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# Characterization of a COVID-Fired Urban Bike Delivery System

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**Abstract.** The Covid-19 pandemic led to a rapid change in consumers' demand for freight, we aim to analyze the results of a local cargo bike delivery system in Montreal, Quebec, that was initiated during the forced closure of non-essential businesses. While Covid-19 restrictions and conditions were evolving almost weekly, logistics providers had to adapt to the rapid increase in deliveries. To evaluate such changing conditions, a multilevel linear regression analysis is used with the delivery weeks and the classification of businesses as clusters. This method allows us to consider the random effects induced by the nested structure of the data. The dataset covers deliveries done by cargo bike in the city of Montreal and is comprised of over 6,700 deliveries over 16 weeks. On average, 62.5% of the deliveries were same day deliveries and the average distance between a shop and a consumer was 1.51 kilometers. The results show that the density of population, the presence of a transactional website for the participating businesses and Covid-19 case numbers are amongst the strongest factors for the success of such initiative. Covid-19 case numbers induced a change in the typology of the demand, demand which led to a rise in the number of deliveries when shops were closed and a brutal fall when shops reopened in May, 2020.

**Keywords**. Cargo bike, urban delivery, freight transportation, Covid-19, multi-level analysis.

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## 1. INTRODUCTION

In Canada and the rest of the world, the new coronavirus disease (Covid-19) has impacted transportation systems, whether they be for passengers or freight. This pandemic has killed over 13,431 people in Canada alone, as of December 13th, 2020 and it has strongly perturbed the daily life of inhabitants, leading to a “new normal” (Albany, 2020).

Local authorities implemented restrictions at a local or national level, such as lockdowns, travel bans between regions and countries, curfews, and quarantine periods to prevent the transmission of the virus. The transport sector has suffered directly from these restrictions, as reported by the WCTRS Covid-19 Task Force: 56.4% of experts reported the limited access to public transportation, 22.2% of them observed online bookings for public transportation (Zhang, 2020). At the very beginning of the pandemic, several commodities knew a shortage as people were preparing for lockdown measures, which created a shock in the supply chain (Sarkis, 2020).

In Quebec, Canada, the government declared the temporary closure of schools and universities, as well as non-essential businesses on March 13th, 2020. Only essential shops were opened, and people were asked to limit their social interactions to prevent the propagation of the virus. This measure was lifted gradually when the number of cases diminished, and the city of Montreal was the last to reopen its non-essential businesses on May 25th, 2020.

Current studies are documenting the behavioral changes linked to the pandemic in transportation systems in different parts of the world (Morita et al., 2020), as well as the direct impacts on the sector (Zhou et al., 2020) and recommendations for stakeholders (Zhang, 2020). As far as we know, most current studies only cover the first wave of the pandemic, while certain countries are already facing their second wave.

This study focuses on a delivery initiative that was implemented within days to help closed businesses deliver goods to close consumers, to alleviate the consequences of the lockdown for them. This initiative is a collaboration between the private and public sectors and only covers the city of Montreal, Quebec. All deliveries were done by cargo bikes, at a competitive rate for participating businesses, thus ensuring their interest in this experiment. Data was collected from this initiative and analyzed using a multilevel analysis approach. This method ensures the proper treatment of nested data structures and the proper identification of explanatory variables at the right levels (Bagley & Mokhtarian, 2002).

The objective of this study is to identify and explain the variables which characterize the deliveries made during the first wave of the pandemic in Montreal, by looking at the evolution of the demand, the characteristics of the participating businesses and the evolution in time of the system.

After this introduction, the paper is organized as follows. In Section 2, we present a literature review, including the evolution of the demand during the pandemic and the presentation of the linear multilevel analysis method. The methodology described in Section 3 covers the preparation of the data needed to conduct a multilevel analysis. As this analysis requires a certain level of context to be understood, a case study based on the city of Montreal is presented in Section 4, along with key indicators. In Section 5, we present the results of our analysis, in particular identifying the variables that are differentiated by importance in the model. Concluding remarks identify potential avenues for future research.

## 2. LITERATURE REVIEW

This literature review is structured into three topics. First, cargobikes as an effective delivery mode is reviewed. Second, we take a closer look at consumer demand during the beginning of the Covid-19 pandemic. Then, examples of transportation articles using a multi-level approach are reviewed.

### 2.1 Cargo bikes

Cargo bikes (or cargo cycles) are an alternative to light goods vehicles in cities (Schliwa et al., 2015), with the advantage of being zero emission. At the beginning, cargo bikes were deployed on a small scale and were not linked vertically to other forms of logistics (Lenz & Riehle, 2013), whereas now they are part of an integrated strategy to deliver parcels in dense urban centers The modal shift to cargo bikes would reduce congestion, delivery times, infrastructure costs, as well as accidents and $CO_2$ emissions (Russo & Comi, 2010). Cargo bikes offer more flexibility than traditional modes, especially when there is a variation in demand and high seasonal fluctuations (Schliwa et al., 2015).

To ensure the delivery efficacy of cargo bikes, local authorities must make clear goals of shifting towards sustainable methods, work on the current regulation and provide measures concerning the infrastructures needed for such initiatives (Schliwa et al., 2015). Buldeo Rai et al. (2019) identify four components for the efficacy of parcel deliveries : (i) volume, (ii) stop density, (iii) urban regulation and (iv) delivery failures. When considering these four elements, cargo bikes can be considered effective assets for parcel deliveries in cities.

## 2.2 Consumer demand evolution during Covid-19

The pandemic forced a brutal change in the demand, which affected certain industries more than others. Statistics Canada studied the retail service price index (RSPI) during Covid-19 and reports that the sporting goods, book and music sector contributed by 3% to the increase of the RSPI. A general increase in online shopping managed to offset the consequences of non-essential shops being closed (Government of Canada, 2020). When looking at the individual level, people who have high-wage occupations are considered relatively not impacted by shocks in the demand (shortage of basics products), whereas low-wage occupations are highly impacted (del Rio-Chanona et al., 2020). The transportation sector is susceptible to experience immediate demand-side reductions, but not a corresponding supply shock. In the same manner, the tourism industry suffered from both a supply and a demand shock at the same time (del Rio-Chanona et al., 2020). Consumer behavior has also changed during the pandemic, with people developing new skills, nesting and staying at home more (Donthu & Gustafsson, 2020). These authors observed that consumers are stockpiling on essentials and are prone to panic buying.

### 2.3 Multi-level analysis in transportation articles

Transportation problems can be appropriate for muli-level analysis models. This type of models is often used to bring back context into the analysis performed. Whether it is to determine the variables that impact the distance traveled while taking into account demographic factors (Mercado & Páez, 2009) or to assess the impact of rain on drivers' behavior (Billot et al., 2009), multi-level analyses reveal important factors to consider while taking into account the specific context of the study. For transportation problems, multi-level analysis is used for a broad range of topics. Studies such as the measure of intention to use self-collection services in last mile delivery (Yuen et al., 2018), the impact of residential neighborhood type on travel behaviour (Bagley & Mokhtarian, 2002), sustainable mobility transitions (Nykvist & Whitmarsh, 2008), departure times choice behavior (Chikaraishi et al., 2009) are exemples of the flexibility of the multi-level analysis.

## 3. METHODOLOGY

### 3.1 Multi-level analysis

The approach chosen for this study is a multilevel analysis and, in particular, the three-level regression model. The need for multilevel analysis emerges from Robinson's fallacy (Robinson, 2009) (first published in 1950), in which he demonstrated that the correlation for the same two variables can be different at the individual and ecologic level (Subramanian et al., 2009). The two or three level regression model can have several names such as "random coefficient model", "variance component model" or "hierarchical linear model" (Hox et al., 2017). Such models are efficient to demonstrate the links between variables in complex problems (Gao et al., 2008).

The equation for this type of model is adapted from Woltman et al.(2012).

$$Y_{ijk} = \beta_{0jk} + \beta_{1jk} X_{ijk} + R_{ijk}$$

Where :

$Y_{ijk}$ = dependent variable measured for $i^{th}$ level-1 unit nested within the $j^{th}$ level-2 unit and the $k^{th}$ level-3 unit,

$X_{ijk}$ = value on the level 1 predictor,

$\beta_{0jk}$ = intercept for the j$^{th}$ level-2 unit and the k$^{th}$ level-3 unit,

$\beta_{1jk}$ = regression coefficient associated to $X_{ijk}$ for the j$^{th}$ level-2 unit and k$^{th}$ level-3 unit,

$R_{ijk}$ = random error for the ith unit, nested within the j$^{th}$ level-2 unit and the k$^{th}$ level-3 unit.

Also, for this model, level-1 errors follow a normal distribution.

$$E(R_{ijk}) = 0 \text{ and } var(R_{ijk} = \sigma^2)$$

*3.1.1 Assumptions for the model*

There are several assumptions for multilevel models. First, the data must have a nested structure, observations of the lowest levels are clustered by groups. In the context of this study, all deliveries are nested within the shop and all shops are nested within the week during which the delivery took place (Figure 1). Other than the nested design of the data, another assumption for this kind of model is that there is one measure of outcome at the lowest level of the model (Hox et al., 2017).

*3.1.2. Method for model preparation*

Following the method from Hox and al. (2017), a four step method is followed. Step 1 consists of the intercept only model, also known as the null model. This null model does not contain any explanatory variables and gives an estimate of the intra class correlation. Step 2 consists of analyzing the model with only the lowest level variables (level 1). From this step, we can determine how important each predictor is to the model. Step 3 is the repetition of step 2 with the incorporation of variables from the group level (here, level 2 and level 3). Step 4 is the random coefficient model. The goal of this model is to establish if the predictors at the lowest level influence the variance between groups. This step is repeated between level 1 and level 2 and then between level 2 and level 3, as this is a three-level model. Finally, step 5 is to add the interactions between the predictors that are considered significant from step 4 and the group-level explanatory variables. The lme4 package on R is used for this model (Bates et al., 2015) and verifications are done with the nlme package, also on R (Pinheiro et al., 2020).

### 3.2 Data preparation

The database used comprises a total of 6,713 deliveries made by cargo-bikes between March 13th and July 7th, 2020 (102 days) in Montreal, Quebec, Canada. Each record contains: the origin of the delivery (i.e., store); the destination (delivery address); the date and times of call, collection and delivery; the identification number for the delivery person (source A). In total, 44 delivery bikers were employed over 102 days of operation. However, the dataset does not provide the volumes transported. The data is collected and provided by Jalon Mtl (2020).

Additional information is added to the original database by level considered. The clustering by level is important as a multilevel analysis is conducted in this study. Level 1 is the lowest level and refers to the characteristics of each delivery entry in the dataset. For this level, the median income and the population density are added for each delivery address from the 2016 census (Government of Canada, 2017) (source B). The distance between the origin and destination is also computed for each entry. The distance is a linear distance and does not consider the road network. Level 2 refers to the shop level. For each shop, the population density and median income of the neighborhood are added. Two binomial indicators are added to characterize the participating businesses: (i) does the business have a strong ecological mission? and (ii) does the business have a transactional website? For this level, the age of the business in the system is calculated by subtracting the last week for which a delivery is done to the first week that contains a delivery. We also specify the type of commerce (food, leisure etc.). More details are provided in Section 4. Level 3 is the highest level in this study and refers to the week in which the deliveries took place. For this level, the average number of Covid-19 cases (*Données COVID-19 au Québec*, 2020) (source C), the average outside temperature and rain falls are added (Canada, 2011) (source D). A binomial indicator is added to indicate if the delivery week is part of the lockdown or if shops are opened again.

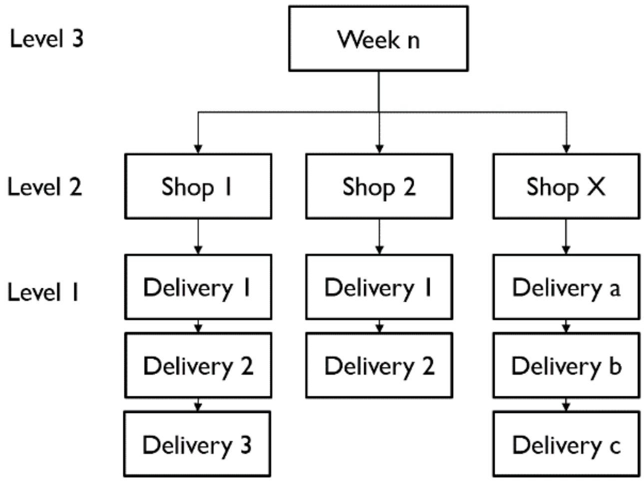


**Figure 1 Levels for the multilevel analysis**

**Table 1 Added variables**

| Variable | Description | Level | Source |
|---|---|---|---|
| Median income of the delivery address | Median income at the place of delivery. | 1 | B |
| Population density of the delivery address | Density of population at the place of delivery. | 1 | B |
| Distance between a shop and an address | Euclidian distance between a shop and the address of the consumer. | 1 | A |
| Time the shop stayed in the system | Difference between the first and the last delivery that occurred. | 2 | A |
| Median income of the origin | Median income at the place of purchase. | 2 | B |
| Population density of the origin | Density of population at the place of delivery. | 2 | B |
| Ecology | Indicator of the importance of sustainability in the shop's business model | 2 | A |
| Transactional website | Indicator of the presence of a transactional website. A transactional website allows the consumer to order and pay online. | 2 | A |
| Number of Covid-19 cases for the week | Number of Covid-19 cases for the week. | 3 | C |
| Average outside temperature | Average outside temperature for the day of delivery. | 3 | D |
| Average rainfalls | Average daily precipitations for the day of delivery. | 3 | D |
| Shop closed/opened | Indicator that the shops were closed or opened according to the public health decisions. | 3 | A |

## 4. MONTREAL CASE STUDY

During the months of March to May 2020, the province of Quebec recorded on average between 500 and 700 new cases of Covid-19 per week over 8.485 million inhabitants. The Quebec government announced the shutdown of non-essential businesses, as well as schools and universities, on March $13^{th}$, 2020. This lockdown was lifted on May $25^{th}$, 2020 for non-essential shops, while schools kept being closed. Whereas most shops still offered curbside pickup options, many consumers opted to have their products delivered at home. Therefore, traditional delivery services were overwhelmed by the demand and orders could take up to several weeks to be delivered (*Postes Canada*, 2020). Cargo bike delivery services are not new in Montreal. They have been used mostly by courier services in the downtown area as a business to business service (B2B). Now they are used for both B2B and business to consumer (B2C) services for parcel deliveries.

### 4.1 Understanding the bike delivery initiative

The bike delivery initiative studied in this paper was implemented a week after the announcement of the shutdown and lasted from March $27^{th}$, 2020 to July $7^{th}$, 2020. This initiative is a joint effort from public and private actors to offer cargo bike deliveries for closed shops with competitive pricing. Conditions to be eligible for this service are: (i) the consumer needs to be within a five kilometer range from the shop, (ii) products requiring specific storage, such as fresh food or frozen products are not accepted. Consumers outside the delivery range are delivered by traditional post. Costs were either assumed by the shop with a minimum amount purchased or transferred to the consumer.

The delivery service considered is on-demand. Shops are responsible for processing the order and call the delivery service when its ready. A delivery person is then dispatched at the store and does the delivery either on the same day or the day after. Two types of bikes are used for the deliveries. The characteristics for each bike are summarized in Table 2.

**Table 2 Cargo bike characteristics**

| Type of cargo-bike | Shape | Capacity (kg) | Battery autonomy (km) |
|---|---|---|---|
| "Long John" |  | 315 | 70 |
| Bike with trailer |  | 110 | 80 |

During this initiative, the data for each delivery was collected. A total of 6,713 deliveries happened over the span of 16 weeks with a total of 44 delivery bikers. On average, there are 84 deliveries per day and a maximum of 318 deliveries was attained on May 5$^{th}$, 2020 . Overall, 62,5 % of packages were delivered on the same day that the shop called for the service. The average distance between a shop and a customer is 1.51 kilometers.

For this initiative, the delivery bikers are paid hourly and not for each delivery done. The number of days worked by each delivery biker ranges from only one day to all of them. As the packages were mostly delivered on the same day, all delivery activity was done from 12 pm to 5 pm (on average), leaving the mornings to shops to prepare all orders. Orders received during the afternoon would either be picked up by a passing delivery biker or left for a next day delivery.

## 4.2 Understanding the demand of consumers during the shutdown of non-essential businesses

In total, 91 businesses participated to the initiative and are divided into categories summarized in Table 3.

**Table 3 Distribution of categories of participating businesses**

| **Category** | **Description** | **Number of shops** | **Number of deliveries** |
|---|---|---:|---:|
| Food | Grocery shops, cafés, delicatessen etc. | 35 | 2,100 |
| Home | Home decor and furniture etc. | 8 | 947 |
| Animal care | Veterinarians and pet shops etc. | 4 | 234 |
| Leisure activities | Board games, crafts, bookshops etc. | 21 | 2,306 |
| Fashion | Clothes, shoes, sport equipment | 11 | 913 |
| Healthcare | Pharmacies | 4 | 108 |
| Other | Miscellaneous | 8 | 45 |
| Total | | 91 | 6,713 |

All businesses participating in the initiative are grouped by commercial street associations (Figure 2). This ensures the delivery service to reach a certain level of consolidation amongst businesses. The average distance between all businesses is 4.58 kilometers. However, all groups do not have an equal distribution of business types within them.

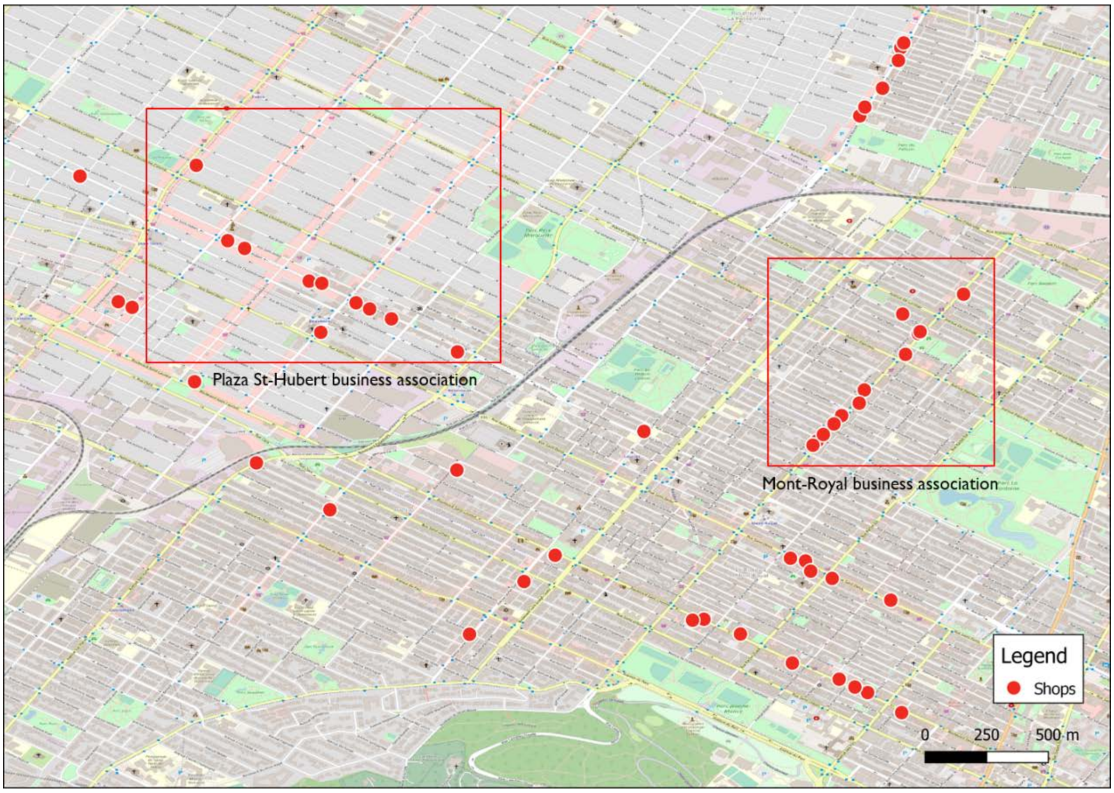


**Figure 2 Sample of the participating business locations in Montreal**

Figure 3 and 4 demonstrate that the demand evolves with time. During the first month, people are mostly ordering food from grocery stores, delicatessen stores and from bookstores (leisure activity category). Then the demand for food stabilizes and the demand for leisure activities (books, crafts, games etc.) and fashion continues to increase.

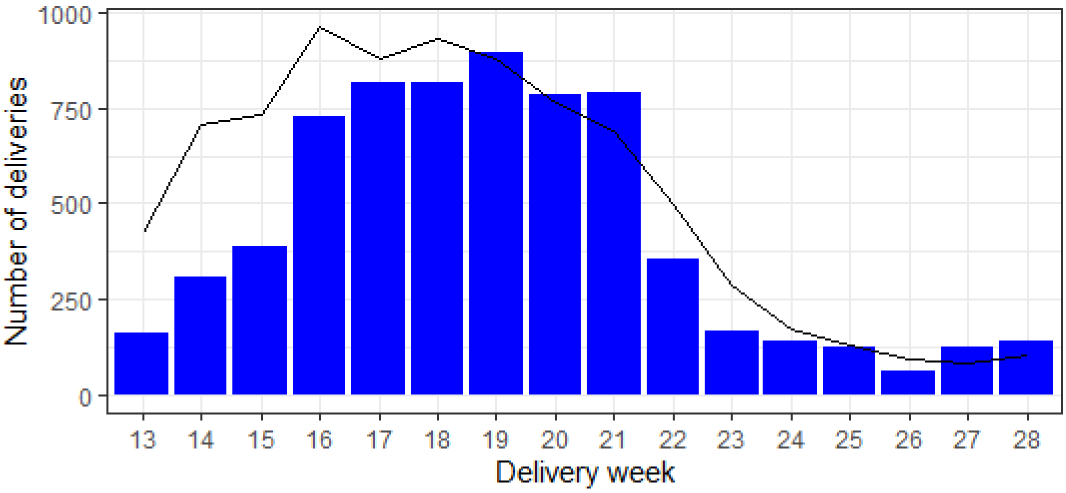


**Figure 3 Evolution of the demand and Covid-19 cases**


**Figure 4 Evolution of the demand by categories**

When Covid-19 numbers are added (Figure 3), it is possible to observe the link between consumer behavior and the directives given by the government. Consumers are told to reduce their physical movements to prevent the propagation of Covid-19, which triggered the rise of home deliveries. The diminution of Covid-19 cases allowed the government to reopen all businesses at the beginning of week 22, which triggered a strong reduction in the need for deliveries.

## 5. RESULTS

In the following section, we present the results of the model. Results from the random intercept model confirm the need for a multi-level analysis and significant variables are identified in the complete model.

### 5.1 Random intercept

First, a random intercept is conducted to determine the intraclass correlation, which is the proportion of variance at the "general classification" (food, leisure etc.) level and at the week of delivery level. The interclass correlation (ICC) is computed with the lme4 package on R and results of ICC and corresponding p-values are presented in Table 4.

**Table 4 Results of the null-model (random intercept only)**

| Random intercept controlled by : | Estimate | ICC | p-value at 95% confidence level |
|---|---|---|---|
| General classification of the shop | 114.50 | 0.72 | 0.005 |
| General classification + delivery week | 85.39 | 0.88 | 0.064 |

The model is controlled by general classification of the shop, meaning the category to which a shop belongs (food, healthcare etc.) and also by week of delivery. As mentioned before, the rapid evolution of the situation impacted the delivery system.

The 0.88 ICC and p-values associated confirm that the two levels considered are significant for the model.

### 5.2 Models with explanatory variables

First, the lowest level variables are introduced in the model. Results for the intercept (Figure 5) indicate that amongst all variables at this level, the density of population at the destination (consumer) is the most significant in explaining the number of deliveries done. The median income at the destination is expected to be less significant as consumers are dispersed in different neighborhoods. As the radius of delivery accepted is only 5 kilometers, the distance does not influence the model, which is to be expected as the business choses the delivery mode for the consumer. Therefore, only distances under five kilometers are part of the model and it cannot establish a significant intercept for this variable when controlled by week and general classification. The lines around the estimates of the intercept represent the 95 % confidence interval. For the income at destination, the spread of the confidence interval is due to the high variability of incomes in Montreal, as the model considers all shops and consumers spread in Montreal, Quebec.

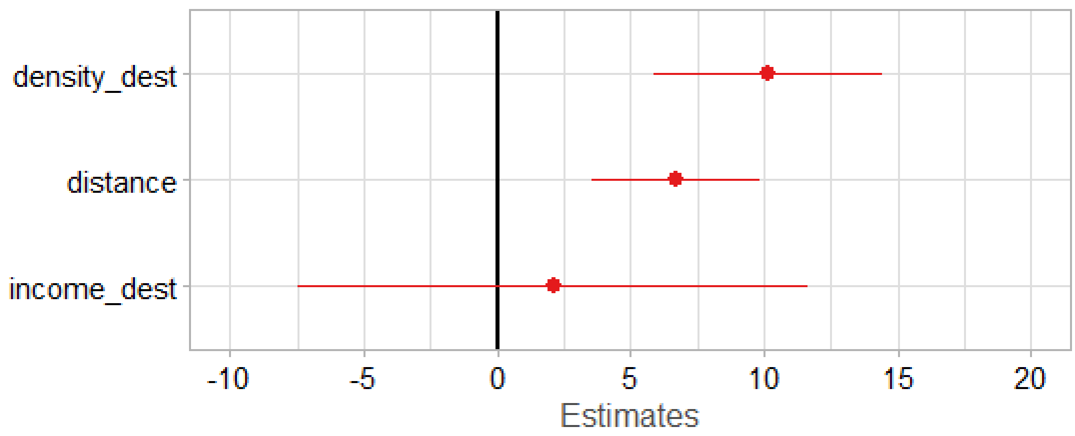


**Figure 5 Intercepts for level 1 variables**

Then, variables for the second level considered are introduced in the linear mixed effect regression (Figure 6). The presence of a transactional website has the largest intercept, followed by the income and the density of the population at the origin of the delivery. The age of the shop in the system, meaning the number of weeks the business participated in the initiative and the fact that a shop is considered to have an ecological mission show less importance than other variables at this level. Shops that have transactional websites increase their chance to sell products (consumers can order easily online or phone to order), therefore increasing the number of deliveries done. In the same manner, we can assume that shops with websites are used to the logistics behind deliveries, thus increasing their use of the delivery system in place. Compared to the model with only level 1 variables, the intercept for the median income at the point of origin is slightly larger than the density of population.

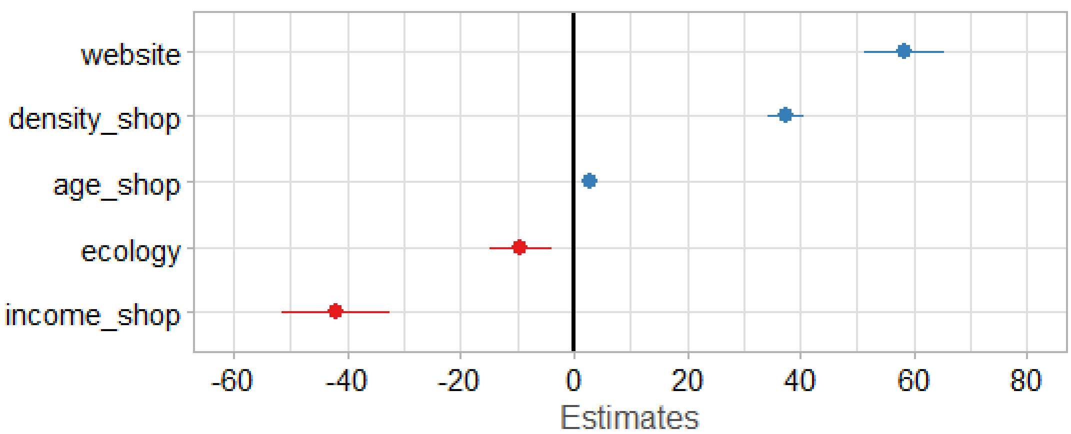


**Figure 6 Intercepts for level 2 variables**

The third part of the model is the integration of the highest level variables: the number of Covid-19 cases, the average rain precipitation and the average outside temperature (Figure 7). In this model, Covid-19 cases variable has the highest intercept, as well as the most spread confidence interval. This can be explained by two factors. The rise of Covid-19 cases triggered harder restrictions from local authorities, which lead to people leaving their home less and thus an increase in home deliveries. The government also encouraged people to buy from local stores to help them during this situation, which could partly explain the rise in deliveries from close shops. The confidence interval reflects the high variations of the number of Covid-19 cases in Quebec at the time of the experiment.

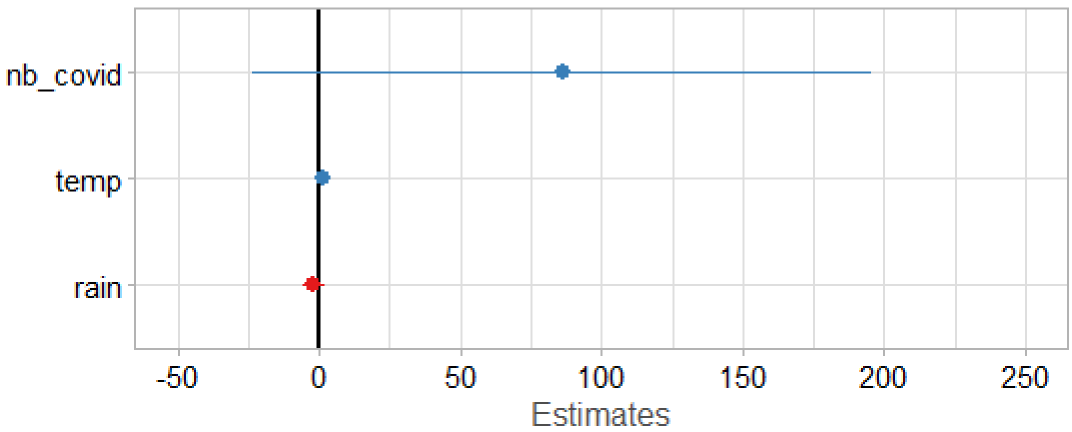


**Figure 7 Intercepts for level 3 variables**

When all levels are together, the model accounts for all interactions between the dependent variables and the independent variables, while taking into account the random effects created by the clustering by week and general classification of shops. When all variables are factored, the variables that have the lowest intercepts (rain, ecology, median income at the origin) can be considered negligeable. The temperature, median income at the point of delivery, age of the business in the system and the density of population at the destination have an intercept around zero, which means that these variables show little to no variance on the mean of the number of deliveries done. Finally, the density of population at the origin, the presence of a transactional website and the number of Covid-19 cases have the greatest impact on the variance, as their intercepts are higher than zero. When put into the perspective for the case study of

Montreal, we could extrapolate that businesses having a transactional website and located in neighborhoods with a high density of population managed to have more deliveries done by cargo bike than others.

**Table 5 Summary of estimates of the intercept by variable**

| **Variable** | **Name of variable in the model** | **Estimate of the intercept** |
|---|---|---:|
| Density of population at destination | density_dest | 4.2109 |
| Income of the population at destination | Income_dest | 2.047 |
| Distance between a shop and a consumer | distance | 9.0617 |
| Age of the shop in the system | age_shop | 2.8778 |
| Ecology | ecology | -9.6814 |
| Presence of a transactional website | website | 57.0785 |
| Density of population around the shop | density_shop | 38.1385 |
| Income of the population around the shop | income_shop | -42.0673 |
| Number of Covid-19 cases | nb_covid | 152.4623 |
| Average outside temperature | temp | 0.2080 |
| Average precipitations | rain | -0.1174 |

## 6. CONCLUSION AND FURTHER WORK

### 6.1 Contributions

This study proposes a linear regression method with random effects due to the evolution of the system in time and the diversity of shops considered in the system. We consider this approach useful for both policymakers and delivery actors to understand which variables to factor when implementing a delivery system. This paper also presents the first effects of Covid-19 on freight transportation systems and aims at providing a deeper understanding of the rapid changes that occur.

### 6.2 Limitations

This study does not take into account several factors which could have significant impacts on the number of deliveries done, such as the presence of a competing delivery system (shops deliver their customers by themselves or via traditional methods only). We also do not incorporate the notion of cannibalism between businesses. The presence of a high number of businesses which are part of the delivery initiative and belong to the same category could lead to less deliveries done, as consumers divide their choices amongst different shops. Furthermore, all of the data considered in this study only covers the first wave of the pandemic in Montreal, whereas a second wave is already taking place with different restrictions imposed by governments. The sample of data only covers participating businesses from main commercial streets.

### 6.3 Perspectives

Further work should be conducted to obtain a broader image of the evolution of the demand as the system and the pandemic are still evolving. Moreover, the data gathered for this initiative does not include consolidation amongst delivery bikers or trips. Consolidating the parcels would lead to a better operational system, which could have an impact on the key variables studied here. As of December 2020, Covid-19 cases in Quebec have reached new highs, and it would be valuable to study the long term impacts of consumers' behavior changes on cargo bike delivery systems.

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