Utilizing relative risk index to diagnose the vulnerability of local markets to COVID-19

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presented by Gyoungju Lee

Department of Urban and Transportation Engineering
Korea National University of Transportation

Introduction

- COVID-19 has negative economic impacts on local markets, such as increases in store closure and decreases in revenue.
- Food service sector which requires face-to-face contact has been particularly hard hit due considerably to various containment measures such as social distancing, etc.
- Persistent store closure in local market since COVID-19 indicates that those areas have suffered from economic losses due to the pandemic.
- Those market areas have been economically more vulnerable than others to the external threat of pandemic.

Introduction

- Analytical tools need to be devised to diagnose negative economic impact of COVID-19.
- The diagnostic tools are expected to be useful to help implement policy actions and cope with the similar pandemic situations we may encounter in the future, which we experienced during the past three and half years.
- Some primary information could be provided for supporting decision-making towards furthering policy efforts to effectively mitigate economic losses.

Introduction

- We suggest analytic tools to diagnose the vulnerability of local markets to COVID-19.
- We defined a relative risk index comparing the closure counts both **before** and **after** COVID-19

  as a key measure for diagnosing the economic vulnerability of local market.
- We interpret local markets with **higher relative risk** have been **more vulnerable** to the pandemic.
- The relative index was demonstrated empirically for food service sector in neighborhood markets in SMC.

Methodology

- Relative Risk Index
  - Contingency table in epidemiology or public health
    - **A** = smoker & lung cancer patient vs. B = smoker & non-patient
      - [**A** + B = all smoker] = Exposed to smoking
    - **C** = non-smoker & lung cancer patient vs. D = non-smoker & non-patient
      - [**C** + D = all non-smoker] = Unexposed to smoking

		Disease (lung cancer)	
		Yes	No
Exposed to smoking	Yes	A	B
	No	C	D

Methodology

- Relative Risk Index
  - Contingency table in epidemiology or public health
    - RR = Numerator / Denominator
    - $Numerator$ = **A** / (**A** + B) : the patient proportion of smoker group
    - $Denominator$ = **C** / (**C** + D) : the patient proportion of non-smoker group
      - per capita rate of disease occurrence (pcr)
    - A = $Observed\ count$ vs. (**A** + B) × pcr = $Exposed$ × pcr = $Expected\ count$

per capita rate of disease occurrence (pcr)

$$RR = \frac{\frac{A}{A+B}}{\frac{C}{C+D}} = \frac{Numerator}{Denominator} = \frac{A}{(A+B)\times\boxed{\frac{C}{C+D}}} = \frac{A}{Exposed\times pcr} = \frac{Observed}{Expected}$$

Methodology

- Relative Risk Index
    - Conceptual framework was extended to the context of store closure in COVID-19.
        - COVID plays a role of smoking, as external threat factor to local economy.
            - 'Exposed to smoking' corresponds to 'after COVID-19', and vice versa
            - $c\_a(i)$ and $c\_b(i)$ correspond to patients in smokers and non-smokers, respectively and represent the closed counts in local market i **after** and **before** COVID, and vice versa.

		Disease	
		Yes	No
Exposed	Yes	A	B
	No	C	D

		Disease (store closure)	
		Yes	No
Exposed (COVID-19)	After COVID	$c\_a(i)$	$n\_a(i)$
	Before COVID	$c\_b(i)$	$n\_b(i)$

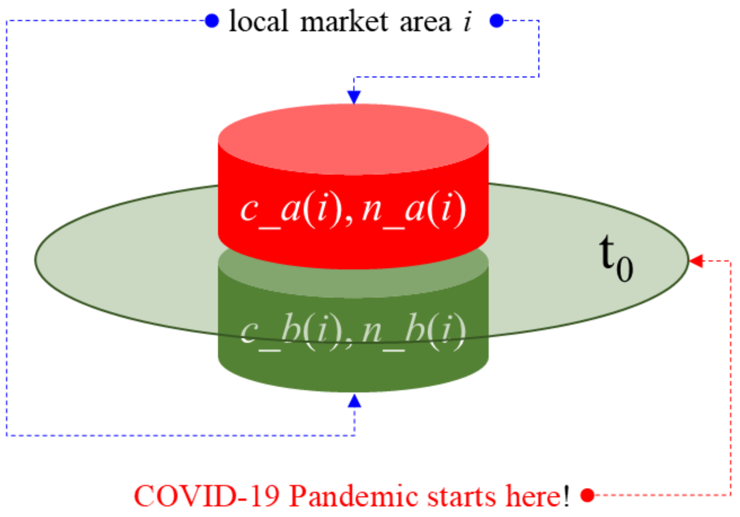
Methodology

- Spatiotemporal Relative Risk Index (STRRI)
  - Extension of **relative risk index** : $STRRI(i)$

		Disease (store closure)	
		Yes	No
Exposed (COVID-19)	Yes	$c\_a(i)$	$n\_a(i)$
	No	$c\_b(i)$	$n\_b(i)$

$$STRRI(i) = \frac{\dfrac{c\_a(i)}{c\_a(i) + n\_a(i)}}{\dfrac{c\_b(i)}{c\_b(i) + n\_b(i)}}$$

$$STRRI(i) = \frac{c\_a(i)}{(c\_a(i) + n\_a(i)) \times \dfrac{c\_b(i)}{c\_b(i) + n\_b(i)}}$$

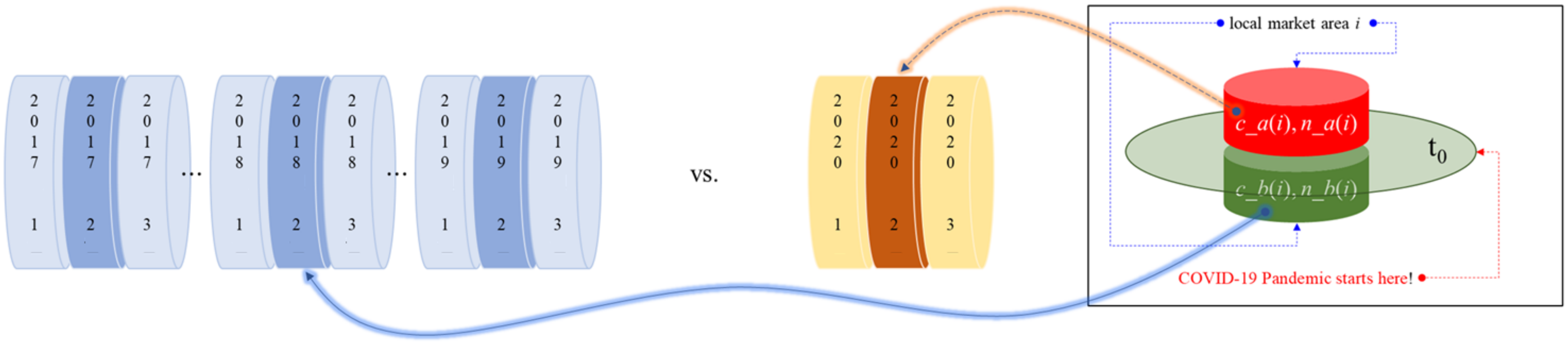


$c\_a(i), n\_a(i)$ = closure, non-closure after t_0

$c\_b(i), n\_b(i)$ = closure, non-closure before t_0

Methodology

- Relative Index
  - We packed 3 months to make temporal variation as small as possible.
    - For example, the obs. count in Feb. 2020 is counted as the sum of obs. from Jan. to March. 2020.
    - In the effort of stabilizing temporal variations, the exp. count is estimated by packing 3 months together and calculating average value of the previous three years before COVID-19 (2017, 2018, 2019).



Methodology

- z-value of STRRI
  - We all know the meaning of RR greater than one.
  - It is another story to interpret any comparative differences of many RRI (≥ 1).
  - We need classification scheme for conveniently summarizing many RRI values, although there seems to be no definite criteria on dealing with RRI (≥ 1).
  - Similar nuisance seems to be true of Location Quotient.

Methodology

- z-value of STRRI
  - For interpretational convenience, we suggest transforming STRRI to z-value as one way around this nuisance.
  - Converted z-values are compared to the threshold on a given significance level provided in the convenient interpretation criteria in standard normal distribution table.

critical z-value(threshold)	degree of vulnerability	p-value
2.57 ~	very high	0.01
1.96 ~ 2.57	high	0.05
1.64 ~ 1.96	moderate	0.1
-1.64 ~ 1.64	random	
-1.96 ~ -1.64	moderate	0.1
-2.57 ~ -1.96	low	0.05
~ -2.57	very low	0.01

- How to interpret the z-value?
- For example, z-value of 3 exceeding the critical value, 2.57 with significant level of 0.01 indicates quite uncommon RR observed purely by random.
- Rather, it would be more reasonable to suspect external factors like COVID may lead to such an unusual relative risk.

Methodology

- z-value of STRRI
  - Some transformation methods of transforming STRRI to z-value[1] : $z[STRRI(i)]$
    - Poisson method : $\frac{O(i)-E(i)}{\sqrt{E(i)}}$
    - Freeman-Tukey method[2] : $\sqrt{O(i)} + \sqrt{O(i) + 1}$- $\sqrt{4E(i) + 1}$
    - Rossi method[3] : $\frac{O(i)-3E(i)+2\sqrt{O(i)E(i)}}{2\sqrt{E(i)}}$

1. Lee, G., Yamada, I., and Rogerson, P.A. 2009. GeoSurveillance: A GIS-based exploratory spatial analysis tool for monitoring spatial patterns and clusters. Manfred M. Fischer and Arthur Getis (eds), Handbook of applied spatial analysis: Software tools, methods, and applications, Springer, Berlin.
2. Rossi, G., Lampugnani, L., and Marchi, M. 1999. An approximate CUSUM procesure for surveillance of health events. Statistics in Medicine, 18: 2111-2122
3. Freeman, M.F. and Tukey, J.W. 1950. Transformations related to the angular and the square root. Annals of Mathematical Statistics 21: 607-611

Methodology

- Summarizing z-values
  - We analyzed 1,090 neighborhood local market areas in Seoul for 34 months (2020.2 ~ 2022.11).
  - Lots of z-values (37, 060) need to be calculated and the method is necessary to summarize them to highlight any key features if any.

Methodology

- Summarizing z-value : $LV(i)$
  - $LV(i)$ is the number of z-values exceeding a critical value (=1.64) in local market i,

    representing how much individual market i is vulnerable to the pandemic.

$$LV(i) = \sum_{k=1}^{34} I_h(Z(i)\_k), \quad I_h(Z(i)\_k) = \begin{cases} 1 & Z(i)\_k \geq cv \\ 0 & otherwise \end{cases}$$

  - Higher $LV(i)$ implies local market i may have experienced serious economic losses **more frequently**.
  - This is the **local summary** for individual market area.

Methodology

- Spatial clustering tendency of $LV(i)$
  - We are curious if there are spatial clustering tendency of local markets with higher $LV(i)$.
  - The vulnerability may not be simply contained within individual market boundary rather arbitrarily designated.
  - The prevalence of higher relative risk over some geographic extents may indicate

    a kind of geographic spillover of local market vulnerability from the negative impact of pandemic.
  - The degree of the geographic spillover can be measured by estimating spatial clustering tendency of

    higher $LV(i)$ values.

Methodology

- Spatial clustering tendency of $LV(i)$
  - The degree of spatial clustering of $LV(i)$ is measured:

$$SC_h = \sum_{i=1}^{n}\sum_{j=1}^{n} I_h(d_{ij})LV(j),\ \ I_h(d_{ij}) = \begin{cases} 1 & d_{ij} \le h \\ 0 & otherwise \end{cases}$$

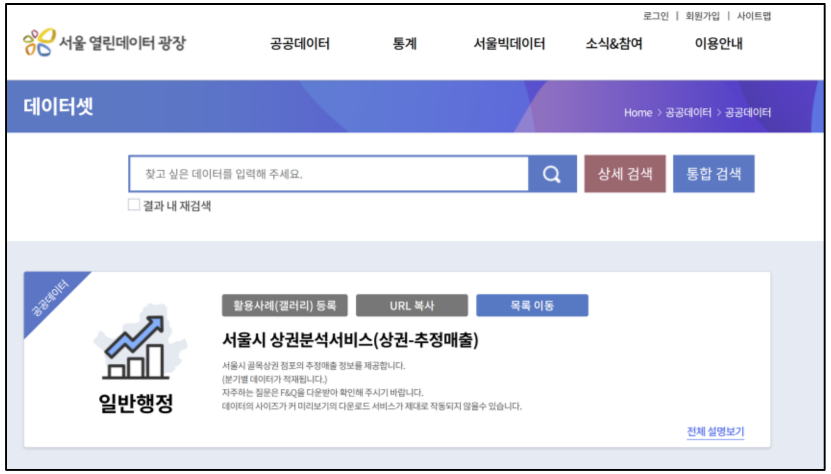
  - Since SC_h is defined as the form of summing $LV(i)$ values, SC_h can be transformed to z-value by carrying out Monte Carlo simulation such that z-values are redistributed randomly.
  - By varying h, identifiable is the geographic extent showing the highest tendency of spatial clustering.
  - This is the **global summary** for highlighting the overall spatial clustering pattern of entire study region.

Data sources

- Data sources (open to public)
  - Store locations, open dates, close dates (csv)
    - Local Government Permit Data[1] (https://www.localdata.go.kr/)
  - Market boundary (shapefile)
    - Neighborhood Market Area Analysis Service Data[2] (https://golmok.seoul.go.kr/main.do)

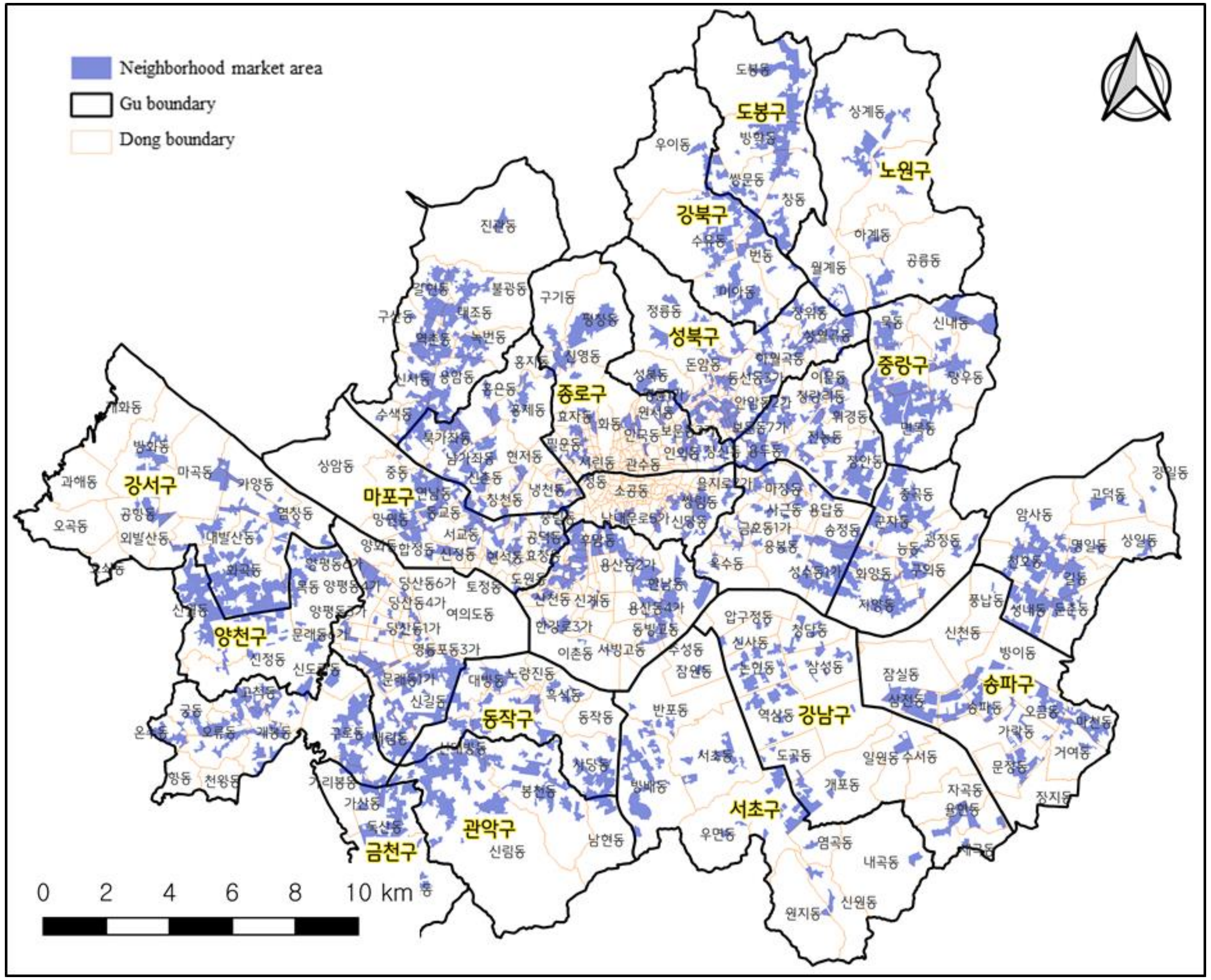
Local Government Permit Data

Neighborhood Market Area Analysis Service Data



Study region

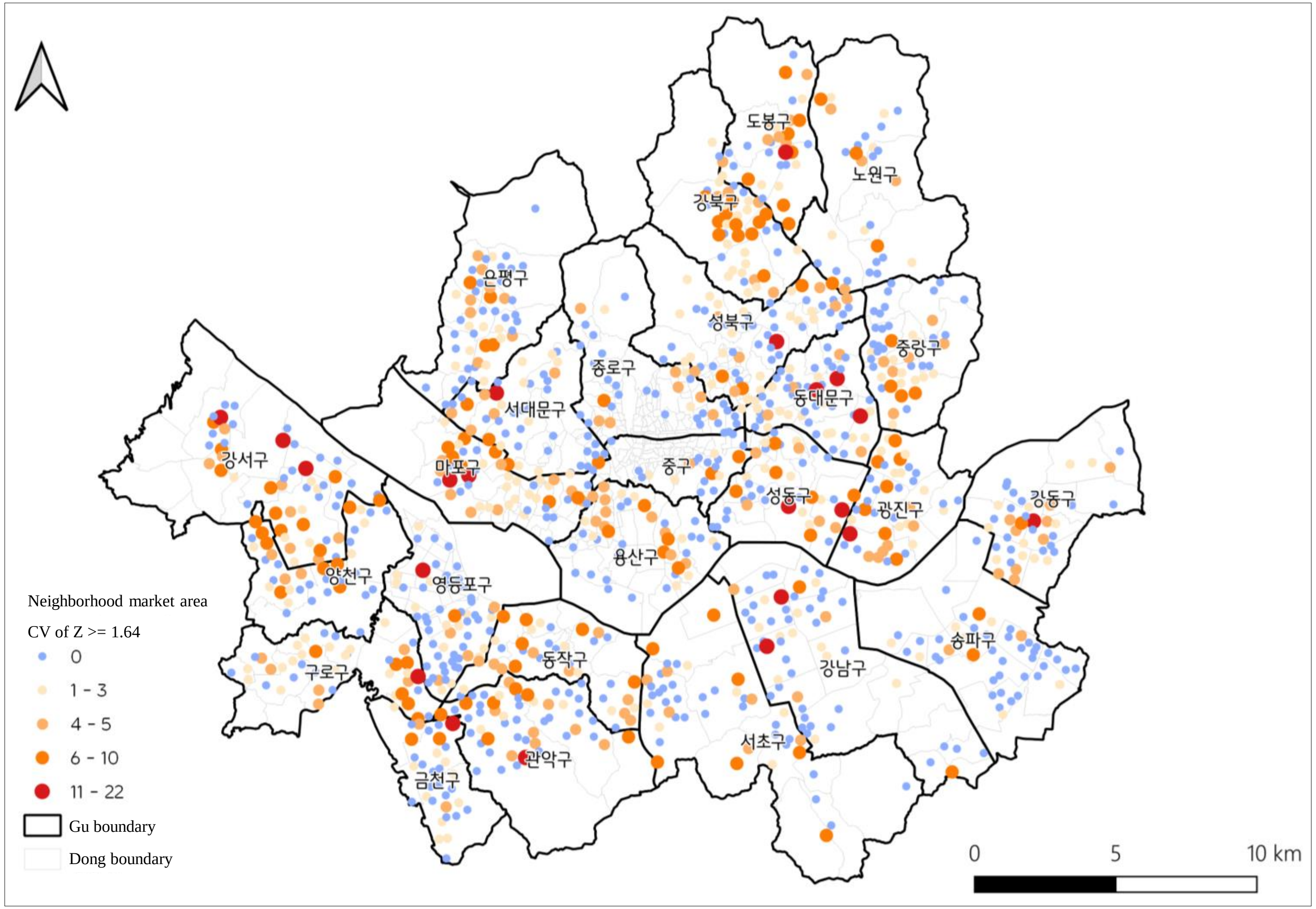
- Administrative divisions and neighborhood market area in Seoul



- The blue polygons shows neighborhood market boundaries.
- Thick black and thin orange lines designate two major administrative divisions corresponding roughly to district and ward.

Empirical analysis and results

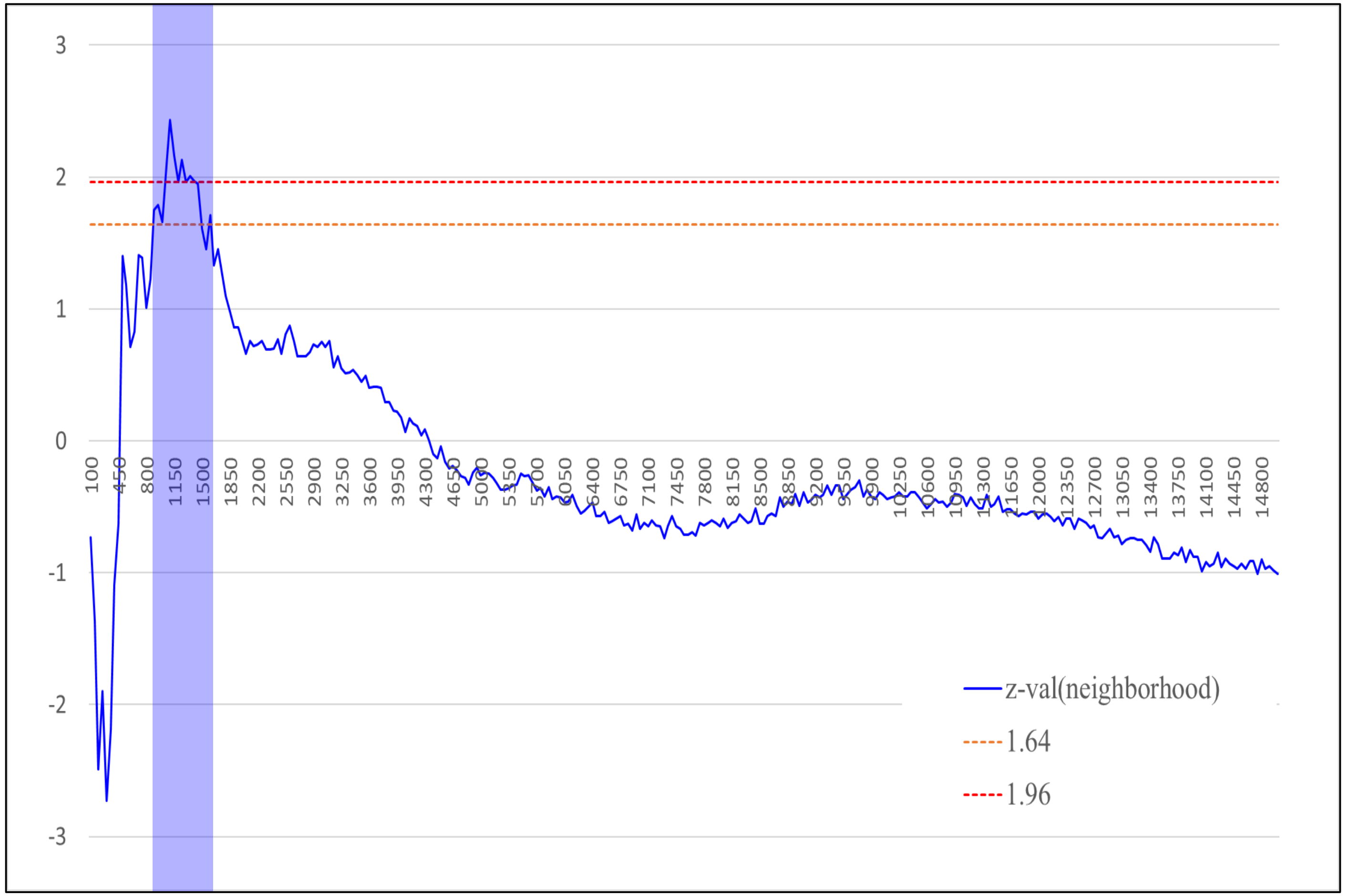
- Spatial distribution of $LV(i)$



- The lager and darker red circles represent markets, where a series of temporal z-values exceed a specific critical value most frequently and thus experienced the most suffering from COVID-19.
- It is noticeable that distinct spatial clusters seem to be widely distributed over the entire region of Seoul.

Empirical analysis and results

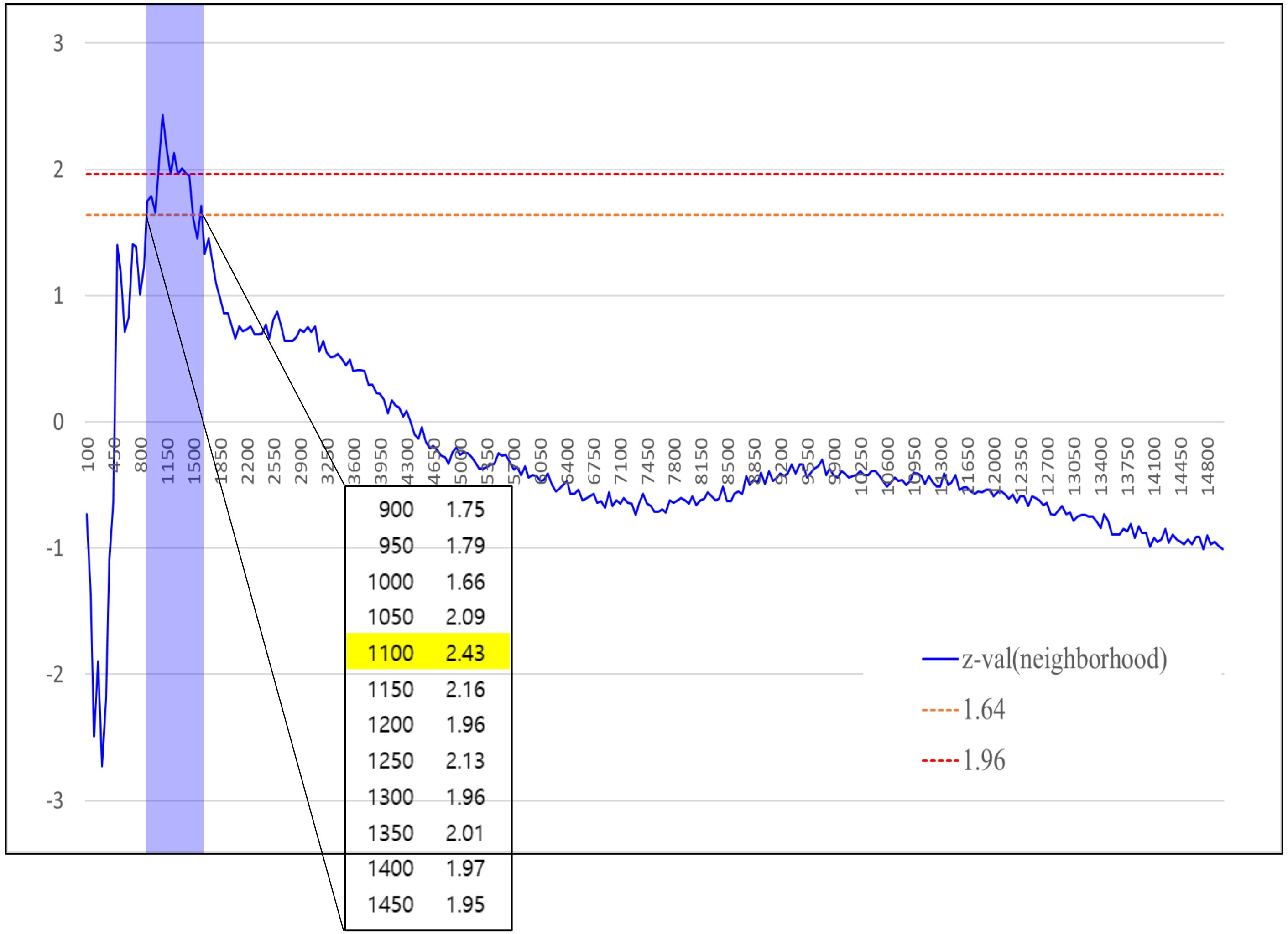
- Changes in SC_h over a range of spatial scale, h



- Blue solid line shows z-values of SC_h, the degree of spatial clustering of $LV(i)$s on a series of spatial scale.
- Dotted lines are two critical z-values.
- Blue masked area highlights a range of spatial scale where statistically significant spatial clustering tendency emerged.

Empirical analysis and results

- Changes in SC_h over a range of spatial scale, h



- Neighborhood markets seem to have the strongest spatial clustering tendency in spatial scale of 1,100m.
- This geographic extent implies the spatial scale the economic suffering was observed most noticeably.
- Daily activities for eating-out seems to have been most drastically shrunken at this scale, leading to most conspicuous declined pattern of local economy since COVID-19.

Conclusion

- We proposed a methodology to diagnose the vulnerability of local markets by comparing the counts of closure **before** and **after** COVID-19 to define the relative risk index.
- Neighborhood markets in Seoul seems to have experienced quite intensive economic losses since the pandemic.
- The most noticeable spatial clustering tendency of local decline were highlighted as far as about 1km.
- This seems to be partly because daily walking activities for eating-out have been shrunken drastically at that geographic extent.

Conclusion

- To enhance the method proposed and find more insights, further research need to incorporate not only store closure data but also data on transaction volumes from credit card companies.
- This study retrospectively examined vulnerability changes since the pandemic using past data.
- Monitoring prospectively the relative risk index may be useful for proactively responding to the potential pandemic situations.
- Strategies may be developed for prompting early intervention in future pandemics before reaching critical stages of vulnerability.