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Abstract. Bikesharing is an active mode of transportation where members can use bikes located at stations to perform trips within cities. The Montreal, Canada "Bixi" system is in place since 2009, with about 5,000 bikes and 400 stations. This paper found its analyses on the collection of the first 6 years of data of the system. The first task is to observe the evolution over these years. Results show that the ridership increased until 2012, and stabilized since then. It also reveals that Bixi members are younger than general biking population, and that the bikesharing network is now mature and consolidated within the most densely populated areas. In the second part of the paper, there is a modelling of the usage of the bike sharing system by members and at station level. The model reveals the negative influence of adverse weather conditions on usage. It also demonstrates the "negative" effects of the startup and ending of the system that is completely removed during Winter.

Keywords: Bikesharing, demand modelling, active transportation, share modes.

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INTRODUCTION

In 2009, as planned in the Transportation plan, the City of Montreal launched its 3rd generation bikesharing system called Bixi (being a pioneer in North America) (1). Bikesharing is an increasingly popular mode of travel where users can perform short bike trips within city, thus helping to improve the active mobility of the citizens (2). While at first the implementation strategy involved two stages over two years, both stages were implemented within 3 months of the launching, reflecting the good reception Montrealers have given to the system. Among other cities, Montreal counts on a significant amount of early adopters that manage to include innovative modes of transport into their daily travels. Actually, Montreal has also been very successful with new transport modes like station-based carsharing, implemented in the mid-nineties, and free-floating carsharing provided since 2013. Finally, it must be noted that in Montreal, transit share is very high for a North-American city, at around 22% of daily trips, reaching some 60% of peak period trips heading for CBD (Central Business District). Hence, in the last six years, people travelling in the city have seen their travel alternatives get richer with bikesharing, station-based carsharing, free-floating carsharing, taxi-sharing, Uber and dynamic ride-sharing.

In the Montreal region, travel demand analysis mostly relies on the data gathered during large-scale cross-section household surveys conducted every five years among 4-5% of the residing population. The more recent survey was conducted in 2013 and focused, as for the previous ones, on one day of travel. While these surveys can help in estimating macro-level indicators and assess various trends at the person and household level, they are not the best tool to measure behaviors related to emerging modes. Fortunately, transaction datasets are sometimes available to do so, as in the case of Bixi Montreal.

The main objective of this research is to develop systematic and objective knowledge regarding the use of bikesharing in Montreal as well as to assess the role this mode can play in the daily travel of adopters. This objective can be declined in two specific goals:

1) Observe and analyze the activity of the Montreal system over 6 consecutive seasons of operation using transaction data (the systems reached a peak of 4.4 million transactions and 40,000 members in 2012, the numbers being stable since).
2) Observe, analyze and model member-based trip generation of bikesharing trips. Using again transaction data, trip generation (trips per member per day and week) models are estimated. The idea is to see whether individual behaviors are changing across seasons with respect to supply and contextual variables.

The paper is organized as follows. First, some background elements regarding the study of bikesharing systems around the world are provided, as well as key contributions to the domain. Then, the second section provides some details regarding the available data and case study. The third section provides some descriptive elements of the use of Bixi over 6 years of operation. The following section exposes the models developed and their results. A discussion with main findings and future research perspectives concludes the paper.

BACKGROUND

Bikesharing systems are spreading around the world. These systems have found to have a positive impact on the level of active transportation, increasing bike use while helping to reduce the use of automobile as daily commuting mode (1).

Members' characteristics

Not surprisingly, researches on the characteristics of bikesharing systems reveal that people who use this mode also have a higher propensity than non-members to use active modes and public transit in their daily travel. Using data from the first year of operation of the Bixi system, Morency et al. (3) showed that Montreal users do between 1.7 and 2.1 trips per day, and that regular members and occasional users have different behaviors. Members are mostly males aged between 20 and 40 years old; the demographic composition of bikesharing users being significantly different than from those who declare cycling trips in the regional surveys. Davis et al. (4) studied the Bay Area system to find that most users will fall in two categories: daily commuter accessing transit stations, and off peak members traveling to areas with denser and diverse opportunities.

Demand modeling

Parikh and Ukkusuri (5) proposed a model to predict the demand at each station of the Antwerpen (Belgium) system. For their approach, they used a Markov process to determine the demand, in combination with a mixed-integer program (MIP) to balance the number of bikes. In another study, Regue and Recker (6) used a gradient boosting machine to predict the state of the stations of the Boston system. As demonstrated by Rudloff and Lackner (7) for the Vienna system, the state of nearby stations also has an influence on the usage of the stations in a bikesharing system.

Faghih-Imani and Eluru (8) presented a demand estimation model for the Chicago system based on station attributes and built environment features of the station's surroundings. Their research showed that for origin stations, users choose stations with longer biking paths nearby, while they tend to choose larger stations for destinations to be sure to find a dropping space for the bikes. Before, Godefroy (9) showed that the presence of subway stations and students nearby bikesharing stations was correlated with increased usage in Montreal. Mahmoud et al. (10) showed that apart from the trip distance, the number of important intersections to cross has an impact on the usage of bikesharing in Toronto. Weather also has a tremendous importance. In Washington system, cold temperatures, rain, and high humidity levels reduced the number and the length of bikesharing trips (11).

System operation

Most bikesharing systems around the world need to balance bikes across the various stations. In the morning, the amount of bikes in the central business districts of cities increases to maximum levels. Bikes need to be transferred from full stations to empty stations to ensure a quality of service all through the day. The repositioning of bikes is a challenging mathematical problem and some methods were proposed to solve it (12, 6, 13). The optimal location of stations has also been studied by García-Palomares et al. (14) using a GIS approach.

Impact

Study by Buehler and Hamre (15) suggest that bikesharing stations may have a positive impact on commercial activities nearby. This impact was also studied by Wang et al. (16) using data from the Minneapolis system. They found that food businesses are significantly related to trip activity, while other retail businesses may not have influence. Bikesharing is also good for tourism activities. It has been perceived positively by tourist in Copenhagen and may be a tourist attraction in itself if usage prices are kept low (17). Bikesharing may have a mixed effect on the use of public transit. Martin and Shaheen (18) showed that in Washington, bikesharing users from the suburbs will use more transit, while users form the central districts may use less transit, because they replace transit trips by bike trips. However, to assess long term impacts of bikesharing usage, there is a need to process longitudinal data covering a longer period, as proposed in the study.

CASE STUDY

Case study

This paper examines the evolution of the Montreal bikesharing system, both in terms of supply and demand, using 6 years of operation data. Montreal, the largest metropolitan area in the Quebec province, launched its system in 2009. Typically operational from mid-April to the end of November, then removed due to the winter season. The system now proposes some 5000 bikes structured around 400 stations.

Data

The database used for this research was made available by Bixi Montreal for research purposes. It is strictly anonymized and its use is managed by a non-disclosure agreement. The following tables are made available covering the 6 years of operation:

- Transactions. Each record of this table provides information on a ride such as origin station, destination station, timestamp and member unique identifier; the database contains 20,049,490 transactions.
- Stations. This table characterizes each station that existed on the system with a validity year period and spatial location; the database contains 500 different stations identification.
- Members. The table contains information on members such as age, gender, home location, fare package, validity period; the database contains 87,144 different members. The table also record 444,340 identifiers of occasional users (one-day users of the system).
- State of stations. This table provides, for 5 minutes intervals, the state of each station in the system, especially the number of empty and filled anchor points; the table contains 166,922,215 records for the 6 years.

Other datasets are used in the research such as the data from the 2008 Origin-Destination travel survey conducted in Montreal (5% sample of the population) as well as population data from the latest Canadian census (2011).

DESCRIPTIVE STATISTICS

The first step of the research is to understand the evolution of various indicators over 6 years. Various elements are examined namely the demography of members, the spatial structure of the system, the accessibility level (day and night population).

Demography of members

As shown in Figure 1, the general demographic structure of the Bixi membership has remained quite stable over time with a small shift towards younger adults (25-39 years old). Hence, there is a clear difference between the Bixi members and both the cyclists as estimated by the OD survey (those who declared at least one cycling trip during the survey day) and the general population. On the one hand, there is more men than women using Bixi but the difference between genders is lower than for regular bikes. On the other hand, there is a clear overrepresentation of the younger active generation (25-39 years old) among the members in comparison with the general population.

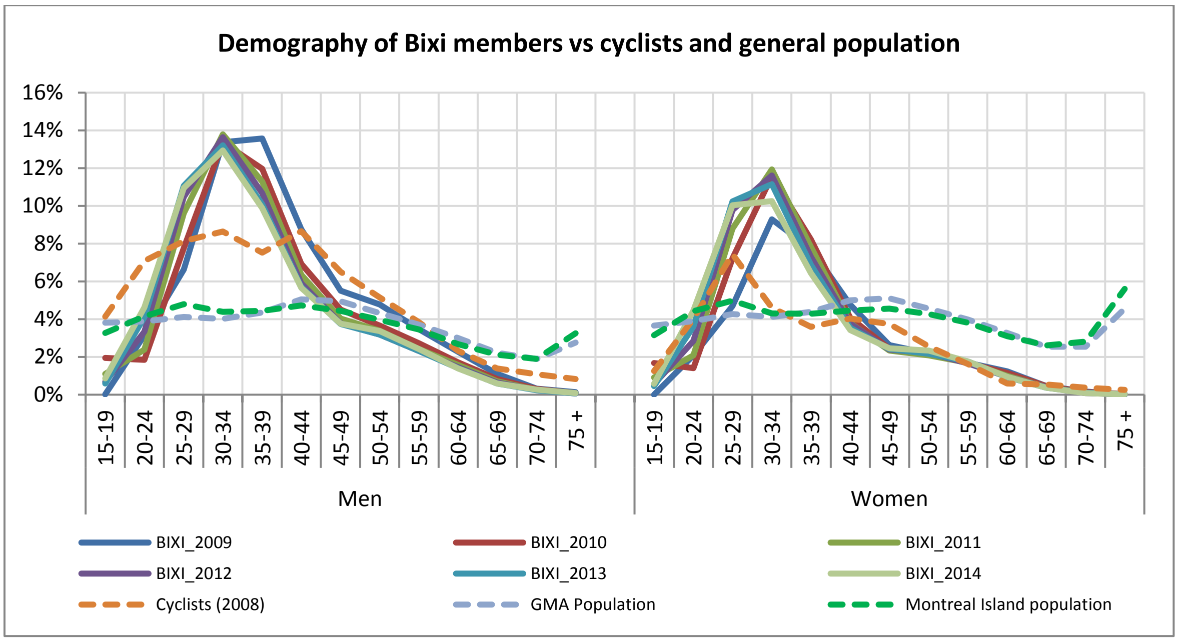

Figure 1. Demography of Bixi members over time vs cyclists (from OD survey 2008) and the general population

Spatial structure of the bikesharing system

Throughout the 6 years of operation, thanks to the portability of stations, the configuration of the network has changed a few times. Excluding 2009 when the system grew rapidly with the weeks, the other years show a continuous increase in the number of stations and anchor points while the number of members peaked in 2012 and is now stable. In 2014, the system gathered some 460 stations, with average capacity of 20 anchor points, more than 5,250 bikes and around 35,000 members (to which should be added occasional users). An average of 100,000 rides per week were supported by the system, of which around 88% done by members. Throughout the years, the proportion of rides done by members increased (around 84% in 2010).

Accessibility to the network

Using data from the 2011 Canadian Census and 2008 OD travel survey, it is possible to assess the accessibility of the system from the home location as well as from other locations. First, membership rates reflect the proportion of the residing population (15 years and older) that has become member of the system. These are estimated at the census tract (CT) level. Globally, considering only the CT where there is at least one station, the membership rate grew from 1.9% in 2009 to 4.7% in 2014. Hence, the membership rate quite varies in space: in 2014, it reaches 22.5% in some central tracts; this high proportion confirms that a non-negligible number of people have adopted this mode and consider it in their daily travel choices.

Second, we estimate the proportion of people who have their home location near a Bixi station. From 2009 to 2015, using the same base population, we observe that the number or people (15 years and older) living within 500 m from a Bixi station has increased by 38%.

Third, it is also possible to estimate how many people have access to the network during a typical weekday by processing the daily trips declared in the regional travel survey and following people throughout their daily travels. Using the 2014 Bixi network, we observe that by the middle of a typical weekday, there are up to 700,000 active people conducting their daily activities within 500 m of a station (below 600,000 for the 2009 network). It is worth mentioning that at lunch time, more than half of the people within 500 m of a station have a home location outside the bikesharing service area.

Weekly patterns of system usage

As mentioned previously, due to the harsh Winter in Montreal, the bikesharing system is implemented in April of each year and dismantled by the end of November. During this period, the level of usage varies in conformity with the changes in average temperature. Figure 2 presents the evolution of rides per week throughout the 6 first seasons of operation. Clearly, the first year is particular, with much fewer rides (32% of them being done by occasional users). What can be observed from the other 5 seasons is that the proportion of rides from the occasional users is changing throughout the seasons (around 16% in 2010 and 2011 and 12% for the other years). For each season, we observe a continuous increase in the number of rides from the beginning of the season (April) up to a peak in July-August and then a decrease until season ends. Also, if we examine weekly patterns, we observe that 80 % of the members' rides are done during weekdays while weekdays only account for 58 % of the occasional users rides. These proportions remained stable throughout the years.

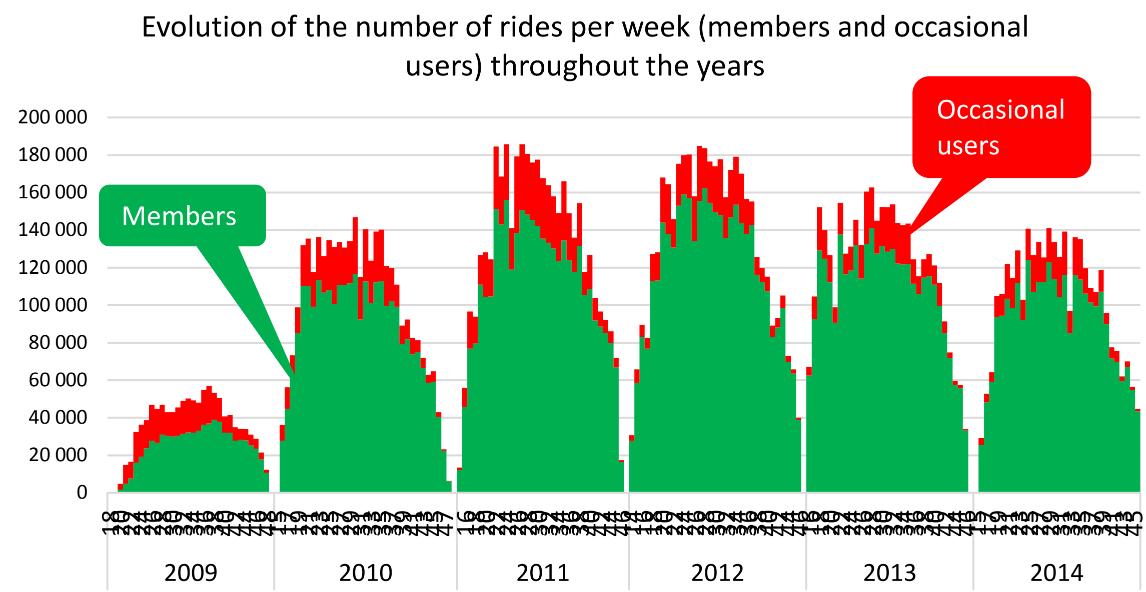

Figure 2. Evolution of the number of rides per week throughout the 6 first Bixi seasons

Travel times distribution

It is possible to observe the distribution of ride durations directly from the database. The average duration of a ride is different among members and occasional users and is influenced by the fare structure, namely the amount of « free minutes » for a ride. In 2009, 90% of the members' rides were 20 minutes or less. This proportion is lower since 2011, at 85% in 2014 for instance, and it is probably not independent from the change in policy regarding free minutes (initially 30 minutes but increased to 40 minutes in 2011). Also, occasional users do, in average, longer rides: in 2014 more than 8% of their rides are more than 45 minutes long. Only 58% of their rides actually are 20 minutes or less (vs. 85% for the members).

Balance ratios

The balance ratio is one interesting performance indicator to understand the differentiated use of stations for travel needs. It is estimated using the total number of pick-ups operations over the total number of drop-offs at a station during a particular period. In our case, the ratio is estimated for each season as well as for every week of operation. The values can be interpreted using three main classes:

1. stations with ratios around 1 (0.9-1.1) are more or less naturally balanced by the bikesharers' behaviors;
2. stations with ratios below 1 (<0.9) have more drop-offs than pick-ups;
3. stations with ratios above 1 (>1.1) have more pick-ups than drop-offs.

The analysis of balance ratios over space confirms that stations that are downhills have higher propensity to be in the second class. Looking at the evolution of balance ratios throughout the 2014 season (estimated for each week), we observe that the proportion of stations in class 1 is lower at the beginning and end of the season, when demand is lower. Throughout the years, the proportion of stations in class 1 is slowly decreasing, from 53% in 2009 to 40% in 2014, indicating an increased challenge related to balancing for the operator.

Hence, a correlation analysis confirms that station capacity is positively correlated with the number of drop-offs, illustrating that users tend to choose a larger station when they have to drop-off their bikes. This confirms the findings by Faghih-Imani and Eluru (2015).

Empty and full states

Another relevant performance indicator to estimate is the proportion of time a station is either full or empty. This indicator is estimated using the state of station table that contains the state of each station for every 5 minutes interval of service. For each year, the proportion of 5 minutes states where the station was empty or full is estimated. From 2009 to 2015, the proportion of empty states varied between 14.7% and 24.9% and showed no particular trend. However, there is a clear and important decrease in the proportion of full states: starting at 15% in 2009 and no being as low as 2% in 2014. We can conclude that the problem of full stations was clearly addressed by the operator.

MODELS AND RESULTS

The next step of our research is the modelling of some usage indicators with the 6 years of data. The objective is to identify variables that contribute to the variability observed throughout weeks, months and years of operations. Two indicators are modelled:

- Transactions per day: the database contains 1,295 days of operations;
- Transactions per day per station: the database contains 490,149 station*days.

Various explanatory variables are developed for potential inclusion in the models: a selection will be made for each model depending on correlation among them as well as level of statistical significance. They are described in the following sub-sections.

Transactions per day

The first model that we develop aims to understand the evolution of the system-wide usage throughout the years as well as the variability during the seasons. The outcome variable is the total number of transactions per day. The following variables are tested:

- Temporal triggers: day of the week, month, year;
- Weather indicators: average daily temperature, millimeters of precipitations during the day;
- System attributes: number of stations, anchor points, members, bikes;
- Context: fuel prices (weekly values).

Before estimating the model, a correlation analysis was conducted; it identified multiple correlations between the potential explanatory variables:

- Positive correlation: members, bikes, fuel price and year 2012; average temperature and July month; members and bikes, fuel price; anchors and year 2014, bikes and fuel price.
- Negative correlation: fuel price and year 2010; average temperature and November.

The model is developed taking the important correlations into consideration. A multiple regression using OLS (ordinary least squares) is first estimated and leads to quite interesting results (with adjusted R-square of 0.86) namely the identification of the most important variables for the explanation of the outcome which are, in decreasing order of importance: number of bikes, average temperature and precipitations. Since the outcome is not normally distributed, we have also estimated a negative binomial regression using the same variables; results are presented in Table 1.

R-square is not relevant to interpret for such model; we examine the Prob > chi2 that confirms that at least one variable of our model has a non-null impact. This model confirms what was observed in the OLS model and highlights the same three important variables, in the same order. Millimetres of rain as well as the month of October have a negative impact on the total number of transactions per day. Hence, the number of transactions is positively related to the number of bikes in the system (in our case, the number of bikes available is estimated daily as there could be some differences due to maintenance). Month dummies account for gradual changes in behavior with the arrival of Summer. Still, their significance is not clear. Estimating yearly models, which is another experiment conducted but not exposed here, helps separate the impact of the system maturation and more clearly expose the variability within each season.

Table 1. Results of the negative binomial regression - transactions per day

Negative binomial regression — Number of obs = 1295; LR chi2(16) = 1590.89; Prob > chi2 = 0.0000

Log likelihood = -12731.635 — Pseudo R2 = 0.0588

transactions	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Average temp	.0341216	.0026303	12.97	0.000	.0289662	.039277
Rain	-.0259302	.0013058	-19.86	0.000	-.0284895	-.023371
Bikes	.0004709	.000011	42.62	0.000	.0004492	.0004926
Monday	.180292	.0359755	5.01	0.000	.1097814	.2508026
Tuesday	.2624206	.0359586	7.30	0.000	.1919431	.332898
Wednesday	.2827833	.0360364	7.85	0.000	.2121532	.3534134
Thursday	.2646376	.0359178	7.37	0.000	.19424	.3350351
Friday	.2992835	.0359556	8.32	0.000	.2288119	.3697551
Saturday	.0905547	.0361953	2.50	0.012	.0196133	.1614961
April	.2021398	.049746	4.06	0.000	.1046394	.2996402
May	.1246777	.0508635	2.45	0.014	.0249871	.2243683
June	.2143911	.0568493	3.77	0.000	.1029685	.3258136
July	.2173397	.062083	3.50	0.000	.0956593	.3390202
August	.0912946	.060456	1.51	0.131	-.027197	.2097862
Septembre	.0274329	.0524887	0.52	0.601	-.075443	.1303089
October	-.1363625	.0453311	-3.01	0.003	-.2252099	-.0475151
_cons	7.09278	.051993	136.42	0.000	6.990876	7.194685
/lnalpha	-2.128462	.0396303			-2.206136	-2.050789
alpha	.1190202	.0047168			.1101253	.1286334

Likelihood ratio test of alpha=0: chibar2(01) = 1.2e+06 Prob>=chibar2 = 0.000

Transactions per day per station

In the second model, we look at the variability of transactions per day, per station. Two types of operation can be modelled: pick-ups or drop-offs. In addition to the aforementioned variables in the previous model, the following variables are tested:

- Station attributes: number of anchor points, elevation.
- Station's Neighborhood attributes: population density, transit level of service (runs per stops per day), demographic attributes, number of people within 500 m at noon, membership rate, cycling infrastructures, etc.

Additionally to a model including all years of operation, yearly models are estimated and yield to more relevant models. Again, a negative binomial regression is estimated for each year of operation. Correlation among explanatory variables is examined in the variable selection process. The results of the best models are presented below (Table 2). Alpha coefficients for each model confirm that the negative binomial model is best suited than the Poisson model.

From the results, we observe the following elements:

- Coefficients among yearly models are quite consistent with respect to scale and direction;
- Elevation of the station has a negative impact on the number of drop-offs; the inverse is observed for pick-ups;

- Rain has a negative impact on the number of drop-offs per day per station while average temperature has a positive impact; rain (days of rain during the month) was also identified by Rixey (19) as a statistically significant variable reducing the average monthly rentals in three US bikesharing systems.
- The most important variables in the description of the number of drop-offs per day per station are, in decreasing order of importance: capacity of the station (in number of anchor points), average daily temperature, membership rate in the census tract where the station is located, population density in the CT, elevation of the station, the number of bus runs per day within 500 m of the station and daily millimeters of rain; these relative importance are similar for all years, except 2009.
- Dummies for days of the week and months have small impacts but allow to take into account the variability of transactions per day observed during each year; consistent across all years is the fact that there are fewer transactions during the week-ends.

Table 2. Results of the negative binomial regression - transactions per day

	2009		2010		2011		2012		2013		2014	
Nb.obs.		48532		75699		79072		83193		81722		87108
Prob > chi2		0.000		0.000		0.000		0.000		0.000		0.000
DROP-OFFS	**Coef.**	**P>|z|**	**Coef.**	**P>|z|**	**Coef.**	**P>|z|**	**Coef.**	**P>|z|**	**Coef.**	**P>|z|**	**Coef.**	**P>|z|**
Anchors	0.03882	***	0.05769	***	0.04493	***	0.04516	***	0.04312	***	0.03849	***
Membership rate	19.71720	***	8.29381	***	6.03748	***	5.48098	***	6.48800	***	8.50090	***
Elevation	-0.00385	***	-0.00387	***	-0.00522	***	-0.00548	***	-0.00528	***	-0.00524	***
Population density	0.00002	***	0.00003	***	0.00003	***	0.00003	***	0.00002	***	0.00003	***
Average temperature	0.04319	***	0.04290	***	0.04370	***	0.04310	***	0.04410	***	0.04470	***
Rain	-0.02512	***	-0.02210	***	-0.02471	***	-0.02663	***	-0.03363	***	-0.02913	***
Bus run < 500 meters	0.00011	***	0.00001	***	0.00004	***	0.00006	***	0.00009	***	0.00007	***
Cycling inf. <500m	-0.00002	***	0.00003	***	0.00002	***	0.00002	***	0.00001	***	0.00000	**
Monday	0.07999	***	0.20344	***	0.08985	***	0.20787	***	0.21513	***	0.19643	***
Tuesday	0.11688	***	0.25767	***	0.23289	***	0.27674	***	0.27108	***	0.26393	***
Wednesday	0.19676	***	0.27860	***	0.22447	***	0.29444	***	0.31893	***	0.30015	***
Thursday	0.20593	***	0.29051	***	0.14588	***	0.28218	***	0.28684	***	0.34036	***
Friday	0.22882	***	0.34511	***	0.19304	***	0.26476	***	0.28094	***	0.34910	***
Saturday	0.12548	***	0.12045	***	0.03583	***	0.07754	***	0.06757	***	0.06128	***
May	0.06356	***	0.07075	***	0.04120	***	0.18159	***	0.20675	***	0.16705	***
June	0.05601	***	0.17071	***	0.10458	***	0.11030	***	0.12168	***	0.16182	***
September	0.09261	***	0.11508	***	0.04939	***	0.11236	***	0.10910	***	0.11646	***
_cons	0.76311	***	0.74330	***	1.30877	***	1.21874	***	1.06105	***	0.77766	***
alpha	0.38029	***	0.28614	***	0.32513	***	0.30419	***	0.29774	***	0.34514	***

The proposed models help to understand the level of usage of the stations across seasons and years. Still, they can be improved. Actually, the residuals of the yearly models were examined using the Moran's I coefficient. The results, presented in Table 3, confirm that there is significant positive spatial autocorrelation among the residuals of the six models. Also, it is higher in 2011 and 2012, the two years with the highest number of transactions.

It is no surprise since usage level at one station probably influences the usage level of the nearby stations, namely when level of usage is generally high (as was the case in 2012 for instance).

This will need further examination; one option we are currently exploring is the use of spatial filtering method to control for this spatial autocorrelation.

Table 3. Moran's I coefficient for the residuals of the yearly models of transactions per station per day

Year	Sample size	Moran's I	Spatially random (expected) "I"	Normality significance (Z)
2009	48532	0.006422	-0.000021	170.897
2010	75699	0.004360	-0.000013	181.542
2011	79072	0.127000	-0.000013	4687.828
2012	83193	0.156015	-0.000012	6261.765
2013	81722	0.017763	-0.000012	750.686
2014	87108	0.021301	0.000011	932.925

CONCLUSION

This paper has presented an analysis of six years of bikesharing activities in the city of Montreal, Canada. The descriptive analysis showed that the level of activity in the system has stabilized over the years, with an increasing proportion of rides done by members. The system is now mature and reaches a broader range of population within the central district. Two trip generation models were produced, thanks to the several million records of data available. The first model describes the number of transactions per day: this number increases with the availability of bikes, but is negatively affected by adverse weather conditions and the end of the biking season. The second model estimates the number of transactions (drop-offs) per station-day. Among other results, this model shows the negative effect of elevations in hilly parts of Montreal.

The model presents some limitations. There is an asynchronicity of some variables over time, due to different dates related to census and household survey (the 2013 household survey data is not available at this date). We look forward to add more variables to the models, especially those related to the availability of other modes like carsharing and private car. As mentioned previously, spatial filters will also be added in the models to account for the spatial autocorrelation among nearby stations. The effects of fare variations (which were indeed small during the period) have not yet been studied at this time. Also, modelling of behaviors at the member level is also among our short-term research plans. Both models of membership and frequency of usage will be developed. Data mining techniques will hence be used to create typologies of bikesharing usage; work by Vogel et al. (20) proposes interesting analysis of activity patterns using such techniques and will be further examined and transposed to the Montreal context.

Alternative modes like bikesharing are not well reported in large household surveys. Because they can play a major role in the reduction of dependency towards the private cars, it is more than urgent that models provide objective knowledge regarding the use of these alternatives as well as an assessment of how they can actually affect daily travels of residents. In further perspective, we are looking forward to develop mode choice models that will include not only private car and public transit, but also alternative modes such as carsharing, taxi and, of course, bikesharing.

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