accelerometer-measured PA relative to non-transit users.

The policy implications of this study are that public health considerations should be factored into public transit infrastructure and service decisions: public transit generates new PA directly and without drawing from other types of PA. We also see a stronger effect on PA associated with LRT relative to bus transit. While there is a great deal of debate surrounding LRT, in particular the expense of LRT relative to bus transit, evidence suggests that the two public transit modes are not equivalent with respect to attracting PA. A challenge is to relate savings in health care costs relative to the cost of public transit provision in cost-benefit analyses (see, for example, Edwards, 2008).

Our analyses are also consistent with the theory that transit-related walking opportunities require attractive destinations in addition to built environment enhancements (Speck, 2013). Mapped GPS points associated with PA clearly concentrate on the east and west transit stops along the new LRT line in the study area, with little PA concentration near the middle stops. The east and west stops are near downtown and a major state office building, respectively. In contrast, proximal to the middle transit stops are the state fairgrounds (with limited attraction for people on most days), low density residential development and automobile-oriented business. The spatial pattern of PA suggest that, in addition to Complete Street enhancements, policy makers need to consider surrounding the diversity and density of activities surrounding transit stops to make walking more attractive to pedestrians.

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Appendix A

This appendix describes the *Trip Identification and Analysis System* (TIAS)-based data pre-processing for identifying trips and travel modes to distinguish between transit-related PA and non-transit-related PA

The first step is identifying trip ends. From the collected GPS data, TIAS automatically flags dwell (stationary) times of 120 s or more as potential trip stops. Also flagged for further evaluation are dwell times between 10 and 120 s. TIAS also identifies and eliminates phantom trips: apparent but false movement generated by a stationary GPS; often occurring when the GPS logger is indoors but near a window or an upper floor of a building. The

software displays the remaining potential trip ends with other georeferenced data such as streets, transit and building addresses. Combined with trip data summaries such as speed/time and accelerometer counts profiles, this allows trained analysts to screen out falsely identified trip ends caused by factors such as traffic delays, drive-through windows and passenger pick-ups and drop-offs.

The second step partitions trips into trip stages, with a trip stage being a segment within a trip with one travel mode (e.g., walk, bike, auto, bus, LRT). This is a two-step process: the first step identifies trip stages based on mode transitions and the second step assigns modes to the identified stages. Following Tsui and Shalaby (2006), we assume that motorized travel can achieve higher speeds and acceleration rates while non-motorized modes exhibit lower and more stable speeds. TIAS detects transitions between motorized and non-motorized travel using the average and standard deviation of speed within a ten GPS point moving window. If the average speed is above 16 m/s, TIAS classifies the sequence within the current window as motorized, non-motorized otherwise. TIAS flags a mode transition if the current window's mode status is different than the last computed one and if the speed standard deviation is greater than 2.25 m/s. Determining the exact point for the transition requires stepping point-by-point through the window and checking if the previous point is below or above the non-motorized speed threshold (depending on the last computed mode status).

The mode assignment phase determines the travel mode for a trip stage by comparing the sequence of GPS points to a set of designated mode-based parameters, namely, the average, standard deviation and maximum speed (NCHRP, 2015; Oliveira et al., 2011). Table A1 provides the speed parameters in kilometers per hour. Based on an assumed normal distribution, the process initially assigns a mode based on the observed GPS average speed falling within 1.96 standard deviations of the designated average speed for that mode, subject to the estimated 95th percentile speed not exceeding the mode's maximum instantaneous speed. The mode can be updated during a subsequent scan if an alternative mode's designated average speed has a lower standard distance to the observed GPS speed or if the absolute difference between designated mode speed standard deviation and the observed speed standard deviation is smaller.

Trained analysts review the trip and stage-level mode assignments within TIAS based on GIS layers, speed profiles, and physical activity profiles. They make adjustments as necessary, including combining multi-modal trips that had been split into separate trips due to lengthy dwell times or to signal loss. For this study, we instructed analysts to look for transit trip stages, especially on the LRT line within the study area. A GIS layer containing all transit lines and stops facilitated the identification of bus, LRT and trips on a nearby commuter rail line. Analysts identified false stops that were actually mode transition periods when participants waited at a transit stop for a bus or train to arrive. In addition, we instructed analysts to look for bike and walk modes by noting both speed and physical activity levels during trips. For trip stages with a bike mode, the combination of the speed levels and elevated PA recorded by the accelerometer helped to differentiate these segments from transit and auto modes.

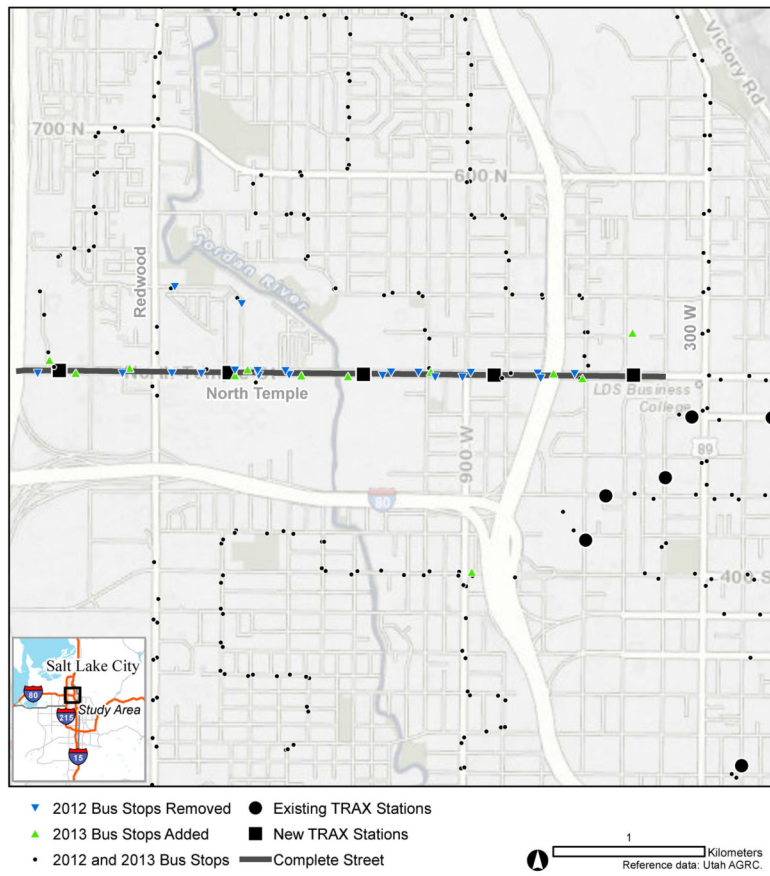


Fig. 1.
Salt Lake City study area.



Fig. 2. Spatial distribution of transit-related physical activity for all transit groups in 2012 and 2013.

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Fig. 3. Spatial distribution of transit-related physical activity for Continued group in 2012 and 2013.



Fig. 4. Spatial distribution of transit-related physical activity for Former (2012) and New (2013) groups.

Table 1

Research hypotheses about within-person changes in physical activity (PA) time based on changes in transit user behavior.

Public transit generating new physical activity implies:	Change in public transit behavior pre- and post-intervention			
	<i>Never used transit</i>	<i>Continued using transit</i>	<i>Former transit users</i>	<i>New transit users</i>
i) No confounding	No change in other (non-transit-related) PA time	No change in other PA time	Decrease in transit-related PA time	Increase in transit-related PA time
ii) No substitution			No increase in other PA time	No decrease in other PA time
Net change in total PA time	No change	Any change (due to possible change in transit-related PA only)	Decrease	Increase

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Average minutes of physical activity per 10 hours wear by year and transit user group: Point estimates and 95% confidence intervals.

Table 2

Transit group		Never (N=391)	Continued (N=51)	Former (N=42)	New (N=52)
Average light to moderate physical activity time in minutes (1000 cpm, 5 min)	2012	17.03 (15.18, 18.89)	32.62 (25.56, 39.69)	28.90 (19.63, 38.16)	22.03 (16.99, 27.07)
	2013	18.30 (16.33, 20.27)	29.77 (24.13, 35.40)	23.36 (15.80, 30.92)	27.30 (21.05, 33.55)
Average moderate to vigorous physical activity in minutes (MVPA) (2020 cpm, all minutes)	2012	17.31 (15.82, 18.80)	33.62 (27.04, 40.19)	28.72 (20.83, 36.62)	23.84 (19.33, 28.35)
	2013	18.68 (16.96, 20.39)	30.97 (25.38, 36.55)	22.02 (15.77, 28.27)	27.86 (22.30, 33.42)

Table 3

Within-person differences over time (2013–2012) in average minutes of physical activity per 10 hours wear by transit user group: Point estimates and 95% confidence intervals for pre–post paired *t*-tests.

Transit group	Never	Continued	Former	New
<i>N</i>	391	51	42	52
Change in total physical activity time (PA-Total)	1.23, (-0.64, 3.09), <i>p</i> =0.20	-2.86, (-8.60, 2.88), <i>p</i> =0.32	-5.54*, (-11.88, 0.80), <i>p</i> =0.085	5.27*, (-1.01, 11.55), <i>p</i> =0.098
Change in transit-related physical activity time (PA-Transit)		-1.15, (-3.03, 0.74), <i>p</i> =0.23	-2.34**, (-3.56, -1.08), <i>p</i> =0.0005	3.46**, (2.20, 4.72), <i>p</i> <0.0001
Change in non-transit-related physical activity time (PA-Other)	1.23, (-0.64, 3.09), <i>p</i> =0.20	-1.71, (-6.62, 3.20), <i>p</i> =0.49	-3.20, (-9.36, 2.96), <i>p</i> =0.30	1.81, (-4.04, 7.66), <i>p</i> =0.54

*
p 0.10.

**
p 0.05.

Table 4

Comparison of average minutes per day of physical activity for transit versus non-transit days in 2012: Point estimates and 95% confidence intervals for group means and within-person paired *t*-tests.

	Group means			Within-person differences for transit users (Transit day) – (Non transit day)
	Non-transit users	Transit users: Non-transit days	Transit users: Transit days	
<i>N</i>	444	285	207	75
Overall PA (PA-Total)	6.47, (5.88, 7.06)	9.59, (7.97, 11.21)	19.65, (17.28, 22.02)	8.54**, (5.00, 12.08), <i>p</i> < .0001
Transit-related PA (PA-Transit)			11.63, (10.08, 13.19)	
Non-transit-related PA (PA-Other)	6.47, (5.88, 7.06)	9.59, (7.97, 11.21)	7.93, (6.21, 9.44)	-2.73, (-5.67, 0.20), <i>p</i> = .068

**
p < 0.05.

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Table 5

Comparison of average minutes per day of physical activity for transit versus non-transit days in 2013: Point estimates and 95% confidence intervals for group means and within-person paired *t*-tests.

	Group means			Within-person differences for transit users (Transit day) – (Non transit day)
	Non-transit users	Transit users: Non-transit days	Transit users: Transit days	
<i>N</i>	434	345	229	94
Overall PA (PA-Total)	6.23, (5.66, 6.80)	9.63, (8.12, 11.14)	19.80, (17.64, 21.97)	11.87 ^{**} , (8.48, 15.26), <i>p</i> <.0001
Transit-related PA (PA-Transit)			11.96, (10.46, 13.46)	
Non-transit-related PA (PA-Other)	6.23, (5.66, 6.80)	9.63, (8.12, 11.14)	7.85, (6.38, 9.32)	–0.17, (–2.87, 2.54), <i>p</i> =.904

^{**}
p < 0.05.

Table A1

Speed-related parameters for mode detection.

Mode	Speed-related parameters (in kilometers per hour)		
	Maximum (instantaneous) speed	Average speed	Speed standard deviation
Walk	15.00	2.83	1.22
Bicycle	35.79	10.44	5.07
Auto	85.00	24.00	12.36
Bus	45.77	12.43	7.39

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