Chapter 1

# The changing nature of work and time use: implications for travel demand

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## 1 Introduction

Since 1970, the labor market has shifted from one characterized by rising prosperity across income and job types to one characterized by polarization and uncertainty. The past four decades have witnessed an increase in "high-skill, good jobs and low-skill, bad jobs, along with a decline in semiskilled well-paying jobs that has shrunk the size of the middle class" (Kalleberg, 2011, p. 14). The impacts of the changing labor market have been felt by all workers, but its effects have been the most dramatic for young adults. Growth of good jobs has not kept pace with demand resulting in a market characterized by unemployment and underemployment (Furlong, 2015, p. 533). This has forced young people to enter the labor market through "low-skill, low-wage jobs" (Furlong, 2015, p. 533). These jobs have been growing rapidly, but are characterized by the lack of full-time employment and lack of commitment from employers to employees (often through zero-hour or temporary contracts (Furlong, 2015, p. 536). Experts expect this multi-decadal labor market shift to continue (Furlong, 2015, p. 534; Kalleberg, 2011, p. 179).

While these societal shifts may seem well away from the world of transport planning, they are central to future travel demand. Currently, much of planning practice implicitly presumes that economic recovery along with low gas prices will bring a return to previously-observed rates of mobility. For example, this is what regions assume when they use trip rates calibrated to older survey data or generate future populations with the employment characteristics of earlier times. However, the labor literature suggests increasing polarity in the economic futures of young people. Some will be lucky enough to gain the skills valued in today's marketplace and attain the coveted "good jobs." However, many will

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be stuck in "bad jobs," which provide uncertain income and hours and may be associated with lower mobility.

The remainder of this article explores how labor market shifts are reflected in the temporal patterns of work and assesses how these patterns connect to demographics and travel behavior. We conclude with an examination of the policy implications of the work.

## 2 Background

### 2.1 Changing young adult labor market

Kalleberg (2011) highlights three overarching causes of labor market shifts observed since 1970. Globalization increased price competition for goods and ultimately increased pressure on firms to lower labor costs or greatly increase productivity. Deregulation of many sectors such as aviation and financial services lessened the role of governments in labor markets—a phenomenon which is especially prominent in the United States but is also true, albeit to a lesser degree, in the United Kingdom. This weakened labor unions and enforcement of labor laws. Finally, shifting societal patterns, particularly the rise of the knowledge economy and women's increased labor force participation, led to a large increase in the service sector. Services previously performed at home such as food preparation, laundry, and childcare began to be outsourced.

The impacts of this changing labor market on young adults have been dramatic. Young adult unemployment and underemployment reached all-time high in recent years. In southern European countries such as Greece and Spain, the majority of young people in the labor market are unemployed (Furlong, 2015, p. 533). Rates of 20% are common in the United Kingdom, Sweden, France, and Belgium and 10% in Germany, Austria, and Switzerland (Furlong, 2015, p. 533).

These dismal statistics are the product of the global financial crisis and a changing labor market. First, there has been a multi-decade trend of lower labor force participation among young people (Furlong & Kelly, 2005). The prime driver of this trend is increased participation of young adults in higher education resulting from government policy and weakening job prospects for those without college degrees (Furlong, 2015, p. 533). For example, close to 95% of 20–24-year-olds in the United Kingdom were in the labor market in 1950 compared with 80% in 2010. Close to 100% of UK males between 25 and 29 years were employed in 1950 compared to approximately 90% in 2010. Second, when young people do enter the labor market, they are often under- or precariously-employed. This type of employment is characterized by the lack of full-time work and lack of commitment from employers to employees (often through zero-hour or temporary contracts (Furlong, 2015, p. 536).

The future employment picture for young people is not rosy. Experts in this area predict increased unemployment and under-employment (Furlong, 2015, p. 534). As Kalleberg (2011, p.179) notes, the multi-decadal shifts in the labor market result from "structural modifications rather than simply fluctuations of the business cycle." Weakened economic prospects for young people have knock-on effects on where they live as well as decisions about education, partnering, and parenthood. Young adults are increasingly continuing to live with their parents as they enter adulthood or finish university. This trend has continued up to today and did not decrease after the worst of the global financial crisis (Fry and Passel, 2014; Office for National Statistics, 2015). Similarly, median age at first marriage has risen steadily since the late 1960s (U.S. Census Bureau, 2016).

## 2.2 Changing young adult travel

Young adults across Europe and North America are driving less today than at the start of the 21st century. This unanticipated decrease is large with reported annual mileage decline of 1000 in the United Kingdom and 2500 in the United States (Kuhnimhof, Armoogum, Buehler, Dargay, Denstadli, & Yamamoto, 2012). Academic and popular investigations of these trends have identified a complex set of explanatory factors including the global financial crisis, changing lifestyles resulting in delayed attainment of life milestones, lower purchasing power due to increased student debt, technological advances allowing for virtual interaction or use of non-auto modes, and changing attitudes and preferences about travel and residential location (Blumenberg, Taylor, Smart, Ralph, Wander, & Brumbagh, 2012; Delbosc & Currie, 2014; Klein & Smart, 2017; Mcdonald, 2015; Polzin, Chu, & Godfrey, 2014; Vij, Gorripaty, & Walker, 2017).

Analyses of the relative influence of these variables have shown that economic and demographic factors explain a substantial portion of the observed declines (though there is debate about the share). Blumenberg et al. (2012, p. 4) state that "employment status, household income, and the like strongly influence the travel behavior of youth and adults" and ultimately conclude the "adage 'It's the economy, stupid' appears to hold." Klein and Smart (2017) find that "decreased employment, lower incomes and less wealth likely explain the differences in car ownership between millennials and older generations." Mcdonald(2015) concludes that lifestyle-related demographic shifts combined with the general dampening of travel demand accounts for over half of the decline in daily trip making. These results have led many to presume that travel demand will return to normal as economies rebound from the global financial crisis. There is even evidence of aggregate and per capita auto travel returning to pre-crisis levels in the United States (Federal Highway Administration, 2016).

# 3 Research questions

Our study links these two works by exploring the time patterns of work for young adults. Our focus is on identifying typologies of work time to understand the implications for work commutes. To do this, we focus on two questions:

1. How have employment and economic characteristics of young adults (18–34 years) changed from 2003 to 2015?
2. What are the work time use patterns of young adults (18–34 years) and how do these vary by demographic characteristics?

## 4 Data and methods

The American Time Use Survey (ATUS) records activity and activity durations in American households and has been conducted annually since 2003 (Bureau of Labor Statistics, 2016; Hofferth, Flood, & Sobek, 2015). The survey is a repeated cross-section with respondents drawn from the sample for the US Census Bureau's Current Population Survey. The ATUS provides a consistent way to assess work patterns and provides information on time spent in travel as well as occupation and employment patterns and demographics.

This analysis uses the ATUS in two ways. First, longitudinal data from 2003 to 2015 on young people (18–34 years) are extracted to provide an overview of shifting labor market and demographic patterns. Second, data from 2012 to 2015 are used to develop a segmentation of work time use patterns among young adults (18–34 years). We focus on young adults because this group has experienced the largest impact of labor market restructuring as well as the largest observed changes in travel behavior.

### 4.1 Segmentation

The goal of the segmentation analysis is to identify groups of young adults sharing similar work time use patterns. To do this we adapt the approach of Lesnard and Kan (2011) and first develop a work time sequence for each respondent; second, quantify differences in work time sequence across respondents; and finally, cluster respondents with the most similar patterns.

The ATUS day starts at 4 a.m. and includes data on all activities over the next 24 hours. For each reported activity, a start and end time is recorded. To construct the data for the work time use pattern, we divide the day into 96 15-minute intervals. For each interval, we identify the activity occurring during that 15-minute segment as work (1) or non-work (0). To be included in the analysis, a respondent must record at least one 15-minute work segment. The ATUS defines work as "time spent working, doing activities as part of one's job, engaging in income-generating activities not as part of one's job, and job search activities... 'Other income-generating activities' are those done 'on the side' or under informal arrangement and are not part of a regular job. Such activities might include selling homemade crafts, babysitting, maintaining a rental property, or having a yard sale. These activities are those that persons are paid for or will be paid" (Bureau of Labor Statistics, 2016, p. 53). This means that a small fraction of individuals included in our analysis have a work activity but are not employed or looking for work.

We quantify the similarity (or dissimilarity) between respondents' work patterns using dynamic hamming matching (DHM). Like other time sequence analyses techniques, DHM compares the differences in time use pattern between any two respondents in each time segment and aggregates the dissimilarities over the 96 time segments. This results in an overall dissimilarity value between any two respondents and dissimilarity matrix that captures differences in work time for the entire sample.

The uniqueness of DHM compared to other approaches is that the dissimilarity between activities for any two respondents depends on when the activities occur. If many people begin work activities and many other people begin non-work activities in time segment $t$, DHM assumes time segment $t$ is a popular time for people switching between activities and therefore the dissimilarity between activities is low in time segment $t$ (Lesnard & Kan, 2011). For example, respondents A and B are considered as having a dissimilar time use pattern between 2:00 and 2:15 a.m., if A does not work and B does work because this is not a popular time that people switch activities. In contrast, respondent A and C are considered as having similar time use pattern between 7:45 and 8:00 a.m. even if A does not work and C does work during this period. This is because many people switch from non-work to work during the period. We conduct the time sequence analysis with the *seqcomp* plug-in for Stata (Halpin, 2014).

We then use agglomerative hierarchical clustering based on the dissimilarity matrix generated by DHM to identify groups of workers with similar work patterns. Agglomerative hierarchical clustering generates a set of nested clusters that are organized as tree, which allows us to compare all possible clustering outcomes simultaneously. This allows us to evaluate whether merging one cluster with the closest one sacrifices information on either group. We employ the method "beta-flexible"[a] with $\beta = -0.3$ to calculate the distance between clusters (Lesnard & Kan, 2011). The beta-flexible method has proved more robust in recovering structure in the presence of outliers and noise than other classical linkages such as Ward's (Milligan, 1980). We used the package "cluster" in R for the clustering analysis. We adopt the 9-cluster solution as it is most succinct and incorporates all major types of expected work time use patterns.

The organization of the ATUS data presents one notable quandary for the current analysis. As the ATUS day begins at 4 a.m., it is difficult to fully capture night shifts. In cases where an individual repeats a night shift, their full work time will be captured, that is, at the start and end of the reporting day. But in cases where individuals vary their schedule day to day, only part of their night shift may be captured. However, because DHM considers the differential in chances of switching between activities at different times across all individuals, it is unlikely DHM will confound the night shift time use pattern with other morning shift time use patterns when creating the dissimilarity matrices. This means our segments are reliable but work time may be underestimated for clusters with large proportions of night shift workers.

a. In beta-flexible linkage, the distance between a given cluster k and a new group (i, j), which is formed by merging two clusters i and j, depends on three components: the distance between i and k, the distance between j and k, and the distance between i and j. All three distances depend on a parameter, beta, which is the weight that is assigned to the distance between i and j. Following Lesnard's method, we use $\beta = -0.3$.

## 4.2 Sample characteristics

We focus on young respondents aged between 18 and 34 years in trend and segmentation analyses. The trend analysis considers all respondents in the age range while the segmentation only includes those who commuted to work on the survey day. Socio-demographic and travel differences between the two samples flow from this. Individuals in the segmentation analysis are more educated, work more, and are less likely to be in school; all expected differences (Table 1.1).

**TABLE 1.1 Sample summary statistics for trend and segmentation analysis (unweighted).**

| Characteristics | Trend analysis, 2003–15 | Segmentation analysis, 2012–15 |
|---|---|---|
| N (Standard Error) | 38,836 | 3,944 |
| Age: avg (SE) | 27.4 (4.8) | 27.9 (4.5) |
| Age: min | 18 | 18 |
| Age: max | 34 | 34 |
| In school % | 20.1 | 15.6 |
| Employed % | 74.9 | 97.2[a] |
| White only % | 79.6 | 78.9 |
| Black only % | 13.3 | 13.9 |
| Hispanic % | 19.6 | 19.2 |
| Never married % | 49.0 | 53.6 |
| Female % | 57.6 | 48.8 |
| Education: some college or college degree % | 61.4 | 68.8 |
| Daily work minutes (SE) | 191.5 (250.1) | 466.7 (168.4) |
| Daily travel minutes (SE) | 77.7 (78.7) | 80.2 (58.3) |
| Usual hours worked per week (SE) | 29.2 (20.6)[b] | 39.9 (13.6)[c] |
| Weekly earnings (2015$) (SE) | 555.5 (589.3)[d] | 725.1 (542.6)[e] |
| Number of children in household (SE) | 1.0 (1.2) | 0.9 (1.1) |

[a] *The percent of respondents not employed but worked in the segmentation analysis is 2.8. Self-employed income-generating activities such as yard sale or maintaining/renovating retail property are also categorized as work activities in the ATUS data.*
[b] *The number of respondents is 37,572 due to 1264 missing values on usual hours worked per week.*
[c] *The number of respondents is 3778 due to 166 missing values on usual hours worked per week.*
[d] *The number of respondents is 37,055 due to 1781 missing values on weekly earnings (2015$).*
[e] *The number of respondents is 3750 due to 194 missing values on weekly earnings (2015$).*

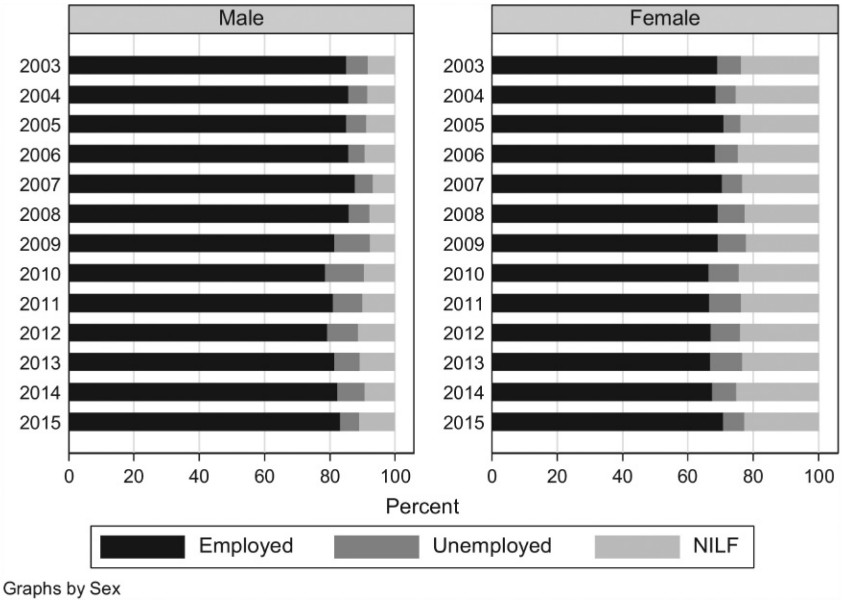


**FIGURE 1.1** **Employment patterns of 18–34 years old by sex: 2003–15.**

# 5 Results

## 5.1 Employment and economic characteristics, 2003–15

Labor statistics from the ATUS reflect the impact of the global financial crisis on young adults. Unemployment and dropping out of the labor force increased for men and women in the late 2000s and only by 2014 or 2015 showed signs of increased employment (Fig. 1.1). Even among those with employment, hours worked and earnings dropped during the GFC and its aftermath (Fig. 1.2). While increase in unemployment affected both men and women during this period, young men showed larger and more sustained impacts. For example, average earnings and hours worked have not markedly changed for employed females, but employed males are earning less today than before the crisis and working fewer hours. These results concord with the literature showing strong gender differences in the impacts of the financial crisis (Albelda, 2013; Bettio and Verashchagina, 2014).

## 5.2 Work time use segmentation

A solution with nine clusters provided the best balance between parsimony and representing behavioral patterns (Fig. 1.3). As expected, a large portion of the sample worked a traditional workday. Clusters 1 and 2 averaged 8 hours of work and differed only slightly in their start time. Cluster 6 worked a long day (9.8 hours) with a median start at 8:15 a.m. and end at 18:30 p.m.


**FIGURE 1.2 Weekly earnings and hours worked, employed of 18–34 years old: 2003–15.**

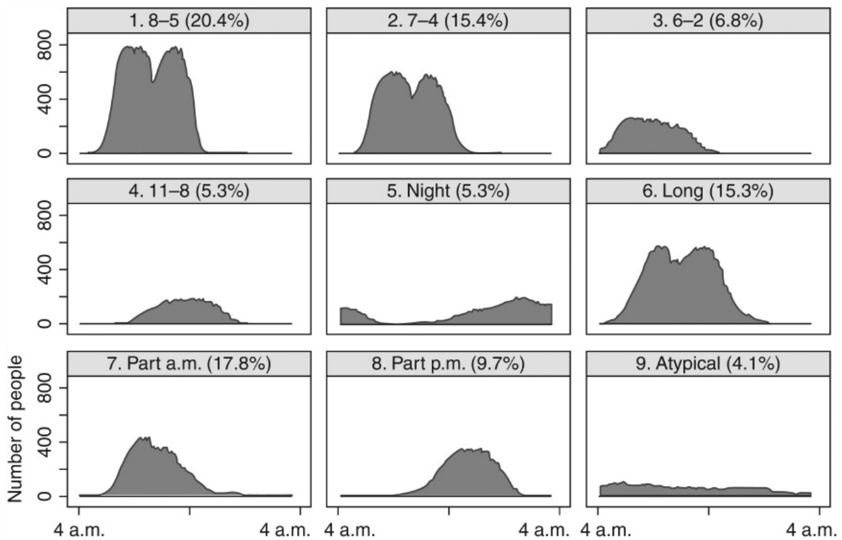


**FIGURE 1.3 Work time segments: 18–34 years old.**

Together these three clusters represent just over half (51.1%) of the sample. These three clusters share similar characteristics. They have high proportions of full-time workers, those employed in management or professional roles, and, not surprisingly, have the three highest average weekly earnings (Table 1.2).

**TABLE 1.2** Economic characteristics by cluster.

| Segment | % In school | % Emp full-time | Usual weekly hours worked | Weekly earnings (2015 $) | % Professional, management, business and financial | % Service, sales and related |
|---|---|---|---|---|---|---|
| 1: 8–5 | 11.7 | 93.7 | 42.1 | 861 | 45.7 | 13.8 |
| 2: 7–4 | 10.4 | 90.0 | 41.2 | 820 | 40.0 | 17.4 |
| 3: 6–2 | 10.1 | 85.0 | 40.9 | 679 | 21.4 | 23.0 |
| 4: 11–8 | 26.9 | 62.0 | 38.0 | 527 | 29.7 | 25.3 |
| 5: Night | 12.9 | 86.6 | 43.0 | 705 | 19.9 | 36.6 |
| 6: Long | 11.3 | 89.9 | 45.6 | 928 | 48.3 | 12.5 |
| 7: Part (a.m.) | 19.3 | 51.9 | 31.6 | 525 | 36.5 | 23.4 |
| 8: Part (p.m.) | 32.0 | 57.6 | 35.4 | 478 | 19.5 | 38.0 |
| 9: Atypical | 13.5 | 82.2 | 45.1 | 739 | 40.4 | 21.2 |
| Total | 15.6 | 78.5 | 39.9 | 725 | 37.1 | 20.8 |

The remaining clusters differ in the timing and time spent at work. Individuals in cluster 3 and 4 work an average of 8.3 hours and typically start around 7 a.m. (Cluster 4) or 8 a.m. (Cluster 3). Individuals in this cluster have the highest number of children on average (1.2). Clusters 5 and 6 work long hours (9.7 and 9.8 hours respectively) but shifted to the evening and night hours. Individuals in Cluster 4 have the second highest rate of being enrolled in school (26.9%) and low weekly earnings ($527). Cluster 5 works in nights and has the highest proportion of respondents reporting they are African-American (23.4%) (Table 1.3).

Clusters 7 and 8 represent part-time work in the morning and afternoon, respectively. Both segments have a higher than average proportion of Hispanics and low weekly earnings. Cluster 8 also has the highest proportion working in service and sales (38.0%). Cluster 9 represents atypical work increments scattered throughout the day and captures many individuals who report work but are not employed or are looking for work.

## 5.3 Commuting in peak periods

Large differences exist across clusters in the concentration of start and end times in traditional peak travel periods. Segments with the highest proportion of workers in retail and sales (Clusters 4, 5, 8) have very few individuals starting or ending work during these periods (Table 1.4). These asynchronous patterns may allow for faster travel for individuals with car access who can avoid the

**TABLE 1.3** Demographic characteristics by segment.

| Segment | Age | % White only | % Black only | % Hispanic | % Never married | % Female | # of Children in HH | % Some college+ |
|---|---|---|---|---|---|---|---|---|
| 1: 8–5 | 29.0 | 82.0 | 12.2 | 16.2 | 43.9 | 49.6 | 1.0 | 75.5 |
| 2: 7–4 | 28.5 | 84.7 | 9.2 | 21.8 | 50.3 | 49.3 | 0.9 | 72.0 |
| 3: 6–2 | 28.3 | 80.2 | 14.2 | 24.3 | 47.6 | 38.6 | 1.2 | 53.6 |
| 4: 11–8 | 26.1 | 73.1 | 17.8 | 17.3 | 77.4 | 52.4 | 0.6 | 67.8 |
| 5: Night | 27.3 | 71.3 | 23.4 | 14.4 | 60.8 | 36.4 | 0.9 | 64.6 |
| 6: Long | 28.5 | 76.9 | 13.1 | 20.1 | 50.7 | 45.0 | 0.7 | 75.3 |
| 7: Part (a.m.) | 27.5 | 77.7 | 14.4 | 19.9 | 54.0 | 56.3 | 0.9 | 65.1 |
| 8: Part (p.m.) | 25.4 | 76.6 | 15.4 | 22.4 | 70.6 | 52.9 | 0.6 | 59.9 |
| 9: Atypical | 28.0 | 74.2 | 18.4 | 12.3 | 52.2 | 42.9 | 0.8 | 68.7 |
| Total | 27.9 | 78.9 | 13.9 | 19.2 | 53.6 | 48.8 | 0.9 | 68.8 |

congestion associated with peak periods. However, for individuals without or with unreliable auto access, traveling outside peak periods often incurs a time penalty or the inability to reach needed destinations (Kaza, 2015). The literature on labor markets suggest these type of work time patterns may be expanding and thereby exacerbating access concerns.

Data on modal travel time show high rates of auto usage and access across all clusters (Table 1.4). However, the clusters with non-standard or long work hours (11–8, long and night) have the lowest proportion of trips in autos. The data also reveal an inverse correlation between hours worked and number of daily trips. Presumably those with longer work hours have less time available for other activities and the travel required to undertake those activities.

## 6 Discussion and conclusions

Labor market analyses show a nearly 50-year pattern of increased precarity among young people. While the extreme effects of the GFC on the number of unemployed young people may recede, there is likely to be continued growth in temporary, part-time, low-wage jobs in the clerical and routine sectors. Our analysis showed that many young adults start and end work outside traditional peak periods. In a fully auto-oriented society, this might not be problematic—and even might present the advantage of avoiding congestion. However, those

**TABLE 1.4** Work and travel patterns by cluster.

| Segment | % | Work hours | % Work start (6:30-9:30) | % Work end (16:30-19:30) | Daily trips | Daily auto trips (% of total) | Daily travel time | Auto travel time (% of total) |
|---|---|---|---|---|---|---|---|---|
| 1: 8–5 | 20.4 | 8.5 | 92.8 | 52.1 | 4.0 | 3.7 (92.5) | 70.8 | 66.8 (94.4) |
| 2: 7–4 | 15.4 | 8.3 | 92.4 | 42.5 | 3.9 | 3.7 (94.9) | 73.3 | 69.9 (95.4) |
| 3: 6–2 | 6.8 | 8.3 | 17.6 | 6.7 | 3.7 | 3.6 (97.3) | 74.4 | 71.5 (96.1) |
| 4: 11–8 | 5.3 | 7.8 | 7.2 | 29.3 | 3.5 | 3.1 (88.6) | 61.4 | 56.3 (91.7) |
| 5: Night | 5.3 | 9.7 | 0.5 | 0.0 | 3.5 | 3.3 (94.3) | 67.6 | 64.2 (95.0) |
| 6: Long | 15.3 | 9.8 | 68.1 | 69.6 | 3.5 | 3.2 (91.4) | 63.1 | 57.6 (91.3) |
| 7: Part (a.m.) | 17.8 | 4.4 | 45.7 | 23.7 | 4.8 | 4.4 (91.7) | 84.3 | 76.9 (91.2) |
| 8: Part (p.m.) | 9.7 | 6.8 | 2.3 | 4.7 | 3.8 | 3.5 (92.1) | 69.4 | 62.3 (89.8) |
| 9: Atypical | 4.1 | 8.4 | 28.2 | 2.5 | 3.9 | 3.7 (94.9) | 71.5 | 68.4 (95.7) |
| Total | 100.0 | 7.8 | 54.6 | 34.6 | 4.0 | 3.7 (92.5) | 71.9 | 66.9 (93.0) |

without reliable car access, will face lower levels of transit service that may in turn restrict their employment options.

What do these findings mean for transport planning practice and research? First, they show the need for transport planners to consider how the story of changing labor markets may affect travel patterns and resulting infrastructure needs and infrastructure planning tools. In the short-term, this may require efforts to incorporate time-based accessibility analyses into transit operations planning. These temporal accessibilities could then be compared to the travel patterns of transit-dependent population. If planners observe mismatches, service schedules could be adjusted.

In the longer-term, planners need to attend to employment projections in demand forecasting processes. Most modeling efforts require construction of future populations including their employment characteristics. These estimates should account for the literature on labor market restructuring, particularly around increased part-time employment. But changes in the labor market also present fundamental challenges to the ability of demographers and planners to project employment—particularly at the small geographic scales required by travel demand models. This, in turn, highlights the importance of quantifying and communicating uncertainty in demand estimates.

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