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Résumé de l'article

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VIEWING THE COVID-19 PANDEMIC FROM SPACE: THE EFFECT OF COVID-RELATED MOBILITY DECLINES ON NIGHT LIGHT BRIGHTNESS IN CANADA

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Abstract: High-frequency economic data for small areas is often difficult to obtain in Canada and other countries. This paper overcomes this limitation by using monthly data derived from satellite night light images as a proxy for economic activity in Canadian Census Divisions. This proxy is used in conjunction with Facebook mobility data to estimate the effects of mobility declines due to COVID-19 on economic activity. I find robust evidence that reductions in movements are strongly negatively associated with declines in luminosity. Further analyses suggest that this effect is weaker in more densely populated areas, but stronger in Census Divisions with a higher concentration of retail businesses. My findings suggest that policies which reduce the need for in-person activities can mitigate the negative effects of COVID-related mobility reductions on economic activity. This paper also further highlights the value of using monthly satellite night lights data in economic analysis.
JEL codes: I18, R12

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INTRODUCTION

The COVID-19 pandemic has upended the organization of economic activities in countries around the world. One thing that has become clear is that data is an incredibly important tool for governments and researchers to understand and implement appropriate policies to combat COVID. Fortunately, an unprecedented effort by both the public and private sectors has resulted in a large amount of data that is geographically disaggregated and at a daily level becoming publicly available shortly after its collection. Numbers of new cases and deaths attributable to COVID are typically available within days of their occurrence in many countries, for example. Companies such as Google and Facebook have also leveraged their users' data to construct measures of mobility in sub-national regions globally, which has become an invaluable resource to proxy for how much people in these regions were moving around versus staying at home.

One data limitation that has remained persistent through the pandemic in most countries is the availability of similarly temporally and geographically disaggregated data on economic outcomes. Without such data, understanding how COVID has affected economic well-being in different regions of a country is challenging. This paper seeks to overcome this issue by using data on night lights captured by satellites as a proxy for economic activity. Specifically, I use this night lights data to determine how reductions in mobility due to COVID-19 have disrupted economic activity in Canadian regions.[1]

I first verify that night lights are a suitable proxy for economic activity by showing that night light intensity is positively correlated with population, population density, as well as business counts. I then find that regions with lowered mobility also had lower economic activity as measured by night light intensity. This main result is robust to a series of specifications, sample restrictions, and alternative weighting. This relationship between light intensity and mobility is strongly positive in both 2020 and 2021, suggesting that there has been no diminishing of reduced mobility's effect on economic activity despite the increased prevalence of masking and vaccination. Finally, I find that the mobility-lights relationship is weaker in denser regions and regions with a higher share of drinks and food businesses and stronger in regions with a higher share of retail businesses.

My paper relates to several strands of literature. The first is the work that has been done to investigate the economic consequences of COVID-19. Most related to this paper is Beyer et al (2021), who explore the relationship between COVID cases and outcomes that include night lights and mobility in the Indian context. Relative to Beyer et al. (2021), my paper uses a developed country setting in Canada and directly explores the link between mobility and night lights. In a complementary working paper, Beyer et al. (2020) find that Indian districts subject to more intensive stay-at-home orders saw reduced satellite night light intensity and mobility; my paper instead studies the relationship between mobility and night lights in Canada, and covers the later stages of the pandemic in 2021. Other work that has explored the economic consequences of COVID-19, particularly in Canada, include Lemieux et al. (2020), Jones et al. (2020), and Beland et al. (2022). My paper expands on this research by using a measure of economic activity available at the monthly level for any geographical aggregation to capture the impacts of COVID-19; this stands in contrast to much prior work on economic outcomes of COVID-19 in Canada that rely on surveys such as the Labour Force Survey, which are limited in their ability to drill down to small geographical areas.

I also contribute to the body of work that has used mobility data from companies such as Google and Facebook to measure citizens' movements in sub-national regions during the COVID-19 pandemic. Chan (2020) looks at the determinants of mobility reductions in Canadian Census Divisions during the early stages of the pandemic using Facebook data. Another related paper that uses mobility measures is Espitia et al. (2022) who, like I do in this paper, use mobility data as a measure of COVID affectedness across countries to estimate the effects of the COVID-19 pandemic on international trade flows. Other work that has used mobility data as either an outcome or explanatory variable in COVID research include Brodeur et al. (2021), Armstrong et al. (2020), Allcott et al. (2020), and Egorov et al. (2021). Relative to this work, I link differences in mobility across time and space to another novel data source: satellite-derived night light intensity.

Finally, there has been a considerable amount of research that has leveraged satellite night light imagery as a source of data to proxy for economic activity. Henderson et al (2012) first pioneered the use of night lights as such a proxy in economics, arguing for their value in contexts where sub-national economic data is scarce. Researchers have since used satellite night light data to examine things such as the effects of the 2018 U.S.-China trade war on Chinese regions (Chor & Li, 2021), economic sanctions on North Korea (Lee, 2018), and foreign aid in Uganda (Civelli et al., 2018). For Canada, little work has been done using night lights as a measure of economic activity; the lone exception in the economics literature, to my knowledge, is work by Feir et al. (2018) that explores using night lights to proxy for per-capita income in remote Indigenous communities. My paper will add to this literature by expanding the use of night lights to regions across Canada in my analysis of how reductions in mobility have affected Canadian economic activity. Compared to Feir et al. (2018), I also use the more recent iteration of night lights, VIIRS, which is more precise and allows for monthly time series to be constructed.[2]

The rest of the paper proceeds as follows: Section 2 describes the data and methods used, Section 3 presents the results of the empirical analysis and discusses their implications, and Section 4 concludes.

DATA AND METHODOLOGY

Data

The main data source used in this paper is the satellite-derived night lights data. Specifically, I make use of the monthly cloud-free DNB (day night band) composites from the Visible and Infrared Imaging Suite (VIIRS) on-board the Joint Polar-orbiting Satellite System (JPSS). The data are available for download in geotiff format from the Earth Observation Group.[3] The monthly data used take advantage of multiple passes of satellites over regions, and composite images from these passes into a monthly aggregate with various data cleaning procedures. I make use of the version of the data that takes advantage of additional coverage using a stray-light correction procedure, since this version of the data provides better coverage at more northerly latitudes. The cleaned, publicly available data provide, at a 15 arc second resolution across Earth's surface, the mean radiance observed in each cell. Radiance is measured in nW/cm2/sr, which is nanowatts per steradian per square meter. For more information on the data construction and the processing procedures, particularly in comparison to older vintages of satellite-derived night light data, please see Elvidge et al. (2013).

1 Regions will be defined as GADM (the Database of Global Administrative Areas) level 2 regions, which correspond to Census Divisions for Canada.

2 For more detail on why the night light data from VIIRS, used in my paper, is different and offers advantages over this older vintage of night lights data from DMSP, see Eldridge et al (2013).

3 https://eogdata.mines.edu/products/vnl/

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I take the satellite data and aggregate it to the GADM level-2 region level by calculating each region's average level of luminosity in a particular month.[4] I use this particular regional definition for two reasons. First, this is the level of geographic aggregation of the Facebook mobility data. Second, GADM level-2 regions are equivalent to Census Divisions in Canada, making it fairly straightforward to map census outcomes to the mobility and night lights data. I therefore use the term region to refer to either interchangeably in this paper.

I next obtain Facebook's mobility data from the Humanitarian Data Exchange, where it has been uploaded and is publicly available.[5] The data make use of Facebook's user location data. Specifically, users who use Facebook on a mobile device and have opted into location history are the basis of the mobility measures. Users are mapped to a particular region based on where that user is observed in the evenings. Facebook then calculates two measures. The main measure of mobility is how many level-16 Bing tiles (which vary slightly by size but are roughly 600m x 600m near the equator) different users are seen in during a given day. The main measure of mobility for a region is then calculated as the mean number of tiles users associated with that region are observed in for that given day. The publicly available measures take this mobility measure and compare it relative to mobility in a given region from February 2, 2020 to February 29, 2020, using this period as the pre-COVID benchmark. The publicly available measure is then reported as a percentage increase or decline in mobility for a region in a given day relative to that February baseline, with a negative percentage representing a decline in mobility.

Facebook also generates an alternative measure that represents whether users stayed put in a region by first calculating the number of users in a region that stayed within a single Bing tile for that day. The publicly available measure then takes this and calculates the share of eligible users in that region that stayed put.[6]

Facebook's data are available only starting in March 2020 and are updated regularly. I take both measures of mobility from Facebook and aggregate them to the monthly level by taking a monthly mean of both variables. This allows me to construct a combined dataset at the Census Division-month-year level beginning in March 2020 and ending in December 2021.

I make use of two further datasets in my analysis. First, I obtain Census Division level populations from the 2016 Census of Population census profiles. This will allow me to weight regions by population in my analysis. I also make use of data from the December 2019 edition of the Canadian Business Counts, which uses the Canadian Business Register to tally the number of active businesses in each Census Division, both in aggregate and by NAICS industry.

The final dataset comprises 262 Census Divisions, with monthly data starting from March 2020 until December 2021 (for a total of 22 months). Some data are missing for some Division-month-year combinations, resulting in a final sample size of 5,524 Division-month-year observations for the main specification.

Much of the missing data issues are driven by missing data from Facebook, which drops Census Divisions during times when there are too few users to report data, or for other issues. Unfortunately there is no way to examine how the data at the Division level was constructed by Facebook. The public files contain only the reported aggregated Division-level variables, and have no further variables that could shed light on what missing data issues exist.

Reassuringly, however, while the number of Census Division with non-missing Facebook data fluctuates throughout the sample period, from a low of 227 (in October 2021) to a high of 262 (from March to May 2020), the amount is always relatively high, staying largely around the 240s and 250s on any given month. Furthermore, when taking the mean of population for Division-month-years that have missing data from Facebook and comparing the mean of population for Division-month-years that do not have missing data, the population mean for the missing sample is much smaller (at 11816 versus 137952). Given that my main regressions weight observations by population, missing Census Division-month-years that are dropped due to missing Facebook data are unlikely to have any sizeable effect on my estimates.

Empirical Methodology

Using the data described in the prior subsection, I estimate the following specification for my main analysis:

$$\operatorname{asinh}(lights_{cmy}) = \beta_0 + \beta_1 \operatorname{asinh}(mobility_{cmy}) + \gamma_{p(c)my} + \delta_{cy} + \epsilon_{cmy}$$

The main left hand side variable is the mean luminosity from the night lights data for Census Division c in month m during year y. This variable is then transformed using the inverse hyperbolic sine transformation. This transformation is increasingly used instead of the log transformation since zeroes and negative values can both be accommodated with this transformation while neither is possible with the log transformation. In addition, as Bellemare and Wichman (2020) show, the coefficient in an asinh-asinh specification can also be interpreted as an approximation of an elasticity, much like in a log-log specification. I also make use of an alternate specification in which I do not transform the light or mobility variables and show that my main results are robust to this alternate methodology.

The right hand side variable of interest is the transformed mobility Facebook measure, $\operatorname{asinh}(mobility_{cmy})$. In my preferred specification, I also include province-month-year fixed effects and Census Division-year fixed effects. The province-month-year fixed effects control for a wide range of confounding variables, such as province-level policies concerning COVID or time-varying differences in concerns over COVID at the province level. The Census-Division-year fixed effects serve an important purpose in my analysis. First, as the mobility measure (the main measure based on movements) is a relative measure based on each Census Division's baseline level of movement in February 2020, it is not appropriate to compare mobility measure values across Census Divisions. The interaction between Census Division and year also helps allow for the unobserved Census Division-level heterogeneity to vary by year (2020 versus 2021). In other specifications, I vary the fixed effects used; in these cases, I specify the fixed effects used in the relevant table.

Standard errors are clustered by Census Division throughout the paper in all regressions. I weight each observation by that Census Division's population as of the 2016 Census, although I also show that the main results hold when weighting all observations equally.

Summary Statistics

I first describe the data in a spatial manner by presenting several maps with several key variables presented visually using graduated scales.

In Figure 1, I display the change in luminosity by Census Division from April 2019 to April 2020. The data on the map are presented in 7 quantiles, with darker colours representing more negative changes. In Figure 1 and in all maps to follow, only Census Divisions in my estimation sample are represented on the map; missing Census Di-

4 I make use of boundary shapefiles from GADM and the Zonal Statistics as Table tool in ArcMap to perform this task. I drop missing data from the calculations, since the VIIRS website states that areas with missing coverage should not be treated as having no lights during a month.

5 As of the writing of this paper.

6 For more information on Facebook's mobility data, please see Dow et al (2020).

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Figure 1. Change in luminosity, April 2019 to April 2020. Data displayed in 7 quantiles, with darker colours representing more negative changes in luminosity

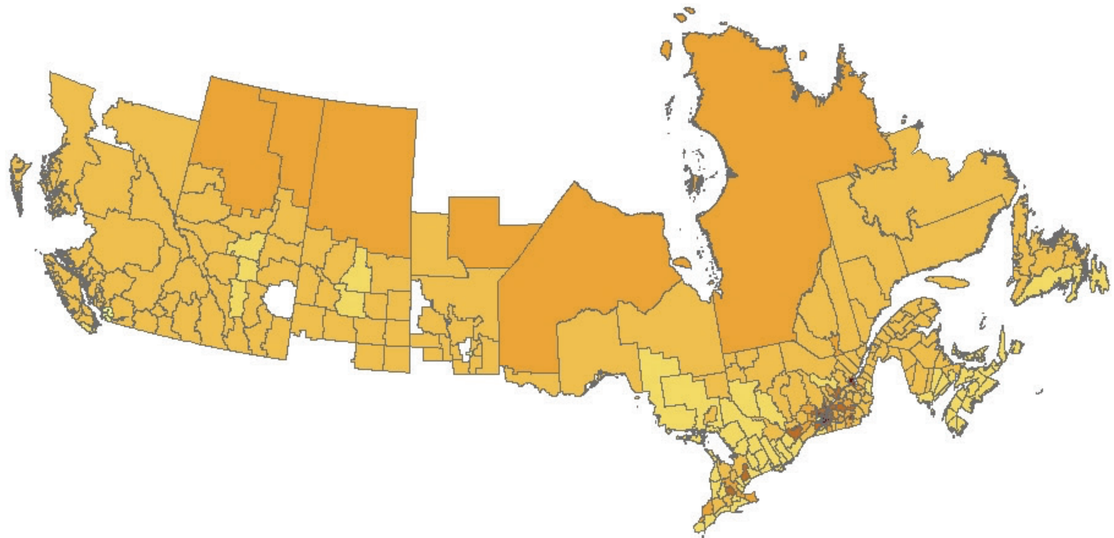


Figure 2. Census Divisions with decreased night light intensity (in darker shade)

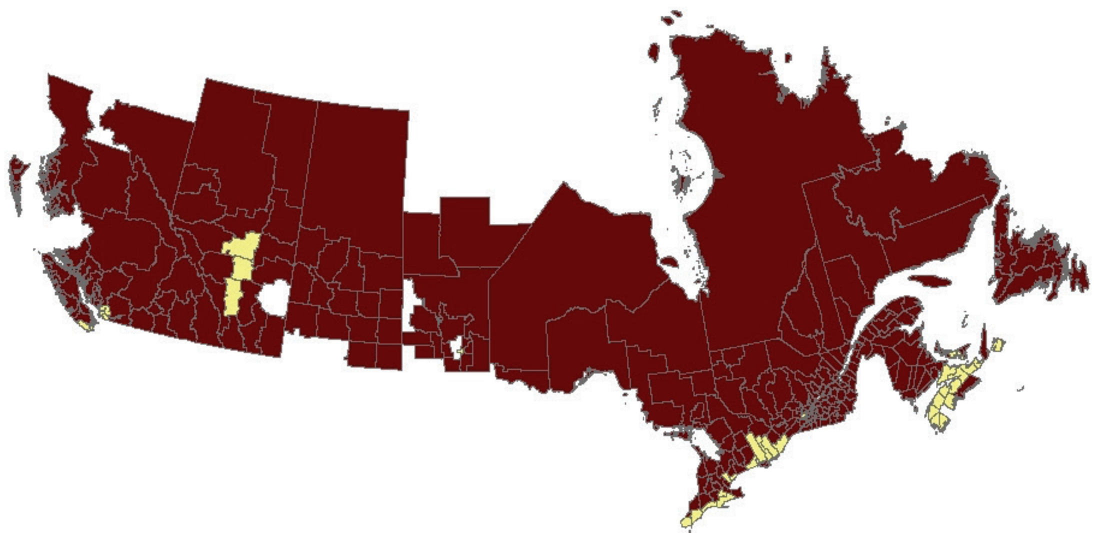
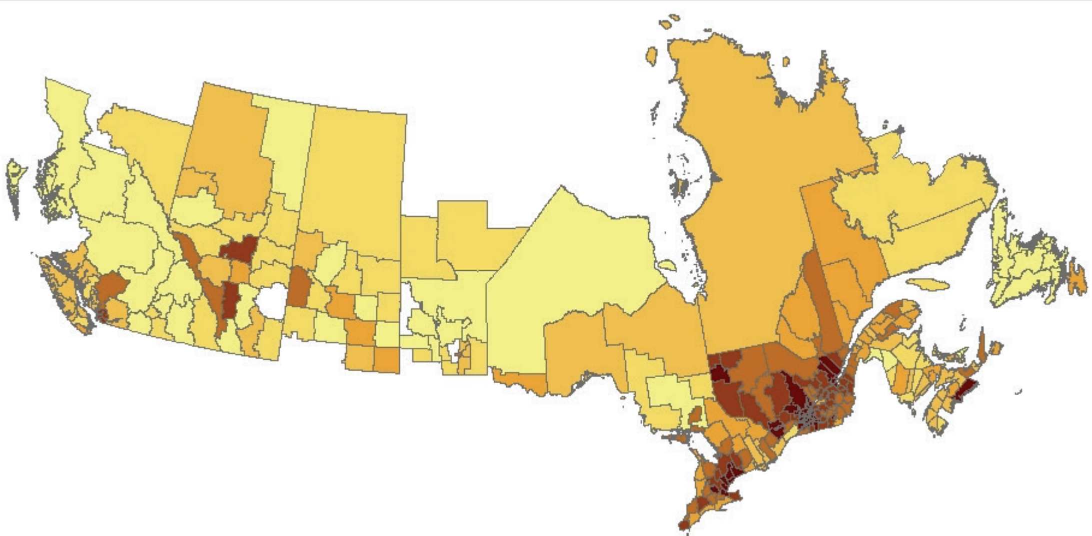


Figure 3. mobility change in April 2020 relative to February 2020



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visions are due to missing data in the Facebook mobility measures.[7] The map shows that the decrease in night light intensity was relatively spread out across Canada, from east to west. The largest decreases in luminosity, however, appear to be concentrated in the relatively urbanized and densely populated areas of Southern Ontario and in Quebec along the St. Lawrence River.

Table 1. Summary Statistics, Time-Varying Variables

Var. Name	Obs.	Mean	SD	Min.	Max.
light	5524	2.666	6.971	0.024	113.193
asinh(light)	5524	1.044	0.899	0.024	5.422
move	5524	-0.027	0.151	-0.640	0.662
asinh(move)	5524	-0.026	0.149	-0.603	0.621
stayput	5524	0.237	0.049	0.097	0.459
asinh(stayput)	5524	0.234	0.048	0.097	0.444
Δlight	5524	-0.039	2.001	-57.624	17.786
Δasinh(light)	5524	0.036	0.197	-1.199	1.065

Table 2. Summary Statistics, Time-Invariant Variables

Var. Name	Obs	Mean	SD	Min	Max
population	262	133,051.469	315,267.417	8,694	2,731,571
asinh(population)	262	11.618	1.107	9.764	15.514
pop. density	262	110.067	420.133	0.052	4,162.841
asinh(pop. density)	262	3.200	1.931	0.052	9.027
mfg. share	262	0.041	0.019	0.004	0.105
asinh(mfg. share)	262	0.041	0.019	0.004	0.104
retail share	262	0.126	0.024	0.072	0.179
asinh(retail share)	262	0.125	0.024	0.072	0.178
drinks, food share	262	0.046	0.012	0.009	0.092
asinh(drinks, food share)	262	0.046	0.012	0.009	0.092
num. businesses	262	4,916.469	12,820.273	230.000	112,181

Note that most Census Divisions underwent a decrease in luminosity during this period; all but the lightest 2 categories on the map represent wholly negative changes in luminosity. This is further confirmed in Figure 2, which shows the Census Divisions that saw a decrease in night light intensity during this period; the map clearly shows that a large majority of Census Divisions became dimmer during the first phase of the pandemic.

In the final map, shown in Figure 3, I present a visualization of the Facebook mobility measure across Census Divisions. The data are again presented in 7 quantiles, with darker colours representing larger reductions in mobility relative to the pre-COVID baseline. As in the decrease in luminosity from Figure 1, there is considerable variation in mobility declines across Canada in this period, but the largest declines appear to be in Southern Ontario and near Montreal in Quebec. The visual evidence therefore suggests that there could be a connection between these two concurrent changes.

I next turn to summary statistics of the key variables in the paper. In Table 1, I present statistics for the time-varying variables. The average luminosity across Census Divisions is relatively low, which is likely due to the large number of Census Divisions that are relatively sparsely populated. There are a number of Census Divisions with high levels of luminosity, however; the maximum value of 113.193, for example, belongs to Toronto. In the next several rows, I describe the Facebook variables. The movement variable, move, shows an average relative mobility change in the negatives, although this value is small at -0.027; this suggests that mobility during the period examined (March 2020 to December 2021) was lower than pre-COVID baseline levels.[8] The summary statistics of the stayput variable show that a minority of Facebook's users stayed in one small area for any given month; while there is some variability even the maximum value of stayput is below 0.5, suggesting that most users moved to at least 1 other Bing tile during the period examined. Finally, I present the mean of the change in luminosity for a given month relative to that same month in 2019, in that same Census Division. The change is negative, although small.

Table 2 presents the summary statistics of the time-invariant variables from the Census of Population and the Canadian Business Counts. The mean population in the Census Divisions in my sample is large, at over 130,000. There is considerable variability, however,

Table 3. Validity of Luminosity

	(1)	(2)	(3)	(4)	(5)
Dep. Var.:	asinh(light)	asinh(light)	asinh(light)	asinh(light)	asinh(light)
asinh(pop)	0.844***				
	(0.0433)				
asinh(pop density)		0.576***			
		(0.0201)			
asinh(num businesses)			0.819***		
			(0.0405)		
asinh(num mfg businesses)				0.789***	
				(0.0455)	
asinh(num retail businesses)					0.871***
					(0.0467)
Province FE	yes	yes	yes	yes	yes
Observations	262	262	262	262	262
R-squared	0.860	0.930	0.862	0.837	0.853

Note: *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level. Standard errors clustered by Census Division. Observations are weighted by each Census Division's 2016 population.

7 Due to privacy concerns or insufficient user counts, Facebook does not report data for all regions in all days.

8 The average reduction in mobility using Census Division-month-years is larger in 2020 on average (-0.033) compared to 2021 (-0.021).

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with the standard deviation being over 300,000. This further stresses the need to weight observations by population size, as I do in the main regressions. I also find that population density is highly variable across Census Divisions as well; in supplementary analyses, I test whether mobility has a differential effect in dense versus sparsely populated areas. In line with both population and density, I also find that the number of businesses varies highly across regions, with a standard deviation over twice as large as the mean number of businesses of 4,916. I next show that both manufacturing and food and drinks businesses make up a small share of total businesses, at approximately 4% each. Retail businesses make up a larger share, at 12.6%.

RESULTS

Main Analysis

I first test the validity of the night lights measure as a proxy for economic activity in Canadian Census Divisions. Table 3 presents a series of cross-sectional regression results where I regress the (asinh transformed) mean radiance measure, in March 2020, against transformed measures for population, population density, the number of businesses, the number of manufacturing businesses, and the number of retail businesses, respectively. The cross-sectional regressions include province fixed effects. The results show that all 5 variables are strongly positively associated with the mean luminosity of a Census Division; this provides some reassurance that night lights are a suitable way to capture economic activity across Canada.

Table 4 presents the main results of the paper, which connect the night light brightness of a Census Division with the Facebook measures of mobility and staying put. Columns 1-4 focus on the movement measure, while columns 5-8 use the staying put measure instead. Column 1 uses un-transformed measures of luminosity and mobility, while including Census Division fixed effects and province-month-year fixed effects. The coefficient of 20.27 in the resulting regression is positive and highly statistically significant, which suggests that reductions in mobility led to a corresponding drop in economic activity as proxied by luminosity. Column 2 instead uses a transformed version of the light and movement variables with the same set of fixed effects, and confirms the finding from Column 1 that the two are positively correlated. In column 3, I use the same fixed effects as in Column 2 but use a differenced version of the transformed luminosity measure by subtracting the same month's mean brightness in 2019 for that Census Division. Although smaller in size and less statistically significant, the resulting coefficient again consistently shows that reduced mobility is associated with lower economic activity levels. Finally, in column 4 I return to regressing the transformed light measure against the transformed movement measure in column 2 but replace the Census Division fixed effects with Census Division-year fixed effects; this is my preferred specification, and I focus on this specification for the rest of the paper. The coefficient is again positive and highly statistically significant. The implied elasticity implies that a 1% reduction in movement is associated with a 0.732% reduction in night light brightness.

In columns 5-8 of Table 4, I instead use Facebook's measure of staying put. The results are generally less robust, with only the coefficients in columns 1 and 4 being statistically significant. In all columns, however, the coefficient is positive. The positive coefficient implies that Census Divisions where more Facebook users are staying put are also brighter. This is an interesting result, given that the transformed measures of movement and staying put are highly negatively correlated, with a correlation coefficient of -0.7948, and given that columns 1-4 clearly show that movement and luminosity are positively correlated. The coefficient in Column 8, however, shows that a 1% increase in staying put is associated with a 1.06% increase in night light brightness. This relationship between the two variables is likely due to increased light usage in residences due to people staying at home. Due to this potential confounding issue, I focus on the movement measure for the remainder of the analysis in this paper.

Table 5 next takes the preferred specification from Table 4, Column 4, and separates the sample by year. This exercise examines whether the relationship between movement and luminosity, and by proxy economic activity, is specific to the earlier stages of the pandemic. If, for example, by 2021 most workplaces and retailers have adapted to a post-COVID environment and moved away from in-person requirements then one would expect the relationship between movement and night light brightness to be weaker in 2021. The results in Table 5 do not support this pattern. In almost all specifications, the association between movement and luminosity remains positive and statistically significant at conventional levels; the lone exceptions are the coefficients in Column 3, which uses the differenced version of the luminosity measure for 2020, and Column 7, which takes a first difference of both the movement variable on the right-hand side and

Table 4. Main Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:	**light**	**asinh(light)**	**Δasinh(light)**	**asinh(light)**	**light**	**asinh(light)**	**Δasinh(light)**	**asinh(light)**
move	20.27***							
	(5.310)							
asinh(move)		0.753***	0.182*	0.732***				
		(0.132)	(0.100)	(0.135)				
stayput					36.67**			
					(15.70)			
asinh(stayput)						0.308	0.315	1.060***
						(0.324)	(0.337)	(0.374)
CD FE	yes	yes	yes	no	yes	yes	yes	no
Prov-month-year FE	yes	yes	yes	yes	yes	yes	yes	yes
CD-year FE	no	no	no	yes	no	no	no	yes
Observations	5,528	5,528	5,528	5,524	5,528	5,528	5,528	5,524
R-squared	0.921	0.989	0.670	0.990	0.920	0.989	0.669	0.990

Note: *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level. Standard errors clustered by Census Division. Observations are weighted by each Census Division's 2016 population.

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Table 5. Main Results, by Year

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.:	light	asinh(light)	Δasinh(light)	light	asinh(light)	Δasinh(light)	Δasinh(light)
Year:	2020	2020	2020	2021	2021	2021	2021
move	13.45**			10.82**			
	(5.587)			(5.263)			
asinh(move)		0.599***	-0.204		0.830***	0.480***	
		(0.146)	(0.127)		(0.166)	(0.160)	
Δasinh(move)							-0.0253
							(0.174)
CD FE	yes	yes	yes	yes	yes	yes	yes
Prov-month FE	yes	yes	yes	yes	yes	yes	yes
Observations	2,600	2,600	2,600	2,924	2,924	2,924	2,414
R-squared	0.964	0.990	0.746	0.905	0.989	0.631	0.531

Note: *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level. Standard errors clustered by Census Division. Observations are weighted by each Census Division's 2016 population.

Table 6. Main Results, Interactions

	(1)	(2)	(3)	(4)
Dep. Var.:	asinh(light)	asinh(light)	asinh(light)	asinh(light)
asinh(move)	1.150***	1.011***	-0.0344	1.702***
	(0.147)	(0.242)	(0.288)	(0.284)
asinh(move) x asinh(pop dens)	-0.189***			
	(0.0375)			
asinh(move) x asinh(mfg share)		-7.503		
		(5.327)		
asinh(move) x asinh(retail share)			5.516**	
			(2.240)	
asinh(move)x asinh(drinks, food share)				-20.14***
				(4.855)
CD-year FE	yes	yes	yes	yes
Prov-month-year FE	yes	yes	yes	yes
Observations	5,524	5,524	5,524	5,524
R-squared	0.991	0.990	0.990	0.990

Note: *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level. Standard errors clustered by Census Division. Observations are weighted by each Census Division's 2016 population.

the light variable on the left. The column 7 results, in particular, removes a significant amount of variation from the data, and also removes the first couple of months of data for 2021 as well, since there is no corresponding data for 2020. The results in the column are smaller and not significant, suggesting that the removal of this variation in the data is important for the results.[9] Nonetheless, taken together, the results of Table 5 are largely consistent with mobility having an effect on economic activity through 2021.

The final table in the main analysis, Table 6, expands on the main results by investigating whether certain Census Divisions with certain characteristics exhibit a stronger or weaker relationship between mobility and luminosity. In Column 1, I include an interaction term between mobility and population density. The resulting negative coefficient on the interaction term suggests that the positive relationship between mobility and luminosity in denser regions is weaker. There are competing explanations for why this could be the case. Denser regions could be unobservably different in some way to sparsely populated Census Divisions along educational, socio-economic, or demographic lines; these differences could translate to different effects of mobility. For example, if denser regions specialize in occupations or industries which are more capable of operating remotely, then one would expect that mobility declines due to COVID would not affect economic activity as severely. Another potential explanation for column 1's estimates are the manner in which Facebook mobility data is constructed. Mobility is defined as changes, relative to a baseline, of the number of approximately several hundred square meter tiles visited by users. Denser regions presumably also offer amenities, such as groceries and food, at a closer proximity in addition to having shorter distances for commutes to work. This might result in more urbanized, denser Census Divisions seeing a smaller

9 T is also not obvious whether this is an appropriate procedure to undertake, since the Facebook data is already differenced, in a sense. The mobility variable is already taken relative to a baseline from pre-COVID, so a further difference from 2020 to 2021 is effectively a change of a change, which may remove too much variation from the data.

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link between mobility as measured by Facebook and luminosity. Similarly, one final possibility is that in denser areas, the proportion of lights comprised of stable, non-varying light sources like street lights is higher compared to less dense areas, where luminosity may better capture mobility. Regardless of the cause, column 1 further highlights the value of luminosity in proxying for economic activity, particularly in less dense regions.

Columns 2 to 4 next test whether Census Divisions which have different industry compositions, as measured by the business count share of various industries from the Canadian Business Counts, have a differential night light response to mobility changes. There is a negative coefficient on the interaction terms for the manufacturing and food and drinks industry shares (although the manufacturing coefficient is statistically insignificant), suggesting that economic activity in Census Divisions with heavier proportions of those industries is less responsive to mobility changes.[10] In contrast, regions with a heavier proportion of businesses that are classified as retail have a larger negative relationship between mobility and luminosity, consistent with the ongoing narrative that in-person retail has been hard-hit during the pandemic.

Robustness Checks

I conduct several robustness checks to verify that the main results from Table 4 are robust. First, in Table A1 in the Appendix, I re-estimate all the specifications from Table 4 but weighting all observations equally; this is in contrast to the main analyses, which weight observations by each Census Division's 2016 population. The results are broadly qualitatively similar to the main results from Table 4, with the coefficients on movement and staying put largely maintaining their sign and statistical significance; the lone exception is the coefficient on movement for the differenced version of luminosity, which becomes insignificant at conventional levels. Nonetheless, the coefficients in Table A1 as a whole corroborate the main analysis.

I next explore different combinations of fixed effects in Table A2 in the Appendix. In column 1, I include only Census Division fixed effects. In column 2, I use Census Division fixed effects and month-year fixed effects. Finally, in column 3 I use Census Division-year fixed effects and month-year fixed effects. These combinations of fixed effects notably do not control for any time-varying provincial unobservables. In all 3 columns, the coefficient becomes negative and is statistically significant, although the magnitude varies somewhat across columns. The results in Table A2 therefore highlight the importance of controlling for omitted variables that are time-varying at the province level. For example, one such omitted variable could be provincial COVID policies, which could either restrict or encourage mobility but could also have an effect on economic activity. Such an omitted variable could therefore lead to biases, either positive or negative, in the estimate of the mobility-luminosity relationship.

To further examine whether my main results are driven simply by the choice of fixed effects or specification, in Table A3 in the Appendix I separately estimate my main specification from Column 4, Table 4, by each of the 4 largest provinces: Ontario, Quebec, British Columbia, and Alberta. The results are all very consistent with my main analysis, and confirm that mobility has a positive relationship with night light brightness within Census Divisions. As these 4 provinces make up the large majority of both the Canadian population as well as the Census Divisions in my sample, Table A3 provides convincing evidence that there truly is a dampening effect on economic activity when mobility declines across Canada.

One concern could be that coverage of some areas is not consistent throughout the year. Specifically, some of the more northerly parts of Canada may be missing coverage in the summer months; this is consistent with Hu & Yao (2022), who present a figure of worldwide coverage of night lights data in June suggesting that this may be the case. To address concerns about summertime coverage, I have included an additional Appendix table, Table A4, where I re-estimate the main specifications dropping one summer month (June, July, August) at a time and also dropping all three. I focus on only the regressions with inverse hyperbolic sine transformations and with either Census Division fixed effects or with Census Division-year fixed effects and only focus on the movement variable, for the sake of brevity. The results show that dropping the months one at a time (including June) does not affect the main estimates' statistical significance. Dropping June and July slightly lowers the size of the estimates, while dropping August slightly increases it.

When dropping all three months, I do find that the regression coefficient on move for the specification with Division-year fixed effects is now only significant at the 10% level, with lower magnitude. This, however, is not surprising given that the removal of approximately 25% of my sample will inevitably lower the precision of my estimates, especially in a specification that includes Division-year fixed effects which relies on variation within a Census Division for a given year. Another possible mechanism that can explain the results in Table A4 is that there are heterogeneous effects in the summertime for mobility's effect on luminosity; it is not obvious, as a result, whether dropping the summer months represents the best possible sample for my analysis. I therefore interpret the findings of Table A4 as being broadly consistent with the main results reported in this paper.

In the main paper, I have used the mean light luminosity of a Census Division as the measure of choice. However, another reasonable choice for an outcome variable is to take that same measure and scale it in per-capita terms.[11] I therefore take the light measure from the main analysis and divide it by that Census Division's 2016 population, and then multiply by a million to rescale the variable. This new measure can be interpreted as mean luminosity per million. Using this measure, I re-estimate the entirety of the main table (Table 4). This robustness check is reported in Table A5 in the Appendix. The results are very similar, in statistical significance and magnitude, to the main results from Table 4; this suggests that my analysis is robust to rescaling the outcome variable to be a per capita measure.

A visual examination of the maps presented in this paper suggests that there could be correlation in the outcome and Facebook variables across nearby Census Divisions. To account for spatial correlation in the variables used in this paper, I therefore re-estimate the main table results from Table 4 but instead use Conley standard errors, which allow for spatial correlation.[12] The errors use the latitude and longitude coordinates of the centroid of each Census Division, with a distance cutoff set to 1000 kilometers. This exercise is reported in Table A6. In summary, the results using the move variable remain highly statistically significant at the 1% level, except for the column 3 result which now is just insignificant (where it was previous just significant at the 10% level). The results for the staying put variable do lose some significance for some of the coefficients, further reinforcing the decision to focus on the move variable as the main measure of choice in this paper. The results from Table A6 are largely consistent with the results from the main analysis, and demonstrate that spatial correlation is not a critical issue of concern.

10 One potential explanation for the food and drinks finding is that Census Divisions with a heavier proportion of food and drinks businesses are also more densely populated, suggesting that the findings in Column 3 could be picking up some of the effect from population density in Column 1.

11 Hu and Yao (2022) and Bayer, Hu, and Yao (2022) both use a per-capita measure in their papers, which also use luminosity as a measure of economic activity.

12 I use the reg2hdfespatial package for Stata modified by Ramin Forouzandeh for use in Baum-Snow and Han (2019) and originally developed based on work by Hsiang (2010) and Thiemo Fetzer.

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CONCLUSION

This paper employs time-varying satellite night light data for the first time in a Canada-focused economics paper to estimate the effects of mobility declines on economic activity. I find that a 1% decline in mobility is associated with a 0.723% decline in luminosity, suggesting that COVID-related declines in mobility had a dampening effect on the Canadian economy. The main results are robust to a series of alternative methods and specifications.

The findings highlight the trade-off that politicians incur by restricting mobility to curb the spread of COVID-19. One policy implication that can ameliorate the severity of this trade-off is to further help businesses transition away from a reliance on in-person activities. While in some cases this may not be possible, in-person alternatives such as curbside pickup or remote work have increasingly allowed Canadians to continue with life as the pandemic stretches on. Further developments in such alternatives may reduce the effects of stay-at-home orders and mobility declines on economic activity, although it is troubling that this relationship seems to be just as strong in 2021 as it did in 2020.

My work also demonstrates the value of using satellite night light data as an alternative to obtaining economic data for smaller sub-national areas at a relatively high frequency. While much of the economics literature has focused on the use of such data in developing country settings, where data collection and quality is often poor, this paper demonstrates that developed countries such as Canada, where economic data at a high frequency for small areas is unavailable, can also benefit from the use of this valuable data source in economics research.

REFERENCES

Allcott, H., Boxell, L., Conway, J., Gentzkow, M., Thaler, M. & Yang, D. (2020). Polarization and public health: Partisan differences in social distancing during the coronavirus pandemic. *Journal of Public Economics*, 191: 104254.

Armstrong, D., Lebo, M. & Lucas, J. (2020). Do COVID-19 Policies Affect Mobility Behaviour? Evidence from 75 Canadian and American Cities. *Canadian Public Policy*, 46(S2): S127-S144.

Baum-Snow, N. & Han, L. (2019). *The microgeography of housing supply*, Working Paper, University of Toronto.

Beland, L-P., Brodeur, A., Mikola, D. & Wright, T. (2022). The Short-Term Economic Consequences of COVID-19: Occupation Tasks and Mental Health in Canada. *Canadian Journal of Economics*, 55(51): 214-247.

Bellemare, M. & Wichman, C. (2020). Elasticities and the Inverse Hyperbolic Sine Transformation. *Oxford Bulletin of Economics and Statistics*, 82(1): 50-61.

Beyer, R., Jain, T. & Sinha, S. (2020). *Lights out? COVID-19 containment policies and economic activity*. World Bank Policy Research Working Paper 9485.

Beyer, R., Franco-Bedoya, S. & Galdo, V. (2021). Examining the economic impact of COVID-19 in India through daily electricity consumption and nighttime light intensity. *World Development*, 140: 105287.

Beyer, R., Hu, Y. & Yao, J. (2022). *Measuring Quarterly Economic Growth from Outer Space*. World Bank Working Paper No. 9893.

Brodeur, A., Grigoryeva, I. & Kattan, L. (2021). Stay-at-Home Orders, Social Distancing and Trust. *Journal of Population Economics*, 34(4): 1321-1354.

Chan, J. (2020). The Geography of Social Distancing in Canada: Evidence from Facebook. *Canadian Public Policy*, 46(S1): S19-S28.

Chor, D. & Li, B. (2021). *Illuminating the Effects of the US-China Tariff War on China's Economy*, NBER Working Paper No. 29349.

Civelli, A., Horowitz, A. & Teixeira, A. (2018). Foreign aid and growth: A Sp P-VAR analysis using satellite sub-national data for Uganda, *Journal of Development Economics*, 134: 50-67.

Dow, A., Herdagdelen, A., Mohassel, P., Pompe, A. & State, B. (2020). Protecting privacy in Facebook mobility data during the COVID-19 response [blog post]. Retrieved from https://research.facebook.com/blog/2020/06/protecting-privacy-in-facebook-mobility-data-during-the-covid-19-response/

Egorov, G., Enikolopov, R., Makarin, A. & Petrova, M. (2021). Divided we stay home: Social distancing and ethnic diversity, *Journal of Public Economics*, 194: 104328.

Elvidge, C.D., Baugh, K.E., Zhizhin, M. & Hsu, F.C. (2013). Why VIIRS data are superior to DMSP for mapping nighttime lights, *Asia-Pacific Advanced Network*, 35: 62.

Espitia, A., Mattoo, A., Rocha, N., Ruta, M. & Winkler, D. (2022). Pandemic trade: COVID-19, remote work and global value chains, *The World Economy*, 45(2): 561-589.

Feir, D., Gillezeau, R. & Jones, M. (2018). *Illuminating Indigenous Economic Development*, University of Victoria Department Discussion Paper DDP1806.

Henderson, J.V., Storeygard, A. & Weil, D. (2012). Measuring Economic Growth from Outer Space, *American Economic Review*, 102(2): 994-1028.

Hsiang, S. (2010). Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America, *Proceedings of the National Academy of Sciences*, 107(35): 15367-15372.

Hu, Y. & Yao, J. (2022). Illuminating economic growth, *Journal of Econometrics*, 228(2): 359-378.

Jones, S., Lange, F., Riddell, C. & Warman, C. (2020). Waiting for Recovery: The Canadian Labour Market in June 2020. *Canadian Public Policy*, 46(S2): S102-S118.

Lee, Y. (2018). International isolation and regional inequality: Evidence from sanctions on North Korea, *Journal of Urban Economics*, 103: 34-51.

Lemieux, T., Milligan, K., Schirle, T. & Skuterud, M. (2020). Initial Impacts of the COVID-19 Pandemic on the Canadian Labour Market, *Canadian Public Policy*, 46(S1): S55-S65.

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Table A1. Main Results, No Weighting

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:	**light**	**asinh(light)**	**Δasinh(light)**	**asinh(light)**	**light**	**asinh(light)**	**Δasinh(light)**	**asinh(light)**
move	4.492***							
	(0.936)							
asinh(move)		0.521***	0.0576	0.532***				
		(0.0719)	(0.0390)	(0.0796)				
stayput					6.352*			
					(3.322)			
asinh(stayput)						0.244	0.185	0.691**
						(0.228)	(0.157)	(0.277)
CD FE	yes	yes	yes	no	yes	yes	yes	no
CD-year FE	no	no	no	yes	no	no	no	yes
Prov-month-year FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	5,528	5,528	5,528	5,524	5,528	5,528	5,528	5,524
R-squared	0.859	0.968	0.584	0.970	0.858	0.968	0.584	0.969

Note: *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level. Standard errors clustered by Census Division. Observations are unweighted.

Table A2. Alternate FE

	(1)	(2)	(3)
Dep. Var.:	**asinh(light)**	**asinh(light)**	**asinh(light)**
asinh(move)	-1.053***	-0.249*	-0.422***
	(0.0759)	(0.132)	(0.156)
CD FE	yes	yes	no
CD-year FE	no	no	yes
month-year FE	no	yes	yes
Observations	5,528	5,528	5,524
R-squared	0.964	0.982	0.982

Note: *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level. Standard errors clustered by Census Division. Observations are weighted by each Census Division's 2016 population.

Table A3. Main Results, by Large Provinces

	(1)	(2)	(3)	(4)
Dep. Var.:	**asinh(light)**	**asinh(light)**	**asinh(light)**	**asinh(light)**
Province:	**Ontario**	**Quebec**	**BC**	**Alberta**
asinh(move)	0.872**	0.611***	1.143**	1.348***
	(0.404)	(0.191)	(0.416)	(0.337)
CD-year FE	yes	yes	yes	yes
month-year FE	yes	yes	yes	yes
Observations	1,061	2,121	522	379
R-squared	0.990	0.990	0.990	0.930

Note: *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level. Standard errors clustered by Census Division. Observations are weighted by each Census Division's 2016 population.

Table A4. Main Results, Dropping Summer Months

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:	**asinh(light)**	**asinh(light)**	**asinh(light)**	**asinh(light)**	**asinh(light)**	**asinh(light)**	**asinh(light)**	**asinh(light)**
asinh(move)	0.596***	0.541***	0.677***	0.592***	0.849***	0.809***	0.437***	0.229*
	(0.129)	(0.133)	(0.127)	(0.128)	(0.149)	(0.150)	(0.136)	(0.136)
CD FE	Yes	No	Yes	No	Yes	No	Yes	No
CD-year FE	No	Yes	No	Yes	No	Yes	No	Yes
Prov-month-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,027	5,023	5,025	5,021	5,024	5,020	4,020	4,015
R-squared	0.990	0.991	0.990	0.990	0.989	0.989	0.991	0.992

Note: *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level. Standard errors clustered by Census Division. Observations are weighted by each Census Division's 2016 population.

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Table A5. Main Results, Per Capita

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:	**light pc**	**asinh(light pc)**	**Δasinh(light pc)**	**asinh(light pc)**	**light pc**	**asinh(light pc)**	**Δasinh(light pc)**	**asinh(light pc)**
move	18.55**							
	(8.287)							
Asinh(move)		0.704***	0.169	0.786***				
		(0.137)	(0.110)	(0.146)				
stayput					25.39*			
					(13.91)			
Asinh(stayput)						0.682**	0.822**	1.063***
						(0.325)	(0.351)	(0.396)
CD FE	Yes	Yes	Yes	No	Yes	Yes	Yes	no
CD-year FE	No	No	No	Yes	No	No	No	Yes
Prov-month-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,528	5,528	5,528	5,524	5,528	5,528	5,528	5,524
R-squared	0.864	0.966	0.618	0.967	0.864	0.965	0.619	0.966

Note: *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level. Standard errors clustered by Census Division. Observations are weighted by each Census Divis 2016 population.

Table A6. Main Results, Conley Standard Errors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:	**light**	**asinh(light)**	**Δasinh(light)**	**asinh(light)**	**light**	**asinh(light)**	**Δasinh(light)**	**asinh(light)**
move	20.27***							
	(5.542)							
asinh(move)		0.753***	0.182	0.732***				
		(0.146)	(0.177)	(0.153)				
stayput					36.67			
					(32.76)			
asinh(stayput)						0.308	0.315	1.060*
						(0.560)	(0.581)	(0.621)
CD FE	Yes	Yes	Yes	No	Yes	Yes	Yes	No
CD-year FE	No	No	No	Yes	No	No	No	Yes
Prov-month-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,528	5,528	5,528	5,524	5,528	5,528	5,528	5,524
R-squared	0.013	0.021	0.002	0.017	0.005	0.000	0.001	0.004

Note: *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level. Standard errors are Conley standard errors to account for spatial correlation, using the latitude a longitude of the centroid of each Census Division and setting the distance cutoff to 1000 kilometers. Observations are weighted by each Census Division's 2016 population.

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