# Day-of-Week Weighting of Household Travel Surveys: An Integrated Approach and Its Application

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## ABSTRACT

Travel data collection, modeling, and forecasting has historically focused on a "typical weekday", treating travel patterns for multiple weekdays (e.g., Tuesday, Wednesday, Thursday) as a single average day. This aggregation of days increases the effective sample size for daily travel behavior but loses temporal fidelity and ignores weekend travel altogether. Moreover, many modern household travel survey (HTS) collection platforms collect data for an entire week but only utilize three of the seven days. While justifiable in the past since peak travel demand was centered around weekday work and school travel, travel behavior has significantly shifted since the COVID-19 pandemic, with increased work flexibility and altered travel habits (e.g., online shopping). It is increasingly important to understand travel behavior more granularly throughout the week and to weigh the data appropriately to support statistically reliable analysis. However, segmenting and individually weighting a survey for each day of the week is cumbersome and limits sample size for post-hoc adjustment processes. To overcome these challenges, an integrated day-of-week weighting approach was developed to generate day-specific weights in a single weighting (raking) run, reducing complexity and allowing more seamless downstream adjustment procedures. The results yield a set of weights for each household for each day of the week where travel data are available, including weekends.


**Keywords:** Household Travel Surveys, Survey Weighting and Expansion, Travel Behavior, Day-of-Week, Weekday and Weekend Travel Analysis

## INTRODUCTION

The landscape of travel behavior analysis is undergoing a fundamental transformation, driven by both technological advances in data collection and profound shifts in daily mobility patterns (*1*, *2*). Historically, household travel surveys (HTS) and their associated modeling frameworks have centered on the concept of a "typical weekday," aggregating data from multiple midweek days to maximize sample size and statistical reliability (*3–5*). This approach, while pragmatic in an era dominated by regular work and school commutes, has become increasingly misaligned with contemporary travel realities. The COVID-19 pandemic accelerated trends toward flexible work arrangements, diversified trip purposes, and a blurring of traditional weekday-weekend distinctions. Simultaneously, modern HTS platforms now routinely collect full-week travel diaries, yet a focus on a "typical weekday" result in the discarding of much of this data, focusing analysis on a narrow subset of days.

To compound the issue, many modern travel surveys utilize multiple survey platforms in their collection efforts, such as traditional call centers (i.e., CATI), online browser forms, and more recently mobile phone-based questionnaires (*6*, *7*). Although the surveys themselves may be identical, a trip underreporting bias has been observed in telephone and browser surveys compared to GPS driven mobile phone-based surveys due to the reliance on respondents recall and survey burden (*8*, *9*). Adjusting for this bias in weights typically employs multiple regression estimation to account for endogenous features (e.g., demographics) and ultimately isolate the underlying survey platform bias (*6*, *7*). However, maintaining a sufficiently large sample size is critical to ensuring a robust estimation, which can be cumbersome and labor intensive if recombining weights from independent runs post-hoc.

This paper introduces an integrated day-of-week (DOW) weighting methodology designed to address these limitations. Rather than segmenting the survey sample and executing separate weighting procedures (e.g., iterative proportional fitting or raking) for each day, the integrated approach generates day-specific weights for all days in a single unified run. This innovation not only preserves the temporal fidelity of the data but also streamlines downstream adjustment processes, such as day-pattern and trip rate calibration by diary platform, without the need for cumbersome post-hoc recombination of weights. The proposed approach provides an elegant solution and statistically robust foundation for analyzing evolving travel behaviors across the entire week.

## BACKGROUND

The weighting of HTS data is a foundational step in ensuring that survey samples accurately represent the broader population and its travel behaviors, and help mitigate possible biases such as non-response bias, sampling bias, survey platform bias, and trip underreporting bias (*7*, *10*). Traditionally, HTS weighting procedures have focused on producing a single set of expansion weights calibrated to demographic and geographic control totals for a "typical weekday". While this multiday aggregation is effective for maximizing sample size and supporting weekday-focused modeling, it inherently obscures temporal variation throughout the week and can disregard weekend travel altogether (*11–13*).

Survey weighting involves some form of weight fitting algorithm by which a frequency matrix of samples is calibrated such that the summed product of a weight vector closely matches a set of target totals. Classical iterative proportional fitting (IPF) is one of the most widely used methods for adjusting sample weights in household travel surveys. IPF works by iteratively adjusting the weights of survey records so that the marginal distributions of key control variables (e.g., age, household size, geography) in the weighted sample match known population totals (*14*). This method has long been favored for its simplicity and interpretability and remains the backbone of many HTS expansion processes.

However, classical IPF has limitations, particularly when the number of controls grows or when controls are sparse and high-dimensional, leading to convergence or stability issues. To address these challenges and incorporate more flexible modeling of joint distributions, maximum entropy-based approaches have emerged as a robust alternative. These methods seek the most "uninformative" (i.e., highest entropy) distribution that matches known population constraints, thus minimizing the introduction of bias due to overfitting while preserving as much randomness as possible (*15*). Recent implementations, such as PopulationSim (*16*), leverage maximum entropy optimization to generate synthetic populations or calibrate survey weights to multi-dimensional targets, supporting more granular demographic and temporal controls. Maximum entropy approaches offer theoretical guarantees of uniqueness and consistency under certain conditions and have been shown to outperform classical IPF in complex or sparse-data contexts.

Maximum entropy optimization, as implemented in PopulationSim, is mathematically framed as maximizing the Shannon entropy function $H(w) = -\sum_i w_i \log(w_i)$, where $w_i$ are the survey weights. This method solves for the most uniform and least biased weight distribution that satisfies the target constraints without overfitting. Compared to classical IPF, which adjusts margins one at a time, maximum entropy can handle high dimensional, sparse, and overlapping constraints more robustly. These advantages are particularly useful for day-of-week weighting, in which additional day-of-week specific variables are added, increasing sparsity and dimensionality.

Recent shifts in travel behavior, accelerated by the COVID-19 pandemic, have highlighted the limitations of treating every weekday as a typical or average weekday. Flexible work arrangements, increased telecommuting, and changes in discretionary travel have led to more heterogeneous travel patterns throughout weekdays (*17*). In response, there is an increased need for more granular temporal weighting approaches that can capture DOW effects and support robust analysis of both weekday and weekend travel. However, existing methods typically require segmenting the survey sample by day and conducting separate weighting runs for each DOW, a process that is both labor-intensive and prone to inconsistencies when recombining results for downstream analysis, such as survey platform bias correction.

To address these challenges, an integrated single-stage weighting approach has been developed that leverages the flexibility and performance of maximum entropy fitting algorithm to support a single stage process that calibrates survey weights to multiple temporal and demographic targets simultaneously. This single stage process then seamlessly facilitates a more efficient handling of the entire sample for downstream analysis and adjustment.

To be clear, the proposed approach is not a mathematical breakthrough nor is it fundamentally different from independent day weighting, but it is an elegantly simple innovation that offers substantial efficiency benefits.

## METHODS

Conventional day-of-week weighting of a HTS requires splitting the data into separate data sets for each household's day of the week based on households that responded on each day, i.e., separate household-days. For example, if a household had complete travel data on each day of the week, it would be split into seven separate data sets to be weighted ***independently***, producing seven sets of household weights, person weights, day weights, and trip weights. The weights must then be recombined into a single data set to support analysis. As previously mentioned, this independent weighting approach can be cumbersome and computationally inefficient.

As an alternative approach, rather than splitting the data, one can simply restructure the data such that each household-day becomes a new row in the table. A dummy variable is added for each day-of-week for each household-day that the record represents. For example, a household with seven days of complete travel data would become seven rows of data and the dummy columns form a square matrix with ones along the diagonal for each day the record represents. This table can then be weighted in a single ***integrated*** weighting run, producing a similar set of day-of-week weights.

To facilitate a single weighting run, for each day (Monday through Sunday), day-of-week control totals are created representing the total number of households and persons for that day in the population. Assuming that the number of households and persons, and their characteristics are constant, the day-of-week household and person targets are all equal to the total households and persons in the study area. All other control targets (e.g., household size, income, person-level demographics) are multiplied by seven, reflecting the fact that the sum of weights must equal the total number of household-days (and person-days) in a full week. This ensures that the weighted survey is temporally representative, not just demographically or geographically representative. Weighting is then conducted as is conventionally done but will produce a set of household weights for each household-day and is equivalent to weighting independently on each day. For example, if the total number of households in the region is 100, the household-day control for each day would be 100, and the sum across all days would be 700.

Table 1 presents a simple example of the household-day incidence and weighting structure. Each row corresponds to a specific household on a specific day, with indicators for household and person-level attributes and one column for each day of the week. The final column shows the household-day weight after the single-stage process.

**TABLE 1: EXAMPLE INCIDENCE TABLE FOR DAY-OF-WEEK WEIGHTING**

| | **HOUSEHOLDS** | | | | | | **PERSONS** | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Size | | | Income | | | Gender | | Age Group | | | **DAY** | | | | | | | |
| **HH ID** | 1 | 2 | 3+ | Low | Med | High | Female | Male | Child | Adult | Senior | Mon | Tue | Wed | Thu | Fri | Sat | Sun | **WEIGHT** |
| **158** | 0 | 0 | 1 | 0 | 0 | 1 | 3 | 1 | 2 | 2 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 50.0 |
| **171** | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 2 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0.0 |
| **250** | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 41.8 |
| **543** | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 2 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 39.3 |
| **543** | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 2 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 19.2 |
| **543** | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 2 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 45.2 |
| **543** | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 2 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 24.3 |
| **543** | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 2 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 40.3 |
| **543** | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 39.3 |
| **543** | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 42.5 |
| **574** | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 60.7 |
| **574** | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 30.8 |
| **574** | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 54.8 |
| **574** | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 33.9 |
| **574** | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 59.7 |
| **574** | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 60.7 |
| **574** | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 57.5 |
| **TARGET** | 450 | 200 | 50 | 250 | 400 | 50 | 550 | 550 | 100 | 500 | 500 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | |
| **WEIGHTED** | 450 | 200 | 50 | 250 | 400 | 50 | 548 | 552 | 100 | 500 | 500 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | |

*(Example values only)*

Note that not all households in the example table have a full seven days. This reflects situations where there might be a mixture survey completion due to differing diary platforms or diary incompleteness. The proposed approach handles this reality of household survey collection and helps preserve the maximum amount of the survey possible by including each complete household day.

**Maximum Entropy Weighting Example:**

To illustrate how maximum entropy optimization operates within the DOW weighting framework, consider the example in Table 1. Household ID 543 appears seven times, once each day from Monday through Sunday, representing seven household-day records. Each record contributes to one or more of these targets based on household attributes. Let $w$ be the vector of weights for $n$ household-day records. The optimization problem is

$$\min_{w>0} \sum_{i=1}^{n} w_i \log(w_i)$$

Subject to $Aw=T$, where $A$ is a matrix indicating which records contribute to which targets, and $T$ is the vector of known control totals (e.g., daily household-day totals, demographic subtotals). For Household ID 543, each of its seven records contributes a 1 to the appropriate weekday row in $A$ and may contribute to one or more demographic rows depending on its characteristics (e.g., adult count, income level).

The problem can be solved using different optimization methods (e.g., Newton-Raphson, BFGS, Gradient Descent, IPU, convex optimization, interior point, etc.). PopulationSim uses the common Newton-Raphson method and employs other additional techniques, such as tolerance thresholds, log-space transformations, target importance factors, and weight constraints to ensure numerical stability and extreme weight variance mitigation. In brief, solving via Newton-Raphson method, Lagrange multipliers ($\lambda$) are introduced and the optimal weights take the form

$$w_i = \exp((A^T \lambda)_i - 1)$$

Substituting into $Aw=T$ yields a nonlinear system that can be solved iteratively. Starting with an initial $\lambda$, the residual

$$r_k = A \exp(A^T \lambda_k - 1) - T$$

and the Hessian

$$H_k = A\, diag(\exp\,(A^T \lambda - 1))\, A^T$$

are calculated and used to update

$$\lambda_{k+1} \leftarrow \lambda_k - r_k H_k^{-1}$$

Once converged, $\lambda$ can be used to compute an optimal set of weights. Solving this problem yields weights for each household-day record that match all constraints simultaneously. For instance, Household ID 543's weights for each day-of-week, reflecting how each day aligns with overlapping day-specific and demographic constraints. This single-stage approach ensures internal consistency, avoids post-hoc recombination, and produces a temporally representative weight set suitable for downstream analysis.

## ANALYSIS: Massachusetts Household Travel Survey Case Study

The proposed integrated approach was applied to the Massachusetts Household Travel Survey, which contained approximately 15k household and 29k persons, with approximately 377k trips. The study is composed of three survey platforms: mobile app (rMove), online browser (bMove), and call center. The mobile app will collect up to 7 days of travel data, but the online and call center platforms collect only travel diaries for a single day. Table 2 is a summary count of households, persons, travel days, and trips collected in the survey.

**TABLE 2: SUMMARY COUNTS OF HOUSEHOLD TRAVEL SURVEY**

| Platform | Households | Persons | Days | Trips |
|---|---|---|---|---|
| Call Center | 570 | 741 | 741 | 2,578 |
| Browser | 8,657 | 17,829 | 17,829 | 54,109 |
| rMove | 6,332 | 11,005 | 73,268 | 321,015 |
| *Total* | 15,559 | 29,575 | 91,838 | 377,702 |

## RESULTS

The remainder of this paper will focus on two tasks:

- **Validation:** Simplified comparison of weights by each approach without refinements or constraints.
- **Analysis:** Detailed temporal analysis of day-of-week travel behavior for a full weighting run.

### Validation: Comparison of weights

As a general comparison of the weights themselves, day-of-week weighting was performed both using the proposed integrated approach as well as conventionally slicing and weighting each day of the week independently. For demonstration purposes, neither approach in this test example applied any weight refinements, such as weight trimming (i.e., specifying maximum weights). The objective here is to validate that the two approaches can yield comparable results with minimal artificial constraints that might introduce confounding results.

Figure 1 shows the resulting fit against the targets and the targets' 90% confidence interval margin of error in the ACS. Both are extremely well fit, with a Mean Average Percent Error (MAPE) of 0.22% and 0.19%, and a maximum percentage error of 0.78% and 0.83% for the integrated and independent approaches, respectively. All are well within the 90% confidence intervals for their respective targets.

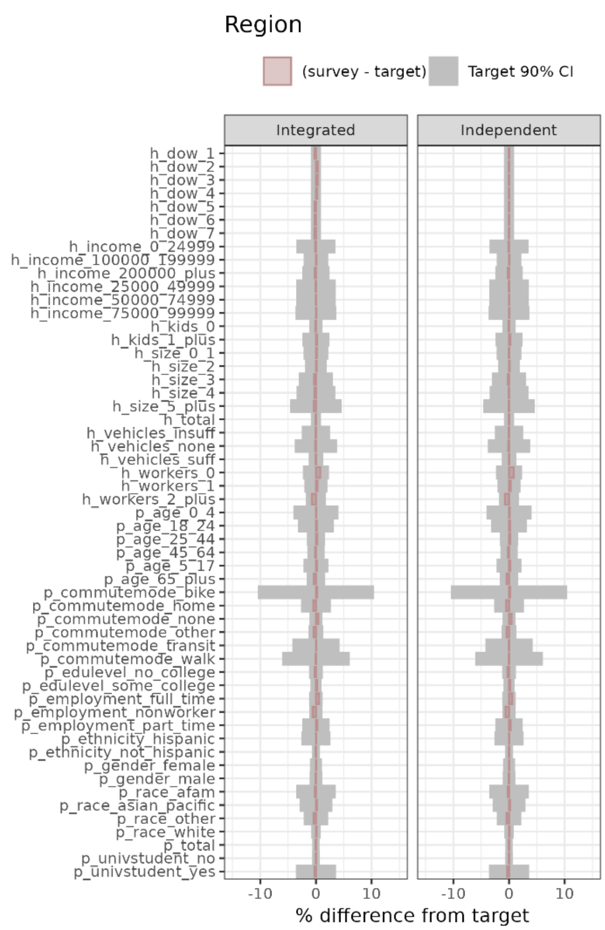



**FIGURE 1: COMPARISON OF OVERALL FIT AGAINST TARGETS AND TARGET MARGIN OF ERROR IN ACS**

Figure 2 (left) shows the comparison of weighted target totals between the independent and integrated approach, which have a MAPE of 0.07% and maximum percent error of 0.38%. It is important to note that this tight fit is a result of a relatively large sample size with no subzone segmentation, weight trimming (max weight constraints), or other refinements. In practice, these weights are likely to be over fit with high variance.

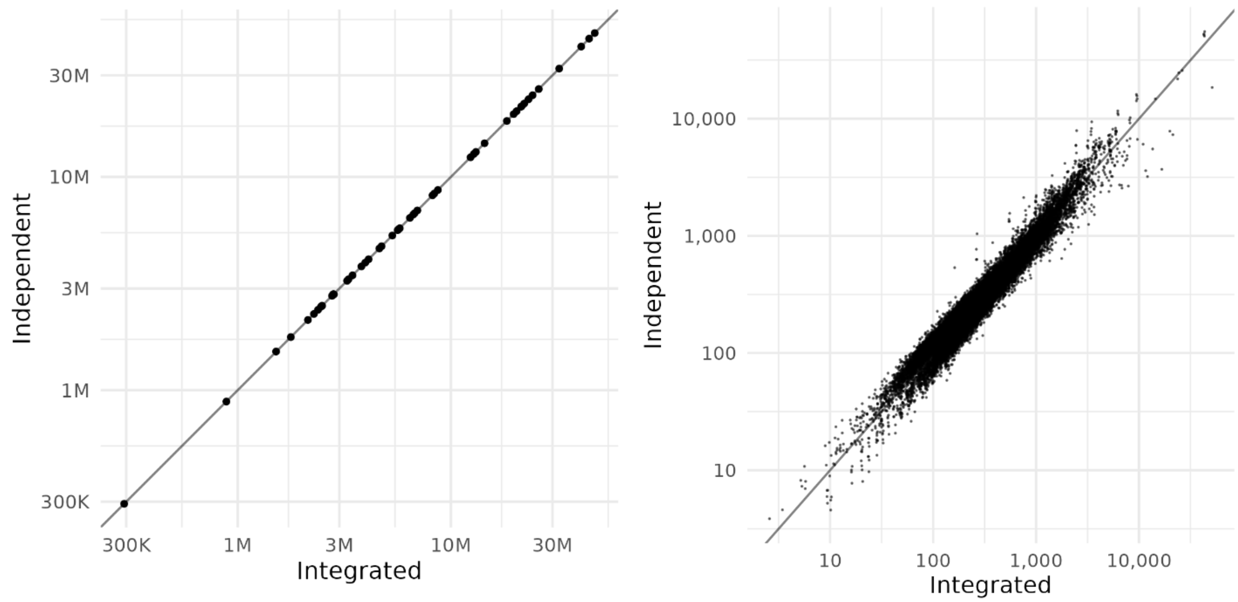



**FIGURE 2: COMPARISON OF TARGET FIT (LEFT) AND INDIVIDUAL WEIGHT (RIGHT)**

Figure 2 (right) is a much more granular perspective, comparing individual household-day weights between the two approaches. The expected high variance is observable in Figure 2 (right), with weights ranging from 10 to 10,000 because this test case included no weight trimming or other refinements. Again, this is for demonstration purposes and to avoid confounding differences introduced through artificial constraints. Weighting refinements will be added in the subsequent full weighting for analysis.

The more granular weight comparison in Figure 2 (right) shows how the methods do begin to diverge. Although there is a very clear correlation between the two weights, the MAPE is 14.5% and a root-mean square error (RMSE) of 1.21. Explanation of this divergence is not immediately apparent but is possibly due to differing constraints imposed for each day of the week in the integrated model, differences in relative magnitude (i.e., multiplying targets by 7), or other convergence artifacts in the solution path. Despite the deviation at the individual weight level, the authors believe this is an acceptable level when considering that the target fits are consistent and these variations are relatively minor compared to when weight trimming and other refinements are introduced.

**Analysis**

For the analysis of travel behavior with day-of-week weighting, a full weighting run is conducted, which includes sub-geography controls and maximum expansion factor constraints. Summary statistics of the estimated household weights by days of the week are presented in Table 3. These were used to derive trip-level weights for analyzing travel behavior across the week and were adjusted for bias associated with non-response and the type of diary platform used (mobile app, online, call center). Differences in travel behavior, specifically in mode, purpose, and trip rates, are evident across days, most notably between weekdays and weekends.

**TABLE 3: SUMMARY OF HOUSEHOLD WEIGHTS BY DAY-OF-WEEK**

| Day | N | Min. | Mean | Median | Max. |
|---|---|---|---|---|---|
| Monday | 7,173 | 2.62 | 393.25 | 197.41 | 2,573.39 |
| Tuesday | 8,698 | 2.18 | 323.56 | 167.50 | 2,087.50 |
| Wednesday | 8,736 | 2.20 | 322.30 | 165.65 | 2,044.43 |
| Thursday | 8,344 | 2.29 | 337.69 | 170.61 | 2,172.42 |
| Friday | 5,876 | 3.14 | 480.05 | 244.29 | 3,178.12 |
| Saturday | 5,860 | 3.13 | 481.46 | 242.26 | 3,177.12 |
| Sunday | 5,836 | 3.17 | 483.66 | 243.77 | 3,183.12 |
| *Total* | 50,523 | 2.18 | 390.58 | 190.82 | 3,183.12 |

Table 4 summarizes the trip rates by day and broad trip purpose category. Most notable is that Friday and Saturday have the highest number of trips per person per day, at 4.0, while Sunday exhibits the lowest, with 3.3. Tuesday, Wednesday, and Thursday, considered "typical" weekdays, show similar trip rates, at around 3.4. Though Monday is often not considered a "typical" weekday, it also shows similar trip rates to Tue-Thu at this level of aggregation.

**TABLE 4: TRIP RATES PER PERSON BY DAY-OF-WEEK**

| DAY | MON | TUE | WED | THU | FRI | SAT | SUN |
|---|---|---|---|---|---|---|---|
| **SHOPPING OR ERRANDS** | 1.5 | 1.5 | 1.5 | 1.5 | 1.7 | 1.6 | 1.3 |
| **DINED OUT, SOCIALIZED, OR RECREATION** | 0.9 | 0.9 | 0.9 | 0.9 | 1.4 | 2.0 | 1.7 |
| **WORK OR WORK-RELATED ACTIVITY** | 0.8 | 0.8 | 0.8 | 0.8 | 0.7 | 0.3 | 0.2 |
| **SCHOOL OR SCHOOL-RELATED ACTIVITY** | 0.2 | 0.2 | 0.2 | 0.2 | 0.1 | 0 | 0 |
| **OTHER** | 0 | 0.1 | 0 | 0 | 0 | 0 | 0 |
| **TOTAL** | 3.4 | 3.4 | 3.4 | 3.5 | 4.0 | 4.0 | 3.3 |

Figure 3 illustrates variations in travel mode share by day. Car travel dominates every day of the week but peaks on weekends, whereas transit use is noticeably higher on weekdays, reflecting the role of public transportation in commuting. Walking and biking remain relatively consistent across all days.

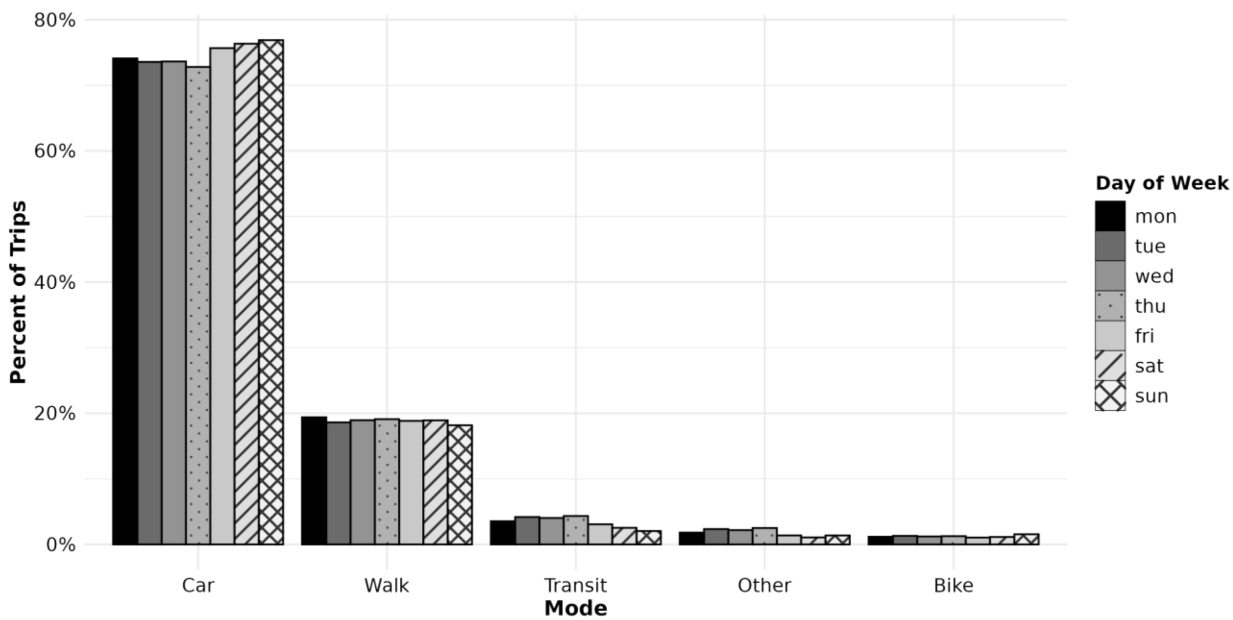



**FIGURE 3: OVERALL MODE SHARE BY DAY-OF-WEEK**

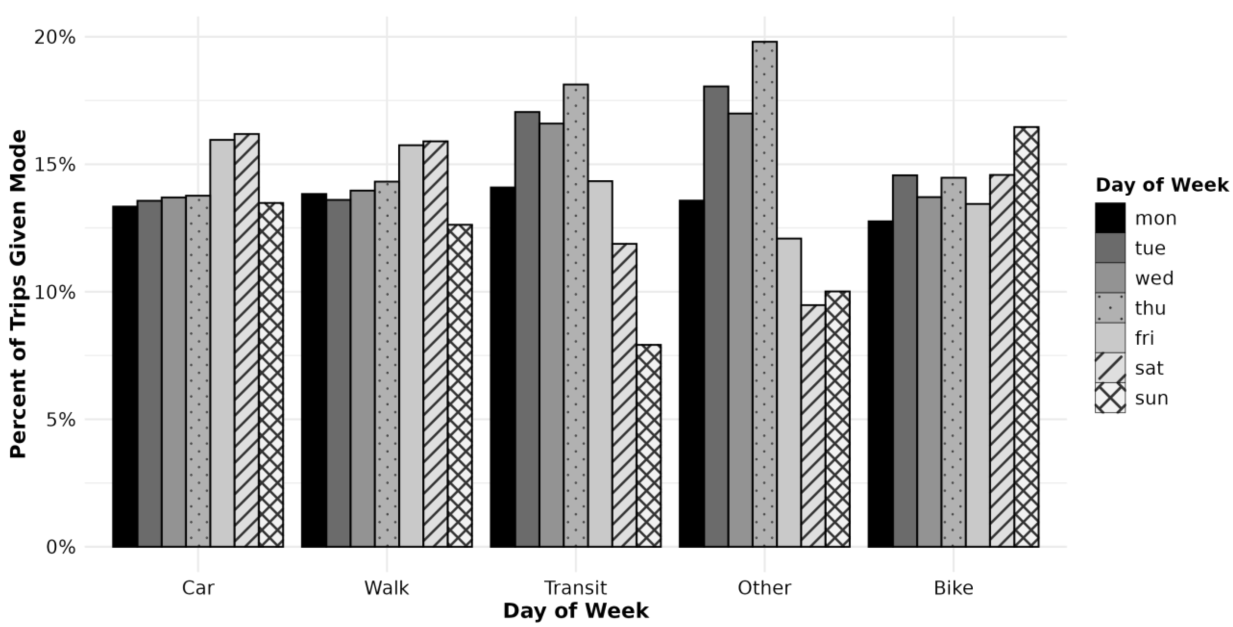



Figure 4 is a more ‘normalized’ perspective that reinforces those trends, displaying the day share of trips for each mode independently. For example, for the transit mode, the share is substantially lower on Saturdays and Sundays compared to the rest of the week, as expected.

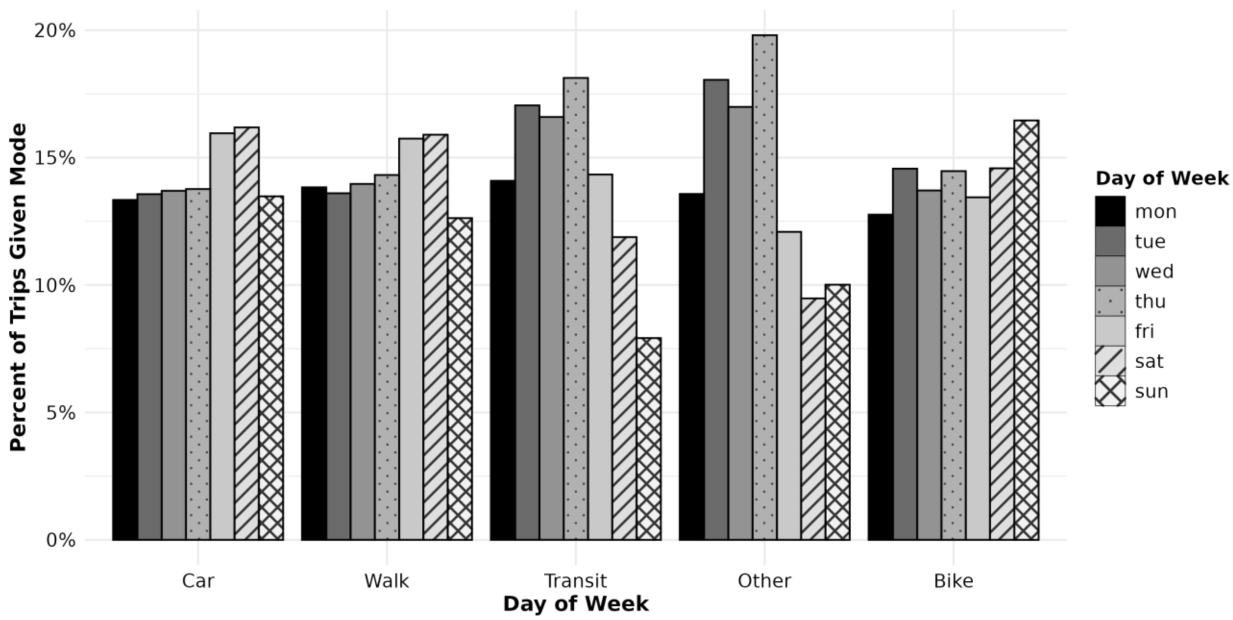



**FIGURE 4: MODE SHARE BY DAY-OF-WEEK**

Figure 5 shows that "shopping or errands" trip purposes dominate weekday travel, recognizing that the overall population includes both workers and non-workers; and discretionary dining, social, and recreation trip purposes are the most common on weekends. Mandatory work and school trips show the biggest shifts between weekdays and weekends, as expected. Interestingly, shopping and errands tapers off on weekends, indicating that people might piggy-back those other obligations with mandatory travel during the week or need to run errands on weekdays based on the service hours available (e.g., medical appointments, banks, post offices), reserving weekends for more discretionary travel.

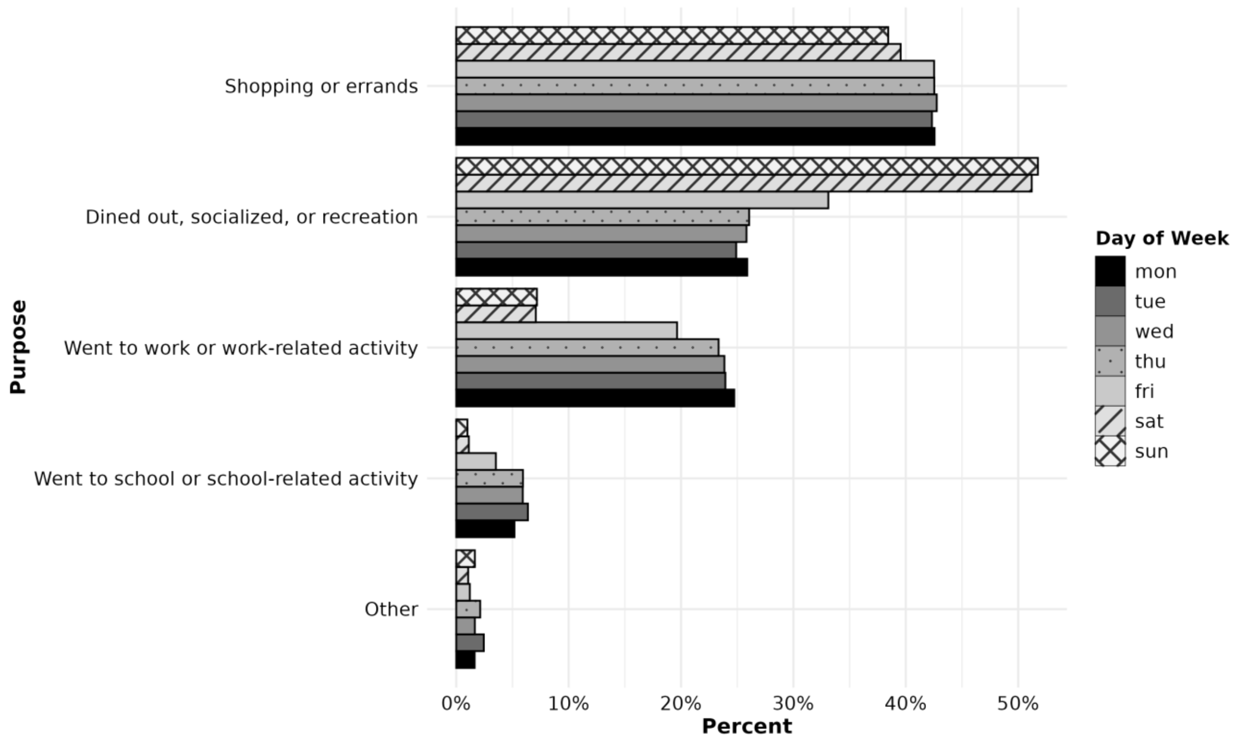



**FIGURE 5: TRIP DISTRIBUTION BY PURPOSE BY DAY-OF-WEEK**

Figure 6 and Figure 7 show the distribution of workday types by day for full-time and part-time workers, respectively. It can be observed that the proportion of full-time workers that commute to work decreases significantly on Friday while remaining steady throughout the rest of the weekdays. The drop in commuting trips on Friday occurs alongside an increase in teleworking. The proportion of full-time workers who did not work on Fridays (e.g., vacation) is also higher than on other weekdays. The share of teleworking only on Mondays is higher than those on Tuesdays and Thursdays, indicating differences in working arrangements and travel patterns among the weekdays. For part-time workers, the share of workers that only commuted to work is similar across all weekdays, but the portion that both commuted and teleworked on the same day is lower on Fridays through Sundays compared to the rest of the weekdays. For both full-time and part-time workers, the share of workers who work on Saturdays and Sundays are noticeably different, suggesting that travel behaviors are not the same on the two weekend days.

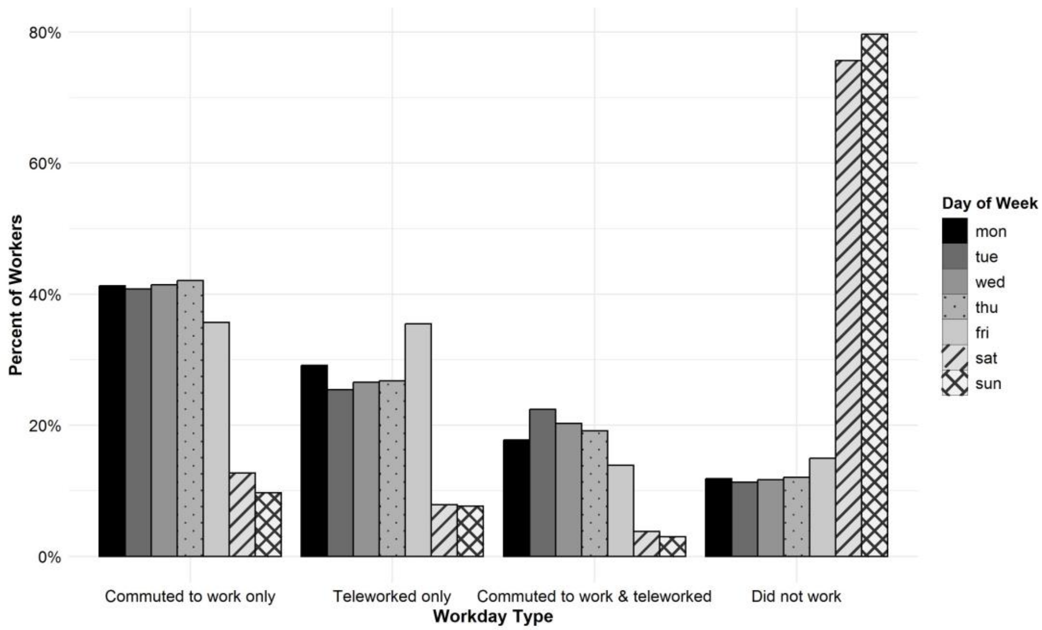



**FIGURE 6: FULL-TIME WORKER WORKDAY TYPE BY DAY-OF-WEEK**

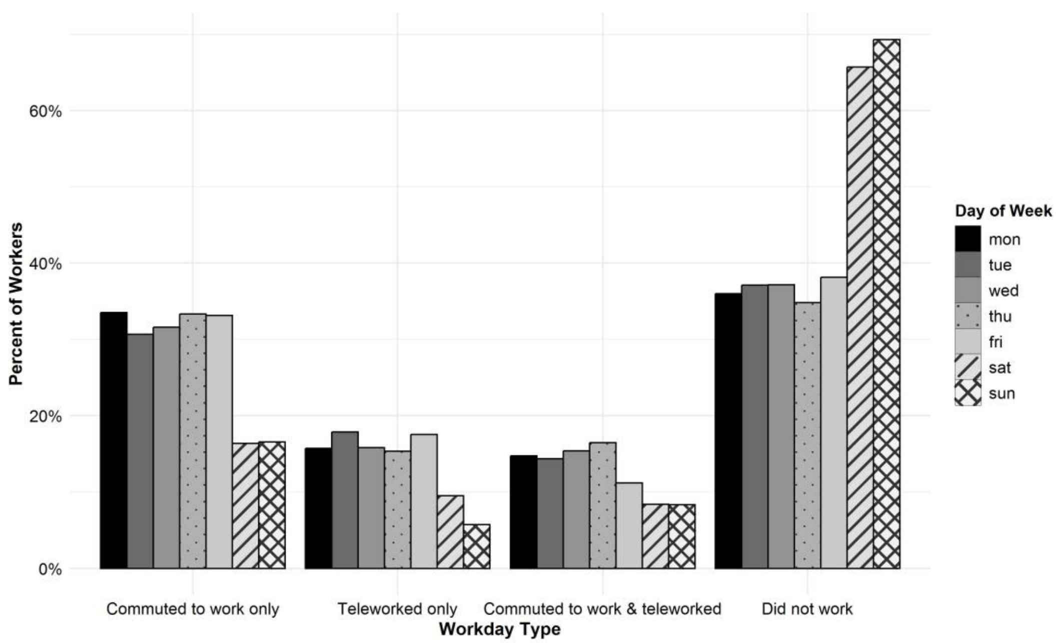



**FIGURE 7: PART-TIME WORKER WORKDAY TYPE BY DAY-OF-WEEK**

The departure times in Figure 8 and Figure 9 illustrate the distribution of departure times by day and purpose. Weekdays exhibit the classic bi-modal departure pattern associated with peak commuting periods, with Friday showing a flatter but longer afternoon peak period. Weekends present a flatter, more unimodal distribution centered around late morning and early afternoon trips. This reflects both the shift in trip purpose and the more flexible nature of weekend travel.

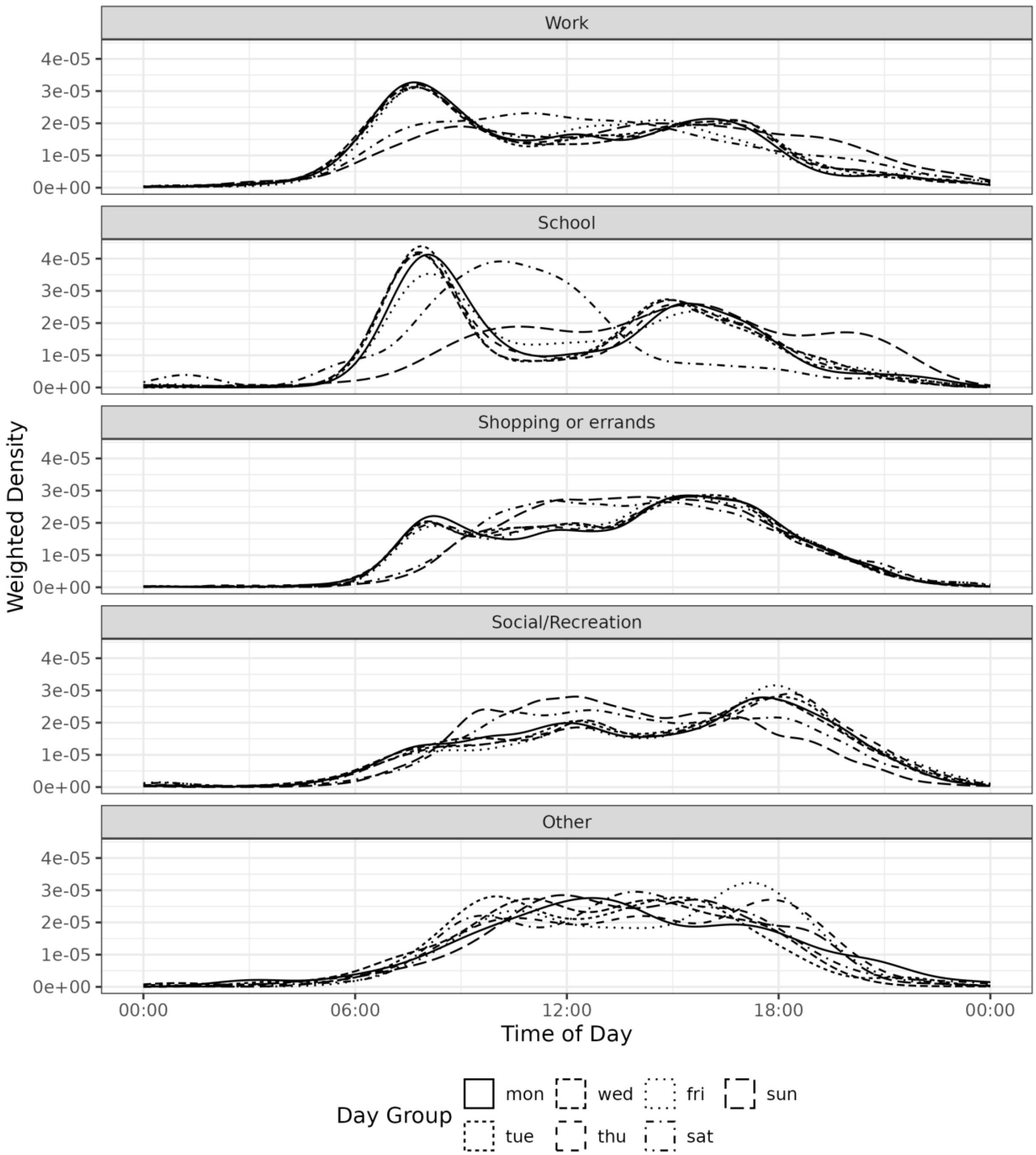
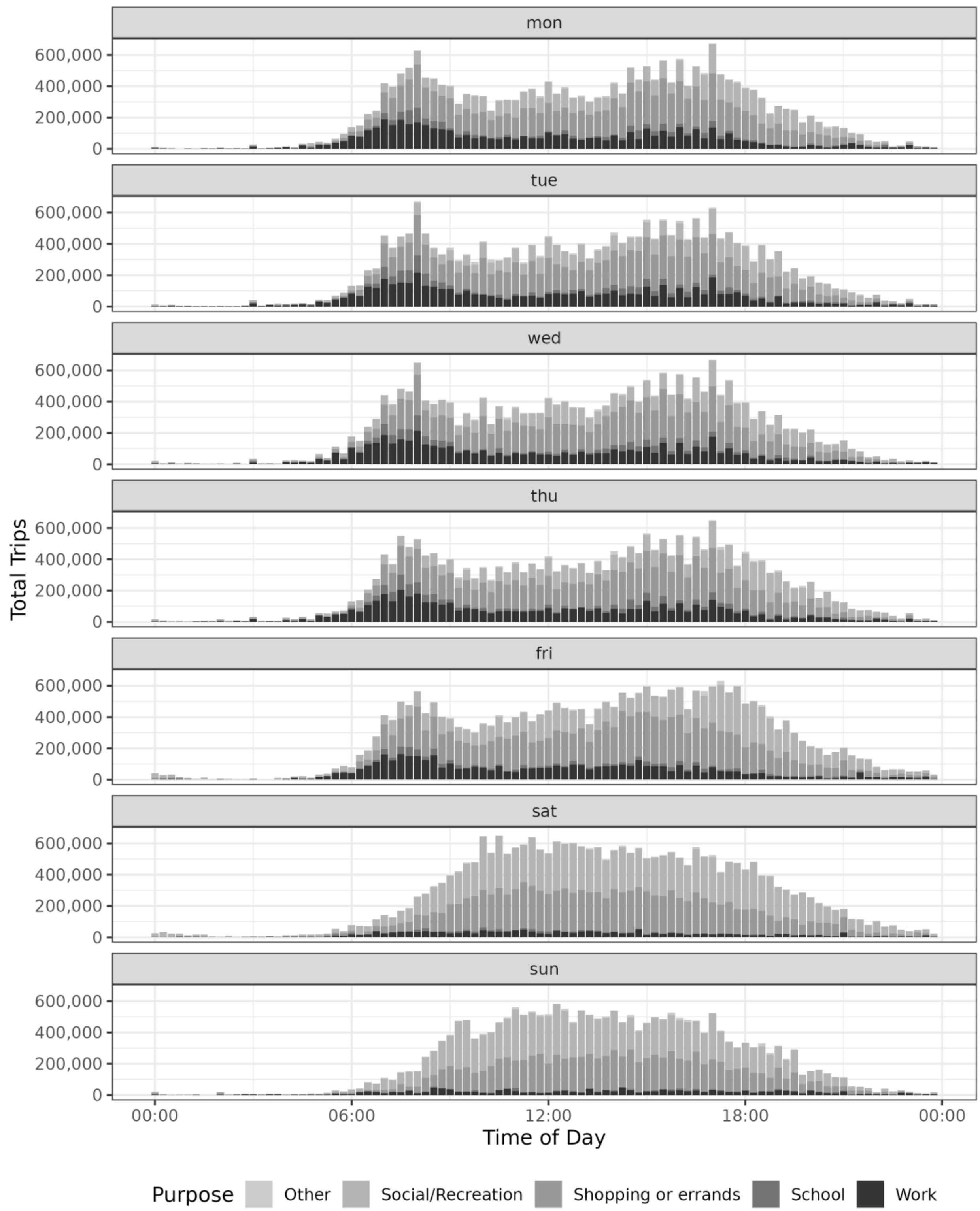



**FIGURE 8: DEPARTURE TIME DISTRIBUTION BY DAY-OF-WEEK AND PURPOSE, DENSITY PLOT**




1

2 **FIGURE 9: DEPARTURE TIME DISTRIBUTION BY DAY-OF-WEEK AND PURPOSE,**
3 **ABSOLUTE MAGNITUDE**

4

Figure 10 and Figure 11 highlight the relative change in trip rates by mode and purpose, respectively. Auto trip rates increase on Friday and Saturday, largely driven by the higher discretionary trip rates on these days, as shown in Table 4. Transit, work, and school trip rates decrease on weekends, consistent with previous findings. Notably, the rise in social and recreational travel on Friday through Sunday further supports the need for day-of-week-sensitive weighting and analysis. Together, these figures underscore the importance of capturing intra-week variation in travel behavior, demonstrating that while aggregate trip rates differ modestly, the nature, purpose, and timing of travel vary meaningfully across the week.

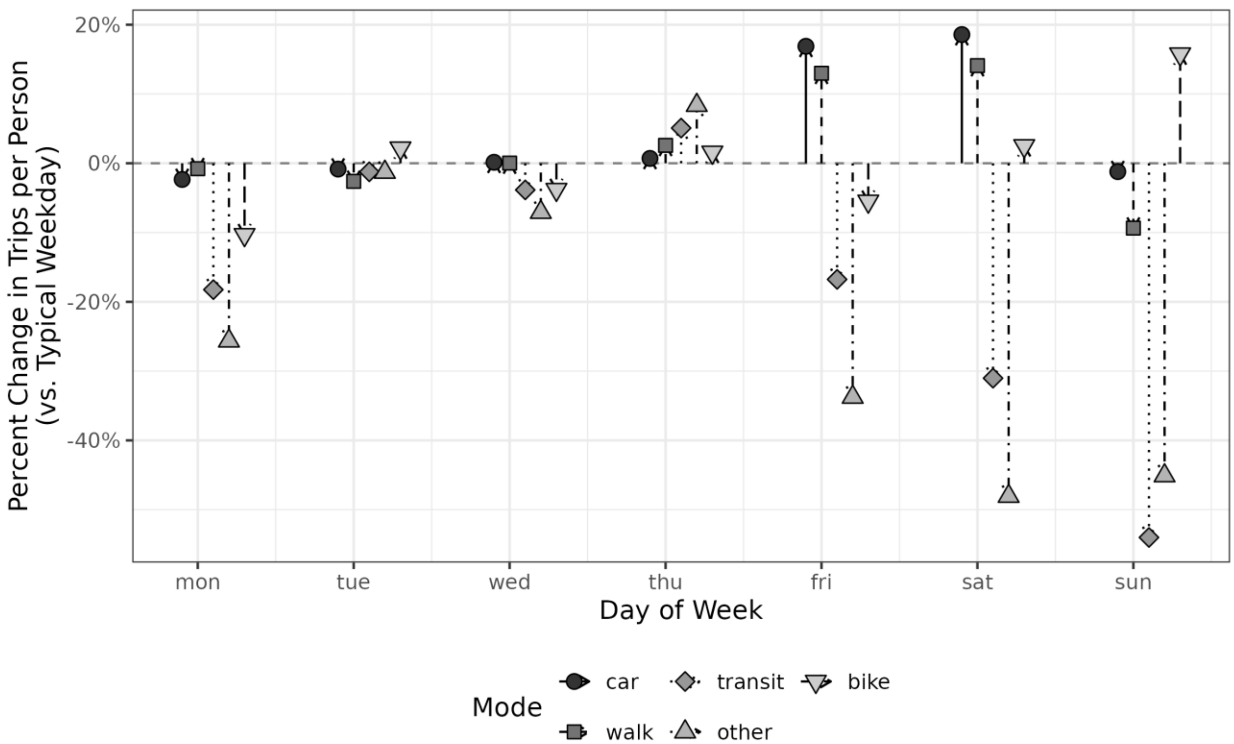



**FIGURE 10: CHANGE IN TRIP RATES BY MODE TYPE AND DAY-OF-WEEK**

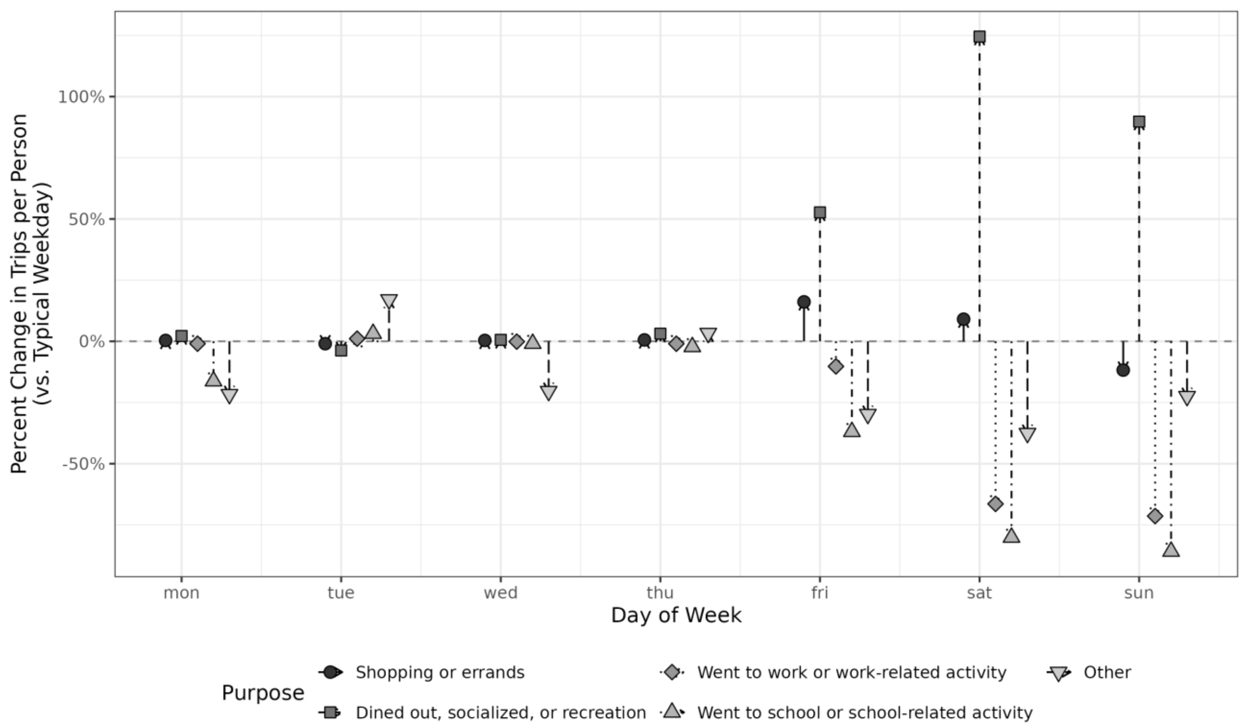



**FIGURE 11: CHANGE IN TRIP RATE BY PURPOSE AND DAY-OF-WEEK**

## DISCUSSION

The results of day-of-week travel behaviors are largely unsurprising and show that mid-week travel is dominated by mandatory trips and weekends by discretionary travel. However, the overall magnitude of trips is not substantially less, merely different, reinforcing the need for day-of-week consideration in travel models. To date, most travel models only model for a "typical weekday", which not only results in the discarding a substantial portion of HTS data but also discounts a large portion of households' weekly travel behavior.

Historically, data availability has been a limiting factor in conducting a more granular day-of-week weighting but with ever growing "big" data sources and multi-day mobile-based collection platforms, this issue is gradually being alleviated. The integrated day-of-week weighting methodology seeks to leverage these growing data sources and to facilitate a more efficient day-of-week weighting methodology.

The integrated day-of-week weighting method provides the following benefits over standard weekday weighting:

- More precise estimation of day-of-week effects and travel behavior, allowing comparisons across days of the week on travel patterns and choices such as travel mode, travel purpose, departure time, and telecommuting patterns, etc.
- Temporal alignment with external population controls,
- Reduced bias compared to approaches that ignore days of the week or apply a single set of weights to all days.
- Flexibility to easily introduce generic and day-specific control targets to improve fit to demographic targets and trip-level targets.

However, it does not fully correct for all possible biases, for example, certain days of the week may have only smartphone-based data, while others include both smartphone and diary-based data. In addition, on days with respondents from all survey platforms, non-smartphone respondents, who report only one day of travel, are under-represented in day-of-week weighting because each household day is treated as a separate household record for smartphone respondents reporting multiple days of travel. While the weighting process adjusts for differences in day-pattern types and trip rates (especially in diary-based data), as well as for socio-demographic non-response, some bias may remain due to incomplete or inconsistent data sources on certain days.

## CONCLUSIONS

This paper provides an overview of the integrated day-of-week weighting approach to generate day-specific weights and some preliminary results. The initial analysis confirms our hypothesis that travel patterns can be substantially different throughout the week. Potential enhancements include adding day-of-week targets such as transit boardings and traffic counts to control and weight the data to match observed travel data. The availability of weighted data for all seven days of the week provides many potential use cases. Use cases as travel demand modeling and planning for weekend travel with different peaks and demand generators from traditional weekdays or for large-scale events with more accurate assumptions on background traffic. Moreover, day-of-week travel is critical to understanding the impact of network capacity changes such transit schedules or road closures on different days and different times of the day, in addition to more accurate analysis of vehicle miles traveled and emission reduction that is traditionally based on a typical weekday.

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## AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: conception and design: Nicholas Fournier; data collection by Resource Systems Group Inc. under contract by MassDOT; analysis and interpretation of results: Teddy Lin, Edna Aguilar, and Nicholas Fournier; All authors contributed to the manuscript preparation, reviewed the results, and approved the final version.

## DECLARATION OF CONFLICTING INTERESTS

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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