Social equity impacts of rail transit investments using community perceptions: evidence from Chongqing

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Abstract:

Urban transit systems have differential impacts across population groups, including the perceptions of impacts. Nevertheless, the evaluation of difference in perceived benefits of transport investment is under researched, and few attempts have been made to quantify the extent to which transport provision meets users' requirements. This paper explores how the impact of rail transit on development and regeneration differs across different income groups and migrants, assessing equity dimensions that arise through surveys on residents' perceptions, using evidence from Chongqing, China. The analysis utilises both MANOVA and discriminant analysis. The result shows that the lowest income group perceives they benefit least from the rail transit impacts, while the highest income group perceives they benefit most. There is a significant unequal perceived benefit distribution between migrants and local residents within the low-income groups. Reflections are made on policies and planning interventions which might be introduced to achieve greater social equity in impacts.

Keywords:

Rail transit; impact assessment; social equity; perception survey; discriminant analysis; MANOVA

1 Introduction

In 2012, the Chinese central government announced a stimulus of about CNY ¥800 billion (Chinese Yuan Renminbi) (about USD $127 billion), to be used over the next three to eight years for building subways and elevated rail lines across twenty-five cities in China, with the aim of increasing mobility for the population in a rapidly urbanising nation (Zhou 2016). By 2020, the central government announced 44 cities had begun operating 233 rail transit lines in China. The economic, ecological and social impacts of urban transit investments are dramatic across many Chinese cities, but these impacts vary spatially with different population cohorts using the new transit systems and living in the neighbourhoods and new residential developments surrounding the new transit stations (Zhao and Li 2019). Hence the social impact of transport investment can be differential, spatially and across

population groups (Geurs, Boon, and van Wee 2009). Indeed Banister (2018)) suggests there may be 'double inequity' whereby investment can potentially have positive impacts for higher income groups and negative impacts for lower income ones.

Social equity is a critical issue for Chinese society. Policy making increasingly focuses on meeting the specific needs of citizens with public transport and to assess social outputs (MoT. 2011). However, research gaps still exist. Existing research on transport equity is mainly conducted on the spatial distribution of transport facilities from the supply side or in terms of the level of accessibility to particular activities. Few attempts have been made to quantify the extent to which public transport and associated impacts relate to users' perceptions, thus to connect the specific views of people, population groups or spatial areas with the provision. Also, the evaluation of perceived benefit distribution of transport investment among different population groups is not well researched in the Chinese context.

Understanding the spatial variation in the impacts of transit investment can be challenging, as many of the impacts are indirect and are likely to evolve over time (Banister and Thurstain-Goodwin 2011). It is still not clear how best to define or measure the different dimensions of social impact, but they can be viewed in distributional terms, spatially and across the population (Jones and Lucas 2012). Social equity is hence usually viewed as a fair access to opportunities, livelihood, education and resources (Hickman et al. 2017). There are also important trade-offs affecting equity (Feitelson 2002) in terms of access to activities and urban development facilitated by new transit lines. Residents' views on these issues may include changes brought about by the rail transit relative to the socio-economic background of the users. Nilsson et al. (2020)), for example, examine whether light rail affects residents' stated propensity to move out of these neighbourhoods, e.g. leading to displacement. The variations in individual perceptions reflects the extent to which the transit benefit meets the specific needs of different population cohorts and the social equity issues of transit impact, and can be incorporated into relevant decision making to meet diverse demands of people.

This paper uses a case study of the newly emerging metropolitan city of Chongqing, China, to help

examine the perceived social equity impacts of transit investment. The paper aims to understand whether the new transit developments in Chongqing have been for the benefit of all citizens, by examining the ways in which individuals, with different socio-economic profiles and neighbourhood locations in the city, perceive the impacts of new transit developments. Income and migrant status are selected to reflect the variations, as they are critical factors that represent social division in the Chinese society. These perceptions are analysed using a survey conducted by the author. MANOVA and discriminant analysis are used to explore variations in these perceptions aiming to explore the underlying factors that account for the variations. Understanding these views can inform the development of a more user-orientated and socially equitable transit investment strategy.

2 Literature review

With the rapid urbanisation trend in China, the role of public transport has usually been emphasised as a policy tool to encourage public transport usage, solve traffic congestion and environmental issues, but with less attention to impacts on social equity. A critical issue concerns how rural migrants are accommodated in the city and how they use the public transport systems. Migrants are often economically disadvantaged and excluded from the subsidised public services in the city due to the lack of hukou registration (the household registration system that gives access to housing, health, education and other public services). There are increasingly severe social consequences of different levels of mobility, particularly in combination with income and hukou disadvantage (Zhao and Howden-Chapman 2010). This has forced policy makers to reconsider the role of public transport which was conventionally considered as an urban development tool (Li and Deng 2016). Earlier in 2011, the central government had emphasised the social role of public transit by including it in the 12th Five-Year Plan for Transportation (MoT. 2011). This emphasises the use of public transport to meet the citizens' basic travel and living needs, and states every individual in China deserves access to an affordable urban public transport service. However, there is still much debate concerning how this should be applied and what form of measures are required for implementation (Deng et al. 2016).

The primary benefit of transport infrastructure investment is usually understood as improving access to

the transport system (Banister and Berechman 2000). So-called 'indirect effects' are also important, such as macro-level economic impacts (including levels of employment, inward investment and productivity)(Crescenzi, Di Cataldo, and Rodríguez‐Pose 2016; Li, Gao, et al. 2020); micro-level impacts, such as urban development; and social distribution of usage and activity participation (Llewelyn-Davies, Banister, and Hall 2004; Yang, Niu, and Sun 2020; Li and Huang 2020). Social impacts of transport can exert both positive and negative influences on individuals, which can be understood through travel behaviours and also attitudes and preferences to transport systems and associated urban development. These impacts can occur at multiple levels: either as individuals, or collectively as groups, or at the level of the whole society, and can be inequitable spatially and across population groups (Geurs, Boon, and van Wee 2009). Local communities may derive little benefit from the transport investment and be negatively impacted by severance effects, such as living environment degradation, being displaced by rising living costs, or even property damage caused by construction (Jones and Lucas 2012).

The distributional dimensions hence require careful consideration. Typically, this has been framed in terms of space and location in the city. Spatial equity is usually analysed relative to the geographic location of an individual, group or region affected by a transport project (van Wee and Mouter 2021). Previous research explores this by quantitatively examining the distribution of impacts across space (Mollanejad and Zhang 2014; Jang et al. 2017; Park and Chang 2020), but there are also complex cumulative and temporal impacts across social-economic characteristics of an individual and groups which are difficult to assess (Feitelson 2002).

There is increasing focus on inequities related to social factors, such as income, gender, ethnicity, sexuality and age (Fainstein 2010) and how spatial and social factors may actually reinforce one another to worsen social impacts (Harvey 1973; Koglin and Rye 2014; Bodnar 2015; Gössling 2016; Cao and Hickman 2019). In the related research on transport poverty (Lucas et al. 2016), there is evidence that low-income populations are forced to reduce travel due to the cost of accessing transport, and hence participation in activities is affected (Cervero 2004; Lucas 2012). These groups are also likely to live in

the periphery of the city, where public transport is not available and thus have less access to transport, or at least much longer journeys (Clifton and Lucas 2004; Currie 2009). However, there is little research from the perspective of individual attitudes, e.g. evaluating the extent to which the needs of the individuals are met by the transport infrastructure investment.

An approach to explore this is by examining people's perceptions of transport investment and associated impact. Some studies reveal that the socioeconomic variables significantly influence the perceptions of accessibility and safety of the public transport system, and thus influence people's travel behaviours (Delbosc and Currie 2012; Curl 2018; Chowdhury et al. 2018; Masoumi 2019). A perception study on the Jubilee Line extension finds the opening of the line alleviated the physical barrier of the River Thames, while the extent is positively correlated to existing attitudes held by residents towards their living areas (Gatersleben et al. 2007). Nilsson et al. (2020)) find that there is little relationship between light transit investment and intention to move. However, there is still limited research in establishing the relationship between people's perceptions and the social equity of the distribution of indirect transport impacts.

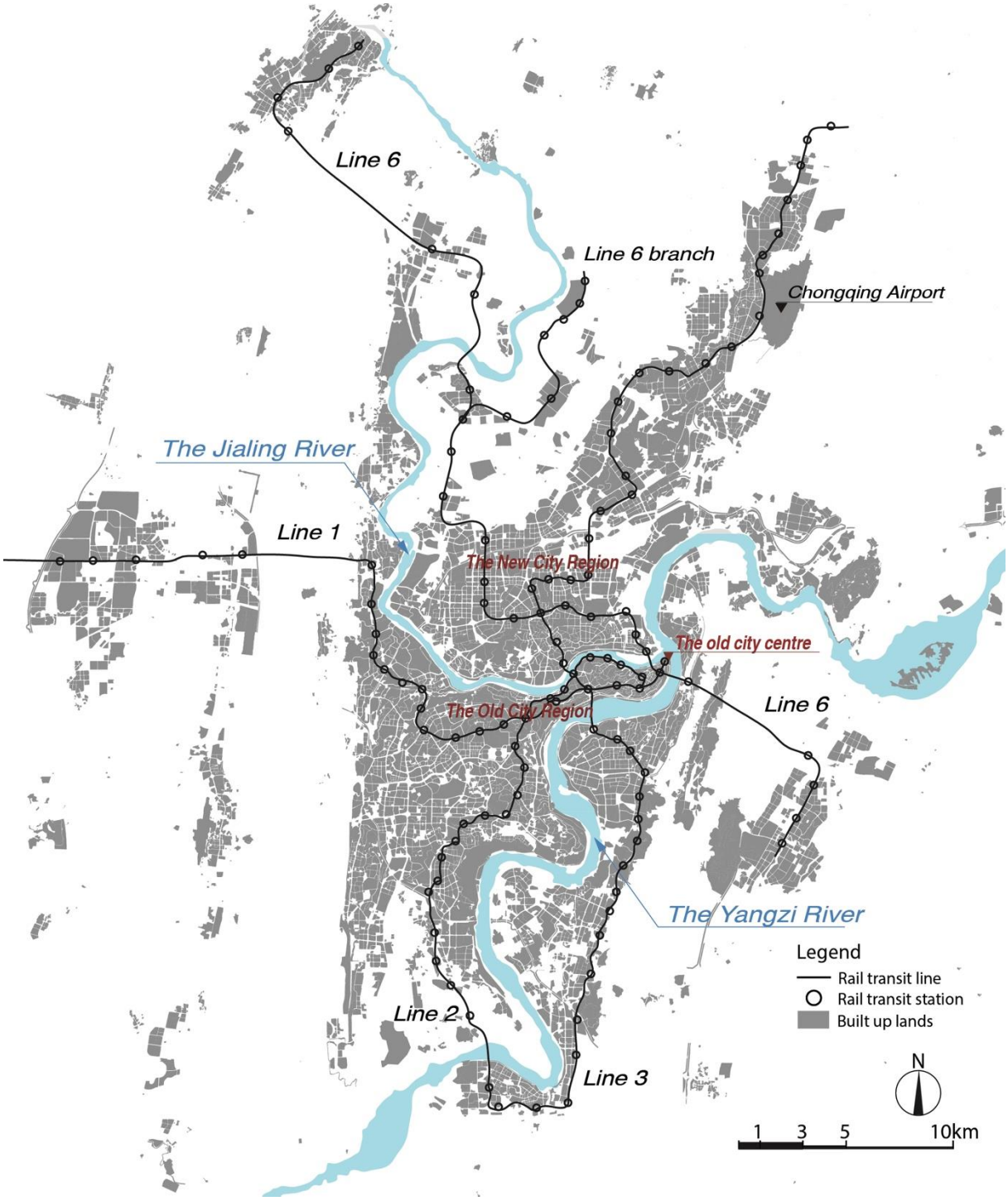
Much of the literature on this topic is also from a North American or European context. There is an emerging set of analysis in China and other Global South contexts, but there is still little empirical evidence on the social impacts of public transport. Most studies explore the distribution of accessibility, for example by examining the economic activity related to travel, but do not take into account the social-demographic attributes (Yang, Niu, and Sun 2020; Li, Lyu, et al. 2020). Wang, Kwan, and Hu (2020)) carried out research to compare the relationships between income differences and accessibility, finding that low-income groups have a significant lower level of overall access to public transit and commercial facilities. Nevertheless, most studies focus on the direct impact of transport, concerning the mobility and accessibility changes brought about by public transport. Little attention has been paid to the equal distribution of a wider range of indirect impacts, and still less to the perceived impact of transit investment at the individual level. Some of this is due to the unavailability of relevant datasets.

This paper aims to fill these research gaps. It conducts a study of the perceived distributional impacts of rail transit investment, by utilising an opinion survey to explore whether the perceived benefit distribution of rail transit meets the specific needs of different population groups. The analysis compares the relationship between income, migration and the perceived social impacts. Social equity issues are hence explored by examining the differences between the population groups and over space.

3 Case study, method and data

The city of Chongqing is used as the case study for the analysis. As one of the four municipalities in China, there is a main urban area within a wider metropolitan area spreading across the region, located on the upper Yangtze River in Southwest China. As of the 2014 Census, the main urban area of 5,473 sq.km. has a residential population of 8.2 million, which has increased about 30% during the past 10 years. By 2017, four lines of the public transit Metro network were in operation in Chongqing (lines 1, 2, 3 and 6), with a total length of 202 km stretching over the central core area (**Error! Reference source not found.**), and there is now an extensive Metro network. The old city centre in Chongqing is located at the junction of the two rivers. With the development of the airport in the early 1990s, extensive development has been witnessed, with astonishing speed, turning the previous farmlands on the north of the river into a prosperous new city centre within just 20 years.

Figure 1: The central core area of Chongqing

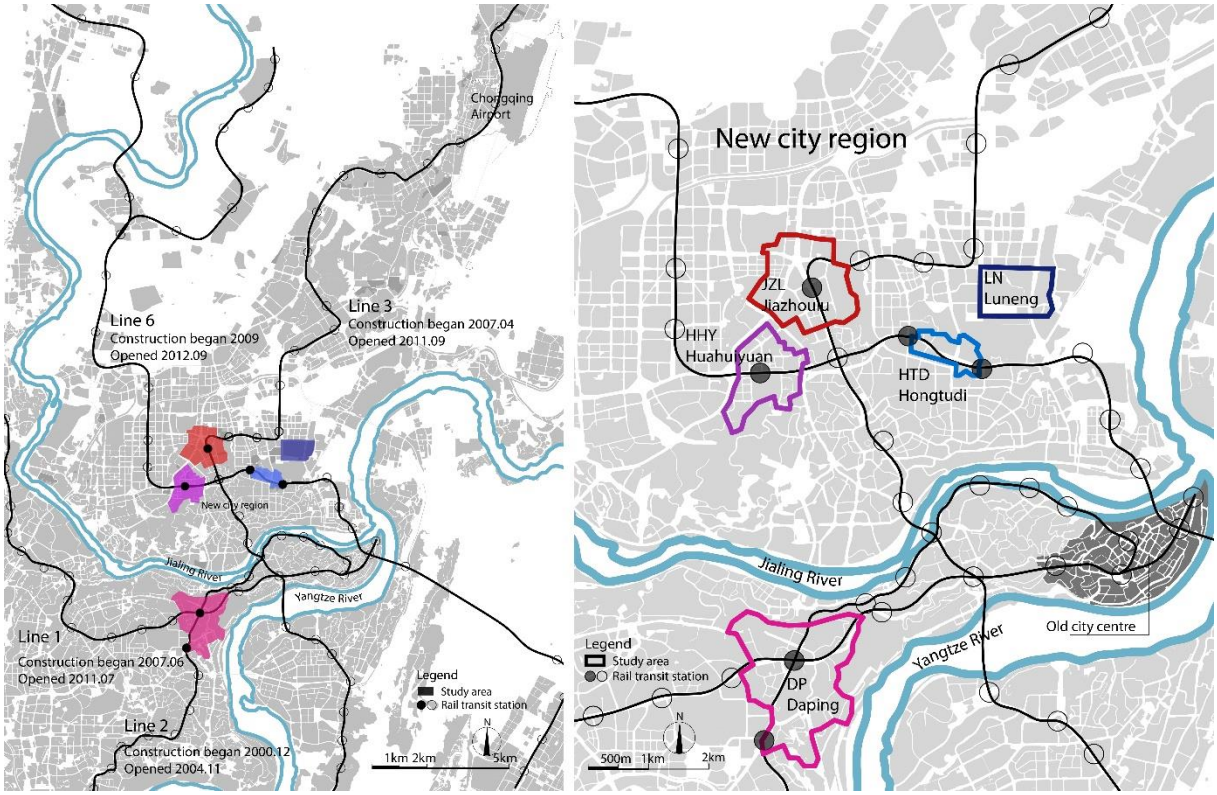


A 'catchment area' is used to observe the impact of rail transit. This uses an 800-metre radius, which is often used as a pedestrian catchment distance and considered to be a reasonable access distance based on 10-minute walk (Cervero 2007; Guerra, Cervero, and Tischler 2012). The catchment distances were

used around the stations, however, a perfect 800-metre radius catchment area is hard to apply for data collection. The smallest administrative units used by local authorities in Chinese cities to collect public demographic census data are called Jiedao, which normally includes several communities. Therefore, in order to collect data for analysis, the catchment areas have to be adjusted to the Jiedao boundaries and five study areas are formed.

Study areas are selected to include the new and old city neighbourhoods, and multi-functional (mixed use) and single-functional residential areas. The five study areas are Daping [DP], Jiazhoulu [JZL], Hongtudi [HTD] and Huahuiyuan [HHY] and Luneng [LN]. All of the areas are located adjacent to transit stations, apart from LN which is located at a walkable distance from a transit station (**Error! Reference source not found.**). Daping is the only selected study area in the old city as data was not available elsewhere. JZL, HTD, HHY and LN are on the north bank of the new city. Both DP and JZL are fast developing areas and experiencing large-scale land development, with commercial centres and office buildings around the stations. HHY, HTD and LN are older residential areas developed around the 2000s.

Figure 2: Location of study areas in Chongqing



A resident survey was carried out by the author, examining people's perceptions and attitudes towards rail transit's effects on their lives. A total of 1,300 surveys were carried out across all the study areas (DP, HHY, JZL, HTD, LN), including 700 surveys in four study areas (DP, HHY, JZL, HTD) and 600 in LN. As a considerable percentage of the respondents are of lower income from the former four study areas, LN was deliberately over-sampled in order to present a comparable dataset of different income groups for analysis. A simple random sampling approach was used to select and interview participants who live in the study areas (Fink 2003). When carrying out the survey, the author and local volunteers interviewed the residents or handed out the surveys to fill. The interviews were carried out on the streets in residential neighbourhoods and public places, selected as typically active places in the study areas. Respondents were required to live in the study area so that they had experience of transit and development impacts as residents. Each face-to-face survey lasted approximately 15 minutes. 1,000 surveys were filled completely and 743 were deemed reliable after checking. Those with incomplete or obvious faulty information were rejected. In the final sample, 342 surveys were used from DP, HHY,

JZL, HTD and 401 surveys were from residents in LN.

Variables are selected to reflect perceptions of impacts on individuals and groups (Lane et al. 2004; Gatersleben et al. 2007). Respondents were asked a series of questions relating to the direct dimension of impact (travel convenience, including accessibility for the daily commute and weekend commute) and various indirect dimensions (e.g. the economic impact indicators, including property price, property rent and living costs) (Cohen and Brown 2017; Rennert 2022; Jin et al. 2022). People's attitudes towards the impacts could either be negative or positive, rated with a score on a five-point scale from -2 (very negative impacts) to 2 (very positive), with 0 as no impact at all.

Multivariate analysis of variance (MANOVA) and discriminant analysis are used to examine the differences between different population groups. In this study, MANOVA aims to investigate whether an individual's income level and migration status are significant in predicting his/her perceptions towards the impact of the rail transit. Nevertheless, MANOVA does not distinguish the cause of the difference found between any two groups. Discriminant analysis can identify more specifically what the difference between any two groups is. In the MANOVA analysis, the different income levels and migration status are the independent variables, while the factors relating to the transit impact (increase in house prices, cost of living, neighbourhood safety, etc.) are the dependant variables, and vice versa in discriminant analysis.

The linear combinations of the variables In differentiating groups are identified as 'linear variates' in MANOVA, and are called 'discriminant functions'[1] (Field 2018). Hence, discriminant function i can be described in a linear format as:

$$V_{ij} = b_0 + b_1F_{1j} + b_2F_{2j} + \cdots + b_nF_{nj} \quad (1)$$

Where V_i represents discriminant function i on the left side of the equation, while F_n represents the

[1] In order to avoid confusion, this paper will use the term 'function' to represent 'variate' in the following analysis.

factors of transit impact (i.e. the dependent variable n) on the right side; j is the index of a row in the data matrix and corresponds to the index of a person in the dataset. b-values in this equation are weights[2], which represents the contribution of each dependent variable to the discriminant function.

4 Exploring indirect impacts across population groups

4.1 Descriptive statistics and their social characteristics

Respondents to the survey were fairly representative of the wider population. For example, 50% of the survey respondents were women (compared to 49% in the census data for Chongqing, 2013). However, 6% of the respondents were above 65 years old (12% in the census data) and migrants accounted for 9% (5% in the census data) (see **Error! Reference source not found.**), hence there is some sampling bias relative to the wider population. The bias is related to the fieldwork strategy, that the survey was mostly carried out on the streets or in public places where there were usually fewer elderly people. Adult responses were the focus of the analysis and there were no responses from children.

Table 1: Comparison: census data and survey data. Source: 2013 Chongqing census data and primary survey data 2014

		2013 Chongqing census data (Permanent residential population)	2014 Perception survey data (survey respondents)
Gender proportion	Male	50.6%	49.9%
	Female	49.4%	50.1%
Age proportion	Below14	16.4%	0.0%
	15-64	71.7%	94.5%
	Above65	11.9%	5.5%
Migrant proportion	From within the greater Chongqing area	95.2%	90.6% (from within the main urban area 59.7%, from outside the main urban area 30.9%)

[2] In discriminant function analysis, the values of b are obtained from the eigenvectors of the matrix HE^{-1} calculated from the data set of the dependent variables of MANOVA. H is the model sum of squares and cross-product matrix (the model SSCP matrix) of the data set, while E is the residual sum of squares and cross-product matrix (the residual SSCP matrix) of the data set. Therefore HE^{-1} represents the ratio of the systematic variance to the unsystematic variance in the model and can access the fitness of the model. The eigenvectors measure the dimensions of a data set. For more information of eigenvectors, suppose that A is a square matrix of size n and λ is a scaler, there is a nontrivial solution X of AX = λX, such an X is called an eigenvector of A with eigenvalue λ. Reference: https://math.mit.edu/~gs/linearalgebra/linearalgebra5_6-1.pdf

Outside Chongqing	4.8%	9.4%

The social consequences of different levels of mobility are reflected most acutely across different income levels (Currie 2009; Lucas 2012) and migrants, especially in the context of China (Zhao and Howden-Chapman 2010). Wider social economic characteristics, such as gender or age, may also be significant but are not the focus of this research. The respondents of the survey were categorised into four groups (**Error! Reference source not found.**), namely: lowest income group (group 1), mid-low income group (group 2), mid-high income group (group 3) and highest income group (group 4). A comparison of income level is made between the survey and the Boston Consulting Group's report (Vincent et al. 2012), which provides a reference for the classification used in the income groups.

Table 2: Comparison of annual household income level between perception survey 2014 and BCG report 2012 (exchange rate: 6.3)

Perception Survey – household annual disposable income 2014					BCG report – Chinese urban-household annual disposable income 2011		
Groups		Income level	Sample amount	Percentage	Groups	Income level	Percentage
Group1	Lowest income	Below ¥50,000	289	38.9%	Poor and aspirants	Below ¥50,400 ($8,000)	43.1%
Group2	Mid-low income	¥50,000-100,000	182	24.5%	Emerging middle class	¥50,400-126,000 ($8,000-12,000)	39.1%
Group3	Mid-high income	¥100,000-200,000	166	22.3%	Middle class	¥126,000-252,000 ($12,000-20,000)	11.7%
Group4	Highest income	Above ¥200,000	106	14.3%	Affluent	Above ¥252,000 ($40,000)	6.1%
Sum			743	100%			100%

Error! Reference source not found. gives a cross-tabulation of the distribution of the income groups across the five study areas from the perception survey (performed in 2014). DP (in the old city region), has the highest proportion of the lowest income group (below ¥50,000), at 72.9%, compared to the other study areas in the new city region: HHY 55.6%, HTD 60.7%, JZL 46.8% and LN 20.4%.

Table 3: Spatial distribution of household annual income level from 2014 perception survey. Source: Primary survey data 2014

Locations and household annual income level (yuan/year)

		Group 1 Lowest income	Group 2 Mid-low income	Group 3 Mid-high income	Group 4 Highest income	Sum
DP	Amount	70	18	7	1	96
	Percentage	72.9%	18.8%	7.3%	1.0%	100%
HHY	Amount	40	20	10	2	72
	Percentage	55.6%	27.8%	13.9%	2.8%	100%
HTD	Amount	68	28	11	5	112
	Percentage	60.7%	25.0%	9.8%	4.5%	100%
JZL	Amount	29	24	8	1	62
	Percentage	46.8%	38.7%	12.9%	1.6%	100%
LN	Amount	82	92	130	97	401
	Percentage	20.4%	22.9%	32.4%	24.2%	100%
Sum	Amount	289	182	166	106	743
	Percentage	38.9%	24.50	22.30	14.30	100%

Table 4: Household income groups and commuting mode share. Source: Primary survey data 2014

Main commuting mode of residents in the survey

		Rail Transit	Bus	Walk	Car or Taxi	Sum
Household Income categories (yuan/year)	Group 1 Lowest income	137	92	36	22	287
		47.7%	32.1%	12.5%	7.7%	100.0%
	Group 2 Mid-low income	104	45	11	21	181
		57.5%	24.9%	6.1%	11.6%	100.0%
	Group 3 Mid-high income	98	24	10	34	166
		59.0%	14.5%	6.0%	20.5%	100.0%
	Group 4 Highest income	41	15	6	42	104
		39.4%	14.4%	5.8%	40.4%	100.0%
Sum		380	176	63	119	738
		51.5%	23.8%	8.5%	16.1%	100.0%

gives people's income groups and their main mode for commuting trips. Main mode is defined as the longest link of the journey by time. Because the survey only sampled residents within the five research areas – four of which are around the transit stations – the transit mode share is much higher than the city-wide transport survey. As shown in Table 4: Household income groups and commuting mode share. Source: Primary survey data 2014

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	Group 3 Mid-high income	98	24	10	34	166
		59.0%	14.5%	6.0%	20.5%	100.0%
	Group 4 Highest income	41	15	6	42	104
		39.4%	14.4%	5.8%	40.4%	100.0%
Sum		380	176	63	119	738
		51.5%	23.8%	8.5%	16.1%	100.0%

, there is a noticeably higher percentage of rail transit use in the mid-low (57.5%) and especially mid-high income group (59%). The mid-income groups appear to make great use of rail transit, and presumably benefit most from the direct impact of new rail transit systems. The lowest income group also has a comparatively high percentage of transit use (47.7%) and the highest share of bus (32.1%) among all the groups. However, the highest income group has only a share of 39.4% of rail transit use, and a particularly high share of private transport (40%). Public transport fares are low in Chongqing, with a journey on the Metro costing CNY 2-10 depending on distance travelled. A one-day travelcard is CNY 18 (2014). The lower income groups use public transport most for their daily commuting trips – both rail transit and bus. They also derive large benefit from the increased travel convenience that results from rail transit investment (as opposed to investment in other transport, such as buses). The question remains whether this high usage of transit actually means they benefit more from the transit system in developmental terms.

Table 4: Household income groups and commuting mode share. Source: Primary survey data 2014

Main commuting mode of residents in the survey

		Rail Transit	Bus	Walk	Car or Taxi	Sum
Household Income categories (yuan/year)	Group 1 Lowest income	137	92	36	22	287
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	Group 4 Highest income	41	15	6	42	104
		39.4%	14.4%	5.8%	40.4%	100.0%
Sum		380	176	63	119	738
		51.5%	23.8%	8.5%	16.1%	100.0%

4.2 Perceived rail transit impacts on different income groups

In order to examine differences between population sub-groups, such as the income groups described in **Error! Reference source not found.**, MANOVA and discriminant analysis are utilised. The analysis considers an individual's perception towards the impact of a new transit station on their lives relative to their economic position. Measurement of the 'transit impact' relates directly to questions raised in the survey, which are the dependent variables in MANOVA. A descriptive statistics table shows the average score for each question graded by different income groups (**Error! Reference source not found.**).

Table 5: Perceived impacts of changes on individual themselves by income groups.
Source: Primary survey data 2014

Survey question No.	Perceived impacts of the changes on individuals	Income groups				
		Group 1 Lowest income (N=268)	Group 2 Mid-low income (N=168)	Group 3 Mid-high income (N=157)	Group 4 Highest income (N=102)	Total average (N=695)
1	Impact of property price rising	-0.83	-0.35	0.10	0.13	-0.36
2	Impact of property rent rising	-0.70	-0.14	0.12	0.16	-0.26
3	Impact of living cost rising	-1.14	-0.91	-0.71	-0.34	-0.87
4	Changes of urban development / recreational facilities	1.25	1.37	1.38	1.18	1.30
5	Changes of walking environment	1.26	1.30	1.29	1.11	1.25
6	Impact of increased noise	-1.30	-1.30	-1.28	-1.28	-1.29
7	Changes of neighbourhood safety	1.60	1.62	1.69	1.76	1.65
8	Changes of local employment opportunities	0.93	0.89	0.67	0.51	0.80
9	Changes of commercial and service facilities	0.07	0.19	0.43	0.56	0.25
10	Impact of community population change/floating population increase	-0.85	-0.59	-0.70	-0.46	-0.70
11	Changes of community harmony	1.36	1.38	1.41	1.30	1.37

12	Changes of access to working place/school/daily shopping	1.35	1.48	1.58	1.47	1.45
13	Changes of access to commercial/cultural/hospital facilities	1.32	1.36	1.40	1.33	1.35

In MANOVA, Pillai's trace is utilised to assess the overall fit of the model ($V = 0.29$). For this data, the F-ratio is $F(39,2043) = 5.55$, $p = 0.000$ and it is therefore highly significant. But, considering the Pillai's trace value of $V = 0.29$, it is still a small effect. This is equivalent to saying that around 29% of the variance in perception is accounted for by the variance in income levels. However, this analysis does not tell us which groups differed from which. To determine the nature of the effect, discriminant analysis is adopted. The output of discriminant analysis on the income group data reveals three discriminant functions. In **Error! Reference source not found.**, the second column shows the eigenvalue of each discriminant function. In the third column, the first discriminant function (Function 1) explains around 79.2% of the variance, whereas the second (Function 2) explains 15.8% of the variance. Canonical correlation is also shown in the final column (which can also be squared to give an effect size, similar to an R^2, of the model). When the values of the last column are squared and added up, the result is equal to the value of Pillai's trace of income groups ($V = 0.29$). Calculated in the model, these three discriminant functions in combination significantly differentiate the income groups, $p = 0.000$. After removing Function 1 (second row), Function 2 and Function 3 significantly differentiate the groups, $p = 0.002$, and after removing Function 1 and 2 (last row), Function 3 reveals no significance, $p = 0.376$.

Table 6: eigenvalues of discriminant functions of differentiating income groups

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative Variance %	Canonical Correlation Sig.
1	0.28	79.2	79.2	0.47
2	0.06	15.8	95	0.23
3	0.02	5	100	0.13

The values in **Error! Reference source not found.** are the correlation coefficients between the discriminating variables and discriminant functions. These discriminant functions are used to differentiate groups. Theoretically the variables with high correlations contribute most to group separation in the function. Variables No. 1, 2, 3, 8, 9, 7 load highly on the first function, which means they contribute most to group separation in Function 1. As calculated in Equation 1, the income group

whose members indicated high values on these factors in the survey generally has a high score on Function 1. Variables No. 4, 5, 12, 13 load highly on the second function. Similarly, the group whose members indicated high values on these factors has a high score on Function 2.

Table 7: Structure matrix: discriminant analysis of perceived impacts by income groups.

Structure matrix

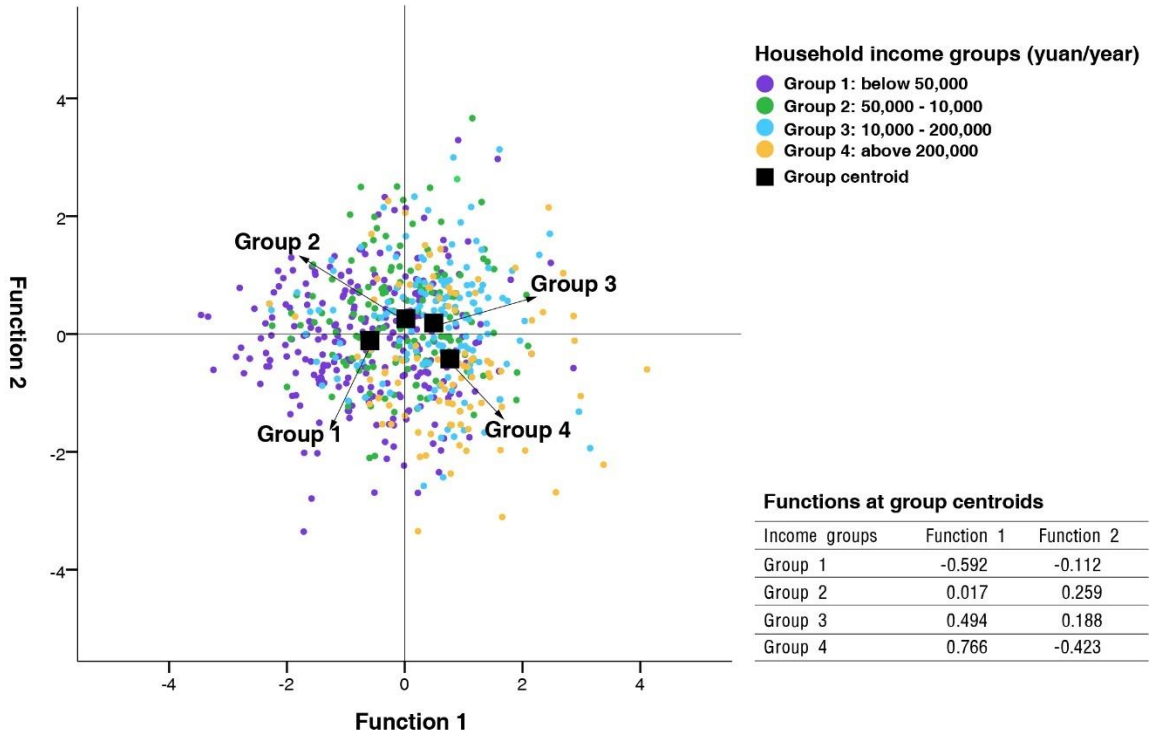
Survey question No.	Discriminating variables	Discriminant functions		
		1	2	3
1	Impact of property price rising	0.779*	0.185	-0.248
2	Impact of property rent rising	0.730*	0.313	0.140
3	Impact of living cost rising	0.620*	-0.362	0.213
8	Changes of local employment opportunities	-0.373*	0.294	0.255
9	Changes of commercial and service facilities	0.324*	-0.125	-0.175
7	Changes of neighbourhood safety	0.184*	-0.150	-0.074
4	Changes of urban development/recreational facilities	0.030	0.483*	-0.083
5	Changes of walking environment	-0.075	0.376*	-0.099
12	Changes of access to working place/school/daily shopping	0.235	0.300*	-0.208
13	Changes of access to commercial/cultural/hospital facilities	0.062	0.150*	-0.088
10	Impact of community population change/floating population increase	0.248	-0.033	0.675*
11	Changes of community harmony	-0.008	0.190	-0.195*
6	Impact of increased noise	0.015	-0.006	-0.049*

* Largest absolute correlation between each variable and any discriminant function.

Error! Reference source not found. plots the scores of Function 1 and 2 for each person, grouped according to their income level, as defined in **Error! Reference source not found.**. The function scores are calculated as shown in Equation 1. The centroids of the four groups are shown by the black squares. The values of the centroids on the x and y-axis are the mean scores of Function 1 and 2, respectively, for each group. Groups with centroids of opposite signs (positive or negative) on the x or y-axis are being discriminated by the function. For example, looking at the horizontal distance among the centroids, Function 1 discriminates the lowest income group, group 1, from other groups. By looking at the vertical distances among the centroids, Function 2 differentiates the mid-low and mid-high income groups, group 2 and 3, from group 1 and 4. But this difference is not as dramatic as for Function 1, because, as explained in **Error! Reference source not found.**, Function 2 explains 15.8% of the total variance while Function 1 explains 79.2%.

In summary, perceived impact relating to the 'critical living items', including accommodation (property price, property rent and living cost rising), employment (changes of local employment opportunities), important facilities for living (commercial and service) and neighbourhood safety, in combination contribute to the differentiation between groups 1 and other groups. The centroid of group 1 has the lowest value on the x-axis of Function 1. As calculated in Equation 1, and also explained above, this means that the evaluation of these variables by the lowest income group is significantly lower than by other income groups, especially the highest one. This also suggests that the lowest income group is the most sensitive to these changes. 'Changes of local employment opportunities' differentiate the lowest income group in a reverse way (-0.373*, No.8 in **Error! Reference source not found.**). This means the lowest income people perceive the impact on themselves is better than the other income groups (see descriptive statistics in **Error! Reference source not found.**). Perceived impact of urban development ('changes of urban development/recreational facilities'), accessibility ('walking environment, access to working place/school/daily shopping and commercial/cultural/hospital facilities') on the individuals contributes to the differentiation of group 2 and 3 from groups 1 and 4. The centroid of group 2 and 3 has the highest value on the y-axis of Function 2. This means the impacts of these factors on the mid income groups are perceived significantly better than the other groups. Again, as in Function 1, the lowest income group assigns a comparatively low value to these factors.

Figure 3: Canonical discriminant functions of perceived impacts of income groups



Functions at group centroids

Income groups	Function 1	Function 2
Group 1	-0.592	-0.112
Group 2	0.017	0.259
Group 3	0.494	0.188
Group 4	0.766	-0.423

4.3 Perceived rail transit impacts on migrants of the low-income groups

A subsequent analysis is carried out on the perceptions of migrants of the low-income (lowest and mid-low) groups, as these groups of people are assumed to benefit least from the impacts the rail transit brings (Zhao and Cao 2020). The low-income (lowest and mid-low) groups are divided by the origins they indicated in the survey, from within the main urban area, outside the main urban area, or outside Chongqing. The group from outside the main urban area is the most likely to be the rural migrants from peripheral areas. The group from outside Chongqing is assumed to be from nearby provinces or other cities, but this group of people is quite small (9.4% in **Error! Reference source not found.**). The last two groups are aggregated to be 'migrants'. Four groups are formed as low-income local, low-income migrants, mid-low income local and mid-low income migrants. Table 8 shows the average score for each question in the survey by different migrant/local resident groups.

Table 8: Perceived impacts of the changes on individual themselves by migrant/local resident groups. Source: Primary survey data 2014

Survey question No.	Perceived impacts of the changes on individuals	Migrant/local resident groups				
		Group 5 Lowest income migrants (N=114)	Group 6 Mid-low income migrants (N=72)	Group 7 Lowest income local people (N=151)	Group 8 Mid-low income local people (N=95)	Average (N=432)
1	Impact of property price rising	-0.90	-0.42	-0.77	-0.27	-0.63
2	Impact of property rent rising	-0.83	-0.19	-0.59	-0.12	-0.48
3	Impact of living cost rising	-1.17	-0.99	-1.13	-0.83	-1.05
4	Changes of urban development / recreational facilities	1.15	1.32	1.34	1.41	1.30
5	Changes of walking environment	1.17	1.26	1.33	1.33	1.27
6	Impact of increased noise	-1.30	-1.14	-1.29	-1.42	-1.30
7	Changes of neighbourhood safety	1.48	1.51	1.68	1.70	1.60
8	Changes of local employment opportunities	0.98	0.82	0.89	0.93	0.91
9	Changes of commercial and service facilities	0.11	0.18	0.06	0.20	0.12
10	Impact of community population change/floating population increase	-0.66	-0.49	-0.98	-0.66	-0.74
11	Changes of community harmony	1.27	1.29	1.44	1.44	1.37
12	Changes of access to working place/school/daily shopping	1.33	1.42	1.36	1.52	1.40
13	Changes of access to commercial/cultural/hospital facilities	1.25	1.26	1.37	1.44	1.34

There is a significant effect of migration by the income level on differentiating people's perceptions of rail transit effect on their individual lives, $V = 0.203$, F (39, 1254) = 2.33, $p = 0.000$. The discriminant analysis reveals three functions. **Error! Reference source not found.** shows that the first discriminant function explains around 56.5% of the variance, whereas the second explains 29.9 % of the variance. Three discriminant functions in combination significantly differentiated the income groups, $p = 0.000$. After removing the first function (second row), Function 2 and Function 3 significantly differentiate the groups, $p = 0.023$, while after removing the first and second functions Function 3 reveals no significance, $p = 0.323$.

Table 9: Eigenvalues of discriminant functions of differentiating migrant/local resident groups

Eigenvalues				
Function	Eigenvalue	% of Variance	Cumulative Variance %	Canonical Correlation Sig.
1	0.125	56.5	56.5	0.334

2	0.066	29.9	86.4	0.249
3	0.03	13.6	100	0.171

The canonical discriminant functions reveal an interesting pattern. A set of variables (No. 2, 1, 3, 12, 9) contribute most to group separation of Function 1 in **Error! Reference source not found.**, which is consistent with those (No. 1, 2, 3, 8, 9, 7) that differentiate income groups in **Error! Reference source not found.**. As **Error! Reference source not found.** shows, Function 1 discriminates the four subgroups by income, i.e. lowest-income and mid-low income groups. The variables relating to the impact from property price/rent/living cost rising (No.1, 2, 3) and changes of commercial and service facilities further significantly differentiate the two lowest income groups from the other two mid-low income groups within the low-income population, which suggests the two lowest income groups are sensitive to the economic changes the rail transit brings about. Variable No.12 'Changes of access to working place/school/daily shopping' emerges as a factor contributing to differentiate the lowest from mid-low income people. It reflects a divergent impact of transit direct benefit between the low-income groups, where the lowest perceive themselves to receive less benefit.

Table 10: Structure matrix: discriminant analysis of perceived impacts on individuals' lives of migrant/local resident groups

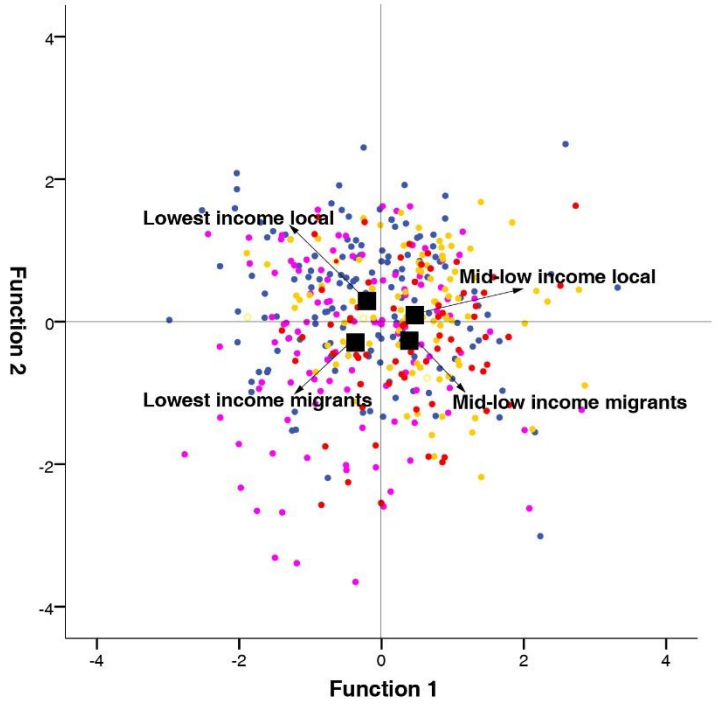
Structure matrix

Survey question No.	Discriminating variables	Discriminant functions		
		1	2	3
2	Impact of property rent rising	0.816*	0.164	0.080
1	Impact of property price rising	0.710*	0.067	-0.133
3	Impact of living cost rising	0.445*	0.058	-0.280
12	Changes of access to working place/school/daily shopping	0.290*	0.092	-0.198
9	Changes of commercial and service facilities	0.128*	-0.081	-0.072
10	Impact of community population change/floating population increase	0.293	-0.662*	-0.051
7	Changes of neighbourhood safety	0.141	0.637*	-0.17
11	Changes of community harmony	0.092	0.478*	-0.128
4	Changes of urban development / recreational facilities	0.312	0.404*	0.053
13	Changes of access to commercial/cultural/hospital facilities	0.157	0.376*	-0.255
5	Changes of walking environment	0.150	0.365*	0.085
6	Impact of increased noise	-0.032	-0.199	0.670*
8	Changes of local employment opportunities	-0.108	-0.057	-0.337*

* Largest absolute correlation between each variable and any discriminant function

Error! Reference source not found. shows that Function 2 (variables No. 10, 7, 11, 4, 13, 5) in **Error! Reference source not found.** discriminates the migrants from the local people, as indicated by the vertical distance between the centroids of lowest/mid-low income local residents (positive value on y axis) and lowest/mid-low income migrants (negative value on y axis). The centroid of lowest income migrants has the lowest value on the y-axis (Function 2). This suggests that the evaluation by the lowest income migrants on the impact of this set of discriminating variables on their lives is the lowest. Those variables can be summarized as 'requirements for the living environment'. These impacts include the living environment (the social environment of 'Changes of neighbourhood safety', 'Changes of community harmony', and physical environment of 'Changes of urban development/recreational facilities') and accessibility ('Changes of access to commercial/cultural/hospital facilities', 'Changes of walking environment'). However, they perceive 'Impact of community population change/floating population increase' on themselves better (-0.662*, No.10 in **Error! Reference source not found.**). This suggests that the impact of these variables on the lowest income migrants might be negative, particularly in contrast to the lowest-income local people, for which the centroid has the highest score on the y-axis. The migrants in the lowest income group perceive that they receive the least benefit either in the 'critical living items' and 'requirements for the living environment'. Nevertheless, 'Changes of local employment opportunities' in Function 3 doesn't play a significant role in differentiating the lowest/mid-low income and migrant/local resident groups.

Figure 4: Canonical discriminant functions of perceived impacts of migrant/local resident groups



Functions at group centroids

Migrant groups	Function 1	Function 2
Lowest income local	-0.204	0.289
Lowest income migrants	-0.367	-0.293
Mid-low income local	0.469	0.094
Mid-low income migrants	0.391	-0.267

5 Conclusions

Urban transit investment has been a critical factor in shaping the urban environment internationally, since the development of the streetcar in the US and Europe in the late 1800s. It is in China that the greatest scale and speed of urban transit investment and developmental change is currently being experienced. In Chongqing, the urban form is being shaped around the new transit networks, with the stations often acting as important focal points of new neighbourhoods.

Three main findings are drawn from the analysis. First, the perceived benefit from the rail transit development is unevenly distributed across income groups. As the survey indicates, the lowest income group perceives they benefit least from the rail transit's indirect impacts relating to the 'critical living items', while, on the contrary, the highest income group perceives they benefit most. There is strong evidence of the dual inequity problem (Banister 2018). These impacts include accommodation, living cost and safety. These findings support an emerging body of evidence which suggests that there are

important social equity impacts associated with new infrastructure investment, and that the low-income groups often bear the most adverse impacts (Agyeman, Bullard, and Evans 2002; Mitchell 2005; Beyazit 2015). This is similar to the unbalanced level of Metro spatial coverage, together with housing unaffordability, which impacts lower income people and results in inequity in Melbourne (Saberi et al. 2017). Whilst transit investment in Chongqing does seem to have resulted in significant perceived social equity impacts, there are also subtle differences to wider experience. In Chongqing, it is the lower income groups that tend to use urban transit, and presumably benefit from increased levels of accessibility to employment and other activities. However, the lowest income groups also suffer most from the adverse impacts associated with rail transit provision, such as rising property prices, rent and living costs. The perceived benefit from travel convenience is therefore diluted by the adverse impacts that residents experience. As a result, the lowest income group gives the lowest evaluation of the impact of new rail transit on their lives.

Second, rail transit's indirect impact benefits the disadvantaged group in some aspects, such as 'changes of the local employment opportunities'. The lowest income group perceive that they receive more benefit in local employment than the high-income groups and there is no significant difference between the migrants and local people. In these terms, the infrastructure investment can be viewed as progressive. This is in contrast to some previous research, which finds that redevelopment by metro stations is often seen as a negative process for local communities due to the process of gentrification, including for local employment opportunities. The new transport infrastructure results in home and business displacement and decrease of jobs for local residents (Lin and Yang 2019; Hickman et al. 2021; Tornabene and Nilsson 2021) or little increase in local employment opportunities due to mismatched skills (Lane et al. 2004). Meanwhile, it is the middle-income groups that benefit most from the increased accessibility and make full use of the transport provision to leverage their opportunities.

Third, the results indicate social inequity arises from transport-related development. There is a significant unequal perceived benefit distribution between the migrants and local residents within the low-income groups (lowest and mid-low income), relating to the 'requirements for the living

environment'. It reflects the sensibility of the migrants towards the new community environment they are living within (both the social and physical environment) and the critical needs of accessibility to urban services and facilities. The redistribution effect of the transit results in people moving into the areas where there are already low-income residents. The migrants are attracted by the opportunities found in these areas, such as lower property rent and good public transport accessibility near to the station. However, the results indicate that the migrants view these changes unfavourably. This might be because they tend to be excluded from the communities and suffer from a lack of participation in their new communities, as they are often regarded as the 'outsiders' by the incumbents. Their better perception of 'community population change/floating population increase', relative to the incumbents, reflects this in the reverse way. The most critical point is that the migrants of the lowest income group, who are already most disadvantaged in the urban development process, perceive they benefit the least. As is argued, transport investment specifically needs to redistribute transport resources towards currently disadvantaged population groups and deprived areas (van Wee 2012; Lucas, van Wee, and Maat 2016), but often this spatial dimension of transit investment is overlooked. With the rapid urbanisation trend in China, many rural migrants have moved to the city, becoming urban migrant workers. This is a controversial part of the urbanisation process in China and has led to multiple difficulties in Chinese society.

There are some limitations in the methodological approach used in this study. These are acknowledged here and possible improvements are also discussed. Concerns about spatial variation in the social equity dimension of rail transit could have been assessed in the primary survey. However, the sample size was not large enough to carry out the analysis in terms of spatial variation. There was an uneven distribution of samples across different areas and it was therefore not suitable to include locational differences in the model. Therefore, social equity was explored in terms of variations between different income groups, using the whole sample. Although the spatial variation in the social equity of transit's indirect impacts could not be investigated here, this is an important avenue that should be explored in future research. More extensive data would allow further analysis across a range of population categories. Other statistical methods can be utilised, such as multivariate analysis, to see the association of the key

population variables with perceptions while controlling a set of other factors.

A number of reflections are made for practice. It is important to accommodate newcomers into the city, to integrate them into surban life, and to help them live compatibly with the established urban residents. Specifically, joint efforts should be promoted by local employers, training organisations and neighbourhood communities, to provide low-income local residents with appropriate training and improved skillsets to benefit from the development and employment opportunities associated with transport investment. A more comprehensive transport and urban development appraisal system can be developed, drawing on evidence such as provided here, which moves beyond questions of economic efficiency and incorporates social equity dimensions. This would involve assessing the likely equity impacts of transit projects on different population groups, including the net levels of benefits and burdens. This could be a requirement at the project preparation stage, before projects are authorised by central government. This is critical in a country such as China, where social equity and societal cohesion are important political objectives. Improved methods of community participation are required for transit investment projects, whereby communities are incorporated into the decision-making process, including establishing communication with disadvantaged groups such as rural migrants. For example, consultation with potentially affected parties should be ensured at the project preparation stage, to help prevent and mitigate effects such as locational displacement arising from transport infrastructure.

The developmental impacts in the areas surrounding the transit lines in Chongqing are extensive in scale. But, to a large degree, we have seen that much of the assumed developmental impact is related to the surrounding planning strategy, and is far from an ‘automatic’ impact from the transit investment. If the planning strategy is well formulated, and much development is planned and implemented, then the developmental impact of the transit investment – including the resident perception of this – can be significant and also be shaped to give appropriate social equity outcomes. This has fundamental implications for transit planning, as often funding is given to the projects where there are assumed high developmental benefits (indirect benefits), alongside high ‘user’ benefits (direct benefits). In addition, differences in resident views are rarely incorporated in project planning, which is usually undertaken by

the analyst and reflects the analyst viewpoint. Hence the importance of the topic: metro investments have very important developmental and social distribution impacts, including perceived impacts, and it is critical that we understand these more clearly, so that our future investments can more effectively serve the different cohorts in the population.

(7574 words plus references)

Ethics committee approval

This research was approved by the UCL Research Ethics Committee with Project ID 5392/002.

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