



Tracking job and housing dynamics with smartcard data

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Residential locations, the jobs–housing relationship, and commuting patterns are key elements to understand urban spatial structure and how city dwellers live. Their successive interaction is important for various fields including urban planning, transport, intraurban migration studies, and social science. However, understanding of the long-term trajectories of workplace and home location, and the resulting commuting patterns, is still limited due to lack of year-to-year data tracking individual behavior. With a 7-y transit smartcard dataset, this paper traces individual trajectories of residences and workplaces. Based on in-metro travel times before and after job and/or home moves, we find that 45 min is an inflection point where the behavioral preference changes. Commuters whose travel time exceeds the point prefer to shorten commutes via moves, while others with shorter commutes tend to increase travel time for better jobs and/or residences. Moreover, we capture four mobility groups: home mover, job hopper, job-and-residence switcher, and stayer. This paper studies how these groups trade off travel time and housing expenditure with their job and housing patterns. Stayers with high job and housing stability tend to be home (apartment unit) owners subject to middle- to high-income groups. Home movers work at places similar to stayers, while they may upgrade from tenancy to ownership. Switchers increase commute time as well as housing expenditure via job and home moves, as they pay for better residences and work farther from home. Job hoppers mainly reside in the suburbs, suffer from long commutes, change jobs frequently, and are likely to be low-income migrants.

commuting pattern | job dynamics | housing dynamics | mobility group | smartcard data

Linking mobility patterns to socioeconomic characteristics of city dwellers is important to economists, sociologists, geographers, and urban planners (1–4). Recent studies have explored the distribution of poverty and wealth, mobility rhythms of returners and explorers, human contact networks, demographic characteristics and neighborhood isolation phenomena from human mobility patterns by mobile phone call records, GPS data, transit smartcard data, and geocoded messages from social media (3, 5–8). In the era of big data, studies have uncovered individual patterns and scaling laws and pose the prospect of predicting human mobility (9–11). Of course, one advantage of big data is volume, but big data rarely include socioeconomic attributes directly and the availability is usually of a short duration. In contrast, household surveys (relatively small data in comparison) provide more socioeconomic attributes and travel information. Investigating human mobility, including travel behavior and the journey to work, has traditionally relied on household surveys (12, 13). Still, some limitations exist in the surveys such as the data resolution of travel trajectories and time use.

Mobility patterns can reflect human movement at various spatial scales so that they can be used to critique and address increasing social challenges. Recently, many researchers have investigated patterns of international or intercity migration (14–16), while fewer have explored intraurban migration or residen-

tial mobility (17). In the field of residential mobility, empirical studies often harness the life course framework (18), while theoretical models describe housing choice with the trade-off between commuting cost and housing expenditures (19). Indeed, the jobs–housing relationship, job and housing tenures, and their dynamics affect daily commutes and travel behavior and vice versa (2, 20, 21). However, few studies have assessed the job and housing dynamics with a longitudinal analysis at the individual level.

Transit station choice can be a proxy to capture patterns of individual mobility in a city (22). With the help of smartcard data, we probe consecutive trajectories of workplaces and residences over 7 y in Beijing to understand urban dwellers' job and housing dynamics. We identify the most preferred station near each traveler's workplace and residence (i.e., the work and home stations) according to individual commuting regularity (23). As transit use is a major part of commutes in megacities, regular public transport commuters present higher temporal regularity than nonregular commuters (Fig. 1A). From 2011 to 2017, the annual proportion of regular commuters rose from 23.74% to 31.40%, and their trip records account for over 80% of transit trips. We observed that 5,001 regular commuters retained their smartcard for seven consecutive years. The sampling process is shown in Fig. 1B. After assessing the spatiotemporal regularity of trips, we find 4,248 sample commuters whose workplaces and residences can be identified successively. The sample size is more than equivalent to a travel survey. Each sample commuter

Significance

This paper uses transit smartcards from travelers in Beijing retained over a 7-y period to track boarding and alighting stations, which are associated with home and work location. This allows us to track who moves and who remains at their homes and workplaces. Therefore, this paper provides a longitudinal study of job and housing dynamics with group conceptualization and characterization. This paper identifies four mobility groups and then infers their socioeconomic profiles. How these groups trade off housing expenditure and travel time budget is examined.

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Data deposition: The dataset about home stations, work stations, average travel time in the subway, and housing expenditure estimated from 4,248 regular commuters from 2011 to 2017 has been deposited at english.ignrr.cas.cn/sd/dataset/201811/t20181108_201066.html.

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generates at least four trips per week, and they generated more than 271,000 transit records over 7 y. With this dataset, we conduct an empirical study of job and housing dynamics at the intraurban scale.

Results

This paper tracks trip records by a unique smartcard ID. Smartcards, if they are retained, are likely to be held by the same card owner. We use the method in ref. 23 to identify the home and work station of regular commuters with 1-wk trip records by years (SI Appendix, section R1). With 7-y trajectories of workplaces and residences estimated, four mobility groups can be captured (Fig. 2A) so that we can answer the first question:

Who Are They? Commuters whose home locations and workplaces remained constant are “stayers” (*st*) (16.38%), which is the group with stability. Commuters who relocated residences at least once but their workplaces were constant are “home movers” (*hm*) (11.09%). Commuters who changed workplaces but retained a constant residence are regarded as “job hoppers” (*jh*) (11.18%). “Job and residence switchers” (*sw*) (61.35%) changed both jobs and homes during the period studied. On average, switchers changed jobs 2.65 times and home locations 2.51 times over 7 y, while home movers and job hoppers averaged fewer than two moves each.

From 2011 to 2017, Beijing experienced rapid economic development and urban transformation (25). Under this background, stayers seem to find satisfactory locations to live and work, as well as acceptable commuting routes, distance, and time. With the categories above, we propose the first hypothesis:

Hypothesis 1. Stayers have shorter commutes than other non-stayer groups, including job hoppers, home movers, and job and residence switchers.

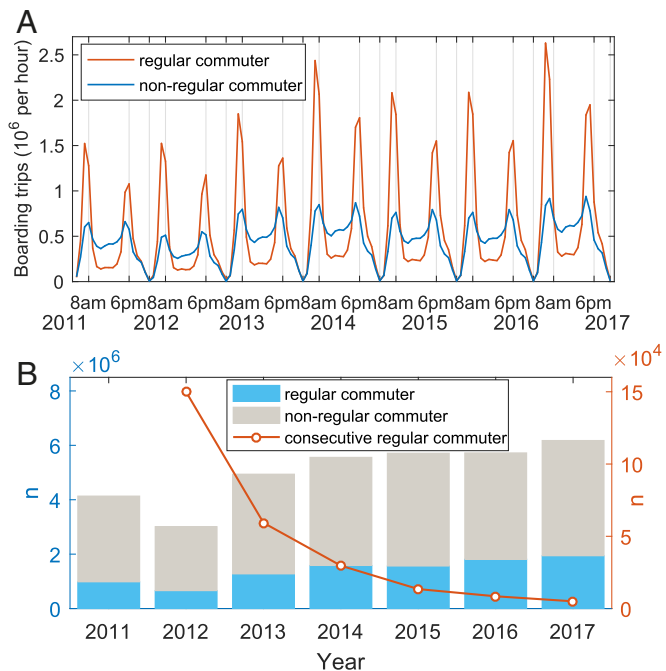


Fig. 1. (A) Diurnal curve representing temporal distribution of commuters by boarding trips. (Regular commuters are passengers who take transit four or five weekdays during 1 wk. Nonregular commuters are passengers who access the subway system 1–3 d/wk. One-week datasets were prepared from 2011 to 2017. In each year, all trips are sorted by boarding time.) (B) Consecutive regular commuters from 2011 to 2017. n denotes the number of commuters.

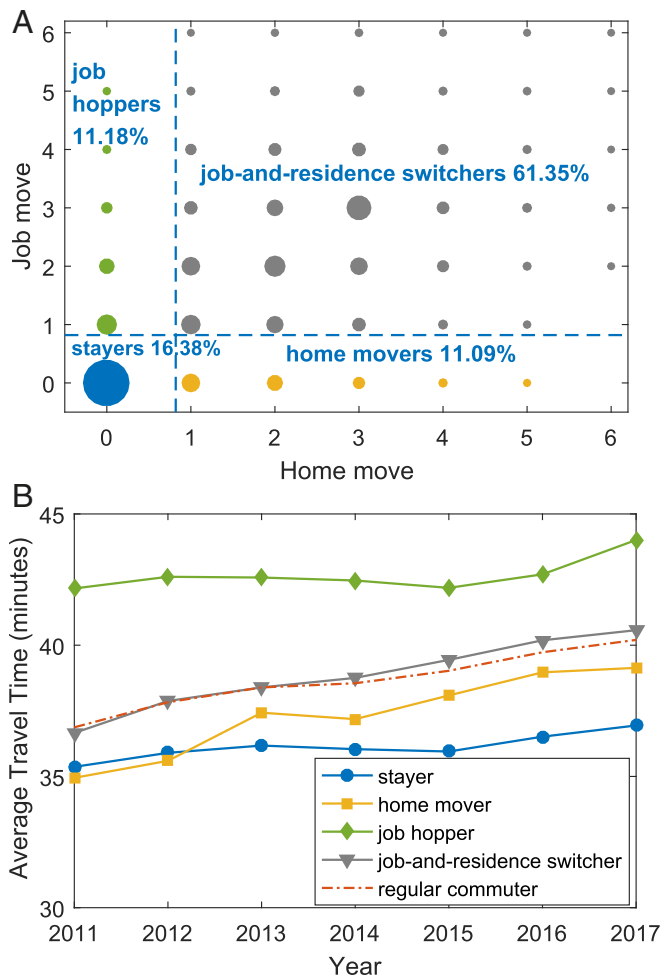


Fig. 2. Classification of regular commuters. (A) Quasi-four-quadrant diagram classifying regular commuters and percentages of groups. (B) Average travel time in the subway system by groups from 2011 to 2017. [It is worth noting that the trip in the subway system is the major part of a daily commute for a regular commuter (24), although we cannot estimate the travel time between the actual workplace and residence.]

Table 1 corroborates the hypothesis that average travel time of stayers was less than that of nonstayers, as measured before the nonstayers’ moves. All models show statistical significance. Furthermore, correlations of average travel time for home movers, switchers, and job hoppers are studied. The travel time of job hoppers tends to exceed that of switchers and home movers. To sum up, we find the relationship $t_{st} < t_{hm} < t_{sw} < t_{jh}$. In this paper, t denotes the average travel time in the subway system,

Table 1. t-Test analysis for average travel time in the subway system

Year	$t_{st} < t_{sw}$	$t_{st} < t_{jh}$	$t_{st} < t_{hm}$	$t_{hm} < t_{sw}$	$t_{sw} < t_{jh}$
2011	2.0199*	6.7690***	0.4437	2.2983*	7.2125***
2012	3.0377**	6.8172***	0.3236	2.9955**	6.1161***
2013	3.3931***	6.6184***	1.3159	1.2549	5.4220***
2014	4.1547***	6.4971***	1.2041	2.0515*	4.7716***
2015	5.2661***	6.5101***	2.2643*	1.7364*	3.5064***
2016	5.4152***	6.3995***	2.5833**	1.5320	3.1390***
2017	5.1918***	6.9654***	2.2971*	1.7537*	4.1152***

t value is reported. *** $P < 0.001$, ** $P < 0.01$, * $0.01 < P < 0.05$. st , sw , jh , and hm denote stayer, switcher, job hopper, and home mover.



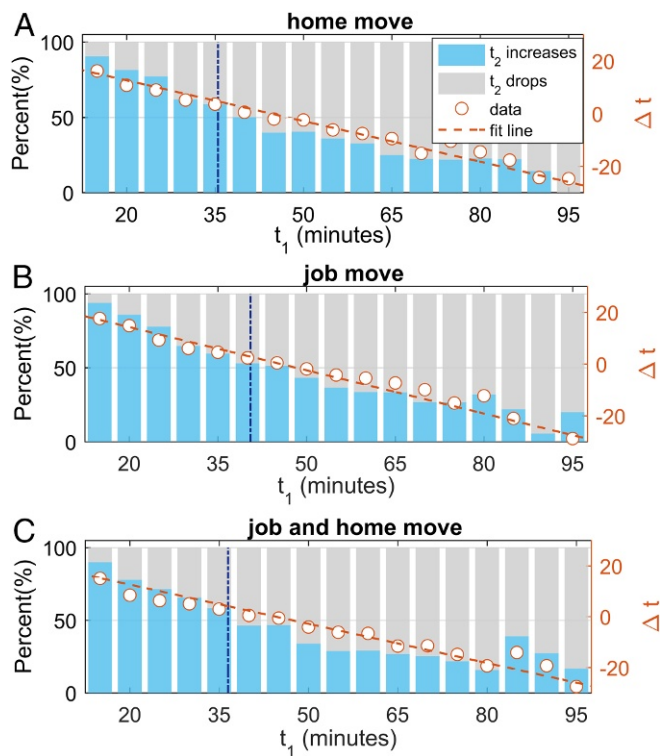


Fig. 3. Time variation from before to after a move. Percentage of increasing time and decreasing time for each interval is calculated. Δt denotes time gap from t_1 to t_2 , where t_1 denotes average time before a move and t_2 denotes that after a move. Vertical lines indicate average commute time before moves. (A) Home move: $\Delta t = -0.556t_1 + 24.446$, $R^2 = 0.80$. (B) Job move: $\Delta t = -0.5569t_1 + 25.428$, $R^2 = 0.85$. (C) Job and home move: $\Delta t = -0.5146t_1 + 22.902$, $R^2 = 0.79$.

which is estimated from the boarding and alighting times of trips between home and work stations.

Meanwhile, the tendency in Fig. 2B supports the conclusion once again. The average travel time of stayers remains significantly lower than that of other groups. Stayers' travel time remains around 36 min, while job hoppers' time is volatile. Moreover, the travel time of regular commuters steadily grows from 36.87 min to 40.20 min. Home movers and switchers follow this trend. This phenomenon indicates that congestion arises in the subway system, often manifested as the commuter being unable to board the first (or second) train that arrives due to crowding, breakdown of the timetable, construction delay, and/or transfer delay. The travel distance of noncommuting trips, and their number, probably increases with network expansion, which helps explain subway crowding and delays.

With suburbanization and subway network expansion, the increase in commuting time corroborates several studies based on travel surveys (26, 27). These studies suggest that employment decentralization results in a slight increase of commuting time (28). However, this paper provides empirical evidence that contrasts with that of US studies on the “colocation” or “rational locator” hypotheses (29–31). These studies argue that the stability of automobile commuting time emerges from the process when people periodically change their workplace and/or residence. They suggest that transit commuting times result from a different spatial process than automobile commuting times.

Why Do They Move? To answer this question, we calculate variation in average travel time from before to after a move by individuals over 7 y. Fig. 3 aggregates the percentage of increasing or decreasing commute time for each interval. Switching jobs can be used as an opportunity to reduce commute times, while suburbanizing residences increases commute time (21). Here, we find that three categories of moves affect commute time similarly. We pose two hypotheses:

Hypothesis 2. The commute time drops from before to after a home or job move if the commute was longer than average.

Hypothesis 3. The commute time rises from before to after a home or job move if the commute was shorter than average.

There are several reasons we may expect people with longer (shorter) commute time to shorten (lengthen) commute time when they adjust workplaces and residences. To some extent, these phenomena can be described as “regression to the mean” (RTM) (21, 32). RTM implies that samples at the extreme end of a distribution will be closer to the mean of the distribution in the follow-up observation even without any treatment (33). Recent studies find that effects of RTM decay with increasing between-group divergence related to within-group variation (32, 34). Another reason is that there are more opportunities to relocate to places with longer (shorter) commutes for people with shorter (longer) travel time (21). We believe a third reason is that these phenomena relate to questions about whether travel time possesses positive or negative utility (35).

To test the hypotheses, a negative linear correlation can be captured between commute time t_1 before a move as a baseline observation and time variation Δt from before to after a move (Fig. 3). RTM might be generated by several processes. Naively, if travel time were the only factor, and people simply are part of a random distribution around the mean time, and if this interpretation of RTM held, someone who moved would be equally likely to have an above or below average commute after the move, independent of what the condition was before. That clearly does not hold here. Fig. 3 shows that people with longer (shorter) than average commutes before the move will still tend to have longer (shorter) than average commutes after the move.

Table 2. Analysis of change $\Delta \bar{t}$ with t test

Period	$\Delta \bar{t}$ without cutoff model				Baseline cutoff model, $t_1 < 45$ min				Baseline cutoff model, $t_1 > 45$ min				Moves
	Stay	Move 1	Move 2	Move 3	Stay	Move 1	Move 2	Move 3	Stay	Move 1	Move 2	Move 3	
2011–2012	0.50***	1.22*	0.95	1.58***	1.09***	3.35***	5.19***	3.67***	-1.09***	-5.55***	-6.34***	-5.03***	2,300
2012–2013	0.53***	3.47***	0.54	-0.68*	1.58***	5.96***	5.57***	1.97***	-1.99***	-4.82**	-9.02***	-7.40***	2,093
2013–2014	-0.08	0.84	-0.13	2.31*	0.56***	4.07***	5.14***	7.23***	-1.54***	-9.71***	-9.28***	-11.43***	1,376
2014–2015	0.08	1.65**	1.00	1.18	0.86***	5.56***	5.48***	6.44***	-1.75***	-8.86***	-7.17***	-18.20***	1,394
2015–2016	0.50***	1.33*	1.40*	0.29	1.13***	4.16***	5.16***	5.83***	-0.89***	-7.28***	-4.92***	-12.03***	1,383
2016–2017	0.39***	1.99*	1.55*	-0.11	0.67***	5.40***	6.02***	3.22***	-0.16	-6.72***	-4.63***	-7.12***	2,242

$\Delta \bar{t}$ with P value is shown. *** $P < 0.001$, ** $P < 0.01$, * $0.01 \leq P < 0.05$. Move 1 means “home move.” Move 2 means “job move.” Move 3 means “job and home move.”

Alternatively, if we thought of RTM as a process like a directed “random” walk, job and/or home moves for longer commutes would be equivalent to those for shorter commutes, but in the opposite direction.

In the relocation decision, people who consider a marginal additional amount of travel time as a disutility usually aim at shortening commutes. This follows the conventional principle of minimizing travel expenditures (36). In contrast, people who regard a marginal additional amount of travel time as giving a positive utility should be willing to increase travel time (37), at least to some extent, so that they can get better jobs or houses. In Fig. 3, the inflection point of taking travel time as utility or disutility is whether commute time before a move is 44.71 min (on average). Rounding to 45 min as the cutoff where the behavioral preference may turn, we investigate variation in average commute time as shown in Table 2. Compared with the model without cutoff, models with baseline cutoff present the tendency more clearly. The magnitudes of year-to-year changes in travel time (Δt) for people with longer than the cutoff are larger than for those with shorter than the cutoff (in 18 of 24 cases), and the signs are in the opposite direction in all 24 cases. Thus, there is an RTM process, as shown by the “stay” category; people who do not move still see drifts in their commuting times toward the mean as network speeds change, and the magnitudes are similar on both sides of the inflection point. However, people who do move have much larger directional movements than stayers, yet are likely to remain on their own side of the point, indicating an additional intentionality process which is neither a random draw around the overall mean nor a random walk from their current commute position and cannot be explained solely by random drift.

Trade-Off Between Travel Time and Residential Expenditure. Following the linear monocentric city model of Alonso (19, 38, 39), people trade off travel time and housing costs. In Beijing, housing expenditure exponentially decreases as the distance to city center increases, while average travel time grows exponentially (Fig. 4). This spatial configuration fits well with the formulation of a monocentric city model. For a longitudinal study, this paper investigates whether variations of travel time affect the residential expenditure at the individual level. We posit two hypotheses:

Hypothesis 4. If the commute time drops from before to after a home move, people pay more for housing.

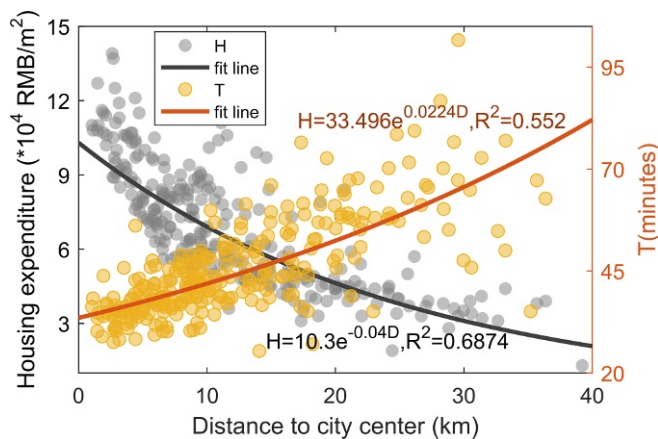


Fig. 4. Housing expenditure (h) by distance to city center (d) and average travel time in the subway system (t). (Data are aggregated at metro station level. h is based on the data in April, 2018. t is based on Smartcard data in April, 2017.)

Table 3. t-Test analysis for hypotheses 4 and 5

Period	$t_1 > t_2, h_1 < h_2$		$t_1 < t_2, h_1 > h_2$	
	Home mover	Switcher	Home mover	Switcher
2011–2012	−4.5658***	−7.1308***	4.2075***	5.1748***
2012–2013	−4.3176***	−1.9548**	5.9975***	9.2623***
2013–2014	4.0598***	−5.4329***	4.5737***	7.8512***
2014–2015	−2.9210**	−7.0077***	4.2045***	6.4971***
2015–2016	−2.5336**	−5.5216***	5.7138***	6.8683***
2016–2017	−5.5278***	−4.4181***	3.7759***	3.7535***

t value is reported. *** $P < 0.001$, ** $P < 0.01$, * $0.01 \leq P < 0.05$. t_1 and t_2 denote the year before and after a move. h_1 indicates the housing expenditure around the station before a move, and h_2 denotes that after a move. This analysis splits home moves by home movers and switchers.

Hypothesis 5. If the commute time increases from before to after a home move, people pay less for housing.

This paper performs t tests to investigate the residential expenditure from before to after a home move. In such a case, average resale price per unit area around metro stations is prepared. Here, this paper uses the real estate data in April, 2018 so that we held the price from 2011 to 2017 constant by stations. The analysis can avoid the influence of overall price volatility when we examine gaps of housing expenditure. It is also worth noting that the spatial pattern of real estate price remains relatively constant, despite the price volatility. For instance, the price of places in the inner city tends to be higher than that of those in the suburb; and the price of areas perceived to have higher-quality residential environment and schools tends to be higher than that in other areas. Hence, the constant dataset still reflects the spatial pattern of housing expenditure across the city. The results of home movers and switchers in Table 3 corroborate hypotheses 4 and 5.

Table 4 correlates distance to city center with average travel time by home movers and switchers, and they present a positive linear relation. The coefficient of home movers tends to grow, while that of switchers declines. Home movers’ elasticity of housing expenditure rises and it is higher than switchers’.

In addition, average housing expenditure of stayers is about 6.9×10^4 RMB/m², and that of job hoppers stays at around 6×10^4 RMB/m². Indeed, housing expenditure of job hoppers evolves to be minimum among four groups in 2017. With a t test, $h_{jh} < h_{hm}$ holds at $t - stat = 5.80$; $h_{jh} < h_{st}$ has $t - stat = 6.85$; $h_{jh} < h_{sw}$ is with $t - stat = 11.12$. On the other side, switchers’ housing expenditure tends to be maximum simultaneously ($h_{st} < h_{sw}$, $t - stat = 3.30$; $h_{hm} < h_{st}$, $t - stat = 3.35$). Recall the correlation in Table 1; although job hoppers usually suffer from long

Table 4. Regression analysis for distance (kilometers) with average travel time (minutes), correlation between job moves and home moves

Year	Home mover		Switcher		χ^2
	Coefficient	t stat	Coefficient	t stat	
2011	0.2125	13.7***	0.1949	26.42***	-
2012	0.2625	15.89***	0.2018	25.09***	955.67***
2013	0.2339	14.56***	0.1948	26.64***	994.90***
2014	0.2453	14.42***	0.1967	26.36***	49.93***
2015	0.2417	14.48***	0.1934	25.83***	35.69***
2016	0.2459	14.61***	0.2055	27.82***	147.88***
2017	0.2582	14.49***	0.1613	21.23***	1,662.20***

t stat is t value. *** $P < 0.001$, ** $P < 0.01$, * $0.01 \leq P < 0.05$. In the χ^2 test in each year, the predictor is whether commuters moved their workplaces, and the response is whether they relocated their houses.

commutes, they settle where housing is more affordable. Switchers do not follow as closely the trade-off between travel time and housing expenditure, because they usually spend more on housing while retaining relatively long commutes, compared with other groups.

Job and Housing Dynamics. Evidence indicates that job and housing dynamics mutually influence each other. With a χ^2 test, the job move affects the home move in the same year (Table 4). Also, subgroups along the diagonal are much larger than others, and the number of job moves is proportionally correlated to home moves (Fig. 2B).

The total number of moves decreased from 2011 to 2016, but has grown since 2017 (Table 2). Indeed, job and housing dynamics may present periodic variations. Generally, job and housing stability should increase when we focus on the observation of samples over a short term. Between 2011 and 2014, the rate of job and home moves dropped from 28.63% to 5.18%, while it went up from 4.97% to 34.35% from 2015 to 2017. Following the classification in Fig. 24, the status of individual sample commuters was tracked (Fig. 5). Compared with the previous period, the proportion of switchers increased from 38.98% to 41.74%, while the proportion of other groups varies less. Job and housing dynamics emerge when the study extends over a long term, as across the life cycle, mobility periodically varies with life-course events (40).

Figs. 6 and 7 show job and housing patterns by groups so that we can infer their socioeconomic profiles. Overall, regular transit commuters reside and work mainly in the north of Beijing. Compared with the south, northern areas have been better developed with better residential environment including good schools, hospitals, and competitive job opportunities (SI Appendix, Fig. S3). Moreover, the subway network is better connected with higher station density in the north.

A recent study suggests that transit commuters may be economically underprivileged (41), while stayers present a different story here. They mainly work in two business centers of the inner city or a new business center in the northwest. These centers aggregate high-tech and financial industries, offices of headquarters, and government departments. In China, the rental market remains unstable and immature, and tenants rarely rent an apartment for a long period. Therefore, homeowners are likely to be of middle to high income with stable job positions. Their shorter transit trips can be explained by their preference for public transport and self-selection in residential location (42). Another reason for commuting by transit may be the vehicle license restriction in Beijing (43).

Similarly, home movers work at similar places to those of stayers (Fig. 7A and D). They are more likely to be middle-income

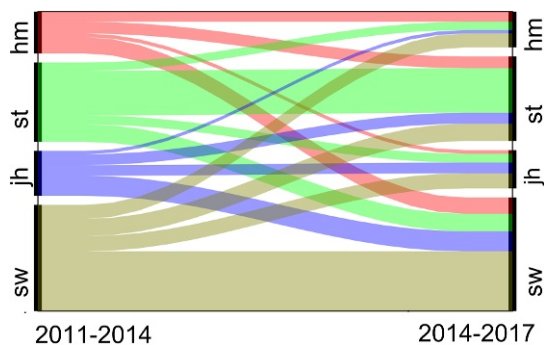


Fig. 5. Variation of job and housing status. (st, sw, jh, and hm denote stayer, switcher, job hopper, and home mover.)

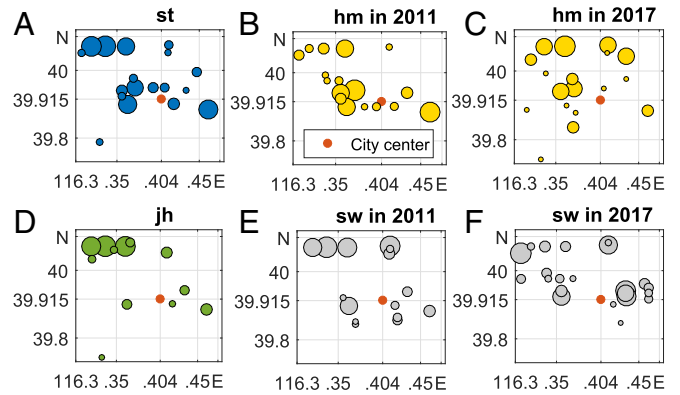


Fig. 6. Spatial pattern of residences. (A–F) Top 20 stations according to the number of commuters. Plots may have fewer than 20 when they exclude stations outside the study area, but may have more stations when they are evenly ranked. The bubble size indicates the number of commuters. st, sw, jh, and hm denote stayer, switcher, job hopper, and home mover.

groups, as home movers tend to relocate to residences farther away. One inference is that they upgrade from tenancy to ownership. At first, they would like to rent near their workplaces, as the rent is affordable for them. This explains the shortest commute time by home movers in 2011 (Fig. 2B). Then they gradually upgrade to ownership. Consequently, their housing elasticity increased (Table 4) and they settle down at places where housing is more affordable. For this group, being a homeowner justifies an increased commute time.

Stayers' and job hoppers' housing patterns remain constant but are distributed differently (Fig. 6A and D). Only 12 stations are as far away from the city center as others are. A total of 65% of job hoppers live in suburbia (beyond the fifth-ring road), while 41% of stayers reside there. These job hoppers tend to change jobs frequently, and their workplaces disperse evenly across the city. They are likely to be migrants who are temporary workers subject to low-income groups.

Switchers may be a “coming-up” group among regular commuters. Their housing pattern has converged toward the same pattern as stayers' residences from 2011 to 2017 (Fig. 6A and F). Unlike home movers, switchers tend to move in. In such a case, switchers pay more for housing for a better residential environment. Hence, their housing elasticity declined (Table 4). From 2011 to 2017, average housing expenditure of switchers increased from $6.87 \times 10^4 \text{RMB/m}^2$ to $7.11 \times 10^4 \text{RMB/m}^2$. Simultaneously, switchers' workplaces slightly move out toward the new

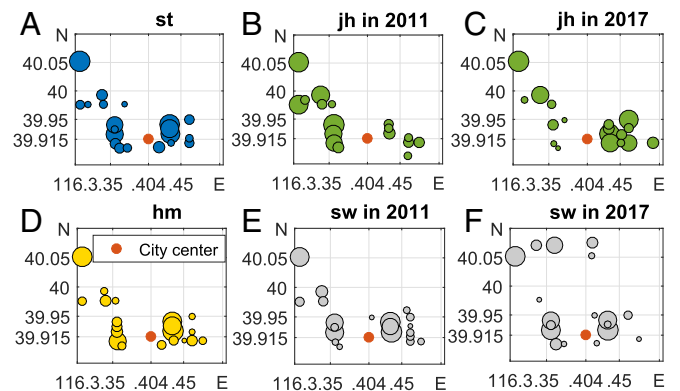


Fig. 7. Spatial pattern of workplaces. (A–F) The notation is the same as in Fig. 6.

northern business center. Hence, spatial mismatch occurs with this group, which explains why switchers' housing costs and commute times both increased.

Discussion

This paper investigates job and housing dynamics by assembling and analyzing longitudinal transit smartcard data in Beijing. The research framework identifies stayers, home movers, job hoppers, and job and residence switchers. It illustrates the resulting commuting pattern by groups and quantifies trade-offs between travel time and housing expenditure.

This paper demonstrates that longitudinal transit smartcard data allow scholars to track and examine individual commuters' workplace and residential location choices, which sheds more light on the forces underpinning urban spatial structure (44). Meanwhile, it unravels four groups' residential mobility and commuting patterns. Spatial mismatch was found at the subgroup level, which suggests that group characterization should be considered in housing studies, transport demand management, and urban planning. Finally, it identifies a 45-min inflection point where the travel behavioral preference changes. It implies that commuters in metropolises like Beijing may have a tolerable limit of in-metro time by transit. This finding is useful in transit network design, and transport planners should improve the accessibility where commuters suffer from the in-metro commute time over 45 min. For example, direct transit

services could be introduced between workplaces and residences where there is a concentration of regular commuters identified.

Still, several limitations need to be mentioned. One limitation is that we focus on the study of rail transit users, which reflects over 20% of commuters in Beijing (24). We did not observe job and housing dynamics for commuters by other modes, e.g., private cars, taxis, or buses. With various datasets (e.g., GPS data, mobile records), we may capture job and housing dynamics and travel behavior for other social groups. With more spatial data and/or social background (e.g., income level at the suburban level), we may be able to provide more specific profiles and predict where people move.

Materials and Methods

Extensive data including smartcard data, average real estate resale price at the metro station level, and their geographic attributes are prepared. The smartcard dataset includes 1-wk trip records (400 million per day) in April from 2011 to 2017. The Beijing subway network nearly doubled from 228 km to 609 km in 7 y (45). This paper conducts a year-to-year analysis to capture the moving behavior under network expansion, and rules are listed in *SI Appendix, section R2*.

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