APPENDIX

A Additional Empirical Findings

A.1 Excess People: Visitors minus Residents

An alternative way to quantify the changes in the number of workers and visitors during the day in all districts is to define the share of "excess" people (visitors minus residents), $\mathbb{S}_{i,t}$, at district i on day t as follows:

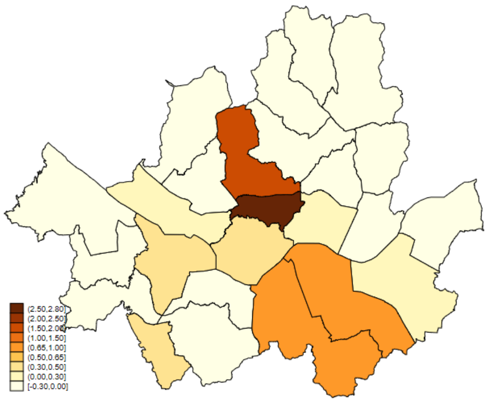
$$\mathbb{S}_{i,t} \equiv \frac{N_{i,t}^{w} - N_{i,t}^{r}}{N_{i,t}^{r}} \tag{13}$$

where N_i^w is the number of people at district i during working hours and includes people at work, visitors, and residents. This number is approximated by the number of subscribers in each district at 3pm every day. N_i^r is the number of residents of district i, which is approximated by the number of subscribers in the district at 3am every day. The share of excess people is generally positive in downtown since during the day it receives many visitors and many people living in the suburbs commute there for work-related reasons. On the other hand, the share of excess people is negative in residential districts such as the suburbs since most of their residents commute to other districts for work.[9]

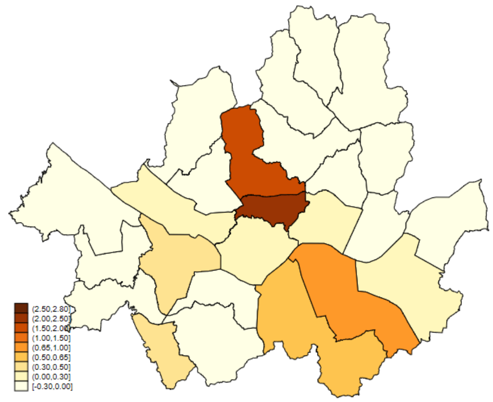
Figure A1 shows the share of excess people in January and February in each of the districts of Seoul. In the downtown districts, the share of excess people is positive and large in both months: Jung (272 percent), Jongno (162 percent), Gangnam (99 percent), Seocho (69 percent), Yeongdeungpo (44 percent), and Yongsan (34 percent). Nonetheless, in February there is an important decline in the share of excess people in these districts. This decline is particularly large during weekends. Panel (c) and (d) show that during weekends there is an important decrease in the movements of people in February relative to the previous month.

[9] In the analysis that follows, we do not consider the commuting patterns observed during the New Year's Day and the Korean New Year Holidays.

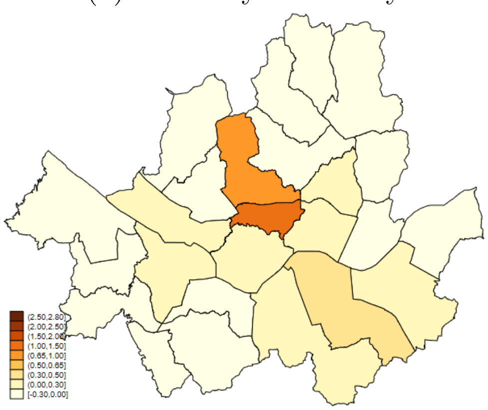
Figure A1: The Share of Excess People in Weekdays and Weekends



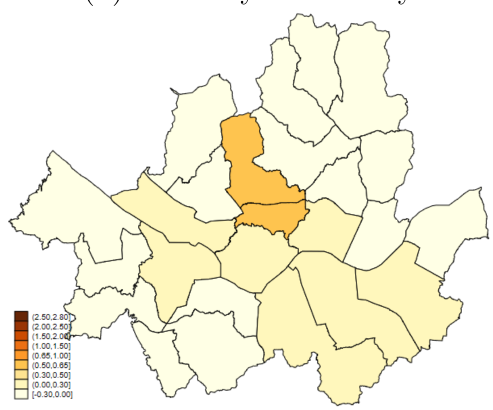
(a) Weekdays: January



(b) Weekdays: February



(c) Weekends: January



(d) Weekends: February

Notes: The figure shows changes in the share of excess people, as defined in equation (13) in each district of Seoul during weekdays and weekends during the months of January and February.

Table AI reports the share of excess people (reported in percent) in each of the six downtown districts. It shows that in all districts the share of excess people decreased in February relative to the previous month. The decrease in the share of excess people is less significant in the district of Geumcheon-gu, a district with an industrial complex that does not have touristic attractions. For the workers commuting to this district for work, the possibilities of working from home are likely to be limited given that the activities that take place in this district are labor intensive (e.g. manufacturing). We observe larger changes in the share of excess people in this district during the weekends.

Table AI: The Share of Excess People in Six Downtown Districts

	Weekdays		Weekends	
District	January	February	January	February
Jung-gu	2.72	2.46	1.02	0.64
Jongno-gu	1.62	1.51	0.97	0.61
Gangnam-gu	0.99	0.95	0.34	0.28
Seocho-gu	0.69	0.64	0.29	0.24
Yeongdeungpo-gu	0.44	0.42	0.15	0.11
Yongsan-gu	0.34	0.29	0.19	0.13

Notes: The reports changes in the share of excess people in six downtown districts during weekdays in January and February.

We use the following specification to test whether the disclosure of the detected cases in each district impacted the commuting patterns of people commuting to those districts:

$$\ln \tilde{\mathbb{S}}_{i,t} = \alpha + \beta \ln N_t + \gamma \ln N_{i,t} + \theta_i + \epsilon_{i,t} \tag{14}$$

where $\tilde{\mathbb{S}}_{i,t}$ denotes the absolute value of the share of excess people in district i on day t. N_t is the cumulative number of confirmed cases on day t in Seoul and N_{it} is the cumulative number of confirmed cases in district i on day t. We include district fixed effects, θ_i. Table AII reports regression results. Column (1) shows that when the number of confirmed cases in Seoul increases by 10 percent, the share of excess people decreases by 0.6 percent. Importantly, a 1 percent increase in the local cases reduces the share of excess people by 7.5 percent. This effect is mostly explained by reductions of commuting during the weekends, precisely when people are more likely to respond to the disclosure of information of the confirmed cases.

We investigate the heterogeneous effects of the public disclosure policy using interaction terms. Columns (5) and (7) show that the commuting of both young and old groups is very sensitive to changes in the number of confirmed cases in each district during the weekdays. Unsurprisingly, the commuting of those between 20 and 60 years of age is unaffected during the weekdays given that their commuting is likely tied to their work responsibilities and to the fact that the government did not impose a lockdown. On the other hand, the same group during the weekends respond drastically to the changes of both the total cases in the city and the total cases in their districts. The table shows that the people in Seoul changed their commuting behavior in response to both to aggregate information and district specific information.

Table AII: Heterogeneous Responses by Demographic Groups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
|Share of Excess People|							
Total Cases	-0.065***	0.041***			0.021	0.077***	-0.003
	(0.012)	(0.008)			(0.015)	(0.014)	(0.007)
Total Cases × Weekend		-0.344***			-0.375***	-0.488***	-0.114***
		(0.035)			(0.072)	(0.063)	(0.027)
Local Cases	-0.754***	-0.080	-0.750***	-0.078	-0.906***	0.881***	-1.108***
	(0.242)	(0.192)	(0.215)	(0.173)	(0.305)	(0.320)	(0.221)
Local Cases × Weekend		-2.632***		-2.719***	-0.889	-4.481***	-0.730
		(0.730)		(0.677)	(1.360)	(1.266)	(0.636)
Observations	16,200	16,200	16,200	16,200	2,700	8,100	5,400
R-squared	0.831	0.840	0.866	0.867	0.882	0.818	0.903
District × Age × Gender	Y	Y	Y	Y	Y	Y	Y
Time	N	N	Y	Y	N	N	N
Group	All	All	All	All	Age<20	20<Age<60	Age>=60

Notes: The table shows the results of estimating equation (13). The dependent variable is the absolute value of the share of excess people in a given district and day. The independent variables are the cumulative number of confirmed cases on a given day in Seoul and the cumulative number of confirmed cases in given district and day.

B Model with Tradable and Non-traded Goods

B.1 Non-Traded Goods

In the baseline version of the model, we consider an economy with a single a single tradable final good. In this section we discuss an extension of the model that introduces non-traded goods. The extension allows for the consumption of non-traded goods at a worker's place of work.

B.2 Workers

As in our baseline frameowrk, workers are risk neutral and have preferences that are linear in a consumption index: $U_{ijo} = C_{ijo}$. This consumption index in this case depends on the consumption of the non-traded good (c_{Nijo}) at workplace location j and the consumption of the traded good (c_{Tijo}). The aggregate consumption index is simply:

$$C_{ijo} = \frac{z_{jo}}{d_{ij}} \left(\frac{c_{Tijo}}{\alpha}\right)^{\alpha} \left(\frac{c_{Nijo}}{1-\alpha}\right)^{1-\alpha} \tag{15}$$

Utility maximization implies that total expenditure on the non-traded good for workers residing in location i and working in location j is a constant share of their income at their place of work:

$$p_{Nj} C_{Nij} = \alpha w_j H_{Mij}$$

where H_{Mij} is the total measure of workers (summing across the two sectors) that work in block j and reside in block i.

The indirect utility from residing in district i and working in district j can be expressed in terms of the wage paid at this workplace (w_j), price of non-traded goods (p_{Nj}), commuting costs (d_{ij}) and the idiosyncratic shock (z_{jo}):

$$u_{ijo} = \frac{z_{jo}}{d_{ij}} \left(\frac{w_j}{p_T}\right)^{\alpha} \left(\frac{w_j}{p_{Nj}}\right)^{1-\alpha} = \frac{z_{jo} w_j}{d_{ij} p_{Nj}^{1-\alpha}} \tag{16}$$

where we have used utility maximization and price for traded goods is normalized to 1 as a numeraire.[10]

Each worker chooses the commute that offers her the maximum utility and can choose to

[10]Commuting costs are proportional to wages to capture changes over time in the opportunity cost of travel time.

work at the home sector. We assume that people in home sector are only engaged in tradable goods consumption and production. The probability that a worker commutes for work to district j during weekdays and weekends is the same as in the baseline framework.

B.3 Production

Production of both tradable and non-tradable goods occurs under conditions of perfect competition. We assume that the production technology for the tradable good is

$$Y_{Tj} = A_j H_{Tj} \tag{17}$$

As a result, $w_j = A_j$. The non-traded good is assumed to be produced according to a constant returns to scale technology with a unit labor requirement:

$$Y_{Nj} = H_{Nj} \tag{18}$$

Perfect competition and constant returns to scale imply that the price of the non-traded good is equal to the wage $p_{Nj} = w_j$. Using this condition along with utility maximization and aggregating across residence locations i for each workplace location j, and using the goods market clearing for the non-traded good for each workplace location j we find:

$$Y_{Nj} = (1 - \alpha) H_{Mj}$$

Combining this result with the production technology, employment in producing non-traded goods in each workplace location is a constant share of total employment in that workplace location $H_{Nj} = (1 - \alpha) H_{Mj}$ while the remaining share of total employment is allocated to producing traded goods $H_{Tj} = \alpha H_{Mj}$. Thus, a fraction of workplace employment is allocated to the traded sector, with the remaining fraction allocated to the non-traded sector.

The aggregate production in the economy is defined as:

$$Y \equiv \sum_{j \in J} (Y_{Tj} + Y_{Nj}) = \sum_{j \in J} (A_j H_{Tj} + H_{Nj}) \tag{19}$$

where J incorporates all districts and home sector.