# Impact of Public Transit on the Propagation of Influenza

Vincent Chandler

*Université du Québec en Outaouais*

*Abstract*: The purpose of this paper is to determine the impact of public transport on the propagation of influenza. This paper takes advantage of a 51-day public transit strike in Ottawa (Canada) to study the impact of the availability of public transit on the number of visits to emergency rooms due to influenza by using a difference-in-difference methodology. It finds a statistically significant decrease in the number of emergency room visits related to influenza during the strike relative to comparable cities. Overall, public transit is a significant vector of propagation of influenza. Public authorities could respond by asking commuters to wear masks, by cleaning surfaces more often, and by filtering the air to enable commuters to travel more safely.

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Corresponding author: Vincent Chandler, Vincent.chandler@uqo.ca

## 1. Introduction

Public transit inadvertently offers an ideal environment for the propagation of the influenza virus or any other airborne virus. Indeed, a bus full of commuters provides the virus a densely packed group of hosts waiting to be infected by breathing aerosolized droplets or by touching infected surfaces (Tellier, 2009). Past research has shown a correlation between influenza and public transit (Guerrisi et al., 2019; Troko et al., 2011), and new evidence suggests a similar link for the COVID-19 virus (Desmet and Wacziarg, 2020; Harris, 2020; McLaren, 2020).

Research on contagious diseases is important, knowing the pending risk of a pandemic (Webby and Webster, 2003) and the enormous cost associated with such an event (Fan, Jamison, and Summers, 2016). The COVID-19 pandemic has provided a striking example. Not only are pandemics associated with the loss of lives and labour force from individuals infected by the virus, but they can also lead to congestion in the health sector and delay treatment of individuals with other diseases. Moreover, the economic harm caused by measures to stop the pandemic

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comes at a great cost. Even in the absence of a major pandemic, influenza and other similar contagious diseases cause great harm every year (Centers for Disease Control and Prevention [CDC], 2018).

Even though previous studies have associated public transit use and influenza propagation, they are unable to identify a causal relationship. Indeed, they suffer from one important drawback: individuals taking public transit may be different from those who do not. This paper addresses this issue by taking advantage of a long strike in public transit in Ottawa, Ontario (Canada): between 10 December 2008 and 2 February 2009, commuters in Ottawa were unable to use public transit. Since Ottawa residents are otherwise similar to those of neighbouring cities, this natural experiment makes it possible to study similar individuals with and without public transit.

This approach is similar to that of Cauchemez et al. (2009), who take advantage of school closures, or Adda (2016), who uses national train strikes/expansions to assess their impact on influenza propagation. In both cases, the exogenous reduction in the number of social contacts had a significant negative impact on propagation. In terms of methodology, these strikes offer a unique opportunity to understand causal channels because their occurrence is unrelated to other epidemiological phenomena.

Using individual visits to the emergency rooms from 1 January 2008 to 31 December 2009 in Ottawa and in five neighbouring cities, I study the impact of the strike on the number of visits with influenza diagnosis using a negative binomial regression. I find that the number of daily visits for influenza cases decreased in Ottawa during the strike by 50 percent. The same results are robust to two different specifications: (i) whether influenza was the main diagnosis or one of ten possible diagnoses and (ii) whether I exclude the period during which the H1N1 pandemic took place (in the second part of 2009).

On top of the effect of the strike on the propagation of influenza, the strike also could have increased the transportation cost to visit an emergency room and reduced willingness to travel to the emergency room. Since I can only observe emergency room visits and not the number of real influenza cases, the strike simply could have led to a decrease in the number of visits but not in the number of cases. To remove this plausible explanation, I conduct the same analysis for visits due to urinary tract infections. I find no evidence of a decrease of visits for this type of illness, suggesting that the results are not due to the increase in transportation cost.

## 2. Methods

OC Transpo provides public transit services in the city of Ottawa. With 95.6 million passengers/trips using OC Transpo in 2007 (OC Transpo, 2010), it is a crucial element of the city’s urban transportation strategy. OC Transpo came to a halt on 10 December 2008 when the Amalgamated Transit Union local 279 went on strike. The strike ended 51 days later when the federal government threatened to impose back-to-work legislation on 29 January 2009. The O-Train restarted service on 2 February 2009, after some work on maintenance. Bus service resumed a week later (9 February 2009).

Throughout this paper I define the strike as starting on 10 December 2008 and ending on 2 February 2009, the time lapse during which there was absolutely no public transit.

The data on emergency room visits were obtained from the Canadian Institute of Health Information (CIHI). The dataset contains all visits to emergency rooms[2] between 1 January 2008 and 31 December 2009 in the following six cities in Eastern Ontario:[3] Ottawa, Brockville, Cornwall, Kingston, Smiths Falls, and Peterborough. They are all located in an area within a radius of approximately 200 kilometres of Ottawa. They are close enough to suffer similar health shocks but far enough to avoid some spill-over effects.

The control cities are small in comparison to Ottawa and have a less developed transit and healthcare system. Unfortunately, the only large city in the vicinity would be Toronto,[4] which is 500 kilometres away and is itself much larger than Ottawa.

The dataset contains 1,074,003 visits to emergency rooms. For each visit, the data contain information on the city of the visit, the day of the visit, the main diagnosis, and a maximum of nine other diagnoses coded following ICD-10-CA. Cases of influenza are defined using the following codes:

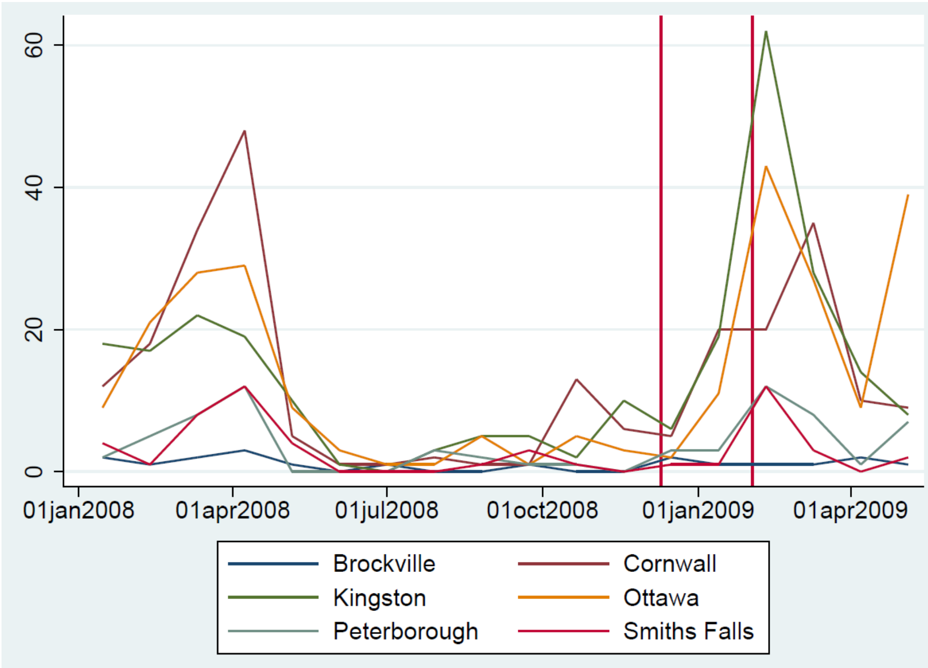
- J09 (Influenza due to identified avian influenza virus).
- J10 (Influenza due to identified influenza virus).
- J11 (Influenza, virus not identified).
- J12 (Viral pneumonia, not elsewhere classified).

For the main analysis, a visit is associated with influenza if one of these codes is mentioned in one of the ten possible diagnoses. For robustness, I also conduct the analysis for cases for which influenza is the main diagnosis.

Figure 1 below shows the biweekly number of visits by city between 1 January 2008 and 1 June 2009. One can see that all six cities have similar trends. The period following 1 June 2009 is excluded from the figure to avoid graphical issues with the H1N1 pandemic at the end of 2009. The data is stationary according to the Levin-Lin-Chu, Harris-Tzavalis, and Breitung tests.

[2] Unfortunately, data from walk-in clinics or family doctors are unavailable.
[3] CIHI does not have any health data from Québec, and Québec hospitals use a different system to classify symptoms that make it difficult to reconcile both systems.
[4] Unfortunately, it is impossible to use Gatineau or Montreal because the province of Québec does not share data with CIHI and uses a different classification system.

**FIGURE 1. Number of Visits with Influenza Diagnosis**




*Note: This figure shows the biweekly number of cases in all six cities considered for this study in the period between 1 January 2008 and 1 June 2009. All six cities have similar trends. The vertical red lines indicate the beginning and the end of the transit strike.*

Table 1 provides some summary statistics. Since Ottawa is larger than cities in its vicinity, there were more visits in Ottawa (6.415 visits/day) than in the other cities in the sample (1.215 visits/day), as shown in Table 1.

To focus on the pre-H1N1 period, I also calculate the averages for the period before 15 October 2009, during which there were 1.531 daily visits in Ottawa and 0.331 in control cities. During the strike, however, there were only 0.361 daily visits in Ottawa and 0.309 in the control cities.

The difference between the daily number of visits during and outside the strike is statistically significant at the 1 percent threshold. A rough estimate of the impact of the strike would be 0.327 fewer cases on a daily basis.[5]

[5] A difference-in-differences estimator would correspond to (0.389-0.667) - (0.352-0.303).

**TABLE 1. Average Daily Number of Visits with Any Diagnosis Related to Influenza**

| | Ottawa | Control Cities |
|---|---|---|
| Whole Sample | 6.415<br>(0.665) | 1.215<br>(0.665) |
| Before 15 October 2009 | 1.531<br>(0.091) | 0.331<br>(0.011) |
| Before 15 October 2009 Outside Strike | 1.637<br>(0.098) | 0.333<br>(0.0117) |
| Before 15 October 2009 During Strike | 0.361<br>(0.077) | 0.309<br>(0.033) |

*Note: These numbers were calculated using a total of 1,074,003 visits to emergency rooms in six cities (Ottawa, Brockville, Cornwall, Kingston, Smiths Falls, and Peterborough) in the period between 1 January 2008 and 31 December 2009. The difference between the average number of visits in Ottawa before 15 October 2009 outside the strike (1.637) is different from the average number of visits in Ottawa before 15 October 2009 during the strike (0.361) at a p-value of 0.0046. The same is not true for control cities (p-value: 0.804). Standard errors are in parentheses. The numbers in the whole sample are inflated by the H1N1 pandemic at the end of 2009.*

Since the daily number of visits related to an influenza diagnosis is count data (an integer greater than or equal to 0), I conduct the following negative binomial difference-in-difference regression:

$$\begin{aligned}\ln(\text{Number of visits})_{it} = {} & \ln(\alpha) + \beta_1 \text{ Strike*Ottawa}_{it} + \beta_2 \text{ Strike}_t + \beta_3 \text{ H1N1 epidemic}_t \\ & + \beta_4 \text{ Pre-strike}_t + \beta_5 \text{ Post-strike}_t + \beta_6 \text{ Pre-strike * Ottawa}_{it} \\ & + \beta_7 \text{ Post-strike * Ottawa}_{it} + \beta_8 \text{ Month-year fixed effects}_t \\ & + \beta_9 \text{ City fixed effects}_t + \epsilon_{it} \qquad (1).\end{aligned}$$

The *i* subscript refers to a city and *t* to a day. The coefficient of interest is $\beta_1$. If the strike decreased the number of visits related to influenza in Ottawa during the strike, this coefficient should be statistically significant and negative. If the number of visits related to influenza decreased in all cities during the strike, the coefficient $\beta_2$ will be negative. The coefficient $\beta_3$ captures the fact that the number of influenza cases increased tremendously during the H1N1 pandemic from 15 October 2009 to 30 November 2009 across Ontario.

To make sure that the trends in the five control cities are the same as those in Ottawa, I also include pre-strike interaction terms. The pre-strike period is defined as the month preceding the strike (10 November 2008 to 10 December 2008). If the coefficient $\beta_6$ is statistically significant, Ottawa probably experienced a city-specific shock before the strike, suggesting that the common trend hypothesis is violated. The coefficient $\beta_7$ assesses the persisting impact of the strike on the number of visits. This period is defined as 2 February 2009 to 2 March 2009.

To control for the seasonality of influenza epidemics, 23 month-year fixed effects are included in the regression; and since visits to the emergency room could vary from one day of the week to another, day-of-the week fixed effects are added. For example, there could be more visits on Saturday than on Friday. Since Ottawa is larger and more developed than the other cities, I include city fixed effects.

To further provide evidence of the common trend hypothesis, I conduct the main regression with a sample limited to the pre-strike period and create fake one-month-long strikes. Out of the 12 regressions, one had a positive coefficient for the interaction term *fake_strike*Ottawa* with a p-value of 0.17, and one had a negative coefficient with a p-value of 0.10. All other coefficients had very large p-values.

Since there are many days with zero visits for influenza in a given city, the distribution of the dependent variable is highly skewed. For this reason, the analysis is conducted with a negative binomial regression. All results are robust to Poisson regression.

The public transit strike not only may have decreased the speed of propagation of the influenza virus, but it also increased the cost of travelling to the hospital. During the strike, some individuals infected with influenza and dependent on public transit may have decided not to go to the hospital. The coefficients could therefore capture both the willingness to travel to the hospital and the propagation of the virus.

To address this issue, I study the impact of the strike on the number of visits for another diagnosis for which patients may not require urgent medical attention: urinary tract infection (ICD code: N39). For this robustness test to be valid, I assume that the strike had no direct impact on the number of cases.

To my knowledge, there is no mechanism linking a public transit strike to the number of cases of urinary tract infections. If there were fewer visits to the emergency room for this diagnosis, one could assume that the strike also influenced the decision to consult a physician in cases of influenza, suggesting the coefficient overestimates the effect. If not, one can assume that this decision is not related to the availability of public transit.

Finally, I conduct the difference-in-difference analysis for the main regression by removing each control city individually to make sure no control city is responsible for the results. The results remain the same if Kingston or Smiths Falls are removed; they are stronger if Peterborough or Brockville are removed; and they are weaker if Cornwall is removed (still significant at 5 percent for the last specification).

## 3. Results

Table 2 shows that there were significantly fewer visits with any influenza diagnosis during the strike in Ottawa. In a negative binomial regression, the coefficient represents the difference between the logarithm of the expected number of daily visits during the strike in Ottawa (when the variable takes the value of 1) and the logarithm of the expected number of daily visits not during the strike (when the dummy variable takes the value of 0). In mathematical terms, it corresponds to:

$$(\ln(\text{expected value}|x=1) - \ln(\text{expected value}|x=0)) \quad (2).$$

Coefficients in the neighbourhood of -0.78 like the ones in Table 2 would therefore correspond to a decrease from 0.68 daily visits outside the strike to 0.31 daily visits during the strike, which cuts the number of visits in half.

The lack of significance of the interaction term *Pre-strike*Ottawa* suggests that Ottawa suffers from the same shocks as the cities in the control group in the period preceding the strike.

**TABLE 2. Impact of the Strike on Influenza – Any Diagnosis**

| | (1) | (2) | (3) |
|---|---|---|---|
| Strike*Ottawa | -0.777*** | -0.790*** | -0.803*** |
| | (0.296) | (0.297) | (0.297) |
| Strike | 0.596* | 1.269** | 1.337*** |
| | (0.333) | (0.496) | (0.505) |
| H1N1 | 2.155*** | 2.157*** | 2.201*** |
| | (0.116) | (0.116) | (0.115) |
| Pre-strike | | 0.463 | 0.475 |
| | | (0.396) | (0.399) |
| Post-strike | | 1.121*** | 1.166*** |
| | | (0.407) | (0.412) |
| Pre-strike*Ottawa | | -0.871 | -0.883 |
| | | (0.551) | (0.551) |
| Post-strike*Ottawa | | -0.367 | 0.379 |
| | | (0.240) | (0.239) |
| Month-Year FE | Yes | Yes | Yes |
| Day of week FE | No | No | Yes |
| Constant | -0.596*** | -0.589*** | -0.811*** |
| | (0.103) | (0.103) | (0.116) |
| N | 4386 | 4386 | 4386 |

*Standard errors in parentheses*

*$* p < 0.10$, $** p < 0.05$, $*** p < 0.01$*

*Note: This negative binomial regression explains the number of visits with any diagnosis related to influenza. The variable strike takes the value 1 between 10 December 2008 and 2 February 2009, and otherwise 0. The H1N1 variable takes the value 1 between 15 October 2009 and 30 November 2009. The pre-strike period stretches from 10 November 2008 to 9 December 2008,* *and the post-strike period from 3 February 2009 to 2 March 2009. There are 23 month-year fixed effects for the period and 6 day of the week fixed effects.*

Table 3 confirms the results of Table 2 by considering only visits for which influenza is the main diagnosis. The coefficient of interest is very similar to the results from Table 2, and the common trend hypothesis is also confirmed.

**TABLE 3. Impact of Public Transit on Influenza – Main Diagnosis**

| | (1) | (2) | (3) |
|---|---|---|---|
| Strike*Ottawa | -0.787** | -0.800** | -0.813** |
| | (0.333) | (0.334) | (0.334) |
| Strike | 0.657* | 1.235** | 1.316** |
| | (0.355) | (0.549) | (0.561) |
| H1N1 | 2.165*** | 2.168*** | 2.219*** |
| | (0.123) | (0.123) | (0.122) |
| Pre-strike | | 0.283 | 0.299 |
| | | (0.456) | (0.460) |
| Post-strike | | 1.085** | 1.137** |
| | | (0.447) | (0.454) |
| Pre-strike*Ottawa | | -0.772 | -0.784 |
| | | (0.641) | (0.641) |
| Post-strike*Ottawa | | -0.362 | 0.376 |
| | | (0.255) | (0.255) |
| Month-Year FE | Yes | Yes | Yes |
| Day of week FE | No | No | Yes |
| Constant | -0.857*** | -0.851*** | -1.114*** |
| | (0.114) | (0.114) | (0.129) |
| N | 4386 | 4386 | 4386 |

*Standard errors in parentheses*

** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

*Note: This negative binomial regression explains the number of visits with any diagnosis related to influenza. The variable strike takes the value 1 between 10 December 2008 and 2 February 2009, and otherwise 0. The H1N1 variable takes the value 1 between 15 October 2009 and 30 November 2009. The pre-strike period stretches from 10 November 2008 to 9 December 2008, and the post-strike period from 3 February 2009 to 2 March 2009. There are 23 month-year fixed effects for the period and 6 day of the week fixed effects.*

Table 4 reports the results when the sample is restricted to the period preceding the H1N1 pandemic. As expected, this restriction decreases the absolute value of the magnitude of the coefficient of interest from -0.8 to -0.7, but these results are qualitatively very similar.

**TABLE 4. Impact of Public Transit Before the H1N1 Epidemic – Any Diagnosis**

| | (1) | (2) | (3) |
|---|---|---|---|
| Strike*Ottawa | -0.660** | -0.723** | -0.721** |
| | (0.291) | (0.295) | (0.294) |
| Strike | 0.379 | 1.158*** | 1.093** |
| | (0.300) | (0.449) | (0.456) |
| Pre-strike | | 0.431 | 0.401 |
| | | (0.384) | (0.384) |
| Post-strike | | 1.170** | 1.135** |
| | | (0.344) | (0.345) |
| Pre-strike*Ottawa | | -0.812 | -0.810 |
| | | (0.554) | (0.555) |
| Post-strike*Ottawa | | -0.205 | 0.210 |
| | | (0.208) | (0.208) |
| Month-Year FE | Yes | Yes | Yes |
| Day of week FE | No | No | Yes |
| Constant | -0.387*** | -0.419*** | 0.272*** |
| | (0.195) | (0.197) | (0.216) |
| N | 3102 | 3102 | 3102 |

*Standard errors in parentheses*

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Note: This negative binomial regression explains the number of visits with any diagnosis related to influenza. The sample is restricted to observations before 1 June 2009 to avoid any issues related to the H1N1 pandemic. The first wave started on 1 June 2009, but the second wave in November was more important. The variable strike takes the value 1 between 10 December 2008 and 2 February 2009, and otherwise 0. The pre-strike period stretches from 10 November 2008 to 9 December 2008, and the post-strike period from 3 February 2009 to 2 March 2009. There are 23 month-year fixed effects for the period and 6 day of the week fixed effects.*

Table 5 shows the lack of impact of the strike on the number of visits with diagnoses of urinary tract infection. These non-significant results suggest that the decrease in the number of visits for influenza cases presented in Tables 2 to 4 are not due to the increase in the cost of transportation but to a decrease in the number of influenza cases in the population.

**TABLE 5. Impact of Public Transit on Urinary Tract Infection – Main Diagnosis**

| | (1) | (2) | (3) |
|---|---|---|---|
| Strike*Ottawa | -0.044<br>(0.055) | -0.040<br>(0.055) | -0.041<br>(0.054) |
| Strike | 0.129*<br>(0.073) | 0.142<br>(0.112) | 0.0701<br>(0.110) |
| Pre-strike | | 0.037<br>(0.107) | -0.107<br>(0.106) |
| Post-strike | | 0.021<br>(0.084) | 0.015<br>(0.083) |
| Pre-strike*Ottawa | | 0.126<br>(0.114) | 0.125<br>(0.112) |
| Post-strike*Ottawa | | 0.081<br>(0.106) | 0.084<br>(0.104) |
| Month-Year FE | Yes | Yes | Yes |
| Day of week FE | No | No | Yes |
| Constant | 3.698***<br>(0.179) | 3.704***<br>(0.180) | 4.007***<br>(0.214) |
| N | 4386 | 4386 | 4386 |

*Standard errors in parentheses*

** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

*Note: This negative binomial regression explains the number of visits with any diagnosis related to a urinary tract infection (ICD Code: N39). The variable strike takes the value 1 between 10 December 2008 and 2 February 2009, and otherwise 0. The H1N1 variable takes the value 1 between 15 October 2009 and 30 November 2009. The pre-strike period stretches from 10 November 2008 to 9 December 2008, and the post-strike period from 3 February 2009 to 2 March 2009. There are 23 month-year fixed effects for the period and 6 day of the week fixed effects.*

## 4. Conclusion

A public transit system inadvertently provides the perfect environment for a virus: warmth, contact with the hands of commuters, and a large number of concentrated potential victims who breathe the same air for long periods of time. To determine the causal impact of public buses on the propagation of the influenza virus, this paper uses a natural experiment: a long public transit strike in Ottawa.

This paper finds a negative impact of the strike which translates into approximately 0.3 daily visits fewer to the emergency room during the strike for a case of influenza, for a total of 15 fewer visits during the whole period (51-day strike). Given a cost of $7030/influenza patient estimated in 2006 (Keren et al., 2006), the savings associated with this strike correspond to more than $105,450, not considering the increase in health cost since 2006.

The paper suffers from one important caveat: it only studies visits to the emergency room. These represent the tip of the iceberg and the most serious cases. The estimates therefore underestimate the effect of the strike on the total number of influenza cases that would include milder influenza cases that would not require a visit to the emergency room.

Two important policy implications can be drawn from these findings. First, in the event of an important pandemic, closing down the public transit system could decrease the propagation speed of influenza or a similar disease like COVID-19. Obviously, such a decision would come at an important cost: all workers would have difficulty commuting to work, thus affecting production. The impact on health care workers could ultimately increase the death toll in hospitals. Further research is necessary to better understand the cost-benefit analysis of such a decision. Second, even in the absence of an important pandemic, public transit systems could invest in low-cost strategies to minimize its impact on the propagation of air-borne diseases like influenza.

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