The Geography of Social Distancing in Canada: Evidence from Facebook

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L’auteur analyse quelles caractéristiques sont en corrélation avec les réductions de la mobilité au cours de la pandémie de la COVID-19, à partir de données sur la mobilité, au niveau des divisions de recensement pour le Canada, tirées de Facebook. La mesure dans laquelle la distanciation physique a été appliquée en avril, par rapport à la période qui a précédé en février, varie sensiblement. Selon les constatations de l’auteur, la population et la densité de population d’une division de recensement sont en étroite corrélation avec de plus importantes réductions de la mobilité. Inversement, l’auteur observe que les secteurs dans lesquels la proportion d’immeubles d’appartements affichent des réductions de la mobilité plus modestes, ce qui laisse croire que les personnes dont les conditions de vie sont plus rigoureuses risquent de se rendre compte qu’il leur est moins possible de rester à la maison durant la pandémie. Enfin, l’auteur s’intéresse à la persistance des réductions de la mobilité en mai et montre que dans les secteurs dont la proportion d’immeubles d’appartements est plus grande, le maintien de la distanciation physique dans le temps est davantage probable.

Mots clés : COVID-19, Facebook, réductions de la mobilité, rester à la maison

This article analyzes which characteristics are correlated with mobility reductions during the COVID-19 pandemic, using census-division-level mobility data for Canada from Facebook. There is significant variation in the extent to which social distancing was applied in April, relative to a preperiod of February. I find that the population and population density of a census division are strongly correlated with larger mobility reductions. Conversely, I find that areas with a larger share of dwellings that are apartments exhibit smaller mobility reductions, suggesting that those in tighter living conditions may find it less possible to stay at home during the pandemic. Finally, I examine the persistence of mobility reductions into May and show that areas with a larger apartment dwelling share are more likely to maintain their social distancing over time.

Keywords: COVID-19, stay-at-home, mobility reductions, Facebook

Introduction
The COVID-19 pandemic has radically altered the lives of Canadians in a very short span of time. In the absence of a vaccine, the primary tactic of public health officials to combat this virus has been to encourage social distancing and staying at home. In a limited window around the middle of March, all provinces enacted states of emergency, encouraging or mandating staying at home and shutting down large swathes of the economy.

Preliminary data suggest that mobility reductions around the world have been steep since the declaration of the World Health Organization that COVID-19 was a pandemic on 11 March 2020. Cases of COVID-19 and deaths have continued to climb in many countries around the world, including Canada. This only reinforces the importance of maintaining social distancing while medical researchers work to develop a vaccine. Unfortunately, the extent to which different regions, even within the same country, have adhered to social distancing has varied. Researchers around the world have examined the determinants of why some areas reduce their movements more than others, but Canada has lagged because of a lack of finely disaggregated data on mobility. Anecdotal evidence suggests, however, that social distancing has not been a primary concern for everybody. News reports have abounded of people flouting such guidelines across Canada.1

Despite this clear anecdotal evidence that social distancing is not uniformly important to all Canadians, no academic research has been done in Canada on the determinants of social distancing using finely disaggregated mobility data at the subprovincial level. This article presents this important first evidence, using recently released

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mobility data from Facebook. Importantly, these data are available at the census division (CD) level, which allows me to utilize significant geographical variation in various characteristics to understand why social distancing varies across Canada. Figure 1 below presents the variation in mobility reductions in April relative to February, across all Census Divisions in my sample. The map, whose colours are broken into seven quantiles, with darker colours representing greater mobility reductions, clearly illustrates the variation that I aim to exploit. Put simply, the extent of mobility reductions post-COVID vary across Canada, and this study will increase our understanding of why this is the case.

I present two key results. First, I estimate a series of regressions estimating how mobility reductions (in April, relative to February) are correlated with a series of CD-level work, demographic, and geographic variables. I find that population and population density consistently and significantly increase the mobility reductions across CDs; in other words, CDs with more people living more densely reduce their mobility by more. I also show that areas in which health occupations are a larger proportion of employment have reduced their mobility less, likely reflecting continued employment as essential workers.

I then examine the decay of mobility reductions over time by comparing April mobility reductions with May mobility reductions. I show that, although mobility has started increasing across Canada in aggregate, this is not occurring differentially by most CD-level characteristics. The one exception is apartment dwelling share, which is correlated with continued mobility reduction into May. These findings highlight the fact that lockdown fatigue, which can cause decreased social distancing adherence, does not appear to be correlated with a host of likely characteristics such as income, age, and education.

My article has two main contributions. First, I provide first academic evidence for the determinants of social distancing in Canada, particularly using data below the mobility data from Facebook. Importantly, these data are available at the census division (CD) level, which allows me to utilize significant geographical variation in various characteristics to understand why social distancing varies across Canada. Figure 1 below presents the variation in mobility reductions in April relative to February, across all Census Divisions in my sample. The map, whose colours are broken into seven quantiles, with darker colours representing greater mobility reductions, clearly illustrates the variation that I aim to exploit. Put simply, the extent of mobility reductions post-COVID vary across Canada, and this study will increase our understanding of why this is the case.

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Figure 1: Mobility reductions by census division, April relative to February
provincial level. I show that denser areas are more likely to reduce their movements, but areas where apartments are a larger share of dwellings are less likely to do so. I also provide evidence on how social distancing has changed over time, a topic that is becoming increasingly important as so-called lockdown fatigue chips away at stay-at-home policies’ effectiveness.

This paper relates to a small amount of prior work that has attempted to understand how mobility in Canada has changed post-COVID. Chan (2020) uses Google Mobility Trends data to provide some preliminary evidence at the provincial level of how mobility has declined in Canada. Cardoso and Wang (2020) used data from Environics Analytics, a private company, to provide some descriptive maps of mobility reductions in Canada at a subprovincial level. Environics Analytics also published a blog post looking at mobility reductions in relation to their marketing consumer categories. My article greatly expands on this existing analysis by using subprovincial data that are now freely available to analyze the determinants of social distancing academically, using applied econometric methods.

My article also relates to work from other countries that have studied the determinants of mobility reductions. Anderson et al. (2020), Chiou and Tucker (2020), and Gupta et al. (2020) examine the determinants of US sub-state-level social distancing. While the prevalence of immediately available data from companies such as SafeGraph, Google, and Descartes Labs led to a large part of the early mobility literature being done on the United States, other countries’ researchers have also started expanding this research to other countries. Dahlberg et al. (2020), for example, conduct an analysis of mobility reduction in Sweden, while Egorov et al. (2020) study how mobility has declined across cities in Russia; Egorov et al. (2020), in particular, focus on ethnic fractionalization. Similar to these studies, I provide first subprovincial academic evidence of the determinants of social mobility reductions in Canada.

Data

The data used in this paper come from two main sources. First, I make use of Facebook’s Movement Range Maps data, which provide subprovincial information on mobility reductions freely and at no cost for the first time. The data are gathered from users of the mobile app version of Facebook with Location History enabled. Data are aggregated to the census division level for data privacy, and mobility reduction indices have been constructed by Facebook showing the percentage of relative change in mobility at a daily level starting from 1 March 2020 relative to February movement levels. The relative mobility change variable is constructed by Facebook using small tiles of roughly several hundred square meters and calculating, for all people in their data, the number of tiles each person is observed in each day; using this, an average measure of tiles visited is calculated, with some noise added for privacy. This tile-based measure is then compared with a baseline average number of tiles visited in February (on that same day of the week) to calculate a relative measure of movement change based on these tile visits for all users in each region.

I take the daily level data and take the mean for each CD and month after March, resulting in a data set that measures the mean levels of mobility reduction in April and May relative to February. Readers interested in the specific methodology used in the construction of this data can refer to a working paper by Facebook (Maas et al. 2020).

Much like any other mobility-based dataset based on cell phone or location tracking, one might be concerned about the representativeness of the Facebook data. Unfortunately, there is little that can be done to verify that Facebook data are representative of the Canadian population for each census division. An overview of Canadian social media in 2017 by Gruzd et al. (2018) estimates using online survey data that 84% of online Canadians have Facebook accounts, with 79% of Facebook users reporting daily usage. Importantly, 75% of respondents aged 55 and above reported having a Facebook account, suggesting that a bias towards younger Canadians is not likely to be a major concern with the Facebook data. The prevalence of Facebook use and regular daily use among Canadians is also reassuring for external validity purposes.

I pair the Facebook data with CD-level variables from census profile data based on 2016 Census of Population. The variables I use are taken from these profiles or are constructed from them. The variables used can be divided into three categories: (a) work (log median household income, share of total income made up by government transfers, the unemployment rate, share of employed workers in health, share of employed workers in sales and service occupations), (b) geographic/population (log population, log population density, share of occupied private dwellings that are apartments), and (c) demographic (share of immigrants, log median age, married population share, share of couples with children, share of the population with no postsecondary education).

I calculate CD-level weather for February, April, and May using monthly climate summaries at the weather station level. For each CD, I find the weather station that is closest to its centroid and use that station’s data to represent weather for that CD. I make use of the mean temperature and the total precipitation in that month to capture weather in a given CD month.

I also make use of GIS data for CD shapefiles from GADM to help facilitate matching the Facebook data and the census data.

After merging all data together, I am left with 260 CDs with non-missing data. For reference, there are 293 CDs across Canada. The 260 CDs contain 34,763,738 out of

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35,151,728 total people in Canada. Importantly, as data on the territories are not consistently available, I omit them from the analysis and focus on the provinces.

**Descriptive Statistics**

In Figure 2, I first display a population-weighted aggregated time series of movement reductions in Canada from 1 March onwards. The figure clearly shows that movement remained relatively stable in early March, until approximately 11 March, when the WHO first declared a pandemic. Shortly thereafter, provincial governments declared states of emergency. By late March, mobility reductions had reached their greatest extent; although movement reductions started trending upwards starting in April, movement was still notably low relative to the February baseline.

In Table 1, I display summary statistics at the CD level for my key variables, with statistics calculated by weighting each CD by its 2016 population. Importantly, the relative change variable from Facebook measures significant mobility reductions in April relative to February. On average, mobility declined by over 38 percent at the CD level. This suggests, consistent with Figure 2, that movements of Canadians were much lower after the onset of the pandemic and the subsequent policies associated with it. In addition, changes in mobility seem to vary substantially across CDs, as can be seen in its standard deviation. Consistent with the map-based evidence in Figure 1, this suggests that social distancing was not uniform across Canada. Another notable statistic is the mean level of mobility reduction in May relative to February. This mean is notably lower, suggesting that movement was only about 20 percent lower on the average in May, relative to February. While some of this may be due to seasonal trends, it motivates my analysis of changes in movement reductions across April and May across CDs, to test whether the same determinants of movement reductions are also correlated with the decay in social distancing adherence over time.

I next list the top and bottom five CDs by their mean change in mobility in April relative to February in Table 2. The CDs with the largest mobility reductions are all in Quebec and have approximately 50% mobility reduction in April relative to February. In contrast, the bottom 5 CDs in terms of movement reduction are spread over a variety of provinces and have reduced their movement by significantly less, by 5–13% relative to the baseline February period. This again suggests that there is considerable heterogeneity in social distancing across Canada.

In the final descriptive result, I illustrate the correlations between the various dependent and independent variables of interest in the regression analysis. These correlations are calculated by weighting each CD by its population in 2016, as in the regressions. These are
presented in Table 3. Many of these correlations display the expected relationships between various variables, such as the strong positive correlation (0.74) between log population density and the share of dwellings that are apartments. The table also suggests that there exists some strong correlations, both positive and negative, between the change in mobility during April (in the first column of the matrix) and various CD characteristics such as population, population density, education, immigrant share, and apartment dwelling share. In Table A.1 in the Appendix, I also present unweighted Spearman rank correlation coefficients between all left- and right-hand-side variables.12

### Empirical Results

I test what types of characteristics at the CD level help determine mobility reductions by estimating the following regression specification:

$$m_{c,\text{Apr}} = \beta_0 + X_c \beta_1 + W_{c,\text{Apr-feb}} \beta_2 + \gamma_p + \epsilon_c.$$

$m_{c,\text{Apr}}$, the dependent variable, is the mean level of mobility reduction in April for CD $c$. I regress this against a vector of CD-level characteristics, $X_c$, which are described in the data section. I control for CD-specific weather changes using a vector of control variables $W_{c,\text{Apr-feb}}$, which captures the change in the mean temperature and total precipitation experienced by CD $c$. Finally, I include province fixed effects; this removes the effect of provincewide policy changes such as province-specific restrictions on work or movement. In the analysis, standard errors are clustered by province. Observations are weighted by each CD’s population in 2016.

Table 4 shows the results from these regressions. In the first three columns, I estimate the work, geographic, and demographic variables separately in sets. Column 1 estimates the impact of the work variables. I find that, in contrast to American results in Chiou and Tucker (2020), higher-income CDs actually reduce their mobility by less. In addition, I find that CDs that rely more on government transfers also reduce their mobility by less. Finally, the size of the coefficients suggests that CDs with a higher service and sales occupation employment share (which likely had their employment adversely impacted) were more likely to reduce their mobility, while health-employment-intensive CDs (where employment likely continued) were less likely to reduce their mobility, although the health coefficient is not statistically significant.

I then move on to column 2 of Table 4, which shows the impact of geographic/population variables on mobility reductions. I find that CDs with a higher population and a higher density are associated with larger mobility reductions. This suggests that larger, more dense urban areas may have reduced their mobility by more than their non-urban counterparts. The share of dwellings that are

### Table 1: Summary Statistics

| Variable                                      | Mean (SD)       |
|----------------------------------------------|-----------------|
| Relative change in mobility, April           | −0.384 (0.091)  |
| Relative change in mobility, May             | −0.197 (0.106)  |
| ln(population)                               | 12.873 (1.486)  |
| ln(pop density)                              | 5.032 (2.342)   |
| Apartment share of dwellings                 | 0.332 (0.199)   |
| Income share of government transfers (scaled from 0 to 100) | 12.247 (4.312)  |
| Unemployment rate (scaled from 0 to 100)     | 7.722 (2.355)   |
| Employed workers share of health             | 0.073 (0.013)   |
| Employed workers share of sales and services | 0.248 (0.021)   |
| Population share of immigrants               | 0.220 (0.156)   |
| ln(median age)                               | 3.723 (0.097)   |
| Married population share                     | 0.577 (0.040)   |
| Population share without postsecondary education | 0.447 (0.057)  |

Source: Author’s calculations, using data from various sources (see text for details). Each variable’s summary statistics calculated using the 260 Census Divisions in my sample, with each CD weighted by its 2016 population.

### Table 2: Top and Bottom Five CDs, Change in Mobility

| Rank | Province | CD               | Change in Mobility |
|------|----------|------------------|--------------------|
| 1    | Quebec   | L’Assomption     | −0.503             |
| 2    | Quebec   | Les Moulins      | −0.500             |
| 3    | Quebec   | Montreal         | −0.500             |
| 4    | Quebec   | Laval            | −0.499             |
| 5    | Quebec   | Les Pays-d’en-Haut | −0.492            |
| 256  | Quebec   | Les Iles-de-la-Madeline | −0.131          |
| 257  | Alberta  | Division No. 18  | −0.130             |
| 258  | Manitoba | Division No. 8   | −0.125             |
| 259  | Newfoundland and Labrador | Division No. 9 | −0.084             |
| 260  | Newfoundland and Labrador | Division No. 4 | −0.051             |

Source: Author’s calculations, from Facebook mobility data.
### Table 3: Correlation Matrix

| Variable                                 | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  | 11  | 12  | 13  | 14  | 15  |
|------------------------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 1. Relative change in mobility, April   | 1.00|     |     |     |     |     |     |     |     |     |     |     |     |     |     |
| 2. Relative change in mobility, April-may| 0.06| 1.00|     |     |     |     |     |     |     |     |     |     |     |     |     |
| 3. ln(pop)                               | -0.63| -0.61| 1.00|     |     |     |     |     |     |     |     |     |     |     |     |
| 4. ln(density)                           | -0.84| -0.29| 0.82| 1.00|     |     |     |     |     |     |     |     |     |     |     |
| 5. Share apartments                      | -0.56| -0.13| 0.67| 0.74| 1.00|     |     |     |     |     |     |     |     |     |     |
| 6. ln(income)                            | -0.09| -0.50| 0.30| 0.00| -0.36| 1.00|     |     |     |     |     |     |     |     |     |
| 7. Government transfers                  | 0.30| 0.67| -0.67| -0.36| -0.15| -0.81| 1.00|     |     |     |     |     |     |     |     |
| 8. Unemployment rate                     | 0.31| 0.10| -0.18| -0.31| -0.14| -0.18| 0.32| 1.00|     |     |     |     |     |     |     |
| 9. Share health                          | 0.43| 0.42| -0.38| -0.33| -0.13| -0.45| 0.48| 0.24| 1.00|     |     |     |     |     |     |
| 10. Share service                        | -0.07| 0.01| 0.19| 0.22| 0.35| -0.41| 0.27| 0.29| 0.35| 1.00|     |     |     |     |     |
| 11. Share immigrants                     | -0.59| -0.68| 0.87| 0.75| 0.55| 0.29| -0.59| -0.13| -0.56| 0.10| 1.00|     |     |     |     |
| 12. ln(median age)                       | 0.33| 0.39| -0.56| -0.33| -0.24| -0.57| 0.76| 0.13| 0.44| 0.28| -0.48| 1.00|     |     |     |
| 13. Share married                        | 0.48| 0.11| -0.58| -0.64| -0.84| 0.42| 0.05| -0.04| -0.05| -0.44| 0.46| 0.24| 1.00|     |     |
| 14. Share couples w/ child               | -0.63| -0.50| 0.70| 0.60| 0.23| 0.61| -0.68| -0.19| -0.62| -0.17| 0.77| -0.74| -0.17| 1.00|     |
| 15. Share w/o postsecondary             | 0.69| -0.06| -0.60| -0.66| -0.61| -0.13| 0.40| 0.28| 0.11| -0.16| -0.42| 0.23| 0.43| -0.33| 1.00|

Source: Author’s calculations. Calculated by weighting CDs by population.

Apartments is positive and statistically significant, indicating that apartment dwellers stay at home less.

Column 3, using demographic variables, shows that CDs with higher population shares of immigrants have larger mobility reductions. I also show that the share of the population without postsecondary education is also correlated with lower mobility reduction, staying at home less than those living in more educated CDs; it is possible that this is being driven by omitted work variables, though, which I test in the following set of results. I also show that the share of couples with children is negatively correlated with mobility changes, suggesting that areas where couples are more likely to have children stayed at home more in April than other CDs.

Finally, I estimate a regression with all variables and report results in column 4. Many prior variables that were statistically significant are now no longer so. For example, log income and service employment share is of much smaller magnitude and no longer significant in this last column, suggesting that the prior results were partly driven by correlation with omitted variables. I find that the mobility reductions by population and population density remain statistically significant and of similar magnitude, further verifying that these area characteristics have a strong relationship to social distancing adherence. Similarly, the apartment dwelling share and the health employment share remain statistically significant and are still associated with less mobility reduction (with its positive coefficient). These four variables therefore seem to have the most robust association with changes in mobility post-COVID, even after controlling for a host of mitigating factors.

Having examined the determinants of mobility reductions across CDs, I now turn to analyzing whether the same determinants are correlated with the persistence of mobility reductions across time (specifically, from April to May). As Figure 2 showed, mobility reductions clearly decline over time. I provide evidence as to whether these declines in social distancing exhibit a pattern across CDs. To do this, I estimate a variant of my original specification:

$$m_{c, May} - m_{c, Apr} = \beta_0 + \mathbf{X}_c \beta_1 + \mathbf{W}_{c, May - Apr} \beta_2 + \gamma + \epsilon_c.$$  

I use the same main regressors, but the dependent variable now measures the difference in the mean mobility reduction in May and the mean mobility reduction in April. This captures the average change in mobility reduction that occurred within a given CD. I also alter the weather control variable so that it now accounts for the change in weather that occurred across April and May. The results for these regressions are displayed in Table 5.

I do not explain the bulk of the results in this table, in part for brevity but also because many of the determinants do not seem to be robustly correlated (positively or negatively) with persistence in mobility reductions once all variables are included in the final column. The one exception is the apartment dwelling share, which is negatively correlated with mobility reduction persistence from April to May. In this specification, this means that CDs with more apartments as dwellings persist more in their social distancing from April to May. Otherwise, none of the other determinants from Table 4 are statistically significant. This implies that the declines in mobility reductions seen in April to May are not correlated with...
Table 4: Change in Mobility and CD Characteristics

| Variables               | Regressions |         |         |         |
|-------------------------|-------------|---------|---------|---------|
|                         | (1)         | (2)     | (3)     | (4)     |
| ln(income)              | 0.0697***   | 0.00121 |         |         |
|                         | (0.0158)    | (0.0645)|         |         |
| Government transfers    | 0.0186***   | 0.00373 |         |         |
|                         | (0.00287)   | (0.00287)|        |         |
| Unemployment rate       | −0.00282    | −0.000841 |         |         |
|                         | (0.00411)   | (0.00188)|        |         |
| Share health            | 0.728       | 0.464*** |         |         |
|                         | (0.492)     | (0.163) |         |         |
| Share service           | −0.668***   | 0.0475  |         |         |
|                         | (0.187)     | (0.186) |         |         |
| ln(pop)                 | −0.0320***  | −0.0112*** |         |         |
|                         | (0.00249)   | (0.00357)|        |         |
| ln(density)             | −0.0186***  | −0.0161*** |         |         |
|                         | (0.00237)   | (0.00162)|        |         |
| Share apartments        | 0.134***    | 0.135*** |         |         |
|                         | (0.0342)    | (0.0566)|         |         |
| Share immigrants        | −0.156***   | −0.106  |         |         |
|                         | (0.0195)    | (0.0716)|         |         |
| ln(median age)          | 0.0127      | 0.0611* |         |         |
|                         | (0.0557)    | (0.0306)|         |         |
| Share married           | 0.0706      | 0.0953  |         |         |
|                         | (0.0714)    | (0.140) |         |         |
| Share couple w/ child   | −0.337***   | 0.0382  |         |         |
|                         | (0.0692)    | (0.168) |         |         |
| Share w/o postsecondary | 0.509***    | 0.215   |         |         |
|                         | (0.0682)    | (0.150) |         |         |
| Observations            | 260         | 260     | 260     | 260     |
| R-squared               | 0.829       | 0.904   | 0.903   | 0.942   |

Notes: Regressions also include weather control variables and province fixed effects. *** denotes statistical significance at the 1% level, ** denotes statistical significance at the 5% level, and * denotes statistical significance at the 10% level. Standard errors are clustered by province. The dependent variable is the mean change in mobility in April, relative to February. Observations are weighted by each CD’s population. Source: Author’s calculations.

any particular characteristic. Going back to the motivating example of Trinity Bellwoods Park on 24 May 2020 in the Introduction, my results imply that this is not the by-product of certain types of areas becoming more fatigued by long-running lockdowns.

Conclusion

This paper provides evidence on the determinants of geographical mobility reductions during the COVID-19 pandemic at the subprovincial level in Canada. One of the most striking results is that population and population density are strongly correlated with more mobility reductions. I also find that areas with a higher apartment dwelling share are less likely to have reduced mobility; one potential explanation for this result could be that those living in apartments are unable to socially distance as effectively, owing to their living, social, or work situations.

This suggests that more work needs to be done to examine how COVID-19 has impacted the most vulnerable segments of the Canadian population, to ensure that their economic circumstances are not translating into inequality of outcomes during the pandemic.

I also highlight the fact that area characteristics are not correlated with the persistence of mobility reductions into May, with the exception of apartment dwelling shares. This highlights that, if Canadians are becoming tired of staying at home and moving around more over time, this is not differentially the case for different types of CDs. Policymakers and the general public should not therefore believe this fatigue is isolated to one particular demographic or region.

Another aim of this paper was to highlight the usefulness of subprovincial data in tracking adherence to social distancing both across geographies and over time. My
work aggregated the timing of the data to the monthly level, but other work by researchers could take advantage of the daily frequency to examine more specific incidents or leverage even more variation.

**Notes**

1. In Toronto during Victoria Day weekend, for example, outrage focused on images and videos of a crowded Trinity Bellwoods Park.

2. Cross-hatched areas represent CDs where data are unavailable or are not in my sample. These largely belong to the territories, or are CDs where population density is very low.

3. While informative, this US-based work also highlights that more work needs to be done in the Canadian context. For example, Anderson et al. (2020) find that sick leave mandates increased staying at home in the US during the COVID-19 pandemic. Given that only 42.4% of employees in Canada have employer-provided sick leave (see Chen and Mehdi 2019), a similar study in Canada may find different results.

4. Observations in the Facebook data nearly always match up one to one with 2016 CDs. The lone exception is for Strathcona and Comox Valley, which are presented as one unit in the Facebook data. I simply assign the aggregated value from the Facebook data to each of the two aforementioned CDs in the analysis.

5. Unfortunately, the data are only available from 1 March 2020 onwards. This precludes the use of any preperiod data to form a counterfactual level of movement.

6. There is also another measure in the data that measures the amount of “staying put” that takes place each day in each CD. This is the number of users who stay in one tile during

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**Table 5: Change in Mobility’s Persistence and CD Characteristics**

| Variables                  | (1)     | (2)     | (3)     | (4)     |
|----------------------------|---------|---------|---------|---------|
| ln(income)                 | 0.0499*** | 0.0229  |         |         |
|                            | (0.0150) | (0.0302) |         |         |
| Government transfers       | 0.00629*** | 0.00224 |         |         |
|                            | (0.00121) | (0.00265) |         |         |
| Unemployment rate          | -0.00284 | -0.00134 |         |         |
|                            | (0.00230) | (0.00164) |         |         |
| Share health               | 0.510*** | 0.197   |         |         |
|                            | (0.0695) | (0.207) |         |         |
| Share service              | -0.120   | -0.00971 |         |         |
|                            | (0.0824) | (0.0655) |         |         |
| ln(pop)                    | -0.00928 | 0.00139 |         |         |
|                            | (0.00530) | (0.00445) |         |         |
| ln(density)                | -0.00213 | -0.00201 |         |         |
|                            | (0.00180) | (0.00228) |         |         |
| Share apartments           | -0.00417 | -0.0233*** |         |         |
|                            | (0.0195) | (0.0982) |         |         |
| Share immigrants           | -0.0639  | -0.00343 |         |         |
|                            | (0.0477) | (0.0772) |         |         |
| ln(median age)             | 0.0767   | 0.00803 |         |         |
|                            | (0.0481) | (0.0562) |         |         |
| Share married              | 0.0705   | 0.0264  |         |         |
|                            | (0.108) | (0.0909) |         |         |
| Share couple w/ child      | -0.0586  | -0.133  |         |         |
|                            | (0.106) | (0.117) |         |         |
| Share w/o postsecondary    | 0.0261   | -0.0170 |         |         |
|                            | (0.0346) | (0.0977) |         |         |
| Observations               | 260      | 260      | 260      | 260     |
| R-squared                  | 0.870    | 0.862    | 0.888    | 0.894   |

Notes: Regressions also include weather control variables and province fixed effects. *** denotes statistical significance at the 1% level, ** denotes statistical significance at the 5% level, and * denotes statistical significance at the 10% level. Standard errors are clustered by province. The dependent variable is the difference in the mean change in mobility in May minus the mean change in mobility in April. Observations are weighted by each CD’s population.

Source: Author’s calculations.
a given day, divided by all eligible users in that CD. I do not use this measure because there is no pre-COVID level of staying put that I can use as a baseline, unlike the change in movement variable, which compares movements to February baseline levels.

7 Data, as of 8 June 2020, are available at Statistics Canada (n.d.).

8 This includes certificates and diplomas, not only bachelor’s degrees and above.

9 The Facebook data have GADM geographical identifiers. Using GADM data helped to map the GADM identifiers to the CD codes used by Statistics Canada.

10 Many of the missing data constraints come from the Facebook mobility data, likely due to data privacy issues.

11 The Spearman rank correlation coefficients convert all variable values to the rank that each particular observation has in terms of the value of that variable. They then correlate the ranks of two different variables, instead of the actual values. This has the benefit of producing a correlation matrix that is invariant to monotonic transformations of variables, such as taking logs. The correlation coefficients are calculated without weighting for population.

12 These variables’ coefficients are omitted for brevity.

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## Appendix

### Table A.1: Spearman’s Rank Correlation Matrix, Unweighted

| Variable                                      | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  | 11  | 12  | 13  | 14  | 15  |
|-----------------------------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 1. Relative change in mobility, April         | 1.00|     |     |     |     |     |     |     |     |     |     |     |     |     |     |
| 2. Relative change in mobility, April–May    | -0.36| 1.00|     |     |     |     |     |     |     |     |     |     |     |     |     |
| 3. ln(pop)                                    | -0.35| -0.37| 1.00|     |     |     |     |     |     |     |     |     |     |     |     |
| 4. ln(density)                                 | -0.67| 0.04| 0.63| 1.00|     |     |     |     |     |     |     |     |     |     |     |
| 5. Share apartments                           | -0.60| 0.23| 0.50| 0.56| 1.00|     |     |     |     |     |     |     |     |     |     |
| 6. ln(income)                                  | -0.03| -0.56| 0.52| 0.11| -0.03| 1.00|     |     |     |     |     |     |     |     |     |
| 7. Government transfers                       | 0.08| 0.58| -0.60| -0.18| -0.10| -0.91| 1.00|     |     |     |     |     |     |     |     |
| 8. Unemployment rate                          | 0.48| -0.03| -0.33| -0.52| -0.32| -0.29| 0.39| 1.00|     |     |     |     |     |     |     |
| 9. Share health                               | 0.17| 0.18| -0.08| -0.01| 0.10| -0.41| 0.39| 0.31| 1.00|     |     |     |     |     |     |
| 10. Share service                             | -0.00| 0.04| 0.15| 0.07| 0.29| -0.24| 0.28| 0.49| 0.44| 1.00|     |     |     |     |     |
| 11. Share immigrants                          | -0.01| -0.75| 0.64| 0.32| 0.09| 0.59| -0.72| -0.28| -0.24| -0.03| 1.00|     |     |     |     |
| 12. ln(median age)                            | 0.13| 0.36| -0.47| -0.13| -0.17| -0.74| 0.79| 0.33| 0.41| 0.35| -0.44| 1.00|     |     |     |
| 13. Share married                             | 0.23| -0.05| -0.25| -0.21| -0.55| 0.25| -0.11| -0.17| -0.30| -0.44| -0.09| 0.08| 1.00|     |     |
| 14. Share couples with child                  | -0.29| -0.30| 0.50| 0.31| 0.22| 0.73| -0.71| -0.35| -0.37| -0.28| 0.39| -0.91| -0.10| 1.00|     |
| 15. Share without postsecondary               | 0.59| -0.13| -0.43| -0.56| -0.60| -0.18| 0.23| 0.33| -0.11| -0.24| -0.17| 0.06| 0.16| -0.17| 1.00|

*Source: Author’s calculations. Calculated without weighting CDs by population.*