TRAVEL DEMAND CHARACTERIZATION FOR A LARGE URBAN TRANSIT INFRASTRUCTURE USING SMART CARD TRANSACTION DATA

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ABSTRACT

This paper demonstrates the use of smart card transaction data to analyze the regularity of demand, which is an important aspect in travel demand characterization. The proposed methodology uses basic statistics to examine and quantify the regularity of demand based on three dimensions: time, space and user subgroups. Results show that the level of regularity varies according to the season, day of the week, station and fare type and category. It is therefore imperative to differentiate the total demand into various components in order to appreciate the different demand patterns. Given this additional knowledge, transit agencies would be able to adapt their service and fare structure to suit the needs of existing and potential users.

Keywords: demand, regularity, variability, smart card, public transit

INTRODUCTION

Travel demand is tightly linked to the activities of the population and is known to manifest day-to-day and seasonal variations due to changes in activity patterns. In the North American context, transit service is usually organized around the concept of a “typical” day due to operational constraints or the lack of supporting information. Data from periodic travel surveys and passenger counts, based on the expansion of a small sample, are seldom detailed and precise enough to be used to differentiate and characterize the various components of the total demand.

As a consequence, the effects of the variation of demand on transit services and fare revenues are not thoroughly explored by transit agencies. In addition, due to the uncertainties in transit funding and the pressure to offer competitive transit service, transit agencies also need to better allocate resources to resolve operational challenges, such as overcrowding in some cases and excess capacity in others.

The emergence of passive data collection technologies, such as the smart card automatic fare collection, the development of micro-simulation platforms along with other information technologies provide transit agencies a novel analytical tool. Smart card transaction records are generated when a fare is validated. Typically, they represent a continuous source of data capturing most of the entries into the transit network. Depending on the configuration of the fare system, data containing partial or complete original-destination information are gathered, along with precise time stamp and some operational details. They allow the characterization of the various components of the demand, by detecting subtle variation at the day-to-day scale as well as the structural variation at the seasonal level. Micro-simulation model allows the use of fine-grain data such as modified GTFS data and smart card data for a schedule-based transit assignment. Model outputs contain both spatially and temporally detailed indicators on each object in the transit infrastructure. It allows the assessment of the effects linked to various components of the demand on a transit network. The policy implication is enormous as the tool can be used to improve service planning, monitor service quality and innovate on fare structure, which are all important matters of concern in the transit industry.

The objective of this paper is to examine and quantify the extent to which travel demand follows a regular pattern over multiple time intervals at the subgroup level using a database of smart card transactions and basic statistical tools. This contributes to the effort of characterizing travel demand for a large urban transit infrastructure.

DATA AND METHODOLOGY

Related works

Previous research has established the value of transit smart card on for measuring and understanding variability in demand. Bryan and Blythe (2007) recognize the additional knowledge on transit users that smart card data provide as well as its potential benefits to service planning. Morency *et al.* (2007) used the object-oriented approach and data-mining techniques to measure spatial and temporal variability of transit use with smart card data. Chu and Chapleau (2010) propose the use of anchor to characterize multi-day trip pattern at the individual level. Lee and Hickman (2011) analyse the travel patterns of regular users over several days using smart card data. Chu and Chapleau (2013) summarize multi-day travel pattern at the individual level and look at its variation in time and space.

On the other hand, the development of micro-simulation models allows dynamic and agent-level transit assignment. Spurr *et al.* (2012) demonstrate the assignment of a demand derived from smart card data into a transit network and produce highly-detailed operational indicators on various objects in the network.

Data

Smart card data provide a continuous stream of observations at the card level, giving analysts the ability to examine multi-day travel patterns at a disaggregate level (Chu and Chapleau, 2013). In order to examine the day-to-day and seasonal variations in demand, smart card validation data are taken from a large-scale transit network, covering one week from two different times of the year. Table 1 summarizes the smart card data used in the study.

Table 1 Summary of data

	Week 1 (August)	Week 2 (November)
Temporal coverage	Week of August 5, 2012 Sunday August 5 05:00 to Sunday August 12 02:00	Week of November 4, 2012 Sunday November 4 05:00 to Sunday November 11 02:00
Mode coverage	Metro only	Metro only
Representation	A typical week in the summer season	A typical week in the autumn season
Number of transactions	3 913 162	5 351 517

Transit agencies in the Montréal region share a common smart card automatic fare collection system. Each entry into the metro system (tap-in) generates a single transaction record which contains the fare equipment identification, fare card identification, date and time of the transaction, route and run data (which are less relevant for the metro system) and fare product used. Data dictionaries are necessary to interpret these data. Exit transaction (tap-out) is not available.

Methodology

Regularity, in this paper, is used to describe the recurrent patterns in space and time. It is an important aspect in travel demand characterization. Variability, in contrast, is used to describe the absence of recurrent patterns in space and time. The terms are sometimes used interchangeably. However, the concept of regularity is more interesting for transit planning as regular transit service is designed around recurring demand. The aim of the proposed methodology is to demonstrate the ability to identify variability in a seemingly regular patterns and regularity within variability. Smart card data offer the fine granularity required to examine this question.

Regularity of demand is analyzed based on three dimensions: time, space and transit user subgroups. Because of the disaggregate nature and the volume of smart card data, in order to examine data in a meaningful and practical way, data need to be aggregated and classified. Three approaches brought forward in previous works (Chu, 2010), namely the totally disaggregate approach, informational approach and the object-oriented approach, are nonetheless central to smart card data analysis.

The analysis of temporal regularity requires the treatment of entry time at a detailed resolution. Although transaction times are recorded to the nearest second, they are aggregated into 10-minute or 1-hour slices. Two temporal scales of regularity are scrutinized:

- Seasonal: comparing two weeks from different months with different supposedly activity patterns;
- Weekly: comparing weekdays within the same week.

The weeks are chosen to illustrate recurrent variations in the demand and not variations due to holidays.

Ideally, the analysis of spatial regularity requires the transformation of entries at the smart card reader level into a trip or an itinerary. That would require a data processing technique that associates the entry-only transaction records with a destination (see Trépanier *et al.*, 2007; Spurr *et al.*, 2012). For simplicity, only the metro network and the entry stations are considered.

Transit usage (demand) can be studied as a whole, as in the case of aggregate data provided by turnstile count or automated passenger counting (AFC). Two properties of smart card data are useful in differentiate the total demand into various components, which may or may not manifest different levels of regularity:

- In many cases, because of the durability of the fare medium, long-term transaction history can be associated with a card based on a unique card number. Therefore, the travel pattern of an individual card can be summarized and provides an additional dimension for analysis.
- Each entry is associated with a fare or a fare product, depending on the fare system in question, which provides some additional information on the transit user or the nature of the demand.

Assuming the rational objective of transit users is to minimize the monetary cost of travel, the fare type (such as a monthly pass or a per-ride ticket) implicitly reveals the frequency of transit use of the cardholder and the fare category (such as regular fare or reduced fare) to some extent reveals the socio-demographic status on the cardholder. Therefore, the fare product can be used as a proxy, or a “condensed” version, of the historic travel pattern at the individual level.

Fare product is also a natural classification to look at the regularity of demand by subgroup. One approach to examine regularity is to classify users based on some measures of travel patterns and is often done using data-mining techniques. Alternatively, one can also study regularity of subgroup sharing the same attribute, such as the choice of fare product.

The fare system in Montréal, Canada is based on fare products. They are classified into seven subgroups based on the fare category and fare type. Table 2 summarizes the relative share of each class for both sets of data. A pass allows unlimited entries into the metro system; a per ride ticket allows only one entry. Reduced fares are available to children, students and seniors.

Table 2 Proportion of entries by fare category and fare type

Fare category	Fare type	Week 1 (August)	Week 2 (November)
Regular fares	Annual/monthly pass	48.3%	49.9%
	Daily/weekly pass	11.2%	6.3%
	Per ride ticket	19.6%	15.8%
Subtotal		***79.1%***	***72.0%***
Reduced fares	Annual/monthly pass	16.4%	24.8%
	Daily/weekly pass	0.3%	0.2%
	Per ride ticket	2.7%	2.0%
Subtotal		***19.4%***	***27.0%***
Others		***1.5%***	***1.0%***

Figure 1 gives a general idea on how the entries and fare products are distributed in time. It shows the number of entries into the metro in a weekday in November by ten-minute slice.

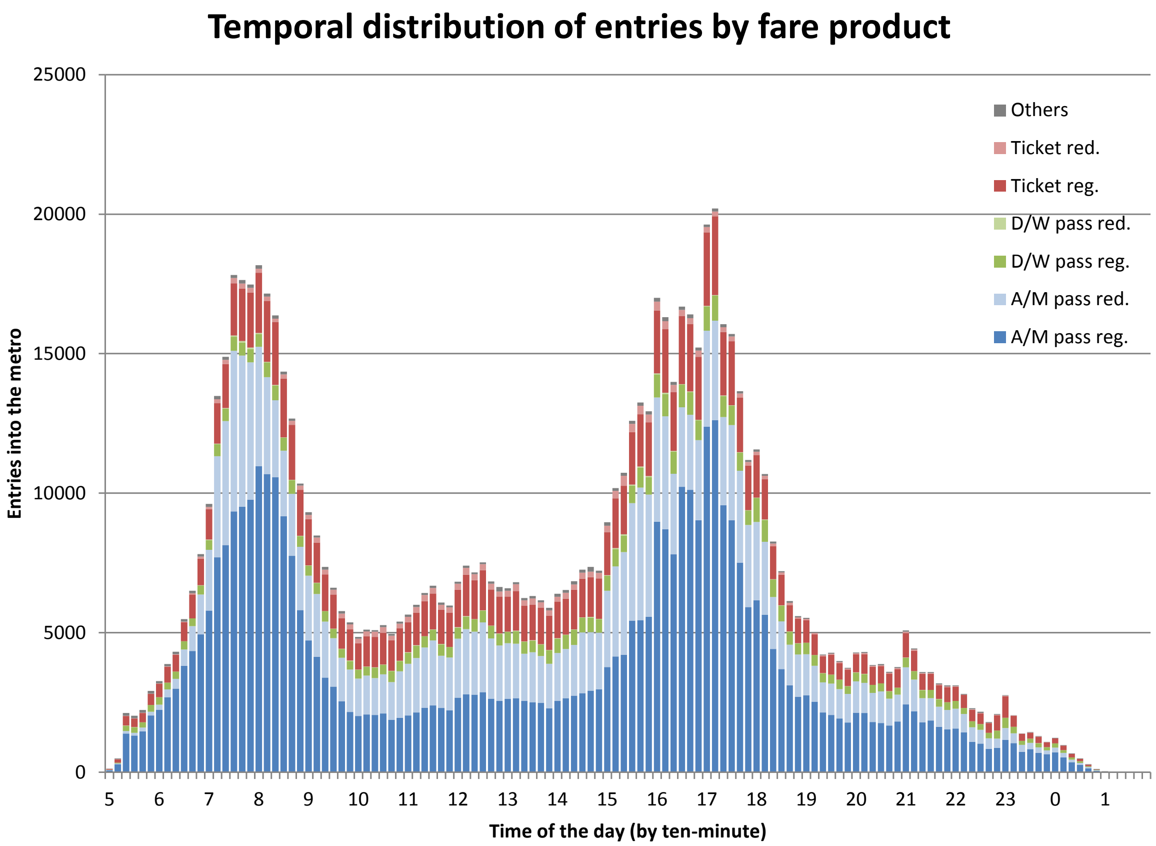


Figure 1 Temporal distribution of entries by fare product in one day of week 2 (November).

Measure of regularity

As a descriptive study, this paper tries to measure regularity using basic statistical tools, such as normalized difference, coefficient of variation and linear regression. The results are interpreted and explained with common knowledge.

RESULTS

Seasonal regularity

The obvious observations between the two sets of data are the difference in magnitude of the demand (Table 1) and in the composition of fare products (Table 2). Since most students are in summer holidays in early August, it is logical that the proportion of entries with reduced fares is lower in August. In additional, fewer trips made are by education-related workers and workers having summer holidays.

In fact, the hour-by-hour global demand in August is a very good predictor of the demand in November as illustrated by the linear regression model (Figure 2). One might conclude that the hourly distribution of demand is quite similar in both cases. However, if one differentiates the demand by fare product, the conclusion is somewhat different (Figure 3). Users with regular fare annual/monthly (A/M) pass display a remarkable regularity. Reduced fare holders are less consistent than their regular fare counterparts. Regular fare ticket users display less variability compared to holders of regular fare daily/weekly (D/W) pass.

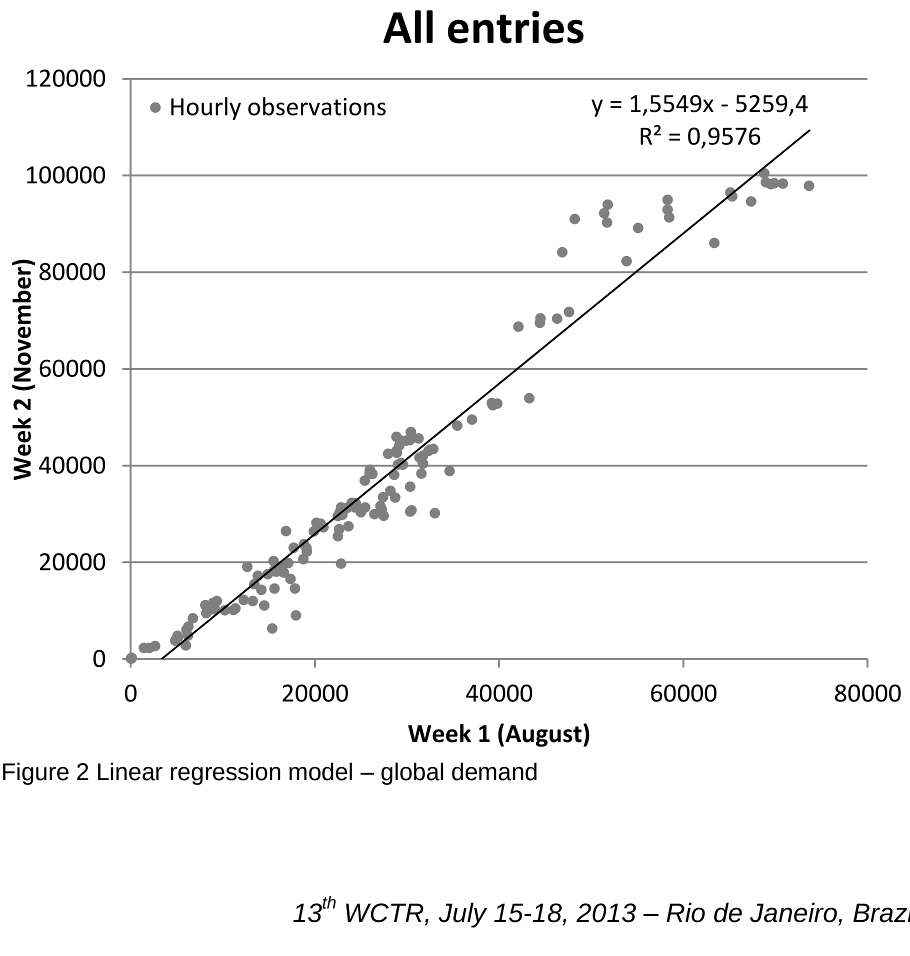


Figure 2 Linear regression model – global demand

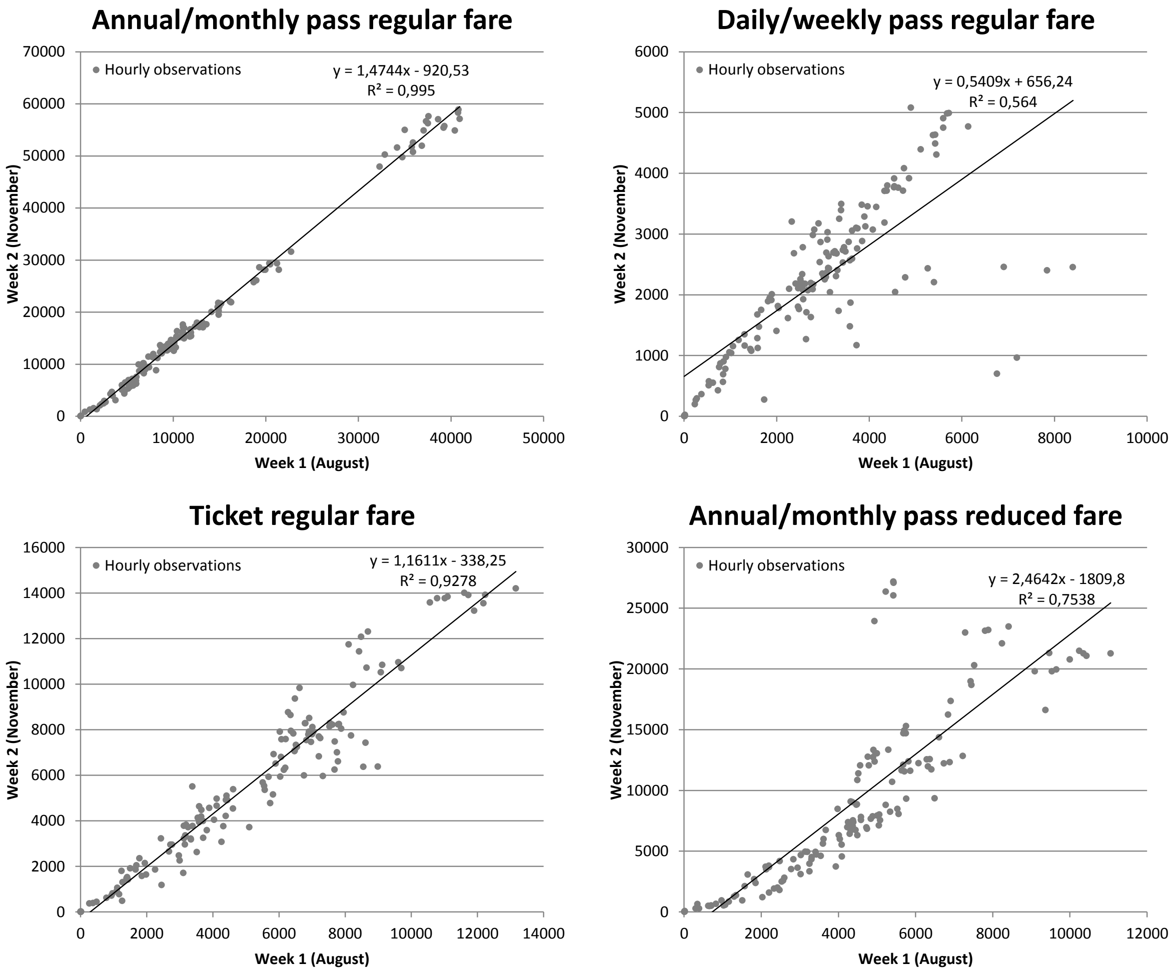


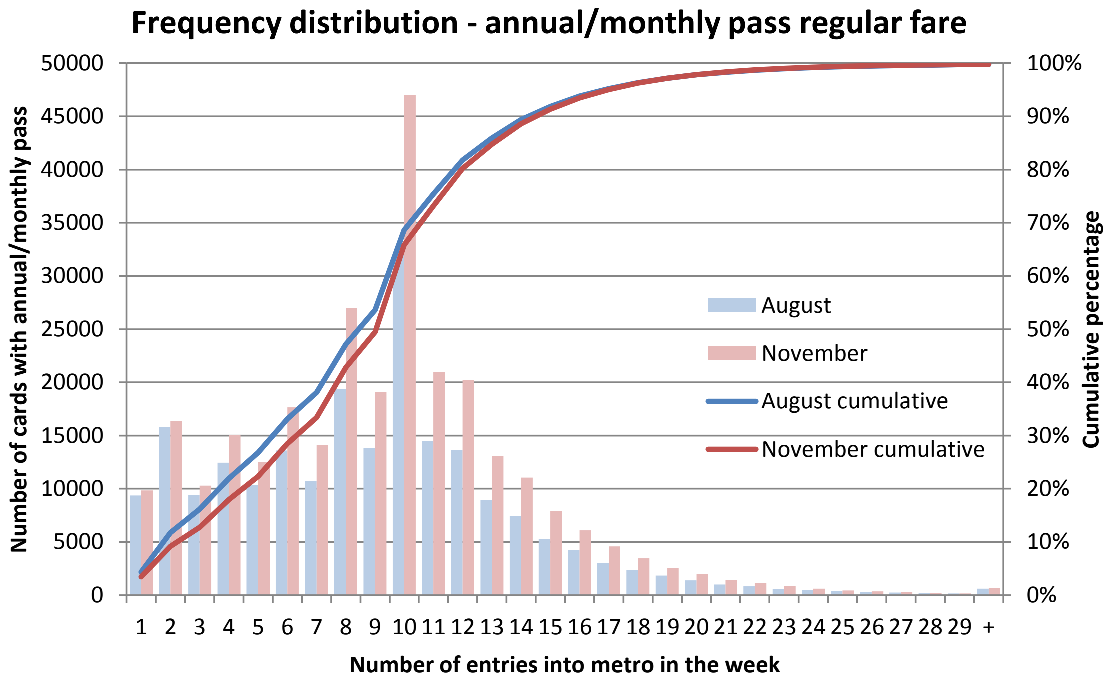
Figure 3 Linear regression models – demand differentiated by fare type and fare category

It can be hypothesized that regular fare annual/monthly pass holders are adults who primarily commute for work trips. As opposed to school and leisure trips, they are less likely to be affected by seasonality (change in weather and activity schedule). Reduced fare annual/monthly pass holders are mostly students or seniors who travel for study and discretionary purposes. It is logical that the ridership in summer, when many students are having holidays, is a less powerful predictor of ridership in autumn. Regular fare daily/weekly pass holders are probably attracted to the product for intensive transit use within a short time. Therefore, by definition, their trips are more irregular in nature. The regularity exhibited by regular fare ticket users suggests there is a distinctive pattern at the aggregate level even for occasional trips.

An interesting exercise is to analyze the outliers in the regression models. That would reveal the time when the users drift away from regular pattern. Understanding the reason behind the variability can lead to the identification of hard-to-detect pattern.

Another way to look at regularity across season is to compare usage rate of a fare product. Figure 4 shows the frequency distribution of a fare product based on the number of entries into the metro in the week:

- The form of the frequency distribution is different between the regular fare (top) and reduced fare (bottom) annual/monthly pass. The former has a distinction peak at ten entries in the week for both seasons. There is a higher proportion of reduced fare pass that has a low usage rate.
- The usage rate varies between the seasons but depends on the type of fare product. Both regular and reduced fare passes shows higher usage rate in November compared to August. However, the variation is more important for the reduced fare pass. It is revealed by the form of cumulative percentage curves of August and November and the area between them.



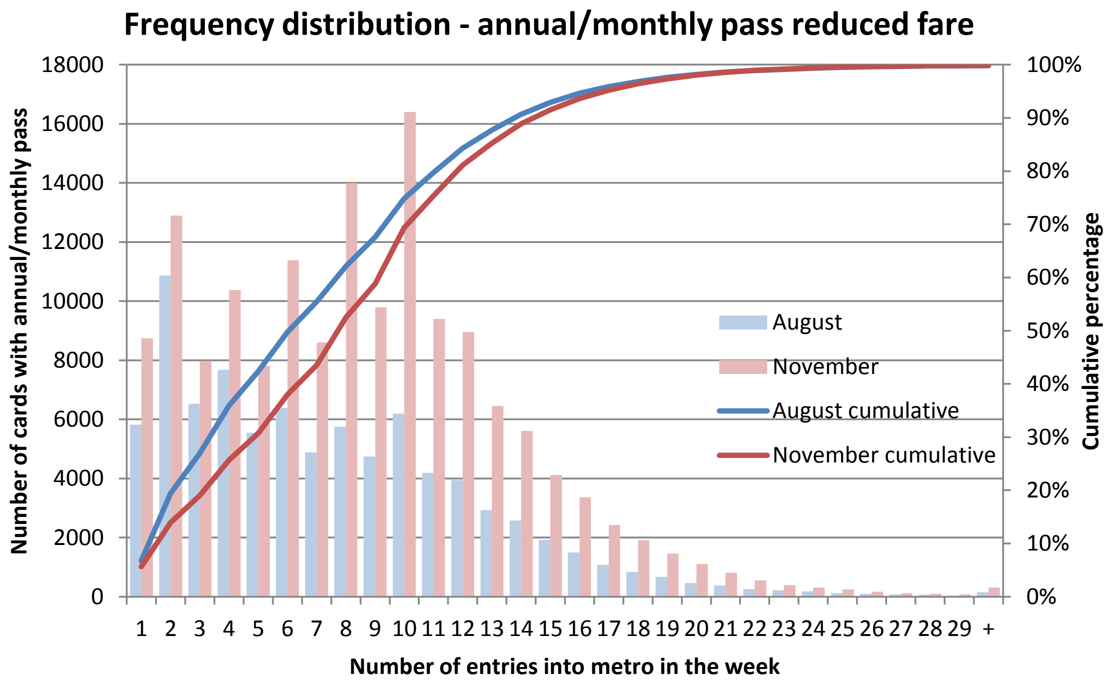


Figure 4 Frequency distribution of fare product based on the number of entries

Weekday regularity

A concept often used in transit planning is an "average weekday". This assumes demand is constant and the service is supplied the same way throughout the weekdays. The reason behind this assumption may not be based on facts but rather based on operational constraints. Nonetheless, with funding cut, some operators examine the possibility of introducing a Friday timetable (Lu and Reddy, 2012).

The following colour-formatted table (Figure 5) shows the normalized difference of the number of entries by regular fare annual/monthly cardholders. The reddish cells indicate that the number of entries is low compared to the mean while the colour green indicates that the number is somewhat higher than mean. The results confirm some well-known facts but also provide some new insights.

		Day						Day				
Time of the day (hour)	**Average number of entries**	20120806 Monday	20120807 Tuesday	20120808 Wednesday	20120809 Thursday	20120810 Friday	**Average number of entries**	20121106 Monday	20121107 Tuesday	20121108 Wednesday	20121109 Thursday	20121110 Friday
5	5 356	-0,05	0,03	0,05	0,01	-0,04	6 668	-0,01	0,03	0,01	0,03	-0,05
6	15 713	-0,05	0,04	0,03	0,03	-0,05	21 417	-0,02	0,02	0,02	0,03	-0,05
7	34 557	-0,05	0,04	0,04	0,04	-0,07	50 632	-0,01	0,04	0,00	0,02	-0,05
8	36 327	-0,04	0,03	0,03	0,03	-0,06	55 410	-0,01	0,02	0,04	0,02	-0,07
9	14 782	-0,04	0,01	0,01	0,03	0,00	21 214	-0,06	0,03	0,02	0,02	-0,01
10	9 220	-0,05	-0,01	0,02	0,03	0,02	12 619	-0,04	0,00	0,00	0,01	0,02
11	9 633	-0,04	-0,02	-0,01	0,02	0,05	13 956	-0,04	-0,01	0,00	0,00	0,04
12	11 395	-0,09	-0,03	-0,03	-0,02	0,16	17 170	-0,05	0,00	0,03	-0,02	0,04
13	11 416	-0,07	-0,02	-0,04	-0,03	0,16	16 016	-0,06	-0,01	0,01	0,00	0,06
14	12 915	-0,08	-0,04	-0,02	-0,01	0,16	17 655	-0,05	-0,03	-0,01	-0,01	0,10
15	20 837	-0,07	-0,02	-0,02	0,02	0,09	29 609	-0,03	-0,01	-0,02	-0,01	0,07
16	38 578	-0,04	0,02	0,02	0,05	-0,04	54 554	0,01	0,02	0,02	0,01	-0,05
17	39 184	-0,01	0,04	0,04	0,04	-0,11	56 207	0,01	0,05	0,04	0,02	-0,12
18	19 778	-0,05	0,01	0,00	0,08	-0,04	27 239	-0,05	0,03	0,03	0,03	-0,04
19	11 624	-0,11	-0,04	0,02	0,11	0,03	15 186	-0,13	-0,02	0,01	0,13	0,01
20	8 771	-0,11	-0,02	0,02	0,12	0,00	12 714	-0,11	-0,03	0,04	0,15	-0,05
21	8 931	-0,18	-0,02	-0,04	0,16	0,08	13 326	-0,14	0,00	0,02	0,15	-0,03
22	6 544	-0,08	0,05	-0,03	0,02	0,04	8 571	-0,20	-0,04	0,01	0,04	0,19
23	5 362	-0,11	-0,04	0,00	0,03	0,13	5 974	-0,15	-0,11	-0,05	0,05	0,26
0	2 569	-0,18	-0,02	-0,11	-0,01	0,32	2 871	-0,28	-0,15	-0,19	0,01	0,61
1	19	Not enough data					29	Not enough data				

Figure 5 Normalized difference by day and time of the day

First, ridership on Monday is lower than the mean of the week and it is true almost for all the hours of the day. The effect is especially marked during midday and late evening. This may be simply because more workers taking a day off on Mondays and fewer discretionary trips made after the weekend. Second, fewer work trips may explain the lower ridership during Friday AM peak. Third, ridership is higher on Thursday evening. This coincides with the longer retail operating hours (usually until 21:00) as well as the pay day every second week. The two patterns are present in both datasets.

The results also show patterns tied to a specific season. In August, ridership is significantly higher on Friday early afternoon and lower in the PM peak. The same pattern is present but is less pronounced in November. A possible explanation could be a half-day work schedule on Friday, which is more common during the summer months. Workers make their trips a few hours earlier compared to the rest of the week, resulting in an increase of ridership in early afternoon and decrease in the PM peak. The variation is highlighted by a yellow arrow in Figure 6.

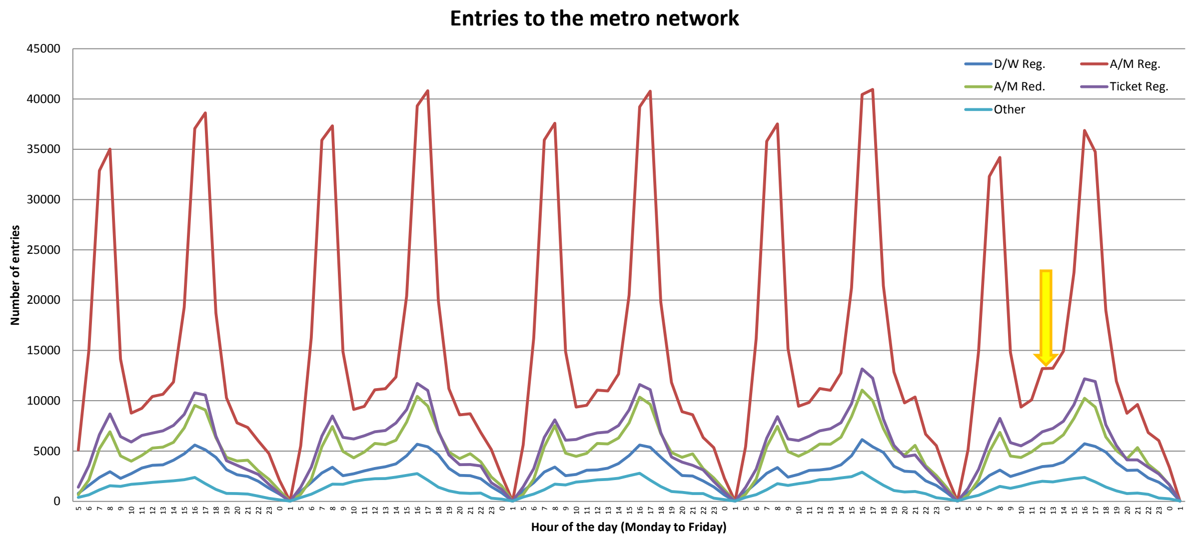


Figure 6 Entries by fare type and category on weekdays (week 1 – August)

The analysis illustrates that detailed ridership data can reveal more profound travel patterns hidden behind an aggregate ridership.

Weekday and seasonal regularity

Figure 7 shows the coefficients of variation of the hourly entries made by regular fare annual/monthly pass holders. It aims to measure the magnitude of variability of the hourly ridership across weekdays. The results summarize the information in the previous analysis and identify the time of day when the variability is high. For example, the variability during the early afternoon in August is high possibly, due to the change in work schedule of some users on Friday. The results also confirm that the effect is more important in August than in November.

The coefficients of variation can be calculated without Friday in order to assess how the ridership of Friday contributes to the indicator. In fact, by removing the data point, the coefficient drops significantly during the early afternoon and the PM peak. However, there is little effect during the AM peak and the evening, meaning that the Friday is not the major contributor to the variation of the total ridership during those periods.

Time of the day (hour)	Weekdays of August	Weekdays of August without Friday	Weekdays of November	Weekdays of November without Friday
5	0,04	0,04	0,03	0,02
6	0,04	0,04	0,04	0,02
7	0,05	0,04	0,03	0,02
8	0,04	0,03	0,04	0,02
9	0,03	0,03	0,03	0,04
10	0,03	0,03	0,03	0,03
11	0,03	0,03	0,03	0,02
12	0,09	0,03	0,04	0,03
13	0,09	0,02	0,04	0,03
14	0,09	0,03	0,06	0,02
15	0,06	0,04	0,04	0,01
16	0,04	0,04	0,03	0,01
17	0,07	0,03	0,07	0,02
18	0,05	0,06	0,04	0,04
19	0,08	0,09	0,09	0,11
20	0,08	0,09	0,10	0,11
21	0,13	0,14	0,10	0,12
22	0,06	0,06	0,14	0,12
23	0,09	0,06	0,16	0,09
0	0,19	0,09	0,36	0,15
1	Not enough data			

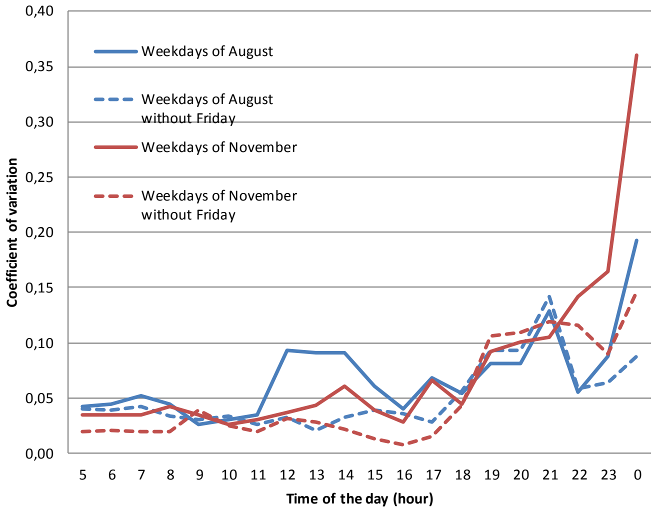


Figure 7 Coefficients of variation by time of the day for entries made by regular fare annual/monthly pass holders

Spatial regularity

Until now, the analyses focus on the regularity of the demand covering the whole network. The same analyses can be performed on the demand of individual station, or other cases, individual line. Individual station can exhibit somewhat different regularity, in terms of pattern or magnitude, compared to the whole network. Table 8 shows the normalized difference of the number of entries made by regular fare annual/monthly cardholders at two stations, McGill and Université-de-Montréal (U-de-M), in November. They can be compared to the results from the whole network in Figure 5.

Both stations are located near major universities, but within different environmental settings. McGill is located in downtown with business, retail and entertainment activities nearby whereas Université-de-Montréal is located within a residential area. The effect is revealed in their respective regularity pattern:

- Increase in ridership at McGill in Thursday evening may be attributed to retail and entertainment activities. This effect is not present at U-de-M. In contrast, the lower ridership in Monday evening at McGill may be attributed to fewer retail and entertainment activities compared to other weekdays.
- Work-related trips in Friday evening are significantly lower than the mean at U-de-M. This may be generally true for all stations. However, demand generated from retail and entertainment activities at McGill may more than compensate for the decrease in work-related trips.

		McGill						Université-de-Montréal				
Time of the day (hour)	Average number of entries	20121106 Monday	20121107 Tuesday	20121108 Wednesday	20121109 Thursday	20121110 Friday	Average number of entries	20121106 Monday	20121107 Tuesday	20121108 Wednesday	20121109 Thursday	20121110 Friday
5	9	0,30	-0,35	-0,13	-0,02	0,20	18	-0,35	0,14	0,20	0,03	-0,02
6	72	-0,03	-0,12	0,02	0,09	0,04	28	-0,03	0,04	-0,03	0,01	0,01
7	216	-0,06	0,02	0,06	-0,03	0,00	97	0,08	0,11	-0,08	-0,07	-0,04
8	333	0,00	0,00	0,04	0,03	-0,06	122	-0,08	0,00	0,03	-0,03	0,08
9	211	-0,05	0,12	0,01	-0,04	-0,03	67	-0,21	-0,02	0,07	0,01	0,15
10	273	0,00	0,02	-0,05	-0,02	0,05	126	0,15	-0,10	-0,04	-0,03	0,02
11	497	-0,05	-0,07	0,03	-0,07	0,15	230	-0,19	-0,03	-0,10	0,18	0,14
12	784	-0,10	-0,01	-0,01	-0,01	0,12	253	-0,10	0,00	0,06	-0,08	0,12
13	818	-0,07	0,02	-0,06	0,03	0,07	160	-0,19	0,07	0,07	-0,01	0,07
14	939	-0,05	-0,05	-0,02	0,00	0,12	253	-0,14	0,01	-0,07	0,03	0,17
15	2 067	-0,04	-0,03	-0,04	-0,03	0,14	701	-0,02	0,12	0,03	-0,08	-0,05
16	5 140	0,01	0,02	0,00	-0,01	-0,03	1 215	0,00	0,00	0,04	0,00	-0,05
17	5 498	0,03	0,06	0,02	-0,02	-0,09	854	0,04	0,00	0,07	0,04	-0,16
18	2 456	-0,04	0,00	0,02	0,07	-0,05	492	0,05	0,17	0,08	0,03	-0,34
19	1 263	-0,17	-0,09	-0,03	0,20	0,10	316	0,16	0,09	0,03	0,10	-0,37
20	979	-0,21	-0,13	-0,04	0,29	0,09	247	0,07	0,09	0,20	0,09	-0,44
21	958	-0,28	-0,11	-0,01	0,31	0,09	438	0,12	0,33	0,11	0,00	-0,55
22	314	-0,33	-0,06	-0,03	0,15	0,27	183	-0,12	0,37	0,12	0,18	-0,54
23	243	-0,13	-0,13	-0,08	0,08	0,26	98	0,00	-0,04	0,18	0,01	-0,14
0	136	-0,12	-0,03	-0,07	-0,16	0,38	20	-0,23	-0,08	-0,18	0,58	-0,08
1	0	Not enough data					0	Not enough data				

Figure 8 Normalized difference by day, time of the day and station

IMPLICATIONS FOR RESEARCH AND POLICY

Research and policy

In the North American context, due to uncertainties in transit funding and the pressure to offer competitive transit service, transit agencies need better allocation of resources to resolve operational challenges, such as overcrowding in some cases and excess capacity in others. On the other hand, transit agencies also reflect on new fare structures that can increase ridership, maximize passenger revenue, suit the needs of the users as well as maintain social equity.

However, transit service is usually organized around the concept of a “typical” day due to the lack of supporting information or operational constraints. The effects of the variation of demand on transit services and fare revenues are not thoroughly explored by transit agencies, which may lead to less-than-optimal use of resource in terms of service and range of fare products offered.

With a large dataset from Montréal, this research has shown that smart card data can effectively be used to characterize demand in terms of regularity. Using basic statistics, seasonal and weekday regular is described. Variability in demand is often masked at the aggregate level and becomes more apparent when working at a finer level of granularity. By including user (fare product) subgroups and spatial reference in the analyses, it is possible to differentiate pattern and quantify magnitude of the regularity in demand.

The immediate implication is that smart card data can provide supporting information for examining alternative service structures. The additional knowledge on the regularity of demand can be incorporated by an operator into service planning in order to tailor the services more precisely to the observed demand and to devise incentives to manage demand in case of overcrowding. Alternative fare structures can also incorporate the same knowledge in order to develop loyalty among existing users and attract potential new customers.

As passive data collection becoming the norm for transit agencies, lessons are learned on how to handle and utilize massive datasets. Many of them have multi-day property which is previously not available.

Further research

It would be necessary to continue the methodological development that allows the characterization of multi-day demand, but at the more individual level. Since the latest micro-simulation allows the preservation of individual characteristics, the logical next step would be to integrate these individual-level characteristics into a transit assignment model.

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